PRECISION LIVESTOCK FARMING '22

Edited by:

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Editorial

We are happy to welcome all participants of the 10th European Precision Livestock Farming Conference to Vienna, Austria.

The last years have shown us how closely animal and human health, and their shared environment are interlinked. In this context Precision Livestock Farming (PLF) has the potential for prudent use of resources and for early detection of disease so that both intra- and inter-species disease transmission can be reduced. Prevention and early treatment of disorders can contribute to a reduction in the use of pharmaceuticals and minimise antibiotic resistance. Therefore, PLF technology is a key element in the One Health initiative to achieve the Sustainable Development Goals (SDGs) and looking to the brighter future.

Focus on the One Health initiative will be highlighted in the opening session of the conference by keynote speakers but also in several scientific sessions on pigs, cows and poultry. Growing importance of computer vision in Precision Livestock Farming is represented by many sessions such as Computer Vision in Weaners and Growers or Computer Vision and Vibration Sensors in Sows. Unique sessions of the conference will be dedicated to Adoption and Barriers of PLF; Decision and Economics; Product Development and Over the Fence: Use of PLF in other Species.

During the conference, Vienna is the central meeting point for the world's leading scientists, manufacturers, farmers, veterinarians and other stakeholders interested in Precision Livestock Farming technologies. One of the key elements for further development and adoption of new technologies in livestock farming is education of a new generation of students in the interdisciplinary field of Precision Livestock Farming. This topic will also be addressed in scientific sessions and a workshop.

We are happy to announce the opening of a unique, new master programme on Precision Animal Health offered by Vetmeduni Vienna and its partners. This master programme will support students in acquiring skills to understand and explain the technological basis and principles underlying the application of information driven technologies in the areas of veterinary medicine, animal husbandry and agricultural production.

Our thanks to the Committee of the EA-PLF for accepting our bid to host the 10th ECPLF; we hope that we can continue the tradition of high quality and impactful meetings, which have characterised previous ECPLF Meetings.

We would like to thank all authors for their papers and presentations, the numerous reviewers for their important comments and contributions which have helped to ensure the high quality of the papers. We want to thank our organising committees and conference partners. We especially would like to thank our sponsors and supporters, without whom we could not run this conference successfully.

We hope that the 10th European Conference on Precision Livestock Farming will stimulate fruitful discussions and networking, identify common goals and develop new research collaborations. We hope that delegates enjoy their visit to Vienna.

Maciej Oczak, Michael Iwersen, Karen Wagener ECPLF2022

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The conference was organised as a joint event of ECPLF and PDC. Only contributions from the ECPLF are presented in the conference proceedings.

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SESSION 1

Cows: Behavior I

Automatic classification of dairy cow activity using ear tag-housed accelerometers – comparison of strategies

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Abstract

Dairy cows may display a variety of behaviours throughout the day. The behavioural patterns of cows differ between individuals, and deviations from an individual cow's normal behaviour may indicate a change of state, such as onset of disease or oestrus. In the Intelligent Ear Tags project, we are developing machine learning-based models to classify the behaviour of dairy cows from 3D-accelerometer data collected with sensors housed in the cows' ear tag. The annotated accelerometer data were used to train random forest models. In this preliminary study, we systematically compared various strategies for data pre-processing and model training on a sub-set of our available data.

Key words: Behaviour classification, dairy cow, tri-axial accelerometer

Introduction

The monitoring of animal activity and behaviour is often a part of welfare and health control in production facilities, and solutions for wearable accelerometers exists for this purpose (Hendriks et al., 2020). These generally make the sensors part of additional equipment, which the farmer would not otherwise need to buy. Since per EU regulation (EU, 2019) all cows need to be ear-tagged, it seems sensible to investigate the utility of acceleration data collected by ear tags for monitoring purposes. The long-term goal with these models is to be able to monitor the behaviour of individual cows, automatically learn the normal behaviour pattern of each individual, and detect and classify significant deviations from these normal patterns. It is well known that the cow's behaviour will change while the cow is in heat, and some studies have also shown that changes in behaviour can be seen shortly after the onset of mastitis (e.g. Yeiser et al., 2012). This is intended to be a preliminary study with the aim of identifying an optimal set of parameters and strategies for classifying dairy cow behaviour based on 3D-accelerometer data.

Materials and methods

Data collection and annotation

Ear tags were placed on 14 lactating cows for different periods between October 31st 2020 and January 6th 2021, for a total of 364 cow-days. Acceleration data in three dimensions were recorded at a rate of 10 hertz and sent by RFID to a server, resulting in 864000 rows of data/day. Cameras were placed in the stable, and the relationship between time stamps from the cameras and the ear tags was determined in a synchronisation experiment, as described in a separate paper. The 14 cows were painted with different symbols on both sides of their bodies, so that the individuals could be identified from the videos (see Figure 1). The videos were stored and used for manual annotation of the accelerometer data. A total of five different people would have the task of watching the stored videos, and noting down the behaviours whenever a marked cow was in frame. The labellers were thoroughly instructed by one of the authors in order to ensure consistent labelling. A total of eight different behaviours were recorded, namely lying, standing, walking, feeding, milking robot, mounting other cows, being mounted by other cows, and drinking. Mounting and being mounted were omitted, since these only observed 26 and 44 times and only in 3 and 5 individual cows, respectively. Drinking was omitted, as the labellers could not consistently label this behaviour. The different labellers were assigned different cows and/or dates to annotate, with no overlap between the various labellers.

For this study, only data from one cow was used. This cow had data available for a total of 15 days of labelled observations, all of which were labelled by the same person.

Figure 1: A: the intelligent ear tag (orange). B: An example of how the cows were marked for identification from video when manually recording the cows' behaviours

<u>Data pre-processing</u>

All pre-processing of the data and model training was done using R version 3.5 (R Core Team, 2017). A unique event is a coherent period where the cow performs one behaviour. Individual behaviour events which had lengths shorter than the 2.5th quantile or longer than the 97.5th quantile for the event's behaviour class were removed as outliers.

Each variable of the 3D data (X, Y, Z) were transformed using summary statistics (minimum, 1st quartile, mean, median, 3rd quartile, and maximum) applied over a running window. Different window lengths were systematically used, namely 10, 50, 100, 200, 500, 1000, 1200, 1500 observations. Ten observations corresponds to 1 second.

Three different methods of balancing the training data were compared: no balancing, balancing by random re-sampling, and balancing using Borderline SMOTE (BL-SMOTE) (Han et al., 2005). For the random-resampling, three different levels were used: (1) simple under-sampling, where the all classes are randomly sampled without replacement, so that all classes were represented with a number of observations corresponding to the size of the smallest class, (2) random re-sampling to the size of the median class; classes smaller than the median are sampled with replacements, classes larger than the median are sampled without replacement, and (3) simple over-sampling where the classes smaller than the largest class are sampled with replacement to reach the size of the largest class. For BL-SMOTE, only the median and the largest classes were used. Only the training set was balanced, while the test set was kept unbalanced.

Model building

The training and testing was done in a 10-fold cross-validation. For each of the five behaviour classes, all unique events were randomly assigned a number between 1 and 10. All events with a given number would then iteratively be assigned to the test set, while all events with different numbers would be assigned to the training set. Data balancing was performed after each split into training and test sets.

The (balanced) training set was then used to train a random forest with a given number of trees. This number was kept constant at 10 trees, except during the experiment to determine the optimal number of trees. During this experiment, the number of trees were defined by 2^j, where $j \in \{1, 2, 3, 4, 5, 6, 7, 8, 9\ 10\}$, following the example of (Oshiro et al., 2012)the associated literature provides almost no directions about how many trees should be used to compose a Random Forest. The research reported here analyzes whether there is an optimal number of trees within a Random Forest, i.e., a threshold from which increasing the number of trees would bring no significant performance gain, and would only increase the computational cost. Our main conclusions are: as the number of trees grows, it does not always mean the performance of the forest is significantly better than previous forests (fewer trees. Additionally, 10 trees were also used in this experiment.

The random forest was trained to take an input vector of 21 values (the X, Y, and Z values for a given observation as well as the rolling summary statistics associated with that observation), and provide the probabilities for five behaviour classes (lying, standing, walking, feeding, milking robot) as its output. The class with the highest probability was the final predicted class for a given observation.

The predicted and observed classes were combined from each iteration of the 10-fold cross-validation, and the overall per-class accuracies were calculated as the number of observations within a given class which was correctly labelled as that class by the random forest. Finally, the major mean accuracy (MMA) was calculated as the simple mean of the five per-class accuracies. In some experiments, a mean MMA was also calculated as the simple average of the MMAs from each of the 10 test sets of the cross-validation, and the standard deviation of these were used to calculate the 95 % confidence interval (CI).

Results and Discussion

Descriptive statistics

Table 1 shows the descriptive statistics for the data used for this study. For each of the five considered behaviour classes, the table shows the number of events, which were included and excluded, after the removal of outliers.

Table 1: Descriptive statistics of the data. Ten observations corresponds to 1 second

Behaviour class	Included events	Excluded events	Event lengths (observations)		
			Median	Mean	1st Qu. – 3rd Qu.
Lying	48	4	33304	39057	23192 – 50408
Standing	138	8	2703	4840	760 – 6196
Walking	103	6	367	516	228 – 706
Feeding	48	4	10516	10064	6531 – 13354
Milkning robot	20	2	4675	4092	3691 – 5046

Optimal window length

Table 2 shows the overall MMA as well as the per-class accuracies given the various window lengths, when all other parameters are kept constant. For lying and feeding, which have the longest event lengths, the optimal window length is 1000 observations.. Walking and milking robot both achieve their best performances with the smallest window length, i.e. 10 observations, and their performance rapidly decrease with longer windows. Standing achieves the best performance with a window length of 200 observations, and the difference compared to 100 observations is only 2 percentage points. The best MMA is achieved with a window length of 100 observations (i.e. 10 seconds), which represents the best compromise between the different classes. Therefore, the window length will be kept constant at 100 observations in the following sections. In future studies, the utility of making class-specific models with different window lengths should be investigated.

Moving averages are used as a pre-processing step in many studies related to detecting undesired events in production animals, e.g. mastitis in dairy cows as summarized by van der Voort et al. (2021). Several studies on classification of animal behaviour also applied various summary statistics to the accelerometer data, e.g. (Barwick, 2020; Fogarty et al., 2020; Jin et al., 2021). While Jin et al. (2021) used a rolling window approach similar to the ours, others calculated the summary statistics from non-overlapping windows (Barwick, 2020; Fogarty et al., 2020). Fogarty et al. (2020) compared window lengths of 5, 10, and 30 seconds, and achieved their best performance with window lengths of 10 seconds, which is the same optimal time window we find when optimizing the MMA.

Table 2: The major mean accuracy (MMA) and per-class accuracy given various window lengths used for transforming the data with a rolling summary statistics window

window length (observations)	MMA	Per-class accuracy				
		Lying	Standing	Walking	Feeding	Milking robot
10	0.47	0.58	0.40	0.46	0.52	0.40
50	0.52	0.70	0.49	0.38	0.65	0.37
100	0.53	0.76	0.54	0.30	0.70	0.32
200	0.52	0.81	0.56	0.20	0.75	0.30
500	0.52	0.85	0.56	0.12	0.79	0.28
1000	0.49	0.87	0.55	0.01	0.80	0.22
1200	0.48	0.87	0.54	0.01	0.80	0.18
1500	0.48	0.87	0.52	0.00	0.79	0.23

Data balancing

Table 4 shows the MMA and per-class accuracies given the various combinations of balancing methods and balancing levels. The worst MMA is achieved when no balancing is performed, while the best MMA is achieved when using simple down-sampling, i.e. when all classes are randomly sampled to only include the same number of observations as the smallest class. The three smallest classes all achieve the highest per-class accuracy when using simple down-sampling. In all cases, the best per-class accuracies and MMA are seen when using random re-sampling rather than BL-SMOTE or no balancing.

Table 4: The overall major mean accuracy (MMA) and per-class accuracies given the methods and levels of data balancing

Method	Level	MMA	Per-class accuracy				
			Lying	Standing	Walking	Feeding	Milkning robot
Nothing	NA	0.45	0.88	0.45	0.06	0.70	0.17
Random sampling	Min	0.52	0.76	0.53	0.29	0.70	0.33
	Median	0.47	0.84	0.49	0.10	0.73	0.20
	Max	0.46	0.87	0.44	0.07	0.72	0.18
BL-SMOTE	Median	0.50	0.83	0.48	0.23	0.72	0.25
	Max	0.47	0.82	0.51	0.15	0.70	0.20

A direct comparison between random sampling and BL-SMOTE can be made by comparing the MMAs achieved when these two methods are used to balance the data to the median and maximum class sizes. From Table 4 it is seen that BL-SMOTE outperforms random sampling in both of these cases, although neither outperform the simple under-sampling. Table 5 shows that the differences seen for between random sampling and BL-SMOTE cannot be shown to be statistically significant.

Table 5: Statistical test of the difference between the major mean accuracy (MMA) when BL-SMOTE and random re-sampling (RS) are used to re-size all classes to the sizes of the median class and the maximum class

Level	Comparison	MMA estimated difference	95 % CI estimated difference	p-value
Median	BL-SMOTE - RS	0.03	-0.11-0.17	0.67
Max	BL-SMOTE - RS	0.02	-0.11-0.15	0.80

In the literature, we found one study which did not balance the training data (Barwick, 2020), one which compared using BL-SMOTE, under-sampling, and no balancing (Jin et al., 2021), one which used no balancing, random under-sampling, and over-sampling using SMOTE (Homburger et al., 2014), and four studies which only used random under-sampling (Smith et al., 2016; Abell et al., 2017; Sakai et al., 2019; Fogarty et al., 2020).

Simple under-sampling has the potential drawback that informative observations are removed from all classes, which are larger than the smallest class. Simple over-sampling has the drawback that a large number of identical samples are created, which might cause the model to over-fit to those repeated observations (Barwick, 2020). One might then suspect that a reasonable middle ground could be to randomly re-sample all classes to the median class size. From Table 4, however, this is seen not to be the case. Our finding that simple under-sampling yields better MMA is in concordance with the findings of (Homburger et al., 2014). Similarly, our finding that balancing the data by any method yields better performance than no data balancing is in concordance with the findings of (Jin et al., 2021). Our finding that random under-sampling is the optimal data balancing method is, however, in opposition to the findings of (Jin et al., 2021), who found that using BL-SMOTE yielded considerably and significantly better performances than using simple random under-sampling when training a model to classify the behaviour of slaughter pigs from 3D-acellereomter data. Our findings do, however, match the findings of (Homburger et al., 2014), who found that random under-sampling yielded better performance than when balancing to the size of the largest class using SMOTE. Given the prevalence of unbalanced data sets within our field, further studies on larger data sets are warranted to search for a best practice for data balancing.

Number of trees

Table 6 shows the performances for random forests trained with different numbers of trees. The overall MMA is the MMA calculated from all predictions of the 10-fold cross-validation while the mean MMA is the average of the 10 MMAs in the cross-validation.

Table 6: The major mean accuracy and the per-class accuracies for, given the number of trees in the random forest, when all other variables are kept constant

No. of trees	Overall MMA	Mean MMA	Per-class accuracy				
			Lying	Standing	Walking	Feeding	Milking robot
1	0.45	0.45	0.64	0.45	0.26	0.58	0.31
2	0.45	0.46	0.64	0.45	0.26	0.58	0.31
4	0.50	0.50	0.71	0.50	0.29	0.65	0.32
8	0.52	0.53	0.75	0.53	0.29	0.69	0.32
10	0.52	0.53	0.76	0.53	0.29	0.70	0.33
16	0.53	0.54	0.77	0.55	0.30	0.72	0.32
32	0.54	0.55	0.78	0.55	0.30	0.73	0.32
64	0.54	0.55	0.79	0.56	0.30	0.74	0.33
128	0.54	0.55	0.79	0.56	0.31	0.74	0.33
256	0.55	0.55	0.80	0.57	0.31	0.74	0.32
512	0.55	0.55	0.80	0.57	0.31	0.74	0.32
1024	0.55	0.55	0.80	0.57	0.31	0.74	0.32

In our study, the number of observations in the training sets used in the 10-fold cross-validation ranged from 2,328,842 to 2,566,185 with a mean value of 2,480,284. The number of input variables for the random forest was 21, and the number of output classes was 5. Thus, according the density function defined by (Oshiro et al., 2012), the average density of our training data was 4.31. Thus our data meet definition of high density, proposed by Oshiro et al. (Oshiro et al., 2012), and the density of our data set is on the same order as the highest density data set analysed by Oshiro et al. (Oshiro et al., 2012).

Oshiro et al. (2012) found that the performance of a random forest trained of high density data sets did not, on average, improve when the number of trees went beyond 32. This is well in concordance with our findings, where the mean MMA peaks with a value of 0.55 at 32 trees. At 32 trees, the overall MMA is 0.54, and it does not increase to 0.55 until the number of threes is 256. Furthermore, the increase in overall performance when going from 16 to 32 trees is only 0.01. Similarly modest improvements beyond 16 and 32 trees are seen for all behaviour classes. Thus, for the full version of our data set, training a model with either 16 of 32 trees will likely be sufficient.

Final performance

Figure 1 shows the final normalized confusion matrix resulting from the predictions and observations from all iterations of the 10-fold cross-validation, when the following parameters were set: rolling window length = 100 observations, data balancing method = random under-sampling, number of trees = 32. This results in an overall MMA of 0.54 and a mean MMA from the 10-fold cross-validation of 0.55. The per-class accuracies can be seen from the diagonal of Figure 1. As is seen, the two most well-represented classes (Lying and Feeding) achieves the best per-class accuracies, even though the data have been balanced. Similarly, the least well represented class (Walking) achieves the worst class-performance. Standing is most often mistaken for Lying, which makes sense as these are both passive behaviours. Milking robot is mostly mistaken for Feeding, followed by Standing/Lying. This makes sense, because the cow will eat and stand while in the milking robot. When Feeding is misclassified, it is mostly mistaken for Standing. This makes sense, as the cow will stand while eating.

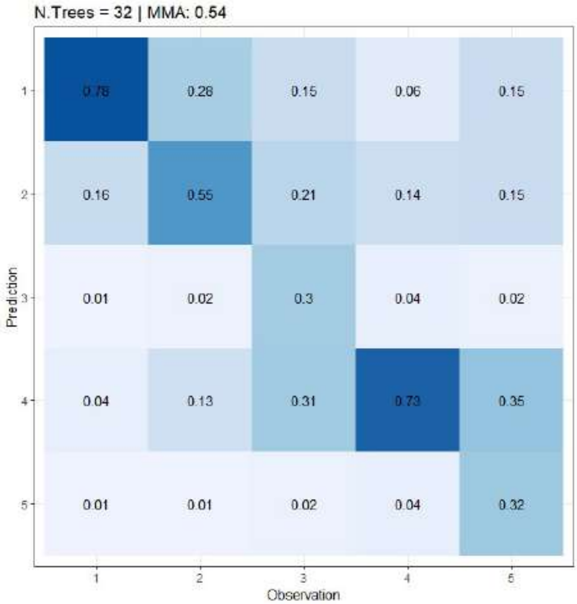

Figure 2: The normalized confusion matrix resulting from the final 10-fold cross-validation. 1 = Lying, 2, Standing, 3 = Walking, 4 = Feeding, 5 = Milking robot

Conclusion

In this preliminary study, we compared the performances of random forests for classifying behaviours of one dairy cow, using different strategies for data pre-processing and model training. The final parameters resulted in an average MMA of 0.55. The final parameters will be used in a follow-up study involving data from multiple cows.

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Validation and comparison of different sensor technologies to classify behaviour of dairy cows on pasture

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Abstract

Sensor-based monitoring of animal behaviour can provide valuable insights into animal health and welfare. A prerequisite for using sensor technologies is their validation, which has already been performed, e.g., for the RumiWatch system (RWS, Itin + Hoch GmbH, Liestal, Switzerland) on pasture. To our knowledge, HOBO-loggers (HBL, HOBO Pendant G logger, Onset Computer Corporation, Bourne, MA) and the SMARTBOW system (SBS, Smartbow GmbH/Zoetis LLC, Weibern, Austria) have not been evaluated for detecting lying behaviour and rumination on pasture yet. The main objective of this study was to validate the SBS for rumination and both systems (SBS, HBL) for lying behaviour under grazing conditions. Another aim was the direct comparison among three different RumiWatch Converter (RWC) versions in different time resolutions. The study was conducted at the Teaching and Research Farm of our University. Ten lactating cows were equipped with the SBS, RWS and HBL concurrently during four non-consecutive weeks. Cows spent 2 to 6 hours a day on pasture for fifteen days in total. Animal behaviour was video recorded with a drone-mounted camera. Preliminary analyses showed moderate correlations between 1-min lying data of visual observation (VO) and SBS (r_S = 0.51; CCC = 0.44) and almost perfect correlation between VO and HBL (r_S = 0.95; CCC = 0.95). Correlations of 1-min rumination data between VO and SBS were r_S = 0.84 and CCC = 0.84. The agreement of the three RWC versions between each other was almost perfect (CCC > 0.9). These findings suggest that HBL are suitable for estimating lying times and the SBS for rumination times on pasture, respectively. There are only minor deviations between the RWC versions comparing rumination times.

Keywords: cow behaviour, lying and rumination monitoring, pasture, sensor technology, accelerometer, validation

Introduction

The use of precision livestock farming (PLF) technologies in research and dairy farming has rapidly increased over the last decades. These technologies can help alleviate the manual monitoring of the herd, not only in large-scale farms, but also for small and part-time farms. In research, automated monitoring of animal behaviour can supplement or replace the time consuming task of visual observation of study animals (Pereira *et al.*, 2021). Independent validations of technical devices and sensor systems are of high importance to determine their reliability and accuracy. Many PLF-technologies have been introduced to agriculture. However, most of them are used under confined conditions in intensive livestock farming. Extensive research has already been carried out in order to validate a variety of sensor systems under different conditions, as reviewed by Chapa *et al.* (2020) and Stygar *et al.* (2021). The ear-attached accelerometer system SMARTBOW (SBS, Smartbow GmbH/Zoetis LLC, Weibern, Austria) has been validated for rumination and heat detection under indoor housing conditions (Borchers *et al.,* 2016; Reiter *et al.*, 2018; Schweinzer *et al.*, 2019) and for grazing behaviour on pasture (Pereira *et al.*, 2020). However, this system has not been evaluated for monitoring rumination and lying behaviour on pasture.

HOBO-loggers (HBL, HOBO Pendant G logger, Onset Computer Corporation, Bourne, MA) have already been validated for the use on cows and calves in the barn to classify standing and lying position (Ito *et al.*, 2009; Ledgerwood *et al.*, 2010; Bonk *et al.*, 2013). They were also employed in research for cows on pasture (Sepúlveda-Varas *et al.*, 2014). However, to our knowledge, these accelerometers have never been validated for the use on pasture, although there might be a difference in performance, possibly due to uneven terrain, which is often found on pastures in mountainous regions.

Another sensor system, which comprises a noseband-pressure sensor combined with accelerometers on the halter and the leg (RumiWatch system, RWS, Itin + Hoch GmbH, Liestal, Switzerland), was already validated by many researchers in the barn (Zehner *et al.*, 2017) and on pasture (Werner *et al.*, 2018). As a result, further development led to adjustments of the classification software. Currently, different versions of the converter software are available. Some studies have already compared two converter versions with each other or one converter version with visual observation (Steinmetz *et al.*, 2020; Norbu *et al.*, 2021; Pereira *et al.*, 2021), but a direct comparison of all three versions within the same dataset has not yet been conducted. In order to complement the current state of scientific validations, this study focused on further evaluation of three of the above mentioned sensor systems on pasture: SMARTBOW ear-tag, RumiWatch system and HOBO-loggers. To our knowledge, this is the first study that evaluated several sensor technologies for their use in cows on pasture by using video observation with a drone-mounted camera as reference. The main objective of this study was the validation of the SBS for classifying rumination and lying behaviour on pasture as well as the validation of HBL for detecting lying behaviour on pasture by using indirect visual observation as gold standard. The second objective was the direct comparison of three different RWC versions in different time resolutions.

Material and methods

All procedures that involved animals were discussed with the ethical committee (ETK) of the University of Veterinary Medicine and approved by the Austrian Federal Ministry of Education, Science and Research (BMBWF) (GZ: 2021-0.236.444).

Experimental farm

The study was conducted during the grazing periods in 2020 and 2021 at the Teaching and Research Farm (VetFarm) of the University of Veterinary Medicine Vienna, Austria. On the farm, approximately eighty Simmental cows are kept in a free-stall barn with cubicles. The lactating herd is milked twice daily in a tandem milking parlour. The pasture area available for this study was approximately 1.5 ha in total.

Study design

Ten lactating cows were enrolled in the study during four non-consecutive weeks throughout the grazing season. Each period consisted of four days a week, on which only the study cows were moved to pasture in the morning for 2 to 6 hours. In the second week of the experiment, they were also moved to pasture after the evening milking for 2 to 2.5 hours. In the remaining time, they were housed indoors within the herd. For the validation experiment, the cows were equipped with different sensor systems: accelerometers (ear-attached and leg-mounted) and noseband sensors. Indirect visual observation by using a camera-equipped drone (DJI Phantom 4 Pro V 2.0, SZ DJI Technology Co., Shenzen, China) was carried out during the time on pasture to serve as a gold standard for the behavioural classification. Noseband sensors, pedometers and data loggers were always mounted on Sundays, prior to the start of the experimental week on Monday, to allow habituation to the sensors. No further manipulation was necessary for the ear-tag, as this sensor system is permanently in use at the VetFarm for several research projects and for management purposes. During the experimental periods, cows were checked twice daily after the milking times for potential bruises caused by the sensors and to adjust sensor position if needed. Prior to the start of the experiment, cows were habituated step by step to the sensor systems, the grazing regime and the drone flight during two weeks. All sensor systems were time synchronised using UTC as reference.

Sensor systems

The SMARTBOW system is an ear-tag with an integrated accelerometer, which collects data at 10 Hz frequency for research purposes. Data are sent to receivers and passed on to the on-farm server, where raw data are classified into, inter alia, ruminating, standing and lying. For outdoor use, there are specific receiver stations, which are supplied by solar-powered batteries. The SBS is described in more detail by Schweinzer *et al.* (2019).

The HOBO data loggers are accelerometers with gyroscope function. The logging frequency was set to log once per minute. Raw data were written to an internal memory and read out by using a proprietary cable. The data loggers were cushioned and fixed with bandage material to the cows´ left hind legs for capturing standing and lying times.

The RumiWatch system consists of two parts: The first part is a halter with a pressure tube integrated into the noseband as well as an accelerometer on one side of the cheek. The second part is a pedometer and can be attached to any leg of a cow. Both parts can be used separately. In terms of animal behaviour, the RWS is able to detect rumination and lying behaviour. A more detailed description of the RWS can be found in Zehner *et al.* (2017).

Visual observation

A drone was used to record cow behaviour on pasture with a mounted RGB-camera by following the group of animals. Therefore, the whole study group was visible on almost the entire video footage. This facilitated the analysis and behaviour classification in the video recordings in a highly efficient manner. Another advantage of this observation strategy was to avoid the influence of animal behaviour by human presence. Due to the maximum flight time of 30 min (limited by the battery) the video footage of cow behaviour could not be recorded continuously. Two independent observers labelled the video footage using the software Mangold® Interact (Mangold International GmbH, Arnsdorf, Germany). The behaviours were classified as 'lying' and 'not lying' as well as 'ruminating' and 'not ruminating', if the cow was visible in the video and behaviour was identifiable.

Data preparation

Data from SBS were provided by the company. Each minute was classified as 'lying'/'standing' and 'rumination'/'nothing' by their proprietary algorithms, according to the predominant behaviour. The HBL had to be read out manually. Raw data were available as acceleration and tilt data in the x-, y- and z-axes and were classified into 'standing' and 'lying' in 1-min time resolution as described by Ito *et al.* (2009). Corrections of erroneous values were carried out according to Ledgerwood *et al.* (2010). RumiWatch raw data were read out using the RumiWatch Manager 2 software (RumiWatch Manager 2.2.0.0., Itin + Hoch GmbH, Liestal, Switzerland). Raw data were converted into classified csv files (10-min and 1-hour time resolution) using the three latest RumiWatch Converter (Itin + Hoch GmbH, Liestal, Switzerland) versions: V0.7.3.36 (RWC36), V0.7.4.5 (RWC05) and V0.7.4.13 (RWC13). Classified data were merged by sensor identification number (ID) and timestamp. The output of indirect visual observation (VO) was resampled to 1-min time resolution (originally seconds) and merged with ear-tag data and the lying/standing-classification of the data loggers.

Statistical analyses

For statistical analyses, the software SPSS (version 27, IBM Corporation, Armonk, NY) and R (version 4.0.4, Copyright 2021, The R Foundation for Statistical Computing) were used. Inter-observer-reliability of indirect VO was assessed by calculating Cohen´s kappa coefficient (κ) from randomly selected overlapping labelled video footage. Sensor data were checked for normal distribution using Shapiro-Wilk test and histograms. For calculation of sensitivity, specificity, positive predictive value and accuracy a confusion matrix was computed, for HBL (lying) versus VO, SBS (lying) versus VO and SBS (rumination) versus VO, respectively. For assessing the agreement between each sensor system and VO, the concordance correlation coefficient (CCC) and Spearman´s rank correlation coefficient (r_S) were calculated. For the comparison between the three different RumiWatch Converter versions (RWC36, RWC05 and RWC13), the concordance correlation coefficient (CCC) and Spearman´s rank correlation coefficient (r_S) were calculated for each version with the other two, both in 10-min time resolution and in 1-hour time resolution.

Results and Discussion

Results of the validation of the two systems SBS and HBL by VO are presented separately from the comparison of the three different RWC versions with each other. Due to the initial objectives of this study and the preliminary available time resolutions of the data, a direct comparison between RWS and VO was not carried out in preliminary analyses.

Validation of SBS and HBL on pasture

For the validation experiment, data of eleven days were available for analysis. Four days were excluded due to significant data loss of one sensor system. On one day, cows were not brought to pasture because of rainy conditions. As one cow was dried-off one week prior to the end of the experiment, only nine cows were available for the last three days. For the comparison of sensor data against the gold standard (VO), approximately two thirds of labelled video footage were available for preliminary analysis. The number of valid minutes for analysis after merging sensor with VO data is presented in Table 1. From the total amount of analysed video footage, 10 % were classified as rumination behaviour and 23 % as lying behaviour by visual observation. Inter-observer-reliability was calculated from 728 overlapping minutes. Cohen´s kappa was $\kappa = 0.96$ for rumination and $\kappa = 1.0$ for lying, considered as a 'perfect agreement' between observers according to Landis and Koch (1977). Results from computing the confusion matrix and correlation coefficients for each sensor system are shown in Table 1.

Table 1: Agreement measures for 1-min time resolution data of visual observation and the two sensor systems (HBL = HOBO-logger, VO = visual observation, SBS = Smartbow system, SE = Sensitivity, SP = Specificity, AC = Accuracy, PPV = Positive predictive value, CCC = concordance correlation coefficient, r_S = Spearman´s rank correlation coefficient, N = number of minutes)

Parameter and system	SE (%)	SP (%)	AC (%)	PPV (%)	CCC	r_S	N (min)
Rumination							
SBS vs. VO	82.0	99.0	90.5	90.2	0.84	0.84	8,747
Lying							
HBL vs. VO	95.5	99.3	97.4	97.5	0.95	0.95	8,929
SBS vs. VO	35.4	99.2	67.3	92.9	0.44	0.51	8,910

Other studies that compared hourly rumination data of the SBS to visual observation under housed conditions reported agreement of CCC = 0.96 (Borchers *et al.*, 2016) and correlation of $r > 0.99$ (Reiter *et al.*, 2018). The lower results of the current study (CCC = 0.84, r = 0.84) are due to an underestimation of rumination time by the SBS. This is expressed by the sensitivity and specificity given in Table 1 and can possibly be explained by the conditions on pasture. As observed in the video footage, searching for food while ruminating (leading to low head position and irregular rumination chews) and intense head shaking induced by increased amount of insects could cause misclassifications. As we were mainly interested in time budget measures in this study, and the swallowing and regurgitation of cuds could not be detected clearly on the entire video footage, rumination was defined as the onset of rumination until the last bolus was swallowed. Therefore, we did not take into account the pauses between two rumination bouts, which in turn could rather be considered an overestimation by visual observation. Further investigation of the data, including the comparison of the SBS to the RumiWatch rumination data, can help to understand this in more detail. When comparing those two systems with each other, it has to be considered that RWS was intended to be used for research purposes and SBS for commercial applications.

HBL showed almost perfect agreement with VO for lying behaviour. Even though the results in this study are slightly lower than reported by Ledgerwood *et al.* (2010), HBL can still be considered suitable for detecting lying and standing behaviour of cows on pasture. There is only a moderate agreement (CCC = 0.44) between SBS and VO for lying behaviour. Although insects on pasture could also explain misclassification to some extent, it is obvious that the detection of lying and standing position in cows by HBL is more accurate.

Comparison of RumiWatch Converter versions

For the comparison of the different RWC versions, sensor data of eight entire days were included for preliminary analysis. In total, 1796 data points of 1-hour and 10815 data points of 10-minute time resolution were available for each converter version. Results of overall correlation measures for 10-min-classification and hourly data are given in Table 2.

Table 2: Lin´s concordance correlation coefficient (CCC) and Spearman´s rank correlation coefficient (r_S) for the comparison of three different RumiWatch Converter versions (7.3.36, 7.4.5, 7.4.13) in two different time resolutions (10-minute-resolution, hourly resolution)

Converter versions	CCC 10 min	r_S 10 min	CCC hour	r_S hour
Lying				
RWC36 vs RWC05	1	1	1	1
RWC36 vs RWC13	1	1	1	1
RWC05 vs RWC13	1	1	1	1
Rumination				
RWC36 vs RWC05	> 0.999	> 0.999	> 0.999	> 0.999
RWC36 vs RWC13	0.993	0.984	0.998	0.997
RWC05 vs RWC13	0.993	0.984	0.998	0.996

According to the results, a perfect agreement between the different converter versions was found. This provides evidence that these RWC versions can be used interchangeably for the classification of lying behaviour. Nevertheless, minor deviations for rumination were detected. This has to be evaluated in more detail. In this study, the data for agreement in terms of time spent ruminating were examined. It was not differentiated whether data were collected in the barn or on pasture for preliminary analysis. Other studies investigated parameters such as rumination chews, prehension bites and mastication chews. Norbu *et al.* (2021) reported different levels of agreement with visual observation for RWC36 and RWC13, depending on whether cows were in the barn or on pasture. Steinmetz *et al.* (2020) compared RWC05 against direct visual observation in 1-min and 1-hour time resolution and found high agreements for rumination (r = 0.95) and ruminating chews per bolus (r = 0.96). Although those results cannot be compared directly with the findings of the current study, they provide evidence for different performances of the RWC versions. Werner *et al.* (2018) evaluated the RWC36 for rumination in 1-hour time resolution under grazing conditions and reported almost perfect agreement with direct visual observation (CCC = 0.99, r_S = 0.98). Further aims of the current study include the comparison of VO with the different RWC versions for a better understanding of the preliminary results. More detailed analyses are currently being conducted.

Conclusion

The preliminary findings of this study show a lower agreement of rumination time on pasture between the SBS and VO compared to results from studies under confined conditions. However, the influence of the video labelling process as well as the algorithms that were used can be discussed and need further investigations. Preliminary evaluation of the HBL yielded only slightly lower results compared to studies conducted in the barn. Thus, it was concluded that the HBL is appropriate for the use on pasture. First results for detection of lying behaviour by the SBS suggest that adaptions of the current classification algorithm are needed for the conditions on pasture. Currently, the use of leg-mounted sensors for estimating lying times is recommended. Using the pedometers of the RWS, no significant differences between the three RWC versions were found. However, when comparing the three different systems used in this study, it has to be taken into account, that SBS is designed for commercial purposes, whereas both RWS and HBL are mostly being used as research tools. Further in-depth analysis using the video footage and sensor data in different time resolutions is currently in progress.

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Validation of proximity sensors to monitor social proximity in dairy cows: a pilot study

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Abstract

Social interactions of group-living farm animals can have important implications for animal welfare, health, and productivity. Understanding which factors can affect social behaviour is thus important to improve management strategies. We investigated the social structure of a group of 19 lactating dairy cows during a 14-day period through the use of proximity loggers. The proximity devices collected data on dyadic proximity of cows. The devices are non-invasive, weight 2.7 g, are powered by a lithium coin battery (3 g). The sensors have been attached to the cows by using custom collar-mounted cases, and were set to detect proximity events within a distance of 1–1.5 m. Colocation of animals at this distance indicated a close-contact situation, during which social interactions between animals might occur. In addition, proximity sensors were placed in strategic locations of the barn (e.g., feeding trough, drinkers, cubicles) as fixed tags in order to evaluate the use of the space and resources by the cows. Video observations of the cows, their interactions and their location were used to assess the repeatability of the measurements produced by the sensors. At the time this paper was written, data analysis was still ongoing. Preliminary results indicate the proximity sensor technology used in this study has the potential to provide high resolution data that can be used to monitor the social behaviour and the location of dairy cattle. Further analysis is deserved to better evaluate the functioning of these type of proximity sensors within common dairy cow housing, especially in freestall barns.

Keywords: proximity sensors, dairy cows, validation, contact patterns, social behavior

Introduction

Gregarious animals form social relationships with group members, and there is growing evidence that social behaviors are positively correlated with the survival and reproductive success of individuals (Silk, 2007). In production settings, management practices can modify the social interactions of group-living farm animals, depending on group composition and available space (Keeling, 2001). Nevertheless, the social behavior of farm animals is plastic and dynamic, and allows animals to adapt to varying environmental and social conditions within a confined group (Estevez et al., 2007). In recent years the livestock production industry has intensified efforts to improve animal health and well-being due to increasing ethical issues and public concern about animal welfare. Animal welfare is influenced by the social environment and by the opportunity to express certain social behaviors despite the limitations due to bounded space and management practices (Sevi et al., 2001). Moreover, social behavior plays an important role in the spread of infectious diseases, and where the contact rates vary markedly between individuals, the dynamics of directly transmitted infections might better be predicted using contact or proximity networks (Craft, 2015).

Nevertheless, social behavioral analysis of animals is non-trivial. Recent technological advances allow us to measure animal social interactions using proximity sensors, in a variety of contexts, at very different spatial and temporal scales (e.g., Boyland et al., 2016; Wilson-Aggarwal et al., 2019). Automatic data collection by proximity sensors provide objective data that are relatively cost effective, and overcome many of the errors encountered in recording and interpreting visually observed behavior. Visual observations require extensive labor and training, are not continuous, necessitate observers to simultaneously identify and assess multiple animals at the same time and the presence of observers can alter the animals' behavior. The development of automated data collection using proximity sensors that are attached to animals has enabled greater insight into both individual and group behaviors not previously possible, although they cannot reliably detect all behaviors that a human-observer can (Rushen et al., 2012). However, while visual observations provide the most descriptive assessment of an individual's behavior, these may not be the most appropriate to meet the criteria of a reliable and valid welfare assessment criteria in extensively managed livestock production enterprises. There is a need for studies that use continuous behavioral measures to identify the direct links between independent measures of stress and changes in social interactions, which will provide greater detail on welfare assessments than what has previously been achieved using visual observations.

Proximity sensors can gather data on animal proximity and social interactions in an objective way and by means of non-obtrusive methodologies. Although it seems to have been assumed that the use of proximity loggers for recording social interaction removes sampling problems, the data from proximity loggers can be prone to error (Boyland et al., 2013), for example signals can be interfered with by metal or other objects, in particular in indoor settings. Whilst this innovative technology has been rapidly embraced by the scientific community, devices for recording contact patterns are often deployed without thorough testing or consideration of the potential sampling biases. We propose that such assumptions requiring thorough testing and validation in performance is likely to result in fundamental errors in data collected for animal social networks, such as the presence of false-positives (i.e., the contacts did not occur but were registered by the sensor) or false-negatives (i.e., the contacts took place but were not registered by the sensors). The main objective of this study was to validate RFID-based proximity sensors applied to dairy cows housed in freestall barns.

Material and methods

Proximity sensors

The proximity sensing platform has been designed by the SocioPatterns collaboration consortium (http://www.sociopatterns. org). The hardware is open-source and based on the design developed by the OpenBeacon project (http://www.openbeacon.org). The proximity sensors used in this study have been previously deployed in social network studies on animals (Wilson-Aggarwal et al., 2019; Ozella et al., 2020; Fielding et al., 2021; Ozella et al., 2022). The devices measure 3 cm in diameter and weight 2.7 g, are powered by a lithium coin battery (3 g CR2032), leading to a final weight < 6 g. Sensors in close proximity exchange with one another a maximum of about 1 power packet per second, and the exchange of low-power radio-packets is used as a proxy for the spatial proximity of the animals wearing the sensors (Cattuto et al., 2010). In particular, close proximity is measured by the attenuation, defined as the difference between the received and transmitted power.

In this study we set the attenuation threshold at -75 dBm to detect proximity events between devices situated within 1–1.5 m of one another. This distance between sensors allows detection of a close-contact situation, during which social interactions between animals might occur and during which a communicable disease infection might be directly transmitted, either by airborne transmission or by direct physical contact. A "contact event" was identified when the devices exchanged at least one radio package during a time interval of 20s. After a contact is established, it is considered ongoing as long as the devices continue to exchange at least one radio package for every subsequent 20s interval. Conversely, a contact was considered broken if a 20s interval elapses with no exchange of radio packages. Each device has a unique identification (ID) number that is used to link the information on the contacts established by the individual carrying the device.

For the present study, the system was operated in a distributed fashion: contact data was stored in the local memory of individual devices. After collecting the devices at the end of the study, data from individual devices were downloaded and the time-resolved proximity networks recorded by individual devices were combined to build a global, time-resolved proximity data set. The output from each proximity sensor provides a record of the date and time of the start of every contact with any of the other proximity sensors, each of which has its own individual identification number, and the duration of each contact.

<u>Animals and data collection</u>

The study took place on a commercial dairy farm located in the province of Mantova, Italy, over a 14-day period in June 2021. Nineteen adult Holstein cows were involved in the study. All the animals were fitted with a sensor tag. The tags were placed in a custom 3d-printed plastic container that was designed to be attached to a neck collar. The sensors were held on the upper-left side of the cows' neck, by means of a weight attached to the lower part of the collar (Figure 1). During the course of the study, the cows were continuously housed in a free stall barn (Figure 2). Additional tags were placed within the barn at 10 static locations, including feeding trough, drinkers and cubicles.

In order to acquire visual observations of proximity events, 5 cameras were installed within the barn. At the end of the experiment, two trained human operators observed the video recordings and manually recorded proximity events, which were defined as: 1) two tagged animals get within 1.5 m of each other or 2) one tagged animal get within 1.5 m of a static tag.

The operators observed a 2h video footage for every tagged cow involved using a *focal animal sampling* method. For each contact event, the operators recorded the date and time of the start and of the end of the event as well as the animals and/or the static tags involved. Direct behavioral observations were recorded at 1 min resolution. The video recordings contained a time reference that was synchronized with the sensors. This allowed to compare the data generated by the sensors and by the human observers.

Figure 1: A cow wearing the proximity sensor

Figure 2: An overview of the freestall barn where the experiment was carried out

Data analysis

All data analysis was carried out using R (version 3.6.1.). Various tests were conducted to evaluate the agreement between the sensors and the visual observations. The contact events generated by the sensors were analyzed in comparison with the data recorded by the human observers, which were considered as the gold standard. For contact event detection (qualitative), sensitivity was calculated using the package “caret”. The package “epiR” was used to calculate the concordance correlation coefficient (CCC) for the duration of contact events (numeric). For events duration, Bland–Altman plots and related statistics were also obtained using the package "BlandAltmanLeh". Briefly, Bland–Altman analysis was developed to visually evaluate the agreement between two quantitative measurements by plotting the difference of the two paired measurements against the mean of the two measurements.

Results and Discussion

In total, 292 interaction or dyadic proximity events (within a 1.5 m range) have been recorded by the human observers. Confirmed events lasted from 1 min to 120 min (recorded on 2-h observation periods). Shorter interactions tended to be quick social interactions among animals, with both animals standing or walking, while the longer interactions were recorded when cows were lying in close proximity (i.e. in two adjacent freestalls). The sensors were capable of detecting 222 out of the 292 confirmed interactions, resulting in a sensitivity of 0.76. Most of the events that have not been detected by the sensors were short interactions, typically lasting less than 2 min.

The sensors tended to split single proximity events into multiple recorded interactions. On average the sensors recorded 3.16 interactions (range from 1 to 52) for every confirmed event of dyadic proximity. This often occurred for events that lasted for more than 3-4 minutes and is likely due to signal losses that may have occurred during the same actual proximity event. As water (which constitutes a large proportion of animals' body tisses) is known to affect the radio signal used by the sensor system, it is possible that movements of the animals or the position of the tags affected signal quality during some interactions.

The Bland and Altman analysis carried out on the 292 confirmed interactions (Figure 3) indicated that the sensors significantly underestimated the duration of the events. The mean difference (or bias) between the duration of proximity events recorded by the sensors and by the human observers resulted to be -454 s, or -7.56 min. Figure 3 indicates that the sensors' error increased with increasing actual event duration. The CCC for the duration of contact events resulted to be 0.48, which also highlighted a low to moderate agreement between the sensors and human observations.

Similar to water, metal is also known to affect radio signals so the equipment installed within the barn (e. g. freestalls, posts, fences, feed barrier) is likely to have affected the functioning of the sensors. To our knowledge, most previous experiences regarding the application of this type of proximity loggers on cows and small ruminants involved grazing animals while studies with housed animals, especially dairy cows in freestall barns, are still very sparse. This can partially explain why the sensitivity and accuracy of the sensors tested in the current study are somehow modest and generally lower than those reported in other studies involving similar RFID-based proximity loggers (Milwid et al., 2019; Fielding et al., 2021).

At the time this paper was written, data analysis was still ongoing so the results presented in this paper have to be interpreted as preliminary. The data generated by the sensors revealed a very complex structure which required the adoption of specific data handling and analysis techniques. Further analysis will be performed to assess false positive records and specificity of the sensors. Also, to reduce the error induced by the extensive presence of metal within the housing environment, different settings for the data filtering algorithm will be tested.

It is also worth noticing that the sensors tested in the current study are intended to monitor dyadic proximity events. The sensors, at least at the current stage of development, are unable to detect whether actual social interactions occurred nor inform about the type of interaction. Dyadic proximity events, however, have the potential to provide valuable information about the social behavior of dairy cows and better understand the complex social dynamics that exist in cattle herds. Proximity loggers could also be used to monitor the position of the cows within the barn and particularly the animal attendance in key areas such as close to the drinkers or at the feed fence.

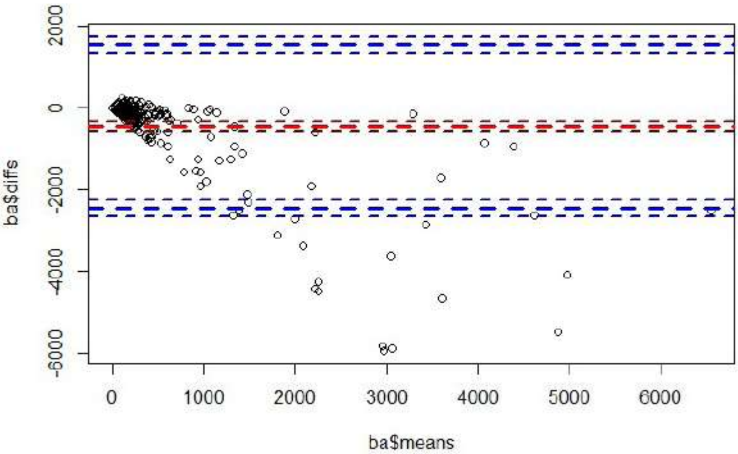

Figure 3: Agreement between the sensor measurements and human observations of contact events duration, displayed in Bland–Altman plot (dashed lines indicate bias, upper and lower limits of agreement, each with 95% CI)

Conclusions

The results, although still preliminary, indicated that RFID-based proximity sensors can be a viable tool to automatically monitor social proximity in dairy cows. However, the relatively low sensitivity and significant bias recorded in the current study highlighted that these sensors need to be thoroughly tested and validated before being employed in scientific studies or even in practical herd management applications. Further, as for most RFID-based technologies, the application of this type of proximity sensors within common livestock housing, especially freestall barns, can suffer from the presence of metallic equipment and structural elements.

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Cow behavioural activities classification by convolutional neural networks

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Abstract

As has been shown in several studies, behavioural activities of animals provide important parameters for the evaluation of their health and welfare. In recent years the use of wearable sensors to record animal activity has become an important practice especially in extensive farms, where there is an infrequent farmer-to-animal contact. Accelerometers allow the measurements of movements of a body in space and are currently very popular in the zootechnical field for monitoring livestock, as they can be worn without being invasive for animals. The objective of this work was to address the task of classifying cow behavioural activities using a Convolutional Neural Network (CNN) to discriminate five classes: feeding in standing position, feeding while walking, walking, lying and rumination in lying position. To carry out this study, accelerometer data were acquired at 4 Hz by customized devices attached to cow collars, containing triaxial accelerometers. The acquired samples were previously labelled by using video-labelling, and then grouped in windows and pre-processed. The developed model is a CNN with 1D convolutions, which receives as input a 3-channel batch of windows, where channels are the three axes. Firstly, the model processes the data in parallel branches, which analyse-different combination of channels. Features maps obtained from each branch are concatenated and provided as input to another cascade of convolutional layers. The model finally returns the prediction of the behavioural class. Our approach classified the five behavioural classes with an average F_1 score of 81.51%. When merging the feeding in standing position and feeding while walking classes, F_1 score reached 90.01%.

Keywords: sensor-based systems, MEMS, cow welfare, automated monitoring systems, convolutional neural networks, deep learning

Introduction

The use of wearable sensors is becoming a key technology for monitoring the health and welfare of animals in farms. In the literature several sensors have been used to monitor animals, and among these the most used are accelerometers. They are not expensive and can be worn by breed animals by using collars or pedometers. By processing the large volume of data provided by pedometers, it is possible to acquire new knowledge on the behaviour, habits, and health of animals supporting the development of automatic monitoring systems. Over the years, various monitoring systems based on wearable sensors have been developed using different approaches, such as manual identification of thresholds (González *et al*., 2015) (Arcidiacono *et al*., 2017a, 2017b), statistical models (Konka *et al*., 2014), machine learning (Benaissa *et al*., 2019) and more recently deep learning (Rahman *et al.*, 2016). While initial studies involving the use of accelerometers focused on the analysis of indoor behaviour, in recent years the scientific community, in accordance with the development and improvement of Internet-of-things (IoT) technologies, is showing a growing interest in solutions that can be adopted in extensive farms. In these, obviously, the need for automatic monitoring systems is greater because due to the large extension of the farms, the contact between the cattle and breeder is much less frequent than indoor. For example, in extensive livestock farms, especially those with a large number of animals, the monitoring of the daily budget of each behavioural activity (e.g., feeding, lying or rumination) becomes an essential information to allow farmers to both solve management issues and identify early some health-related problems (Mattachini *et al.*, 2016; Anzai and Hirata, 2021). Martiskainen *et al.* (2009) proposed a method based on Support Vector Machines to classify and detect eight behavioural activities in dairy cows (e.g., feeding, rumination, lying, and standing) using tri-axial accelerometer data, the accuracy achieved was: over 80% in each behavioural class, with overall precision of 78%. Smith *et al.*, (2016) proposed an ensemble model to classify five classes of cow behaviour activities based on the union of binary classifiers, one for each considered cow behavioural activity, trained to discriminate each cow behaviour activity from the other ones. Recently, research has increasingly employed deep learning (DL) techniques, which, despite the greater computational cost, allow for better generalizability and less human intervention in their design, since discriminative features are learned by the model itself. Convolutional Neural Networks (CNNs) were employed in Kasfi & Hellicar (2016) to classify cow behaviours; the model achieves 82.5% precision and 89.6% recall, though performance analysis is carried out by considering the majority class (grazing) against all other classes, due to dataset imbalance. In Peng *et al.*, (2019), a recurrent model based on Long Short-Term Memory networks classifies eight livestock behaviour classes using inertial measurement units (IMU), with 88% of accuracy, precision, and recall. CNNs are also proposed by (Pavlovic *et al.*, 2021), achieving 84% precision, 82% recall and 82% F1 score on three classes (rumination, eating and other).

The goal of this study is to propose a Convolutional Neural Network model to classify behavioural activities of grazing cows, which processes data in parallel branches considering various combinations of the channels (x, y, z) of the input data.

Material and methods

The herd

Data collection is carried out in a 180 hectares semi-natural pasture, located in Sicily (Italy) and characterized by good availability of meadow and cultivated grazing areas. This farm adopts "cow-calf line" breeding system, that involves keeping calves with mothers during the lactation period until weaning (6-8 months). Cows live in pasture all year. Data were acquired on 18-22 May 2021 and 27-30 June 2021, during a period of the day from 7:00 AM to 6:00 PM, when animals are confined in a large enclosure of about 2 ha, near the farmer's house; during the remaining hours of the day, they are moved to the pasture. This study monitors two 19-month-old cows, which are part of a group of 10 Limousines replacement heifers.

Data acquisition and labelling

The data required to classify grazing cow behaviours were acquired by a customized device equipped with tri-axial MEMS accelerometers, omnidirectional antennas, 32bit Cortex Microcontrollers, GSM/GPRS quad band modules, LiSOCL2 high-capacity batteries and flash memories. One of these devices was placed at the neck of each of two cows under analysis, with a leather-reinforced mesh collars having dimensions 130 cm × 4 cm. To avoid rotation of the device around the neck, a 1-kg weight was hung to the collar. This made it possible to choose the right distance of the device from the jaw to detect the accelerations due to the rumination phase. Acceleration measurements are acquired through the x, y, z axes at a 4 Hz rate. Collected data are sent every hour through GSM/GPRS network to a cloud service for storage. During the day, cow activities were video recorded by an operator. Subsequently, the data acquired by the devices were labelled by using video labelling technique. The data were acquired on two-time intervals, from 6:00 AM to 10:00 AM and then from 6:00 PM to 9:00 PM. Since video recordings were acquired by an operator, those time intervals avoided possible health risks during the hottest hours of the day. Climate conditions in the monitoring period were very critical since they reached on average approximately 27 °C, with maximum value around 41 °C on 30th June 2021. Each sample was labelled into one of the following classes: Feeding in standing position (F-S), Feeding while walking (F-W), Walking (W), Lying (L) and Rumination in lying position (R-L).

Pre-processing

Collected data are pre-processed to normalize the statistical distribution and to remove samples or sequences of samples that clearly represent outliers. Examples of outlier values, in the acquired dataset, were determined by minor cow behaviours, such as ear movement or chasing flies; they acted as an interruption of the observed behavioural activities and therefore introduced noise into the dataset. Sometimes between the end of one video (used for manual labelling) and the beginning of the next, there were discontinuities in labelling. If such discontinuities are shorter than 2 seconds (8 samples at 4 Hz), they were corrected, and the corresponding labels replaced by the one identified by the operator before and after the discontinuity. Data are provided to the classification model in windows of 20 samples (5 seconds) with consistent labels, so that each window can be assigned a single behaviour class. After splitting the dataset into training, validation, and test sets (described in the next section), Z-score normalization is carried out for each axis.

Model and training procedures

The model processed input data sequences in several parallel branches which analysed different combinations of axial measurements (Fig. 1), arranged as input feature channels. The key idea is to encourage the model to learn meaningful features from all axes, by implementing an inhibition mechanism that selectively excludes data from a subset of axes. This approach is motivated by the results of preliminary experiments (Porto *et al.*, 2021), where it emerged that for some behavioural activities the accelerations along all three axes were not required for the recognition. Therefore, the model was designed to ensure that a portion of the extracted features is guaranteed to depend on specific inputs only. In detail, multiple branches of 1D convolutional layers were introduced in the model, such that each branch received as input samples from only a subset of axes, for all possible subsets that include at least two axes. Additionally, to take into account features associated to single channels, a branch with shared kernels between all channels was included to capture global relations while forcing the model to learn axis-agnostic features. The last branch processed the whole input, i.e., all three channels at the same time. After that, features from all branches were concatenated and further processed by a cascade of convolutional layers, interleaved with max pooling blocks to reduce dimensionality. Finally, features were flattened and fed to a linear classifier. Figure 1 illustrates the resulting architecture, with details on the structure of each convolutional layer.

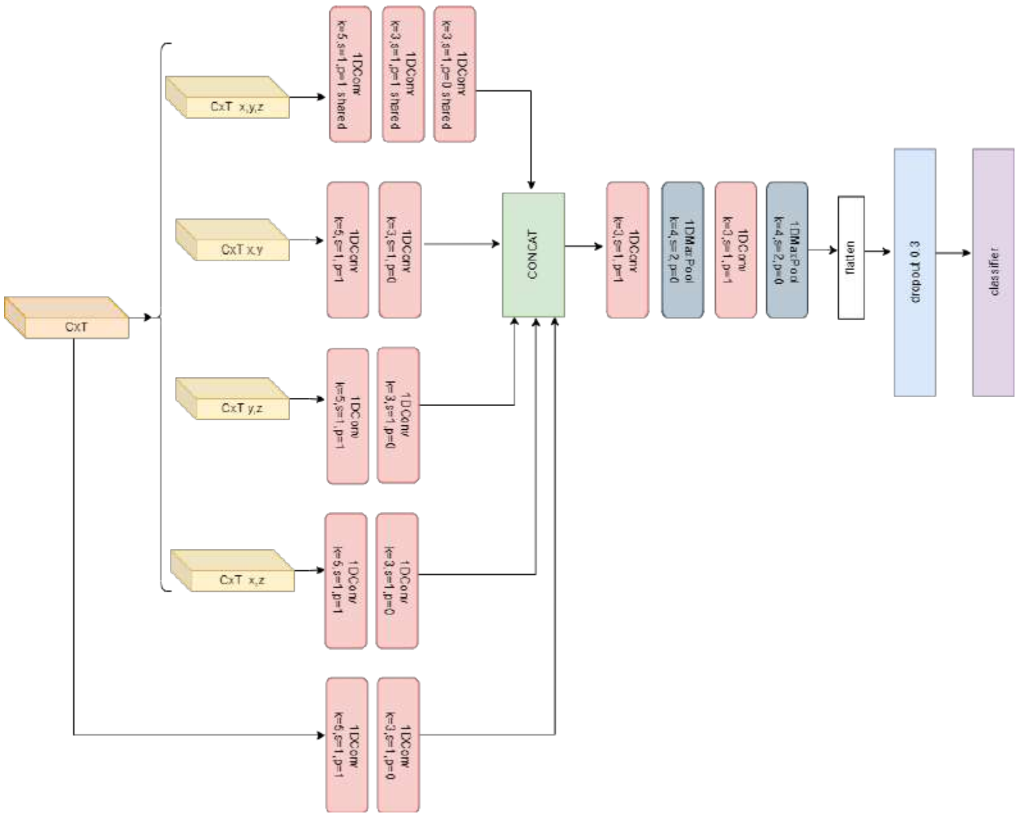

Figure 1: Architecture of the proposed model to classify cow behavioural activities

Each convolutional layer was followed by batch normalization and hyperbolic tangent as activation function. As a regularization method, dropout is employed before the classification layer. The model was trained for 70 epochs with AdamW (Loshchilov and Hutter, 2019) optimizer with a learning rate of 10^{-5} and 5×10^{-3} weight decay. As a classification loss function, cross-entropy was employed.

In order to deal with class imbalance, weighted random sampling was performed at training time, so that the model received on average the same number of inputs from each class, with repetitions.

Results and Discussion

Due to the different time spent by cows in each monitored behavioural activity during the time intervals of observation, samples related to the behavioural classes were unbalanced (Tab. 1). Therefore, we report results in terms of average precision, recall and F_1 score over classes, weighted by number of samples in each class, employing 10-fold stratified cross validation. At each cross-validation iteration, 10% of the training data are used as a held-out set to perform model selection among instances at different epochs. Results were reported in terms of mean and standard deviation over the 10 folds.

Table 1: Behavioural activity samples in pre-processed dataset

Behaviour	Samples	Percentage (%)
Feeding in standing position	12185	15.17
Walking	15498	19.30
Feeding while walking	16222	20.19
Lying	9194	11.45
Rumination in lying	27220	33.89
Total	**80319**	**100.00**

Two different experiments were carried out, considering two sets of different classes: in the first, all classes are included (5-class scenario); in the second, activities related to feeding (feeding in standing position and feeding while walking) were merged into a single class (4-class scenario). In this study, the proposed model was compared with two baseline neural network architectures: a 1D CNN model that process data from all axes and consists of a variant of the proposed model when only a single branch is used (the bottom one in Fig. 1); a multi-layer perceptron (MLP). Results of the experiments of the two scenarios were reported, respectively, in Table 2, showing that the proposed architecture significantly outperforms the baselines and is at least on par, if not better, than state-of-the-art approaches (although a direct comparison is not possible, due to the usage of different datasets and the lack of released implementations). It is interesting to note that all models performed better in the 4-class scenario than in 5-class scenario (Tab. 2). In particular, the performance of the branched model was lower for the feeding activities in the 5-class scenario (Tab. 3). This could be partially attributed to the similarity of the acceleration values recorded for the two behavioural classes. The confusion matrix illustrated in Figure 2 confirms that the source of indecision for the model is associated to the feeding while walking and feeding in standing position classes: when the two classes were merged, the accuracy of the model in recognizing the feeding activity was very high (Tab. 4).

Table 2: Test performance of the different models

Model	Scenario	F_1 Score (%)	Precision (%)	Recall (%)
Branched model	5-class	81.50 ± 1.29	81.00 ± 0.81	80.75 ± 0.95
Simple 1D CNN	5-class	78.96 ± 0.97	79.01 ± 1.02	78.93 ± 1.06
MLP	5-class	74.76 ± 1.26	75.11 ± 1.14	74.42 ± 1.32
Branched model	4-class	90.01 ± 1.49	90.10 ± 1.20	89.89 ± 0.91
Simple 1D CNN	4-class	87.26 ± 0.35	87.21 ± 0.75	87.32 ± 0.62
MLP	4-class	84.79 ± 0.65	85.13 ± 1.10	84.45 ± 1.36

Table 3: Test performance of the branched model in the 5-class scenario

Behavioural activity class	F_1 Score (%)	Precision (%)	Recall (%)
Feeding in standing position (F-S)	62.00 ± 6.87	65.75 ± 7.08	58.75 ± 7.50
Walking (W)	84.20 ± 2.38	83.75 ± 2.21	85.75 ± 3.40
Feeding while walking (F-W)	76.75 ± 4.11	73.75 ± 4.01	80.25 ± 3.94
Lying (L)	78.50 ± 5.32	74.00 ± 8.60	83.75 ± 1.50
Rumination in lying position (R-L)	86.25 ± 3.50	92.50 ± 2.08	88.75 ± 2.50
Weighted average	81.50 ± 1.29	81.00 ± 0.81	80.75 ± 0.95

Table 4: Test performance of branched model in the 4-class scenario

Behavioural activity class	F_1 Score (%)	Precision (%)	Recall (%)
Feeding (F)	95.25 ± 0.50	95.50 ± 0.57	95.00 ± 0.81
Walking (W)	85.00 ± 3.70	84.75 ± 3.60	85.00 ± 4.01
Lying (L)	81.25 ± 4.00	79.25 ± 2.50	83.25 ± 4.50
Rumination in lying position (R-L)	90.25 ± 2.75	91.50 ± 3.02	90.00 ± 2.16
Weighted average	90.01 ± 1.49	90.10 ± 1.20	89.89 ± 0.91

Conclusions

The results obtained in this study seem promising and the comparison with other neural network models shows that input processing through parallel branches, analysing different axes combinations, can be a valid approach for the classification of behavioural activity in cows using accelerometer data. The results obtained in this study are preliminary as the dataset used is small. The performance obtained when considering the 5-class scenario can be increased by acquiring more data, in different periods and considering a larger group of animals. However, the merging of the two classes related to feeding activity made it possible to increase the values of F1 score, precision and recall by about 8.51, 9.10 and 9.14 percent points, respectively. Taking into account the relevance for the farmer of the feeding activity, regardless of position assumed by the cows, i.e., standing or while walking, further experiments will regard the optimization in terms of computational cost of the 4-class branched model with the final aim to be implemented in a device to be worn by the cows.

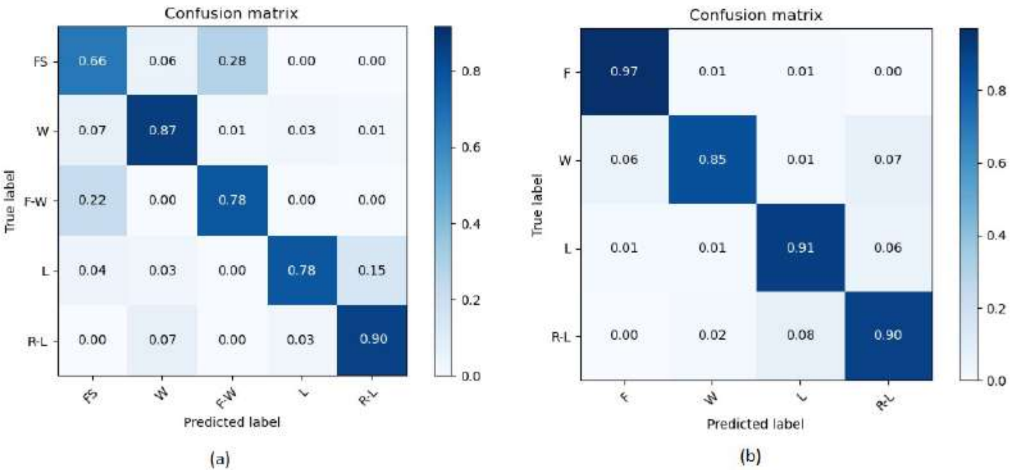

Figure 2: Confusion matrix of branched model for the 5-class scenario (a) and for the 4-class scenario (b). Accuracies are normalized per class

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Prototype design of an integrated system to monitor dairy cow welfare

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Abstract

In the last decades many automatic methods have been developed to detect indicators of reduced welfare in dairy cows. However, there is still a need to integrate data from single sources to obtain a complete picture of cow welfare. We designed a prototype of an integrated system to monitor cow behaviour and environmental conditions in the barn. From a literature review we identified the main issues that challenge cow welfare (e.g. heat stress) and well-established indicators (e.g. lying behaviour) that could detect these issues on the farm. We also started the development of a prototype of an integrated system, based on existing automatic methods to monitor barn climate and cow behaviour. In our approach we identified several indicators, e.g. reduced feed intake, that are common to most welfare issues and that are therefore suitable to detect reduced welfare in general, while other indicators mainly identify one welfare issue, e.g. increased respiratory rate or ambient temperature, as indicators of heat stress. Combining these two different types of indicators would result in efficient integrated automatic welfare monitoring. The main environmental parameters included in the designed prototype are: internal air temperature, humidity and speed, black globe temperature, gas concentrations (NH3, H2S, CO2), sound level, drinking water temperature and intake, presence of flies; while cow behaviour (lying, standing, eating and ruminating) is detected with a neck accelerometer. Combining these parameters provides a good starting point towards integrated automatic welfare monitoring that could assist farmers in detecting reduced cow welfare on their farms.

Keywords: barn climate, cow behaviour, accelerometers, Precision Livestock Farming

Introduction

Even though the welfare of dairy cows has long been underestimated by both public and legislation, recently dairy cow welfare was identified as the second greatest animal welfare problem in the EU (Nalon & Steveson, 2019). Therefore, there is an urgent need to improve cow welfare on the farm, for which an accurate assessment is the first step. With increasing farm sizes and automation in farming, the need to assess cow welfare automatically, as is dictated in the concept of Precision Livestock Farming (PLF), has also risen. This has resulted in various strategies based on both environmental and animal-based sensors to automatically monitor cow welfare on the farm (e.g. Halachmi *et al.*, 2019). However, for an accurate welfare assessment, the three different welfare aspects (i.e. biological functioning, affective state and natural behaviour; Fraser *et al.*, 1997) should be integrated into a complete picture. An integrated system would provide such a complete picture. On the one hand it could facilitate a broader assessment of reduced animal welfare in general. On the other hand, it could enable the differentiation between different welfare issues (e.g. between lameness and heat stress). To meet these opportunities, however, a careful selection of suitable indicators is needed.

Moreover, it is also important to test the feasibility of integrating data from different sources in practice. To promote the development of integrated systems for assessing cow welfare on the farm we first conducted a literature review to obtain an overview of the major issues that determine dairy cow welfare and to identify reliable environmental and animal-based indicators of these welfare issues. Second, we started to develop a prototype of an integrated system, using existing as well as new automatic methods to monitor barn climate and cow behaviour.

Literature review

The main issues that determine cow welfare were extracted from two international welfare reports, i.e. the Welfare Quality Assessment Protocol (2009) and a report from the European Food Safety Authority (Algers *et al.*, 2009), as well as two books on cow welfare (Philips, 2002; Rushen *et al.*, 2008). In total, 17 welfare issues were identified, of which eight related primarily to biological functioning, six to affective state and three to natural living (see Figure 1; Leliveld & Provolo, 2020). A maximum of five reviews were consulted for each welfare issue as well as for each welfare concern in general. From each review, references of indicators that could be measured automatically were counted (references that overlapped between reviews were only counted once) and the direction of the association between the welfare issue and indicator was noted. To determine which indicators best reflect reduced cow welfare in general, the indicators were ranked according to the number of welfare issues they were reported to associate with and on the number of references. To identify indicators that allow to single out specific welfare issues, a binomial test was used to test if there was a significant positive or negative association with each welfare issue. Associations were compared between welfare issues to identify unique associations (i.e. no similar associations existed with other issues).

Indicators of reduced welfare in general

Using this approach we identified 76 indicators, supported by a total of 1143 references, which could be categorized as environment- or animal based. With the exception of positive emotions, which is still much understudied, all reviewed welfare issues reflect reduced welfare. Therefore, indicators that associate positively with these welfare issues reflect reduced welfare, while indicators with negative associations reflect improved welfare. Of all identified indicators, feed intake, showed the broadest and most consistent (in terms of direction) association with welfare, almost always indicating a negative association (Table 1; Leliveld & Provolo, 2020). For some welfare issues, feed intake was identified as a cause, e.g. metabolic disorders (Esposito *et al.*, 2014), whereas for others it was a consequence, e.g. heat stress (Liu *et al.*, 2019). Milk yield had also a consistent negative association with cow welfare. However, milk yield is argued to be an unreliable indicator of cow welfare as it can be influenced by many other factors (Rushen *et al.*, 2008). While physical activity, lying behaviour and body condition score all also associated with many welfare issues, they did not show a consistent direction of association. For instance, lying increases during lameness (Dittrich *et al.*, 2019), but decreases during heat stress (Hoffmann *et al.*, 2020). This means that for an accurate interpretation they need to be combined with other indicators to provide context. Other indicators that showed a consistent direction of association with multiple issues are e.g. rumination, standing, agonistic behaviour, body temperature, heart rate, ambient temperature and humidity. For these indicators, as well as for less studied indicators, such as feeding frequency, more research is needed to determine how broad and consistent their association is with cow welfare.

Table 1: Ranking of indicators according to the number of welfare issues they were reported to have associations with (only indicators associated with ≥ 4 welfare issues are shown). ↑/↓ indicates the total number of references indicating a positive association versus the total number of references indicating a negative association. Significant differences between the number of positive and negative associations are highlighted in bold (binomial test, $p < 0.05$; adapted from Leliveld & Provolo, 2020)

Environment/ Animal Based	Indicator	No. Welfare Issues	↑/↓
animal	feed intake	16	9/91
animal	milk yield	15	36/102
animal	lying behaviour	12	26/21
animal	physical activity	12	17/19
animal	rumination	11	2/24
animal	body condition	10	35/24
animal	body temperature	10	53/0
animal	feeding time	10	1/22
animal	heart rate	9	24/0
animal	standing behaviour	9	20/1
animal	agonistic behaviour	7	16/4
animal	vocalizations	6	30/0
animal	milk quality/ content	6	2/12
animal	body weight	6	0/9
environment	ambient temperature	5	30/3
animal	somatic cell count in milk	5	10/0
animal	feeding speed	5	4/4
animal	social behaviour (unspecified)	5	2/4
environment	humidity	4	23/1
animal	abnormal behaviour	4	21/0
animal	altered body posture	4	18/0
environment	wet/slippery floors	4	10/1
animal	feeding frequency	4	2/8
animal	locomotion behaviour	4	2/7
animal	milking frequency	4	6/3
animal	grooming	4	4/4
animal	elimination	4	5/0

Indicators of specific welfare issues

In figure 1, the solid lines indicate unique significant associations (i.e. not existing with other welfare issues), meaning that the indicator could be used to identify a specific welfare issue. For instance, respiratory rate was only found to increase in case of heat stress and, therefore, could be used to identify heat stress specifically (as opposed to reduced welfare in general). Interestingly, welfare issues that have been studied most, like heat stress and lameness, have more specific indicators and may be therefore easier to identify. Therefore, care should be taken when choosing specific indicators, since a lack of other significant associations in the same direction may only be due to a lack of studies testing these associations. Further research is therefore important to better understand understudied associations between indicators and welfare issues.

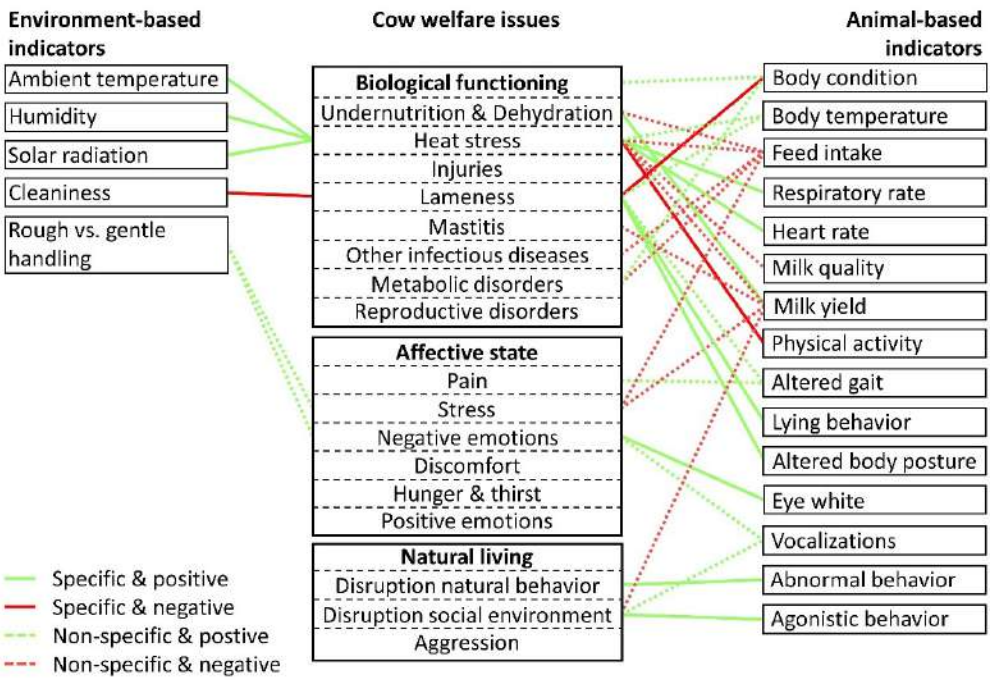

Figure 1: Significant associations (binomial test, $p < 0.05$) between indicators and single cow welfare issues. Straight lines indicate that the indicator has no similar association (in terms of direction) with other welfare issues (specific). Dotted lines indicate that a similar association occurs also with another welfare issue (non-specific). Positive associations are indicated by light green lines and negative associations by dark red lines (adapted from Leliveld & Provolo, 2020)

Further considerations

Combining indicators of reduced welfare in general with indicators of specific welfare issues in an integrated system would enable a broader assessment of welfare in in general as well as enable the identification of single welfare issues. However, several considerations would have to be made to ensure good data integration. For instance, different indicators of the same welfare issue may not always occur simultaneously. This could happen if one indicator is a cause of that specific welfare issue (e.g. reduced feed intake for metabolic diseases) and another a consequence (e.g. altered gate for lameness) or if one indicator has a quicker response than another (e.g. respiratory rate vs. milk yield in response to heat stress). Another important consideration is the setting of reliable thresholds for generating alerts. For some well-established indicators, fixed thresholds have been proposed. For instance, for the Temperature-Humidity Index (THI) as an indicator of heat stress, thresholds have been proposed in the range of 68-72 (e.g. Armstrong, 1994; Polsky & Keyserlingk, 2017). However, for most reviewed indicators there is not yet enough research done to be able to set a threshold. Moreover, for many animal-based indicators a dynamic threshold (i.e. based on a deviation from the 'normal' range of an individual) would be better suited for detecting potential welfare risks for each individual animal (e.g. de Mol *et al.*, 2013).

Prototype design

<u>Locations</u>

The prototype system was installed on three dairy farms, located in Northern Italy. The farms hosts herds of 100-300 Italian Holstein cows. All farms have a loose housing system, with free stalls and straw or solid digestate as litter. All farms have forced ventilation above the lying area and sprinklers above the feeding area in the monitored sections. On farm 1, the monitored section has three lines of cubicles in a total area of 808 m² and hosts about 90 lactating cows. The structure is open on all sides and has an insulated roof with a ridge opening. On farm 2, the monitored section has two lines of cubicles in a total area of 2121 m² and hosts about 145 lactating cows. The structure is open on all sides and has an insulated roof with a ridge opening. On farm 3, the monitored section has two lines of cubicles in a total area of 1785 m² and hosts about 120 lactating cows. The structure is partially closed on three sides (only one long side is open) and has an insulated roof with a ridge opening.

<u>Barn sensors</u>

Depending on the possibilities in each monitored area, a series of custom-made sensors was installed to measure the microenvironmental conditions. On all three farms eight sensor nodes, containing sensors to measure air temperature, black globe temperature, relative humidity and light intensity, were installed. In addition, two sensor nodes that measure air quality (CO2, H2S, NH3) and sound level and three sensor nodes that measure wind speed and direction were installed. All these sensors were placed in different sections of the barn at a height of approximately 3 m. On farm 1 and 2 also four sensor nodes that measure litter temperature and humidity were installed. Furthermore, sensor nodes were installed to measure the temperature and consumption of both sprinkler and drinking water (on farm 2, only sprinkler water consumption could be measured). Depending on the size of the monitored area, two (farm 1) to four cameras (farms 2 and 3) were installed to monitor any activities and events in the barn. In addition, a camera-based system was developed to monitor the prevalence of flies in the barn. A weather station was also developed to measure external air temperature, relative humidity, wind speed and rain. These weather stations are positioned in a field close to the monitored barns.

Figure 2: Schematic drawing of the system architecture (source IBT Systems s.r.l.)

<u>Cow sensors</u>

In addition to the barn sensors, accelerometer-based sensors were developed to monitor cow behaviour. 3D accelerometers were embedded in a custom-made device, which is based on a 35 x 45 mm System-on-board (SoB) and included an antenna and a host-board with power supply circuitry and the battery holder. It works both with Bluetooth and a dedicated 4 GHz radio channel. The device was fitted in a hard plastic case, which was mounted on a neck collar with a weight to keep the sensor in place. To develop an algorithm to detect multiple behaviours, 32 cows (18 from farm 1, 6 from farm 2 and 8 from farm 3) were observed while wearing these collars for a total of 108 hours. The following behaviours were scored: standing, lying down, standing and ruminating, lying and ruminating, eating, drinking, walking and other (i.e. behaviour that did not fit in the other categories). The visual observations were combined with the accelerometer data to train the algorithm. For behaviour identification 10-minute intervals were selected and accelerations were sampled at 25 Hz. After data collection and windowing, features extraction, reduction and classifier learning were performed. Ten features (out of 64 candidate features) were kept and five classifiers plus one combined classifier a-posteriori were built. The Decision Tree algorithm was concluded to be the best in terms of computational/memory complexity and accuracy. Training and validation were done using a 75%/25% of dataset partitioning. The final algorithm was able to detect six behavioural categories (lying down, standing, lying and ruminating, standing and ruminating, feeding and other) with an average accuracy of 85.12%. At each farm 60 cows were fitted with these neck collars. Comparisons with existing commercial systems are being made to validate the performance.

Data transmission and integration

All data measured by the different sensor nodes (both barn and cow-based) is sent every 10 minutes to a gateway via a 2.4 GHz radio channel (figure 2). This gateway then transmits the data to the cloud and can be remotely accessed via an online dashboard. On this dashboard, graphs visualize the data of single sensors as well as computed data, such as mean values from multiple sensors and the Temperature-Humidity-Index. For further processing the data can also be extracted in excel or csv format. Further steps will focus on combining the information gathered by the different sources to create a complete picture of the situation in the barn. Herd data, including health records and milk yield, are collected to tests the system's suitability to detect reduced welfare conditions.

Conclusions

Currently, there are many indicators of reduced dairy cow welfare that are well-established and that could be measured automatically. Of these indicators, some would allow for a general detection of reduced welfare, whereas a few other indicators would allow to identify single welfare issues. Combing these two types of indicators provides a good basis for an integrated automatic welfare assessment system. A prototype of such a system has been developed and installed on three dairy farms, serving as a first step in the practical implementation of integrated automatic welfare assessment. Further work will focus on validating the suitability of this system to detect situations of reduced welfare on the farm. In the end, this would enable the farmers to monitor the welfare of their cows continuously and remotely, thereby supporting them in their decision-making process.

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Effect of separation at weaning on the activity of cows and calves reared in a cow-calf contact system measured with accelerometer sensors

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Abstract

One welfare challenge of dairy cow-calf contact (CCC) rearing systems is the separation of the bonded cow-calf pair at weaning. Here, activity of 14 cow-calf pairs in 3 different CCC systems (no contact (control, CT), 4 pairs; part-time contact (PT), 5 pairs; full-time contact (FT), 5 pairs) was investigated. Each animal was equipped with a 3D-accelerometer (sampling rate: 12.5 Hz) attached to a neck-collar from two months pre-separation to one month post-separation. For each animal, the magnitude of the acceleration was calculated and segmented into 10-minutes windows from which six accelerometer features were computed. Each feature was modeled according to the treatment (*CT*, *FT*, *PT*), phase (*pre-separation*, *separation*, *post-separation*), interaction, and animal as a random effect. ANOVA and Tukey's pairwise comparison test were applied. Overall, FT calves expressed more high energy expenditure behaviors and activity peaks than CT calves ($p < 0.05$). More high intensity behaviors were expressed in post-separation both for FT and PT calves ($p < 0.05$) but the trend observed from pre-separation to separation phase was different depending on the treatment (interaction ; $p < 0.05$). For cows, higher overall activity ($p < 0.05$), more intense behaviors ($p < 0.05$) and more activity peaks ($p < 0.05$) were observed after separation compared to pre-separation, regardless of treatment. Ongoing experiments should help to link activity change and distress in order to propose recommendations in CCC systems.

Keywords: Cow-calf contact rearing system, activity, wearable 3D-accelerometer, distress

Introduction

On most commercial dairy farms, calves are separated from the cow within 24 hours postpartum as this enables better management of calf disease exposure and colostrum provision. However, this practice is criticized by consumers as they view the practice as unnatural. Cow-calf separation at birth can lead to the expression of abnormal behaviors and thus may compromise cow and calf welfare (Ventura et al., 2013). In response to these concerns, cow-calf contact (CCC) rearing systems, where a bonding period and prolonged contact time between calves and dams is allowed, appear to be promising. However, separation of the bonded cow-calf pair (weaning) is still a major welfare challenge (Johnsen et al., 2016) and a better understanding of the stress surrounding this event and its long-term impact is required before recommendations can be made

(Meagher et al., 2019). CCC rearing systems can differ in the type of physical contact allowed between the dam and her calf, such as full-time CCC (i.e. unrestricted physical contact including suckling) or part-time CCC (i.e. contact only during specific times of the day). Evaluating the stress experienced during and after the separation in different CCC systems would be a major step forward in providing recommendations on how the systems should be used. Most measurements of stress focus on changes in physiology and behavior surrounding the stressful event (Rault et al., 2017). Measuring changes in behavioral activity can be done by encoding animal behavior but it is time consuming. Alternatively, wearable accelerometer data-loggers are already used to continuously monitor the activity and behavior of ruminants (Riaboff et al., 2022) in order to detect a change linked to reproductive events (Benaissa et al., 2020) or welfare and health disorders (Burgunder et al., 2018)we investigated fractal patterns in the behavioural activity of domestic sheep (Ovis aries. In that sense, the change in behavior and activity related to distress during and after the separation of the bonded pairs in different CCC systems could be measured with accelerometer sensors. The aim of this study is to investigate the change in activity of cow-calf pairs in 3 different CCC systems, control (no contact; CT), part-time contact (PT) and full-time contact (FT), using accelerometer sensors.

Materials and Methods

This study was conducted at Teagasc Moorepark Research Farm (Fermoy, Co. Cork, Ireland; 50°07′N; 8°16′W) from February 1 to May 18, 2021. Ethical approval for this study was provided by the Teagasc Animal Ethics Committee (TAEC; TAEC2020-290) and procedure authorization was granted by the Irish Health Products Regulatory Committee (HPRA; AE19132/P124). All experimental procedures were performed in accordance with European Union (Protection of Animals Used for Scientific Purpose) Regulations 2012 (S.I. No. 543 of 2012).

<u>Animals, Management, and Experimental Design</u>

This experiment compared two different CCC rearing systems (full-time access (FT) and part-time access (PT)) to a conventional Irish rearing system (control, CT). Fourteen cow-calf pairs were assigned to one of the different rearing systems: 4 CT pairs, 5 FT pairs, and 5 PT pairs. Each cow received the same management up to calving, but the systems differed immediately post-calving. After calving, CT pairs were separated within 1 h and cows joined the rest of their treatment group. The FT and PT pairs were moved into bonding pens (approx. 17 m^2) after calving, where they stayed for 2-3 d to allow for bonding. FT and PT calves received colostrum from suckling their dams. After the bonding period, the FT and PT pairs joined the rest of their respective treatment groups.

<u>CT pairs</u>. The CT cows and calves were managed in accordance to normal, conventional rearing and management practices at Teagasc Moorepark Research Farm. Once separated from their dam and moved to a straw-bedded individual pen, CT calves were artificially fed their mothers colostrum < 2 h post-birth (quality ≥ 22% on Brix refractometer) at a rate of 8.5% of their birth weight. After receiving colostrum, calves were fed their own dam's transition milk (at a rate of 10% of their birth weight) twice a day

for their next 5 feedings. After transition milk, calves were fed 2.5 L milk replacer (26% crude protein; Volac Heiferlac Instant, Volac, Hertfordshire, UK) twice a day. At 7 d old, CT calves were transferred to a group pen (48 m^2; ~15 calves) where they were fed with an automatic milk feeder at a rate of 6 L/calf/day. Calves also had *ad libitum* access to hay, concentrates, and water. Calves were gradually weaned at 56 d using the automatic feeder. After calving, CT cows joined a herd of 40 cows. Cows were managed following typical Moorepark grazing management practices; cows were predominately grazed day and night, but were housed indoors during periods of inclement weather and offered *ad libitum* access to grass silage (Kennedy et al., 2009; 2011). CT cows were milked twice a day (7 am and 2:30 pm) and were supplemented with concentrates during milking. CT cows did not come into contact with any calves.

Pre-separation phase

PT Pairs. PT pairs were allowed full (unrestricted) access to each other during the night (16:00 to 08:00) and had no access to each other during the day (08:00 to 16:00). PT calves were housed in a shed in a straw-bedded pen (67 m^2) during the day that was adjacent to a free-stall pen that they can access at night (total area: 270 m^2). PT cows were housed indoors in this free-stall pen area during the night, and went outside to grass during the daytime. During daytime periods of inclement weather, PT cows were housed indoors in their free-stall pen, where they could see their calves but no access was allowed. PT cows were milked once a day in the morning (08:00). During the night, PT cows had *ad libitum* access to grass silage and water and PT calves had *ad libitum* access to grass silage, water, concentrates, hay, and milk (*via* dam). During the day, PT calves had *ad libitum* access to water, concentrates, and hay only. Over the course of the experiment, PT herd density ranged from 6 to 18 cow-calf pairs.

FT Pairs. FT pairs were allowed full (unrestricted) access to each other and were kept at pasture (2501 m^2), except during periods of inclement weather when they were kept indoors (as above) in housing identical to the PT pairs. At pasture, cows had *ad libitum* access to water and calves had *ad libitum* access to water, milk (*via* dam), concentrates, and grass. When housed indoors, cows and calves had *ad libitum* access to grass silage rather than fresh grass. Over the course of the experiment, FT herd density ranged from 6 to 14 cow-calf pairs.

Separation phase

FT and PT pairs were gradually separated and weaned over a 7-day period at 56 days of age. On day 1, the pairs were moved into adjacent pens, where gates allowed for the exchange of visual, auditory, and sensory cues, but prevented suckling. For the first 3 d, cows and calves were allowed 1 h of unrestricted contact after the AM milking, and for the rest of the day could interact through the gate. For the next two days, cows and calves were housed in the same pens but no period of unrestricted contact was allowed. On day 6, cows were removed from the weaning pen after the AM milking and joined the general herd of cows at grass. Calves were kept in the weaning pen for another two days. PT cows were switched to twice a day milking at day 1 of weaning and separation.

Post-weaning and separation phase

After weaning and separation, all calves were moved into a group pen (33 m^2) where they were provided with *ad libitum* access to grass silage, hay, water, and concentrates. The calves stayed in this group pen for 1-2 weeks until they were moved to pasture, where they stayed until the end of the experiment. At pasture, calves were provided with grass and *ad libitum* access to water and up to 1.5 kg DM concentrate. Post-weaning and separation, cows were kept with the general cow herd, grazed day and night and were milked twice a day.

Accelerometer sensor and device

Activity AX3 dataloggers (https://axivity.com/product/ax3) were used for the experiment. Activity AX3 are MEMS 3-axis accelerometers and Flash based on-board memory (512 MB), measuring 23 × 32.5 × 7.6 mm and weighting 11 g. The sampling rate was 12.5 Hz (battery life: ~ 30 days) with a range of ± 8 g. Each datalogger was wrapped in cling film and cotton wool, then attached to the collar with vet wrap and insulating tape. All data loggers were placed in the same orientation on the collar.

Data collection

Neck-collars were attached to the 28 cows and calves 7 days after calving. Collars were adjusted to ensure they remained in place on the neck, on the right side for cows and on the left side for calves. The x-axis detected the down-up direction, the y-axis detected the backward-forward direction and the z-axis detected the left-right direction. Neck-collars were removed every two weeks to extract the accelerometer data and recharge the battery, and attached again two days later. The collars were permanently removed about 1 month after the separation. During the whole data collection, health scoring was completed every 2-5 days using a system adapted from Barry et al. (2019). In addition, all animals were inspected daily by the farm manager. In the event of an adverse health event, animals were treated in accordance with normal management procedures at the research farm. If a calf required removed from the group pen it was placed in an individual pen for treatment, its collar was removed temporarily.

Accelerometer signal preprocessing

Preprocessing was applied using R software (R Core Team, 2021; version 4.1.2). For each accelerometer time-series, the magnitude of the acceleration (so-called *Amag*) from which the static component has been removed was first calculated as follows:

$$Amag = \left| \sqrt{{x_{axis}}^2 + {y_{axis}}^2 + {z_{axis}}^2} - 1 \right| \tag{1}$$

The *Amag* time-series was then split into 10 minutes-windows without overlap. A set of 6 accelerometer-features was calculated within each 10-minutes-window, namely (i) the Mean and Median as an indicator of the overall level of activity, (ii) the Standard-Deviation (SD) and the Motion Variation (MV ; see equation (2)) as an indicator of the level of intensity of the behaviors - quiet *versus* dynamic -, (iii) the Maximum as an indicator of the presence-absence of activity peaks and (iv) the Spectral Entropy (Hs

; see equation (3)) as an indicator of the periodicity of the behaviors - random *versus* predictable -.

$$MV = \frac{1}{M}\left(\sum_{i=1}^{M-1}\left|x_{axis_{i+1}} - x_{axis_i}\right| + \sum_{i=1}^{M-1}\left|y_{axis_{i+1}} - y_{axis_i}\right| + \sum_{i=1}^{M-1}\left|z_{axis_{i+1}} - z_{axis_i}\right|\right) \quad (2)$$

$$Hs = -\sum_{k=1}^{N} P_k \ln(P_k)\, with\ P_k = \frac{|\lambda_k|^2}{\sum_i |\lambda_i|^2}\ for\ the\ frequency\ \lambda_k \quad (3)$$

For each cow and calf, accelerometer features extracted from the 10 minutes-windows were averaged. For each of the FT and PT cows and calves, features were also averaged per *phase* i.e. *pre-separation* (~ 2 months), *separation* (7 days) and *post-separation* (~ 1 month). There is no calculation per phase for the CT pairs as they were separated immediately after calving.

Statistical analysis

Statistical analysis was carried out using R software (R Core Team, 2021; version 4.1.2). For cows and calves separately, a linear model was applied to model each feature in function to the *treatment*, as follows:

$$F_i = \mu + T_i + e_i \quad (4)$$

Where F = feature (Mean, Median, SD, MV, Maximum or Hs), η = mean; T_i = treatment (i = 1: CT, i = 2: FT, i = 3: PT) and e_i = residual error term.

A second linear model was also applied to model each feature in function to the *treatment* (FT or PT), the *phase* and the interaction between the *treatment* and *phase*, as follows:

$$F_{ij} = \mu + T_i + P_j + T_i \text{ x } P_j + C_{ij} + e_{ij} \quad (5)$$

Where F = feature (Mean, Median, SD, MV, Maximum or Hs), = mean; = treatment (i = 1: FT, i = 2: PT), P_j = phase (j = 1: *pre-separation*, j = 2: *separation*, j = 3: *post-separation*), T_j x P_j = interaction between treatment and phase, C_{ij} = random cow/calf effect within the treatment i and the phase j and e_{ij} = residual error term.

For each model, an analysis of variance (ANOVA) was applied followed by a Tukey's *post-hoc* test. Normality assumption was checked with QQ-plots and Shapiro's test, and the homoscedasticity assumption was evaluated with a Spearman's test, both applied on the residuals. Box-cox transformation was applied to meet the ANOVA assumptions if necessary.

Results and Discussion

Effect of the treatment on the activity of cattle

The results of the effect of the CCC *treatment* on cattle activity is shown in Table 1.

Table 1: Effect of the CCC treatment on the features of calves and cows activity

Features	Mean	SD	Median	Maximum[3]	MV	Hs
Calves						
Treat[1]	NS	**	NS	**	**	NS
CT[2]	$0.068^{A} \pm 0.01$	$0.039^{A} \pm 0.00$	$0.062^{A} \pm 0.01$	$-0.288^{A} \pm 0.06$	$0.022^{A} \pm 0.00$	$3.62^{A} \pm 0.37$
PT[2]	$0.058^{A} \pm 0.01$	$0.045^{AB} \pm 0.00$	$0.050^{A} \pm 0.01$	$-0.004^{B} \pm 0.05$	$0.026^{AB} \pm 0.00$	$4.26^{A} \pm 0.33$
FT[2]	$0.068^{A} \pm 0.01$	$0.050^{B} \pm 0.00$	$0.060^{A} \pm 0.01$	$-0.007^{B} \pm 0.05$	$0.029^{B} \pm 0.00$	$4.06^{A} \pm 0.33$
Cows						
Treat [1]	NS	NS	NS	NS	NS	NS
CT[2]	$0.065^{A} \pm 0.00$	$0.064^{A} \pm 0.00$	$0.049^{A} \pm 0.00$	$1.04^{A} \pm 0.07$	$0.048^{A} \pm 0.00$	$5.68^{A} \pm 0.14$
PT[2]	$0.063^{A} \pm 0.00$	$0.062^{A} \pm 0.00$	$0.048^{A} \pm 0.00$	$1.20^{A} \pm 0.06$	$0.044^{A} \pm 0.00$	$5.59^{A} \pm 0.13$
FT[2]	$0.063^{A} \pm 0.00$	$0.066^{A} \pm 0.00$	$0.046^{A} \pm 0.00$	$1.24^{A} \pm 0.06$	$0.046^{A} \pm 0.00$	$5.80^{A} \pm 0.13$

Note: [1]Significance of the *treatment* effect: *** p<0.001, ** p<0.01, * p<0.05, ƚ p<0.1, NS: Not significant; [2]Adjusted mean ± standard-error for each treatment; [A-B] Groups from Tukey's pairwise comparison; [3]Box-Cox transformation applied on this feature. Abbreviations: SD: Standard-Deviation ; MV: Motion Variation ; Hs: Spectral Entropy

For calves, a significant *treatment* effect was found for the SD, Maximum and MV features ($p < 0.05$; Table 1). An increase from CT to FT is observed for all features. SD, Maximum and MV are significantly higher in FT calves than CT calves. Therefore, FT calves expressed more high energy expenditure behaviors (e.g., walking, feeding) than the CT calves, and had more activity peaks (e.g., running, playing). This result matches the activity expected, as the FT calves were kept outdoors with their dams during the pre-separation phase, which provided them with more opportunities to express dynamic behaviors. Although offered greater than required space allowance, the CT calves were housed in the smallest pen and only had the opportunity for social interactions with calves their own age, not with their dam and other cows, thus were less likely to perform high energy expenditure behaviors.

No significant *treatment* effect was found for cows which may be explained by the high variability observed between cows within treatments (*data not shown*). An individual analysis on a larger set of cattle may be helpful to characterize the different trends observed in the CT cows.

<u>Effect of the separation on the activity of cattle in the FT and PT treatments</u>

No significant difference is found between FT and PT *treatments* for cows and calves when considering all separation phases. The results of the effect of the separation *phase* on cattle activity is shown in Table 1.

Table 2: Effect of the separation phase on the features of calves and cows activity

Features	Mean³	SD	Median³	Maximum	MV	Hs
Calves						
Phase¹	**	*	**	NS	***	NS
Pre-²	-13.85ᴬ ± 0.97	0.046ᴬ ± 0.00	-16.20ᴬ ± 1.43	1.03ᴬ ± 0.05	0.024ᴬ ± 0.00	4.09ᴬ ± 0.25
Sep²	-12.86ᴬᴮ ± 0.97	0.046ᴬ ± 0.00	-15.23ᴬᴮ ± 1.43	1.01ᴬ ± 0.05	0.029ᴬ ± 0.00	4.32ᴬ ± 0.25
Post-²	-11.41ᴮ ± 0.97	0.052ᴮ ± 0.00	-13.34ᴮ ± 1.43	0.98ᴬ ± 0.05	0.034ᴮ ± 0.00	4.28ᴬ ± 0.25
T x P¹	ƚ	*	NS	ƚ	ƚ	NS
Cows						
Phase¹	***	***	***	**	***	NS
Pre-²	0.060ᴮ ± 0.00	0.059ᴬ ± 0.00	0.044 ᴮ ± 0.00	1.15ᴬ ± 0.06	0.041ᴮ ± 0.00	5.803ᴬ ± 0.07
Sep²	0.053ᴬ ± 0.00	0.057ᴬ ± 0.00	0.039ᴬ ± 0.00	1.28ᴮ ± 0.06	0.037ᴬ ± 0.00	5.789ᴬ ± 0.06
Post-²	0.078ᶜ ± 0.00	0.077 ᴮ ± 0.00	0.056ᶜ ± 0.00	1.35ᴮ ± 0.06	0.057ᶜ ± 0.00	5.745ᴬ ± 0.06
T x P¹	NS	NS	NS	ƚ	NS	NS

Note: ¹Significance of the *phase* and *interaction* effect: *** p<0.001, ** p<0.01, * p<0.05, ƚ p<0.1, NS: Not significant; ²Adjusted mean ± standard-error for each phase (Pre-: Pre-separation, Sep: Separation, Post-: Post-separation); ᴬ⁻ᶜ Groups from Tukey's pairwise comparison; ³Box-Cox transformation applied on these features. Abbreviations: SD: Standard-Deviation; MV: Motion Variation ; Hs: Spectral Entropy.

For calves, a significant *phase* effect was found for the Mean, SD, Median and MV features ($p < 0.05$; Table 2). The increase from pre-separation to post-separation suggests a gradual rise of the overall activity over the experiment, probably linked to the calf growth. For MV and SD, a significant increase is observed after separation for both features. These findings suggest an impact of the separation, leading to more high energy expenditure behaviors (e.g., walking, feeding) in post-separation, which could be related to calf distress. *Interaction* between treatment and phase is significant for the SD feature ($p < 0.05$; Table 2), suggested a different response to the separation between treatments. An increase of SD is observed in PT from the pre-separation to the separation phase while a decrease is observed in FT calves during the same period (figure 1). This suggests less high energy expenditure behaviors during separation in FT calves compared to pre-separation, probably linked to the change of housing. Conversely, PT calves expressed more high intensity behaviors during separation compared to pre-separation. As the space allowance was smaller during separation, this suggests that the weaning and separation process had an impact on calf behavior, which could be linked to calf distress.

For cows, a significant *phase* effect is found for the Mean, Median, SD, Maximum and MV features ($p < 0.05$; Table 2). A significant decrease is observed for the Mean and Median from the pre-separation to the separation phase, which then significantly increase post-separation. These findings suggest a decrease in the overall activity during the separation that may be due to the change in housing. The increase in overall activity post-separation can also be explained by the return to pasture post-separation. This assumption is consistent with the trend observed for MV, suggesting less high energy expenditure behaviors (e.g., grazing, searching, walking) during the separation compared to previous phase, and then more high intensity behaviors post-separation. The SD feature is significantly increased post-separation, suggesting more dynamic activities in this phase. The Maximum feature also increased post-separation, suggesting more activity peaks (e.g., running, playing, fighting). It's worth noting that these features are significantly higher post-separation than pre-separation (see Table 2) while FT and PT cows were on pasture in both phases. These findings suggest an impact of the separation regardless of treatment, leading to an increase of the overall activity level, more high intensity behaviors and more activity peaks in the post-separation phase, that could be linked to cow distress. For the *interaction* effect, no significant effect is found, suggesting a similar response to the separation, regardless of treatment.

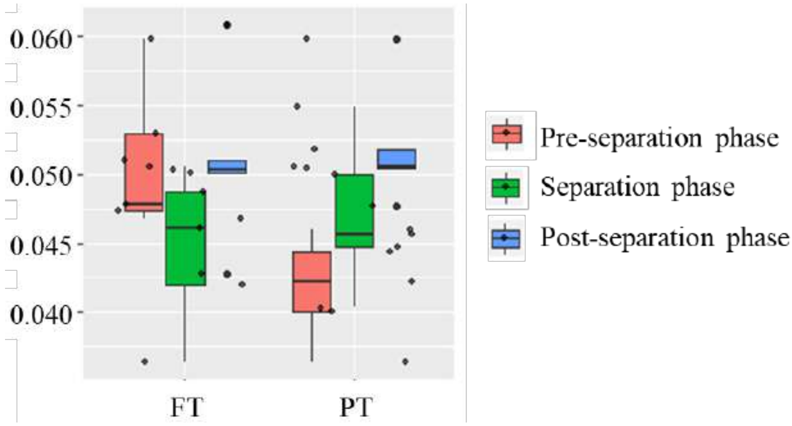

Figure 1: Interaction between phase (*pre-separation*, *separation. post-separation*) and treatment (*PT*, *FT*) effects for the SD feature for cows

It should be noted that (i) cattle welfare scores to align with the accelerometer 10 minutes-windows and features and (ii) a model to classify cattle behavior from accelerometer data, including both positive (e.g., playing, grooming) and negative (e.g., tongue rolling, head out of pen) behaviors, would be both helpful to further interpret the observed change in cattle activity in relation with distress caused by the separation. Further experiments are in progress and should help to propose recommendations in CCC rearing systems.

Conclusion

In this study, the activity of 14 cow-calf pairs was measured in different cow-calf contact systems (no contact, partial-time contact, full-time contact) using accelerometer dataloggers attached to a neck-collar. The change in activity related to the separation between cows and calves depending on the CCC system was also investigated. Although it is difficult at this stage to conclude whether calves undergo different levels of distress following separation based on their CCC system, it is clear that separation leads to a change in the amount of high energy expenditure behaviors, with calves having a different response depending on the treatment. An increase of high intensity behaviors and activity peaks was also observed in cows after separation compared to the pre-separation phase, regardless of CCC system. Further experiments are underway to better understand the change in activity observed in cows and calves related to the separation in order to propose recommendations in CCC rearing systems.

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SESSION 2

Pigs: Computer Vision in Piglets and Weaners

Dense tracking of pig behavioral features before tail biting

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Abstract
Tail biting (caudophagy) in pigs represents a serious yet complex problem in farm animal husbandry. There is increasing evidence in scientific papers that a change in pig behavior can be observed up to six days before the first bloody tail lesions occur. The detection process described in the literature is mostly carried out using human observations where a wide margin of error exists and is too time consuming. In this paper, we present a software system for automatic real time tracking of different types of behavior. We focus on the detection of tail posture by evaluating videos from the day of a tail biting event up to 12 days back, because tail-posture is reported as a fundamental indicator of an early warning system. In general, the system can be seen as a toolbox and can be easily applied to analyze different forms of dynamic behavior. This is possible because body parts of pigs and their place and movement are detected.

Keywords: pigs, tail biting, tail posture, automated behavioral monitoring

Introduction
Tail biting is a serious problem in modern pig husbandry. In recent years, many studies have been conducted to identify possible risk factors for this behavioral disorder, providing that tail biting is a multifactorial problem (Moinard *et al.*, 2003). Genetics, health status, sex, age and weight of the animals are discussed as possible endogenous and external influencing factors, as well as group size, weaning age and management, stocking density, feed, feeding technique, air quality and enrichment material (Schrøder-Petersen and Simonsen, 2001; Taylor *et al.*, 2010; Sonoda *et al.*, 2013).

To effectively prevent an outbreak of tail biting, taking timely countermeasures is essential. Changes in pig behavior for early detection of an impending tail biting outbreak have been intensively researched in recent years. Here, it was shown that a change in animal behavior could already be detected up to seven days before the first bloody tail lesions appear (Zonderland *et al.*, 2011; Wedin *et al.*, 2018; Larsen *et al.*, 2019). The resting periods of the animals are shortened with a simultaneous increase in activity (Zonderland *et al.*, 2011; Larsen *et al.*, 2019), the pigs increasingly sniff and nibble on the tails of their pen mates and the proportion of hanging or tucked tails increases (Ursinus *et al.*, 2014; Larsen *et al.*, 2018; Wedin *et al.*, 2018).

Based on these findings, more and more studies are looking at automated detection of altered tail position via video surveillance (D'Eath *et al.*, 2018). This technological innovation of automated behavioral monitoring has great potential to integrate into existing operations and support early detection of disease and injury (Han *et al.*, 2017). Thus, tail biting outbreaks could be reduced or even avoided.

To come to a sound foundation for technical development with practical applications, some important requirements should be fulfilled by the desired system.

The system should be able to:

— analyze the behavior in a modern pen with different functional areas and conventional group size
— detect individual pigs and their movement (tracks) over some time
— detect the tail posture and some actions like chasing, tail-in-mouth-behavior
— fulfill its requirements without applying sensors or markers on the pigs
— achieve scene detection by use of low-cost cameras

Seen from a technical perspective, recognition in a pen with different functional areas, as shown in Figure 1, is a much more advanced requirement compared to some previous attempts referenced in literature (Nasirahmadi *et al.*, 2019; Li *et al.*, 2020; Wutke *et al.*, 2021, Sun and Li, 2021; van der Zande *et al.*, 2021). Here, video scenes were recorded from pens with low stocking density, without functional areas inside the scene and with a homogeneous pen floor occupied by only a few pigs.

Figure 1: Camera View into the observed pen of our study

Material and methods

Experimental Data

The video recording for behavioral analysis was carried out in February and March 2021 at the Agricultural Test Center VBZL Haus Duesse of the Chamber of Agriculture North Rhine-Westphalia in Bad Sassendorf, Germany. The experiment was conducted in two conventional rearing pens with a group size of 35 animals each. The animals were weaned at the age of 4 weeks and had an average weaning weight of approximately 7.64 ± 1.2 kg. The tails of the piglets were not docked and male piglets were castrated. The housing environment was characterized by increased space allowance (0.5 m² per animal). The pigs had ad libitum access to dry feed, open drinking bowls, and various enrichment materials. The behavior of the animals was continuously recorded on video for the entire duration of the rearing period of six weeks. For this purpose, two stationary HD cameras (Bascom Bullet Camera Plus VB40, 1080p, 20 bps) were installed in each pen. Further evaluation took place on the basis of this video recording.

Human Observations

For manual behavioral evaluation by human observer, we analyzed the videos of the affected pen 7 days prior to and the day of tail biting outbreak (day -7 to day 0) by instantaneous scan sampling. Videos were analyzed by the same observer with an interval of 10 minutes from 06:00 to 19:50 h. Tail posture was examined only in standing pigs. In the evaluation, a distinction was made between curled and hanging/tucked. Only pigs that were visible from head to tail were considered.

Technical Observation

The technical observation reported in this paper focuses on one tail-biting event. Thirteen days, including the day of event and the 12 days before, were recorded and automatically analyzed between 14:00 and 18:00 h.

In general, the dense tracking system can be seen as a toolbox and can be easily applied to analyze different forms of dynamic behavior. We will be describing its main components in the following sections.

Temporal Input Blocks

For each pen, one single camera is continuously delivering videos. From these videos, consecutive blocks of frames are collected. One block contains 40 frames, corresponding to two seconds followed by a break of two seconds without extracting frames. Experience in the project shows that two seconds are sufficient to detect fast movements, tail posture, and different interactions such as tail-in-mouth events.

Extraction of Neck, Tail and Backline

All important steps are performed by using neural networks and supervised training. As described in our previous paper (Wisskirchen *et al*., 2021) a neural network for human pose recognition (Osokin, 2020) was modified to detect neck and tail positions as well as a directed connection line between those (Wisskirchen *et al*., 2021). As training data, in addition to our own manual annotation, we used the public data set of the University of Nebraska after some modifications for fitting neck and tail positions (Psota *et al.,* 2019). The network delivers heatmaps for the neck position, tail position, and two maps for the vector field of the backline positions. These still uncoordinated heatmaps are assigned to the individual pigs. For this purpose, a specific clustering of the backline vector field was performed.

Tracking

The detected positions are coordinated in a time sequence, resulting in short time tracks of maximally two seconds for each block. The pose network delivered suboptimal results in cases where pigs were standing or lying very close together or moving very fast. For generation of stable tracks we applied the IOU (intersection over union) principle (Bochinski *et al*., 2018) so the heatmaps for neck, tail position and backline are used to generate overlapping ellipses.

Tail Posture Detection

Due to practical performance considerations, a simple approach was chosen to detect different types of tail postures by using a small convolutional network as a deep classifier. Only three classes (invisible, normal, abnormal tail posture) were trained. Thus, hanging tails as well as fast wiping tails were labeled by the same attribute as abnormal. During training only fully curled tails were annotated as normal. The classifier uses patches positioned around the tail postures in the tracks. To achieve stable recognition, we used the entire tail track for each tail of a single pig and gave the same label to the 40 positions. This was possible because observation showed that tail posture changes very rarely in such a short time. The rate of positive predictions for the test videos from the pen is 79% for the three classes. The error rate for the normal/abnormal relationship is less than 10%.

Pen Annotation

By use of a small interactive annotation editor as part of the toolbox, functional areas of the pen (feeding and drinking area, enrichment area, resting area, activity area) were extracted and stored as polygons, so that the location of the pigs can be easily tracked at any point in time. This way, the use and occupation of these areas can be easily collected.

Results

Human Observation

On 7 to 3 days prior to the tail biting outbreak the percentage of pigs with hanging or tucked tails was below 30% and had its minimum at day -6 (27.02%, Fig. 2a). Immediately before the outbreak, the percentage of animals increased above 30% (day -2 and 0 relative to tail biting outbreak, Fig. 2a). When analyzing the course of the day, the manual behavioral evaluation of pigs' behavior showed a peak of activity between 14:00 and 17:50 h (Fig. 2b, grey line). During this period, the percentage of pigs showing hanging or tucked tails was higher than the rest of the day (fig. 2b, black line). For this reason, this period was chosen for automatic analysis.

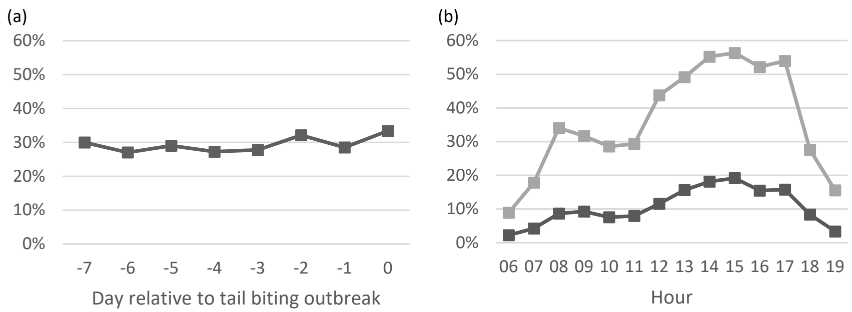


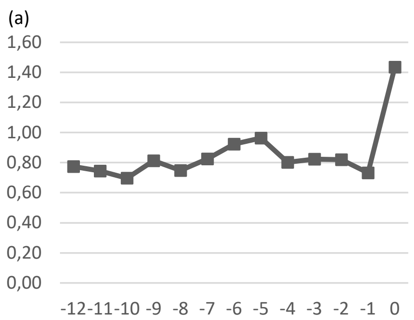
Figure 2: Number of pigs with hanging/tucked tails as a percentage of visible standing pigs (a) per day relative to tail biting outbreak and (b) per hour as mean value of evaluation days (black line); the number of pigs standing as a percentage of y visible pigs (grey line)

Technical Observation

Main technical observations focused on the automated detection of normal and abnormal tail postures. Therefore, the relation of abnormal/normal tail postures was calculated. The classifier showed on testing data a deviation between the true relation and the predicted one of less than 10%. This performance is sufficient for statistical evaluations.

Technical analysis was performed for videos between 14:00 and 18:00 h at 12 days prior and the day of tail biting outbreak (day -12 to day 0). The pigs were vaccinated at the midday of the tail biting outbreak (day 0), so this day is not described further because in the evaluated time window the behavior of the animals was strongly affected.

Across the whole group, the technical analysis showed the first peak of abnormal tail postures 5 days before the tail biting outbreak (Fig. 3a). After this day, the ratio of abnormal to normal tail postures decreased until day -1 with an increasing proportion of pigs showing curled tail postures. With a focus on the area around the feeding trough, the first peak of abnormal tail postures occurred on day -6 prior to tail biting (Fig. 3b).



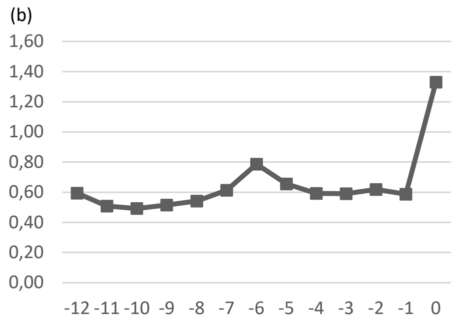


Figure 3: Relation of abnormal/normal tail postures on days relative to tail biting outbreak evaluated (a) for the whole group and (b) only for pigs standing in the feeding area

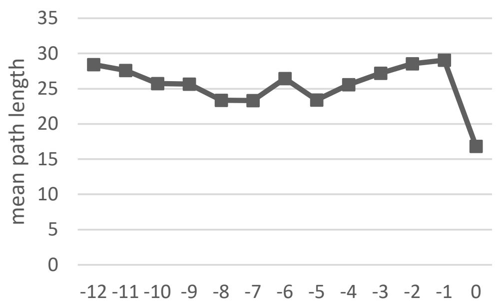


Figure 4: Activity of pigs on the days prior to tail biting outbreak as mean path length per day in pixel

As a measure of the activities of the different afternoons, the path length (in pixels) was evaluated for the tracks of the pigs in all two-second blocks. Figure 4 shows a decrease in activity from 28.42 pixels to 23.31 pixels between day -12 to -7 relative to the day of the outbreak (Fig. 4). After a peak on day -6 (mean path length of 26.46 pixels) the activity of the pigs increased from day -5 to -1 relative to the tail biting outbreak (23.40 pixels to 29.05 pixels; see Fig. 4).

Further statistical evaluation of the parameters as well as the comparison of the two evaluation methods are still pending at the current time.

Discussion

The human observation of the analyzed tail biting outbreak showed a moderate increase of hanging or tucked tails on the two days prior to the outbreak. This corresponds with the findings of Lahrmann *et al.* (2017), who also observed an increased proportion of hanging tails from around 23% on day -3 to around 33% on day -1 relative to the tail biting outbreak. In our findings, the proportion of hanging or tucked tails varied between 27% and 33% of standing pigs. This proportion is much lower than in Wedin *et al.* (2018), who observed a much higher proportion of pigs with uncurled tails with 45% uncurled tails on day -7 to about 55% uncurled tails on day 0. In the same study the proportion of tucked tails increased by about 10% as well.

Both the human and technical observation of the analyzed tail biting outbreak showed an unexpected low percentage of hanging/tucked tails and abnormal tail postures on the day before the tail biting outbreak (day -1). This contradicts the previous findings of other authors who observed a constant increase of the proportion of hanging or tucked tails on the days prior to a tail biting outbreak (Lahrmann *et al.*, 2017; D'Eath *et al.*, 2018; Wedin *et al.*, 2018). To determine if this low proportion of abnormal tail postures on day -1 is a unique phenomenon in our survey, additional videos of other tail biting outbreaks need to be analyzed and statistically matched.

As mentioned before, in the technical observation all non-curled tail postures were annotated as abnormal. In human observation, only hanging or tucked tail postures were counted as not curled. This difference in defining behaviors results in a high percentage of abnormal postures than in the human observation. Besides this, the human observation was carried out between 06:00 and 19:50 h per day whereas the technical analysis was performed between 14:00 and 18:00 h per day. Both aspects must be taken into account in the statistical comparison of the methods, which is yet to be done.

During the technical evaluation, in addition to the analysis of tail posture, the activity of the animals was also evaluated. Expressed in path lengths no clear alteration of activity was found 12 days prior to the tail biting outbreak as the activity decreased from day -12 to -7 prior to the tail biting and then again increased until day -1 to the same level of day -12. This increase in activity in the five days directly prior to a tail biting outbreak underlines the findings in previous studies (Zonderland *et al.*, 2011; Larsen *et al.*, 2019). However, with this result, it should be taken into account that the activity level 12 days earlier had a similar value as on the day directly prior to the outbreak. Therefore, the entire course of activity of a group should be examined in further videos to verify if the activity of the pigs expressed in path lengths is suitable as an indicator of an approaching outbreak of tail biting.

The algorithm should be tested on further video material of different tail biting outbreaks to verify these results. Furthermore, a statistical comparison of the two evaluation methods is still pending.

Conclusions

In the current study, we introduced the technical development of a system for automated behavior observation in pigs. Our findings showed that the automated analysis can be performed with low-cost 2D cameras. We were able to analyze pigs' tail postures on individual basis across the whole pen with a conventional group size of pigs. Additionally, we generated statistics for pigs with specific moving patterns in different pen areas.

The automated analysis of locomotion patterns of pigs in combination with their location in different pen areas and detection of interactions between individuals such as tail-in-mouth behavior or chasing and their tail postures will enable detailed behavior analyses in farm animals without a high time investment for the observer. This will improve understanding of pigs' behavior and therefore animal welfare.

As one of the next steps in our project, the tail posture classifier will be improved by discriminating more classes of tail postures. Analogous to the development of a pose detector that uses patches around tracked tail postures, a tail-in-mouth classifier with patches around close mouth/tail pairs will be developed.

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Parameter testing and systematic performance assessment of machine-learning models for video-based classification of damaging social behaviour in groups of pigs

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Abstract

Damaging behaviours such as tail and ear biting are a major welfare and economic challenge in modern pig production. Automated monitoring of groups of pigs for timely detection of changes in behaviour and the onset of damaging behaviour might enable farmers to take immediate management actions, and thus decrease health and welfare issues on-farm. We aim to develop a computer vision-based tool for automated monitoring and recognition of damaging behaviour in groups of pigs using a pre-trained convolutional neural network (CNN) combined with a secondary artificial network (ANN). For this purpose, this preliminary project compared different data pre-processing and model building parameters to determine the optimal framework. The best model achieved a major-mean accuracy of 65% for video-based classification of damaging social behaviour in groups of pigs.

Keywords: Biting behaviour, convolutional neural network, pig, monitoring

Introduction

The majority of commercial pigs in the EU are raised under intensive conditions that are likely to increase the development of abnormal social behaviour such as ear and tail biting in groups of pigs (Blackshaw, 1981). As biting behaviour is associated with stress and pain (Munsterhjelm et al., 2013), and can in severe cases lead to an infection of the inflicted wounds, it is considered a major welfare and economic challenge in modern pig farming (Niemi et al., 2012; Harley et al., 2014). Current preventive strategies include the removal of risk factors that might trigger the development of biting behaviour in groups of pigs, tail-docking i.e. surgically removing a part of the tail to hamper tail-biting behaviour, or supplying enrichment material. However, as some of these strategies are often considered unfeasible by the farmer or to have severe welfare implications (Herskin et al., 2010; Di Giminiani et al., 2017), timely detection of the behaviour and early intervention still seem to be the most feasible ways of preventing severe biting and potential outbreaks. Within this project, we aim to predict damaging behaviour in groups of pigs using deep machine learning, with the long-term goal of developing a tool which automatically detects such behaviours from farm's own video surveillance. For such a tool to enable farmers to make timely decisions regarding intervention strategies, it is crucial that it reliably detects agonistic behaviour with limited misclassifications. Hence, the aim of this preliminary study is to determine the optimal combination of parameter regarding data pre-processing and secondary ANN model architecture resulting in the best performance for the given data.

Material and Methods

Experimental set-up and data handling

The data used in this study were collected at a commercial Danish piggery. The piglets observed for this study were piglets prior to weaning (30 ± 1.6 days of age). All details on housing and management can be found in a previous publication (Hakansson et al., 2020). Video data was acquired from 26 pens, however, for the purpose of this study only a subsample of five pens was used.

A GoPro Hero 3+ camera (Silver edition, hard-box case, GoPro® Inc.) was fixed approximately 2m above the floor and recorded the entire pen area. The camera recorded RGB videos with a resolution of 1920 x 1080 pixels in MPEG4 format and a frame rate of 59.94 frames per second (fps). Each pen was recorded once for 60 min. Video data were manually labelled by a single observer using all occurrence sampling. Biting behaviour was labelled according to the ethogram (see Table 1) of Hakansson and Bolhuis (2021) and was assessed individually for all piglets within a pen. All details of the data collection can be found in a previous publication (Hakansson et al., 2020).

Table 1: Ethogram of biting behaviour in piglets, adapted from Hakansson et al. 2021

Behaviour	Description
Tail biting	Nibbling, sucking or chewing at the tail of a pen mate, causing a reaction from the other pig.
Tail-in-mouth	Gentle nibbling, sucking or chewing of another pig's tail, without causing a reaction in the other pig.
Tail interest	Sniffing, nosing or manipulating the tail of another pig without taking the tail into the mouth.
Ear-biting	Nibbling, sucking or chewing at the ear of a pen mate, potentially causing a reaction from the other pig.
Other biting	Nibbling, sucking or chewing the body of a pen mate (excl. tail and ears), potentially causing a reaction from the other pig.

Descriptive analysis of the data revealed that the minimum duration of the behaviours included was 1 s. From the continuous video data, still frames were extracted with a framerate of 10 fps, and the images were subsequently connected with their respective metadata. The data were manually post-processed and frames with disturbances, e.g. when the farm staff passed by or entered a pen, were removed. The full data set consisted of 149,560 images, of which 8,690 images showed any kind of biting behaviour (see Table 2).

Implementation

The software used to implement the algorithms was R Version 3.6.0 (R Core Team, 2019) and the library Keras (Version 2.7.0). No data augmentation was applied to the images, but images were converted to greyscale and resized to a resolution of 224×224 pixels to fit the input size of the VGG-16 network. Data from four pens were labelled as outer training set and were further used to detect optimal parameter settings using cross-validation. Data from the remaining fifth pen was labelled as outer test set. The outer training set was subsequently split into inner test and training sets using k-fold cross-validation based on penID (k=4, see Figure 1). At each iteration, one pen was labelled as the inner test set, while the remaining three pens were labelled as inner training set.

Table 2: Descriptive statistics

Pen ID	No. included images	No. images with biting event
1	20710	430
2	31900	3140
3	31240	1600
4	32970	1290
5	32740	2230

Moreover, from each training set 10% of the data were randomly labelled as validation set. Validation sets were used to assess the fit of the model during training, while test sets were used to assess the predictability of a built model on a new (unseen) data set.

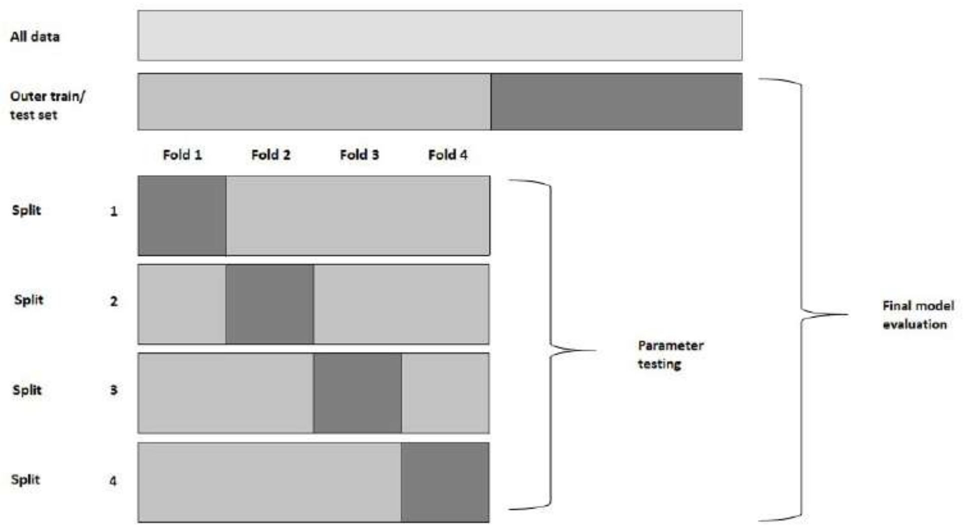

Figure 1: Overview of the cross-validation. Data were split into outer test set (dark grey) and outer train set (light grey), which was subsequently split using 4-fold cross-validation

Algorithm

Within this study, a three-step approach was applied:

1. A pre-trained convolutional neural network (CNN) was used to transform each pre-processed image into a one-dimensional feature vector of length 4096.
2. Using k-fold cross-validation, feature vectors were subsequently input into secondary artificial neural networks (ANN) with different hyper-parameter settings, to determine the set of parameters resulting in the highest accuracy for our data.

3. Using the best set of parameters, a final ANN was trained based on the entire outer training set and tested on the outer test set.

In this study, the pre-trained VGG-16 model (Simonyan and Zisserman, 2014) was used was used to extract relevant spatial features. To this end, the base architecture was modified so that the final output layer was removed. This modified VGG-16 network was used to extract spatial features for each image, resulting in a vector of length 4096 for each image. To reduce computational workload, features with zero variance throughout the data set (N= 222) were removed from both, the training and testing set. Subsequently, the remaining features were combined with the corresponding target variable, and the secondary ANN was trained using these data. The secondary ANNs consisted of an input layer, one or more fully connected hidden layers with the ReLu activation function, and an output layer using Softmax classification. The network was trained for 100 epochs with a learning rate of 0.0001. For the purpose of parameter testing, the model architecture changed depending on the set of parameters used. In this study, the parameters tested for their effect on model performance were either applied to the input features (pre-processing) or to the architecture (hyper-parameter, see Table 3).

Table 3: Parameter specifications, which were compared by the cross-validation

Tuning parameter	Name	Definition	Type	Levels	Range
Pre-processing	Normalization	Normalization of variables in the input vector	integer	3	None, tanh, Sigmoid
	PCA	Dimensionality reduction using PCA and selected number of extracted dimensions.	numeric	4	10, 100, 1000
Hyper-parameter	Layer	Number of FC layers in the secondary ANN	integer	3	1, 2, 3
	Nodes	Number of nodes divided over the FC layers in the secondary ANN.	integer	3	mean, mean/2, sum
	Batch size	Batch size applied to the training of the secondary ANN	numeric	4	16, 32, 64

Parameters applied to the input feature vector were normalization and principal component analyses (PCA). Feature vectors were normalized using the hyperbolic tangent function or sigmoid function, or were not normalized. PCA was applied to the normalized input vector and a selected number of dimensions were extracted. Parameters regarding the model architecture were the number of layers and nodes used in the model layer, and batch size. The number of hidden nodes was calculated based on the number of extracted PCA components, , $N_{PC} \in \{10, 100, 1000\}$, and the number of target classes (N_C=2) using the mean of N_{PC} and N_C ("mean"), the mean of N_{PC} and N_C divided by two ("mean/2"), or the sum of N_{PC} and N_C ("sum"). Consequently, we compared the effects of training nine separate pre-processing parameter and 27 separate ANN architectures, resulting in a total of 486 combinations of parameter for each fold of the CV.

Model performance was measured with respect to detecting biting behaviour using major-mean accuracy (MMA) and the F1-score (F1). In this paper, MMA and F1-score are calculated as follows using the number of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN):

$$MMA = mean\left(\frac{TN}{TN + FP}, \qquad \frac{TP}{TP + FN}\right) \tag{1}$$

$$F1 = (2 \cdot \frac{TP}{TP + FP} \cdot \frac{TP}{TP + FN})/(\frac{TP}{TP + FP} \cdot \frac{TP}{TP + FN}) \tag{2}$$

Identification of optimal parameter settings

Optimal parameter settings for the secondary ANN were identified from the output of the CV. For this purpose, two linear mixed-effect models (LMEM) were made, respectively using F1 or MMA as the dependent variable. The LMEW included penID as a random effect, and the pre-processing and hyper-parameters as the independent variables.

Final model fine-tuning

To further fine-tune the final model, the models resulting in the highest performance with a given set of pre-processing and hyper-parameter settings were used to train the final model on the full outer training set, which was then tested on the outer test set. At this stage, different dropout rates (no dropout, 0.2%, 0.4% and 0.5%) were implemented after each fully connected layer for comparison. These rates were chosen as it is often proposed that dropout rates around 0.5% can result in increased performance (Srivastava et al., 2014; ByungSoo et al., 2017). Similarly, two different learning rates (0.0001 and 0.00001) were tested for their effect on final model performance.

Results and discussion

Parameter testing using cross-validation

Table 4 shows the performance measures aggregated from the output of the cross-validation, as well as from the best-fit model.

Table 4: Results of the cross-validation using the inner train/test sets, with median major-mean accuracy (MMA) (min-max), mean F1-score (F1) (± SD), as well as MMA (95% CI) and F1-score (95% CI) for the best-fit model

	median MMA (min-max) [%]	mean F1 (± SD) [%]
All models	50.0 (29.0-73.0)	37.4 (± 23.0)
Best-fit model	72.9 (72.1-73.7)	76.6 (75.3-77.1)

Visually inspecting the data showed that the strategy resulting in the highest performance in regard to MMA and F1-score was using sigmoid normalization of the input features, reducing the dimensionality of the input data to 100 principal components (PC), and using a secondary ANN with 1 hidden layer, 51 nodes (mean) and a batch size of 32. When analysing the output of the cross-validation using LMEM, the number of layers ($F=25.28$, $p<0.001$) and hidden nodes ($F=3.54$, $p=0.03$) in the secondary ANN, and the number of PC extracted from the features ($F=43.88$, $p<0.001$) all showed a significant effect on F1. Similar, the number of PC ($F=5.89$, $p<0.01$) and number of layers ($F=6.10$, $p<0.01$) had an effect on the MMA when only considering MMA values above 50. Using both ten and 100 PC significantly increased F1 and MMA compared to using 1000 PC. Similarly, using one layer compared to two and three layers increased both F1 and MMA, while using 'mean/2' compared to 'sum' or 'mean' for the number of nodes significantly only increased the F1.

Hence, from the results of the visual inspection of the data and the output of the LMEM, we decided to use the following parameter to fit final secondary ANN using the outer train set: 100 PC, one and two model layer, 'mean' and 'mean/2' and a batch size of 32 and 64. Additionally, varying dropout and learning rates were implemented. The final ANNs were trained on the outer training set and evaluated using the outer test set.

Final model evaluation

When applied to the outer test set, the final model with the best strategy resulted in a MMA of 65.8% and a F1-score of 66.0% (Table 5), and was implemented by using the following set of parameters:

— Sigmoid normalization of the input features
— PCA of the input features, and 100 extracted PC
— Secondary ANN architecture with 2 layers, 13 nodes per layer
— No dropout
— Batch size of 64
— 0.0001 learning rate

Table 5: MMA and F1-score of the secondary ANN model evaluation using the outer test-set, with varying dropout and learning rates

Learning rate	Dropout rate	% MMA (95% CI)	% F1-score (95% CI)
0.0001	No dropout	53.9 (51.8-56.0)	40.3 (35.3-45.1)
	0.2	56.4 (54.2-58.6)	46.6 (42.4-51.2)
	0.4	56.9 (54.5-59.3)	50.0 (45.5-54.5)
	0.5	53.9 (51.8-56.0)	62.0 (59.4-64.4)
0.00001	No dropout	65.8 (63.7-67.9)	66.0 (62.7-69.3)
	0.2	58.8 (56.4-61.2)	58.2 (54.3-62.1)
	0.4	54.5 (52.0-57.0)	58.1 (54.6-61.8)
	0.5	53.9 (51.5-56.3)	58.9 (55.8-62.0)

This study showed that applying PCA to reduce the dimensionality of the extracted image feature data and using the first 100 principal components is a viable pre-processing strategy for the video image data used in this study. Moreover, using a shallower network with fewer layers and nodes compared to a network with more layers and a high number of nodes increased the performance of our secondary ANN. This is in line with discussions on model complexity and the notion that a too complex model architecture has the potential to decrease model performance (Sun et al., 2021). When tested again with a lower learning rate, the final model performed better than a model with the original learning rate. It is often discussed that implementing dropout within a network has the potential to effectively reduce overfitting and to have positive effects on the ability of a network to generalize on a new set of data. For our data set, however, implementing dropout did not enhance model performance.

Figure 2 shows the accuracy and loss curves when training the final model with the specified parameters. With the optimal set of parameters regarding data pre-processing and network architecture, the final model converged with a validation accuracy of 77.4% and a validation loss of 0.47, with nearly identical values for training accuracy and loss. This indicates that the network is not overfitting.

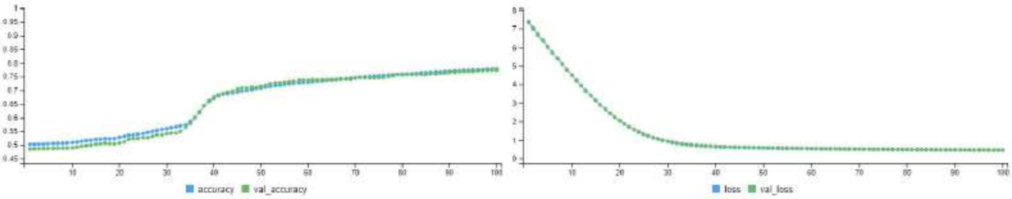

Figure 2: Accuracy (left) and loss (right) curves of the sec. ANN for training and validation set

Our final optimized model has a relatively low performance, as it misclassifies approximately 34% of the images in the final test set. This is likely due to the fact that our model classifies each frame individually, without taking the context of surrounding frames in the video into account. In a similar study, Liu et al. (2020) presented an approach to detect biting behaviour in groups of pigs using a tracking algorithm followed by a combination of CNN and a long-short term memory (LSTM) algorithm. The authors were able to achieve an accuracy of 96.34% on their training set, indicating that the temporal component of the data holds explanatory value. However, no performance of the predictive ability of their model on an independent test set is presented, which makes it difficult to compare their results to those of our study. Furthermore, while Liu et al. (2020) focused entirely on tail-biting behaviour, the current paper focused additionally on other biting behaviour such as ear biting and biting the body. The inclusion of ear and other biting behaviour could have enhanced the informational load of the data, thus making it harder for a model to successfully distinguish biting from non-biting behaviour. It seems reasonable to assume that utilizing time-series analysis considering temporal features of the data (such as e.g. a CNN + LSTM network) has the potential to increase performance when predicting biting behaviour. In future studies, we will aim to optimize the parameters for a two-step approach with an LSTM as the secondary model, thus ensuring a fair comparison between the two types of secondary models.

Conclusion

Within this preliminary study, we systematically compared different pre-processing strategies and model architectures to identify the optimal set of parameter for classification of biting behaviour in groups of pigs based on individual video frames. Varying strategies were compared using cross-validation, and a final network was trained with varying dropout and learning rates. The single best strategy for this classification problem and the current data yielded a major-mean accuracy of 65.8% when evaluated on a test set. The optimal pre-processing strategies for this modelling approach were using sigmoid function and applying principal component analysis to the input features, implementing a model architecture with two layers, 26 nodes, no dropout and a learning rate of 0.00001. Similar to previous work, this paper demonstrates that monitoring damaging behaviour in groups of pigs using deep machine learning techniques is possible, and has the potential to be instrumental to pig farmer.

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First step to remote detection of locomotor play in young pigs: a preliminary study

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Abstract

The performance of play behaviour may be a measure of animal well-being in young pigs. However, play events are usually short in duration and occur sporadically in time. Thus, the use of play behaviour as a measure of animal welfare would benefit greatly from remote, real-time monitoring. We here present a preliminary study into remote detection of play behaviour with computer vision in young pigs, investigating the possibility of recognising locomotor play from other forward movement, using methods requiring low computing power. Two pens of pigs were observed between 1800-2200 h the day after weaning and labelled for events of locomotor play, running and walking. To quantify behavioural intensity, Gaussian mixture models were applied to the videos producing a low and high activity video stream with the background subtracted, from which 10 and 15 frames movement maps were produced for the events of behaviour. From the movement maps, contours were detected, and six contour features were calculated as behavioural descriptor. 1000 behavioural descriptors per class were used as inputs to several classification algorithms of which random forest had the highest accuracy (0.799). Only 76% and 72% of play and running contours were correctly classified, whereas recall was 91% for walking contours. Based on this, it was decided that stronger classifiers would be needed to recognise play from other high-activity forward movements such as running, and that the current method could function as initial classifier of locomotor play to reduce the data amount to be classified with more sophisticated models.

Keywords: animal behaviour, animal welfare, Gaussian mixture model, movement map, contour detection, machine learning

Introduction

Play has been identified as a potential indicator of animal welfare as it can be measured noninvasively, it is often observed in the absence of fitness threats and its mere performance may be rewarding (Held & Spinka, 2011). For pigs in a semi-natural environment, the performance of play peak between week 2 to 6 of age with locomotor play being the most dominant play type (Newberry et al., 1988). However, locomotor play in pigs are short-lasting events that occur spontaneously, making it improbable to monitor for a farmer or other stakeholder of the pig production. Thus, to use locomotor play in young pigs for welfare assessment will demand automatic detection of the behaviour continuously across the day. It has been attempted to detect play in calves from accelerometer data (Gladden et al., 2020; Rushen et al., 2012), while accelerometer data have been used in pigs to detect positive social interactions (Rodriguez-Baena et al., 2020). In pigs, 2D cameras has been used to detect manipulation towards the drinker and enrichment objects (Chen et al., 2020a, b), which could resemble object play. To the authors knowledge, no similar attempt has been made to detect locomotor play in pigs using sensor data. Due to the low economic value of each individual pig, it is unlikely that one sensor per animal, such as accelerometers, will result in a profitable technology. Thus, the aim of project AutoPlayPig was to take the first steps in developing an algorithm for automatic detection of locomotor play in young pigs, by using 2D cameras that monitor the entire pen of pigs with one sensor and that do not disturb the pigs. This paper presents the results of a preliminary study investigating the possibility of using methods requiring relatively low computational power to automatically distinguish locomotor play from other forward moving behaviours (running and walking).

Material and methods

Data origin and labelling

Data included in the study were collected in the experimental facilities of Department of Animal Science, Aarhus University, Denmark, in accordance with the Ministry of Food, Agriculture and Fisheries, The Danish Veterinary and Food Administration under act 474 of 15 May 2014 and executive order 2028 of 14 December 2020, and under consideration of the Arrive Guidelines (du Sert et al., 2020).

Data included video recordings of two pens of pigs on the day after weaning from 1800-2200 h (most locomotor play observed during these hours, without any human disturbances). The pigs were weaned by removing the sow and housing the pigs in their respective farrowing pen designed for loose housing of the sow during lactation. One pen housed 12 pigs of the Danbred sow hybrid, weaned at day 25 of age with an average weaning weight of 6.56 ± 1.57 kg. The other pen housed 10 pigs of the Topigs Norsvin TN-70 sow hybrid, weaned at day 28 of age with an average weaning weight of 8.99 ± 1.56 kg. The two pens were identical, but mirrored, and located in the same room (see Figure 1). Dimensions of the pens were 3.0 × 2.2 m with half solid and half slatted flooring. Each pen included a corner creep area for resting and warmth (0.9 m^2), an 80 × 28 cm polyconcrete feed trough (Jyden A/S, Denmark) and a 31 × 17 × 11 cm water trough (Aqua-Level system with hinged trough; Jyden A/S, Denmark). In the morning hours, each pen was provided with 130 g chopped wheat straw on the solid floor and 400 g saw dust in the creep area. The room temperature was set to 24 °C and artificial light was on from 0700-2200 h. Pigs were fed ad libitum with a standard pelleted weaner diet with no medical zinc oxide added to it. Male pigs were castrated on day 4 postpartum. No pigs were tail-docked or teeth-clipped.

A 2D camera (model DS-2CD2145FWD-I, Hikvision, China) was positioned 2.3 m above each pen, providing a top-view image of the entire pen and recording video with 15 fps. During the 8 hours of included video, events of locomotor play and running were observed continuously with start and stop times. Walking was also observed continuously, but only within the first 5 minutes of each hour. See ethogram of the three behaviour classes in Table 1.

Figure 1: Raw images of the two pens included in the study

Table 1: Ethogram of labelled behaviours

Behaviour	Description
Locomotor play	At least 2 forward hops or gallop-like energetic forward movement (the two forelimbs move in phase, followed by the two hind limbs). Often associated with vigorous ear flapping, moving across a large area of the pen, and occasionally bouncing into other pigs.
Running	Fast forward movement without hops or gallop-like movement.
Walking	Slow forward movement with one leg at a time.

<u>Movement maps and contour detection</u>

To quantify behavioural intensity, a Gaussian Mixture Model algorithm (Zivkovic & Van Der Heijden, 2006), detecting moving pixels, were applied to the two 4-hour videos producing 'all activity' (learning rate = 0.001) and 'high activity' (learning rate = 0.02) video streams with the background and shadows subtracted. 'Low activity' video streams were produced by subtracting the 'high activity' from the 'all activity' video stream. To lower the amount of noise in the resulting video streams, contours detected by Canny edge detection (thresholds of 30 and 150) with an area below 1000 pixels were removed from each frame.

The 'low activity' and 'high activity' video streams were cropped into events of locomotor play, running and walking of varying duration based on the start and stop times of the labelling of the raw video. For each event, the respective 'low activity' and 'high activity' video streams were summarised into 10-frames (2/3 sec) and 15-frames (1 sec) movement maps throughout the frames of the event, with 'low activity' pixels represented by light grey (intensity = 85), 'high activity' pixels represented by dark grey (intensity = 170) and overlap in 'low activity' and 'high activity' pixels represented by white (intensity = 255). See an example of a movement map for each of the three labelled behaviour classes in Figure 2.

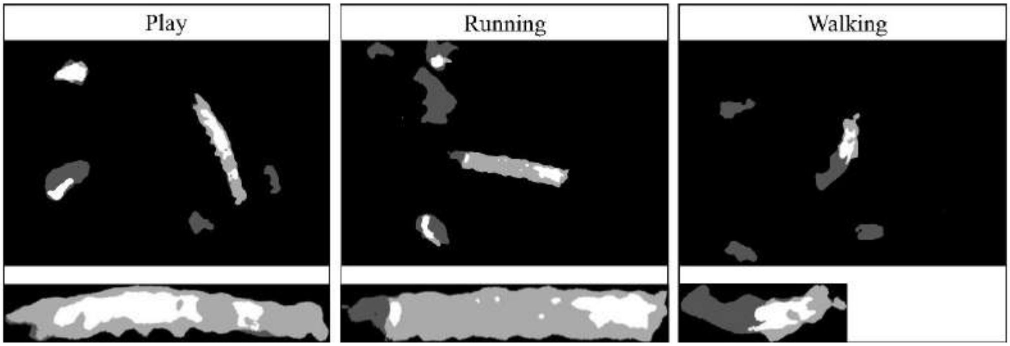

Figure 2: Example of a 15-frames (1 sec) movement map and the segmented contour for each of the three behaviour classes: locomotor play, running and walking

Prior to contour detection, each movement map was median blurred with a 15 × 15 kernel and dilated with a 3 × 3 kernel of ones to close the contours. Contours were detected using Canny edge detection (thresholds of 30 and 150). For each contour in the movement map with a contour area above 5000 pixels and that did not only consist of low activity pixels (dark grey), the minimum area rectangle was produced, and 6 contour features were calculated:

1. Aspect ratio (length of min area rectangle / width of min area rectangle)
2. Extent (area of contour / area of minimum area rectangle)
3. Mean intensity of the contour
4. Ratio of low activity pixels (number of low activity pixels / contour area)
5. Ratio of high activity pixels (number of high activity pixels / contour area)
6. Ratio of overlap pixels (number of overlap pixels / contour area)

These contour features were chosen as they are all relative measures and may not depend on the size of the pig or the distance between the camera and the pigs; thus, hopefully making the model more generalisable.

<u>Modelling and testing</u>

From the data pool of contours, 1000 contours were randomly selected from each of the three behaviour classes: locomotor play (events = 219), running (events = 64), and walking (events = 130). This number was chosen due to limitations on number of running events and thereby running contours.

Differences in mean values of each contour feature between the three behaviour classes were analysed using the non-parametric Kruskal-Wallis test and Dunn's test for post hoc comparison with Benjamin-Hochberg adjustment for multiple comparisons. None of the contour features were constant (had no variation) or had a Pearson correlation coefficient to other features higher than 0.6. Thus, no contour feature variables were excluded based on these two criteria. The mutual information value was calculated for each feature, representing the dependency between the feature and the classification labels.

For algorithm training and testing, the contour data were split into training data (play: n = 764; running: n = 735; walking: n = 751) and test data (play: n = 236; running: n = 265; walking: n = 249) with an approximately 75:25 split.

The normalised contour features were used as input for several multi-level classifiers: k-Nearest Neighbour (KNN), Naive Bayes, Logistic regression, Support vector machines (SVM) and Random forest. Hyperparameters were tuned using 4-fold cross validation on the training data. The set of hyperparameters resulting in the highest accuracy for each classifier were chosen for further training and testing (*KNN*: n_neighbors = 5, metric = 'euclidean', weights = 'distance'; Naive Bayes: var_smoothing = 0.001; *Logistic reg.*: solver = 'lbfgs', penalty = 'l2', C = 1.0; SVM: kernel = 'rbf', gamma = 'scale', C = 10; *Random forest*: n_estimators = 100, max_features = 'sqrt', criterion = 'gini').

The performance of each trained classifier was evaluated on the test data with the following performance metrics calculated (equation 1-4):

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

$$\text{f1} = \frac{2 \,*\, Recall \,*\, Precision}{\text{Recall} + \text{Precision}} \tag{4}$$

Where TP is the number of correctly classified locomotor play contours, TN is the number of correctly classified running and walking contours, FN is the number of locomotor play contours classified as running or walking, and FP is the number of running and walking contours classified as locomotor play. Accuracy is the only performance metric evaluating the performance on classification of all three behaviour classes, while recall, precision and f1-score evaluates the performance of classifying the locomotor play class only. The area under the precision-recall curve with varying classification thresholds was also calculated for all three behaviour classes (mAP).

Results and Discussion

Contour features

The mean of each contour feature was different between at least two of the three behavioural classes, but the ranges overlapped and thus, not a single contour feature could alone solve the classification problem (see Table 2). The ratio of low activity pixels and the ratio of high activity pixels showed the greatest dependency with the behavioural classes, probably as there for these two contour features were clear difference between walking and the fast movements (locomotor play and running). Based on ranges in Table 2, simple rules to distinguish walking and fast movements can be made: if the ratio of low activity pixels ≥ 0.54 or the mean intensity < 104, the contour should be classified as walking. These simple rules would correctly classify 26% of the walking contours in the current data sample. As a high proportion of contours in a real-life setting will represent walking and even slower movements, these simple rules could prove valuable in reducing the number of contours that needs to be classified by more complicated techniques, which could reduce computational power needed to automatically detect locomotor play and other fast movements.

Table 2: Mean and range of each contour feature for each of the three behaviour classes and the mutual information (MI) for each contour feature based on 1000 locomotor play, running and walking contours. Difference in lower-case letters indicate statistical significance on at least a 5% significance level

Contour feature	Locomotor play		Running		Walking		MI
	Mean	Range	Mean	Range	Mean	Range	
Aspect ratio	3.17[a]	1.03-6.60	3.42[b]	1.01-7.95	2.90[c]	1.12-4.92	0.129
Extent	0.59[a]	0.34-0.81	0.64[b]	0.36-0.83	0.71[c]	0.49-0.85	0.180
Mean intensity	165[a]	122-206	172[b]	104-203	142[c]	76-206	0.188
Low activity ratio	0.07[a]	0.00-0.42	0.07[a]	0.00-0.53	0.41[b]	0.00-0.92	0.418
High activity ratio	0.54[a]	0.05-0.95	0.43[b]	0.02-0.98	0.12[c]	0.00-0.82	0.409
Overlap ratio	0.18[a]	0.00-0.56	0.28[b]	0.00-0.58	0.28[b]	0.00-0.65	0.082

Performance on the test data

Performance of each classifier on the test data is shown in Table 3. The highest accuracy, f1-score and mAP were found for the Random forest classifier. Confusion matrix and precision-recall curve for all three behaviour classes for the Random forest classifier can be seen in Figure 3. The classifier performs best in classifying walking with 91% of the walking contours correctly classified; especially when distinguishing walking from locomotor play. On the other hand, the classifier performs worse when classifying locomotor play and running with 76% of the locomotor play contours and 72% of the running contours being correctly classified; especially when distinguishing between locomotor play and running resulting in many false positives and false negatives. This is not surprising, as locomotor play and running are both behaviours involving fast and forward motion, and it can even be difficult for the human observer to distinguish between them from a top-view angle. Thus, other and perhaps more sophisticated techniques are needed to distinguish between locomotor play and other types of fast movements such as running. The minimum area rectangle produced for each contour could be used to segment the raw video into contour videos that could feed as input for e.g. a deep learning classifier that considers both the spatial and temporal patterns in such a video. To lower the computational power needed, the current method could work as an initial classifier to lower the number of contour videos that need to be classified with the more sophisticated methods. In that case, the classification threshold of the current method should be set to maximise recall of the locomotor play class, as false positives will be inevitable.

Table 3: Performance metrics of each classifier on the test data with a classification threshold of 0.50 (locomotor play: n = 236; running: n = 265; walking: n = 249)

Classifier	Accuracy	Recall[a]	Precision[a]	f1[a]	mAP[b]
KNN	0.784	0.725	0.737	0.731	0.825
Naive Bayes	0.751	0.720	0.667	0.692	0.703
Logistic reg.	0.768	0.779	0.687	0.730	0.721
SVM	0.778	0.746	0.715	0.730	0.797
Random forest	0.799	0.763	0.756	0.759	0.828

[a] Recall, precision and f1 score for the locomotor play class.
[b] mAP: area under the precision-recall curve for the locomotor play class.

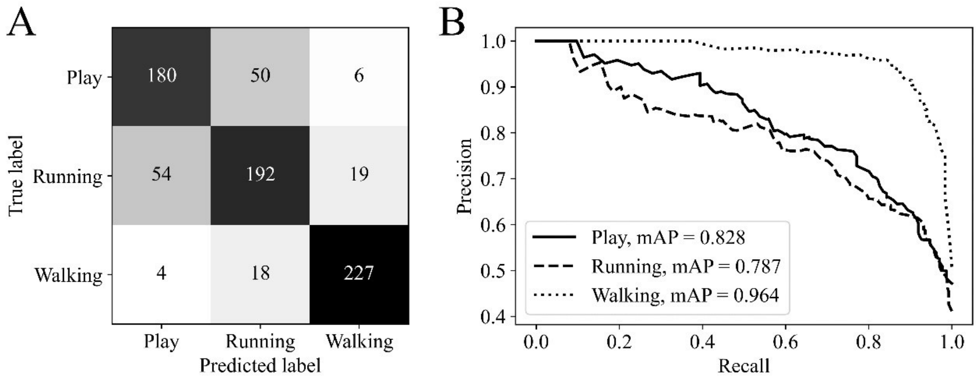

Figure 3: Confusion matrix (A) and precision-recall curve (B) with associated area under the curve (mAP) for the Random forest classifier on the test data, divided between the three classes: locomotor play (n=236), running (n=265) and walking (n=249)

Conclusions

This paper presents a first attempt on automatic detection of locomotor play in young pigs. The presented method was successful in classifying locomotor play from slow forward movement, here represented by walking, but struggled with classifying locomotor play from other fast forward movements, here represented by running. The presented method could be used as an initial classifier of locomotor play resulting in a reduced data amount to be classified with more sophisticated classification techniques, thereby reducing the computational power needed to automatically detect locomotor play in pigs.

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Evaluating piglet activity after different vaccination protocols using automated cameras and drink water monitoring

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Abstract

This study evaluated the impact of different vaccination strategies on piglet's activity using modern camera techniques. Pigs were vaccinated 8 days after weaning with a combination of the same antigens, group W (n=256) with a water-carbomer adjuvant combined with an oral vaccine. Group MO (n=256) was vaccinated IM with a mineral oil adjuvant. Water intake was logged every 6 hours separately for each treatment group and fed into a lineal regression model. Animal activity was monitored using cameras and expressed as the changed pixels percentage between two sequential photos. The resulting data structure representing activity was treated as a time series and analyzed using an Auto-Regressive and Moving Average (ARMA). The ARMA model forecasted appropriately since the observed values were mainly within the predicted 95% CL. Results from group MO highlighted the fact that piglets did not behave as expected. Differences between expected and observed values overtime differed significantly between groups ($p<0.0001$). This was further supported by the differences in drinking water intake. Pigs from the MO group dropped 74% for 1 day (87 ml/kg BW to 21 ml/kg BW) whereas pigs from group W dropped 6% (84 ml/kg BW to 79 ml/kg BW) the day after vaccination and these differences were significant when the 42 hours period was compared between groups. Animal behavior monitoring with objective and noninvasive techniques like camera analysis and drink water intake monitoring proved to be a useful way of assessing animal activity and to compare the effect of two different vaccine platforms.

Keywords: vaccination, side effect, welfare, automated camera, drinking water monitoring, piglet activity

Introduction

Vaccination is one of the most applied interventions to prevent diseases and reduce the use of antibiotics (Bergevoet et al., 2019). Vaccinations are mostly administered by the intramuscular route (IM), but oral administration of vaccines can also be applied, the mostly for enteric pathogens. Vaccination of pigs can result in side effects including pain and elevated rectal temperature that may impact animal activity, and consequently affect the welfare of the pigs. Mineral oil-based emulsions are known to induce local adverse reactions, especially when combined with reactive antigens like inactivated bacteria (Charerntantanakul, 2020) and vaccines based on alpha tocopherol acetate (Miller et al., 2019). One way of recording the response and welfare of pigs following vaccination is evaluating piglet behavior by recording the willingness to approach people (Fangman et al., 2010). These observations of pig activities are time consuming and can be biased due to the presence of researchers and their interaction with the animals. Measurement using camera systems have been proven valuable in replacing human observations for the evaluation of behavioral pig activities (Ott et al., 2014). This study aimed to evaluate the impact of two different vaccination strategies on pig activities using modern camera techniques together with other variables (i.e., water intake, rectal temperature).

Material and methods

A total of 512 24-days old, weaned pigs was equally distributed among 2 study groups accordingly to sow parities. Pigs were vaccinated 8 days after weaning with a combination of PCV2, Mycoplasma and Lawsonia antigens. Group W (n=256) was IM vaccinated with a water-carbomer adjuvant platform (Ingelvac CircoFLEX® and Ingelvac MycoFLEX®, Boehringer-Ingelheim VetMedica) and with an oral live vaccine via drinking water (Enterisol Ileitis, Boehringer-Ingelheim VetMedica). Group MO (n = 256) was IM vaccinated with a mineral oil adjuvant platform (Porcilis PCVMH, Porcilis Lawsonia, MSD 1 IM injection of 2ml). All vaccines were used according to the label including warming of the MO vaccines. At 6 hours post vaccination, rectal temperature was recorded for one randomly selected pig per pen (24 pigs/group). To record the water intake, the drinking waterline between the two treatment groups was split and a digital water logger using the lora network was installed (Maddalena SPA, Italy). Water records were logged four times a day (1.00 hrs; 7.00 hrs; 13.00 hrs; 23.00 hrs). A linear regression model was used to study the association between water intake and vaccine group. The variable “vaccination period” (i.e., pre-vaccination or 42 hours-period prior vaccination, vaccination or 48 hours post-vaccination, and post-vaccination) and their possible interactions were also considered as predictors in the model.

Figure 1: View from one camera overseeing the whole floor of two adjacent pens

To record animal activity, cameras (Healthy Climate Monitor, HCM) were positioned in the middle of the barn, overseeing the full floor surface of the two middle pens (Figure 1). Animal activity was expressed as percentage of the changed pixels between two sequential photos and was continuously monitored by group every 5 minutes. Each photo was screened for quality and abnormal photos were excluded for analysis (e.g., fly on the lens, digital damaged photos). Percentage of daily changed pixel observations during the period prior to vaccination was modeled through an Auto-Regressive and Moving Average model (ARMA) to appropriately consider the data's temporal auto-correlation structure. Results from the model were used to predict (forecast) the next 12hrs point values and their confidence limits to compare with the observed values.

Results

A total of 6 pigs from Group MO showed signs of anaphylactic shock immediately after vaccination, which was statistically higher when compared with Group W in which no anaphylactic shocks were observed ($p<0.05$; Fisher exact test). Rectal mean temperature of Group MO was significantly more elevated compared to Group W (40.7°C, 24 animals vs 39.7°C, 24 animals; $p<0.001$; t -test; Figure 2).

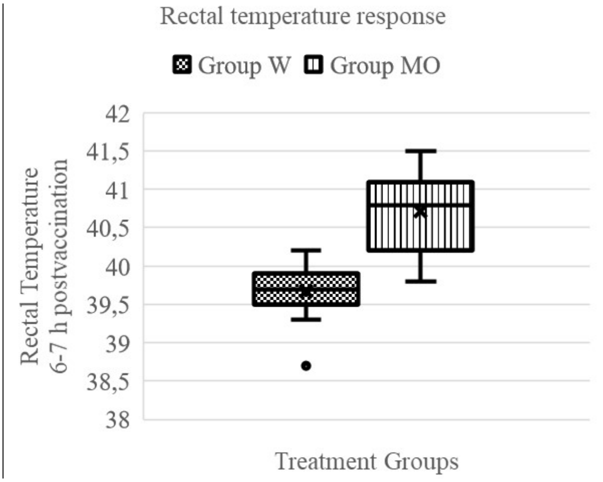

Figure 2: Rectal temperature of both groups 6 hours post vaccination. From both groups 24 animals were at random selected. Rectal temperature of the MO group was significant higher when compared to group W (40.7 vs 39.7 p<0.0001)

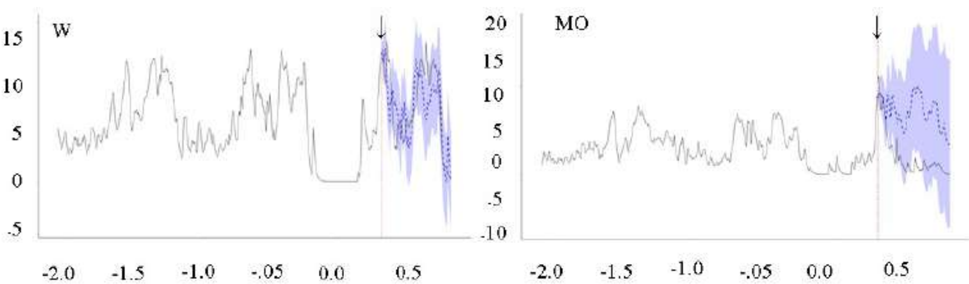

Figure 3: ARMA and prediction models for animal movement after vaccination event by treatment group. Continuous line: observed movement; dashed line: predicted movement; Grey area 95% CL. Time of vaccination indicated by the arrow. Y-axes movement indicated by pixel change (%), x-axes calendar day's relative to the timepoint of vaccination

Results from the ARMA process and forecast are shown in Figure **3**. The graph for Group W shows that the model forecasted appropriately since the observed values are mainly within the predicted 95% Confidence Level (CL) (dark grey areas). On the other hand, results from Group MO highlight the fact that pigs did not behave (dashed line) as expected (continuous line). Mean square differences between expected and observed values overtime differed significantly between groups (p-value < 0.0001).

Figure 4 describes the drinking water intake by intervals of 6 hr difference post vaccination event for the two monitored groups. Pigs from MO and W groups experienced a drop of 74% (87 ml/kg BW to 21 ml/kg BW) and 6% (84 ml/kg BW to 79 ml/kg BW) respectively during a 24h period after vaccination. In addition, the estimated linear model showed that water intake, as an overall, differed between groups (p value = 0.0083). More specifically, this difference was significant only during the "vaccination period" (or 42 hrs post vaccination shown in Figure 4) between groups (p value = 0.0135), being lower for the group MO (Figure 4).

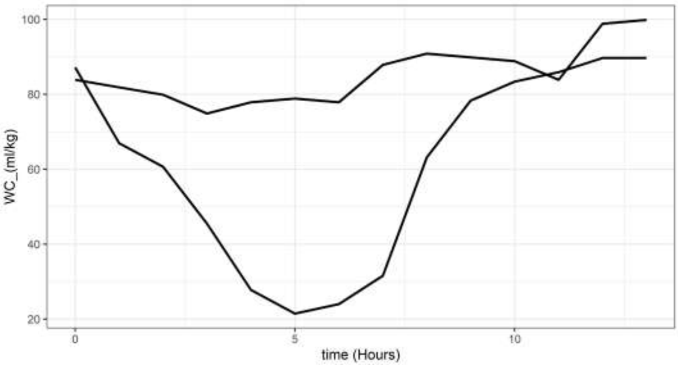

Figure 4: Drinking water intake (ml/kg of piglet body weight for the past 24h) for both groups during the post-vaccination period. Each unit of time refers to a 6hr interval

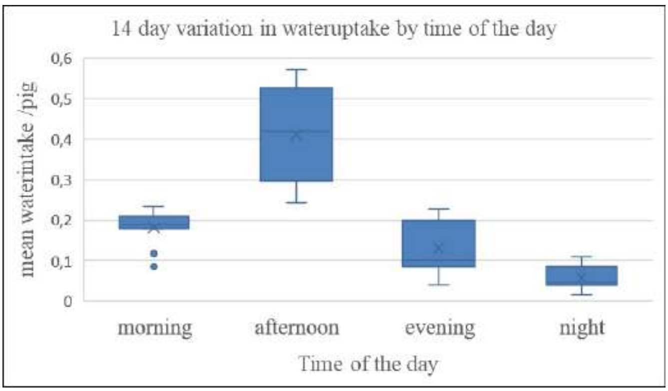

Figure 5: The mean water intake per pig over a 14-day period post vaccination. Water intake showed a consistent variation by time of the day. Pigs drank consistently more during the afternoon (13.00-19.00 hrs.) when compared to the morning (7.00-13.00 hrs.), evening (19.00-1.00 hrs.) and night (1.00-7.00 hrs.)

Another important result collected by both the camera and water logging systems demonstrated variable behaviors at different times of the day. Variation of water intake over a 14 day period shows a marked difference in different parts of the day (Figure 5). The piglet activity levels during 24 hours as measured by the cameras can be seen in Figure 6. Pigs in this setting were more active during daytime.

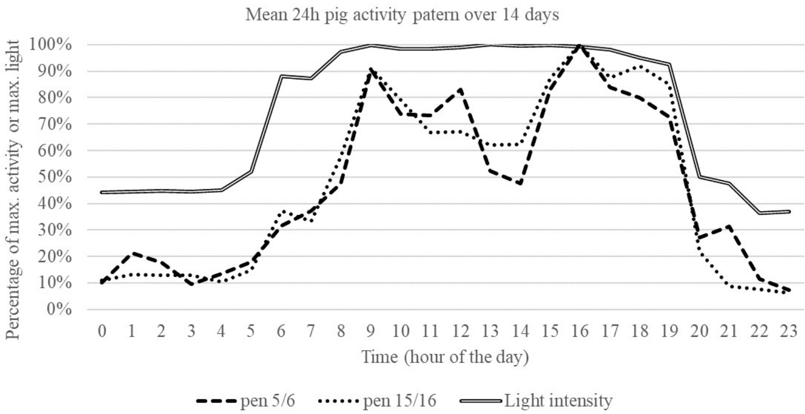

Figure 6: The activity of the pigs, expressed as a percentage relative to the hour with most activity (16.00-17.00 hrs.). Pigs showed higher activity during the daytime. During the day, pigs were most active between 15.00 and 19.00 hrs. Light intensity is expressed as the percentage relative to the hour with the highest light intensity (13.00-14.00 hrs.). The feeding machine starts at 9.00 hrs., daily inspection by the animal caretaker starts at about 11.00 hrs

Conclusions and Discussion:

Results from this study demonstrated a significant impact in pig wellbeing after vaccination with mineral oil adjuvant-based vaccines when compared to those vaccinated with water- carbomer adjuvant-based vaccines. Pigs from Group MO showed a high incidence of anaphylactic shock immediately after vaccination as well as a significant increase of rectal temperature and a decrease in water consumption when compared to Group W. Animal behavior monitoring with objective and noninvasive techniques like camera analysis and drink water intake monitoring proved to be a useful way of assessing animal welfare and to compare the effect of two different vaccine platforms.

Beside the direct effect on animal welfare, the economic performance of a swine herd might also be affected due to vaccine related side effects. In general, most piglets are vaccinated during the late suckling period, potentially reducing their willingness to suckle. The temporary cessation of suckling is associated with lactation estrus (Zimmerman et al., 2020) and can increase the weaning to estrus interval. Vaccination can also be applied at or shortly after weaning. The weaning process is associated with an increase of local inflammation in the intestines due to the anorexia phase(McCracken et al., 1998). It is known that postweaning anorexia is an important risk factor in postweaning *E.coli* diarrhea (Madec et al., 1998). In this way, the choice of vaccines might influence the outcome and severity of post weaning *E.coli* diarrhea or other disease processes.

It has been well documented that a reduction of water intake is associated with lower feed intake in post weaning pigs (Barber et al., 1989; Horn et al., 2014). Water consumption of pigs is easier to measure when compared to the feed intake and could therefore be used to predict reduced feed intake. However, the literature regarding the normal drinking behavior of pigs in the post-weaning period remains scarce. This study provides further insights into piglet drinking behavior and piglet activity patterns.

Further studies to assess the impact of different vaccines are needed for veterinarians to choose the best vaccination regime to maintain the health and wellbeing of the pigs under their care.

Conflict of interest

This work was funded by Boehringer Ingelheim and authors Rutger Jansen, Martijn Steenaert, Herman Prüst & Carmen Alonso are employed by Boehringer Ingelheim, manufacturer of vaccines used in this study.

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An approach towards a practicable assessment of piglet vitality using automatic object recognition based on thermal images

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Abstract

Body temperature is an important characteristic for the vitality and survivability of pigs, especially for newborn piglets with a low birth weight. Suboptimal body temperatures might indicate or lead to increased stress or diseases. More and more thermal imaging technologies are available at the market which offer the opportunity to determine body temperature in a non-invasive, stress less manner including potentially reduced manual effort. Current approaches often use multiple close-up images of different parts of the body (ear, eye, back, forehead and many more) to estimate the rectal temperature, which is laborious under practical farming conditions. Our approach only needs a single (top view) thermal image of a piglet. We first trained a convolutional neural network (YOLOv3-SPP) for detection of relevant areas such as whole body, head, back and rear end (*mAP@0.5= 0.98*) followed by a background segmentation using the Otsu-algorithm to generate precise mean, median and max temperatures of each detected body part. By using a partial least square regression, the predicted rectal temperature *RMSE* of our method was *0.46* °C with a R^2 = *0.65*. The used setup consists of a 'FLIROnePro' (thermal camera) attached to an Android tablet. To sum up, the presented approach is an appropriate method with sufficient accuracy to generate an automatic indication on piglet vitality and with that could be an important assistance tool in animal monitoring under research and practical farming conditions.

Keywords: rectal temperature, thermal images, object detection, piglet vitality, non-invasive

Introduction

Body temperature, along with other traits such as APGAR (Appearance, Pulse, Grimace, Activity und Respiration) -score (Revermann *et al.*, 2018), or birth weight, is an important trait for the vitality of a piglet. Temperatures that are too high or too low may indicate increased stress or disease (Feng *et al.*, 2019). The current standard to monitor body temperature is to manually measure rectal temperature with a thermometer. This, in turn, requires an intervention for each piglet by which behavior, and thus body temperature, of the piglet is affected (Kammersgaard *et al.*, 2013). In extreme cases, this might cause the spread of diseases (Jia *et al.*, 2020). In contrast, estimating rectal temperature using thermal imaging is a non-invasive method and could reduce the manual effort. Feng *et al.* (2019) and Jia *et al.* (2020) used close-up images of various body parts (ear, eye, back, forehead, and more) to estimate rectal temperature of sows. Kammersgaard *et al.* (2013) took a similar approach and used images of the piglet from the back, side and ear to estimate its rectal temperature while Xiong *et al.* (2018) used the max, min and mean temperature of the back of a piglet ear as well as the temperature drop to the ear tip. However, all these approaches have a common drawback. Multiple, and sometimes largely close-up images of different body parts, are used to estimate the rectal temperature of an animal. Thus, the effort remains high and the practicality of the applications remains doubtful. The goal of this work was to reliably estimate rectal temperature with effort as little as possible by keeping the result as reliable as possible. For this purpose, thermal images of piglets (top view) were recorded and automatically evaluated regarding the surface temperature for the total body as well as the body parts head, back and back end using computer vision algorithms (YOLOv3-SPP and Otsu-algorithm). These temperatures were used to generate 60 regressor variables. Which were, together with two environmental variables, fed into various regression approaches to estimate rectal temperature which serves as gold standard for body temperature.

Material and methods

Experimental data

The thermal images were recorded at the experimental farm of the University of Göttingen (Relliehausen) with interruptions (Covid-19) in three runs from March 2020 – August 2020. The piglets were removed from the pen after 30 minutes of life and examined. The examinations took place according to a standardized set-up (Fig.1). Directly after the rectal temperature measurement with a thermometer 'SC 1080' (SCALA Electronic), a thermal image was recorded with a 'FLIROnePro' (Teledyne FLIR LLC) connected to an Android tablet for data-transfer and to a power outlet for power supply (battery life is only one hour). A total of 150 images of 64 piglets were used for further analysis. As additionally data, the piglets bodies were measure with a measuring tape (Fig.1) and weighted. During data acquisition, ambient temperature and humidity were measured inside each pen using a 'TGP-4500' climate data logger (Gemini Data Loggers).

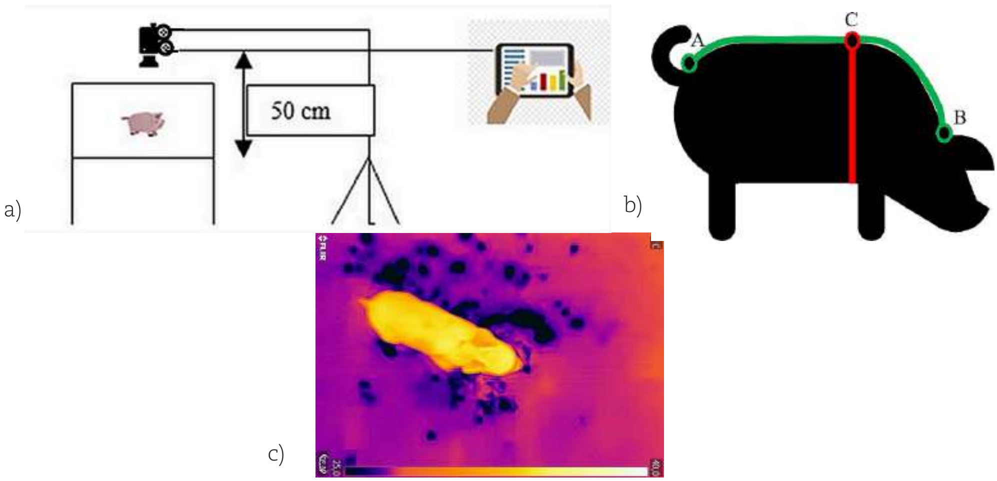

Figure 1: a) Set-up of thermal imaging, b) Measurement of body length (A to B) and girth (C), c) Example of a thermal image, where black indicates low temperature and white high temperature

Object recognition and data processing

For object recognition of the four classes (piglet, head, back, and back end), all 150 images were annotated using the Roboflow tool (https://roboflow.com/annotate). After splitting the data into training, validation and test set (70/20/10-ratio), the convolutional deep neural network YOLOv3 with spatial pyramid pooling block (SPP) (https://github.com/roboflowai/yolov3/blob/master/cfg/yolov3-spp.cfg) was trained at a learning rate of 0.001 for 300 epochs with default hyperparameters (only number of classes was adapted) and evaluated afterwards, both via Google Colabs (Bisong, 2019). To generate accurate mean and maximum values for the body parts, the body part shapes were segmented from the background using Otsu-algorithm (Otsu, 1979) (Fig.2). Whereby, the intersections of the detected bounding box area and the segmented foreground area contain the pixels that were used for further calculations.

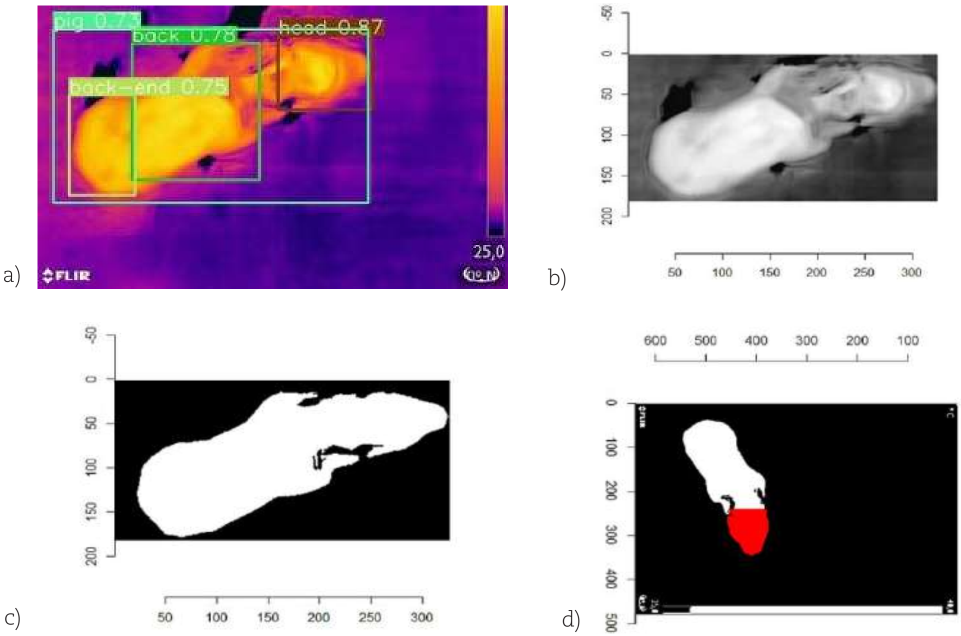

Figure 2: Example Otsu-algorithm for the head of a piglet: a) shows the four bounding box detections of YOLOv3 SPP. b) is an image of the area 'piglet' after gray value conversion (0-255). c) shows a binary image of the piglet, after thresholding with Otsu-algorithm on image b). Image d) shows the overlap of the white foreground area (c.)) and the detected 'head bounding box area' from a). The pixels inside the gray area are used for further calculations of the head

Data preparation

After outlier detection (Fig.3), 16 images were sorted out. The remaining 134 images were processed by using the R package 'Thermimage' (Tattersall, 2017). The metadata of the radiometric JPEG-images was imported and the object radiation for each pixel was calculated by using three formulas (1-3) (Minkina & Dudzik, 2009). The emission value of the piglet skin was set to 0.98 (Soerensen *et al.*, 2014). The temperature of an object is calculated from the object radiation (W_{obj}) and constants from camera calibration, which are saved to the metadata of the image.

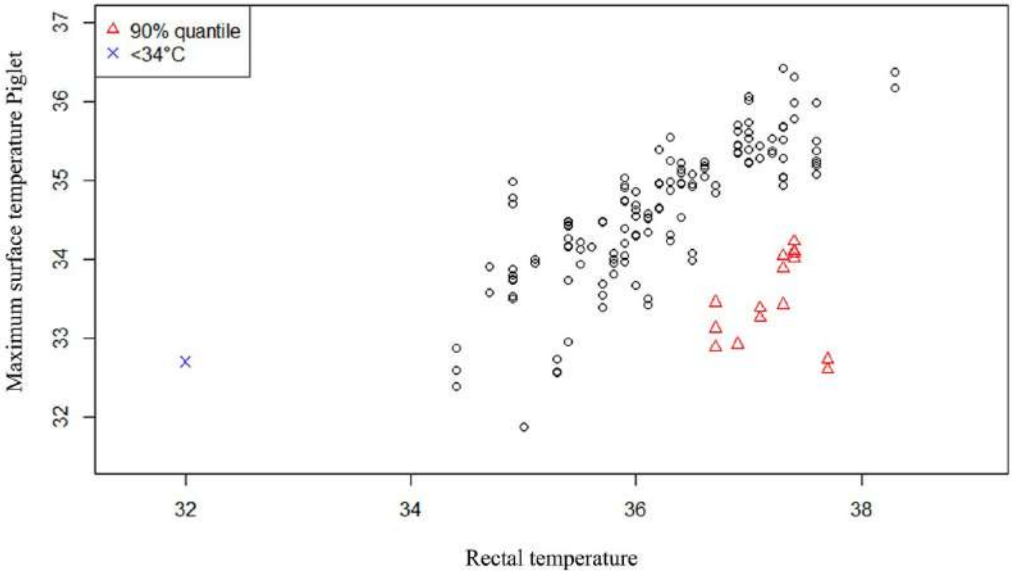

Figure 3: Outlier detection: cross indicates a rect. temp. < 34°C and triangles indicating 10% of the biggest differences between rect. temp and max surface temp. of the piglets

$$W_{obj} = \frac{W_{total}}{\varepsilon\tau} - \frac{(1-\varepsilon)W_{refl}}{\varepsilon} - \frac{(1-\varepsilon)W_{atm}}{\varepsilon\tau^{-}} \quad (1)$$

Where W_{obj}, W_{atm} and W_{refl} are the object, atmosphere and reflected radiation, ε is the emission value of the object and τ is the transmission value of the atmosphere. W_{total} is the total radiation measured by the camera. With the addition of (2) and (3), τ can be calculated.

$$\mathrm{H} = \mathrm{H}_{rel}\, exp(1.5587 + 6.939 \cdot 10^{-2}\mathrm{T}_{\mathrm{atm}} - 2.7816 \cdot 10^{-4}\mathrm{T}_{\mathrm{atm}}^{2} + 6.8455 \cdot 10^{-7}\mathrm{T}_{\mathrm{atm}}^{3}) \quad (2)$$

$$\tau = X_{\ \mathrm{exp}} \left(-\sqrt{d}\left(\alpha_1 + \beta_1\sqrt{H}\right)\right) + (1-X)\ \mathrm{exp}\left(-\sqrt{\mathrm{d}}\left(\alpha_2 + \beta_2\sqrt{\mathrm{H}}\right)\right) \quad (3)$$

Where $H_{rel} \in (0,1)$ is the relative humidity, T_{atm} is the environmental temperature, H is the water vapor content of the air, and d is the distance between the camera and the target. The unknowns X, α_1, α_2, β_1, and β_2 are constants determined by an unpublished FLIR algorithm when calibrating the camera and can be obtained from the thermal image metadata. τ is the transmittance of the atmosphere.

Data analysis

The programming language R (Version 4.1.2) (R Core Team, 2021) was used for data analysis. Several variants of regression were applied (univariate, quadratic, and multivariate (partial least square regression (PLSR) (due to multicollinearity ≥ 10))). A total of 62 characteristics were considered, consisting of maximum, median and mean temperature values of the body parts (n = 12), the quadrat of maximum and mean for each body part (n = 8), 99^{th},95^{th} and 90^{th} quantiles for each body part (n = 12) as well as relative temperature values between the body parts (n = 28) and the additionally measured environmental variables relative humidity and ambient temperature (n = 2). For testing potential improvement, the manually measured characteristics body length and girth were additionally applied to the multivariate model. To automate these measurements, a univariate regression of body length and girth with the Euclidean distance in pixel from the thermal images as characteristics was attempted too.

Results

YOLOv3-SPP was able to detect the trained body parts with a 'mean Average Precision' (*mAP*), which is the arithmetic mean of the 'Average Precision' (AP) from all classes at an 'Intersection over Union' (*IoU=0.5*) was 0.98 (*mAP@0.5 = 0.98*). Univariate and quadratic regression of the max-values of the area head (univariate) and piglet (quadratic), respectively, showing already promising results (Tab.1 and 2). The highest accuracy for rectal temperature estimation was produced by PLSR. Here, four principal components emerged after 10-fold cross-validation, yielding a root-mean-squared $\text{error}_{\text{training}}$ ($RMSE_T$) $= 0.44$ and a root-mean-squared $\text{error}_{\text{prediction}}$ ($RMSE_P$) $= 0.46$ with $R^2 = 0.65$ (Tab. 3, Fig. 4 and Tab. 4). Further approaches to improve the model by supplying additional regressor variables (lenght and girth), which discribe the body constitution of the piglets, improved the PLSR model (this time 3 components) to $RMSE_T = 0.44$ and $RMSE_P = 0.43$ with $R^2 = 0.65$. But these manually measured variables are not given in practical conditions, thus these results are not taken as highest accuracy. The approach to estimate these values with univariate regression, by using the length and respectively width of the piglets in pixels from the thermal images, did not work well ($R^2 = 0.11$ (girth) and $R^2 = 0.05$ (length)).

Table 1: Results of univariate regression of max values of body characteristics on rectal temperature. $RMSE_T$, $RMSE_P$ are the root-mean-square error for training and prediction (test) data set. Y represents the rect. temperature and x the max value of the characteristic. The row highlighted in gray indicates the highest accuracy

Characteristic	Equation	R^2	$RMSE_T$	$RMSE_P$
MAX				
head	y=0.77345x+9.56586	0.65	0.50	0.50
piglet	y=0.77265x+9.48580	0.65	0.50	0.51
back	y=0.62400x+14.75703	0.51	0.59	0.60
back end	y=0.79477x+8.66534	0.52	0.59	0.56

Table 2: Results of quadratic regression of max values of body characteristics on rectal temperature. $RMSE_T$, $RMSE_P$ are the root-mean-square error for training and prediction (test) data set. Y represents the rect. temperature and x the max value of the characteristic. The row highlighted in gray indicates the highest accuracy

Characteristic	Equation	R^2_{adj}	$RMSE_T$	$RMSE_P$
MAX				
head	$y=0.12433x^2-7.77358x+156.36261$	0.67	0.48	0.50
piglet	$y=0.12516x^2-7.85046x+157.91004$	0.67	0.48	0.49
back	$y=0.19383x^2-8.31736x+167.57587$	0.54	0.57	0.57
back end	$y=0.13068x^2-12.45068x+235.26252$	0.57	0.55	0.53

Table 3: Percentage of variance in x (regressor variables) explained by the combination of 1, 2, 3 and 4 components during training. The percentage in brackets indicates the explained variance by a single component

	1st comp	2 comps	3 comps	4 comps
X	49.77 (49.77)	64.82 (15.05)	70.83 (6.01)	81.00 (10.17)

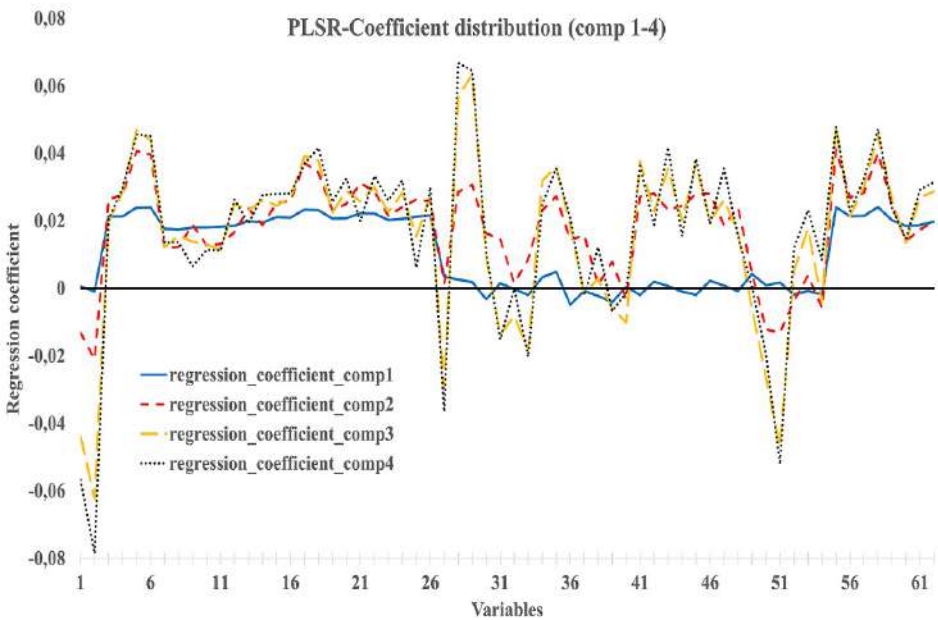

Figure 4: Regression coefficients, for each of the four components of the PLSR. Variable's index can be found in Table 4

Table 4: Indexing of estimator variables. Where mb = max back, mbe = max back end, mh = max head, mp = max piglet and ab =average/mean back, abe = average/mean back end, ah = average/mean head, ap = average/mean piglet

Nr	Environment, Max, Median and Mean (n=14)	Nr	99^{th}, 95^{th}, 90^{th} Quantile (n=12)	Nr	Rel. Temps. (n=14)	Nr	Rel. Temps. (n=14)	Nr	Quadratic Temps. (n=8)
1	Temperature	15	Q_back99	27	mb_mbe	41	mh_ab	55	Max_head^2
2	Air Humidity	16	Q_be99	28	mb_mh	42	mh_abe	56	Max_back^2
3	Max_back	17	Q_head99	29	mb_mp	43	mh_ah	57	Max_be^2
4	Max_be	18	Q_pig99	30	mb_ab	44	mh_ap	58	Max_pig^2
5	Max_head	19	Q_back95	31	mb_abe	45	mp_ab	59	$Mean\_head^2$
6	Max_pig	20	Q_be95	32	mb_ah	46	mp_abe	60	$Mean\_back^2$
7	Median_back	21	Q_head95	33	mb_ap	47	mp_ah	61	$Mean\_be^2$
8	Median_be	22	Q_pig95	34	mbe_mh	48	mp_ap	62	$Mean\_pig^2$
9	Median_head	23	Q_back90	35	mbe_mp	49	ab_abe		
10	Median_pig	24	Q_be90	36	mbe_ab	50	ab_ah		
11	Mean_back	25	Q_head90	37	mbe_abe	51	ab_ap		
12	Mean be	26	Q_pig90	38	mbe_ah	52	abe_ah		
13	Mean_head			39	mbe_ap	53	abe_ap		
14	Mean_pig			40	mh_mp	54	ah_ap		

Discussion and Conclusion

The presented approach shows a suitable method with sufficient accuracy to produce a semi-automatic indication of piglet rectal temperature and, thus, represents an important possibility of animal monitoring under practical husbandry conditions. Except, of a thermal camera, no special hardware requirements are needed for this purpose. If another manufacturer of the thermal imaging camera is used, the formula (1-3) for converting the radiation values to a pixel temperature will probably need to be adapted. The distance of the camera to the piglet was 0.5 m for the current data. Other distances can be used by simple adjustments of the formula (3) inside the R-Code. Unfortunately, the estimation of the body length and girth variables using the pixel distances from the thermal images was not successful for this approach, because no attention was paid to a uniform body position of the piglets when the images were recorded. As mentioned, the presented approach is semi-automatic, because the thermal images were taken manually. But in the case of monitoring reared pigs, a completely automatic individual measurement by e.g. RFID (radio-frequency identification) -controlled recordings of a thermal imaging camera at an individual drinker or feeding spot is imaginable. For this scenario an estimation of body length and girth by a more consistent body posture might also be more promising. The prices of high quality thermal cameras are very high (e.g. 5.000€ -15.000€ (for cameras that were used in mentioned approaches above)). The FLIROnePro is a low price thermal camera (about 400€) and makes it from an economic perspective more suitable for practical farming. However, there are some critical technical specifications like the low resolution (only 19.200px per image (160x120)), 5% measurement uncertainty and only 60-min battery runtime, if there is no power supply. Nevertheless, for this approach, the specifications were sufficient from our view. Another great benefit of our approach is that there is no manual processing of the thermal images needed. All steps, including body part detection, background subtraction (Otsu), extraction of the regressor variables and prediction of the rectal temperature are done automatically inside the R-Code, which makes it even more useful for practical farming.

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SESSION 3

Poultry:
Health and Production

Effect of elevated carbon dioxide on chicken eggs during the early and late incubation periods

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Abstract

Elevated CO_2 during the early or late period of chicken egg incubation has been proven to improve chick quality and shorten the hatch window. In this study, a CO_2 supplementation system was developed and used to increase the CO_2 level to 1% concentration in the early period (0^{th}- 10^{th} day of incubation, E0-E10) and again for the late period (from internal pipping to E21, IP-E21) in an incubator as the treatment group. A control group with an ambient CO_2 level was used as the basis for a comparative assessment of embryonic development, hatching characteristics, and hormones and nutrients between the two groups. Three hundred eggs were hatched in each incubator in each of three experimental trials. The results showed that elevated CO_2 shortened hatching time by 4 hours and hatch window by 3 hours ($P < 0.05$) without affecting hatching quality. The treatment group had a higher relative weight of the heart and intestine at external pipping (EP) and H0 ($P < 0.05$). Elevated CO_2 significantly increased the concentration of plasma corticosterone from IP to EP ($P < 0.05$), promoted the secretion of triiodothyronine and tetraiodothyronine ($P < 0.05$), and increased liver glycogen on E21 ($P < 0.05$). These results indicate that elevated CO_2 (1%) during the early and late periods of incubation accelerate the development of embryonic organs and shortened hatching time and hatch window without affecting hatching quality, and may be explained by the synergistic function of hormones and nutrients.

Keywords: CO_2 supplementation, embryonic organ, hatch window, hormones, nutrients

Introduction

Carbon dioxide (CO_2) is an important factor in embryo development during incubation (Willemsen *et al*., 2008). During natural incubation, the CO_2 concentration surrounding the eggs increases from 0.05% to 0.9% (Boutilier *et al*., 1977; Walsberg, 1980). However, commercial incubators have maintained a high ventilation rate and CO_2 levels at surrounding room ambient levels. Therefore, investigating CO_2 regulation strategies to promote embryonic development and improve hatch quality is necessary.

Several studies have shown that exposure to elevated CO_2 concentrations plays a crucial role in embryo morphology and physiological development (Fernandes *et al*., 2017;

Okur, 2019). High-level CO_2 in the early period of incubation (E0-E10) can promote embryo development and shorten hatching time (De Smit *et al*., 2008; Bruggeman *et al*., 2007; Tona *et al*., 2007). Moreover, this method has been proven to increase the heterophil/lymphocyte ratio, improve the feed conversion of 1-week-old chicks, and attenuate the ventilatory response to hypercapnia in 10-day-old male chicks (Fernandes *et al*., 2014; Rocha *et al*., 2020). However, high-level CO_2 (E18–E20) did not affect organ weight or hatchability but did briefly alter plasma corticosterone profiles, and hatch window was 2.7 h shorter and 5.3 h later than that of the control group (Tong *et al*., 2015b). These studies showed that CO_2 regulation during incubation is beneficial for hatching quality. In addition, this effect is likely mediated by changes in hormones and nutrients. However, the effect of a combination of elevated CO_2 regulation during both the early and late periods of incubation on embryonic development, hatching characteristics, and chick quality is unknown, as is the synergistic mechanism related to any changes.

Therefore, the objectives of this study were to evaluate the effects of elevating CO_2 level to 1% during the early and late periods of incubation on embryonic development and hatching characteristics and the changes in hormone levels and nutrient metabolism.

Material and methods

Egg incubator and CO_2 supplement system

Two identical automatic incubators (OvaEasy 380 Advance EX Series II, Brinsea, Weston-Super-Mare, UK) were used in this study. A CO_2 supplement system was developed in the treatment incubator, which comprised a programmable logic controller (PLC), solenoid valve, CO_2 sensor (VAISALA GMP251, VAISALA, Helsinki, Finland) with an accuracy of 0.1% CO_2, and CO_2 cylinder as the supplemental CO_2 source. The CO_2 sensor collected signals of CO_2 concentrations in the incubator, and the PLC controlled the cylinder solenoid valve to maintain the set point CO_2 concentration. The control incubator had a same CO_2 sensor installed to monitor the concentration. Both incubators were equipped with identical oxygen sensors (EDKORS O_2, ADVICS CO., LTD., Nagoya, Japan) with an accuracy of 0.1% O_2 and temperature and humidity sensors (VAISALA HMP 110, VAISALA, Helsinki, Finland) with a temperature accuracy of ± 0.2 °C and a relative humidity accuracy of ± 1.5%.

Experimental design

The experiment was executed in three consecutive batches (trials), and the two incubators were alternately used for the treatment group and the control group. The CO_2 concentration of the treatment group was maintained at 1% in the early period (0th (E0) to 10th d (E10)) and the late period (from internal pipping (IP) to the 21^{st} d (E21)), and below 0.25% in the other periods while not running the CO_2 supplement system. The CO_2 concentration in the control group was less than 0.25% during the entire incubation period.

Three batches of breeding eggs were collected from the same group of Jing Hong No.1 breeders. For each experimental trial, 600 eggs were randomly selected and divided into two groups, weighed, surface-sterilised, and placed into the two incubators.

Hatching characteristics

The top two hatching baskets in the incubator were selected for video observation. The hatching time of the eggs was recorded. The hatch window was defined as the precise time between the hatching of the first and last chicks. All chicks were weighed and scored for quality by a standard method (Tong *et al.*, 2015a).

The hatchability of fertilized eggs was calculated using Equation (1):

$$\text{Hatchability}=\frac{N_{chicks}}{NE_{breeding}-NE_{sampled}-NE_{unfertilized}}\times 100\% \tag{1}$$

where hatchability is the hatching rate of the eggs (%); N_{chicks} is the chick number after 21 d of incubation; $NE_{breeding}$ is the number of eggs placed at E0; $NE_{sampled}$ is the number of eggs sampled; and $NE_{unfertilized}$ is the number of unfertilised breeding eggs.

Embryonic and organ weight

For each experimental trial, ten samples were randomly selected from each incubator at IP (the point when the shadow of the beak under candle is clearly visible), external pipping (EP, the point when the chick pecked through the shell), hatching time (H0, the point at which the chick newly hatched), and E21. Embryos and chicks were selected when the aforementioned status was observed, euthanised by cervical dislocation.

The heart, liver, intestine, and yolk were weighed using an electronic scale (JCS, Wuxi Yingheng Electronics Co., Ltd., Wuxi, China) with an accuracy of 0.001 g. Yolk free body mass, relative heart, liver, and intestine weights was measured.

Hormones and nutrients

At IP, EP, H0, and E21, three samples were randomly selected from each incubator, euthanised via cervical dislocation to obtain blood, yolk, and liver samples. Plasma corticosterone, triiodothyronine, and thyroxine were measured using a double antibody RIA kit (Beijing SINO-UK Institute of Biological Technology, Beijing, China). To avoid the limited plasma of an embryo cannot determine all hormones, combine two embryo in each period as one sample. The yolk was used to evaluate crude fat content by sox let extraction; the liver was used to evaluate hepatic glycogen levels by anthrone colorimetry.

Statistical analysis

All data were analysed using IBM SPSS Statistics (version 20, Chicago, IL, USA) and expressed as mean ± SEM. Equation 2 was used to analyse the effect of CO_2 treatment on hatching characteristics.

$$Y_1 = \mu + C_j + B_k + CB_{jk} + I_m + \varepsilon \tag{2}$$

where Y_1 is hatching characteristics; μ is the mean value; C is the CO_2 treatment (j=treatment group, control group); B is the batch factor (k=1, 2, and 3); CB is the interaction (treatment × batch); I is the incubator (m=1, 2); and ε is the error influence.

Equation 3 was used to analyse the effect of CO_2 treatment on embryonic weight, hormones, and nutrients:

$$Y_2 = \mu + T_i + C_j + B_k + TC_{ij} + TB_{ik} + CB_{jk} + I_m + \varepsilon \tag{3}$$

where Y_2 is relative organ weight, hormones, and nutrients content; μ is the mean value; T is the incubation stage (i=IP, EP, H0, and E21); C is the CO_2 treatment (j=treatment group, control group); B is a batch factor (k=1, 2, and 3); TC, TB, and CB are the interactions (age × treatment, age × batch, and treatment × batch, respectively); I is the incubator (m=1, 2); and ε is the random error.

Results and Discussion

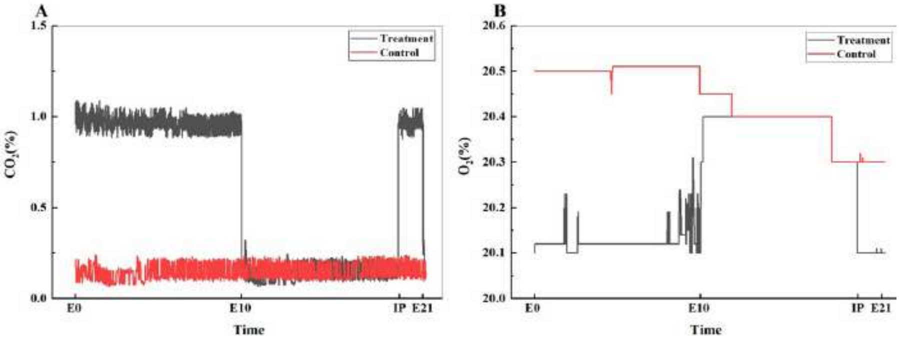

Figure 1: The environment of chicken eggs incubator of elevated carbon dioxide treatment group (1%) and control group (ambient level). A: CO_2; B: O_2

Both of the CO_2 concentrations of the treatment group at E0-E10 and IP-E21 were 0.97 ± 0.05% (Fig 1), while that in the control group was always lower than 0.25%. The 1% CO_2 concentration was based on the gas environment in natural incubation (Boutilier *et al*., 1977) and the literature (Tong *et al*., 2015a). The O_2 concentration in the treatment group was slightly less than the 20.3% O_2 concentration in natural incubation while that in the control group was higher. However, this difference in O_2 concentration is not sufficient to cause changes in embryonic development (Dusseau and Hutchins, 1988).

Table 1: Effect of elevated carbon dioxide (1%) during the early and late incubation periods of chicken eggs on weight and relative weight of embryonic organs

Time	Group	Yolk free embryo weight (g)	Relative heart weight (%)	Relative liver weight (%)	Relative intestine weight (%)
IP	treatment	31.64±2.23	0.61±0.05	2.06±0.29	2.81±0.39
	control	31.20±1.91	0.63±0.06	2.14±0.35	2.91±0.58
EP	treatment	36.01±1.91	0.68±0.09[a]	2.02±0.25	2.64±0.40[a]
	control	35.36±2.75	0.63±0.06[b]	1.94±0.27	2.36±0.27[b]
H0	treatment	34.9±1.84	0.77±0.07[a]	2.45±0.42	3.21±0.46[a]
	control	35.98±2.44	0.73±0.08[b]	2.37±0.28	2.79±0.54[b]
E21	treatment	34.85±1.93	0.86±0.09	2.62±0.33	3.92±0.55
	control	35.24±2.13	0.85±0.07	2.63±0.33	3.79±0.49

Note: Different lowercase letters in the same column for the same time indicate significant level difference ($P < 0.05$). Values are means ± SE of three replicates. Abbreviation: IP, internal pipping; EP, external pipping; H0, the point when the chick newly hatched at the 20th day; E21, the end of the 21th day.

At EP and H0, the relative heart and relative intestinal weights in the treatment group was significantly higher than those of the control group ($P < 0.05$) (Table 1). Those heavier organs indicated that CO_2 stimulated organ growth. However, the difference disappeared at E21. Similar studies (Fernandes *et al.*, 2014) have reported that high CO_2 (0.4%-1%, 0-10th d) did not affect heart or liver weights ($P > 0.05$). However, hatched chicks treated with 1% CO_2 (0-19th d) had heavier hearts and lungs (Maatjens *et al.*, 2014b). Zhang and Burggren (2012) reported that the first half of embryonic development contains critical windows for detrimental effects of hypoxia, while the second half for compensatory response to hypoxia in key organs. This suggests that changes in CO_2 concentration may affect the formation of some organs but depends on the time when changes appear.

Table 2: Effect of elevated carbon dioxide (1%) during the early and late incubation periods of chicken eggs on hatching characteristics

Item	Treatment group	Control group
Hatched egg weight (g)	61.05 ± 3.61	60.79 ± 3.50
Chick weight at 1-day-old (g)	41.41 ± 2.89	41.28 ± 3.28
Hatchability (%)	91.38 ± 0.55	91.25 ± 1.08
Hatching time (h)	475.0 ± 3.0^b	479.3 ± 3.8^a
Hatch window (h)	15.27 ± 5.37^b	18.06 ± 4.00^a
Chicks' quality score at 1-day-old	97.66 ± 4.34	98.27 ± 3.54

Note: Different lowercase letters in the same category of data indicate significant level differences ($P < 0.05$). Values are means ± SEM of three replicates.

There was no significant difference between the egg weights, the weight of 1-day-old chicks, the hatchability, and quality scores between the two groups ($P > 0.05$) (Table 2). The hatching time of the treatment group was 4 h earlier ($P < 0.05$), and the hatch window of the treatment group was significantly shortened by 3 h compared with that of the control group ($P < 0.05$). Hatch window was defined as the time between the hatching of the first and last chicks (Careghi *et al.*, 2005). Extension of the hatch window results in poor uniformity within the batch of chicks and impairs post-hatch growth (Willemsen *et al.*, 2008). Our results indicate that 1% CO_2 in early and late periods of incubation can significantly shorten hatch window. The hatch window was shortened by 3 h, longer than the 2.5 h from Tong *et al.* (2015b), who only provided high-level CO_2 in the late period. This finding indicates that CO_2 supplementation in the early and late stages has a cumulative effect on shortening the hatch window. In addition, the hatching time was shorter than that of control group, rather than being postponed as reported in the literature (Tong *et al.*, 2015b). One possible reason is that supplementation in two periods accelerates the formation of nutrients, leading to a shortened hatching time.

Table 3: Effect of elevated carbon dioxide (1%) during the early and late incubation periods of chicken eggs on hormones and nutrients

Time	Group	Plasma corticosterone (ng/ml)	Triiodothyroxine(T3) (ng/ml)	Tetraiodothyronine(T4) (ng/ml)	Hepatic glycogen (ug/ml)	Crude fat content in yolk (mmol/L)
IP	treatment	4.64 ± 0.53[a]	0.86 ± 0.08	52.57 ± 10.59[a]	5.85 ± 0.73[b]	12.76 ± 2.79
	control	3.93 ± 0.7[b]	0.79 ± 0.09	38.26 ± 9.76[b]	13.54 ± 2.54[a]	12.50 ± 2.99
EP	treatment	4.67 ± 1.56[a]	0.74 ± 0.21[a]	62.73 ± 23.30[a]	12.75 ± 2.14[b]	11.58 ± 2.27[b]
	control	2.77 ±1.22[b]	0.44 ± 0.20[b]	40.41 ± 18.68[b]	14.84 ± 1.73[a]	15.24 ± 1.67[a]
H0	treatment	6.03 ± 1.99	1.05 ± 0.14	79.59 ± 14.33	12.92 ± 2.18[b]	9.72 ± 4.77
	control	5.52 ±1.18	1.00 ± 0.13	77.24 ± 4.63	19.45 ± 3.98[a]	13.31 ± 4.60
E21	treatment	5.37 ± 1.00	0.93 ± 0.27	77.49 ± 11.22	14.67 ± 2.19[a]	7.47 ± 1.37[b]
	control	4.84 ±0.78	0.92 ± 0.08	74.28 ± 27.00	9.31 ± 5.44[b]	12.08 ± 3.06[a]

Note: Different lowercase letters in the same column for the same time indicate significant level difference ($P < 0.05$). Values are means ± SE of three replicates. Abbreviation: IP, internal pipping; EP, external pipping; H0, the point when the chick newly hatched at the 20th day; E21, the end of the 21th day.

The plasma corticosterone concentration in the treatment group was significantly higher than that in the control group ($P < 0.05$) at the IP and EP. At EP, T3 levels in the treatment group was significantly higher than that in the control group ($P < 0.05$). At IP and EP, T4 levels were significantly higher in the treatment group than in the control group ($P < 0.05$) (Table 3). A high-level CO_2 can activate the hypothalamus-pituitary-adrenal axis, which usually starts during the preparation for incubation (Tong *et al*., 2015b; Tona *et al*., 2013). The plasma corticosterone concentration in the treatment group was significantly higher than that in the control group at IP, which may be due to the high-level CO_2 during the first 10 d of incubation. This result can explain the shortening of the incubation time and the hatch window. In addition, the interaction between the thyroid and adrenal axes also affects the hypothalamic-pituitary axis. This interaction initiates and strengthens several important physiological processes during embryonic hatching. De Smit *et al*. (2008) proved that there were higher T3, T4, and corticosterone concentrations and a shorter hatch window in chicken embryos in a high-level CO_2 than in a low-level CO_2. This result indicates that the advancement of the hatching process is related to the increase in the concentrations of corticosterone, T3, and T4 caused by high-level CO_2.

At IP, EP, and H0, the hepatic glycogen levels in control group were significantly higher than those in treatment group ($P < 0.05$). But at E21, the hepatic glycogen levels in treatment group were significantly higher than those in control group ($P < 0.05$). At EP and E21, the crude fat content in the yolk of the treatment group was significantly lower than that in the control group ($P < 0.05$). Long-term stimulation with high-level

CO_2 increases the basal metabolic rate of the embryo and promotes the accumulation of liver glycogen (Maatjens *et al.*, 2014a). The accumulation of liver glycogen is beneficial to embryo development, which explains the higher relative weight of organs in the treatment group than the control group. The crude fat content of the egg yolk in the treatment group was lower than that of the control group. This result may be due to the high-level CO_2 promoting the hatching process, which is accompanied by absorption of the egg yolk.

Conclusions

The findings of this study indicate that elevating CO_2 to 1% during the early and late periods of incubation (E0-E10 and IP-E21) shorten hatching time and hatch window, and accelerate embryonic organ development without changing chick hatchability or hatchling quality which may be due to the increases of corticosterone, T3, T4, and hepatic glycogen concentrations under synergistic effect during IP-EP.

Acknowledgements

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Development of an autonomous roving data collection platform for caged poultry production

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Abstract

The Chinese poultry industry continues to use cages for growing both broiler and layer chickens in most commercial facilities with no plans to ban their use in the immediate future. In contrast, cages have been banned and are being phased out in Europe. In particular, broilers are and have been kept in large flocks on a littered floor. Both systems however, do have issues related to indoor environment, health and welfare. Various precision livestock farming (PLF) inspired systems have been developed to better monitor and thus improve the climatic conditions for floor based poultry systems (RoboChick, Octopus, ChickenBoy)

For the caged housing system, a large consortium of Chinese and UK industry and academia developed a dedicated autonomous data collection platform. The data platform combines robot technology with advanced sensors and indoor environmental management using real-time monitoring to maintain the best environmental and animal welfare conditions, improving production yield, and providing early detection of poultry disease and minimal anti-biotics use.

The prototype autonomous navigating robot was developed in the UK and fitted with the sensors and datalogging systems. A bespoke user interface was developed to map the environment the robot would be operating in and allow assignment of monitoring positions. The navigation systems were tested in a caged poultry facility in the UK and proven to be highly accurate and reliable in positioning the robot and avoiding obstacles essential for autonomous operation. The jointly developed monitoring systems were integrated with the platforms software and bespoke cloud based databases.

Keywords: poultry, robotics, environment

Introduction

China is the world's largest producer of eggs and a big chicken grower (FAOSTAT, 2015). Over the years there has been a steady shift in both the egg and poultry meat sector from small to medium sized local production facilities too large to very large integrated farms. The latter are typically owned by large often vertically integrated companies. Contrary to Europe, most houses in China/Asia are cage based for both poultry meat (broiler) and egg production. In common with most poultry houses worldwide, only a few monitoring devices are used for environmental control. The installation of numerous devices in the multi-tier caged housing common in China, is unlikely to reflect the whole environment from floor level to the top tier of cages and will be unaffordable. Secondly, sub-clinical and clinical disease (Zhuang *et al.*, 2014) affect animal and gut health, reducing food conversion and welfare and increasingly cause huge financial losses .

To improve the health and welfare of the birds and environmental conditions in caged facilities, an autonomous robot moving between the cages and sampling the environment at multiple levels and observing the birds could provide the necessary data (Demmers, Dennis, Norman, Butler, & Clare, 2019; Dennis, Abeyesinghe, & Demmers, 2020). The robot collected data will give a 3D view of all parameters including temperature, humidity, air velocity, CO_2. On-board cameras will allow visual assessment of the conditions in the cages. Importantly the development of an automated version of a VOC sampling & sensing system will allow early detection of diseases to be possible for the first time. Compilation of the data gathered will not only detect diseases before symptoms are seen, but by cross-reference allow predictive modelling. Thus, for the first time the poultry farmer could potentially reduce sickness in birds, reduce the use of anti-biotics/treatments; improve bird welfare, production yield and rebuild consumer confidence in the quality of his product.

Material and methods

Autonomous navigation platform

For the purpose of the project a prototype robot, capable of autonomous navigation through a caged poultry house was designed and developed by Ross Robotics Ltd, based on the requirements provided by the farm managers and the research team. The navigation systems tested in a small scale layer facility at Harper Adams University and a commercial poultry farm. The robot's navigation system consist of a LIDAR system. The navigation software development was based on the existing autonomous roving platform (Ross Robotics Ltd). The robot has a fully automated docking and recharging station. The sensors and cameras are mounted on a 3m high mast with flexible spacing and their data acquisition and control systems are integrated into the base of the robot.

Sensor systems

The environmental sensors were selected based on suitability, size and price. 3D Sonic anemometers (Wind Master, Gill Instruments Ltd) were used to measure air speed and direction; PT100 and conductivity probes for temperature and humidity (HC2 probe, Rotronic Ltd); electrochemical diffusion sensor for ammonia concentration (DOL53, Drager GmbH); Non-dispersive infrared absorption for Carbon Dioxide (CoZir-A; GSS Ltd); Optical sensor for the dust concentration and size fractions (OPC-N3; Alphasense Ltd) and a spectroradiometer for the light intensity (SM2000; Optimum Corp.). All sensors were powered and data logged from a purpose built data acquisition system based on a Raspberry Pi model 4B combined with a data acquisition processor (STM32; STMicroelectronics).

In addition, a camera module, based on a small form PC (X86 UP Board; UP Ltd) recorded images of the birds in the cages using 4 video camera (xcg-CG240C; Sony Ltd) and lens (FL-DD0614A-2M; Ricoh GmbH). Data collected were transferred during charging of the robot to a dedicated data base prior to analysis using AI technology (outside scope of paper).

Figure 1: Autonomous navigating robot inside access corridor poultry facility with camera and wind speed sensors fitted (Ross Robotics) and or the right the CAU built platform inside a layer house in Beijing District, China

The collected real time data, time and location stamped by the robot during roaming the building are transferred wirelessly to a server (host pc) and/or transferred during recharging to a bespoke database (MS access) build by the Chinese Agricultural University (CAU) and hosted in the cloud.

Delays in the project due to the Covid19 pandemic and budget reductions imposed by the funding body, forced Ross Robotics to withdraw from the project. A simplified version of the robot was built by CAU and used for data collection, incorporating the original sensors, cameras and data acquisition modules.

Building sensor systems

The building at the commercial layer farm in China used for the robot trials (Beijing DeQingYuan Agriculture Technology Co) housed 110,000 birds two floors each with 6 rows of cages (see figure 2). The house is tunnel ventilated with air inlets at the gable end and along the sides of the building (minimum ventilation) and the fans all at the opposite gable end. There are only a few sensors available for monitoring and controlling the environment located at 3 points in the building (see figure 2). All sensor are fitted in one plane across the building.

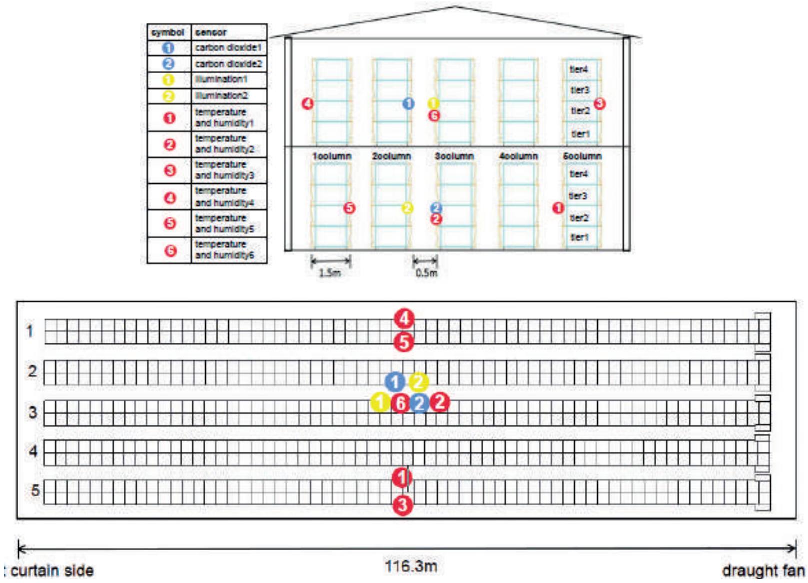

Figure 2: Sensors and sensor location in the layer farm at Beijing DeqingYuan

Results and Discussion

The navigation and stability of the robot was tested in the access corridor of a commercial farm (100m length) and a small caged bird research facility (25m length). The robot was able to navigate both environments with great accuracy (return to set waypoints, error within 0.025m). However, due to reflections from the walls and objects, the main lidar system detected "ghost" objects and the robot was unable to proceed at certain locations. The addition of a short range forward facing camera and changes to the software solved this issue. The bespoke user interface worked well during training of the navigation system in the research facility.

The alternative robot uses a very similar navigation system, but has fixed waypoints based not on coordinates but on markers in the corridors between the cages. Using this system, data were collected from early December 2021 till the 29th of December 2021 (interrupted for Winter Olympic Games).

The data shown in figure 3 are the temperature, humidity, carbon dioxide, ammonia and particulate profile for the building at the ground floor. The data for the farm sensors at the time are given it table 1.

The farm temperature sensors and robot profile match well for sensor 5 (23.8 C v 23.8 C) but are under reading on the robot for location 1 and 2 in this instance. However, it is also very clear that over the length of the building the gradients for all measured parameters are even larger. For temperature the range is from 20.1 to 24.9 C for locations nearest the front and fans respectively. Similar gradients are observed for carbon dioxide (2900 – 3800 ppm) and ammonia (7.3 – 14.3 ppm). As expected the gradient is less for air speed (0.25 – 0.3 $m.s^{-1}$).

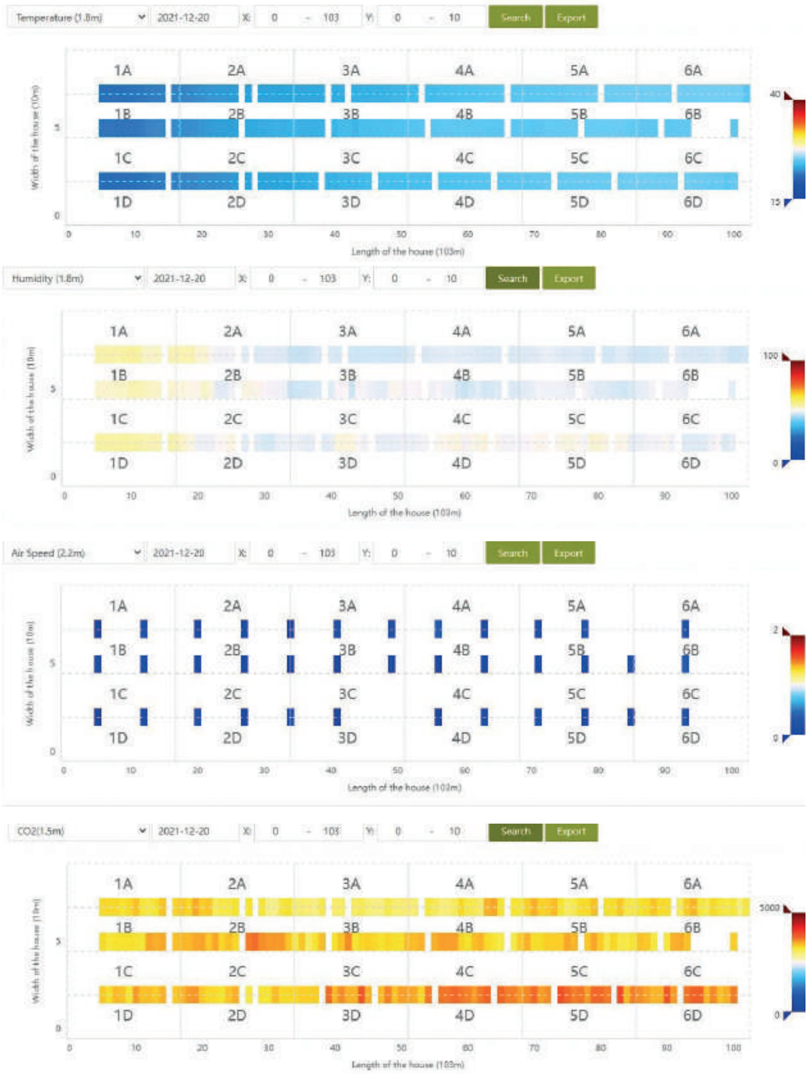

Figure 3: The temperature, humidity, carbon dioxide and airspeed profile as measured with robot at the layer farm on 20 12 2021 from 8 till 10am between rows 1-2, 2-3 and 4-5. The air speed is only give for the locations where the robot was stationary

The data are currently being analysed and real time advice on the environmental conditions in the houses is being provided to the farm manager on a daily basis. Ultimately, the aim is to understand better how to can manipulate the environmental management system (fans, cooling, heating) to optimise the environment in the complete building to maximise the welfare for all birds rather than a small section in the centre of the building. The robot data are essential in this process. Additionally, the camera system on the robot will provide detail on the behaviour of the birds as well as the number and location of death birds, whereas a volatile organic component sensor capable of detecting the unique "finger" print for specific poultry diseases (Coccidiosis for instance) will add the health status of birds in regions of the house. Taking all data together we will be able to create a scoring system that will be used in the end user Dashboard.

All the data will be reported to the farm manager in the form of "tickets" reporting daily issues and through and interactive dashboard created for the data received.

Table 1: The temperature, humidity, carbon dioxide and light measured with stationary house sensors at the layer farm on 20 12 2021 at 9am

Location	Temperature [C]	Humidity [%]	CO2 [ppm]	Light [lux]
1	25.9	55.3	3580	xx
2	27.0	54.8	3125	xx
3	26.9	60.2		
4	25.6	59.8		
5	23.8	59.3		
6	27.4	56.8		

Conclusions

The developed autonomous roving data platform(s) can navigate the caged poultry house environment effectively and accurately collecting data from a range of environmental, welfare and health sensors at known locations throughout the house.

The data will enable optimisation of the environmental conditions in the house using an interactive system of notifications and an end user dashboard.

Acknowledgements

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Can AI imaging technology be used for monitoring specific behaviours in broiler flocks?

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Abstract

Commercial poultry production, e.g. optimum bird growth, requires an optimally controlled environment, which is currently based upon temperature, humidity, CO2 and air pressure, whilst water and feed consumption are also measured.

PLF systems exist to monitor (reduced) movement or change of positioning of the broilers in the house, However, other parameters related to animal welfare and health such as feeding, drinking and movement behaviour are still largely dependent on visual observations by the stockman 2-3 times a day when the flock is checked. This not only relies on the quality of the observations by the stockman, but also doesn't guarantee fast, effective management of the flock.

Automated 24/7 visual monitoring of broiler flocks using Artificial Intelligence (AI) imaging technology to classify specific behaviours in real time might provide unbiased information relating to health and welfare of the flock. Small changes in behavioural observations might lead to early detection of disease and optimized climate control.

A current feasability project has started to test which behaviours can be identified using AI technology and how these quantified behaviours could be used to optimize health and welfare of the flock being monitored.

Keywords: poultry, broilers, artificial intelligence, behaviour, labelling

Introduction

Poultry meat consumption worldwide has increased worldwide and compared to beef and pork is requires less environmentally damaging inputs (FAOSTAT, 2015). In general, commercial poultry meat production uses large houses with tightly controlled indoor environments to grow broiler chickens at high stocking densities. The management of the birds focusses mainly on keeping environmental parameters, temperature, humidity, carbon dioxide, air pressure and ammonia and production targets, e.g. water and feed consumption within tight margins. Automated climate control systems and remote monitoring services (OptiFarm) assist the farm managers with this process (Wathes et al., 2008).

Relatively small deviations from the optimum environmental climate cause significant changes to the chicken's behaviour and wellbeing, with stress a major contributor to mortality and morbidity. Observations of behaviour(s) are a proven indicator of animal health and welfare (Abeyesinghe et al., 2021), both positive and negative. Small changes in the behaviour of individual chickens and/or the flock, often reduced movement or a change in position within the house, can be indicative of the onset of disease or another ailment (Colles et al., 2016; Dawkins et al., 2012).

Farmers have limited resources to monitor behaviour other than through the twice daily visual inspection of the birds. Camera based systems such as EyeNamic provide information on general bird activity and distribution and have been linked to welfare status (Peña Fernández et al., 2018) whereas the OptiFarm monitoring service uses the real-time camera images to check for major issues only.

Whilst it is not possible to track and identify the behaviour of all individual birds in the house, it might be possible to identify the behaviour of birds at a specific time point. A new project aims to record which set of behaviours are being displayed by which proportion of birds at specific times during the day and will also include current environmental conditions.

Automated welfare monitoring using camera systems offers more to the industry than simple visual benefits, providing quantified data assessment of health and welfare of chickens. This assessment would benefit individual partners through improved performance and thus profits.

Material and methods

Data annotation is the process of applying labels, whether automatically or though manual operations, in order to generate samples of accurate results expected of a well-functioning AI model. These samples are known as ground truth data. Ground truth, or training data, encompasses the total knowledge of a machine learning model in a specific domain.

The creation of training data requires the right tooling, and the right talent to use such tools. In most cases it involves experienced labelers applying tags, bounding boxes, or encircling items with polygons on a graphical user interface. Furthermore, this system must follow an immutable yet comprehensive taxonomical schema that allows machine learning developers to train the various types of models expected in the project. The system must also be accessible via a web browser, synchronize globally across teams, and enabling an efficient review experience for stakeholders.

To build a data set of behavioural patterns throughout a broiler growing cycle short video clips (max 5min duration) will be taken at key moments in the growing cycle. For this purpose 2 GoPro7 cameras have been installed in one of the houses at a commercial broiler farm (64.000 birds per house) managed by Hudson & Sander (trading as Applied Poultry Group) and monitored by the OptiFarm service. Environmental data and issues and/or recommendation by OptiFarm data review experts will be recorded and stored.

The video will be cropped to a 4 m * 4 m square, which at the current stocking density will show approx. 250 birds at any time. For each video frame, the labellers will use the V7 annotation platform to perform a polygonal segmentation around each chicken, indicating their current behaviour with a tag. The use of polygon annotations, although more time consuming than bounding boxes, allows for the identification of individual chickens while clustered. A minimum of 400 instances of each behaviour over the duration of the crop will need to be identified and labelled. A larger number of labelled data will improve the AI model. This will generate a dataset where each chicken is in a behavioural state, enabling the AI to understand the visual differences between behaviours.

The specific behaviours selected for this feasibility study and deemed to provide a reasonable behavioural assessment are:

— eating
— drinking
— resting
— walking
— feather pruning
— wing flapping
— wing flapping and running

The wing flapping behaviour will not be seen till the birds are approximately 15 days old as around that time the wings are sufficiently developed and the birds start using them. Secondly, some of the behaviours will occur more often than others and will therefor require more footage to be reviewed to achieve an acceptable number of labelled incidents.

Although this technology to be used in this project as such is not new, the application of the technology is and uses the expertise of V7 in labelling and training the AI model(s).

The labellers will be provided with example behaviours generated by behavioural experts. Random samples of the labelled data will be expert reviewed.

Results and Discussion

The initial phase of the project has started and collection of video clips is currently underway and labelling is due to start shortly. We intend to present the results of the labelling and AI model training at the conference.

Figure 1: model identified behaviour based on limited preliminary data set with drinking chickens (blue), feeding chickens (orange) and moving chickens (green)

Preliminary work done before the start of the project is shown in figure 1. Here all birds identified by the AI model as drinking are shown in blue, those eating in orange and those moving in green.

The use of the polygon annotations clearly works well in identifying each individual chicken. The model identified most feeding and drinking birds well, but clearly has issues with distinguishing moving and stationary (resting) birds. This is largely due to the very limited data set available for labelling and training of the model.

Conclusions

Using existing artificial intelligence technology to identify specified broiler behaviours is eminently feasible provided the labelling and model training is appropriate for the dataset.

Acknowledgements

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A machine learning-based location method for poultry in complex and small environments

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Abstract

Individuals or groups exhibit a particular range of activity, which is a critical characteristic of domain behavior. Rapid and accurate multi-target localization of poultry in small and complex cage environments is required for the study of poultry domain behavior and contributes to the study of social rank and welfare in poultry. Manual observation of poultry in cages has a large margin of error and is difficult to quantify. This study proposes a Machine Learning (ML) based method for locating poultry in small and complex cage environments. We collect RSSI values from target individuals using UHD-RFID devices and then divide the cage floor area into a predetermined number of grids based on the required localization accuracy. We convert the tag coordinates regression problem to a multi-area classification problem and then use KNN, random forest (RF), and artificial neural networks (NN) to estimate target position. The results show that the NN model can make the best prediction, locating the target within a 40 cm × 40 cm area with 88.74% accuracy or within a 30 cm × 30 cm area with 76.81% accuracy, with average errors of 7.61 cm and 7.97 cm, respectively. This study presents a feasible method for localizing targets in small and complex cage culture environments.

Keywords: Poultry localization, UHF-RFID, Cage environment, Machine learning, Range-based

Introduction

Individuals or groups of animals have a distinct range of activities; the activities of different groups frequently overlap, and they generally avoid rather than expel one another. Numerous studies have demonstrated a connection between domain behavior and animal social hierarchies. Collias (Collias, et al., 1966) discovered that when multiple roosters congregated in a group, a dominance hierarchy developed among the roosters, and that the rooster with the highest ranking was dominant and had territorial priority. McBride (McBride, et al., 1969) observed that dominant roosters retained a fixed territory, whereas lower ranking roosters retained only a small area adjacent to themselves. Odén (Odén, et al., 2004) discovered that roosters with a higher rank occupied significantly more cage space and dominant areas than roosters with a lower rank. Favati (Favati, et al., 2014) discovered that individuals in social species frequently form dominance relationships in which dominant individuals have greater access to resources than subordinate individuals. Additionally, male domestic fowl explored new areas more quickly and maintained vigilance for a longer period of time than female domestic fowl. In broiler chickens, on the other hand, abnormal walking patterns are a strong indicator of decreased welfare. It is critical to understand how captive birds utilize their space in order to promote welfare by optimizing space quality and meeting the animals' biological needs (Aydin, 2016).

A variety of technologies are available for indoor positioning, such as Satellite-based systems (Obeidat, et al., 2021), Inertial Navigation systems(INS), Magnetic-based systems, Sound-based systems (Harsur and Chitra, 2017), and Radio Frequency-based systems(RF) (Denis, et al., 2019)g. Many of them, however, are ineffective at locating small animals. For example, because of building exterior walls, global positioning system (GPS), one of the most widely used satellite-based navigation systems, becomes inefficient at locating indoor objects (Nirjon, et al., 2014). INS can become error-prone, necessitating the use of sophisticated filtering techniques such as the Kalman filter (Hu, et al., 2020). At low frequencies, magnetic technology is precise, but it is susceptible to conductive and ferromagnetic materials (Diaz, et al., 2019). And magnetic-based navigation systems typically rely on disturbances in the Earth's magnetic field within enclosed environments, which occur as a result of the ferromagnetic nature of metal structures within buildings (Shu, et al., 2015). As IoT technology has advanced in recent years, radio frequency-based systems have rapidly developed and are now more suitable for indoor positioning. Such as Frequency modulation technology (Popleteev, 2017), Wi-Fi (Bagosi and Baruch, 2011), ZigBee (Bianchi, et al., 2018), Bluetooth (Wang, et al., 2015), Radio Frequency Identification (RFID) (Tesoriero, et al., 2010), and LoRa (Islam, et al., 2019).

Among these technologies, UHF-RFID technology is becoming more prevalent in agricultural positioning research due to its advantages of long identification distance, high accuracy, rapid response time, and strong anti-interference capability. The positioning methods based on UHF-RFID are classified as range-based and range-free; the former includes distance measurement and angle measurement methods, whereas the latter includes fingerprinting and non-fingerprinting methods (Li, et al., 2019). On the basis of electromagnetic propagation regulation, conventional range-based methods can convert RSSI, time of fight, and phase information to the distance between the reader antenna and the target tag. And the geometry characteristic infers the position of the target tag. Hightower (Hightower, et al., 2000) uses an RSSI-based method, which requires the establishment of at least three base stations to achieve a 3m positioning accuracy. Yongtao Ma (Ma, et al., 2016) increased the accuracy to 0.769m through the use of POA and TOA modeling. Povalac (Povalac and Sebesta, 2011)2011 achieved an average absolute error of 0.14m by improving its phase-based ranging technology.

Subsequently, methods for localization based on reference tags and fingerprinting have been extensively investigated, and these methods have been shown to be more adaptable to complex environments. Lionel Ni (Ni, et al., 2003) proposed a LANDMARC system based on reference tags, which involved deploying a large number of fixed-position reference tags, reading RSSI values relative to target tags, and then calculating target tag positions using KNN. Kyuwon Han, et al. (Han and Cho, 2010; Hu, et al., 2018; Khan and Antiwal, 2009; Xu, et al., 2017) improved the LANDMARC system to achieve a positioning error of less than 15 cm on average. Lingfei Mo, et al. (Mo and Li, 2018; Zhao, et al., 2016; Zhao, et al., 2007) proposed some improved methods based on virtual reference tags and phase varies that improved localization accuracy to within 10 cm.

The environment, however, is extremely complex in large farms, with issues such as temperature and humidity fluctuations, signal masking, and target tag rotation. The majority of the methods discussed previously are based on sophisticated computational models and necessitate stringent experimental conditions. Not only are these methods computationally intensive, but they also lack real-time and robustness. As a result, this article proposes a machine learning-based localization method capable of achieving accurate localization in a complex cage environment using a relatively simple experimental design.

Material and methods

Data Acquisition

In this experiment, we used natural mating colony cages with dimensions of 1.2 m × 1.2 m × 0.65 m as illustrated in Figure 1. On the cage's ceiling, we installed four UHF-RFID antennas with equal spacing, antenna gain of 9 DBi, horizontal and vertical beam-widths of 90°, and all antennas facing vertically towards the floor of the cage, approximately 60 cm from the floor.

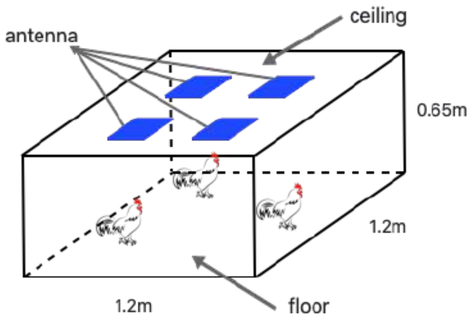

Figure 1: The experimental cage

If the antenna is mounted outside the cage, the metal material of the cage will interfere with the antenna signal, necessitating that the antenna be mounted inside the cage. If the antenna is fixed horizontally at the side or four corners, it will create a blind area of the signal on both sides of the antenna, resulting in data loss. Additionally, when the antenna is fixed horizontally, the signal will be blocked more severely by the poultry in the cage, creating the possibility of pecking and biting the antenna, resulting in damage to the antenna. Therefore, the antenna must be fixed at the ceiling of the cage. Due to the irregular shape of the antenna signal radiation area, close proximity to the signal's edge may cause distortion, we positioned the antennas in such a way that the effective radiation area of each antenna signal covers the entire cage floor to the greatest extent possible. The antennas were mounted vertically downward on the ceiling of the cage as illustrated in Figure 2, with four antennas facing the same direction and spaced 0.4 m apart.

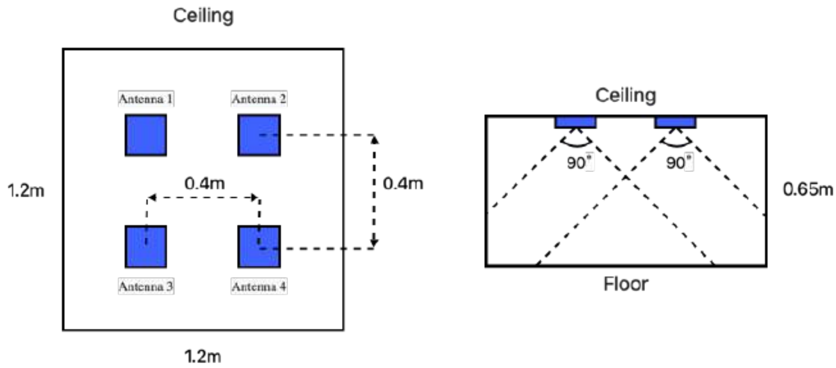

Figure 2: The installation of antennas

Although the RSSI values of tags collected by UHF-RFID antennas are related to the distance between the antenna and the tag, this relationship is not statistically significant (Parameswaran, et al., 2009). Additionally, several other factors affect the RSSI signal, including tag angle, object occlusion, signal distortion, and multipath effects (Wu, et al., 2008). As a result, modeling the RSSI signal and tag distance to centimeter accuracy is a difficult task. However, in a cage environment, where each adult poultry occupies an area of approximately 900 cm2 (30 cm × 30 cm), we only need to locate each observed target within a similar-sized area to conduct behavioral analysis on that target. Therefore, we converted the label coordinates regression problem to a multi-region classification problem in order to avoid the time-consuming exact modeling process and to increase the robustness of the localization model. As illustrated in Figure 3, the cage area is divided in two ways, 30 cm × 30 cm and 40 cm × 40 cm, respectively, corresponding to nine and sixteen classification problems.

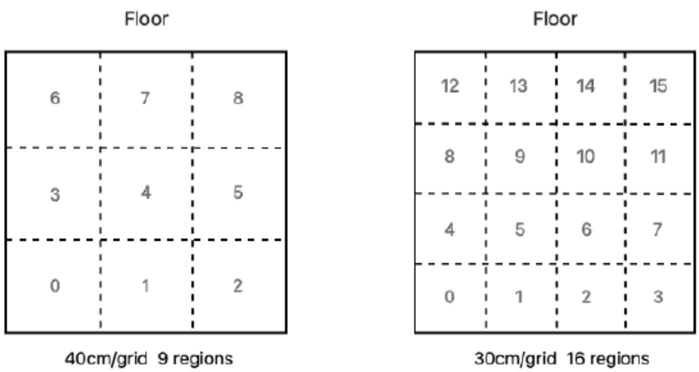

Figure 3: Two ways to divide the floor of the cage

We selected fifty coordinate points distributed throughout the region and sampled RSSI data for three minutes at each coordinate point. RFID tags are typically attached horizontally to the poultry's feet in a cage environment, and their orientation changes as the observed target moves, while the observed target's body can obscure the signal.

To simulate the actual environment, the tag was fixed horizontally on a small rotating platform with a height of 3 cm and a rotation speed of 30 s/r during sampling, and an experimenter's arm shield was randomly added between the antenna and the tag.

Data Preprocess and Analyse

The RSSI value obtained through sampling is between -80dB and -60dB, and the sampling rate of the four antennas was between 60 and 80 samples per second, increasing proportionally to the RSSI strength. Then the collected data is pre-processed, the data sampled from each point is sliced at 1 second intervals, with the average value of RSSI signals received by each antenna calculated as a feature. It should be noted that too large tag distance or inappropriate tag angle will result in low signal strength, low sampling rate, or even data loss. Therefore, for missing data, all should be set to a minimum of -80dB. Finally, all 1 second samples are labeled with nine and sixteen classification labels based on the coordinates of the sampling points, and all samples containing the four features are normalized as follows：

$$\tilde{x}_{ij} = \frac{x_{ij} - x_{j\min}}{x_{j\max} - x_{j\min}} \tag{1}$$

Where the subscript *i* denotes samples and *j* denotes features, x_{min} refers to the minimum value of the feature, x_{max} refers to the maximum value of the feature, and $\tilde{x}_{ij}$ is the standardized variable.

A total of 7774 samples were obtained by processing all of the data in the manner described above. And a randomly selected subset of the data was visualized using the t-SNE (Van der Maaten and Hinton, 2008) method for data dimension reduction, yielding 9 classification and 16 classification data distributions.

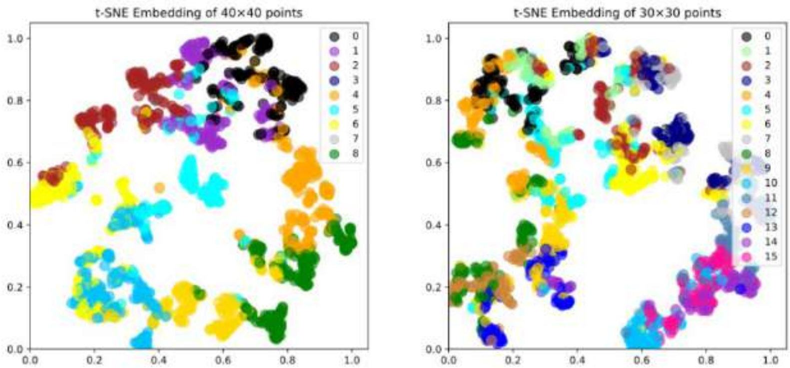

Figure 4: Visualization of samples by t-SNE

As illustrated in Figure 4, samples from different categories are separable in both cases, but the degree of separability is more obvious in the 9 classification.

Model Selection

For classification training, we analyzed three popular classification methods: KNN, random forest, and artificial neural network. KNN is a supervised classification algorithm that is implemented using the distance between sample points in the feature space, and we analyze the correlation between the distribution of sample points in the original four-dimensional feature space and the category using Euclidean distance. Random forest is a supervised classification algorithm based on tree models. It constructs a tree model by recursively creating classification planes perpendicular to the feature space's coordinate axes and then trains multiple tree models to vote on classification results. We used the Gini coefficient as a measure of impurity.

Because both KNN and RF divide data into its original feature space, we chose neural network algorithm with two distinct loss functions to train the feature extraction network and perform the classification task. As a loss function for a classification problem, we first selected cross-entropy (CE).

$$CEloss(y,\hat{y}) = -\frac{1}{n}\sum_{x} y_i(x)\log\hat{y}_i(x) \tag{2}$$

where y for the true label, $\hat{y}$ for the predict value, i for the category label, $i \in 0,1,2,\ldots,7$ or $i \in 0,1,2,\ldots,15$.

While CE is the most frequently used loss function for classification problems, different weights should be assigned to different misclassification cases depending on the classification problem at hand. For instance, as illustrated in Figure 5(A), in a classification task involving a 40 cm × 40 cm grid (9 classifications), assuming the true position of the target is 0, the loss L2 incurred when misclassifying to 6 should be greater than the loss L1 incurred when misclassifying to 1.

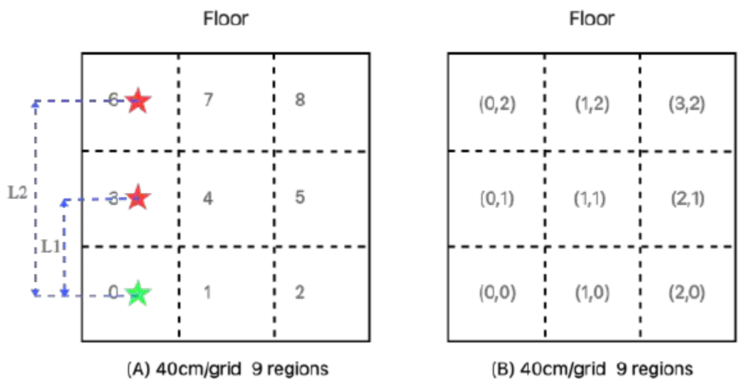

Figure 5: Category labels when using mse

Therefore, we attempted to transform the original classification labels into the coordinate pairs shown in Figure 5(B) and change the loss function to mean squared error (MSE) to reflect the weights associated with different misclassification cases.

$$MCEloss(y,\hat{y}) = -\frac{1}{2n}\sum\nolimits_{x}\left\|y_i(x)-\hat{y}_i(x)\right\|^2 \quad (3)$$

where y for the true label, for the predict value, i for the category label, $i \in 0,1,2,\ldots,7$ or $i \in 0,1,2,\ldots,15$.

Results

KNN and RF Models

The interval of K values in KNN was set from 1 to 50, and the interval of maximum depth D of random forest was from 1 to 20. We used 10-fold cross-validation to test the dataset and evaluate the accuracy of the classification models, and the results were obtained as shown in Figure 6.

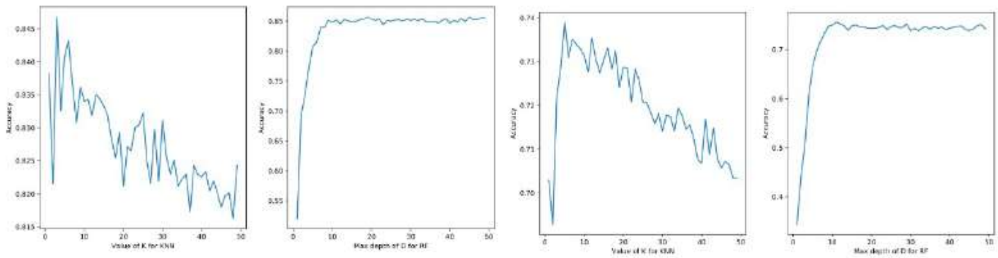

Figure 6: Training results of KNN and RF models

The results indicate that the classification accuracy of the KNN model increases rapidly as k increases, reaches a peak around k equal to 5, and then gradually decreases with a small variation interval. The KNN model's maximum classification accuracy is 84.68% for the 9 classification problems. The KNN model's maximum classification accuracy is 73.94% for the 16 classification problem. The classification accuracy of the RF model is low when the maximum depth D is small, but rapidly increases as D increases. When D reaches approximately 7, classification accuracy reaches a saturation point, and when D continues to increase, classification accuracy ceases to increase. The RF model's maximum classification accuracy is 85.78% for the 9 classification problems and 75.97% for the 16 classification problems.

Additionally, the 9 classification corresponds to a localization accuracy of 40 cm, whereas the 16 classification corresponds to a greater accuracy of 30 cm. It's obviously that models trained on both algorithms perform better on the problem of lower accuracy requirements.

NN Models

In comparison to KNN and RF algorithms, the NN algorithm is more capable of extracting features and can map the original features to a high-dimensional space to improve classification performance. And the performance of a neural network model is highly dependent on the model size. We choose three different neural network model structures of small, medium, and large size for the 9 and 16 classification problems, respectively, and perform the same 10-fold cross-validation on the dataset. The activation function is ReLu, the initial learning rate is 1e-2, the batch size is 50, 3500 epochs are trained, Adam is used as the optimizer, the learning rate decay strategy is used with a decay rate of 0.1 and a decay step of 1000, the models' parameters and training results are listed in Table 1.

Table 1: Model parameters and training results

Classes	Loss function	Model structure		Total params	Mean Accuracy
9	CE	S	4×20×9 ReLu	289	85.73%
		M	4×20×40×9 ReLu	1309	87.14%
		L	4×20×40×40×9 ReLu	2949	87.31%
	MSE	S	4×40×2 ReLu	282	83.62%
		M	4×20×40×2 ReLu	1022	86.76%
		L	4×20×40×40×2 ReLu	2662	88.74%
16	CE	S	4×20×16 ReLu	436	74.35%
		M	4×20×40×16 ReLu	1596	76.63%
		L	4×20×40×40×16 ReLu	3236	76.81%
	MSE	S	4×40×2 ReLu	282	70.34%
		M	4×20×40×2 ReLu	1022	74.29%
		L	4×20×40×40×2 ReLu	2622	76.13%

As shown in Table 1, the accuracy of the 9 classification is generally greater than the accuracy of the 16 classification. The average accuracy of the models for the 9 classification problem is 87.31% when the CE loss function is used and 88.74% when the MSE loss function is used; for the 16 classification problem, the average accuracy of the models is 76.81% when the CE loss function is used and 76.13% when the MSE loss function is used.

Results Comparation

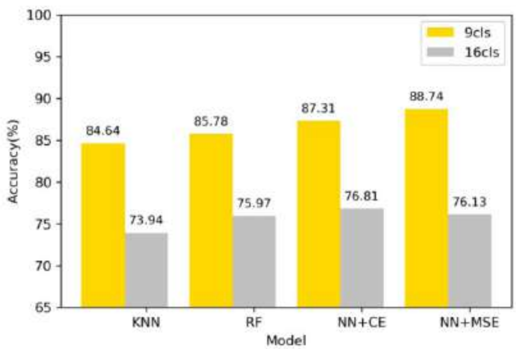

Figure 7: Mean prediction accuracy

First, we compared the prediction accuracy of models trained using three distinct algorithms. As illustrated in Figure 7, the NN model has the highest prediction accuracy, while the KNN model has the lowest. The NN model with MSE achieves the highest prediction accuracy of 88.74% for the 9 classification problem, and the NN model with CE achieves the highest prediction accuracy of 76.81% for the 16 classification problem. By mapping the features to a high-dimensional space learned from the data, the NN model can extract more useful features for completing the classification task and thus has a higher prediction accuracy.

Additionally, as illustrated in Figure 5, judging the model's classification performance solely on the basis of prediction accuracy does not adequately reflect the weights of the error categories, so we weighted the best model's prediction results to calculate the average error, as shown in Table 2.

Table 2: Mean distance error (cm)

Model / Class	KNN	RF	NN+CE	NN+MSE
9	9.70	9.01	7.97	7.98
16	8.70	8.43	7.61	7.72

The RF model's predicted mean distance error is less than the KNN model's, while the NN model's predicted mean distance error is significantly less than both the KNN and RF models', and the CE and MSE loss functions have no significant effect on the prediction error when using the NN model.

In conclusion, the NN model outperforms all other models in terms of prediction accuracy and average prediction distance error.

Discussion

We propose a method for caged poultry localization based on UHF-RFID devices and machine learning algorithms in this study that avoids the complex mathematical modeling required for RSSI signal strength-based localization models and instead finds the relationship between high-dimensional data and the position. By training the RSSI data with machine learning models, we can obtain accurate position prediction results with a robust prediction model which can locate targets to a range of 40 cm × 40 cm with an accuracy of 88.74% or 30 cm × 30 cm with a precision of 76.81%, with an average error of 7.61 cm and 7.97 cm, respectively, which is useful for studying poultry domain behavior.

Additionally, we conducted exploratory research on this method. We trained Gaussian Mixed Model(GMM) on the original dataset, then generated several times as much training data as the original dataset and used it in the classification model's training process. The results indicate that for the nine classification problems using CE's NN model, further training on the generated dataset improves the average prediction accuracy by at least 3 percentage points and the model converges more consistently. This enables us to obtain more accurate prediction results with less experimental data.

However, there are still many issues to be explored in the later work. For instance, we can apply this method to other caged animals or different size cages and RFID devices, and in similar experimental environments, we can install the devices in the same way to collect a small amount of data and then use the existing model for transfer learning. For various experimental environments, we can experiment with varying the number of antennas and their configurations in order to find a configuration that achieves the highest positioning accuracy at the lowest cost of experimental equipment. We can also collect additional data from the actual production environment to create a larger data set, which will improve the model's fit ability. Additionally, some effective post-processing techniques can be used to filter the prediction data in order to reduce prediction error.

In conclusion, there is still much work to be done, and future efforts will be directed toward developing more improvement methods for reducing prediction error.

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Towards an automated camera-based monitoring system for poultry red mite outbreaks

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Abstract

The poultry red mite (PRM), *Dermanyssus gallinae*, is an important ectoparasite that severely affects hen health, welfare and productivity. This mite represents a major threat to the egg production industry as more than ninety percent of the European farms are infested, causing economic losses of over 130 million euros annually. Monitoring and management of PRM is very difficult in practice, as the PRM tends to hide in cracks and crevices in poultry houses, remaining largely unspotted. A key characteristic of PRM behaviour is that they become active during dark periods to feed on the hens' blood. This causes hens to become irritated and display restless behaviours during dark hours. The aim of this study is to identify these behaviours and then capture the related change in behaviour through computer vision algorithms. To this end, a Gaussian Mixture Modelling approach for monitoring hen activity has been developed. A two-dimensional heatmap was created and, in turn, used to extract a feature reflecting the restlessness. The current paper will present the key features of this model and progress currently being made towards the development of a validated monitoring tool.

Keywords: poultry red mite, animal welfare, animal restlessness, Gaussian Mixture Modelling, early-warning system

Introduction

The poultry red mite (PRM), *Dermanyssus gallinae* (De Geer, 1778), is one of the most prevalent and harmful haematophagous ectoparasites (Axtell & Arends, 1990) in the laying hen industry worldwide (Sparagano, 2020). Next to an estimated annual 130 million euros of economic costs in the EU associated to control and production losses, PRM also poses a serious threat to animal health and welfare (Sparagano *et al.*, 2014; Sparagano, 2020). *D. gallinae* hides in cracks and crevices near the hen's nightly resting place and leave their shelter every 2 – 4 days during dark hours to take a 30 – 90 minute blood meal (Maurer *et al.*, 1988; Decru *et al.*, 2020; Pritchard *et al.*, 2015). PRM can survive up to 8 months in the absence of poultry, and thus can infest newly arriving flocks in laying units. In favorable environmental conditions, the reproduction cycle can be completed within 7 days (Pritchard *et al.*, 2015; Chauve, 1998). As such, *D. gallinae* populations can grow to very high numbers in a very short time period when no suitable control measures are taken (Sleeckx *et al.*, 2019; Sparagano *et al.*, 2014). Significant advances in PRM control are most likely to come through integrated pest management (IPM) strategies. Effective IPM programs (Barzman *et al.*, 2015) ideally go hand in hand with accurate monitoring of the growth and decline of the pest population. Being able to monitor and treat the PRM infestations at an early stage can prevent an increase of mite population and significantly reduce the negative effects imposed by the PRM (Mul *et al.*, 2009). Decru *et al.* (2020) reports that more than twenty different types of traps for monitoring mites are available, such as the quantitative corrugated cardboard trap (Nordenfors *et al.*, 1999), the qualitative tube trap with a wooden stick (Rick Stick) or cardboard (AviVet) (Van Emous & Ten Napel, 2007; Lammers *et al.*, 2017) and the qualitative Mite Monitoring Score (MMS) method (Cox *et al.*, 2009). The MMS and Rick Stick methods consist of a subjective, visual assessment of PRM presence at a specific location and are scored between 0 – 5 and 0 – 4, respectively. Most of the existing traditional mite monitoring methods however are very labor intensive, time consuming and are only indicative for the population growth of the PRM. Depending on the number of traps and their location, these monitoring methods are prone to underestimate the infestation levels (Mul *et al.*, 2015).

To overcome the monitoring limitations mentioned above, this study focused on the use of 2D infrared cameras to monitor the night time activity of birds affected by the PRM populations. Therefore, the main objective of this study was to develop a camera-based early-warning system for PRM outbreaks by quantifying nightly restlessness of group-housed hens. To our knowledge, no automated monitoring tool exists that can alert farmers or animal caretakers about increasing PRM populations at an early stage. Therefore, we developed a Gaussian Mixture Modelling (GMM) (Zivkovic & Van der Heijden, 2006) approach to monitor night time hen activity as this allows for a high level of interpretability of the model and produced outputs. We deemed the latter to be of importance in order to incentivize farmers to use sensor technologies on-farm.

Materials and methods

Camera monitoring during IPM trial

A semi-commercial aviary compartment consisting of two separate pens and housing 960 Dekalb White hens per pen, was selected for the implementation of an IPM trial during the whole laying cycle. Hens were 17 weeks of age at arrival on 23rd of June 2020. The hens were naturally infested with PRM in 2020 and 2021. Regarding the IPM strategy, it was decided to use plant-based means, silica-based acaricides or both in order to prevent and control mite population growth during the laying cycle. Whenever the growth exceeded a predefined threshold reflecting a high infestation level, a silica-spray treatment over the full compartment was carried out. The room temperature and relative humidity was kept between 20.0 – 21.2 degrees Celsius and 55 – 68 %, respectively. The dark period was set between 18h00 and 03h00.

A general overview of the monitoring strategy, consisting of six steps, is provided in Figure 1. In a first step, the mite population growth in the two pens is monitored throughout the laying cycle using ten predefined monitoring locations. As such, a corrugated cardboard trap (Nordenfors *et al.*, 1999), a MMS assessment (Cox *et al.*, 2009) and a Rick Stick (Van Emous & Ten Napel, 2007) were used as a reference method to monitor the mite population growth at each of the ten monitoring locations. Cardboard traps were collected, analyzed, emptied and reinstalled every 2 weeks. The analysis of the traps consisted of freezing the cardboard in order to kill the mites, followed by counting the number of PRM under a microscope. MMS and Rick Stick scorings were performed weekly by trained observers. In a second step, and simultaneously with step one, night time recordings of the birds using 2D infrared cameras are continuously collected. In a third and fourth step, video data is stored for future analysis. The last two steps are explained in more detail in sections below.

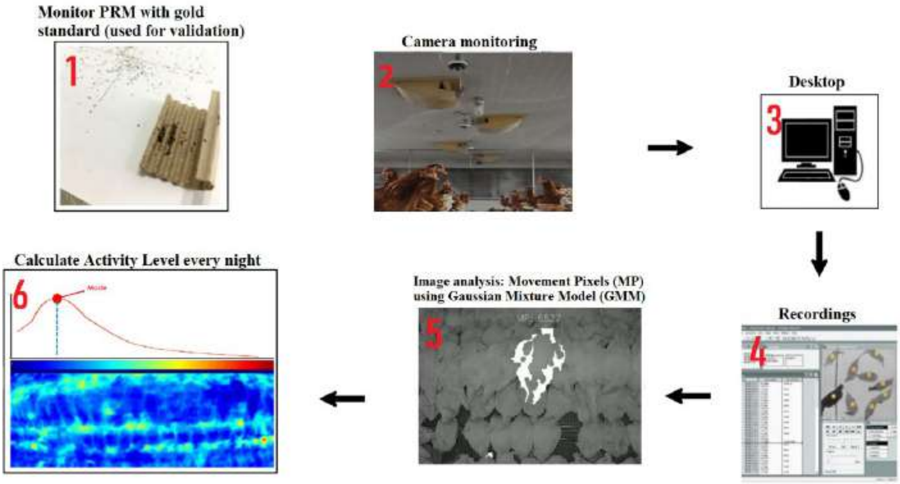

Figure 1: General overview of monitoring strategy

Data collection and video data

Hens were monitored during the dark hours between 20h00, 2 hours after dusk, and 01h00, 2 hours before dawn, using two top view 2D infrared cameras (Dahua DH-SD1A203T-GN) installed 2.1 m above the aviary system in one of the pens (Figure 2). Video data was recorded at five frames per second with a width and height of 960 and 480 pixels respectively.

The third week of December 2020, approximately 6 months after the hens' arrival, is hereinafter referred to as monitoring week 0. The total number of monitoring weeks was 25 for this particular data set. The first analyses were performed on video data recorded between week 10 and week 23. The camera system was set up to record continuously, although for specific dates it was decided not to record due to data management decisions. In addition, recording failures or blockage of the camera view have also led to occasional loss of video data. In week 5 and 6 of monitoring, a silica-based acaricide was used to extensively treat the aviary (both pens) for PRM. In week 11 of monitoring, a localized silica treatment was carried out in the aviary in order to kill remaining aggregates of mites.

Quantifying restlessness with developed Heatmap algorithm

Commonly, laying hens use a decreasing light intensity as a cue for night roosting. A short dusk period before the continuous dark period allows them to settle at a sleeping spot for the night without injuries. Since hens have poor night vision in environments with a low light intensity (Kristensen, 2008), they generally will not displace themselves during dark hours and therefore they will spend the night at a fixed location. As such, any performed behaviours of a particular hen will be expressed in the vicinity of this fixed sleeping spot. We define increased nightly restlessness as an increase in frequency of hens making a transition from an inactive state (sleeping, dozing) towards an active state (any behavior). In turn, from a camera point of view, when a particular hen shows an increase in frequency of transitions from inactive to active during the night, the same pixels will be activated repeatedly. The Heatmap algorithm is therefore developed to quantify the frequency of pixel activations during dark hours.

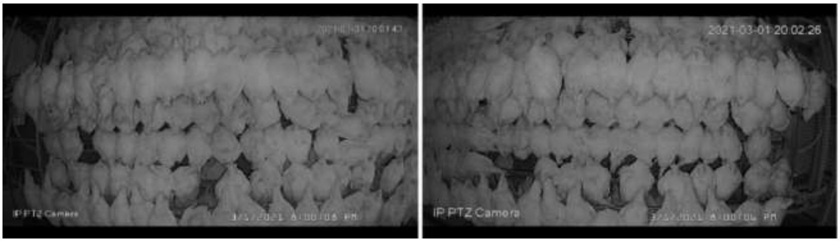

Figure 2: Video data for two top view cameras

In a first step, a GMM-based algorithm for background subtraction was applied to the video data to detect Movement Pixels (MP) in every subsequent frame (Zivkovic & Van der Heijden, 2006), thereby outputting a corresponding binary GMM-frame. A MP is defined as a pixel that showed a statistically significant change in intensity value over a predefined time period. In a second step, all binary GMM-frames within a specified time interval are summed to create a final heatmap (Figure 3). From the heatmap, a color histogram is calculated and features resembling activity are extracted from the distribution. Using these features, the Heatmap algorithm outputs an Activity Score between 0 and 100 and an associated 5-point Activity Level every night of monitoring (Activity Score between 0 and 20 = 'very low' Activity Level; 21 – 40 = 'low'; 41 – 60 = 'medium'; 61 – 80 = 'high'; 81 – 100 = 'very high'). Figure 4 shows an example of a color histogram and the calculated Activity Score and Activity Level.

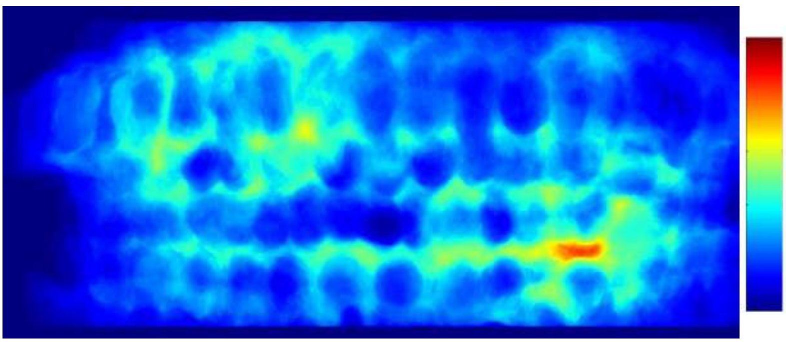

Figure 3: Heatmap for one night of monitoring (20h00 – 01h00)

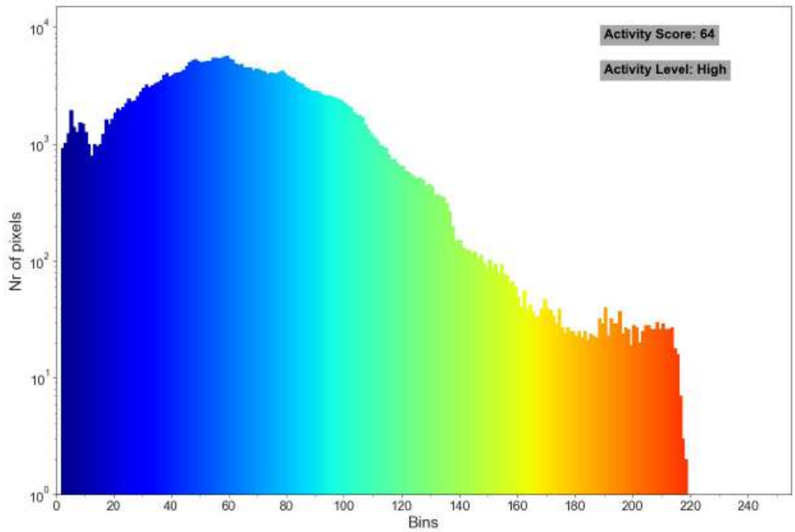

Figure 4: Color histogram of heatmap in Figure 3. Every night of monitoring a corresponding Activity Score and Activity Level (top right corner) is calculated using features extracted from the distribution

Results and discussion

Figure 5a reports mean Activity Scores across the two cameras, while Figure 5b displays the associated 5-point Activity Levels that were derived from the Activity Scores.

Figure 5a shows the nightly – and 7-nightly mean Activity Score on the primary y-axis and the mean cardboard mite count over the two pens on the secondary y-axis. The 7-nightly values represent a mean across the last 7 days where videos were available or analyzed (gaps in video data not taken into account to calculate a 7-nightly mean). The vertical lines pinpoint the events of silica treatment. In order to calculate the correlation between the 7-nightly mean Activity Score and the mite counts, we used all data points of the 7-nightly mean Activity Score (eight in total) and the data points of the mite counts for week 10 until week 24 (eight in total). A Spearman's Rank correlation coefficient of 0.76 was found.

Figure 5b shows the 7-nightly Activity Level on the primary y-axis and the mean cardboard mite count over the two pens on the secondary y-axis. The vertical lines pinpoint the events of silica treatment. The correlation between the 7-nightly Activity Level and mite counts was calculated giving a Spearman's Rank correlation coefficient of 0.92.

Figure 5a and 5b show the post-treatment onset of increasing mite population growth at week 16. Between week 18 and 20, the mean cardboard count increased fivefold. A critical period in mite proliferation is therefore found to be between week 16 and 18. From Figure 5b one can see a steady Activity Level of 2 ('low') when the mean cardboard mite count is at its lowest levels. A transition to 3 ('medium') between week 16 and 17 shows the potential of the developed algorithm to detect the increase in mite proliferation at a critical point and at an early stage (compared to cardboard monitoring). At the peak of the mean cardboard mite count, the Activity Level has shifted to 4 ('high').

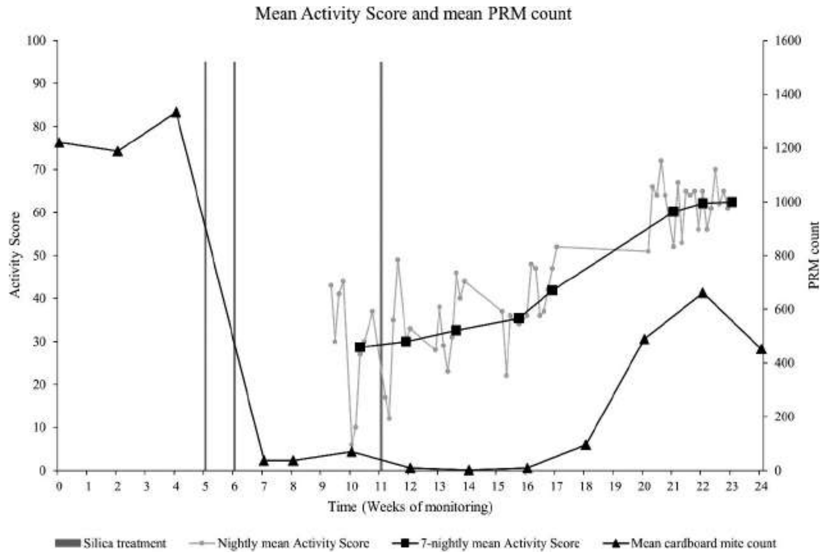

Figure 5a: Mean Activity Score and mean PRM count

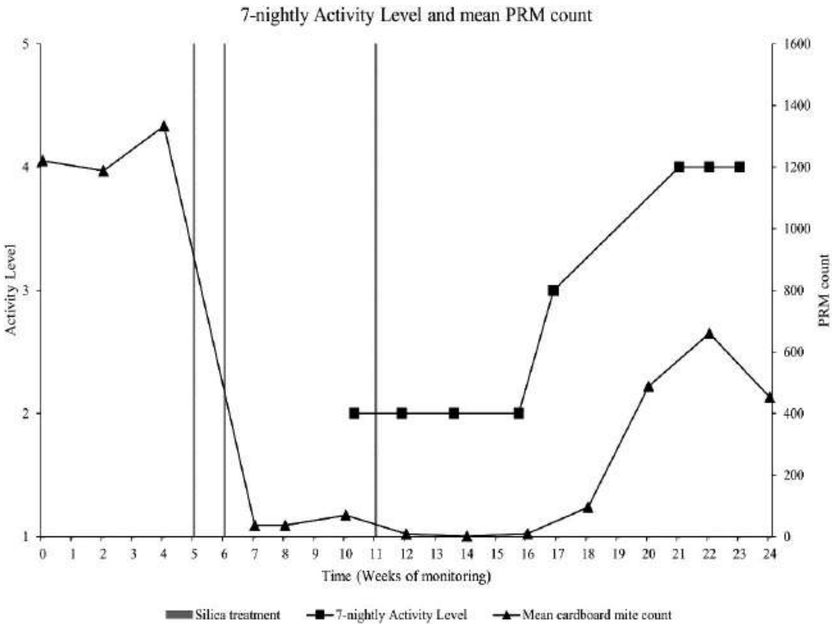

Figure 5b: 7-nightly Activity Level and mean PRM count

Conclusions

Restlessness of group-housed hens can be quantified and monitored over time using the developed algorithm. A strong correlation between the 7-nightly mean Activity Score or – Activity Level and the mean cardboard mite count suggest that quantifying restlessness can be used for the detection of PRM outbreaks. Moreover, the developed algorithm shows potential to monitor the increase in mite proliferation continuously and detect the outbreak at an early stage in an automated manner without the need for manual monitoring efforts. Future work includes enhancing the robustness of the algorithm by normalizing to the total number of hens in the FOV, by improving preprocessing steps and by optimizing hardware (e.g. camera positioning, camera count per area). In addition, future analyses performed at different farms will aid in the process of generalizing the algorithm.

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Obtaining broiler chickens' weight through depth image

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Abstract

Chicken is one of the most consumed proteins in the world. In order to efficiently supply this demand, the rearing system has been intensified and a modern broiler facility holds approximately 20,000 birds with a single caretaker walks the building to assess birds daily. Remote monitoring tools, such as depth cameras, can provide continuous monitoring to improve animal caretaking and provide accurate information for body development of the broilers. This research aims to automatically obtain the bodyweight of broilers through approximating the body dimensions using depth image. The Azure® Kinect depth sensor was used for image collection at top view position above the weighing scale and 10 images were collected from individual broiler. Data analysis and subsequent prediction of body dimensions were performed using an algorithm developed by MATLAB® (R2018a) to estimate the broiler's body weight. The dimensions (minimum and maximum height of standing and sitting birds, head to tail length and width between wings), body volume, and area and animal position were correlated with the measured weight using a multilinear regression algorithm. Data was collected using 80 broilers (Cobb) from 8 days old to 34 days old. Preliminary results indicate that the broiler's body weight can be estimated from their body dimensions, volumes, and area using a multilinear regression model (R^2 = 0.96). The results indicate that this model can be used as a tool to effectively and practically estimate the body weight of the broiler during production phase.

Keywords: depth sensor, image processing, broiler chickens' weight

Introduction

In 1968, ASABE (American Society of Agricultural and Biological Engineers) published curves of body dimensions of production animals (dairy cattle, beef cattle, swine, and chicken), which were used by manufacturers of livestock and poultry equipment to ensure the equipment (feeders, scale, drinkers) are at a proper size or height for the animals or birds of a given age. However, with genetic and nutritional improvement, the standard size of production animals has changed in the last 50 years, making it necessary to update these growth curves.

It is important to emphasize the need to delimit the body dimensions of birds so that the drinking, feeder, and aviary facilities follow the correct dimensions of the animals so that there is no stress due to overcrowding of birds in the shed and discomfort when feeding or increase in fights for food, thus harming the animal welfare of these birds. Another factor that directly interferes with the measurement of bird size is the determination of mass gain. Several authors have used body dimensions of production animals to determine body mass (Condotta et al, 2018; Ajayi, Ejiofor and Ironkwe, 2007; Assan, 2013).

The use of depth image can be applied as a tool for measuring body size. Depth image is a two-dimensional map in which each pixel stores distance values from the sensor to the objects present in the scene (Hoshelham and Elberink, 2012). Condotta et al (2018), used the Kinect v.1 sensor to obtain the body mass of finishing pigs by obtaining the animal's body dimensions. For chickens, the use of depth technology for weight prediction is still scarce, in which few studies have been developed (Lin et al., 2017; Mortensen, Lisouski and Ahrendt, 2016), with this tool being more applied in other animals such as cattle. and pigs (Yu, Lee and Morota, 2021; Alvarez et al., 2018; Condotta et al., 2018; Hansen et al., 2018; Pezzuolo et al., 2018; Martins et al., 2020).

Mortensen, Lisouski and Ahrendt (2016) used the Kinect v.2 sensor to predict the body mass of broilers, through depth image, whose error was 7.8%. Lin et al (2017) used depth image in a neural network model to estimate chicken weight, the authors obtained a root mean square error (RMSE) equal to 0.048 kg and a relative mean error equal to 3.3%.

As depth-sensing technology improves, there is a need to reassess the cameras for livestock management. Thus, the present study aimed to estimate the weight of broilers through body dimensions obtained from depth images, in a non-invasive and stressful way, using the Azure® Kinect sensor.

Material and methods

Experimental data

Images of 80 birds of Cobb broilers were collected weekly from 8 to 34 days of age. The animals were allocated to the Climatic Chamber of the Department of Biosystem Engineering – NUPEA of the "Luiz de Queiroz" College of Agriculture, University of Sao Paulo, located in Piracicaba/SP. The animals had free access to feed and water as performed on a commercial farm.

Data collection and processing

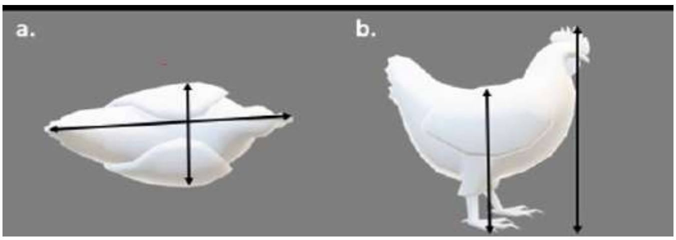

Figure 1: Scheme of the corporeal dimensions that were be collected in this study. Length of bird from head to tail and width of breast and minimum and maximum height of bird

Depth and digital color (RGB) images were collected of the animals using a Microsoft Azure® Kinect sensor, in the top-view position of the birds, at a height of 80 centimetres. Each bird obtained the dimensions recorded while standing and sitting since it causes a change in the body dimension when the animal sits. The minimum and maximum height, chicken width, length, area, and volume were extracted. To estimate body mass, dimensions, volume, and body area were combined using a multilinear regression (correlating manually collected weight with body dimensions). The dimensions obtained from each animal are represented in Figure 1.

For the processing and analysis of the collected images, an algorithm in the mathematical software MATLAB® (R2018a) was developed, thus selecting the region of interest of the image (animal), for later acquisition of the dimensions of the birds. The following steps were followed:

1) Import of depth image, using the 'imread' function;
2) Conversion of the distances from the sensor to the animal into animal heights, by subtracting the distance from the sensor to the surface where the animal is (scale) and the distance between the sensor and the animal. Making pixels outside this limit are equal to zero, using a logical 'if/else' test;
3) In order to eliminate possible noise around the animal, the nearby pixels were turned to zero. Then, a binary mask was applied over the original image in order to select the region of interest (animal).;
4) Dimensions (minimum and maximum height of birds standing and sitting, length from head to tail and width between wings), body volume and area were extracted in an Excel spreadsheet to correlate these data with manually measured weight using multilinear regression $y = a + b_1x_1 + b_2x_2 + b_nx_n$.

The minimum and maximum heights of birds standing and sitting, length from head to tail, and width between wings (in px) were adjusted using eq. 1; to obtain the dimensions in cm.

$$L_{cm} = L_{px} \times 1.9825 \times 10^{-1} \times Z^{0.98} \tag{1}$$

Where:
L_{cm} = length, in centimeters;
L_{px} = length, in pixels;
Z = distance between sensor and object, in meters.
Furthermore, the dorsal area (in px) and projected body volume (in px.cm) were adjusted, using eq. 2 and eq. 3 to obtain the values in cm^2 and cm^3, respectively.

$$S_{cm} = S_{px} \times 4.1590 \times 10^{-2} \times Z^{0.972} \tag{2}$$

Where:
S_{cm} = area, in square centimeters;
S_{px} = area, in pixels;
Z = distance between sensor and object, in meters.

$$V_{\mathrm{cm}^3} = V_{px\ cm} \times 4.1590 \times 10^{-2} \times Z^{0.972} \tag{3}$$

Where:
Vcm^3 = volume, in cubic centimeters;
Vpx cm = volume, in pixels centimeters;
Z = distance between sensor and object, in meters.

Results and Discussion

Broiler chickens' dimensions

The body dimensions obtained from the top-view of the animals are shown in the Figures below, separated into sitting and standing animals. Such measurements were correlated with the animals' body weight since these dimensions extracted from depth images of the animal's superior view can be used as a way of obtaining body weight, as previously performed with growing pigs (Condotta et al., 2018). Figure 2 shows the minimum and maximum heights of the birds (in cm) when they were setting and width between wings (cm) and length head to tail (cm).

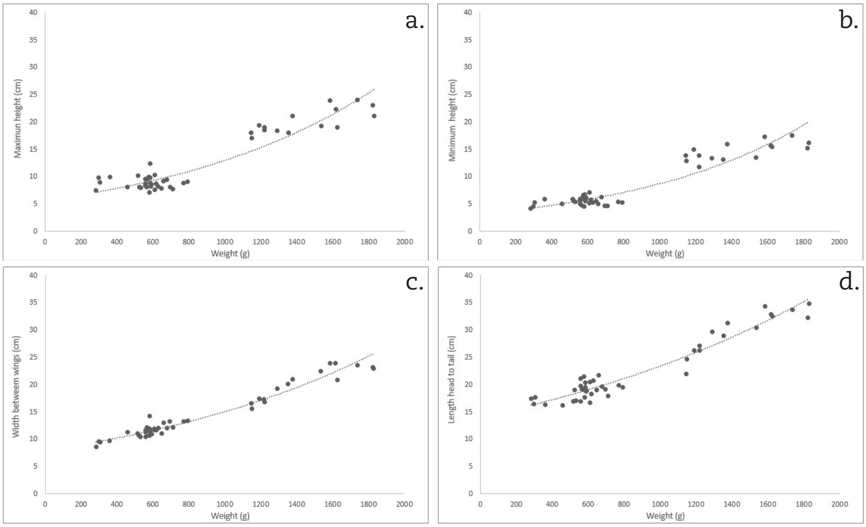

Figure 2: Broiler dimensions as captured using a Azure® Kinect camera from the age of 8 days to 34 days. a. Maximum height (cm), b. Minimum height (cm), c. width between wings (body width) in cm, and d. length from head to tail (cm)

The area (cm²) and body volume in setting position (cm³) are represented in Figure 3.

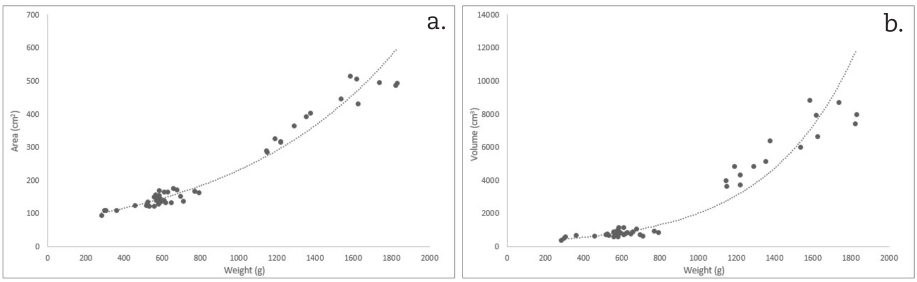

Figure 3: a. Body area (cm²), and b. body volume (cm³) as capture using a Azure® Kinect camera from the age of 8 days to 34 days

The minimum and maximum heights of birds in the standing posture and width between wings (cm) and length head to tail (cm) are shown in Figure 4.

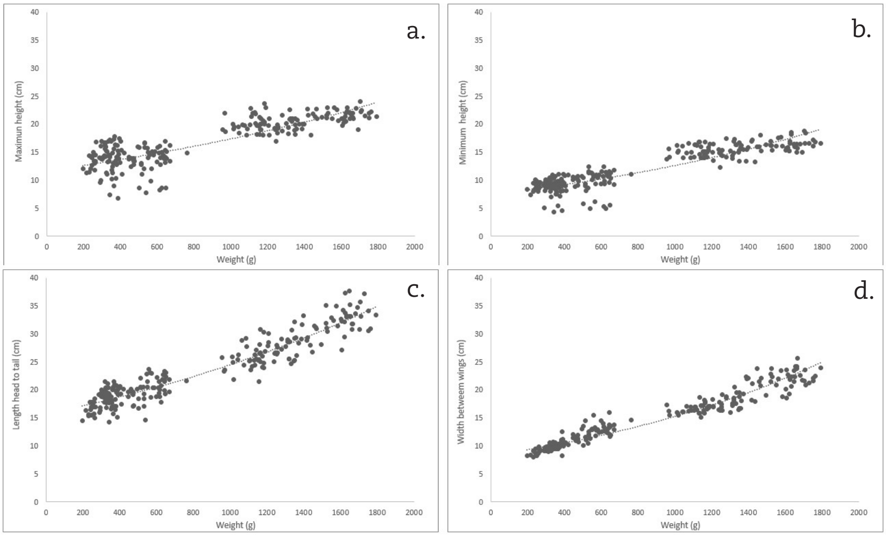

Figure 4: Broiler dimensions as captured using an Azure®_Kinect camera from the age of 8 days to 34 days. a. Maximum height (cm), b. Minimum height (cm), c. width between wings (body width) in cm, and d. length from head to tail (cm)

The area (cm²) and body volume (cm³), in standing position, are represented in Figure 5.

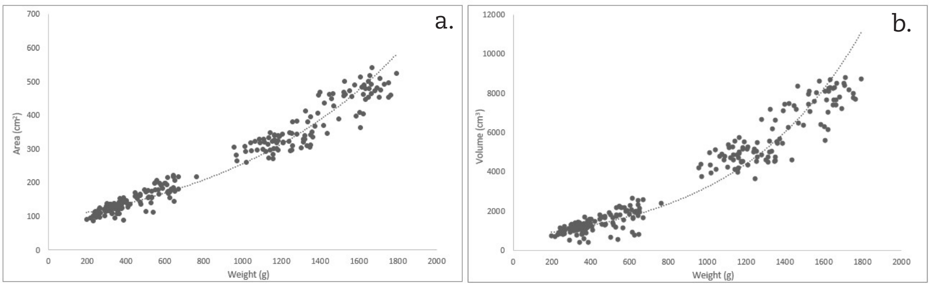

Figure 5: a. Body area (cm²), and b. body volume (cm³) as capture using a Azure®_Kinect camera from the age of 8 days to 34 days

Uses the protocol as described, the dimensions and volumes were automatically determined without the prior knowledge of the bird size, or without manually selected the birds in the image. Thus, making it possible to automate the acquisition of biometric data from chickens at in order to obtain parameters such as growth curve over time and body weight. Condotta et al. (2018), also demonstrated the ability to select animals automatically and predict weight, in this paper, the target species was grow-finish swine.

Broiler chickens' weight

The multilinear regression presented an R^2 of 0.9629, which means that 96.29% of the variability in the weight of the animals is explained by the body dimensions obtained through the depth image collected with the Azure® Kinect sensor (Figure 6). This is an adequate R^2 value, although lower than that observed by Amraei, Mehdizadeh and Salari (2017) (R^2 of 0.98) and Mollah et al. (2010) with R^2 of 0.99.

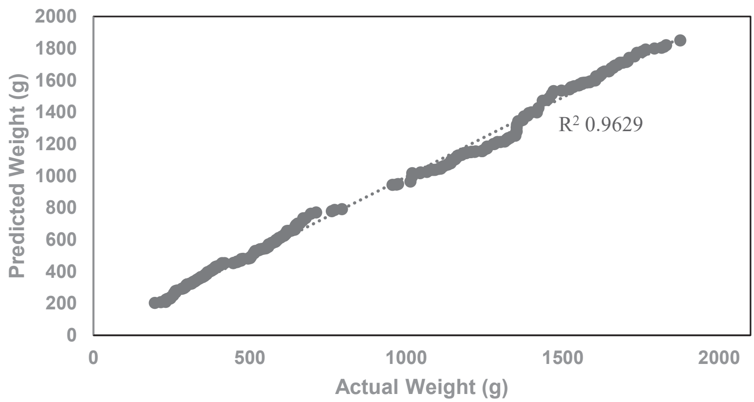

Figure 6: The relationship between actual broiler weight and the predicted broiler weight as obtained using images captured with the Kinect Azure depth camera and an algorithm developed in MATLAB

The model of predicted weight using body dimensions (minimum and maximum height of birds, length from head to tail and width between wings, body volume, area, and sitting or standing position) had a mean error of 3.78% or 35.81grams, a result similar to that found by Amraei et al (2017), whose smallest errors were around 50 grams, and smaller than the percentage error obtained by Mortensen, Lisouski and Ahrendt (7.8%). When looking at the average errors for weight ranges of 200 grams, animals between 700g and 900g had the highest average error (6.30% or 48.43 grams), while birds between 1700g and 1900g had the lowest average error (1.21% or 22.69 grams) (Figure 7).

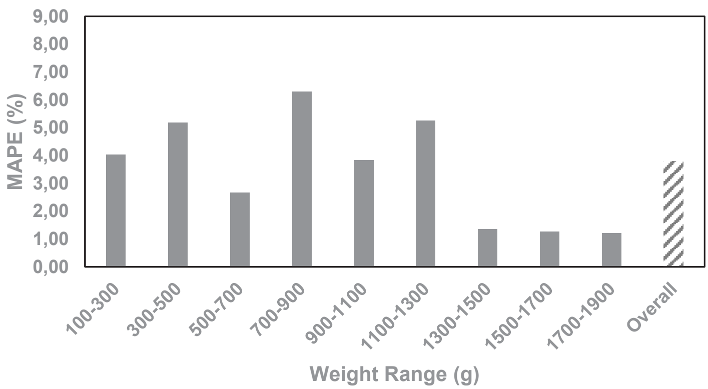

Figure 7: Mean Absolute Percentage Error (MAPE %) in predicted broiler body weight in the 200g ranges

According to the results obtained, it can be concluded that the method developed for weighing broilers using depth image processing showed satisfactory results. The R^2 obtained was lower than that found by other authors. However, the average error obtained was close to the average errors found by other authors.

Conclusions

It was possible to obtain the body dimensions of broilers through depth images. The Azure Kinect® sensor has the potential to automatically obtain the body dimensions of broilers, making it possible to apply it in the development of an image weighing system. In addition, It was possible to obtain the weight of broilers from the body dimensions acquired through depth images. There is a limitation about the maximum camera height because the animals are small, at higher heights the sensor resolution will make it difficult to accurately detect the birds, restricting the installation of the camera above the bedding floor, one way to try to get around this problem would be to install cameras near the feeder regions, regions where the animals are more concentrated throughout the day. A second alternative would be the development of a mechanism that moves the camera along the aviary, at the maximum height that can detect the birds, to obtain the weight during the day, being possible to adjust the height of the cameras according to the growth of the animals. The proposed method showed the possibility of being automated, especially when there is an increase in R^2 and a reduction in the average error of the proposed model by adopting other techniques such as machine learning. With this method, it will be possible for the producer to monitor and access the weight data of a large number of animals from a distance in order to promote a more significant control of the herd and weight gain. In addition to promoting animal welfare, as it is non-invasive and stressful for birds.

Acknowledgments

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SESSION 4

Education

A survey among students about perception of sensor technologies on dairy farms

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Abstract

Digital technologies from milking and feeding robots to animal-attached accelerometers and others are increasingly used on dairy farms worldwide. A wide range of data and information about the health, behaviour and performance of cows is captured and processed by using algorithms and artificial intelligence. By gathering this additional information, an improved management of individual cows and herds should be achieved.

In this study, we used an online survey to obtain information about the perceptions and the acceptance of students of veterinary and agricultural (livestock) sciences about the use of sensor technologies on dairy farms. Students from universities of agricultural sciences (n=8) and veterinary medicine (n=6) took part in the survey.

The survey included i) demographic data, ii) questions about the participants' perception of today's dairy farming, iii) participants' opinion about sensor technologies in everyday life and in dairy farming, iv) associations based on the effects of images v) visions and expectations of dairy farming in the future. Finally, the participants were asked whether they felt well prepared for the digital transformation in dairy farming by their universities.

Keywords: survey, students, digital technologies, dairy farming

Introduction

Technology and digitalisation determine our professional and private everyday life. Digital technologies are also increasingly being used in dairy farming. Sensors and other technologies can capture a wide range of information on animal health, behaviour and performance and can help to improve the management of dairy cows, for example. Therefore, these technologies can contribute to an improved animal health and welfare and change the way farmers work.

Digital technologies in dairy farming are increasingly coming into the focus of a broader public, often in context of animal welfare, climate change, environmental and consumer concerns about food production, as described in a survey on social acceptance of digital livestock farming technologies conducted by Pfeiffer *et al.* (2019). The here presented survey is intended to gain insights into the next generation of farmers and veterinarians and their opinion and acceptance towards sensor technologies in dairy farming. This manuscript presents some of the results of this survey.

Material and methods

Study design

The questionnaire was created using SurveyMonkey (American polling company, San Mateo, USA). It consisted of 23 closed or open questions. The survey comprised six areas of interest, including i) demographic data, ii) questions about the participants' perception of today's dairy farming, iii) participants' opinion of sensor technologies in everyday life and in dairy farming, iv) associations based on the effects of images, v) visions and expectations of dairy farming in the future, vi) preparation for the digital transformation in dairy farming by their universities.

The results presented in this paper refer to areas i), ii), and iii). Area i) consisted of five questions and included gender, course of study, place of study, current semester, and the region of origin where the participants came from. All questions except the question of current semester (open question) were designed as multiple-choice questions.

In area ii) we asked about the students' relationship to today's dairy farming. The given answer options (multiple answers allowed) were 'dairy farming in the family and/or among friends', 'I come from the countryside', 'farm holiday or similar activities' and 'no reference'. Furthermore, the students were asked to give a self-assessment on their knowledge of today's dairy farming. Response options in this multiple-choice question were 'very good', 'good', 'moderate', 'bad' and 'no answer'.

Area iii) included three questions, a) the participants' view on some everyday technologies (smartwatch, fitness wristband, voice assistants and smart-home systems), b) the participants opinion about cows equipped with sensors (described as similar to fitness trackers) with five answer options (question type multiple choice), and c) four statements about sensor technology that were rated on a Likert scale.

The administration or the student body of all veterinary universities in Germany, Austria and Switzerland were contacted, as well as several agricultural science faculties in these three countries. They were asked to forward the link to the survey and a covering letter by email to their students. The survey was open for response for six weeks from November to December 2021. During this time, two reminders were sent in order to increase the number of participants in the survey.

Data pre-processing

The answered questionnaires were exported from the survey software in csv format into the software Excel (MS Excel 2016, Microsoft Cooperation, Redmond, USA). The answers were available in coded form for the closed questions. All questionnaires were checked for errors and plausibility, further answers were coded. Questionnaires that did not contain any answered questions were excluded. In order to be included in the evaluation, at least the questions from area i) had to be answered. For questionnaires returned from the same IP address, the first questionnaire from this IP address was included in the evaluation and other questionnaires were excluded. Although it is possible that more than one questionnaire was sent from a fixed station computer at the university by different students, it could not be ruled out that the same participant sent the questionnaire more than once.

Statistical analysis

Statistical analysis was carried out with SPSS (version 27, IBM Corporation, Armonk, NY). For the descriptive analysis shown in this manuscript, data were available in nominal and ordinal scales. Frequencies were calculated and cross-tables were created.

Results and Discussion

A total of 497 questionnaires were recorded on SurveyMonkey. After excluding 68 questionnaires according to the predefined criteria, 429 questionnaires were used for the analysis. Of these, 296 participants indicated that they were studying veterinary medicine (69 % of the participants) and 133 agricultural sciences (31 % of the participants). Most students of veterinary medicine came from the University of Giessen, Germany, and most students of agricultural sciences from the University of Applied Sciences Triesdorf, Germany.

Knowledge and relationship in today's dairy farming

The self-assessment on the students' knowledge about today's dairy farming revealed that almost half of the participants (42.9 %) rated their level of knowledge as "good", 16.4 % as "very good" and 35.8 % as moderate. This can be explained by the personnel experience of the students. Among students of agricultural sciences, 70.7 % had a relation to dairy farming through their families and/or friends, and among students of veterinary medicine it was a little more than one third (36.1 %, Figure 1).

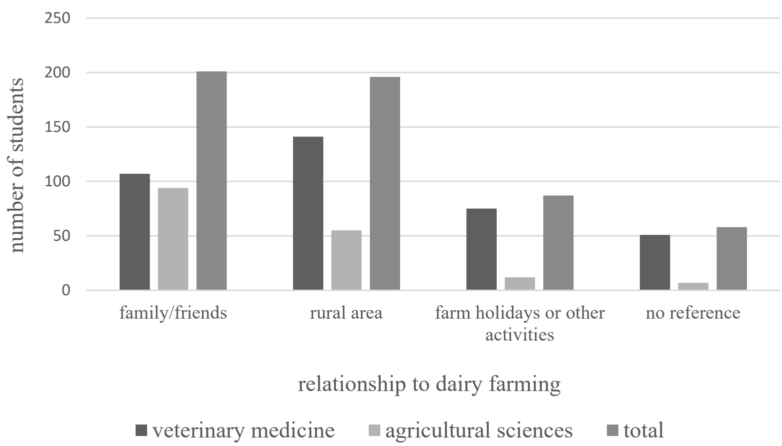

Figure 1: Relation of veterinary or agricultural students to dairy farming. Multiple answers were allowed. The absolute number of participants is shown by bar

Cows equipped with sensor technologies

Participants were asked about their opinion on cows equipped with sensors (described as similar to fitness trackers). The results are shown in table 1. Fitness trackers were only refused by a total of eleven participants. The benefit of fitness trackers in terms of animal health was well accepted by 192 participants (45 %). Another 222 participants

(51.7 %) liked fitness trackers and saw the benefit of fitness trackers for animals and people working on farms.

Table 1: Acceptance of sensors used on cows, described as similar to fitness trackers

Discipline	Answers on the use of 'Fitness tracker on cows' [n (%)]				
	'I like it'	'Acceptable'	'I do not like it'	'Not necessary'	Not specified
Veterinary medicine	130 (43.9)	157 (53.0)	0	5 (1.7)	4 (1.4)
Agricultural sciences	92 (69.2)	35 (26.1)	1 (0.8)	5 (3.8)	0
Total	222 (51.7)	192 (44.8)	1 (0.2)	10 (2.3)	4 (0.9)

Loss of the bond between farmer and cow

We asked students to comment the statement 'I can imagine that with the use of a lot of technology the bond between farmer and cow gets lost'. Almost half of the participants (47.5 %) agreed that the statement applies and about 10 % strongly agreed. One third answered that the statement applies less and only about 10 % answered that it does not apply at all. There was no significant difference between students of veterinary medicine and agricultural sciences.

According to the above-described relation of students to dairy farms, it can be assumed that the participants have already had contact with sensor technologies and were familiar with the potential of these technologies. According to a representative Bitcom study (Rohleder *et al.*, 2020), 82 % of farms in Germany were already using digital technologies or applications in 2020, and a further 10 % are planning or discussing to do so. Milking robots are already used by 21 % of dairy farms.

Although the age of the students was not the subject of the survey, it can be assumed that the majority of the students belong to the 'smartphone generation', who have grown up with digital technologies and these are an integral part of their everyday life.

There were only minor differences with regard to the distribution of responses to the two positive statements between veterinary medicine students and agricultural science students (table 1). In follow-up studies, it would be necessary to examine the extent to which those participants, who indicated a loss of relationships due to sensor technologies, assume that sensor technologies have an impact on farm design and structure. A possible correlation could be that sensor technologies are associated with a larger farm size and therefore a poorer farmer-to-animal ratio.

Conclusions

Improving animal health is important for students and should be the aim of developers and manufactures of new technologies.

Digital technologies should have a permanent place in veterinary and agricultural curricula to prepare students for the current changes in dairy farming and, beyond that, for their future careers. Overall, our survey showed that students of veterinary medicine and agricultural sciences have a positive attitude towards the use of sensor technologies in dairy farming.

Acknowledgements

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Teaching PLF through “Serious Escape Games” based on 3D-imaging, accelerometer approaches and R programming

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Abstract

The spread of precision livestock farming (PLF) services in the agricultural professional field requires more training. This training involves knowledge and skills on the use and the functioning of sensors and data analysis. This is crucial for future consultant or researcher in agriculture. However, some students may be reluctant to this learning. To improve the attractiveness of PLF teaching, we developed “Serious Escape Games” (SEG) that combine the teaching of knowledge and skills with the playful characteristics of an escape game. The developed SEG use the examples of 3D-imaging and accelerometers applications in dairy cows, and a few in sows. The games run under R software, which is free of use and largely taught in universities for data analysis and visualisation. With a total duration of 2 hours, the SEG sequences include 15 min of introduction, 60 min of playing to solve 10 enigmas about PLF and data analysis, and 45 min of debriefing. The students have to mobilize their prior knowledge in R, data analysis and animal science, as well as their collaborative soft-skill to “escape” the game on time. The SEG teaches new skills and knowledge that are specific to PLF: new R procedures, animal indicators, field applications of 3D-imaging and accelerometers, and the process to develop and validate sensors. They were developed in French, but the development of a framework for SEG in English or other languages is under consideration. This will allow a wide free distribution, as well as applications of this concept to other fields and graduation levels.

Keywords: PLF, serious game, R software

Introduction

The spread of precision livestock farming (PLF) services and tools in the agricultural professional field creates new tasks which also require new skills. The skills needed and the level of expertise will vary upon the position: the provider of PLF tools needs the highest level of digital skills, the consultants and salesmen need enough skills to understand the PLF tools and applications, and the farmers need enough skills to use them. In addition, the use of artificial intelligence in PLF tools is increasing more and more, and helps to rapidly transform the raw data signal from the sensors into information that is usefull and comprehensive for companies and farmers.

Students, as future actors of the livestock value chain, need to reach a minimal (basic) level in PLF. Further knowledge and/or development will have to be taken over when students are entering the professional life. As PLF tools and solutions are continuously changing, the "*at minima*" required digital skills are hard to define precisely. Data science is already part of most academic teaching programs in agriculture. Serão *et al.* (2021) indicated that students agreed that "traditional" statistics topics (basic concept of experimental design, classical linear model, analysis on traits with normal distribution) are already well taught but the methods that are increasingly used in big data and PLF (Machine learning, Generalized models for example) analyses are rarely discussed. Besides data science knowledge, students must be able to manage big and complex datasets. Basic coding and data management are therefore requested to work within the field of PLF. Different software and programming languages allow to manipulate complex data and to perform visualization or analysis, as R or SAS software. But Grosjean & Engels (2021) noted that R language and Rstudio software are perceived by biology students as badly or mildly usable tools. Those students claim that an intensive training is needed before using them. Negative emotions such as "fear" or "repulsion" are reported when first using these softwares (Grosjean & Engels, 2021), which resulted in a significant decrease of interest in the learning process.

To overcome this reluctance to data science, education must be progressive and must include more experiential training, like collective or individual data science projects. Gamification is another possibility that is largely used to engage learners in the learning of data sciences (Legaki *et al.*, 2020). Gamification is a popular leverage to engage learners in experiential learning applying game codes and mechanisms. Gamification is also spreading largely in the agricultural education. For example, the GAMAE (games for agriculture, alimentation & environment) platform identified 105 games in France, which aim to be used in training and education, therefore called serious game, in the agricultural sector (Dernat *et al.*, 2021).

The aim of this project was then to use the gamification leverage to teach PLF and R programming by codesigning serious games, based on the escape game concept, which relies on solving one or several enigmas within a limited time (1h). This paper presents the methodology of conception, the two Serious Escape Games (SEGs) created and the first feedback from users.

Material and methods

<u>Context behind the SEGs development.</u>

This study was conducted within a course of training for Master 2 students in animal science about precision livestock farming (PLF). The course addresses both animal science and science relative to new technologies and data science. Until 2020, this course gathered lecture course, farm and PLF company visits, hands-on session and debates. Two of the hands-on activities were performed for 5 years using Excel software to analyse accelerometer data and 3D imaging data. It was then proposed to update these hands-on activities and to involve more students by making them actor of the activity. Moreover, the objective was also to improve their skills on R software for data visualisation and analysis.

In the updated hands-on activities; the objective was to find a ludic way to teach R or data science. Serious games appeared as a possible solution, since the student learns while he is playing. As duration of each of the two hands-on activity was limited, we also chose the escape game option. Indeed, an escape game is a game which involves a team of players that has to escape from a room or a game, by solving a major enigma thanks to specific clues, tools, puzzles within a limited time. It was then possible to include it in an educational sequence of a maximum of 2 hours. The two SEGs developed in this study were originally developed as a "crash test" to test ways to update teaching precision livestock farming to Master 2 students. The success of this "crash-test" led to the current project, aiming at properly develop 2 escape games by including relevant partners and exchanging with an escape game designer on rules of design and conduct.

<u>A collective process to develop the methodology.</u>

The SEGs were developed from January 2020 to January 2021, and were first tested in real conditions with a group of students involved in animal science during spring 2021. Other complementary tests, with different groups of students in different graduate schools and universities, were performed from summer 2021 to winter 2021. This means that the validation phases started in November 2021 and are still under process.

In September 2020, a steering committee was established and gathered researchers, engineers, associate professors, and students. Their background was either in animal science or data science, or both. This group was based on persons who already knew each other and already collaborated in several projects. The first step consisted of defining precisely the target audience, the objectives and the educational sequences for each game. The key point is to gather both the future end-up user, i.e., students and teachers, as well as experts in animal science, PLF, data science and programming. To better define the two SEGs and be sure that we could call it "escape game", the group did an escape game together ("Le Manoir d'Ernestine", see https://escapeyourselfrennes.fr/escape-game-room/manoir-ernestine/ for information). The group then discussed afterwards with the designer to get the rules and specifications of an escape game as well as to have his feedback about making a serious escape game.

Both games were developed simultaneously, by two different groups: "Rscape the office" was developed by researchers and "Panic on the farm" was developed by Master 2-students as their M2-group project, with the supervision of the first group. Exchanges and testing of multiple options, whether or not they were retained in the end, were then possible between the two groups.

<u>Development of the games.</u>

— The application hosting the game

The numeric SEGs were developed with the R software, using its ecosystem of packages, to demonstrate to students that "R is more than only a statistical tool". We specifically developed the games' interfaces as R tutorials using the {learnr} package (Schloerke *et al.*, 2020). The syntax of {learnr} is based on {Rmarkdown}, a package largely used by R users, and easily learnable by anyone that might reuse the code for developing another serious game. As a Rmarkdown report, a learnr tutorial allows to combine texts, images, videos, and R outputs paired with their computing codes but also frameworks to easily add various types of questions, code exercises and independent interactive shiny components (buttons, chronometers etc.). For the player, once the game repository was downloaded, and R, Rstudio (an R IDE) and some selected packages installed, the learnr package allows to leave R studio in one click to a user-friendly HTML interface loaded in a web browser.

— Technical content

The SEG A "Panic on the farm" is based on the use of accelerometers to monitor cow's health and behavior. The learners investigate the functioning of the accelerometer in a simple use case: the use of the Lifecorder +® (Suzuken Co. Ltd., Nagoya, Japan) to monitor grazing time as described by Delagarde & Lamberton (2015). It is a one-dimension accelerometer which provides a pre-processed activity signal. Learners have to define a threshold to discriminate the grazing activity from the other activities, and check the consequences on the predictive performance of the algorithm. To do this, they have access to accelerometer data and grazing time kinetics, recorded by visual observation on dairy cows in the INRAE experimental farm of Mejusseaume (Delagarde & Lamberton, 2015). Some kinetics have been modified for educational purposes.

The SEG B "Rscape the office" aims to make the player to be able to validate a 3D imaging device, as an accurate technology for estimating the body weight of dairy cows. This is based on the device "Morpho 3D" described by Le Cozler *et al.* (2019) and its interest for the estimation and monitoring of body weight. Two datasets are needed for the game to allow learners to experience a complete validation approach. One dataset gathers morphological indicators of 28 Holstein cows measured on 3D images from the Morpho 3D device. Because no perfect dataset was available to show examples of all indicators targeted in the pedagogical objectives, the original dataset was enriched by data created by experts for the pedagogical purpose only. During the game, students have to study the repeatability and reproducibility of the collection of the morphological indicators from 3D images, as well as to estimate body weight based on 3D indicators. A second dataset (created for this purpose) gathered repeated measures of 3 operators on 2 morphological indicators. The Morpho3D device also provided 3D images used as illustrations in the game.

— Media content

Different media were used to build an escape game atmosphere. Teasers videos were realized for both SEGs. Royalty free music from www.bensound.com was used. In the SEG A, videos and photos were collected on a farm, puzzles were built, soundtracks were recorded. In the SEG B, computer screenshots and 3D images were used.

<u>Games validation</u>

A preliminary game validation phase was implemented to: i) evaluate the ease of the game installation, ii) assess the time needed for the completion of the game and the whole educational sequence, iii) identify technical issues iv) check the matching between the difficulty of the SEGs and the level of the learners. This preliminary evaluation was performed in 2 steps. In November 2020, a first evaluation of the SEG B was performed through videoconferences in an agricultural engineering school, UniLaSalle Beauvais, with M2 students. In January 2021, both SEGs were tested in-person with M2 students from another agricultural engineering school, L'Institut Agro Rennes-Angers. During these tests, the game developers investigated learners' behaviours and recorded all technical issues (installation, application bug…). Learners' feedbacks and satisfaction were collected at the end of the educational sequences, both orally and through a survey. Subsequent tests were performed in other schools and universities in the second semester of 2021 and 2022, with updated versions of the two SEGs.

Results and Discussion

A framework of educational sequence

The expert college defined a common framework for the SEGs' educational sequence: a presentation phase (15 min), a performance phase (e.g., the SEG itself, 60 min), a break (10 min) and a knowledge "anchoring phase" to ensure that the key messages were clearly identified by the students. Educational materials support the presentation and anchoring phases for both trainers and learners. Guidelines for the installation of the games and its requirements are also provided. During the game phases, each learner is in front of its computer and a game master is driving the game.

The educational sequence seems appropriate for being implemented in most of the animal science courses in France. At this point, the SEGs were always moderated by the game's developers. More guidelines are needed for other teachers to adopt the SEGs and moderate them as efficient game masters.

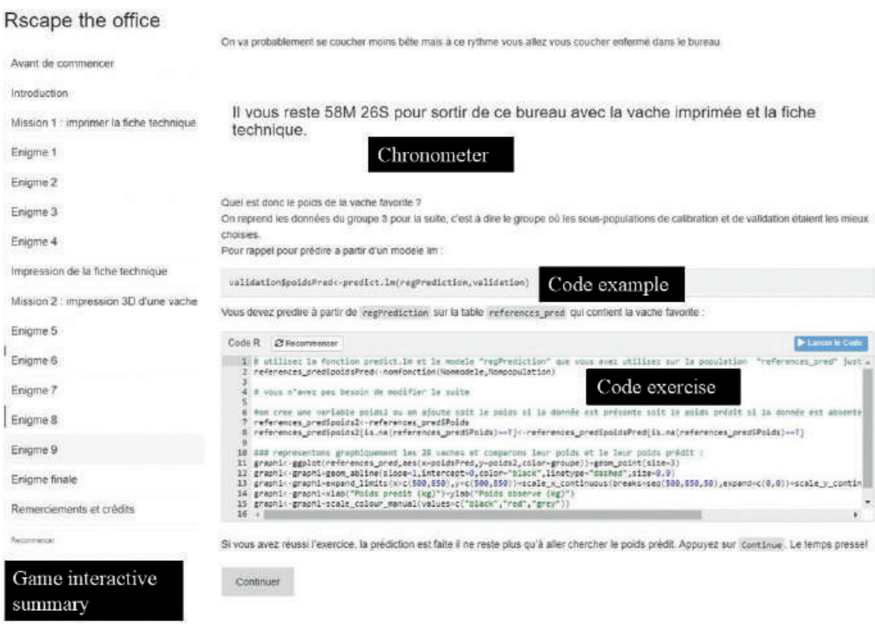

Figure 1: Screenshot of the game interface of the SEG B "Rscape the office" and examples of code exercise component, code example, interactive widgets (summary, chronometer)

A framework of numeric interface

The game interface is a {learnr} tutorial that can be personalized with .css code (figure 1). Learners are progressing in the game from one enigma to another. Different media and/or data visualizations support the students to solve the enigma. Questions and code exercises are included to check the solving of the enigma and the understanding of the notions (figure 1). Whenever they want, learners can step back easily with the interactive summary (on the left in the figure 1). Learners can also reopen and replay the game whenever they want.

Two SEGs with their own objectives and targets

— The SEG A “Panic on the farm” is intended for Licence 3 (bachelor) level students, with no special knowledge in R programming. The games’ mission is to save the cows from a nutrition issue following a malicious act on the farm. To achieve this, the necessary knowledge in animal sciences is mainly related to identification (French context) and animal behaviour. For the “sensors” part, the notions of sensitivity, specificity, ROC curve are mainly put forward, as well as the need to have reference values to validate a sensor in general (Table 1).
— The SEG B “Rscape the Office” is intended for students at Master 2 level who have a basic knowledge in R programming. The mission is to get a 3D print of a cow before the other competitors. Based on 3D imagery, the students will learn references in morphological traits usually used (body weight, heart girth, height), but also, in more original ones (surface area, volume). This escape game also addresses the key notions of repeatability and reproducibility. To be successful in the enigmas, learners have to code in R to achieve different operations (Table 1). An original feature of this second escape game is the need to work in a collaborative manner: given the time, the game can only be won if the students work together.

Feedbacks of their uses

In January 2021, both SEGs were evaluated with a general appreciation level (1 very bad, 5 very good) and a difficulty level (1 very easy, 5 very hard) by 19 learners. Marks of 4.9 and 4.4 were given to SEG A and SEG B, respectively. They were judged mildly difficult with marks of 2.8 for the SEG A and 3.3 for the SEG B. The gamification leverage was convenient for most of the learners but some of them felt the atmosphere “too stressful” and the game rhythm “too intense”. The interface was appreciated in the SEG B. Some of the learners understood the opportunity to reuse the codes presented in the SEG B for their master thesis analysis. The anchoring phases of the SEG A allowed to resolve 68% of the misunderstandings. The installation was the hardest part for the learners. In every test, most of the students achieved to finish the game phases in less than 1 hour. However, doing both SEGs’ sequences in one half day seemed too much engagement needed from the learners.

Table 1: Summary of the educational objectives of both SEGs

Enigma number	SEB A "Panic on the farm"		SEG B "Rscape the office"	
	Education objectives	**Expected Acquisition level**	**Education objectives**	**Expected Acquisition level**
1	Bovine identification system	Learning the notions	Data visualization with tables	Ability to make a variety of tables with available resources
2	Visual appreciation of cow's behaviours	Learning the notions	Data visualization with graphs	Ability to make a variety of graphs with available resources
3	Ethograms and time budgets of different species	Learning the notions	Correlation analysis between 2 variables	Ability to analyse correlations between variables
4	Functioning of an accelerometer	Understanding the notions	Repeatability and reproducibility analysis	Understanding the notions and ability to reproduce the script
5	Abnormal grazing time kinetics regarding sensors' connectivity issues	Awareness raising	Extract the mean of variables	Ability to pick a variable of interest and summarize it
6	Definition of a threshold on the activity signal to discriminate the cow grazing behavior	Understanding the notion	Understand morphological indicators	Knowledge on the dairy cow morphology
7	Sensibility and specificity of a classificatory	Learning the notions	Machine learning methodology: choice of a gold standard and performance metrics	Understanding the notions
8	Roc curves	Understanding the notion	Calibration and Validation of body weight prediction from 3D volume	Understanding the notions
9	Identification of health issues with inter-cows and intra-cow grazing time kinetics	Understanding the notion	Impact of the definition of the calibration and validation population on prediction's performances	Awareness raising
10			Predict the weight of an animal with the identified model	Ability to reuse an existing model

A rigorous evaluation of knowledge and skills acquisition is still necessary. It can be done with classical methods or by recording the responses and the progress of every learner of the questions and exercises, as described by Grosjean & Engels (2021). However, that last method requires to deploy the game on virtual machines and several modifications of the interface are needed.

Conclusions

The use of the gamification leverage through serious escape games seems promising to train students to PLF and the underlying required data science. Learners are fully committed in the SEG and enjoy the educational sequences. The SEGs are still facing some issues, the major being its installation. Nevertheless, this will be improved or avoided by an online publishing. The acquisition of the educational objectives has not been investigated at this stage and will be rigorously investigated in the next steps. The open-source framework of the SEG based on the open-source R language opens the opportunity to adapt the SEGs to other educational context and objectives.

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Trends among young and educated dairy sheep farmers in Italy regarding PLF use and farm modernization

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Abstract
Young farmers are frequently considered a key population of early adopters for Precision Livestock Farming (PLF) technology. In the case of dairy sheep farming, they are viewed as important clients for developed and under development technologies. In the current study, a 25 items questionnaire of yes/no questions and linear scale scoring (1-5) was distributed among Italian extensive dairy sheep farmers (143 sent, 78 received), targeting young farmers via local networks and professional associations. Items included both questions for systemic planning, use of software, and attitude towards technology. Descriptive statistics and single trait assessment were analysed using Microsoft Excel. Reported flock sizes were small (35-40 ha/ ≈ 50-100 animals) with the average farmer's age being 32 (74% age 20-30) and high education levels (65% had a B.A/ BSc). Many farmers reported traits linked to systemic planning such as yearly production evaluation (88%) and yearly adaptation to market change (91%). However, only 24.5% reported having written management protocols, while 0% used computers for activity planning. Computers were frequently used for marketing (84%). None of the farmers used dedicated software or PLF technologies, although 47% were exposed to both products. Additionally, 50% reported mistrust in technological systems. Few (17%) were exposed to direct marketing attempts from commercial companies while 32% were aware of subsidized farm modernization schemes. In conclusion, it can be considered that young farmers are adept in technology and use it predominantly for marketing purposes, however, few are familiar with PLF applicability or include farm modernization in their long-term planning.

Keywords: PLF, extensive sheep farming, technology adoption, farmer's view

Introduction
Precision livestock farming (PLF) aims to offer a real-time monitoring of animals in order to improve the farmer's management capacity. The PLF technologies when integrated into the farming operation provide constant data regarding animal health, welfare and general conditions (Berckmans, 2017). By now PLF systems have become a common sight in many intensive farms their presence in the extensive farming sector remains limited. Extensive dairy sheep farming in particular presents a series of economic and technological challenges for PLF development. A wide variety of solutions including wearable sensors, sensor equipped stations, milk-meters and management software are being developed in order to target farmer's needs (Vaintrub *et al.*, 2021a). The amount of research and development invested in the sector has significantly increased to cover most aspects of production management (Aquilani *et al.*, 2022). However, farmer's acceptance of the new technologies and their market penetration remains limited encountering significant barriers. While the most cited barriers are of economical nature and include the need to

justify the costs of PLF systems, other frequently cited barriers have more personality related attributes. Such barriers include the lack of technology understanding, preference of "hands-on" approach and the increase of complexity related with PLF management (Boothby et al., 2021). Consequently, both developers, policy makers and technology producers see young and educated farmers as "Early adopters" that can facilitate technology integration with the rest of the farers population. However, previous study conducted among young and educated Italian dairy sheep farmers showed lack of familiarity with existing PLF products and their use. Additionally, the majority of the farmers were interested in increasing the value of the current product than increasing the production efficiency of the farm (Vaintrub *et al*., 2021b). In the current work we aim to expand on this attitude and preference among young and educated farmers towards PLF technology and farm modernization. We also aim to identify key field interests that farmer may consider important and so far received less interest from technology developers.

Material and methods

Sample population and selection

The current work specifically targeted young and educated farmers among the dairy sheep farmers in Italy. This segment of the population is very small, comprising 10% of total farmer's population. As such, the use of mailing lists and official databases would have resulted in high numbers of irrelevant responses. Therefore, a more direct approach for identification and contact was adopted. By using local "information brokers" that included veterinarians, agronomists, farm consultancy services and local associations we were able to identify members of the target population individually. The process was repeated across six Italian regions characterized by extensive dairy sheep farming along the Apennine mountain crest (Emilia-Romagna, Marche, Abruzzo, Lazio, Molise and Basilicata). Many of the identified farmers had a mixed production farms in a setting more similar to a self-sufficient homestead than a commercial operation. Therefore, a cut-off was set identifying as a "dairy sheep farmers" individuals with a production farm setting (>4000€/ year net revenue) predominantly oriented towards dairy sheep production. In total 143 farmers were identified with the required characteristics, and were contacted on an individual level via emails provided voluntarily. They were sent a one-page online questionnaire comprised of 25 items, 78 of the farmers provided complete responses suitable for analysis.

Questionnaire construction

Each one-pager questionnaire was composed of 25 items (questions), 15 of which with a linear scale scoring limited answer option (1-5) and 10 with an accumulated multiple choice option (1-5). The topics of the questionnaire were divided as follows:

1. General information e demographic data: 5 items

This section included questions regarding the farmer's age, education, professional experience, professional education and participation in any additional entrepreneurial activity.

2. Farm related information: 5 items

This section included general question regarding farm size in ha of land, flock size, main produce market, reliance on additional labour and related costs.

3. Management practices and technology use in daily life: 5 items

This section included questions regarding overall farm planning schedules, application of management protocols, data collection and adoption of mitigation strategies as well as the use of technologies in such activates.

4. Familiarity with PLF technologies and their application: 5 items

This segment explored the familiarity of farmers with availed PLF technologies, possible application of them, funding schemes and local technology providers. Two questions briefly touched on the availability of CAP schemes for technology implementation on farms.

5. "Wish list" regarding technologies they would like to see in field: 5 items

This section was dedicated to a brief customer analysis, trying to understand the direct interest of the interviewed farmers independently from currently available technologies. It explored their "Pain points" and the needs for technological solution in specific aspects of farm management.

Data analysis

Simple descriptive statistical analysis was conducted for each individual item distribution (single trait). An inductive approach was used for qualitative data in order to identify recurring themes that should be focused upon.

Results and Discussion

General information e demographic

The vast majority of the farmers were male (96%), with only two farmers being women. Only few farmers were "First generation" farmers (9%), the rest had either taken over the entire farm from their parents (35%), split a farm among the family (52%) or took over new farms after working on their own family enterprise (4%). The average farmer's age was 32 with 74% being 20-30 years old. Education levels were also high as all the participants concluded high school level education. Additionally, 65% of them had a B.A/ BSc degree or its equivalent, with 24% conducting their studies in farming related fields such as Agronomy (10%), Forestry and soil science (7%), Wine studies (4%) and Livestock nutrition (3%). Additional 28% of the total had their degree in management related fields which included Rural economics (11%), General economics or accounting (10%) and Truism and hospitality management (7%). The rest (13%) had a variety of degrees with unrelated fields (social science, humanities etc.). Only 14% of the farmers took on additional training and studies after taking responsibility over the farm.

Farm related information

Reported flock sizes were small (35-40 ha/ ≈ 50-100 animals) as the majority of the farmers split from a previous larger farm. Most farmers applied systemic management thinking and yearly evaluation of production efficiencies (88%). Most farmers also tried to fit changes in the market and produce additional revenue streams (91%). This was done either by looking for new clients on a local level (64%) or expanding into new geographical areas (27%). None of the farmers tried to adjust the production line or add value to by-products such as wool.

Management practices and technology use in daily life

Contrary to the application of yearly production evaluation, only a minority among the farmers had a written management protocols (24.5%). The majority of the farmers preferred to rely on experience or immediate conditions considering them more flexible and suitable method. None of the farmers had a management protocol in a form of spreadsheet or dedicated software. While they used computers for information access, they did not consider it as a viable tool in their farm management practices. The most significant use for computers on the farm was for marketing (especially via social networks) and contact with potential or established costumers (84%).

Familiarity with PLF technologies

None of the interviewed farmers used any of the dedicated software for sheep flock management. Neither had any PLF system installed in his farm. A small minority had Precision Agriculture (PA) products (17%), predominantly GPS aids for new tractors. These were installed in order to comply with "farm innovation" scoring methods required for receiving CAP grants. While 47% of the farmers reported familiarity with PLF technologies they haven't seen them operational in field. Few (17%) were exposed to direct marketing attempts from commercial companies while other gained familiarity from a marketing booth at an agricultural faire (11%). A significant number was exposed to PLF and PA technologies via sponsored online adds (19%), but had only limited interest in further exploration. Additionally, 50% reported mistrust in technological systems, predominantly due to communication related problems they encountered with the local GSM coverings. Finally, 32% were aware of subsidized farm modernization schemes but among these, none had applied for a one. This result coincides with official information regarding CAP use in central Italy, with only 15% of the dedicated funds being used on a yearly basis as reported for 2019 (Official CAP report).

Fields of particular interest for PLF application

Specific aspects of production were predominantly important for the farmers in comparison to others. Predation was considered a big problem which led to an overwhelming interest in anti-predation, security and alarm systems. Overall 74% of the farmers considered it as a major problem. This is in line with the population recovery of the Apennine wolf in central Italy and the increased frequency of farm predation (Fabbri *et al.*, 2007). Security remained an important aspect for the farmers also regarding to theft, as animal identification, alarms and individual tractability were considered of high importance to 57% of the farmers. Finally, technologies related to marketing, product quality showcasing and automated scores for the farm ecological services were considered important by 51% of the farmers. Other production aspects such as pasture evaluation, fertility and health conditions had limited interest (<10%) each.

General observations

While important information from the end-user point of view is becoming increasingly available (De Boon et al, 2022), additional key data could be obtained using ground level sampling. The current work supports the hypothesis that young and educated farmers are more open for technology, and use it more frequently in their professional and private life. However, this does not directly translate into interest in PLF technology acquisition. Small and medium scale extensive sheep farming appear to be interested in technologies that can provide protection from what they perceive as external calamities. They are also interested in improved value for their product and better contact with high-paying niche markets. Their interest in production efficiency related technologies seems to be limited and they rarely explore such possibilities by themselves. While CAP schemes play a significant role in providing information regarding PA technologies, the same is not true for PLF on a local level. This could be attributed to different causes such as; a) Lack of familiarity with PLF technologies on the side of the CAP office clerks and technicians (Odintsov Vaintrub et al, 2020), b) Lack of suitable technological solutions fit for the farming sector (Aquilani et al, 2022) c) Tendency of farmers to prefer more general PA technologies over specialized management tools (Boothby et al, 2021).

Conclusions

In conclusion, it can be considered that young farmers are adept in technology and use it predominantly for marketing purposes, however, few are familiar with PLF applicability or include farm modernization in their long-term planning. This may be attributed to knowledge and information gaps regarding available PLF solution. On the other hand, many farmers tend to be interested in technology applications that are more related to protection and marketing rather that improved flock management.

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Preliminary work for the development of an educational web platform for 3-pillar sustainability assessment in European dairy cattle production systems

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Abstract

The objective of this paper is to present the initial steps for developing a web platform for sustainability assessment and improvement in dairy cattle production systems. 8 agricultural platforms, 4 agricultural applications and 8 dairy content platforms were selected and evaluated based on three criteria: a) existence of educational functions; b) type of information provided (e.g. for sustainability assessment); c) characteristics determining the extent of use. The findings suggest that graphical representations, audiovisuals, case studies, updated and well-informed databases, scientific-based information, and environmental, economic, and social information are major characteristics of an educational, agricultural platform. The results of this evaluation and an innovative approach for sustainability assessment in several dairy cattle farm typologies in Europe (i.e. LCA and multicriteria assessment, sustainability indicators' weighting, greenhouse gas and ammonia mitigation strategies) are combined for the development of the platform. Although farmer-centric, the platform is meant to be an educational tool for all the stakeholders of the dairy cattle production systems, providing relevant, well-organized information to the user.

Keywords: dairy cattle production, educational platform, sustainability assessment

Introduction

The interactive distance learning for the acquisition of new skills and knowledge is a phenomenon that emerged from the major application of personal computers and devices (e.g. mobile phones, tablets) that use the worldwide expansion of the internet. Web-based methodologies started to be developed and to be considered as an innovative educational practice at the beginning of the 2000s (Born et al., 1999). Information and Communication Technologies (ICT) are routinely used to promote educational processes via e-learning (Tirziu and Vrabie, 2015). However, these practices started to be used more intensively during the COVID-19 pandemic (Maatuk et al., 2021).

The agri-food sector is of major global importance since it is obliged to supply food products in a sustainable way to a constantly rising population (9.7 to 9.8 billion people in 2050) (FAO, 2009). Furthermore, the agricultural sector is crucial for economic growth contributing 25% of global gross domestic product (GDP) (WorldBank, 2022). Due to the global importance of the agricultural sector, the need for well-structured web-based educational systems that are constantly updated to meet the daily challenges of all sub-sectors should be highlighted.

E-learning educational platforms make value chain challenges more manageable and provide to the agricultural communities (e.g. dairy farmers) potential development (Leary and Berge, 2006). Thus, the use of educational platforms has the potential to provide direction towards the improvement of the sustainability status of dairy production systems for farmers and all relevant stakeholders.

The objective of this paper was to use an evaluation methodology for agricultural systems' educational platforms based on several important parameters regarding their educational functions, the type of information provided and the determination of the extent of their use. In this way, an introduction to the general and specific characteristics of an educational, web-based platform for sustainability assessment and improvement of dairy cattle systems is attempted.

Material and methods

This research essentially involved a detailed investigation of several web literature sources (Scopus, ScienceDirect, Google Scholar, ResearchGate) regarding agricultural education platforms, online applications, and tools. It focused on literature published from 2000 on. The Google search engine was further used to identify widely searched, relevant educational platforms and mobile applications.

The first result of this investigation was to define the evaluation criteria. Three criteria were defined: 1) **Functions for education methodology**. The work of Eichler Inwood and Dale (2019) was used for suggesting the various options for this criterion (e.g. gaming, quiz test, etc.); 2) **Type of provided information**. This criterion was based on the identification of the main causes for applications' development in the agri-food sector (e.g. improved access to multi-source information, improved market connections and distribution networks, etc.) (Qiang et al., 2012; Costopoulou et al., 2016; Eichler Inwood and Dale, 2019; Karetsos et al., 2014); 3) **Characteristics determining the extent for wider use**. The options for this criterion were defined based on the suggested main characteristics (e.g. content, capacity development) for wider development of Information and Communication Technologies in the agri-food sector (FAO, 2015).

The second result was to decide on the web material to be evaluated. The material was separated to web platforms and web applications with their most important difference being that applications refer to a bounded set of operations while platforms to an unbounded set of applications. The material to be finally evaluated included 8 agricultural platforms, 8 dairy-related platforms and 4 agricultural and dairy applications due to the fact that they were increasingly cited on scientific publications, and they can be found as top results in Google search engine and Google Play.

Results and Discussion

Criterion 1. Existence of educational functions

Table 1 collects the existing educational functions for the examined web-based material.

Table 1: Existence of educational functions in the web-based material evaluated

Material	Educational functions						
	Gaming	Graphs	Audiovisuals	Quiz	On-site communication	References	Courses
CGIAR [p]	No	Yes	Yes	Yes	No	Yes	Yes
SAFE [p]	No	Yes	Yes	No	No	Yes	Yes
SFVC [p]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Next FOOD [p]	No	Yes	Yes	No	No	Yes	Yes
SARE [p]	Yes	Yes	Yes	No	No	Yes	Yes
LLOOF [p]	No	Yes	Yes	Yes	Yes	Yes	Yes
WOCAT [p]	No	Yes	Yes	No	No	Yes	Yes
Land PKS [p]	No	Yes	Yes	No	No	Yes	Yes
LEAF [p]	No	Yes	Yes	No	No	No	Yes
(F&BKP) & (NFP) [p]	No	Yes	Yes	No	No	Yes	Yes
InnoDairyEdu [p]	No	Yes	Yes	Yes	Yes	Yes	Yes
Global Dairy Platform [p]	No	Yes	Yes	No	No	Yes	Yes
DairyNZ [p]	Yes	Yes	Yes	Yes	No	Yes	Yes
Dairy Australia [p]	Yes	Yes	Yes	Yes	No	Yes	Yes
PRO-DAIRY [p]	No	Yes	Yes	No	No	Yes	Yes
MILK [p]	Yes	Yes	Yes	Yes	No	No	Yes
AgriApp [a]	No	No	Yes	No	No	No	No
Land PKS App [a]	Yes	Yes	Yes	Yes	No	Yes	No
My cattle Manager [a]	No	Yes	No	No	No	No	No
Farmi [a]	No	Yes	Yes	No	No	No	No

p: platform; a: application

Gaming is used from only a few of the initiatives as an educational approach. Using graphs is a common function for all platforms but not for applications. Moreover, audio-visuals are commonly used by the platforms but not from most of the applications. The quiz function is mostly found in the Dairy platforms. The on-site communication between users is a deficiency for most of the initiatives. Scientific references establish the content quality for most of the initiatives. Finally, courses organization and provision are promoted by all the platforms but by none of the applications.

Criterion 2. Type of information provided

In Table 2 the type of information provided by the material evaluated is presented.

Table 2: Type of information provided by the evaluated material

Material	Type of information						
	Environmental	**Economic and Market**	**Social**	**Governance and regulations**	**Provision of calculators / tools**	**Weather forecast / climate**	**Agricultural news**
CGIAR [p]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAFE [p]	Yes	Yes	Yes	No	Yes	No	Yes
SFVC [p]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Next FOOD [p]	Yes	No	Yes	No	Yes	No	No
SARE [p]	Yes	Yes	Yes	Yes	Yes	No	Yes
LLOOF [p]	Yes	Yes	Yes	No	No	No	Yes
WOCAT [p]	Yes	Yes	Yes	Yes	No	No	Yes
Land PKS [p]	Yes	No	Yes	No	Yes	No	Yes
LEAF [p]	Yes	Yes	Yes	No	No	No	Yes
(F&BKP) & (NFP) [p]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
InnoDairyEdu [p]	Yes	Yes	Yes	Yes	No	No	No
Global Dairy Platform [p]	Yes	Yes	Yes	No	No	No	Yes
DairyNZ [p]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dairy Australia [p]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PRO-DAIRY [p]	Yes	Yes	Yes	Yes	Yes	Yes	No
MILK [p]	Yes	Yes	Yes	No	No	No	No
AgriApp [a]	Yes	Yes	No	No	No	No	Yes
Land PKS App [a]	Yes	No	No	No	Yes	Yes	No
My cattle Manager [a]	No	Yes	No	No	Yes	No	No
Farmi [a]	Yes	Yes	No	Yes	Yes	Yes	Yes

p: platform; a: application

Information regarding the three pillars of sustainability is provided in most of the agricultural and dairy platforms. The environmental pillar is mostly represented and is followed by the economic pillar, while the social pillar is less represented. At least one pillar is represented in every evaluated initiative. Nevertheless, the applications do not include information about the social pillar. Additional features like individual (from platform) tools and calculators (e.g. GHG emissions' estimation, farm management) are included in more than half agricultural and dairy platforms and applications. Governance information and regulations related to the agriculture and the dairy sector are included in half of the platforms and in they are reported by one application. The evaluated agricultural platforms do not provide weather forecasts in their main functions. The dairy platforms introduce climate information and management of climate conditions that are related to dairy production. Weather forecasting is a function of two applications. News is included in every agricultural platform, half of dairy platforms, and two evaluated applications.

Criterion 3. Characteristics determining the extent of use

Table 3 shows the evaluation considering the characteristics of the evaluated material which could determine the extent of their use.

Table 3: Characteristics determining the extent of use for the material evaluated

Material	Characteristics determining the extent of use					
	Language[1]	Geographic coverage	Location[2]	Gender equity	Cost of Use	Data Sources[3]
CGIAR [p]	ENG	Global	Yes (CS)	No	No	L, S, ND, OD, PE, SS
SAFE [p]	ENG, SP, FR,	Latin America	Yes (CS)	No	No	L, PE
SFVC [p]	ENG, SP, RU, AR,CH	Global	Yes (CS)	Yes	No	L, OD, ND
Next FOOD [p]	ENG	Global	Yes (CS)	Yes	No	L, OD, ND DD
SARE [p]	ENG	USA	Yes (CS)	Yes	No	L, OD, ND
LLOOF [p]	ENG	Global	No	Yes	No	L, PE
WOCAT [p]	ENG	Global	Yes (CS)	Yes	No	L, OD, ND, S
Land PKS [p]	ENG	Global	Yes (CS & GPS)	No	No	L, PE
LEAF [p]	ENG	UK	Yes (CS & GPS)	No	No	L, PE, S

(F&BKP) & (NFP) [p]	ENG, DU	Global	Yes (CS)	Yes	No	L, OD, ND, S
InnoDairyEdu [p]	ENG	Global	No	Yes	No	L, OD
Global Dairy Platform [p]	ENG	Global	Yes (CS)	No	No	L, OD, PE
DairyNZ [p]	ENG	NZ	Yes (CS)	Yes	Yes	L, OD, ND, PE, S
Dairy Australia [p]	ENG	AUD	Yes (CS)	Yes	Yes	L, OD, ND, PE
PRO-DAIRY [p]	ENG	USA	Yes (CS)	Yes	Yes	L, OD,N ND, PE, S
MILK [p]	ENG	CA	Yes (CS)	No	No	L
AgriApp [a]	ENG, IND	India	No	No	No	DCD
Land PKS App [a]	ENG, SP, FR	Global	Yes (GPS)	No	No	DCD, S
My cattle Manager [a]	ENG	Global	No	No	No	DCD
Farmi [a]	ENG, FR	France	Yes (GPS)	No	No	DCD

[1] ENG: English, FR: French, SP: Spanish, DU: Dutch, IND: Indian, RU: Russian, AR: Arabic, CH: Chinese
[2] CS: Case Study, GPS: Global Positioning System
[3] L: Literature, S: Satellite, ND: National Data, PE: Practical Experience, SS: Sensor System, OD: Organizations' Data, DD: Drone Data, DCD: Development Company's Data
p: platform; a: application

English is the language of all the evaluated initiatives. Most of the platforms and applications can be used globally. The dairy platforms are specifically linked to the respective countries. Furthermore, the platforms mostly involve location-specific case studies while the applications have integrated GPS systems. Agricultural and dairy platforms promote the social equity (e.g. using specific articles, actions). Moreover, the platforms can be used free of charge while most applications include versions both free of charge and payable. Finally, data sources for platforms are mostly related to the available literature and experience connected to the case studies while generally for the applications, data sources are unclear.

Conclusions

In this paper, 20 web-based initiatives (platforms and applications) were evaluated based on the presence of educational functions, on the type of information provided, and on the characteristics determining the extent of their use. Based on this evaluation, it can be concluded that important educational functions of a modern, web-based platform for sustainability assessment and improvement of livestock systems are graphs and audiovisuals for clear communication of concepts to the user, use of stakeholders' case studies, and justification of the information provided based on scientific references. Regarding the types of information provided, it is of importance to include information on all sustainability pillars and their (quantitative and qualitative) assessment and relevant news feed. Finally, concerning the characteristics determining the extent of use, it is of importance to use English as the main language, to promote social equity, to be used free of charge, to use data sources scientifically accepted and based on the practical experience of the stakeholders and to include a location-specification utility.

Repeated use of such platforms by stakeholders is highly dependent on the user-friendly and comprehensive way the information is provided and on their constant update. These findings are currently being adopted in the development of a platform for European dairy production systems (the "MilKey platform"), which aims to assist farmers and extension service in optimising their dairy cattle production systems and to inform stakeholders, politicians, and consumers on the key elements of region-specific sustainable dairy cattle production systems and to increase their understanding and acceptance. The "MilKey platform" will deliver region-specific suggestions for sustainable, low emission and economically efficient dairy cattle production systems.

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Educating for Precision Livestock Farming: The knowledge, skills and abilities to meet future industry and societal needs

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Abstract

The field of Precision Livestock Farming (PLF) is flourishing throughout the world, being driven by the fast development of accessible hardware and powerful computational technologies in combination with the growing need for solutions that enable sustainable animal production. Research in this field is burgeoning, with the number of publications indexed by Web of ScienceTM exponentially growing since 2016. Moreover, the translation of this science into commercial solutions is also booming, as evidenced by the recent emergence of many new high-tech PLF start-ups. For the continued success of the PLF field, it is important to align education with industry and societal needs. Education of PLF should provide individuals with knowledge, skills and abilities (KSA's) not only to facilitate the innovation of high-quality technologies but to appreciate the practical and ethical issues in their application for sustainable animal production. A sub-group of International Commission of Agricultural Engineering (CIGR) Technical Section II has formed around an action to investigate "Educating for Precision Livestock Farming". The objective is to identify the KSA's needed for success at graduation and to provide pointers on learning paths for students of different backgrounds (animal science, animal production or engineering) and career goals (e.g. PLF researcher, technology developer, system technical support, farmer and veterinarian). To this end, data concerning PLF KSAs will be gathered from two sources: (1) existing course syllabi offered internationally and (2) a survey conducted with representatives of relevant companies. We will present the current results of this action during EC-PLF 2022 and use the opportunity to collect additional information from participants.

Introduction

While the consumption of meat and animal-derived products in the EU has plateaued in recent years, the demand for such foods is still increasing on a worldwide level. This has in turn led to expansion of the meat and dairy sectors globally. As a consequence, topics on the well-being of farm animals and the sustainability of farm management practices are common targets of public discourse. Meeting the meat and dairy consumption trends of the world population in a sustainable way will likely continue to be challenging in the future and demands continuous innovation from those directly involved as well as allied industries. Precision Livestock Farming (PLF) can be considered part of the solution towards addressing these livestock production challenges. PLF systems are information-oriented technologies typically comprising sensors, technology for data exchange as well management systems in an aim to provide decision support to the animal producer/caretaker. However, because animal production is in itself challenging, so too must the supporting technologies. As a result, there is a strong demand on qualified workforce not only in the development of these technologies but also in their accurate implementation.

In this paper, the authors, all of who represent the CIGR sub-group on "Educating for Precision Livestock Farming" will present the work done to date in our study of the educational landscape related to PLF and the preparation work being done to continue the work. We will also present a case study of the development of the 60 ECTS PLF MSc course at Universitat Politècnica de València.

Growth of PLF research and development

While the term Precision Livestock Farming was not used in early in the 2000, the first works in the area started appearing in the 1980s. Hyde et al. (1981) discussed a new dairy management technique of managing by exception. They defined management by exception as "the use of equipment and analysis techniques to detect those animals which are exceptions, i.e., those that are not performing normally." At a similar time, the first patents were issued for robotic dairy solutions in 1983. As shown in Figure 1, there was an exponential increase in patents issued between 1983-2003, and then a reduction in 2004 and a linear increase in patents filed between 2004-2021. Publication trends also show an increase over the same time; however, the trends are different (Figure 1).

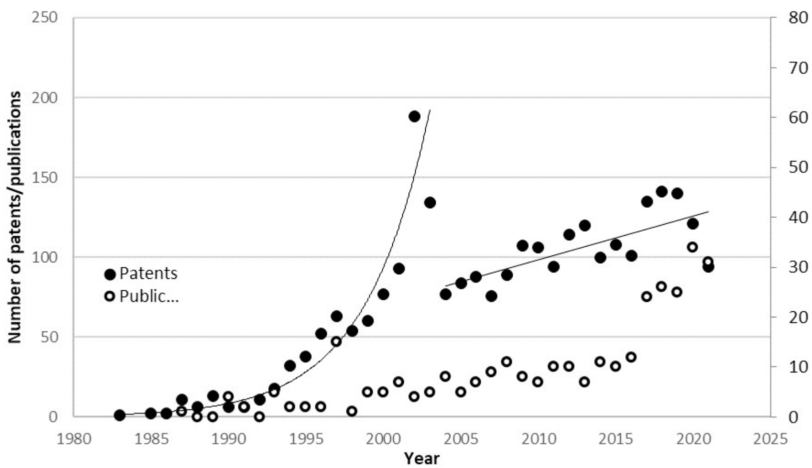

Figure 1: Patents filed and publications from 1983 to 2021 for with the keywords of *robot* and *dairy* as documented by Scopus

From a literature search it appears that the term *Precision Livestock Farming* was first used in a publication by Christopher Wathes (Wathes, 2003). This area of research has really increased (Figure 2) in recent years, with the increase computing power, decrease in cost of technology, along with the decrease is labour availability, and increase in research funding in this area. Since 2009, there have been 15 large European Research projects containing PLF as a key topic, with 50% of those projects being initiated on or after 2019 (CORDIS, 2022). The funding the United States Department of Agriculture started emphasis technology in the animal area about 5 years later, with the formation of the Foundation Food and Agriculture Research in 2014 (FFAR, 2022), and the creation of the a few different funding area IDEAS (Inter-Disciplinary Engagement in Animal Systems) grant in 2019 and the FACT (Food and Agriculture Cyber-informatics and Tools) grants in 2018 helping spur research in this area in the USA (NIFA, 2022).

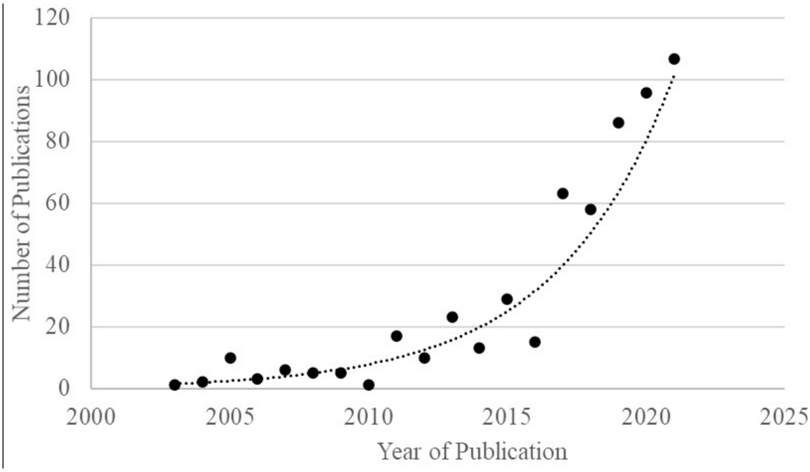

Figure 2: Publications from 2003 to 2021 for with the keyword of *Precision Livestock Farming, Precision Animal Management or Smart Farming* and *Livestock* as documented by Scopus

Growth in the industrial importance of PLF

The investment of companies on PLF is increasing. Merck Animal Health acquired Antelliq, Allflex, and Agrident, (Bioscience Association Manitoba, 2022). Smart Bow and Zoetis formed a partnership (i5invest, 2017) and Boehringer Ingelheim acquired stakes in SoundTalks (Boehringer-Ingelheim, 2019). All three of these cases involve a large pharmaceutical company was investing in technology to improve animal tracking and potential animal health tracking. This establishes the importance of precision livestock technologies in their business portfolios.

Miquel Collell, Global Technical Director of Swine, ReProPig and & Sowcare emphasized the importance of PLF technologies in this statement “There are crucial moments in humankind evolution, agriculture, animal domestication, the wheel, electricity, internet, and PLF will be one of this moments. PLF Is not a fashion, is the only way to keep the world as a more sustainable one. We do PLF or we will not continuate advancing as a society.” Robert Fitzgerald, PIC – Pig Improvement Company, emphasized the need for PLF for labor savings. Dr. Fitzgerald said, “it is common for sow farms today to be operating with a reduced labor force; solutions are needed to help ensure we are caring for our animals, maintaining biosecurity, and improving the efficiency of common, routine tasks."

Moreover, the translation of this science into commercial solutions is also booming, as evidenced by the recent emergence of many new high-tech PLF start-ups present at the innovations such Animal AgTech Summits (ReThinkEvents, 2022), Poultry Tech summits (WattGlobalMedia, 2021) and theAnimal Health, Nutrition and Technology Summit (Kiascoresearch, 2022).

Challenges in educating the future PLF workforce

Overcoming barriers to adoption of PLF, like precision agriculture, is contingent upon having trained individuals who can provide insight and access to the technologies (Kitchen et al., 2002) and can extend theory and application. "Universities play an important role in innovation systems" (Leten et al., 2014) in that they educate and train individuals in fields important for economic and sustainable futures and conduct research critical to progress. Extending this role to PLF specifically, the innovation systems include PLF experts, producers, related industries, … Formal PLF education at the undergraduate level serves to prepare individuals for emerging "knowledge-intensive" career paths, like for PLF, wherein they can deliver on the university education "promise of introducing novelty into the existing industrial texture on the level of problem-definition and problem-solving activities" (Leten et al., 2014). Formal PLF post-graduate programs serve to prepare individuals to lead the field, conduct groundbreaking research, facilitate technology transfer, and establish start-ups that create jobs (CGS, 2008). Like precision agriculture more broadly, there is a need to promote computational and data skills as well as conceptual understanding in conjunction with the "applied, practical experience that incorporates theory of production management" (Kitchen, et al., 2002) and the theory and practicality of animal care.

Ongoing efforts of the CIGR sub-group on Education for "Precision Livestock Farming"

The CIGR sub-group will carry two main actions in their mission to understand the landscape of PLF education and how this meets industry needs. The first is to carry out survey to understand the worldwide availability of courses considered closely connected to the field of PLF. The second action is to see how these courses meet the needs of industry and provide some recommendations on course development into the future. Future actions from CIGR Technical Section II could include providing some core/basic skills in PLF via the CIGR website or partnering member institutes. However, the exact nature of this needs to be worked out in more detail later in this investigation.

The sub-group has already started to conduct the preparation needed for the survey. A very introductory overview of current BSc and MSc study programmes offered in EU and US which have a PLF aspect are shown in Table 1. It is evident that these programmes are offered by Departments with diverse backgrounds. Hence, the major question to be answered, through questionnaires addressed to educators and relevant companies, is what the main outcomes of a PLF study programme should be so to allow graduates to seek and achieve their career goals.

Table 1: Non-exhaustive overview of current BSc and MSc study programmes offered in EU and US that contain a PLF aspect

Country	University	Department	Level	Course	Class
Belgium	KU Leuven	Biosystems	MSc	☒	☒
Germany	University of Hohenheim	Agricultural Sciences	MSc	☒	☒
Italy	University of Naples Federico II	Veterinary Medicine and Animal Production	MSc	☒	
Netherlands	Wageningen University	Biosystems Engineering	MSc	☒	☒
Portugal	Évora University	Rural Engineering	MSc	☒	☒
Spain	Universitat Politecnica de Valencia	Animal Science	MSc	☒	☒
USA	University of Nebraska	Biological Systems Engineering and Animal Science	MSc	☒	☒

The survey is currently being designed and will be distributed amongst academic colleagues working in fields related to PLF. Through it we aim to learn more about the thinking behind the design of these courses, with a focus on understanding the influence on the background of the candidates, typical career paths being targeted and the engagement with industry. In Table 2, we present a subset of the questions to be asked in the PLF education survey. We still expect more questions and alternative ways to phrase questions during the survey preparation.

Table 2: Subset of questions that will be used in the PLF educational survey

- What are the “main” driving factors for the course/programme?
- Who is the target audience?
- Is there a link with industry/professional societies?
- What are the learning objectives
- What are the topics covered in the course
- What are the career paths of your graduates?
- What are the plans to revise the course/programme
- What are your plans for additional courses
- Do you know others who offer courses or programmes?

The main deliverable of this survey will be:

— List of main drivers/objectives for the designing PLF courses
— List of course designs that educators are using to meet objectives
— Identified gaps in education that could be filled through community action

Further possibilities for educators to engage in the survey will be possible at the ECPLF conference. Answers to the survey will then be compiled and analysed and then used as a basis for preparation of the industry consultation, which will be the second part of the full study. After this point we will compare with the related initiatives taken by subgroup members and assess how well these educational initiatives meet the need of industry and research requirements and provide recommendations and further actions for course developers in the future. One initiative that will be used in the comparative analysis will be the recent development of the PLF Master at the Universitat Politècnica de València. This is presented in more detail as a case study below.

Case study: Experience on design of PLF Master in Spain

The experience in designing a new Master Degree on PLF in Spain is presented here. The Universitat Politècnica de València (Valencia, Spain) had the opportunity to create a new master program of one-year duration (60 ECTS). The committee in charge of this task identified three main aspects to be considered: First, the student profile; second, the capabilities of the teaching staff; and third, the company needs in the area of influence of this master (mainly Spain). These aspects were analysed and considered together in order to establish the program as follows.

First, the target students were identified as agricultural engineers and veterinarians, which are the most relevant degree programs in Spain related to the area of expertise of the master committee. These were surveyed for their interests regarding a potential program on PLF, including questions related to the program extension (1 or 2 years), degree of expertise, or other practical questions (for example physical, online or blended format). The results showed that students preferred a blended program, with both online contents and physical practice. The main motivation of students to enrol this master is to find a job (65%), but a relevant share of students had a motivation towards research (32%). Finally, students showed high motivation towards subjects related to biotechnological tools, welfare certification, mitigation of environmental impacts, and technology use in farms. Apart from this, relevant interest was detected for subjects related to massive data analysis and business management.

As a second step, companies related to animal production were contacted to obtain their interest in a profile on precision livestock farming. The companies belonged both to the technology and animal science sectors, and therefore relevant interest on precision livestock farming was detected to be relevant both regarding the animal (for example, biotechnology tools and precision nutrition), and to the facilities (technological tools for precision livestock farming). Companies revealed that they mostly need a profile with wide expertise, which means a person who is able to respond to diverse challenges including animal and technology related ones. This means that this person does not need to be a deep expert in those topics, but must dominate the opportunities and limitations of all them, and must also have relevant skills in data and business management.

As a consequence of these student and company surveys, it was decided that such a master could involve both veterinarians and agricultural engineers and would be focused on showing the most relevant technical and biotechnological tools used in animal production, as well as on data and business management. Consequently, the program identified relevant lecturers within and outside the University, which will be in charge of designing each of the subjects in this master. Apart from those subjects, the program is planning a transversal project on PLF, as well as practices of students in companies and research teams. This master will start in September 2022, and a commission will be established to ensure a proper implementation and evaluate potential changes for the future.

Conclusion

This paper reports the current status of a study being carried out by a CIGR TSII subgroup on *Educating for Precision Livestock Farming*. So far initial work has included compiling initial non-exhaustive information on the research and industry demand for the field, as well as identifying an approach to uncover new information on course design from educators in this field. Future work will include analysing the survey against current initiatives (e.g. PLF course developments at the Universitat Politècnica de València) and industry needs to propose recommendations regarding course design and delivery.

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Digital teaching anatomy solutions in precision livestock farming educational programs

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Abstract

Veterinary anatomy is essential for every aspect of veterinary medicine, including Precision Livestock Farming (PLF) education as well. Traditionally, veterinary anatomy has been taught as a stand-alone course or as part of a problem-solving orientated curriculum.

In the new set up of the post-Covid-19 pandemic, virtual anatomy could serve as a valuable substitute solution. Although it cannot provide the hands-on training of animal dissections, essential for every veterinary student, this new educational tool may efficiently complement the dissections.

On the contrary, in PLF, new technologies are designed to support farmers in livestock management in a continuous, real-time, and automated manner. This is achieved by monitoring and controlling animal productivity, environmental impacts, as well as health and welfare parameters (Schillings *et al.*, 2001) and by ensuring the implementation of best practices and responsible use of medicines in farming.

With the emerging integration of PLF education in all veterinary curricula nowadays, undoubtedly anatomy must be part of this.

Currently, many veterinary schools use 3-D atlases for teaching anatomy. Having assessed our students' experience on a virtual anatomy educational tool during the last year, we are considering its permanent integration in our curriculum. Furthermore, virtual Veterinary Anatomy, as a replacement to animal use for educational purposes, supports and implements 3 Rs principles (Russell and Burch, 1959).

This work aims to review the existing digital solutions for teaching veterinary anatomy and to present an anatomy module to be incorporated into PLF education with the use of new 3-D technology for the benefit of animals, environment, and humans, pairing in the efforts of the ONE HEALTH initiative.

Keywords: veterinary anatomy education, veterinary schools, digital resources, precision learning farming education, basic sciences

The importance of anatomy in veterinary curricula

The existing mural paintings depicting animal superficial anatomy from the Paleolithic era is evidence of the human interest on this subject (Clark, 1944). Although many scientists (BC), from the Greek Alcmaeon of Croton to the Roman Marcus Aurelius (Kubale *et al.*, 2019) observed anatomical organs, it is the Greek Aristotle who is considered the father of comparative anatomy since he performed dissections to different animals from reptiles to insects and mammals (Crivellato and Ribatti, 2007).

Anatomy constitutes the cornerstone of undergraduate veterinary education. As such, it is taught in the very first semesters of almost every curriculum, since it is interwoven in every other aspect of basic and even clinical practice (Wheble and Channon, 2020). Its relevance to radiology, surgery and/or pathological anatomy places anatomical knowledge into the basic veterinarian skills to allow safe and efficient practice of veterinary medicine. Education of anatomy provides the knowledge of the normal location and dimensions of the different organs and gives the opportunity to the student to recognize abnormalities (either by studying the radiographs and/or by palpating the animal) and to come closer to an accurate diagnosis.

A challenging feature of veterinary anatomy and its education is based on the comparison between the different species examined. Almost every animal organ is species-specific not only in size but in location as well. Different veterinary curricula base their teaching in one species (e.g., dog or sheep) and compare the rest of domestic animal species with this one.

Teaching of anatomy in veterinary medicine schools

Courses in syllabi of different veterinary schools worldwide include anatomy education in the same semester with physiology providing detailed information on the structure and function of the animal body in the species most commonly seen in veterinary practice, including companion animals, livestock and avian. Many undergraduate programs include laboratory animals' and exotics' anatomy as well. Teaching includes the laboratory component allowing students to gain experience with the tools and techniques used to study the body on a macroscopic and microscopic level. In other programs students will investigate the connections between the study of anatomy and physiology and clinical veterinary medical and surgical practice on a problem solved base educational context.

Irrespective of anatomy's importance, the latest years there is a tendency to shrink basic veterinary education including anatomy, due to the following reasons:

— Reduction of animal used for educational purposes
— Growth in the numbers of students that would like to study veterinary medicine with diminishing number of faculty members
— Fixation and maintenance methods of the dissected animals
— Last but not least reason for changes into the veterinary anatomy education is the Covid-19 pandemic

The use of animals for educational purposes due to the implementation of 3Rs principle (Russell and Burch, 1959) tends to lessen on an international level. According to the European Directive 63/2010/EU, education and training involving living rats and mice are classified as an animal experiment and demands the implementation of the 3Rs.

For this reason, alternative methods are in place both on domestic and laboratory animals. Corte *et al.*, have developed training devices, simulators, where different techniques such as blood sampling can be learned prior to working on live animals. In the following website: https://www.turbosquid.com/3d-model/animal-anatomy?page_num=2 animal anatomy 3D models can be purchased for educational purposes.

A specific example for alternative methods is the anatomy of the equine foot, which possesses great complexity and huge clinical importance at the same time. The majority of lameness is attributed to foot pathology (Dyson and Marks, 2003; Turner, 2003). For this reason, it has attracted the interest of various researchers. Preece *et al.*, have demonstrated the significant advantages associated with using a physical model in enhancing students' visuospatial appreciation and understanding of the complex anatomical architecture of the equine foot. On the other hand, eHoof: http://www.eurofarrier.org/e_hoof.php or e-hoof.com is based on the thesis of Geyer H, Musterle (https://www.zora.uzh.ch/id/eprint/18910/9/Musterle_diss.pdf) and is the result of many years planning and development. It is a state-of-the-art, interactive web platform that is based around material contributed and peer reviewed by specialists in their fields. It is divided into specific topics, and has a wide range of multi-media tools with thousands of illustrations, photos, films, interactive animations and models.

As it is mentioned in the publication of Inpanbutr *et al.*, (2020) there is a trend of increasing class size in veterinary medical education without the concomitant and proportionate advance in teaching faculty. This is true in our School, where regardless of the EAEVE (European Association of Establishments for Veterinary Education) advice following their recent visitation and evaluation, the number of students entering the school has increased from previous years. Inpanbutr *et al.*, have also developed a Digital Platform ExamSoft in Veterinary Anatomy Assessments in Written and Laboratory Components. This effort comes from the Ohio State University College of Veterinary Medicine, with a class of 162 students.

The ban of formalin use in the fixation and maintenance of animal cadavers, due to its deleterious and toxic effects to humans, has urged professional to investigate other ways of preserving the teaching specimens (Lombardero *et al.*, 2017; Homma *et al.*, 2019) with additional decrease of the cadaveric teaching material.

The Covid-19 pandemic has influenced veterinary anatomy education. At the 2021 XXXIIIrd Congress of the European Association of Veterinary Anatomists, in Ghent among other issues in the Teaching topic, Nongnuch Inpanbutr presented the work entitled: "Making the move to 100% online: an update on teaching veterinary anatomy at the Ohio State University during the COVID-19 pandemic, while Zeeshan Durrani presented the article: "Assessing learning and teaching practices in anatomy education during the COVID-19 pandemic": https://eava2020.ugent.be/

All the previous reasons combined lead to the investigation of other methods for veterinary anatomy education, and mainly into digitized resources.

Digitizing programs for supporting veterinary anatomy

In 1991, Snell *et al.*, described the Veterinary Digital Anatomical Database Project, whose purpose was to investigate the construction and use of digitally stored anatomical models. Since then, a number of approaches have been integrated in veterinary anatomy education.

Following are some examples from the online resources on the issue:

https://www.ivalalearn.com/ providing innovative, interactive learning content with anatomy in 3D reconstruction, high-quality flashcards and multiple choice questions. According to experienced anatomists the program provides accurate anatomical details and enriches the animal dissection procedure and knowledge.

Easy Anatomy is supported by four different Universities: Univ. of Adelaide, in Australia, Univ. of Saskatchewan, in Canada, the University College Dublin in Ireland and the University of Pennsylvania, in the US.: https://easy-anatomy.com/ with you tube presence:

https://www.youtube.com/watch?v=S7FzCebbG58&ab_channel=EasyAnatomy: it is trusted by veterinary students, educators and professionals in over 120 countries and provides virtual dissection and adaptive quizzes regarding dissection labs, clinical studies, and procedures.

https://www.cvmbs.colostate.edu/vetneuro/VCADissection.html, from the college of veterinary medicine and biomedical sciences of Colorado State University, providing Virtual Canine and other domestic animal Anatomy and directing students in the process of dissection, with photographs, descriptions, and animations. The detailed dissection descriptions not only assist students during lab, but also allow them to study outside of lab when instructors and cadavers are not available. Along with canine, there is feline, bovine and equine anatomy and a guide to neurological exam.

Figure: the official websites of the Colorado State University and RVC presenting their digital veterinary anatomy courses provided by their institutions

Gemma Gaitskell-Phillips *et al.*, 2012 created the OVAM (Online Veterinary Anatomy Museum), a website with veterinary anatomical resources, closely linked to the WikiVet project. It is a combined effort from 20 partners from around the world and provides an intuitive, engaging and dynamic environment created by student-user focus groups in collaboration with academic staff.

Finally, at the website of the Royal Veterinary College (RVC) in London, there is the Anatomy online webpage: https://www.rvc.ac.uk/e-anatomy, where the RVC has captured an astonishing collection of digital images from specimens kept in the Anatomy Museum of the same College. Another collaboration between staff from University of Murcia in Spain and students of RVC was presented as a: http://www.live.ac.uk/Media/LIVE/PDFs/LIVEprojectreport2011_AmyRubio.pdf. This project was created with the use of Dragster software to reinforce learning in veterinary anatomy by means of drag and drop labels on images and videos. The authors developed a 150-computer based veterinary anatomy interactive learning resources covering topographic anatomy, osteology, soft tissue dissection, radiology and histology.

The example of Vet School in Aristotle University of Thessaloniki (AUTh)

The Laboratory of Anatomy, Histology and Embryology at the School of Veterinary Medicine, Faculty of Health Sciences, AUTh, has a long-standing history on the veterinary education in Greece since its commencement in the mid 50s. Its teaching curriculum was presented at the 2010 XXVIIIth European Association of Veterinary Anatomists Congress in Paris. In 2021, during the first lockdown due to Covid-19 pandemic, Colorado State University was offering the digitized version of canine and equine anatomy for a short period of time to support veterinary students in learning anatomy online, since they were not allowed to attend the classes face to face. Following my inquiry, the set-up of the program was achieved through a collaboration between the Colorado State University (https://virtualanimalanatomy.colostate.edu/vaanopcomm) and the technical support of the eLearning platform of our university. Hence the program was installed for our third semester students (Anatomy and Histology III: digestive and reproductive system of domestic animals, avian anatomy) who got the opportunity to use this resource for a few months, as an additional self-directed study program. Following the completion of the semester over 200 students were asked for the evaluation of the resource, and few students (less than 10%) replied to the call. Mainly, although the 3D reconstruction of the anatomical areas, in a layer-oriented manner (musculature, blood supply, nerves etc.) was helpful to understand parts of the organs that were not allowed to see in reality, the terminology of the different anatomical parts in English limited their understanding. For the same reason, the students could not be examined, although they did better at the final exams of the course. Their better results cannot be attributed to the program, since there were other many factors, such as the online exam procedure through eLearning, that had been applied for lockdown purposes. Conclusively, there is a need to create the equivalent information in Greek in order to facilitate the learning procedure.

Veterinary anatomy in PLF

Precision Livestock Farming education was increased in recent years. There are e courses such as the following: https://tice.agrocampus-ouest.fr/course/view.php?id=917 given to students in Animal Science, animal caretakers and/or to the suppliers, or advanced courses: https://edu.iamz.ciheam.org/Precision_Livestock_Farming/en/, where among other course outcomes are animal monitoring through PLF technologies, or understanding the principles to generate PLF solutions and many more other initiatives.

PLF relates master programs also exist, like the one given in Italy: https://www.mvpa-unina.org/corsi/Livestock.xhtml, with a two year duration, or in France: https://www.isa-lille.com/academics/master-programs/agricultural-science/course-precision-livestock-farming/. All these teaching activities include basic anatomy teaching and it is necessary to create a veterinary anatomy module for the needs of PLF. Since the changes in veterinary anatomy that Salazar suggested in 2002, where a more applied approach was asked for, twenty years later, we can conclude that the prediction was visualized. More user-friendly anatomical approaches are needed to integrate into the PLF learning process. The main aspects of PLF consist on environmental, economic and social sustainability of livestock productions that could impact on both farmers and the community and consumers (Lovarelli *et al.*, 2020). These are the pillars where the veterinary anatomy module should be built on, where cutting edge technology will be used for the benefit of animals, environment, and humans. This way, the new anatomy education tool, will support ONE HEALTH initiative.

Conclusions

This paper depicts the importance and the current concepts of teaching veterinary anatomy. It provides the trends towards the use of alternative methods and digitized software programs in the veterinary curricula. Finally, it describes the temporary use of the canine and equine virtual anatomy provided by the Colorado State University from the students of our School. Since PLF education is on the rise, the same module in a less detailed manner should be also introduced.

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SESSION 5

Cows:
Feed Intake

Real-time classification of cattle behaviour using accelerometer sensors

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Abstract

In this study, we develop and validate a supervised machine-learning algorithm to monitor grazing and ruminating behaviours of cattle using accelerometer sensors. The method is specifically designed for performing real-time classification on resource-constrained sensor nodes. Twenty multiparous Holstein cows were used for this study. Each cow was wearing an AX3 accelerometer sensor attached to a neck-collar. The cows had daily access to a pasture between 7:30 AM and 2 PM for three weeks. Direct observations of the cows' behaviours were made to validate the sensor data. A new decision-tree algorithm (DT) was developed to classify the raw data. The decision-tree algorithm was selected for its low computational costs, which makes it implementable on the on-cow nodes. The DT presented an overall accuracy of 91% with a sensitivity and precision between 89-94% for ruminating and grazing behaviours. The hourly difference between the predicted and the observed (total) ruminating and grazing times (in min/h, mean±standard error) were 1.9±0.09 min/h (3.1% of the observed time) and 2.2±0.07 min/h (3.7%) respectively. This validation illustrates the potential of the collar-mounted accelerometer to classify grazing and ruminating behaviours.

Keywords: Accelerometer, dairy cows, machine learning, behaviours classification, precision dairy farming, grazing behaviour.

Introduction

Changes in behaviours could provide relevant information about nutrition, (re)reproduction, health, and welfare of dairy cows. Progress has been made in monitoring cows with electronic and biosensor devices (Lee and Seo 2021). In particular, wearable accelerometers have been widely used to automatically assess cow behaviours (Chapa *et al.* 2020). For example, grazing and ruminating times were recorded using HOBO accelerometers attached to the cows' jaws (Rayas-Amor *et al.* 2017). Martiskainen *et al.*, (2009) developed a method for automatically measuring and recognising several behaviours of dairy cows, including feeding and ruminating behaviours, based on a multi-class support vector machine (SVM). Although it yields high classification accuracy, it is well known that SVM require high computational costs (Abdiansah and Wardoyo 2015). In another study (Vázquez Diosdado *et al.* 2015), a decision-tree (DT) algorithm was used among other machine learning techniques to differentiate between lying, standing, and feeding behaviours with a neck-mounted accelerometer. The proposed algorithms did not consider ruminating behaviour and they also required a high sampling rate (50 Hz). Other studies (Greenwood *et al.* 2017; Kasfi, Hellicar, and Rahman 2016; Martiskainen *et al.* 2009; Smith *et al.* 2016) used algorithms with high computational load (e.g., deep learning), which could not be directly implemented on the on-cow sensor.

In practice, the on-cow sensors used for animal behaviour monitoring have very small batteries with low processing and storage capabilities. Furthermore, such batteries would need to operate properly and autonomously for long periods of time (e.g., five years) without being recharged or replaced; specifically for application on commercial farms. Therefore, data storage capability and energy consumption are important issues in using sensors for monitoring behaviour of dairy cows. A simple DT algorithm could be a crucial to reduce the energy consumption and maintenance requirements associated with recharging of batteries while maintaining acceptable performances.

In this paper, we validate a DT algorithm to monitor grazing and ruminating behaviours in dairy cattle using accelerometer sensors. This method, based on the DT, is specifically designed for performing classification in real time on resource-constrained sensor nodes. Consequently, it reduces the energy consumption and maintenance requirements associated with recharging of batteries while maintaining acceptable performances. The proposed algorithm and system further support the transition towards a continuous and large-scale monitoring of ingestive-related behaviour of dairy cattle.

Material and methods

Animals and housing

In total, 20 multiparous Holstein cows (milk yield 33.7 ± 3.5 kg/d; mean ± SD) were used in this study. Experiments were conducted between June and August 2020 at the Flanders Research Institute for Agriculture, Fisheries and Food (ILVO), Melle, Belgium. The cows had daily access to pasture between 7:30 AM and 2 PM for three weeks (grazing period). Drinking water was available ad libitum. Inside the barn, the cows were housed in an area compartment of 30 m long and 15 m wide with 24 individual cubicles and a concrete slatted floor. The cubicles (n = 24, width 115 cm, length from curb to front rail 178 cm, front rail height 70 cm, neck rail height 109 cm, neck rail distance from curb 168 cm) were bedded with a mixture of chopped straw, lime and water (Mader *et al.* 2017). The cows were fed roughage ad libitum and concentrates were supplied individually by concentrate feeders.

Data collection procedure

Each cow was wearing an accelerometer sensor (Figure 1). The accelerometer was attached to the left side of the collar of each cow as shown in Figure 1. The acceleration data (i.e., 3 orthogonal accelerometer vectors) were logged with a sampling rate of 10 Hz (10 samples each second) using Axivity AX3 loggers (Axivity Ltd, United Kingdom). The clocks of the observer and the accelerometers were synchronized at the start of the measurement.

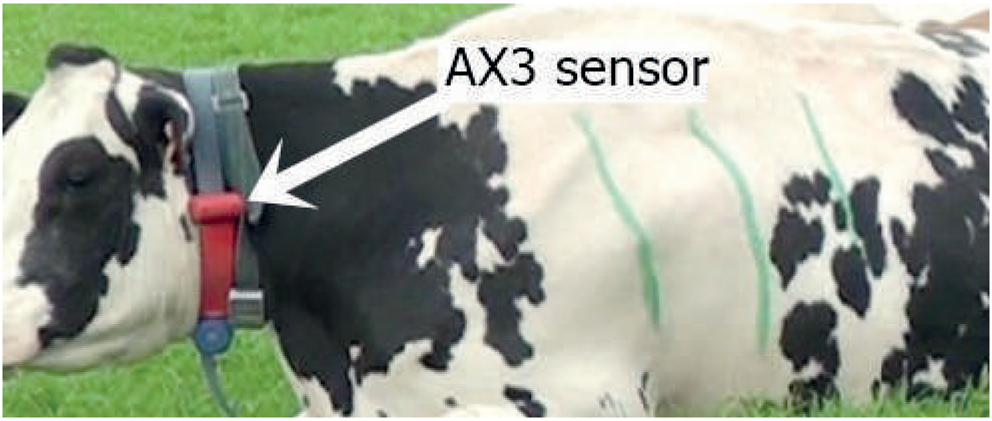

Figure 1: A cow wearing an AX3 sensor in the grazing field

Observations on the behaviour of the cows were made directly in the grazing field by a trained researcher. Table 1 lists the behaviours recorded along with their descriptive definitions. Every one-minute time window was assigned a label to refer to grazing, ruminating, and other activity (not grazing and rumination), respectively, based on the most frequent behaviour in that minute. As 5 hours of visual observation were available for 20 cows, 6000 samples of observed behaviours were obtained (i.e., 6000 min).

Table 1: Description of the observed behaviours and the number of samples of each behaviour (Number of 1 min time intervals for each observed behaviour)

Observed Behaviours	Description	Number of samples
Grazing	A cow has her muzzle close to or near the ground and is ripping the forage and chewing it (head position up and down).	2220 (37 %)
Ruminating	A cow is chewing and swallowing a ruminating bolus while moving her head and jaw with a circular motion.	2520 (42 %)
Other activity	Anything that was not grazing and rumination	1260 (21 %)
Total (SUM)		6000 (100 %)

Processing of sensors data

The data processing was performed using MATLAB software (Release 2019b, The MathWorks, Inc., Natick, Massachusetts, United States).

The accelerometer data (i.e., acceleration along X, Y, Z axes) were downloaded to a laptop and converted to .csv files using OmGui software version 1.0.0.43 (Newcastle University, UK). Similar to Benaissa *et al.* 2019, the acceleration sum vector (A_{sum}) was calculated as follows:

$$A_{sum} = \sqrt{a_X{}^2 + a_Y{}^2 + a_Z{}^2} \qquad (1)$$

Where a_X is the acceleration along the X-axis, a_Y is the acceleration along the Y-axis, and a_Z is the acceleration along the Z-axis.

Figure 2 shows a flow graph of the DT algorithm that was designed to distinguish between the three considered behaviours. As shown in Figure 2, the DT uses the overall dynamic body acceleration (ODBA) calculated from the A_{sum} values as presented in Benaissa *et al.* 2017.

The thresholds of the DT (Figure 2) were determined using the nested cross-validation technique as explained in Benaissa *et al.* 2019. The mean value of 19 obtained thresholds were 0.033 g with a standard deviation of 0.001 for the threshold 1, and 0.013 g with a standard deviation of 0.002 for threshold 2. The coefficient of variation was 6 % for both thresholds. These low values indicate the general applicability of the thresholds for other cows.

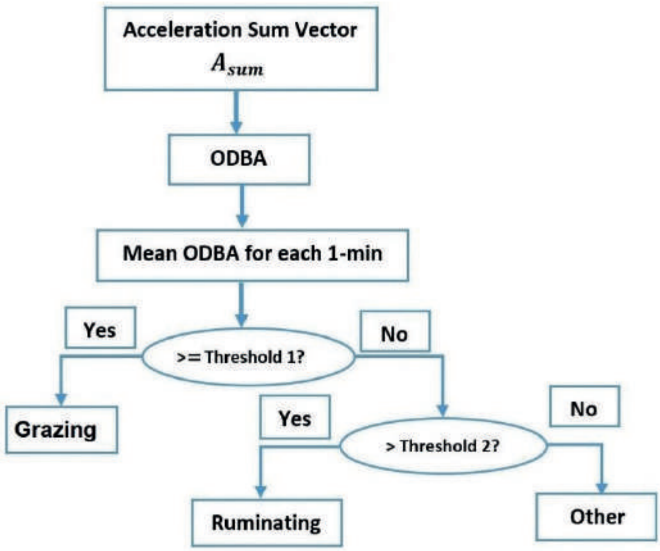

Figure 2: Classification approach using DT algorithm based on the overall dynamic body acceleration (ODBA). The scheme was designed to be implemented on resource-constrained embedded systems

Evaluation

To evaluate the classification algorithm, the precision, the sensitivity, the specificity, and the overall accuracy were used. In addition, the performance of the algorithm was evaluated in terms of the difference in ruminating and grazing times reported by the observations compared to the sensor. As explained in Benaissa *et al.* 2019, the leave-one-out cross-validation strategy was used to calculate the average precision, sensitivity and overall accuracy.

Results and Discussion

The precision, sensitivity, and specificity of the DT algorithm for each considered behaviour are listed in Table 2. The sensitivity of ruminating (92%) and grazing (90%) was higher than that of other activity (83%). Similarly, the precision of ruminating (89%) and grazing (94%) was higher than that of other activity (82%). The specificity was similar for grazing (97%) and other activity (96%) and lower for ruminating (91%). The overall accuracy was 91%. Table 3 lists the absolute difference in ruminating and grazing times (in min/hour and in % of the observed time) between observation and sensor (predicted). The hourly absolute difference between the predicted and the observed ruminating time (in min/h, mean±standard error) was 1.9±0.09 min/h (3.1% of the observed time). For the difference in grazing time, 2.2±0.07 min/h (3.7%) was obtained. This means an error between 6.6 and 11 min, which is less than 4 % of the observed grazing time (the observed grazing time ranges from 3 to 5 hours). Similarly, based on Grant (2007), a lactating cow spends 7 to 10 hours ruminating. This means that the daily error of the DT algorithm ranges from 13 to 19 min. This is less than 3 % of the daily ruminating time. Thus, the proposed DT algorithm can accurately detect grazing and ruminating times.

Table 2: Precision, sensitivity, and specificity [%] of the DT algorithm for each behavioural class

	Ruminating	Grazing	Other
Precision [%]	89	94	82
Sensitivity [%]	92	90	83
Specificity [%]	91	97	96

Table 3: Absolute difference in ruminating and grazing times (in min/hour and in % of the observed time) between observation and sensor (predicted)

	Ruminating time		Grazing time	
	Difference in [min/h]	Difference in [%]	Difference in [min/h] (mean±SD)	Difference in [%]
Mean	1.9	3.1	2.2	3.7
Standard error	0.09	0.15	0.07	0.12

Conclusions

This paper validated a DT algorithm applied to data from a neck-mounted accelerometer to monitor grazing and ruminating behaviours of dairy cows. The calculation procedure and the thresholds of the DT provided in this work could be useful for rapid and real-time implementations on resource-constrained embedded systems. The proposed method allows a possible reduction of the power consumption of the sensors and enable a large-scale deployment of the monitoring system. Future work will address the estimation of the power consumption reduction and a possible deployment in commercial farms.

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Grazing behaviour of cows can be predicted from accelerometer data using LoRaWAN to track activity in real time on commercial dairy farms

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Abstract

Knowledge of animal location and grazing behaviour can improve efficiency of management, especially if data are in real time. Two experiments were carried out in 2018 and 2020 on commercial dairy farms in England. In Experiment 1, collars were fitted to a total of ten cows selected at random across three commercial farms. Accelerometer data were collected at 10 Hz in three dimensions and stored to an Secure Digital card. Cows were observed in-person between morning and afternoon milking at 120 second intervals for six-hour periods daily over four days during the grazing season. Behaviour was classified and recorded as grazing, ruminating or other. These data were used to derive a regression between accelerometer data and manually-observed cow activity ($p < 0.001$, predictive accuracy 95%, specificity 91%, sensitivity 98%). In Experiment 2, bespoke Long Range Wide-area Network (LoRaWAN)-enabled collars were fitted a total of thirty-two cows selected at random across four herds to collect the same accelerometer data. Data were summarised at 120 second intervals for a total of twenty-one days and the regression derived in Experiment 1 was used to predict grazing activity. Summarised results along with GPS position were uploaded to a LoRaWAN gateway at 120 second intervals. The data showed clear patterns of grazing and ruminating with the longest period of grazing in the evening and little or no grazing at night.These results can be used to test the hypothesis that grazing patterns can be modified and to determine grazing patterns within a field and over time.

Keywords: dairy cow, grazing behaviour, LoRaWAN, GPS, real-time data collection

Introduction

Previous work has shown that accelerometer data can be used to predict feeding activity (Pereira *et al*, 2020) and that cow position can be tracked by GPS (Williams *et al*, 2016). Modern LoRaWAN technology allows this data to be collected in real time. Developments in electronics and battery capacity allows commercial application with a 'fit and forget' approach possible from a farmer's point of view. Collecting such data from commercial dairy farms would allow grazing practices to be assessed and improved. Cow management could be altered to better match the cow's activities. Grazing times and the duration of milking routines could be monitored and bench marked to improve commercial herd performance. This paper presents initial results from work carried out to deploy such technologies on commercial dairy farms in southern England.

EXPERIMENT 1

Material and methods

Data were collected using dataloggers (Adafruit Feather M0 Adalogger) linked to a triple-axis digital accelerometer (ADX1345) and a real time clock (DS3231). They were powered by a single D-Cell battery (SAFT LS33600) mounted in an industry standard enclosure. The enclosures were attached to collars (Kerbl) to give a total weight of 350g. Collars were fitted to the neck of each cow such that the enclosure hung ventrally. Data (timestamp and three acceleration values in mG) were collected at 10 Hz and written to a 16 Mb Secure Digital card. Cows were fitted with collars after an afternoon milking and identified with high-visibility neck collars and several debrided Estrotect patches (Estrotect, USA). Data collection ran between morning and afternoon milkings the next day. Collars were removed on the third day and the data downloaded from the SD cards.

Cows were selected randomly from three commercial herds (Table 1) and were in an established management pattern of grazing day and night with milkings through a herringbone parlour morning and evening.

Table 1: Details of commercial herds used in experiment 1

	Herd size	Milk yield	Number of cows observed	Date of trial
C1[a]	270	9,300	2	2 May 2018
C2[a]	270	9,300	4	25 May 2018
M	250	9,500	2	15 May 2018
W	160	8,000	2	7 June 2018

[a] Farm C was used on two occasions

All cows were observed by one person (ATC) whilst they were at grass with observations recorded every 120 seconds. Three activities were identified – 'eating', 'ruminating', 'other'. Data and timestamps were encoded into Excel (2016). Where the eating activity was the same on successive observations it was assumed the activity was constant throughout the 120 second period. Where the activities at start and end of the 120 second period differed the data were rejected.

Data analysis

The three acceleration values were combined into a single vector and the magnitude recorded. For each 120 second interval the standard deviation (SD) of the 1200 magnitude readings was calculated. The SD of the acceleration vector was compared to the observed animal behaviour using logistic regression (Minitab, v16) to model the probability that the cow was grazing ($p_{(graze)}$) at the time.

Results

A total of 1456 useable observations were collected from the ten cows with 959 being for grazing behaviour and 497 for ruminating. The logistic regression equation was

$p_{(graze)}$ = exp(Y')/(1 + exp(Y')) where Y' = -3.87 + 0.043 SD (1)

R^2 = 0.824, $p < 0.001$, predictive accuracy 95%, specificity 91%, sensitivity 98%

Figure 1 shows distribution of the observations by eating activity and calculated $p_{(graze)}$ value. There is a very clear separation of the two eating activities with very few observations with intermediate $p_{(graze)}$ values.

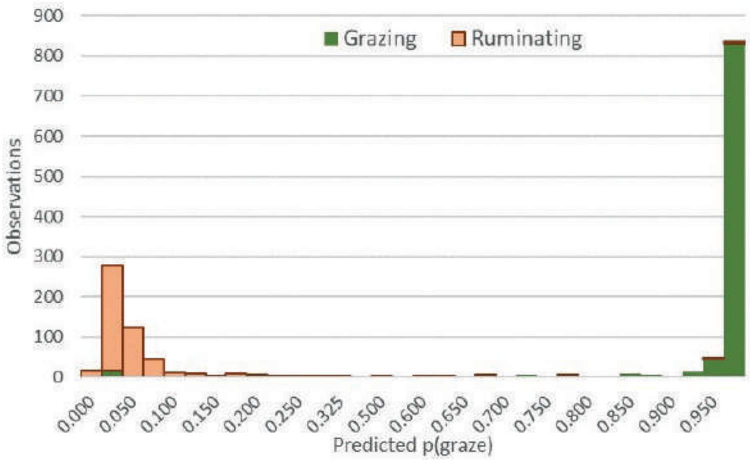

Figure 1: Separation of the 1456 feeding behaviour observations by the derived logistic regression equation (1)

EXPERIMENT 2

Methods and materials

Bespoke Long-Range Wide-Area (LoRa) collars were developed by SK (www.hoofprints.xyz) . The collars collected triple axis accelerometer data at 10 Hz and reported the standard deviation of the 1200 vector magnitudes (as in Experiment 1). GPS fixes were obtained every 120 seconds and reported to six decimal places. The sensors and electronics circuit board were housed in a standard enclosure and powered by a single SAFT D cell battery (as above). Battery life was more than eight months. The enclosure was mounted on a weighted cow collar (Kerbl) to give an overall weight of 850 g. The collar was hung on the cow such that the enclosure lay high on the left side of the neck just behind the ear.

A LoRaWAN Gateway was installed on a suitable farm building to be as high as possible (8 – 12 m high) to give good line-of-sight to all grazing paddocks. Data were transferred over the mobile phone network through The Things Network to the Google Data Studio website where a series of bespoke reports were developed to handle and process the data and derive the $p_{(graze)}$ parameter as defined in Experiment 1.

This paper will present results from one cow (number 1701) on one day (9 Aug 2020). Cow 1701 was in a group of approximately. 150 grazing cows grazed night and day and milked twice a day through a 54-point rotary parlour.

Results

Collars were fitted to thirty-two cows across four commercial farms (eight cows per farm) and data were collected for twenty one consecutive days during the summer grazing season. Figure 2 shows the GPS fixes obtained for cow 1701 on 9 August 2020. During the first night grazing (00:00 to 06:00) the cow grazed the paddock labelled A. She then walked to the buildings and milking parlour (B) before returning to a new paddock (C) for the daytime grazing. She returned to the milking parlour at about 14:00 and then went to a new paddock (D) from 15:00 to 24:00. Sunrise was at 05:48 and sunset at 20:44 with a minimum temperature of 15°C at 05:00 and maximum of 27°C at 17:00 (www.darksky.net)

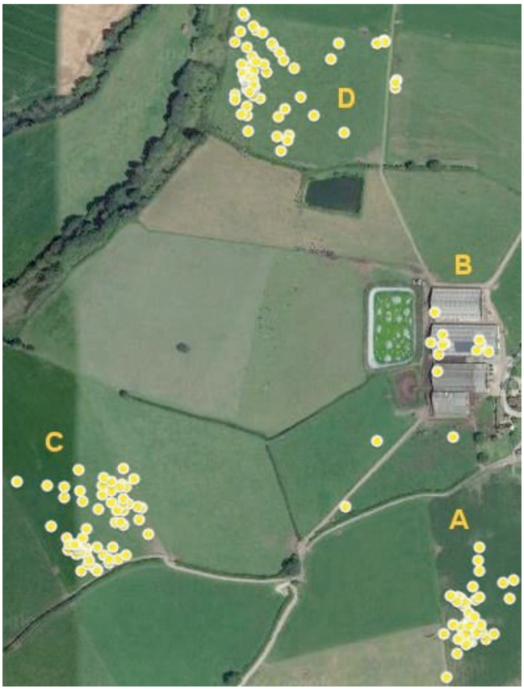

Figure 2: Google Maps image overlain with GPS position fixes for cow 1701 collected over the LoRaWAN network every 120 seconds. A, C, D symbols mark successive grazing paddocks, B is the milking parlour and associated buildings

Figure 3 shows the pattern of grazing over the 24-hour period. There was very little grazing during the hours of darkness with a single short bout around 02:00. There was an intense grazing period immediately after morning milking until 08:22 and then a period of ruminating until 10:30. From 10:30 until milking at 14:20 there was a mix of short grazing periods and rumination bouts. After the afternoon milking there was a long grazing bout from 15:10 to 17:02 and, after a short period of rumination (17:08 to 17:50), there was another long grazing bout until 20:28 after which the cow ruminated until midnight. There seem to be two distinct states during the rumination periods, a state with very low $p_{(graze)}$ value (under 0.05) and a second state with slightly higher $p_{(graze)}$ values between 0.05 and 0.2.

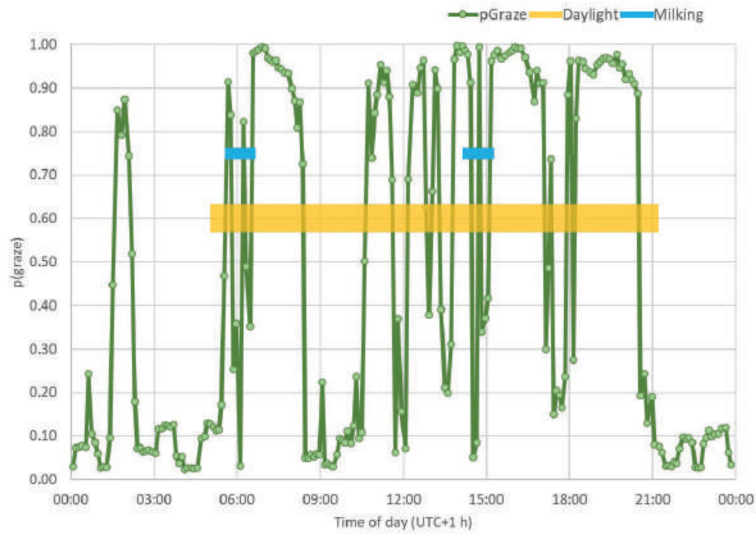

Figure 3: Pattern of grazing and ruminating [$p_{(graze)}$] over a 24-hour period on 9 August 2020 for cow 1701. Daylight hours overlain in yellow and milking times as blue bars

Figure 4 shows the GPS fixes for the grazing pattern when the cow was grazing paddock C during the day (06:40 to 14:00) . On entering the paddock, she moved to the NW quadrant walking large distances between GPS fixes (colour coded yellow) before moving to the SW quadrant where she remained from about 07:00 to 10:00 (colours yellow, green, light blue); from 09:00 to 10:00 her movements between GPS fixes were much smaller. From 10:00 through to 14:00 she moved to the NE quadrant with more movement between the GPS fix points (coded blue, purple, brown).

Figure 5 shows the cow's eating activity plotted across the grazing paddock. The cow mainly grazed (blue diamonds) over the paddock in the NE and SW areas of the paddock leaving a diagonal band ungrazed. She ruminated in the SE quadrant with little movement between the GPS fixes and even spend some time in the very low $p_{(graze)}$ state (yellow, stars). Her activity when in the NE quadrant shows bigger distances between fixes suggesting she was walking more and only occasionally ruminating.

Figure 4: GPS fixes for cow 1701 on 9 Aug 2020 from 06:00 to 14:00. Fixes only plotted every 360 seconds for graphical clarity. Fixes numbered and colour coded according to the hour of the day

Discussion and Conclusions

This paper presents initial results from tracking the location and grazing activities of milking cows on commercial dairy farms. The use of the SD of the acceleration vector magnitudes yielded a very accurate logistic regression with clear separation of the two eating activities and very few intermediate values (Figure 1). It is likely that these data can differentiate other activities. There appears to be two separate states in the 'rumination' category (Figure 3). On farm observations suggest that the very low $p_{(graze)}$ values are associated with a 'sleep' state and the higher values with actual rumination and bolus chewing. Further attempts to formalise this observation have been hampered by the observer affecting the cow behaviour.

Figure 5. GPS fixes for cow 1701 on 9 Aug 2020 from 06:00 to 14:00. Fixes only plotted every 360 seconds for graphical clarity. Fixes numbered and symbol coded according to $p_{(graze)}$ band. Band 1 (yellow, star) is very low $p_{(graze)}$ [< 0.05], 2 (red, cross) is rumination [$p_{(graze)}$ 0.05 - 0.25], 3(grey, square) is uncertain feeding activity ($p_{(graze)}$ 0.25 - 0.75) and 4 (blue, diamond) is grazing ($p_{(graze)} > 0.75$).

The GPS data clearly identify where cows graze. These data could be used to monitor pasture productivity at the individual paddock level which might aid re-seeding and other management decisions. As the dairy industry starts to quantify the carbon-sink potential of long-term grassland such data might give some formal objectiveness to such decisions. Whilst these data can already be recorded on farm (eg www.agrinet.ie) our approach would minimise the daily data recording that is often a challenge on a busy farm. The data can also help measure timing and duration of milking (i.e. time away from grazing grounds). Intensive housed systems in North America generally set a target of 3 hrs/day for cows to be away from their housing/feeding area

(Gomez & Cook, 2010) to maximise milk production but such monitoring is rarely carried out on grazing units.

Figure 3 shows the pattern of eating during the day and this graph is typical of data for other cows and on other days (data not shown).

— Cows do not graze very much at night – once the sun sets there is minimal grazing until sunrise
— There is a major grazing bout after afternoon milking – here split by a short period of ruminating. This may be particularly important in hotter weather (27° C at 17:00) where cows suffer heat stress during the day and efforts should be made to allocate extra evening grazing in such situations.
— There is a major grazing period just after morning milking. On this farm the cows do not get the opportunity to graze before morning milking as there is little time between sunrise and milking starting. After the morning grazing there was a long period of rumination.
— From 10:30 the cow's activity was more disjointed with short grazing and short rumination periods, and it is likely that intakes (kg DM/hour) were lower at this time. The major grass intake periods, on this farm, were early morning (until 10:30) and after afternoon milking.
— There was a short, intense period of grazing staring at 13:50 until the cows were brought in for afternoon milking at 14:29 (Figure 3). On-farm observations confirmed that this was common to all cows and all days and helped to increase total daily feed intake. In practice the maximum benefit from this grazing period will only be achieved if cows are brought in for milking at a consistent time.

Figure 4 shows a clear diagonal band in the field that cow 1701 did not use. The ground slopped down to the NW exposing several gravel ridges across the field and on inspection the area she ignored only supported low grass growth. Such observations suggest that our results could be used to assess variations in grass supply within fields.

Careful inspection of Figures 3, 4 and 5 allow an eating time-line to be constructed. Cow 1701 entered the field at about 06:30 after milking and grazed intensively up into the NW quadrant before moving to the SW quadrant where she moved around and grazed less and even showed some 'sleep' behaviour. At around 11:00 she moved to the NE quadrant where she grazed and ruminated until she moved to the buildings for milking.

The initial results presented in this paper suggest that the approach used could be exploited on commercial farms to improve the precision management of grazing systems. The authors have since used these results to investigate if timing new grazing allocations to fit cow behaviour will increase grass intakes and milk production.

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Development and evaluation of an autonomous and automatic monitoring system for grazing cattle

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Abstract

Increasingly, consumers shift to more sustainable food. Accordingly, cattle farmers pay increased attention to each animal using individualised automated monitoring. This is easy for cows in production, i.e. during milking, but complicated for grazing cattle. Therefore, we aim to develop and evaluate an individualised monitoring system for grazing animals based on electronic identification.

One indicator of welfare is the ability of animals to move, so we developed an energy-autonomous monitoring system located at the single entry to the trough. Using the RFID electronic identification tag, it automatically acquires the times of passage to the trough for each animal with a detection rate of 100%. Our hypothesis is that an animal that is unable to water needs human intervention. Although the animal is still able to water, its health condition may still deteriorate, so we take advantage of the animal's watering passage to collect information on its morphology using 3D cameras. The monitoring of well-being via point clouds is generally based on data from the animal's pelvis, so our gantry aims to collect 3D data from the pelvis from two different points of view.

When an animal is detected, each camera acquires a sequence of three-point clouds. 87% of these point clouds contain an animal and 29% can be used and selected automatically for further processing, all directly on site. In the future, the monitoring system could also collect data from wearable animal sensors.

Keywords: Welfare monitoring, Pasture, 3D point cloud

Introduction

The diminution of genetic diversity in herds as a result of intensification of milk production reduces herd resilience (Makanjuola and Taylor-Robinson 2020). Moreover, organic milk represents a growing portion of the production (from 3.5% in 2019 to an expected 8% in 2031 in Europe) (EC, 2021) to meet consumer demand for increased attention to health and animal welfare. Individualised monitoring of each animal is therefore increasingly essential on cattle farms.

Monitoring animals at the barn is facilitated because it is a protected environment that can easily be monitored by sensors or human observers. Pastures are an uncontrolled environment, sometimes located far away from the farm, which limits the possibility to install sensors and the time available for direct observation of the animals. Monitoring grazing herds is therefore a critical point in the management of a farm (Spigarelli *et al.* 2020).

There are two main approaches to monitoring grazing animals using sensors to help the farmer to monitor a herd: systems relying on stationary sensors or ones relying on sensors attached to animals (Frost *et al.* 1997). Ruuska *et al.* (2016) already compared these two approaches to monitor eating, rumination and drinking behaviour. It appears that sensors attached to animals can be expensive in the case of a large herd while the current trend in livestock farming is to increase the size of farms and herds. Fixed sensors could be capable to observe all animals, but size of the pastures makes it difficult to cover all the area. For this purpose, the waterhole access is an ideal location to observe free range animals as it constitutes a regular visiting point.

Each animal should then be identified so that measurements can be individualised. Different solutions can be considered. The first is to use visual recognition of the animal via computer vision. Given the decreasing price of cameras and processing hardware, this solution is financially interesting but most of the time they are based on the cow's coat which is a problem for breeds with very similar individuals (Okura *et al.* 2019), such as Aubrac or Limousin cattles. This technology is therefore restricted for herds where the individuals have a different coat from each other, such as Holsteins or Belgian Blue Whites. Another solution is to take advantage of electronic identification and use RFID chips placed directly in the animal's earring (Williams *et al.* 2020). This method avoids the problems associated with the breed of animal and is much more robust.

The identification of the animals at the entrance to the watering trough therefore makes it possible to monitor the frequency of watering of the animals (Williams *et al.* 2020). This indication can be used to detect an abnormality in the animal's behaviour. For example, an animal that does not come to the watering during the day, when in these climatic conditions it normally comes two times a day, may be unable to move to the watering trough and therefore need the intervention of the farmer.

Coupled with watering detection, monitoring the animal's physical development can provide useful information to the farmer. Therefore, regular evaluation of indicators such as Body Condition Score (BCS) or animal mass is a common tool for herd management (Anglart 2010). Most successful algorithms of this type are based on 3D data of the animal's pelvis (Spoliansky *et al.* 2016; Rodríguez Alvarez *et al.* 2018)BCS is performed manually by experts. This paper presents a 3-dimensional algorithm that provides a top- ographical understanding of the cow's body to estimate BCS. An automatic BCS system consisting of a Kinect camera (Microsoft Corp., Redmond, WA, so, adding 3D cameras on the watering access could produce valuable data for the farmer.

This data must be acquired and processed automatically to be completely free of human intervention. Another sensitive point linked to positioning in pastures is the energy aspect, as the monitoring tool must be able to operate autonomously since most pastures are far from the grid access.

The objective is therefore to propose an energy autonomous and automatic monitoring tool that can be placed on pasture, to produce qualitative data on cattle health and well-being.

Material and methods

This section presents the autonomous measuring gantry that was created to be installed on the water through passage to record animal accesses and 3-D views to fulfil the monitoring objective

Structure

Our gantry is made of galvanised steel. A 3D representation and the plans of the gantry are shown in Figure 1. It is 2.9m long and 3.4m high. The bars are hollow tubes of 6cm diameter for the lower part of the gantry. The roof is made of square tubes of 6cm side as well. All tubes are 3mm thick. The passageway is trapezoidal, 80cm wide at the base and 140cm at 2.3m high. Stability is ensured by two 140cm U-shaped beams placed towards the ground perpendicular to the passage of the animals. The details of the plans and the used materials are available online[1].

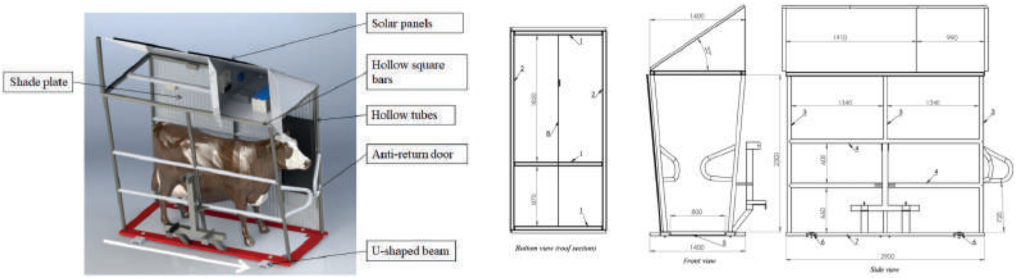

Figure 1: 3D representation (left) and plans (right) of the measuring gantry

One-way passage is ensured by an anti-return door located at the end of the passage. On top of the gantry, two solar panels are installed on a 33° slope roof for Belgium latitude. Under this roof there is a box where elements that need to be protected from the rain are stored. A shade plate is placed on one side of the gantry. This plate should be south facing in the north hemisphere when the gantry is installed so that maximum shading is provided over the measurement area during the day.

To test the structure of the gantry, it was installed in pasture for two pasture seasons. The first season was from 13 August to 23 October 2020 and the second was from 12 May to 15 November 2021. During these two periods, the maximum air temperature was 34°C, the minimum air temperature was 0°C and the maximum daily rainfall was 139mm. These measurements have been recorded by the meteorological station of the farm where the gantry was installed. This station was 700m away from the gantry for the first season and 160m away for the second season of measurements. The appearance of the gantry and observed damages to it after the two seasons of use was studied to conclude on the robustness of the device.

1 Permanent link: https://gitlab.uliege.be/Justine.Plum/ecplf-justine-plum

Taking measurements

As they pass by, the animals are identified via an Agrident ASR650 RFID reader for their ear tags placed on the animals' left ear. This detection triggers the acquisition of point clouds using two Intel Realsense D435 cameras via an on-site computer (AAEON UP Squared UPS-APLC2F-A20-0432). The acquisition code (python3.7) is available online[1]. After two months of experimentation, we were finally able to adjust the position of the RFID antenna to reach a 100% detection rate. The antenna (Agrident APA160 100 x 60cm panel antenna) is placed at 40cm from the ground. As animals tend to lower their heads to pass through the gates (Figure 2), this arrangement ensures detection during each passage. When an animal is identified, the time of its passage is recorded.

Figure 2: Typical passage of an animal through the non-return door (left) and Protective housings containing Intel RealSense D435 cameras (right)

To verify the performance of the RFID sensor, we placed a trap camera in front of the gate to record all animal passages through the gate. The camera was placed for one day and recorded the passages of each animal on the pasture during that day. The images from the camera were then manually compared to the passages recorded by the camera and those recorded by the RFID reader.

The point clouds are acquired via the two 3D cameras. They are placed at 2.3m from the ground, one is placed facing the ground, allowing a NADIR view of the animal. The other is placed at an angle of 33° to the horizontal. Both are placed 1.3m from the RFID antenna, at the beginning of the gantry. This arrangement ensures that the animal's pelvis is visible by the cameras when the head of the animal is positioned at the RFID antenna. The Intel RealSense D435 cameras are protected in customized housings. They have been created by machining aluminium casting waterproof enclosures (Figure 2).

For the camera with a NADIR viewpoint, the resulting point clouds must be usable for the most common algorithms for BCS estimation base on 3D data. Criteria have been established to define whether a point cloud is usable or not. A point cloud is therefore valid if it represents the entire area useful to the algorithms. From this point of view, a point cloud is considered valid if the pelvis of the animal is clearly visible and not cut off, if the point cloud does not contain any holes and if the noise of the point cloud is not too high. Examples of a valid and of an invalid point cloud are shown in Figure 3.

Figure 3: Valid (left) and invalid (right) point cloud example

Regarding the camera with a tilted view, this type of view is not widely used in the literature. The criteria are therefore not yet established and need to be studied further.

Energy

The energy requirement of the gantry was estimated at a maximum of 600Wh per day with a peak power requirement of 30W. These values were obtained as follows: according to the manufacturer, the typical consumption of the computer is 18W, since it works 24 hours a day, we estimated the consumption of the computer at 432Wh, considering that it does not go on standby. When the computer was processing point clouds, its measured consumption rose to 25W maximum, the estimated calculation time per day being a maximum of 3 hours for a herd of 30 animals, the additional consumption linked to calculations is 21Wh. To obtain this calculation time, we counted 10s for a heavy processing per point cloud. Each animal can pass up to five times and each pass generates six point clouds. We therefore obtain a total of 9000s of processing for 30 animals and therefore 2h30min, rounded up to 3h for safety. According to our measurements, the RFID reader consumes up to 5W when an ear tag was detected. Since the reader works 24h a day, we have a consumption of 120Wh per day. The total maximum consumption is therefore 573Wh with a maximum peak of 30W.

We decided to use solar panels to power the gantry on the pasture because of the wide availability during the grazing season. The amount of energy produced depends on the amount of sunlight. A typical grazing season is from April to September, so we focused the sunshine during this period for the location. The average 24h exposure during this period is 4087Wh/m² in Belgium, where the experiment took place. The orientation of the panels will also have an influence. In Belgium, the recommended panel inclination is 30 to 35°, supporting the 33° applied to the roof of the gantry. Given the cloudy weather occurrence probability, it was decided that the gantry should be able to operate for three days without producing a significant amount of electricity. To meet these needs under these conditions, the gantry was equipped with two 300Wp monocrystalline solar panels, a 48V 60A MPPT controller, a 12V 200Ah GEL Ultracell battery, a 12V-5V converter and a 12V-12V converter. A summary diagram is presented in Figure 4. With this material, we can expect a production of 23kWh for our location and the most limiting month (November) while the monthly consumption is estimated at 18kWh.

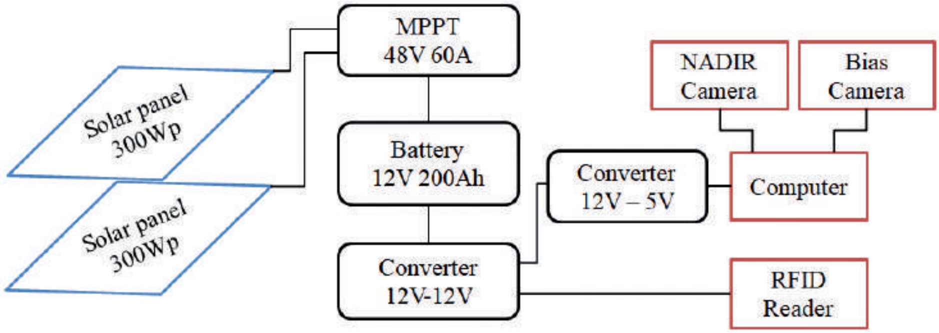

Figure 4: Diagram of the electrical installation

Results and Discussion

Performance of the gantry structure

Initially, the box containing the equipment related to electricity generation was attached to the side of the gantry (Figure 2). This arrangement was modified as the box was a sensitive point of the gantry because of cow scratching themselves leading to a fell down during the first measurement campaign. The equipment is now placed under the roof of the gantry.

Both the galvanized steel and the shading panels held up for 2 seasons of measurements. No damage was found, neither from animals nor from the weather. The gantry remained in place during both seasons despite the interaction of the animals and the wind on the pasture. The structure also supported the various transports via tractor and forks for a total of six displacements. Currently, a three-point hitch is used to attach to the gantry during transport. As other transport methods than by tractor 3-point hitch can be more convenient as fork lifter, the structure can be adapted so that it can support the farmer's favorite carrier.

Measurements performance

The observation with the trap camera resulted in a 100% detection rate of the 21 passages of the day. Typical cases of passage were represented during this day. These included animals passing quickly and slowly, animals of different sizes and two animals following each other directly. The RFID sensor is therefore robust and works perfectly for this type of use.

The second season of measurements recorded 1478 animal passages, with an average of about 14 hours between two passages for the same animal. The total number of passages in one day and the number of animals present on the pasture that day are presented in Figure 5. We see that the number of passages is not proportional to the number of animals present on the pasture, which means that external elements influence the behaviour of the animals, pushing them to move more or less frequently to the watering place. These factors will be investigated further in a later study.

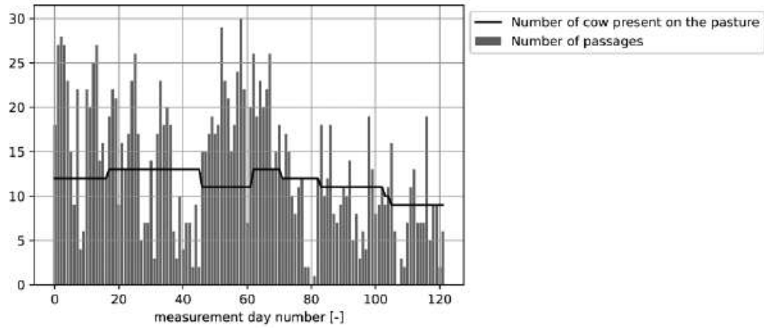

Figure 5: Number of passages recorded per day and the number of animals present on the pasture for the second measurement campaign

The 3D camera with a NADIR viewpoint was able to obtain 87% of point clouds containing an animal. A rate of 29% was constituted of valid images for conventional processing. This proportion results from the fact that during each passage, a set of 3 successive point clouds is acquired to accommodate the variable speed animals move through the gantry. As the acquisition frequency of the camera is set 3Hz, the time elapsed between the first and the last image is 1sec. This delay allows the animal to move through the gantry. In the case of a fast passage, the last image tends to be invalid and the first tends to be valid, whereas in the case of a slow passage the opposite phenomenon is observed.

During the first season, interruptions were recorded in the measurement process, due to hot summer combined resulting in overheating of the computer equipment placed in plastic cases. These cases were replaced by aluminum enclosures to dissipated excess heat, which solved the problem. This problem will depend on the consumption of the computer equipment placed on the gantry and therefore on the application of the gantry. In both seasons there were interruptions due to hardware failures in the USB ports. The problems were related to the hardware itself, so they shall not be repeated in other conditions.

Energy autonomy

There were no interruptions due to a lack of energy. However, the point clouds have not yet been processed locally. In our energy consumption calculations we estimated the extra consumption due to computing at 21Wh per day. The current energy design allows for this increase in consumption. Moreover, we estimated a calculation time of 10s per point cloud, whereas our algorithms give us a calculation time of less than 2s, the overconsumption linked to calculations does not therefore represent a problem to be addressed.

Data obtained and usage

The data obtained during the passages are a time of passages to the water point and point clouds. The processing of the point clouds consists, first of all of, segmenting them in order to extract the points representing the animal. It then consists on sorting them into valid and invalid point clouds. Our firsts algorithms give us encouraging results, both for the estimation of the BCS and for the sorting of valid and invalid point clouds. The passages study allows us to hope to use the monitoring of passages at the watering point as a tool for monitoring the health status of the animals. In all cases, algorithm development is still in progress.

Conclusions and perspectives

We conducted research to develop a monitoring tool for grazing cattle herds. To do so, we built a gantry to acquire data to calculate indicators of the health status of the animals. We then tested the gantry during two grazing seasons to prove its resilience to climatic conditions, the presence of animals and to several displacements in the farm. At the same time, we established the ideal positioning for sensors classically used for the calculation of animal health indices. We also tested the aspect of energy autonomy provided by solar panels and battery on the gantry level.

The gantry has met the requirements for two seasons. It can therefore be used for further research and for practical implementation. On this basis we built three new gantries. These will be placed in three more farms in order to collect a large amount of new data with a higher variability. This new measurement campaign will also be used to get feedback on the use of the gantry on the farm. These gantries have been adapted to each farm, with a customised attachment for movement according to the farmer's needs.

As the gantry is placed in a pasture, it is planned to integrate a data transmission system to facilitate access to the data. For example, a Low Power Wide Area Network, such as LoRaWAN, could be used to report indicators such as the BCS.

Acknowledgements

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Evaluation of bunk cameras to characterize individual feeding behavior in conventional pens

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Abstract

Feed efficiency and dry matter intake (DMI) have major economic impacts on feedlot cattle production. Individual monitoring of DMI can provide data for evaluating animal health and informing marketing decisions. Currently, there are no commercial technologies available to accurately measure individual animal DMI. To evaluate the feasibility of using bunk cameras to identify cattle feeding behaviour for use in DMI prediction, forty-eight Angus-cross steers were housed in four pens with concrete bunks. Pens were equipped with solar-powered camera modules placed 4.6 m above the ground. Steers were uniquely identified using colored adhesive patches that were placed at varying locations along the spine. Images were taken at one-minute intervals, and initial machine vison algorithms were developed to test identifying patch combinations and recording frequency of daily bunk visits (BV) and mealtime (MT). Individual MT were summed to daily eating duration (ED). Trained observers reviewed camera images and reported daily BV and ED for each steer. Algorithm BV and ED predictions were compared to those reported by the reviewers. The effect of camera image interval on MT was evaluated using reviewers that observed steers pen-side. Based on 166 records, average ED was reported as 132 ± 31 by image reviewers. Algorithm ED predictions averaged 13 min less than reviewer ED, based on 137 individual records. On average, MT measured pen-side was two minutes less compared to MT predicted by the algorithm. These results suggest that bunk cameras can identify ED and may be useful for individual steer DMI prediction in group pens.

Keywords: feedlot, cameras, dry matter intake, bunk management

Introduction

Accurate prediction of animal dry matter intake (DMI) is fundamental for optimization of feedlot cattle production. With increasing pressure for a reduction in greenhouse gas emissions from the livestock sector, enteric methane emissions must be accurately quantified. Models predicting enteric methane intensity require DMI, as methane production is proportional to feed consumed (van Lignen *et al.*, 2019). Improvement in feed efficiency, measured as unit of live weight gain per unit of feed consumed, is constrained by the inability to commercially measure DMI on an individual basis.

Current methods for measuring individual animal DMI are costly and impractical in conventional production systems. Previous research has estimated DMI using dietary net energy, animal requirements, and body composition (Oltjen *et al.*, 1986; Hicks *et* *al*., 1990; NRC, 2016). However, such models typically over or under predict, as DMI is controlled by a multitude of complex factors, including feeding behaviour (Allen, 2014).

Eating duration, meal frequency, and other feeding behaviours have been positively associated with DMI in beef (Kelly *et al*., 2020; Parsons *et al*., 2020) and dairy cattle (del Mol, 2016). These studies focused on identifying correlations in small research pens with limited animal competition, which may not accurately reflect feeding behaviour in larger, commercially viable pens. The aim of this study is to use bunk cameras and a machine-learning vision algorithm to evaluate the feasibility of monitoring individual animal feeding behaviour in conventionally, group-housed cattle.

Material and methods

This study was conducted with an approved University of California, Davis Institutional Animal Care and Use Committee protocol at the UCD Feedlot (Davis, CA). Forty-eight Angus-cross steers (initial body weight 343 ± 27 kg) were weighed, stratified by body weight (BW), and allocated to four pens (12 steers/pen), so each pen had a similar mean initial BW. Cattle were managed to a slick bunk and fed a high-energy diet twice daily.

Pens were equipped with 12 m concrete bunks and an automated waterer. Solar-powered, WiFi-enabled Precision Livestock Technologies, Inc. (PLT; Dallas, TX, US) camera modules were placed 4.6 m above the ground at the end of bunks. Two pens had a single camera module, and two pens had two camera modules, one at each end of the bunk. The cameras captured bunk images at one-minute intervals from sun-up to sun-down, and at 15-min intervals through the night. Steers were uniquely identified using colored adhesive patches that were placed at varying locations along the spine (Fig. 1). An initial version of a machine vision algorithm was developed by PLT to identify steers by patch combination and record daily the daily frequency of bunk visits (BV) and mealtime for each visit (MT). Patch color combinations and orientations were correlated, and the algorithm recognized individual animals and recorded their presence within a defined zone (e.g., head in bunk). Images were then compared in sequence to record the duration of time a steer spent within a particular zone. This initial machine learning algorithm was developed using a two-stage approach: 1) a YOLOv5 model was used to detect steers in an image, and 2) the deep features were extracted from the detected regions using a convolutional neural network model that was trained with ArcFace loss for animal identification using a dataset that was gathered and annotated by PLT. Cosine similarities were calculated between the resulting embeddings to group and identify images of steers by visual similarity. Such advanced techniques were used to also estimate individual animal BW within the defined zone.

Individual animal MT within a day were summed, and daily eating duration (ED) was calculated for all animals in the pen. Algorithm predictions were evaluated using a 28-d observational period. Six interns were trained to identify steers by patch combination and record the BV start and end time using images from the cameras. Observer training consisted of a 2-hr instruction session and successful completion of a training dataset. Observers ED totals were required to be within ±5% of the trainer's estimate.

Figure 1: A camera image capturing steers eating at the bunk

To ensure the images taken at one-minute intervals were an accurate depiction of actual animal MT and ED, trained observers reviewed animals pen-side. One reviewer was assigned to a single pen and recorded BV frequency and MT for all 12 animals in the pen. Pen-side reviewers observed cattle for 3-d during the observational period. On days of review, observation began at feeding time (0630 h) and continued until 1000 h, and again in the afternoon at feeding time (1430 h) until 1800 h. Mealtime observed pen-side was compared to MT predicted by the algorithm and camera observations only during the time pen-side observers were present.

Statistical Analysis

All statistical analyses and plot generation were performed in R (version 1.3.1093). Plots were generated using the ggplot2 package. Correlations were evaluated in the base R package, using the cor.test function.

Results and Discussion

Across 240 daily individual animal observations, average ED was 142 ± 31 minutes based on camera reviewer observations. Observers were able to successfully identify cattle by patch combination in pens with single and double cameras. Algorithm predictions from pens with single cameras were inaccurate, an image from both angles was required. Thus, algorithm results are only presented for pens with two cameras. Table 1 presents the mean daily BV frequency and ED by observers using camera data and the proposed algorithm across 137 animal records. Average ED in the current study was consistent with the average ED (142 ± 25 min) reported by Kelly *et al.* (2020).

Table 1: Mean daily bunk visit (BV) frequency and daily eating duration (ED) for camera observation and algorithm predictions

Parameter	Camera Observation	Algorithm
Daily BV frequency	9.03	7.68
Mean ED, minutes	92	79
SD ED, minutes	29	28

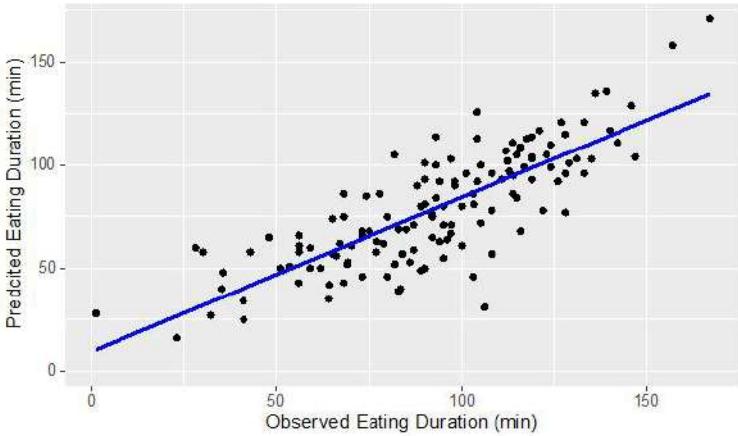

Figure 2: Algorithm Prediected vs. Observer Eating Duration

Figure 1 depicts ED predicted by the algorithm compared to ED observed by the reviewer (R2 = 0.64). Algorithm and observed ED were highly correlated (r = 0.80; P < 0.001). Compared to observations by reviewers, on average, the algorithm underpredicted ED by 13 minutes and the frequency of BV by 1.3. Analysing differences in reviewer and algorithm data indicates opportunity for further algorithm development. The algorithm would occasionally miss the last one or two BV of the day when daylight was decreasing, at approximately 1930 h. Considering this, the data was re-analysed, omitting BV during periods of low light. By omitting these data points the R2 improved to 0.74. These results indicate supplemental visible or infrared illumination could improve algorithm ED estimates. Further, at times of maximum bunk capacity the algorithm struggled differentiating patch combinations. However, this shortcoming could be eliminated through additional algorithm training and more precise placement of adhesive patches.

Table 2: Mean mealtime (MT) for pen-side camera observations and algorithm predictions

Parameter	Pen-side	Camera	Algorithm
Mean MT, minutes	43	42	41
SD MT, minutes	15	17	17

Images taken at one-minute intervals were sufficient for accurate measurements of cattle MT and ED. Table 2 shows the average MT for pen-side observations, camera observations, and algorithm prediction. Compared to the mean ED values in Table 1, MT data in Table 2 differs because cattle were only watched at and immediately after feeding time. Pen-side and camera observations were highly correlated (r = 0.93; P < 0.001). When pen-side MT observations were compared to algorithm predictions, a slight reduction was observed (r = 0.83; P < 0.001). Figure 3 compares pen-side and camera MT observations. Eating duration predicted by algorithm and pen-side observations are shown in Figure 4. Mealtime observed by camera reviewers followed pen-side

MT observations more closely ($R2 = 0.86$) than algorithm MT predictions ($R2= 0.75$). The authors believe if pen-side reviewers had watched cattle continuously, from sunrise until sunset, that total daily ED predicted by the algorithm would more closely match pen-side ED. However, considering the difference in R2 values in Figures 3 and 4, these results suggest the algorithm could be further refined to improve MT predictions.

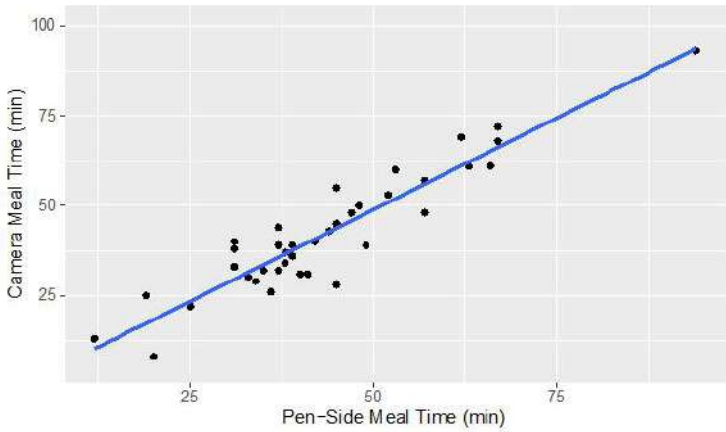

Figure 3: Meal Time Observed Pen–side vs. Camera Observed

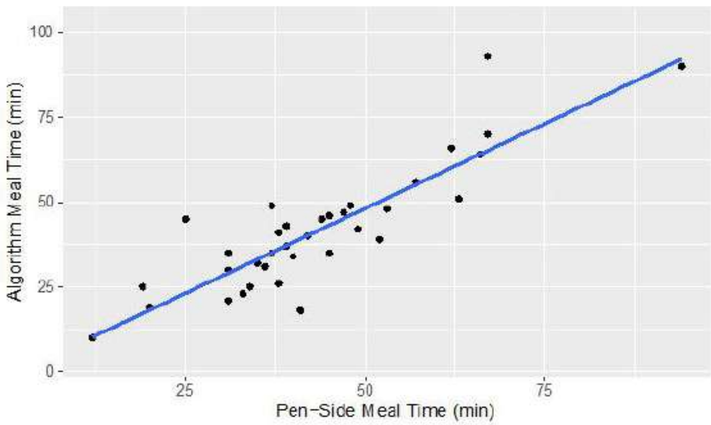

Figure 4: Meal Time Observed Pen–side vs. Algorithm Predicted

The current results suggest the algorithm can predict individual animal ED with reasonable accuracy. Eating behaviour data collected from cameras using algorithm could be used in equations to estimate daily individual animal DMI. However, the initial version algorithm did not accurately predict the daily BV frequency. The frequency of BV may be more important than MT and ED when predicting DMI. Parsons et al. (2020) reported a positive correlation for BV frequency and DMI but detected no relationship between DMI and ED. Head down ED, which was not discernible from the initial algorithm developed, was the most influential on DMI (Parsons *et al.*, 2020). Adding additional illumination and further algorithm training could improve prediction results.

Conclusions

In the current study, labour was a major constraint. The dataset could be improved with continuous pen-side observation for comparison of daily ED totals and BV frequency. The identification patches frequently fell off and required re-application. In a commercial setting, patching cattle would not be possible. However, many commercial feedlot and dairy production systems use radio frequency identification tags that may be able to be correlated with camera images and identify when individual animals are at the bunk. Further evaluation is required to determine camera ability to identify eating behaviour overnight and during inclement weather when visibility is limited. Additional research to develop DMI prediction equations using animal feeding behaviour is being conducted.

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A prototype imaging method for feed estimation in beef cattle

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Abstract
Research and commercial precision livestock management tools have been developed to provide individual management for swine and dairy industries. However, few tools have focused on beef production due to the extensive nature of the production system. Current feed management relies on visual assessment of residual feed by skilled workers, making it time-consuming and prone to error. This study tested the ability of a low-cost depth camera (Microsoft Azure Kinect® DK) mounted directly above an individual feeding bunk to estimate the weight of residual feed within the bunk. Two typical feedlot finishing diets with variation in composition and bulk density were tested: 1) high bulk density with more high moisture corn and 2) medium bulk density with more sweet bran. Each diet was weighed in increments and added into the bunk to approximately 23 kg. Twelve top-down depth images were captured for each feed addition, and the feed was randomly stirred after each picture. The volume of the feed was approximated by using background subtraction and voxel summing. The estimated volume and measured bulk density of each diet as-fed were used to calculate the estimated weight. Results show that a linear model can be used to determine the weight of high-density feed (Diet 1, SE of the estimate (S) = 0.52 kg), whereas a 2-order polynomial model was a better fit to estimate the weight for less dense feed (Diet 2, S = 0.45 kg). This work demonstrates that the proposed PLF tool can provide accurate bunk management information for beef cattle.

Keywords: bunk management, depth sensors, feed residue, image technology, PLF

Introduction
The agricultural sector has adopted different mechanization systems to achieve sustainable production. For the livestock industry, Precision Livestock Farming (PLF) was identified as an alternative tool to provide solutions to current and emerging issues the industry is facing (Berckmans, 2014). Advanced technology capable of providing individualized and accurate information for improved animal health, well-being, and production management has been developed for the swine and dairy industries. However, to date, development of these technologies has been limited within the US feedlot/feedyard production systems.

Feedlot management is one of the most crucial stages in cattle production. According to the Iowa State University (ISU) Extension publication – Beef Feedlot Systems Manual, with typical inventory turns of 1.7 times per year, calves can gain an average of 272 kg in a period of 203 days when properly cared for and managed (Euken *et al.*, 2012). Labor plays a vital role in feedlot management. For a US feedlot to be profitable, at least 8-10 employees are needed to manage and care for 10,000 cattle, indicating a minimum of 10 hour/day and 6 day/week workload from the employees (Wagner *et al.*, 2014). The intensive labor requirement is a huge challenge for the industry due to recent reductions of available labor and the increased difficulty of recruiting agricultural workers in rural areas. Farmers and feedlot owners will increasingly depend on technology that will allow them to keep their feedlot profitable and maintain systems that are sustainable for the future of the industry. One obvious area for adaptation of advanced technology is to provide producers with the ability to accurately assess daily pen feed intake (often referred to as “bunk calling” by producers). Currently, feed bunk management is solely determined by a subjective human visual determination of residual feed refusal estimates (kg of feed present 24 hr. post feed delivery). A potential solution for enhancing bunk management is to use innovative computer vision technologies that rapidly and accurately determine residual feeds, thus providing a significant improvement in bunk management.

Many studies have been conducted on PLF, focusing on improving the production, reproduction, health, and welfare of the animals, and reducing the environmental impact from livestock farming (Berckmans, 2014). Alternative monitoring tools such as imaging technologies, proximal sensing, and sound monitoring, have been evaluated to better understand animal productivity and well-being for livestock species, including beef, swine, and poultry (Condotta *et al.*, 2018). For example, real-time sound analysis was studied to assist in diagnosing respiratory diseases in pigs by using microphones and algorithms to distinguish between a cough of a healthy pig and for a sick pig (Berckmans, 2014); real-time image analysis was used to monitor the behavior of housed broilers using eYeNamic system with RGB cameras (Berckmans, 2014). PLF is a fast-growing research area with many opportunities for alternative technology and innovation for robust management in the livestock industry.

Imaging technologies have been explored in PLF with added advantages, as these proximal sensing tools are more efficient in data collection and can monitor individual objects. Among different imaging sensing technologies, consumer-grade depth cameras have been studied on pigs and in cornfields to assess their efficacy for agricultural applications (Condotta *et al.*, 2020). Condotta *et al.* (2018) conducted a study using depth images to obtain dimensions of the pigs for weight estimation. In their study, different biometric characteristics of a standing pig in the crate including length, width, shoulder width, and height were measured using depth cameras (Kinect I, Microsoft, Seattle, WA, USA). Approximation algorithms were developed using MATLAB, and the animal’s volume and weight were accurately estimated with a standard error of 3.01 kg and a linear regression coefficient of determination (R^2) of 0.99 (Condotta *et al.*, 2018). We believe that the use of depth cameras presents a potential for accurate feed residual estimation that can be used for automated feed bunk management for feedlot cattle.

The **objective** of this research was to evaluate the feasibility of using a low-cost time of flight depth camera (Microsoft Azure Kinect® DK) mounted directly above a fiberglass feed bunk to estimate the weight of residual feed from two commonly fed mixed diets within the bunk.

Material and methods

This research was conducted in the Ruminant Nutrition Animal Lab in the Animal Science Department at the University of Nebraska-Lincoln. All data collection was conducted in an empty individual pen with no animal involvement.

This research used the Azure Kinect DK time of flight depth camera (Microsoft, Seattle, WA, USA) for depth image collection – the upgraded generation of the previous Kinect I and Kinect II. It is equipped with a 1-mega pixel (MP) resolution depth sensor with both wide and narrow field of view (FOV) options, a 12 MP resolution color (RGB) camera for adding color streams that align with the depth streams, accelerometer, and gyroscope (IMU) for sensor orientation and spatial tracking (Microsoft, 2020). This project obtains and utilizes both RGB and depth images for measuring the geometric characteristics to calculate the objective depth profiles of the mixed diet feed in the feed bunk.

Data collection

A fiberglass feed bunk used for individual cattle feeding was used in this study for proof of concept. Two typical Nebraska (US) feedlot finishing diets with variation in composition and bulk density were tested: 1) high bulk density with more high moisture corn and 2) medium bulk density with more sweet bran. Table 1 lists the ingredient composition and dry matter inclusions of the selected mixed diets. The as-fed bulk densities of both mixed diets were measured prior to data collection and are included in Table 1. The visualization of the two selected mixed diets is shown in Figure 1. The depth camera was positioned at the top of the bunks facing down the center of the bunk to obtain RGB and depth images of the bunk bottom surface (Figure 2).

Figure 1: Visualization of the two selected mixed diets commonly used in Nebraska beef feedlots. Left: Diet 1. Right: Diet 2

A C++ program leveraging OpenCV and the Kinect SDK were written in the Microsoft Visual Studio (version 2019) and used to acquire images, obtain factory calibration data, and correct for lens distortion. Prior to adding feed in the bunk, an empty bunk image was taken and stored as the background image. This background is subtracted from each subsequent image (with feed present) to measure the volume of the feed. Effectively, the 3D space considered by each pixel in the depth image is a long, skinny pyramid emanating from the camera center. The pyramid, which would otherwise extend to an infinite distance, is truncated with the bottom established by the background depth and the top established by the top surface of the feed. The summation of the individual volumes of these truncated pyramids forms the total feed volume.

Table 1: Composition and ingredient inclusions (expressed as percent dry matter contents) and measured bulk density for the two selected mixed diets used in the study

Overall Parameter	Diet 1	Diet 2
Diet bulk density (kg/m^3)	518.78	449.01
Diet dry matter (%)	67.09	59.21
Composition	**Dry matter inclusions (%)**	
Dry rolled corn	26.67	13.33
High moisture corn	53.33	26.67
Sweet bran	–	40.00
DDGS	–	–
Silage	15.00	15.00
Supplement	5.00	5.00

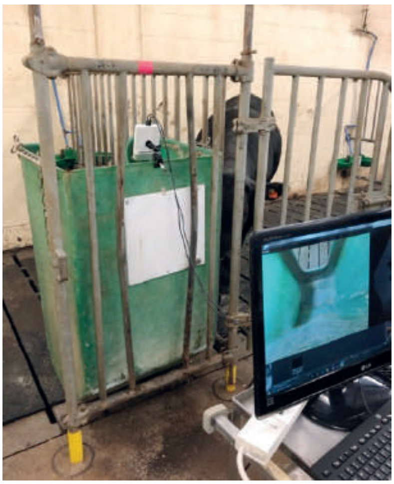

Figure 2: Depth camera and bunk setup. The monitor shows the RGB picture of the bunk bottom

Each diet was weighed in 2 – 2.5 kg increments using a calibrated scale and was added into the bunk to approximately 23 kg. Twelve top-down depth images were captured for each feed addition, and the feed was randomly stirred after each picture to simulate animal feeding events.

Data analysis

The images were processed using MATLAB (version 2021b) to estimate the volume of the feed in the bunk. The volume of the feed was approximated by using background subtraction and voxel summing. Figure 3 demonstrates an example of the images collected for Diet 1. The estimated volume and measured bulk density of each diet as-fed were used to calculate the estimated weight. For each diet, the scale-measured weights were used as independent variables (X) and were plotted against the image-estimated weights as dependent variables (Y). A linear regression or polynomial model was fitted between the measured and predicted weights. Model fitted equations, associated coefficients, and coefficient of determination (R^2) are provided. The goodness of the fit was represented by R^2 and the standard error of the model predicted weights were calculated from the residual standard errors.

Results and Discussion

Figure 3 provides an example of the raw colour and depth images collected for Diet 1 at 18.18 kg, and the corresponding processed depth image after background subtraction and voxel summing. Figure 4 illustrates the relationship between scale-measured weights as the independent variables (X) and estimated weights from image-predicted volumes and bulk density as the dependent variables (Y) for the three mixed diets (top – Diet 1 and bottom – Diet 2). The model fitted equations and the R^2 values were included. The 95% confidence bands of the regression of each mixed diet are demonstrated on each plot.

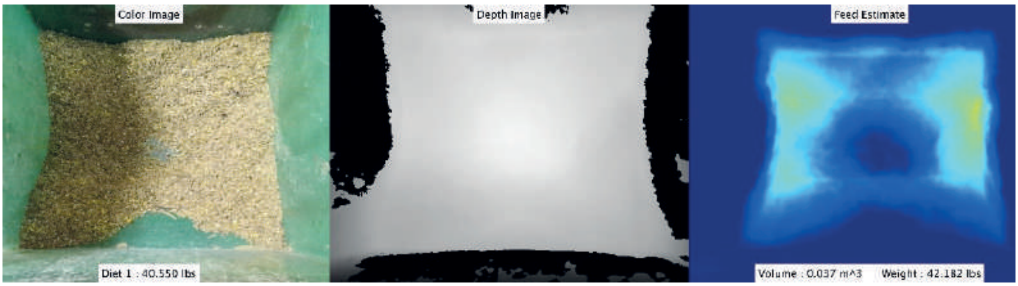

Figure 3: Example figures showing the raw color and depth images and the corresponding processed depth image after background subtraction and voxel summing for Diet 1 at 18.18 kg

Results show a strong linear and polynomial relationship between the scale-measured weight and predicted weight for Diet 1 and Diets 2, respectively. While all regressions showed an R^2 over 0.99, the standard error of the regression (S) was 0.52 kg and 0.45 kg for Diet 1 and Diet 2. This difference in the standard error of the regression can be caused by the characteristics of the mixed diets, including the dry matter inclusions, composition, moisture content, bulk density, and particle sizes. As shown in Figure 2, Diet 1, consisting of a higher amount of high moisture corn, demonstrates slightly bigger ingredients than that of Diet 2. With different ingredient particle sizes, different moisture contents, and non-uniform interior air spaces, this creates difference in estimating the volume of diet with substantially different bulk densities. However, when compared to the almost solely manual observation of bunk calling being done in commercial feedlots where 3 – 5 kg error in decision making for the next-day feed delivery is common, the results demonstrated much smaller errors of less than 1 kg. Thus, a linear model can be used to determine the weight of high-density feed (Diet 1, SE of the estimate (S) = 0.52 kg), whereas a 2-order polynomial model was a better fit to estimate the weight for less dense feed, Diets 2, S = 0.45, respectively.

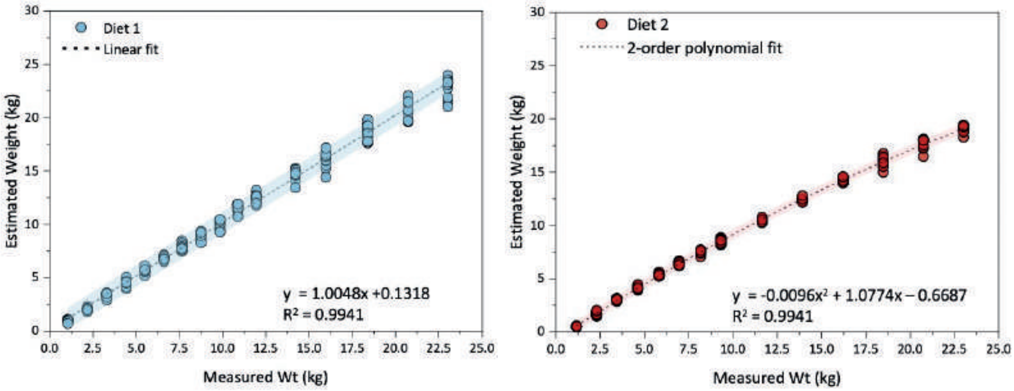

Figure 4: Relationship between scale-measured weights and estimated weights from image-predicted volumes and bulk density for the three mixed diets (top – Diet 1 and bottom – Diet 2). The model fitted equations and the R^2 values were included

Conclusions

This paper evaluated the feasibility of using a low-cost time of flight depth camera mounted directly above a fiberglass feed bunk to estimate the weight of residual feed from two Nebraska feedlots commonly fed mixed diets within the bunk. Results show that a linear model can be used to determine the weight of high-density feed with a standard error of the estimate of 0.52 kg, whereas a second order polynomial model was a better fit to estimate the weight for less dense feed with a standard error of the estimate of 0.45 kg. This work demonstrates that the proposed PLF tool can provide accurate bunk management information for US feedlots.

Acknowledgements

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SESSION 6

Pigs:
Computer Vision
and Vibration Sensors in Sows

Sow posture and feeding activity monitoring in a farrowing pen using ground vibration

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Abstract

Automated monitoring of sow welfare and behaviors is a crucial tool in precision swine farming, giving farmers access to continuous streams of sow health information. Monitoring the activity of the sows helps farmers detect stress, sickness and signs of farrowing, which enables the farmers to provide timely care. Prior work in swine monitoring frequently uses video cameras, which have lighting and large storage and processing requirements. Alternatively, other work has used wearable sensors, which have limited longevity due to durability and battery requirements and suffer from scalability challenges due to the need for individual sensors worn by each sow.

The objective of the study was to determine the effectiveness of geophone sensors mounted under the floor that measure the structural vibration of a farrowing pen to determine posture changes and animal feeding activity. A total of 6 farrowing/lactating sows and litters have been used in these studies. The data were collected from a minimum of 3 days before farrowing to approximately 25 days post-farrow. Up to five geophones were used for activity classification. Machine learning classification methods are used to detect the position and feeding activity of the sow and her piglets, including tree classifiers and principal component analysis. Accuracies of over 95% were achieved in sow posture and feeding activity classification, indicating the potential of monitoring ground vibration as a source of health information.

Keywords: swine monitoring, structural vibrations, geophones, feeding, posture

Introduction

Precision swine farming requires means to continuously monitor pig health information. While manual intervention and observation by farmers and veterinarians remains the ideal, increasing productivity demands increasing scalability. Thus, numerous sensing approaches are being developed to observe more fine-grained details which can allow swine farmers to optimize the care of their animals.

The period between farrowing and weaning is a particularly sensitive time where pigs must be closely monitored. Currently, the average preweaning mortality in US swine industry is nearly 18% (Stalder, 2017). Illness, piglet size, and parent-induced injury all contribute to this issue (Alonso-Spilsbury et al., 2007; Baxter et al., 2011). These issues can be improved if addressed by caregivers in a timely manner. Thus, this period is especially crucial for continuous pig health monitoring.

Prior work to continuously monitor swine utilizes video cameras or wearable sensors, each with their own drawbacks. Wearables face cost, application on the animals, battery life, and data transfer challenges which hamper true scalability (Lao et al., 2016; Graña Possamai et al., 2020). Video cameras can monitor whole farrowing pens at once, but at the cost of large bandwidth, storage, and data processing requirements (Chen et al., 2008; Leonard et al., 2019; Condotta et al., 2020). In most cases, this leads to crucial health information only being available to farmers after weaning when this data can be retrieved and processed.

Ground and floor vibrations have shown promise as a means to monitor health and behavior of humans and animals. Instead of directly applying a sensor to the pigs, this approach instruments the farrowing pen structure (Alwan et al., 2006; Jia et al., 2016; Pan et al., 2019). Activity and motion on that structure then create vibrations, which we measure to indirectly observe the activities that caused them. In humans, this has enabled indirect measurement of weight, pulse, gait, and overall activity level (Jia et al., 2016; Fagert et al., 2020; Bonde et al., 2021; Codling et al., 2021).

Applying structural vibration monitoring to swine farming comes with its own set of unique challenges. Since these sensors both need contact with the structure on which the pigs reside, and need to avoid damage from the pigs, they are mounted underneath the farrowing pen. This location prevents the pigs from damaging the sensors directly but creates its own challenges. First, the location exposes sensors to refuse and spillage that falls through the pen floor necessitating increased device ruggedness. The sensors' location beneath the pen also makes them inaccessible while the pens are occupied and thus the system needs to be manageable and configurable remotely. Finally, the location creates obstacles between the sensors and data receiver, making Wi-Fi communication unreliable (Ariyadech et al., 2019; Bonde et al., 2021; Codling et al., 2021).

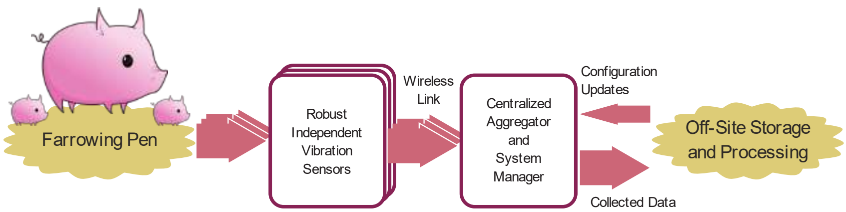

Figure 1: Sensor Network Data Flow Diagram

This paper evaluates the utility of geophone sensors on the floor for automated pig health monitoring, using feeding activity and posture recognition as example applications. We present the design strategy of the novel geophone monitoring approach to address the challenges of corrosion, remote management, and unreliable communications. First, the experimental deployment setup will be presented, evaluating the overall system in terms of longevity, data volume, and survivability in the farm environment. Then, the machine learning and signal processing tools will be outlined which allow observation of feeding behavior and posture using the collected vibration signals. Finally, the resulting recognition accuracy will be discussed with its implications for future development of piglet and sow monitoring systems.

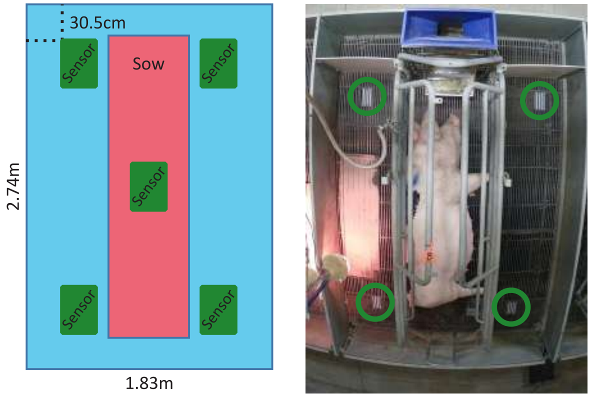

Figure 2: Geophone instrumentation of a farrowing pen. On the left, green boxes indicate the location of each sensor node, while the right shows a photo of an instrumented pen with a pregnant sow in it. One sensor is not visible because the sow is directly on top of it

Material and methods

Data collection was performed in accordance with federal and institutional regulations regarding proper animal care practices and was approved by the U.S. Center for Animal Research Institutional Animal Care and Use Committee as EO#143.0.

Sensing System for Farrowing Pens

To provide a continuous stream of pig health information, a semi-autonomous network of custom-built vibration sensors is deployed in the farrowing pens. These sensors use geophones to collect the vibrations in the pen structure which are caused by the movements of pigs, workers, equipment, and other environmental sources. The signal content of these vibrations is unique depending on pig, location, and structural parameters, allowing us to differentiate activities and the pigs' body posture from them.

This sensor network is based on a design originally proposed for deployment in rural Thailand (Ariyadech et al., 2019), then refined to improve system reliability (Bonde et al., 2021; Codling et al., 2021). Figure 1 shows the flow of data in the current iteration. Vibration information travels left to right, starting at the physical sources in the farrowing pen, collected by the sensors, transmitted to the aggregator, then uploaded for processing away from the farm environment. The only data flowing back into the system is management information, such as configuration changes and monitoring connections, enabling the network to run with minimal interaction when combined with self-recovering sensors.

For evaluation, we deployed this network in 3 adjacent farrowing pens with 5 sensors in each, laid out as shown in Figure 2. Since the ideal placement of these sensors in the farrowing pen is unknown, they are spread so as to cover the entire pen equally. The experiments were repeated twice, starting data collection at least 3 days pre-farrow and weaning up to 25 days post-farrow according to the normal schedule followed at USMARC. The right side of Figure 2 shows a pregnant sow within 3 days of farrowing in a pen instrumented for this study.

Sow Posture and Feeding Activity Monitoring

After collecting the ground vibration data, the signals and predict the sow postures and feeding activities were analyzed through machine learning. Ground vibrations induced by the sow and the piglets are first preprocessed to reduce environmental and sensor noises. Combination of a low-pass filter (200Hz) with a Wiener filter that adapts to different noise thresholds removes noises and higher frequency content that are less related to the pig activities in the signals. This allows activities which cause lower amplitude signals, such as nursing, to be observed in the ground vibrations.

After noise filtering, ground vibration signals, such as those shown in Figure 3, are segmented into 5-second sliding windows for feature extraction. In this study, the length of 5 seconds is chosen based on the observations of the minimum duration of the sow maintaining a single posture (specifically sitting, which typically serves as a transition between kneeling and standing). These sliding windows are overlapped by 50%, which allows any temporal dependency between adjacent windows to be captured.

To monitor the posture and feeding activities of the sow and piglets over time, vibration signal features that are representative of their motions are extracted. These features include the mean, variance, the maximum and the minimum value of signal magnitudes in the time and frequency domains, which are found to be effective in classifying different types of activities in prior works.

Time- and frequency-domain features are extracted to represent the sow postures and activities. The time-domain signal features, such as the voltage at each sample from the geophone, typically contain information about the intensity of the movements, which allows us to separate activities from the heavier sow from those of the lighter piglets. Frequency-domain signal features, such as the Discrete Fourier Transform (DFT) magnitudes of the time domain signal, provide valuable information about the types of forces that the sow or piglets exert on the floor. For example, the sow's standing posture results in vibration data that have a wide frequency band because of the sow's stepping impulses. As a result, a total of 60 features were extracted.

The features extracted above are compressed through principal component analysis (PCA). A preliminary test shows that the first 10 components cover 98% of variances in a sample day of vibration data.

The postures of the sow are divided into three categories: standing, sitting/kneeling and lying, as shown in Figure 5. To predict these postures, we use a gradient boosted tree classifier with the compressed features. The gradient boosted tree is chosen because it automatically handles missing data due to hardware disconnections. In our model, the maximum depth of each tree estimator is 3 and the total number of estimators is 100. This enables non-linear fitting through the combination of many weak learners. The classifier is trained and tested through a 5-fold cross validation with the data collected during the deployment.

In order to remove the outlier windows that are filled with environmental disturbances or sudden excitement from the piglets, the predicted results are then smoothed through a moving majority vote algorithm over 5 windows. As shown in Figure 6, the noisy windows from the original predictions are corrected by their adjacent windows.

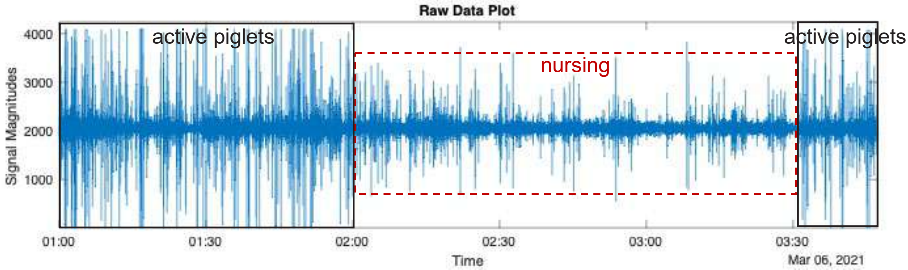

Figure 3: A sample of raw ground vibration signals. Periods of piglet activity and nursing are marked, showing a marked change in signal between these states

Figure 4: Pictures of sows in different postures

Figure 5: Photos of sow ingesting and nursing during the sensor deployment

The feeding activities include sow ingestion and piglet nursing. Figure 5 shows photos defining each of the activities we predicted based on the geophones' data. Sow ingestion activities are detected through the vibration of the feeding trays and the water nozzles, for eating and drinking respectively. These components have different materials and shapes and therefore generate different vibration signals that propagate to the ground. Nursing activities are characterized by a collection of short, high frequency impulses from different piglets superimposed. Ingestion activity is then detected through a random forest classifier, which gave the best performance during the preliminary testing with one day's data.

Results and Discussion

These results are drawn from performance data from deployment at the U.S. Meat Animal Research Center. The sensor layouts were described in the methods section, and cameras were installed above the pens to provide ground truth. These results are based on the final of several experiment repetitions but are indicative of the full study. Each repetition monitored a different trio of sows in the same conditions over the same time period relative to farrowing.

<u>Sensing System Applicability for Farrowing Pens</u>

The applicability of the geophone sensor network is evaluated based on reliability and data efficiency. The sensors are powered by wall plugs, obviating the traditional power constraints of wireless sensor systems. However, reliability remains a concern because of the environment under the floor and the obstructions for Wi-Fi communication.

The number of sensors active during a given hour was tracked over the course of each repetition to determine the overall reliability of the sensor network. While up to half of the sensors experienced errors simultaneously, all sensors recovered eventually, and all pens retained at least one functioning node during the entire farrowing period. These temporary faults are most likely due to firmware errors and wireless interference which prevented data transmission. Using Wi-Fi unfortunately creates an opening for such interference, trading off bandwidth improvement and central management for the possibility of intermittent connection loss due to the metallic building.

Data efficiency is a concern for precision farming applications due to the remote and rural locations of farms. With low frame rate and high compression, cameras produce upwards of 600 MB of data per hour, which then requires large capability processing to extract information from the image stream. These geophone sensors, in contrast, generate approximately 3.6 MB per hour per sensor before compression with our typical sample rate of 500 Hz. This suggests that a geophone-based system will be easier to adapt to applications within the data constraints of the farm environment.

<u>Posture and Activity Monitoring Results</u>

The gradient boosted tree classifier used to determine sow posture achieved 99.9%, 95.5%, and 100% test accuracy in detecting lying, sitting/kneeling, and standing respectively. Figure 7a shows the confusion matrix for this result. It is noted that most confusions occur between lying and sitting, which makes sense given the similarity in load distribution between the lying sow and a sitting or kneeling sow.

Our smoothing method, described above, reduces the errors caused by data samples when the sow is not moving. During such periods there is less vibration, so the variations in structure response caused by changing sow posture are difficult to detect. The majority vote smoothing uses knowledge of the sow's movement speed to fill in these low-signal periods with information from the surrounding time windows. Figure 6 shows plots of the posture prediction as a dotted line, compared with a solid line for ground truth. We can see a close match between the predicted and observed postures over the course of the 4.5-hour period shown.

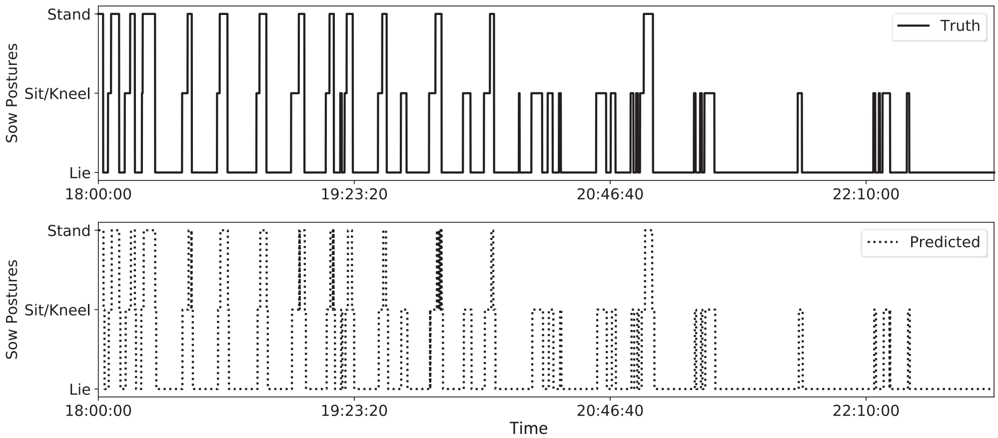

Figure 6: A sample series of sow posture changes compared between ground truth and predictions from geophone data. The solid plot above is the ground truth, observed from video footage

The gradient boosted tree classifier used to determine sow posture achieved 99.9%, 95.5%, and 100% test accuracy in detecting lying, sitting/kneeling, and standing respectively. Figure 7a shows the confusion matrix for this result. It is noted that most confusions occur between lying and sitting, which makes sense given that similarity in load distribution between the lying sow and a sitting or kneeling sow.The system achieved 96% F1-score in sow ingestion, matching the confusion matrix in Figure 7b. From observing the 10 features used by the ingestion classifier, the mean and variance of magnitudes in lower frequency bands are significantly more important in detecting the ingestion activity. This indicates that the ground vibration induced by the sow feeding equipment concentrates in the 0-50 Hz frequency bands. Since eating and drinking have rhythms of movement, the variance of these bands is also important.

For piglet nursing activities, the system has an average 91.3% F1-score, which is much lower than the activities induced by the sow. The confusion matrix for this classification is shown in Figure 7c. There are two main reasons under consideration for this drop in accuracy. First, the piglet's activities have much smaller intensity than the sow due to their age and smaller size, so their movements are harder to detect. Secondly, the nursing activity is an irregular pattern of relatively low amplitude vibration pulses (see Figure 3). which can easily be mistaken for the case where some piglets are moving around while others sleep. Future work will investigate these two challenges to seek algorithmic means to improve recognition accuracy.

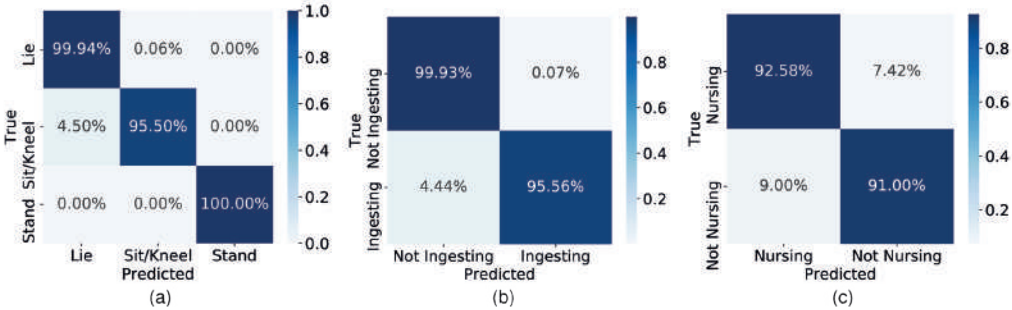

Figure 7: Confusion matrixes for each of the vibration data classifiers. (a) shows the accuracy in predicting sow posture, (b) for sow ingestion, and (c) for nursing

Conclusions

This paper has evaluated ground vibrations as an alternative modality for precision swine farming. Sow posture, feeding, and nursing detection in a farrowing crate were explored as example applications to demonstrate the potential of this new approach. This evaluation in a research farm shows that a vibration-based system can provide a continuous stream of pig health information without the overhead inherent in existing approaches. This suggests that vibration sensing can provide a scalable, reliable, and accurate source of health information to aid farmers in caring for their livestock.

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Computer vision for monitoring hay rack use behavior in sows

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Abstract

Access to rooting material in confined pigs is widely considered to be beneficial for the welfare of animals. For sows housed on a concrete floor, straw serves as bedding that improves the thermal and the physical comfort of the floor. Provision of straw for pre-parturient sows results in more nest-building behaviours. As a compromise considering the needs of the sow for access to straw, farrowing pens with slatted floors are equipped with straw dispensers (racks) accessible by sows. This allows sows to gather straw from dispensers to form a nest during the nest-building phase without a risk of blocking the slurry drainage system. The experiment took place in the research farm of The University of Veterinary Medicine in Vienna, Austria. The sow herd counted 80 Large White sows in total with 12 animals included in the experiment. Behaviour of each sow was video recorded in a period before farrowing and hay rack use was labelled for all the animals. Object detection algorithm RetinaNet was applied to detect several key body points of sows such as head, ears, nose and a hay rack. Feature variables were extracted based on the centroids of detected key body points (e.g. distance between nose and hay rack). Decision tress classifier was used to classify events of hay rack use with 78.6% sensitivity, 96.6% specificity and 96% accuracy. The developed algorithm could be used to automatically estimate hay rack use as part of nest-building behaviour in sows and possibly increase performance of farrowing prediction.

Keywords: sow, nest-building, computer vision, hay rack use, automated monitoring, deep learning

Introduction

Access to roughage in confined pigs is widely considered to be beneficial for the welfare of animals (Müller, 1979). Straw is the most studied rooting material for pigs, and the effect of other studied materials is very often compared with the effect of straw (Studnitz et al., 2007). For sows housed on a concrete floor, straw serves as bedding that improves the thermal and the physical comfort of the floor (Fraser, 1975). Provision of straw for pre-parturient sows resulted in more nest-building behaviours (Burne et al., 2000).

Compared to straw, good-quality hay might provide additional nutritional benefits for lactating sows, including higher metabolizable energy and crude protein levels (Kamphues, 2004) as well as a high content of secondary plant substances (Ziolkowska et al., 2020), contributing to pigs' health. Hay might also be preferred as enrichment material over straw by young piglets as it is softer and therefore easier to chew.

One disadvantage farmers might face when applying roughage as enrichment material is that on slatted floors long-stem forage can drop into the slurry and block the drainage system. As a compromise considering the needs of the sow for access to adequate nest building material, farrowing pens with slatted floors are equipped with straw dispensers (racks) accessible by sows (Oczak et al., 2015). This allows sows to gather small amounts of roughage from dispensers to perform nest-building behaviour (Arey et al., 1991) with lower risk of blocking the slurry drainage system compared to pens with straw bedding. The limitation of such dispensers in practical farm conditions is that they are re-supplied with a standard amount of roughage by farm staff on a daily basis according to the appropriate regulations (e.g. defined by the Austrian Tierhaltungsverordnung (BMG, 2012), but without consideration for individual needs of the sow, which might vary between animals (Maschat et al., 2020).

Application of PLF technology for automated monitoring of individual use of roughage in a farrowing pen might offer a possibility to improve individual care in pre-parturient sows by supporting the decision of farm staff on when to re-supply the dispensers with nest-building material. Additionally, our hypothesis is that automated monitoring of rack use by sows might improve the performance of models for farrowing prediction which are based only on general activity level of animals. This might be especially relevant for improving sow welfare in farrowing systems designed for temporary sow confinement in crates (Oczak et al., 2019).

In this study we aimed to develop a computer vision algorithm based on an object detection model for monitoring the use of the dispenser with nest-building material in pre-parturient sows. The second objective was to analyze if output of this algorithm could potentially improve the performance of farrowing prediction compared to current state-of-the-art techniques for farrowing prediction based solely on activity levels (Oczak et al., 2019; Traulsen et al., 2018).

Materials and methods

Animals and housing

The experiment was conducted between June 2014 and March 2016 at the pig research and teaching farm (VetFarm) of the University of Veterinary Medicine Vienna, Vienna, Austria. In total, 12 Austrian Large White sows and Landrace × Large White crossbreds sows were included in the experiment from five days before farrowing to the end of farrowing. These sows were housed in two types of farrowing pens, which offered the option of either keeping the sows free or confined in a farrowing crate. Out of 12 sows, 6 were kept in SWAP (Sow Welfare and Piglet Protection) pens (Jyden Bur A/S, Vemb, Denmark) and 6 in trapezoid pens (Schauer Agrotronic GmbH, Prambachkirchen, Austria). None of the animals included in the experiment were confined in a farrowing crate from the introduction to the farrowing pen until the end of farrowing (Fig. 1). The SWAP pens had an area of 6.0 m2, while the trapezoid pens had an area of 5.5 m2. In both pen types a rack with nest-building material hay was mounted in the front area of the pen, in close proximity to the trough.

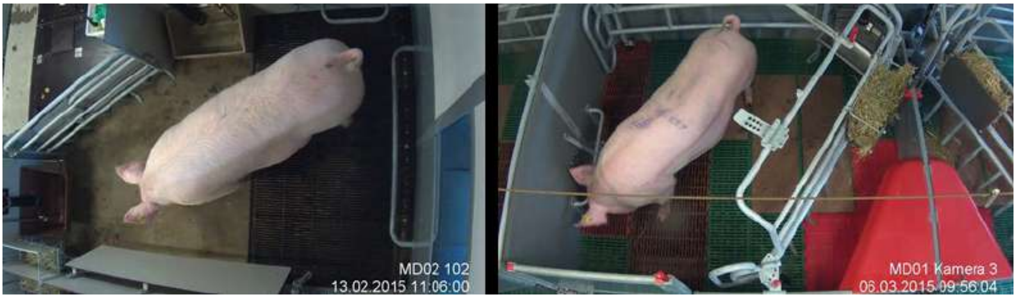

Figure 1: Farrowing pens with possibility of temporary crating. (a) SWAP pen, (b) trapezoid pen

To fulfill the need for adequate material to explore and for nest-building, sows and piglets were offered hay in the aforementioned rack throughout their stay in the pens. Farm staff half filled the racks in the morning and whenever the racks were empty.

<u>Video recording</u>

Behaviour of sows was video recorded 24/7 from introduction to the farrowing pens until 24 h postpartum with 2D cameras in order to create a data set that could be labelled. Each pen was equipped with one IP camera (GV-BX 1300-KV, Geovision, Taipei, Taiwan) locked in protective housing (HEB32K1, Videotec, Schio, Italy) hanging 3 m above the pen, giving an overhead view. Additionally, infrared spotlights (IR-LED294S-90, Microlight, Bad Nauheim, Germany) were installed in order to allow night recording. The videos were recorded with 1280x720 pixel resolution, in MPEG-4 format, at 30 fps. The cameras were connected to a PC on which Multicam Surveillance System (8.5.6.0, Geovision, Taipei, Taiwan) was installed. The system allowed simultaneous recording of videos from 9 cameras. Recordings were stored on exchangeable, external 2 and 3 TB hard drives.

<u>Dataset</u>

The dataset composed of video material of 12 sows recorded in a period from introduction to farrowing pen until 24 h after the end of farrowing was divided into two subsets, the first for training and the second for validation of computer vision algorithm for classification of hay rack use.

Table 1: Dataset divided into subset for training and validation of algorithm for classification of hay rack use

Pen type	Training	Validation
SWAP	3	3
Trapozoid	3	3
Total	6	6

The subset for training consisted of the same number of animals (n = 6) as the subset for validation (n = 6) of the algorithm (Table 1). The animals in both subsets were equally distributed between SWAP and trapezoid pens. (Table 1).

Data labelling

Video with recorded sow behaviour was manually labelled in order to create a reference dataset on the basis of which further data analysis could be performed. In the first step of the labelling process, the time of the onset of farrowing of each individual sow (n = 12) was labelled. The onset of farrowing was defined as the point in time when the body of the first piglet born dropped on the floor. The time of birth of the last piglet indicated the end of farrowing. Reference for automated estimation of hay rack use by sows was based on manual labelling of 4 behaviours by one trained labeller. These behaviours were pulling hay, nose close to the rack, exploratory behaviour and bar biting. Occurrence of any of 4 labelled hay rack use behaviours indicated that sow was using the rack.

RetinaNet object detection model

Pytorch implementation of RetinaNet object detection algorithm (source code available at https://github.com/yhenon/pytorch-retinanet) was used for the task of detecting parts of the body of sows i.e. left ear, right ear, head and the whole body and also the hay rack in the farrowing pen (Lin et al., 2017). The process of training and validation of this algorithm for detection of sow body parts and the hay racks in the farrowing pens was described in Oczak et al. (2022). Activity level of every sow was estimated based on Euclidean distance between centroids of sow bodies on consecutive frames as described in Oczak et al. (2021).

Feature variables

The output of the RetinaNet algorithm - rectangles corresponding to the parts of the body of a sow and a hay rack - was further processed by extracting their centroids. In the following steps centroids of rectangles were used as a basis for calculation of 40 feature variables, which were further used for training of a Random Forest (RF) model for classification of hay rack use.

Figure 2: Distance from nose to rack and from head to rack

The first feature variable was calculated as Euclidean distance between the sows head and the hay rack. The second feature variable was calculated as Euclidean distance between the centroid of sows nose and the centroid of the hay rack (Fig. 2). The next calculated feature variable was the orientation of the sow towards the hay rack based on a line perpendicular to line joining centroids of ears of the sow. The fourth calculated feature variable was orientation of the sow towards a rack based on the location of the centroid of the nose of the sow. To calculate the next 36 feature variables Euclidean distance was estimated between centroids of head, body or nose. For each of these three body parts Euclidean distance was calculated between consecutive frames of individual body parts. Finally, the sum and the mean of Euclidean distance were calculated on windows of size 2 s, 5 s, 10 s, 20 s, 30 s and 45 s (3 body parts x 6 window sizes x 2 statistical metrics = 36 feature variables). The main purpose of extraction of these 36 feature variables was to provide information to the model for classification of hay rack use on movement of different parts of sow body in various time windows (from 2 s to 45 s).

Random forest classifier

RF classifier was used for classification of hay rack use events in pre-parturient sows. RF are machine-learning methods for constructing prediction models from data. RF classifier is an ensemble classifier that produces multiple decision trees, using a randomly selected subset of training samples and variables (Breiman, 2001). Furthermore, this classifier can be successfully used to select and rank those variables with the greatest ability to discriminate between the target classes (Belgiu and Drăguț, 2016). Python package scikit-learn was used to train and validate the model on a labelled dataset with 12 sows (Pedregosa et al., 2011).

Importance of 40 feature variables extracted from video data was evaluated with MDI. For the impurity importance, a split with a large decrease of impurity is considered important and as a consequence variables used for splitting at important splits are also considered important. Based on this idea, the impurity importance for a variable X_i is computed by the sum of all impurity decrease measures of all nodes in the forest at which a split on X_i has been conducted (Nembrini et al., 2018).

Results and Discussion

AUC and accuracy of automated detection of hay rack use behaviours in the validation set was 96%, sensitivity was 78.6% and specificity was 96.6% (Table 2).

Table 2: Performance metrics of classification of hay rack use in validation set

Metric	Value
Sensitivity	78.6%
Specificity	96.6%
Accuracy	96%
AUC	96%

These results are comparable with results of Chen et al. (2020) in which long short-term memory (LSTM) was used to detect pig enrichment engagement behaviours. The objective in this research was similar to ours in terms of behaviour of pigs i.e. to detect engagement with enrichment material. In this research it was possible to detect the interaction with enrichment material in weaner pigs housed in group pens with performance from 96.5 % to 97.6% accuracy depending on which type of enrichment material was used. An important difference between algorithms applied in our study and in the study of Chen et al. (2020) was that LSTM applied in their study included temporal information on modelled variables, while RF model applied in our study infers only based on current values of modelled variables.

The most important feature variables for automated estimation of hy rack use behaviour were distance from nose to rack (MDI = 0.13) and orientation of head towards rack based on nose location (MDI = 0.13). Results of our study and Kashiha et al. (2013) indicate the importance of nose location and head orientation for recognition of behaviours in which pigs interact with other objects (i.e. drinker, hay rack). Touch and nose contact have an essential role in communication, recognition, social grooming and the maintenance of dominance relationships (Newberry and Wood-Gush, 1986). Results of our study confirm the important role of the nose for pigs, also apparent from ethological studies such as of Stolba and Wood-Gush (1989) who showed that pigs spend around half of the daylight period foraging with the nose for feed in a semi-natural environment.

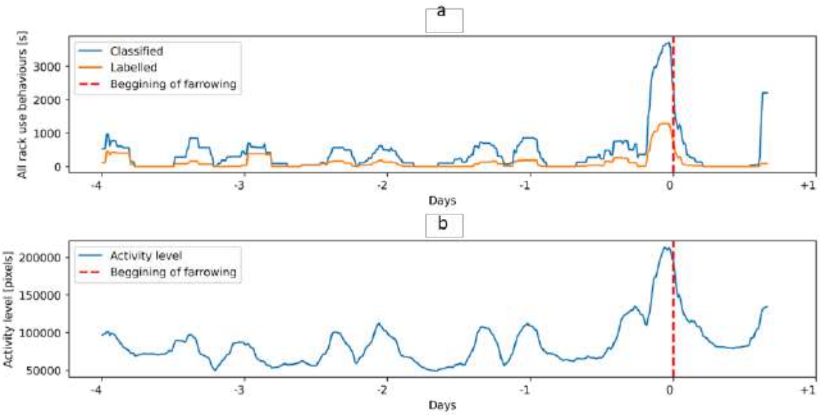

Figure 3: Labelling and classification for sow 147127 10 from the validation dataset of a) hay rack use behaviours. c) Activity level estimated on the basis of euclidean distance between centroids of sow's body in consecutive frames. Presented variables are calculated on a sliding window of 4 h with 15 min steps

Analysis of manually labelled hay rack use behaviours and comparison of these variables to the automatically estimated activity level of sows in a period before farrowing indicate high variability of expressed hay rack oriented behaviours. In 11 out of 12 sows the increase of activity level was very clear with a peak visible several hours before the start of farrowing (Fig. 3), which is consistent with reported dynamics of sows' activity level in this period (Oczak et al., 2019). In contrast, only 6 out of 12 sows reached their peak of labelled hay rack use behaviours at the same time as their peak of activity level (Fig. 3). The other animals had no clearly visible peak in labelled hay rack use behaviours or the peak was reached at different time than the peak of activity level i.e. around 24 h or 48 h or 72 h before the start of farrowing.

What became apparent from examination of confusion matrice was that although AUC, accuracies, sensitivity and specificity were high, the overestimate by the trained models of all hay rack use behaviours was also relatively high. In the validation set the labelled duration of all hay rack use behaviours was 25 h 40 m and 50 s, while automatically classified duration was 44 h 34 m 42 s.

Comparison of manually labelled hay rack use behaviours with results of classification within individual animals suggests high consistency of overestimates. Peaks of detected behaviours occurred in the same time as labelled by human observer and dynamics of variables was very similar (Fig. 3). Only in one sow out of 12 it was possible to observe 2 automatically detected peaks in hay rack use behaviours which were not labelled by human observer at 5.5 and 4 days before the beginning of farrowing.

The possibility to perform nest-building behaviour should be offered to all sows in modern management systems. For this possibility, space and the provision of adequate nest-building material are two relevant prerequisites (Wischner et al., 2009). Automated monitoring of hay rack use in pre-parturient sows might add important information on sow nest-building behaviour. This could support individual care for the sow in this sensitive period, considering that the necessary amount of enrichment or nest-building material is not defined in the law. Based on the information provided by such a monitoring system the farm staff could offer more nest-building material (refill the dispenser) to the sows which use it more frequently.

The second objective of our study was to analyze if output of algorithm for hay rack use detection could potentially improve the performance of farrowing prediction compared to current state-of-the-art techniques for farrowing prediction based solely on activity levels (Oczak et al., 2019; Traulsen et al., 2018). Our idea discussed in Oczak et al. (2019) was to automatically detect and differentiate between behaviours that constitute nest-building behaviour i.e., rooting, pawing, and manipulation of pen or crate (Oczak et al., 2015). In the current study we focused only on automated detection of one of these behaviours, ie. hay rack use. In Oczak et al. (2019) we hypothesised that such capability could provide more detailed information on sows' behaviour and possibly also increase the performance of developed models. Analysis of the performance of the developed models for automated detection of hay rack use in context of farrowing prediction suggests that outputs of the models could be useful for this purpose, as the algorithm correctly indicated dynamics of labelled behaviours i.e. picks in labelled hay rack use behaviours are automatically detected by the algorithm at the same time as by the labeller in 11 out of 12 sows.

Conclusions

In our study we applied object detection algorithm RetinaNet with RF for classification of hay rack use behaviours performed by sows in farrowing pens in a period before farrowing. Distance between the sows' nose and the hay rack was the most important feature variable, which indicated the importance of nose location for recognition of behaviours in which pigs interact with other objects. The developed models could be applied for automated monitoring of the use of nest building material in pre-parturient sows. Such monitoring might be especially important in sows housed on slatted floors considering that the necessary amount of enrichment or nest-building material is not defined in the law.

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Monitoring sow postures, feeding and nursing activity using the combination of deep learning and image segmentation methods

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Abstract

Monitoring sow activity is valuable in moving towards more flexible housing during lactation as it strongly influences piglet survival. Detecting sows that are calm, do not suffer from health problems and nurse their litter efficiently is necessary to develop welfare-friendly systems. We developed procedures to automatically analyse sow activity including postures, feeding and nursing. The method was trained on nearly one million images collected from 10 sows over 5 days each. Sow activity was recorded using two RGB cameras to observe the sow from the front and from the back. Three convolutional neural networks (CNN) were developed for the top front view, the top rear view and for the two angles of view. They were combined so that the lack of consistency in prediction from the two single-view analyses triggered the third analysis. The sequential analysis of few successive images allows to confirm each detection. CNN were trained to identify eight main sow activities, with a mean precision of 85% for all traits. CNN were also coupled with an image segmentation based procedure to measure the intensity of nursing activity with distinction of pre and post massage from milk ejection.

Keywords: welfare, sow behaviour, image processing, deep learning, real-time

Introduction

For ethical, economical and societal reasons, it is necessary to reduce piglet mortality, especially when it depends on the sow, in connection with farrowing and lactation difficulties and if it results from the crushing of piglets by their mothers. In the future it would be beneficial, more profitable and more acceptable to the industry to produce sows that are able to rear more of their piglets to weaning. Guidelines limiting the use of strong restraint systems in pig farming are being adopted, but keeping sows blocked for several days around farrowing is still the only solution to limit losses by crushing in numerous populations. A Norwegian study evidenced that maternal behaviour has a genetic background (Vangen et al., 2005) that could be exploited in selective breeding to reduce piglet losses indirectly, for example by choosing sows that give easy access to the udder to their piglets. Being careful in their posture changes is also a desirable trait that would be worth to consider in selective breeding. Apart from a few ethological studies based on observer's video analyses (Baxter et al., 2012), it has never been recorded and measured.

Monitoring animals over a long time period enables to detect changes in activity level. With the fast evolution of sensor technologies, we can expect automatic collection of large amounts of various behavioural data. If accelerometers have been widely tested to record pig behaviour (e.g. Ringgenberg *et al.*, 2010; Matheson *et al.*, 2017), embedding the sensor on the animal is a main limitation to their general use. More sophisticated sensors may facilitate these kinds of behaviour measurements (Lao *et al.*, 2016, Dore *et al.*, 2020). Cameras raise increasing interest because they are non-invasive, and can be used to monitor several features, such as posture and water intake pattern. For example, sow postural activity in a crate can be estimated from images using a CNN with a very good accuracy (Nasirahmadi et al. 2019, Bonneau *et al.*, 2021), but also from unsupervised methods (Okinda et al. 2018). In this work, we study the potential of using two cameras, to monitor the main postures of the sows and milking detection. A group of lactating sows was video recorded, with two cameras positioned at the front and at the rear part of the crate. Video data were acquired over long periods of time, day and night. The set of image data extracted from the videos has been the subject of a detailed study to develop image processing techniques and artificial neural network. This article presents the methodology developed to determine, postural activity, including sow feeding activity. In addition, an image segmentation method was developed to measure sow nursing activity.

Material and methods

<u>Monitoring Framework</u>

Measurements were performed on lactating sows of the Large White breed, on an experimental farm. An artificial vision system was developed to carry out image acquisition. Ten sows were raised in crate from the entrance to the exist of the farrowing unit. Two IP cameras (Bascom model) have been installed to visualize the front and rear part of the sow. Cameras recorded at 10 Hz, regular RGB images from 6am to 6pm, and B&W acquired from infrared (IR) the rest of the time. The objective was to obtain, from the acquired videos, sow activity information on different acquired videos, during several days (night and day). Figure 1 below shows the two cameras used for one crate (a) and examples of night (b) and day (c) images acquired by the two cameras. For (b) and (c), the images from the front and rear camera are merged.

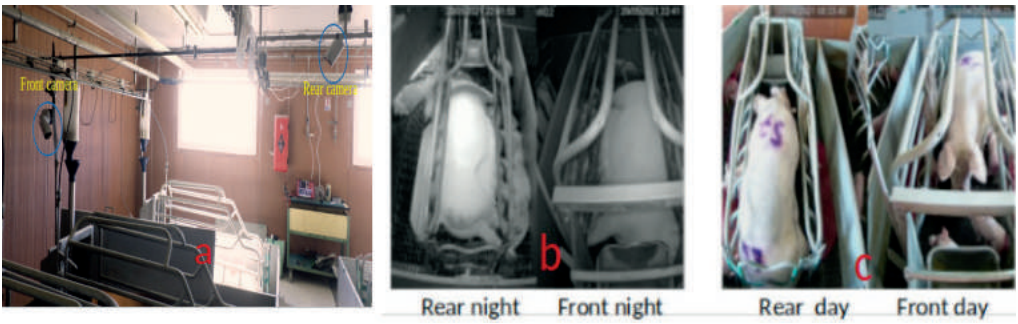

Figure 1: Vision device with two cameras fixed at the front and rear part of the crate, with night and day image visualisation

We were interested in the identification of ten main activities and postures of the sow: standing with and without feeding activity, sitting, lying sternally, nursing activities lying on the left or right sides, considering for each side, two possibilities (with and without piglet). Figure 2 presents images acquired with the two cameras, for the eight main sow activities. For each behavioral trait, the left and right images are respectively the images acquired with the rear and front cameras.

Figure 2: Images for the eight main sow activities under study, acquired from the rear camera (left side) and front camera (right side)

Posture detection

The study focused on a set of videos acquired and recorded for 50 days (10 sows over 5 days each). From these videos, an image-by-image scan was carried out to create the database of labelled images (Kabra et al., 2013), with the aim of subsequently train and evaluate some CNN to predict sow posture. The training image database included about one million images, for the 8 activities, divided into 3 groups: 330000 images from the rear camera, 330000 images from the front camera and 330000 images obtained by concatenating the images of the rear and front cameras. Three neural networks were developed for this study, using the python library Tensorflow. Several CNN architecture were tested, and Inception V3 was retrained, as it provided the best empirical results. The Inception V3 neural network model is a CNN developed by Google, which was trained on the basis of ImageNet images which includes millions of images and about 1000 categories, and which is composed of a training phase and a classification phase (Szegedy et al., 2015). The number of convolutional and fully connected layers is 48, in Inception V3 architecture. As the training phase has already been carried out, we are therefore only interested in the classification or data extraction phase (re-learning only of the last network layer), which is very fast and efficient. CNN were re-trained using transfer learning, by re-learning only the last layer of the network, which greatly speed-up the training process without dramatic loss of accuracy (30 minutes to create each of the three CNN).

Figure 3 presents the learning method general principle which includes a back propagation algorithm, in order to create a CNN, by minimizing errors inside the CNN layers, and the prediction task used for sow activity identification, for a given image. The three neural network trained independently were created from the image database for eight activities. From acquired images by the two cameras, a fusion data method (Figure 4) was used to obtain the final prediction result: if at least two CNN give the same prediction result, then the final prediction is this one, otherwise, if three prediction results are different then the sow activity is not determined.

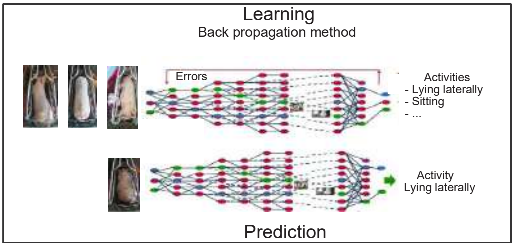

Figure 3: CNN development

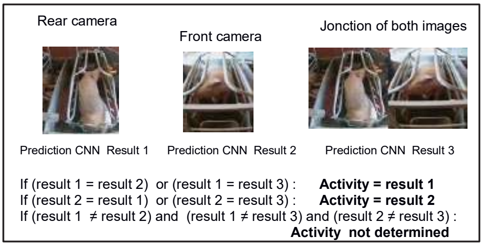

Figure 4: Fusion method for sow activity identification

Nursing Activity

When the sow is defined as lying on her side, when she is in one of two nursing situations (laying left with nursing or laying right with nursing), obtained during the first operation of the developed software, corresponding to sow activity identification, then a second operation, corresponding to the measurement of the nursing activity is launched. The image processing developed to carry out this operation consists in a first time to find automatically the rectangular area which contains the udder of the sow, in the rear image. For this, an artificial vision algorithm composed of image segmentation and mathematical morphology functions is used. Then the measurement algorithm is applied: it counts the number of points (pixels) that change of color intensity in the Red, Green and Blue color space, with defined thresholds for Red, Green and Blue components, in this area, between two successive images acquired at times t and t + 0.1 seconds. The intensity of nursing activity, is obtained by calculating the ratio between the number of points that change color and the rectangular area of the udder. The Figure 5 presents the rectangular area of sow udder and the points with a significant color change between two successive images (blue color), that characterize the nursing intensity.

Figure 5: Illustration of nursing measurements detected from level of udder movement

Evaluation

On the big set data of acquired images (about 330000 images for rear camera, for front camera and for junction of both images), an image processing algorithm was applied in order to remove similar images, particularly for sternal, lying left or lying right activities (little movement of sows and the piglets). A dataset containing about 200000 images for each of the three image type, was obtained with this algorithm. From this dataset, a random set with about 150000 images for each of image type (rear, front and junction) was extracted for CNN developement (training) and a second one with about 40000 images, for CNN testing and evaluation. For each activity, precision, sensitivity and f1-score values were computed to compare the three CNN and the fusion method, for the test images, with the following computations for each activity called p, from three confusion matrix data (True Positive (TPp), False Positive (FPp) and False Negative (FNp)) obtained in the prediction results:

$$Sensitivity_p = \frac{TP_p}{TP_p + FN_p} \qquad Precision_p = \frac{TP_p}{TP_p + FP_p} \qquad f1-score_p = 100 \times \left(2 \times \frac{Sensitivity_p \times Precision_p}{Sensitivity_p + Precision_p}\right)$$

Results and Discussion

Table 1 presents the confusion matrix obtained for the eight activities with the three networks corresponding to individual CNN (rear camera (a), front camera (b) and junction of both images (c)) and with the fusion method (d), for analysing and comparing the three CNN performances, for sow activity prediction. The first column presents the eight activities, the second one presents the TP_p values, the others values in the matrix 8x8 are the FN values in horizontal lines and the FP values in vertical columns. FN_p and FP_p are the mean values for each activity p.

Table 2 presents the precision (P), sensitivity (S) and f1-score (F) values for the eight activities and the four prediction methods: CNN for Rear camera (CNN-R), CNN for Front camera (CNN-F), CNN for the TWO cameras (CNN-TWO) and Fusion Method (FM). Regarding the four methods, you can see, making a comparison between all the results, that the best results are obtained with the Fusion method, with high mean success rates for Sensitivity, Precision and F1-score equal to 85%. For the three individual CNN, the best results are obtained with CNN-R (84%). This CNN-R network (rear camera) can work alone to predict with accuracy, the sow activities. We can see that the best results are generaly obtained for Sitting, and Standing activities (about 99%). For Laying left or right activities, without or with nursing, the result quality is variable, between 65% and 85%. Also, the activities such as Sternal and Lying left or right, without any piglets, can be difficult to discriminate. This point can be explained by the fact that it is difficult to annotate (expertise) these three activities, with accuracy, in the CNN training operation. If we take into account the sequential aspect of the measures in real time, in our software, improvements are done, for identification of these activities (Sternal and the four Lying activities). This principle permits to reduce false identification.

Table 1: Confusion matrix for eight activities for four methods (three individual neural networks and a fusion method)

Sternal	5422	138	8	59	309	210	278	146
Sitting	14	3254	2	2	0	3	0	7
Standing feeding	0	1	2902	18	0	0	0	0
Standing not feeding	45	191	229	2923	4	11	3	4
Lying right	115	0	0	1	589	181	24	3
Lying right nursing	224	13	2	1	433	4815	30	61
Lying left	110	3	0	4	159	134	2269	380
Lying left nursing	484	76	8	25	54	1545	677	8395

a

Sternal	4756	135	20	63	1087	133	335	217
Sitting	58	3179	16	13	4	1	3	1
Standing feeding	5	18	2814	85	0	1	0	0
Standing not feeding	57	332	388	2588	6	17	7	4
Lying right	42	0	0	1	785	80	3	6
Lying right nursing	203	14	3	5	1323	3828	49	1428
Lying left	44	2	0	0	18	8	2811	212
Lying left nursing	262	157	13	25	90	365	2295	8105

b

Sternal	5384	223	10	86	512	235	268	66
Sitting	38	3191	5	46	0	0	0	1
Standing feeding	0	44	2803	70	0	4	0	2
Standing not feeding	19	218	262	2870	2	8	51	21
Lying right	17	1	0	0	742	123	19	10
Lying right nursing	152	20	2	6	1044	4304	156	1222
Lying left	32	3	0	0	48	32	2906	72
Lying left nursing	399	150	15	18	215	1374	2006	7116

c

Sternal	5462	419	2	47	527	93	188	90
Sitting	13	3260	4	3	0	1	0	1
Standing feeding	0	42	2849	32	0	0	0	0
Standing not feeding	42	137	278	2980	1	6	11	3
Lying right	36	1	0	0	768	105	6	4
Lying right nursing	194	47	1	1	765	4615	17	1288
Lying left	29	5	0	1	27	26	2846	164
Lying left nursing	325	257	14	11	57	930	1204	8574

d

The developed algorithm analyses the images acquired with the two cameras, identify the sow activity and record the results (the postural activity and the nursing intensity) into one file, with a frequency of 1 Hz, in live mode. Due to the absence of dedicated dataset, nursing activity was only evaluated by visual observations. This algorithm makes it possible to carry out detailed analyzes of the sow activity, to study their behavior over time and to carry out various comparisons between sows. Figure 6 presents the results obtained for one sow, during about 24 hours (86400 seconds).

The activity numbers between 1 and 8, are associated respectively to the following activities: Lying left, Lying left with nursing, Lying right, Lying right with nursing, Sternal, Sitting, Standing without feeding and Standing with feeding.

Table 2: Quality of four methods

	CNN-R Prediction result			CNN-F Prediction Result			CNN-TWO Prediction Result			FM Prediction Result		
	S	P	F	S	P	F	S	P	F	S	P	F
Sternal	0,83	0,76	0,79	0,71	0,83	0,76	0,79	0,88	0,84	0,83	0,87	0,83
Sitting	0,99	0,92	0,95	0,97	0,86	0,91	0,97	0,88	0,93	0,99	0,87	0,93
Standing feeding	0,99	0,93	0,96	0,96	0,89	0,92	0,96	0,92	0,94	0,97	0,92	0,95
Standing not feeding	0,86	0,98	0,91	0,75	0,94	0,84	0,83	0,94	0,88	0,86	0,98	0,92
Lying right	0,65	0,78	0,71	0,86	0,7	0,77	0,81	0,76	0,78	0,83	0,81	0,82
Lying right nursing	0,86	0,68	0,76	0,56	0,79	0,65	0,62	0,67	0,65	0,67	0,75	0,71
Lying left	0,74	0,85	0,79	0,91	0,77	0,84	0,94	0,77	0,85	0,92	0,86	0,89
Lying left nursing	0,75	0,82	0,78	0,72	0,69	0,7	0,63	0,73	0,68	0,75	0,75	0,75
MEAN RESULTS	0,83	0,84	0,83	0,80	0,81	0,80	0,82	0,82	0,82	0,85	0,85	0,85

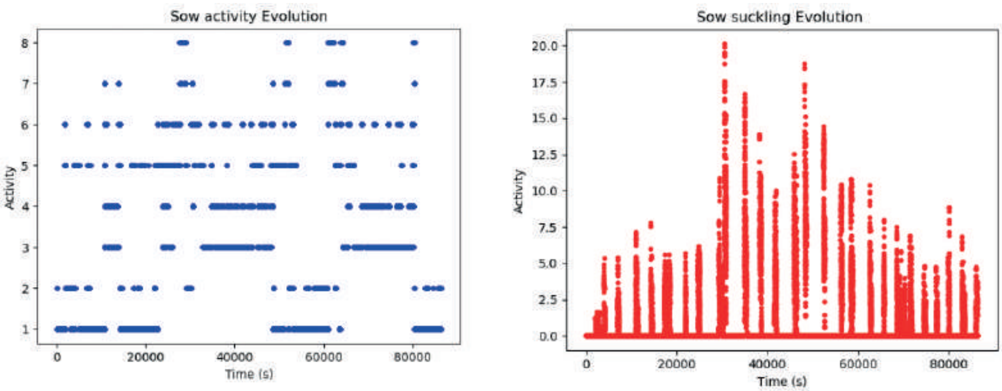

Figure 6: Results obtain during a long time (sow activity (blue) and nursing (red))

A detailed analyze of piglet nursing activities results obtained with the image segmentation algorithm, for several sows and for different time ranges (during day or night), showed that these results are similar to the nursing general activity, that we can see in many experimentation and tests of the piglet behavior: there are three main periods in one nursing activity. The first one is a first operation of piglets to obtain, to eject milk (a lot of movement of the udder (high intensity values)), the second one is the nursing (weak movement of udder (slow intensity values)) and the last one consists, like the first operation, to eject milk (big movement of the udder (high intensity values) to begin to prepare the next feeding (about one hour after) (Figure 7).

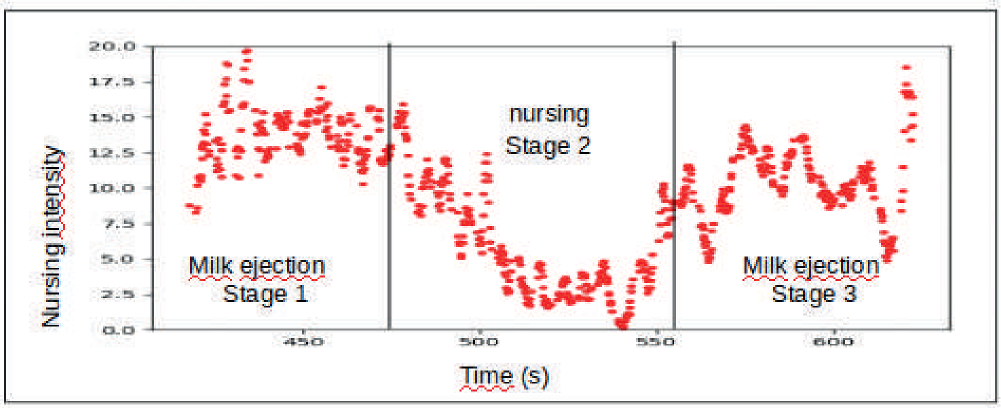

Figure 7: The three stages of piglet nursing activity – Artificial vision results

Conclusion

This paper proposed an artificial vision device constituted by two IP RGB cameras (with IR integrated sensor for night acquisition), connected to a computer, with the development of a real-time algorithm (working frequency of 1 Hz), for sow activities identification, using deep learning and image processing methods. The obtained result with the developed software permit to obtain data file which show the duration and the time range for the main activities, for long periods, night and day, including the measurement of feeding activities for sows and piglets (nursing activity). The image processing software can be used with only the rear camera or with the two cameras to increase the accuracy of prediction, for Sitting or Standing with feeding activities. To optimize the sow activity identification, sequential analysis of few successive images will be tested to allow to confirm each identification, and so to improve the activities identification, for Sternal and Lying activities.

The measures obtained permit to finely analyse the activity pattern of sows over long periods of time, to define variations over time for each sow and to compare different sows, in order to identify, in particular, the individuals which present a deviant profile by comparing them to those which have a normal profile. The developed device will be installed in different pig farms in order to test and validate the developed software, with the objective to see if the complete device including the two cameras and the developed software is able to operate in various environments, with different floor colours, various barrier positions, and also modifying the position and orientation of the two cameras. In order to improve the software, new images acquired in various pig farms will be annotated to enrich the training image database, and updating the neural networks. This type of method used for sow farms, using video devices to take measurements, will be tested for other animals such as sheep, cattle and goats.

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Posture detection of sows housed in farrowing crates using composite image models

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Abstract

Determining changes in sow posture can provide information on the production and health of animals. However, manually evaluating images is extremely time-consuming and standard image processing approaches can require seconds per image to process. The use of deep learning techniques has the advantage of being a more efficient method when compared to traditional image processing. However, transition sow postures such as sitting, and kneeling are difficult to discern using RGB images alone. The aim of this study is to compare the use of different images as input to models based on deep learning for the detection of sow postures. Using Kinect v.2 cameras, images were collected from 7 sows housed in farrowing crates. A total of 4229 images were labeled manually according to the postures (standing, kneeling, sitting, ventral recumbency, and lateral recumbency). Deep learning algorithms (AlexNet) were adapted to detect sow postures from five types of images: color (CNN_{rgb} model), depth (depth image transformed into grayscale: CNN_{depth} model), and three fused images composed with the color and depth images (CNN_{blend}, CNN_{diff}, and CNN_{fcolor} models). The results showed that depth and fused models presented the best results. CNN_{fcolor} presented 95.5% of average accuracy, followed by CNN_{depth} (94.3%) CNN_{blend} (90.3%), and CNN_{diff} (86.7%). CNN_{rgb} model presented 76.8% average accuracy. The results of this study illustrate the improvement in the classification of postures using depth or fused image methods. Other studies may contribute to the development of increasingly rapid and accurate models by using a larger database, evaluating different fused methods, computational models, systems, breeds of sows, and incorporating additional postures.

Keywords: computer vision, deep learning technique, image pre-processing, sow posture detection.

Introduction

Currently in the US swine industry, lactating sows are housed in farrowing crates to protect the piglets from overlays. However, even with the use of farrowing crates, the pre-weaning mortality for piglets is 17.3% (Stalder, 2018). The risk factors contributing to pre-weaning mortality are generally classified into three main categories: piglet factors, sow factors, and environmental factors. Muns et al., (2016) highlights the need to understand sow comfort, as sow comfort impacts piglet development and the risk of crushing.

Accessing the behaviour of pigs is important to identify their state of health and well-being and can provide important information about the performance of the production system (Brown-Brandl et al., 2013). Sow posture changes can result in piglet crushing, mostly by sows lying down (Damm et al., 2005). More importantly, it appears that the sow's control over the final stages of laying is critical (Johnson & Marchant-Forde, 2008). Slower postural changes may be a sign of more protective mothers and be related to lower piglet mortality rates from crushing. Therefore, to evaluate the interaction between the crates and the sow there is a need to develop automatic detection methods.

However, the investigation of behaviours is still performed manually, depending on trained observers and time to evaluate the data, which makes it impossible to generate quick answers for decision making. Thus, Deep Learning techniques have been used as an automatic way to assess the behaviour of lactating sows. Such computational models, based on artificial intelligence, allow a quick interpretation of data, and have great potential for use in production systems. On the other hand, the type of data used to train these models plays an important role in getting the most accurate results.

Several works use RGB and depth images to detect sow postures (Bonneau et al., 2021; Kasani et al., 2021; Lao et al., 2016). Despite providing a good representation of the scene, the RGB image is a two-dimensional function representing a three-dimensional scene. By losing depth information, detecting transitional postures such as sitting, and kneeling is more challenging. On the other hand, depth images, even adding depth information, lose in terms of color representation and scene details, important information to differentiate the animal from the other objects in the image.

Zheng et al. (2018) studied a Convolutional Neural Network (CNN)-based posture detector and used only depth images from sows in its development. The authors obtained an average accuracy of 93.58% (five posture classes). The highest accuracies were for the standing, ventral, and lateral recumbency classes and the lowest for the sitting and sternal recumbency positions. In another study, Zhu et al. (2020) used the same database for the detection of postures but used different methods of merging RGB and depth images in the development of the computational models. All models that used fusion methods obtained better results and, in the most accurate model, the accuracies for all posture classes were above 90%.

These studies demonstrate that CNNs are promising in identifying sow postures. Furthermore, combined image fusion methods can contribute to the development of more accurate models. New studies may contribute to the development of increasingly accurate models for the detection of different postural categories in different systems, with different species of sows. Thus, this study aims to develop a computational model for the classification of sow postures using different types of images as the input of the classifiers. The hypothesis is that by merging the RGB and depth images, some features in the images can be highlighted which can help the models to classify the sow postures.

Material and methods

The experiment was conducted at the United States Department of Agriculture - Agricultural Research Service of the US Meat Animal Research Center in Clay Center, Nebraska, the United States. Data collection was performed in accordance with federal and institutional regulations regarding proper animal care practices and was approved by the U.S. Center for Animal Research Institutional Animal Care and Use Committee (2015-21) (IACUC approval: 1837).

The collections were carried out from January 2020 to April 2021 in a farrowing facility where the 546 sows (Landrace x Yorkshire) were individually installed in 3 rooms with a capacity for 20 animals each. Inside of each room, the animals were distributed in two rows of ten metallic pens, separated by 1.2 m. The building has a microclimate controlled with sensors and controllers so that the air temperature inside the rooms was kept around 25°C and was gradually reduced to 20°C until the end of the lactation cycle. The installation consisted of individual feeders and two nipple drinkers. Animal waste fell from the stalls through fully slatted metal floors into a shallow, sloping pit in each room.

At the top of each crate, at a height of 2.55 m, a single depth camera (Kinect V2®) was installed in waterproof plastic boxes that were fixed to a metal structure to collect images (top view) of the stalls and animals. Such cameras were responsible for collecting color (RGB) and depth (distance matrix) images. Images were collected 24 hours a day at an average rate of one image every 2.5 seconds. The cameras were connected to minicomputers (Windows 10 Home, Microsoft, Redmond, WA, USA) located in front of each of the bays that ran the image collection program developed in MATLAB® R2019b software (The MathWorks Inc.). The minicomputers were connected via Ethernet cables to data storage stations (DS1621+, Synology Inc, Bellevue, WA) with five hard drives (ST10000VN0004, Seagate Technology LLC, Cupertino, CA, USA).

Sow posture classification

For this analysis, images of seven sows were used for a period of 12 hours. The images were divided into five categories of sow postures (Table 1): standing, sitting, kneeling, ventral recumbency, and lateral recumbency.

Table 1: Ethogram of the postures used for the classification of images and for the development of the computational model

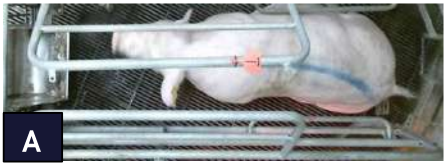
Posture	Description
Standing	Animal supporting the body on all four legs
Sitting	Animal supporting the body on both front legs (bent hind legs)
Kneeling	Animal supporting the body on its hind legs (folded front legs)
Ventral recumbency	Animal lying vertically with front legs hidden/hind legs and udder could be visible (right side, left side) or not;
Lateral recumbency	Animal lying on its side with all four legs turned to the side

A total of 4229 images were used in the development of the computational model (Figure 1): 1041 images for the standing class, 403 for the kneeling class, 1029 for the sitting class, 724 for the ventral, and 962 for the lateral recumbency classes.

Image pre-processing

Five types of images were used to participate as inputs of the computational model (Figure 1): color (RGB image), depth (depth image transformed into grayscale) and three merged images composed with the depth and color images (blend, diff, and false color). The merged images were created according to the MATLAB functions: blend is the image composed of the color and depth images using an “alpha blending”, which gives a degree of transparency to one of the images before superimposing them. The “diff” creates a difference between the color and the depth, and the “false color” creates a composite color image showing the two images superimposed in different ranges of colors. Gray regions in the composite image show where the two images have the same intensities. The magenta and green regions show where the intensities are different (MathWorks, 2020).

Label	N images
Standing	1041
Kneeling	403
Sitting	1099
Ventral recumbency	724
Lateral recumbency	962
Total	4229



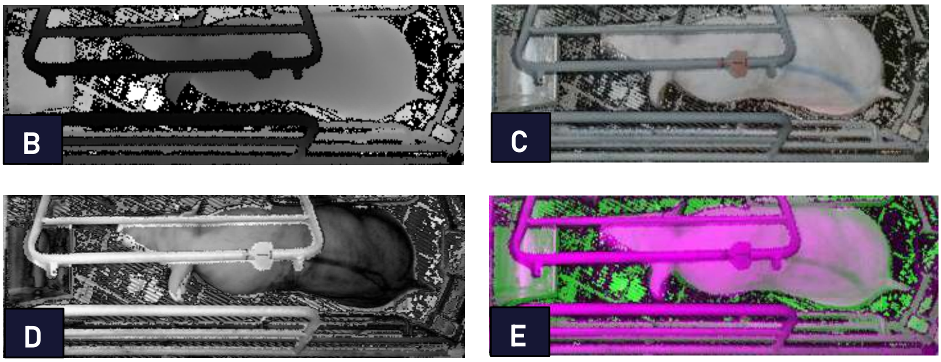


Figure 1: The number of images for each posture class and examples of the five types of images that were tested as input to the computational model: (A) color image; (B) depth image transformed into grayscale; (C) fused images – blend; (D) diff; and (E) false color

Development of computational models

Classifier computational model based on Convolutional Neural Network was developed with MATLAB® R2020b software using the Deep Learning Toolbox package. The first step in developing the model was to divide the data (images) into training, validation, and testing sets. Percentages of image distribution between the groups were 80%, 10%, and 10%, respectively. Such data was provided to the classifier model through the input layer. Data augmentation techniques (reflection and translation) were used to increase the training database.

For the development of the computational model, the pre-trained AlexNet (Krizhevsky et al., 2012) network was used, replacing the last classification layer with the new learning categories: the sow postures (standing, sitting, kneeling, lateral, and ventral recumbency). The hyperparameters - number of epochs, learning rate, batch size, and solver were defined empirically and through literature. The classifier's performance was evaluated using metrics extracted from a confusion matrix, comparing real responses (classified by an observer) and the responses predicted by the model. Through the confusion matrix, it is possible to evaluate the efficiency of the classifiers in terms of average accuracy, precision, recall, and F1-Score. These metrics were thoroughly described and summarized by Sokolova & Lapalme (2009) and can be computed using the formulas described in the Table 1. All metrics were calculated based on the values identified in the confusion matrix as true positives (t_p), true negatives (t_n), false positives (f_p), and false negatives (f_n). Values identified as t_p are those correctly identified as belonging to the class and t_n are the values correctly identified as not belonging to the class. The f_p values are those misidentified as belonging to the class and the f_n misidentified as not belonging to the analyzed class (Sokolova & Lapalme, 2009).

Table 1: Metrics extracted from a confusion matrix for multiclass classification

Measure	Formula	Measure	Formula
Average Accuracy	$\frac{\sum_{i=1}^{l} \frac{tp_i + tn_i}{tp_i + fn_i + fp_i + tn_i}}{l}$	*Precision*$_\mu$	$\frac{\sum_{i=1}^{l} tp_i}{\sum_{i=1}^{l} (tp_i + fp_i)}$
F1 – Score$_M$	$\frac{2 \times Precision_i \times Recall_i}{Precision + Recall}$	*Recall*$_\mu$	$\frac{\sum_{i=1}^{l} tp_i}{\sum_{i=1}^{l} tp_i + fn_i}$

Values identified in the confusion matrix (t_p) true positives, (t_n) true negativas, (f_p) false positives, and (f_n) false negatives. Recall and precision values were calculated by class: (μ) micro-average. F1-Score was calculated for all classes: (M) macro-average.

Results and Discussion

Metrics extracted from the confusion matrices were used to evaluate the efficiency of CNN-based classifier models that used different images: color (CNN_{rgb}), depth (CNN_{depth}), blend (CNN_{blend}), diff (CNN_{diff}), and false color (CNN_{fcolor}). The results showed that the inclusion of depth information improved the performance of the models, as both CNN_{depth} and all merged models (CNN_{depth}, CNN_{diff} and CNN_{blend}) present higher accuracies than CNNrgb (Figure 2). Among all models, CNN_{depth} and CNN_{fcolor} had the highest accuracies and F1 scores. The accuracies achieved were 94.3% for CNN_{depth} and 95.5% for CNN_{fcolor}. Respectively, F1-Score values were 4.5% values. The lowest average accuracy value was found for CNN_{rgb} (76.8%). Kasani et al. (2021) investigated eight deep learning-based feature extraction frameworks to classify four sow postures (sitting, lying right, lying left, and standing) from RGB image dataset collected from animals (Yorkshire x Landrace) housed in gestation crates. Different from this study, all models that used RGB images presented high average accuracy (> 99%). An explanation for the inferior performance of CNN_{color} may be the number of postures (five) used for classification in the current study. Furthermore, postures such as kneeling, and the division of the lying posture into two categories added greater challenges to the training of the models.

Zheng et al. (2018) studied a CNN-based posture classifier using depth imaging and found an average accuracy of 93.58% and an F1-Score of 90%, values slightly lower than those found for this study when only depth image was used. Although the results were close, some differences in the studies may explain the improvement in the performance CNN_{depth}. One of them may be related to the type of facility in which the animals were housed. While the sows in this study were confined in farrowing crates, the sows in the aforementioned study were in free farrowing pens, which may have added variations in the images analyzed, as the sow can move freely through the pens.

Other differences between this study and the one developed by Zheng et al. (2018) indicate that the performance of CNN_{depth} can still be improved. Despite having used the same number of postures as in the current study (five), the authors did not use the “kneeling” posture and used the “ventral decubitus”, which is a more static posture. The authors also used strategies used to improve the images, including random noise compensation, hole filling, and image depth enhancement. Furthermore, they used a pre-trained network (ZFNet) as a model to detect sow postures. In the current study, the distance values of the depth image were only transformed into a grayscale range, and the AlexNet network was used to detect postures. These data indicate that the models used in the current study showed good average accuracies and that they can still be improved with the use of a larger database, different image pre-processing strategies to further improve the quality of these images.

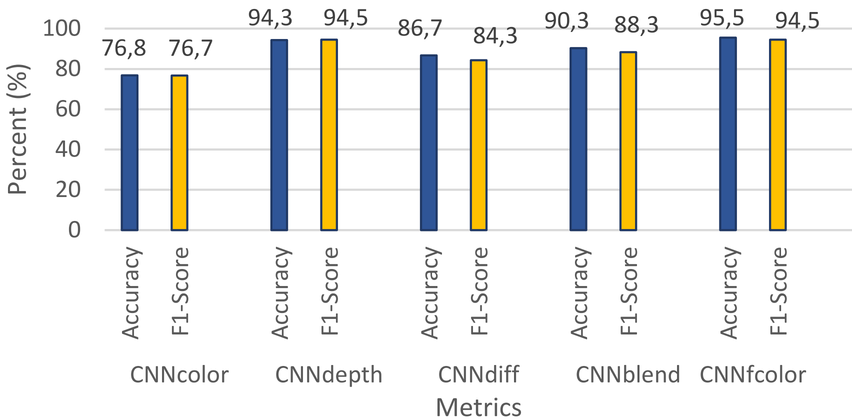


Figure 2: Metrics (Average Accuracy and F1-Score) extracted from the confusion metrics obtained from the classifiers

CNN_{fcolor} was the best model according to the average accuracy and F1-Scores and the confusion matrix with the predictions of this model in the posture categories can be seen in Table 2. As mentioned earlier, the correct classifications accounted for an average accuracy of 95.5%, distributed in the class “kneeling” (9%), “lateral recumbency” (22.7%), “sitting” (24.9%), “standing” (23.5%), and “ventral recumbency” (15.4%).

The CNN_{fcolor} presented high values of precision (mean = 95.2%) and medium to high values of recall (mean = 93.3%). The lowest values of precision and recall were in the “ventral recumbency” (90.3%), and in the “kneeling” class (77.6%), respectively. The precision results indicate that CNN_{fcolor} committed a few mistakes when bringing in data from other classes and classifying them as if it were the desired output (mean error < 5%).

Regarding the recall results, the only class that presented a value lower than 95% was “kneeling” (77.6%). This means that the model classified 77.6% of the “kneeling” samples correctly and classified the remaining 22 % of kneeling images as other classes as “sitting” (10%),”standing” (10%), and “ventral recumbency” (2%). One possible cause for this misclassification is that “kneeling” is a transitory posture between “standing” and “lying”. In this position, the model probably uses the height difference between the rump and the sow’s shoulder as an indication of this posture. The height difference when the sow is seated might be similar to the height differences in some of the “kneeling” images, leading to the model misinterpreting five of the images as if they were sitting. While in the standing position, a difference in height between the croup and the shoulders may be very similar to kneeling in cases where she has her head down, contributing to five misclassifications. The same can be thought of for the ventral recumbency position if the sow presents the head raised. In addition, this was the category with the lowest number of examples for training the model and this may have hampered the learning of the model for this category. Nevertheless, a larger database with more examples in this category may improve the model’s accuracy.

Zhu et al. (2020) studied different computer models and different image fusion methods to detect sow postures (“standing”, “sitting”, “sternal recumbency”, “ventral recumbency” and “lateral recumbency”). As with the results of this study, all image fusion methods presented better results than the models trained with RGB, and the depth images separately. The authors found the best model using an image concatenation method, the precision values for the postures: “standard”, “sitting”, “sternal recumbency”, “ventral recumbency” and “lateral recumbency” were, respectively, 99.74%, 96.49%, 90.77%, 90.91%, and 95.47%. The sows (MeiHua) were housed individually in open farrowing pens (Zheng et al., 2018). Similar to the current study, there were classification errors between sitting, sternal and ventral recumbency postures that may have similarities due to the variation in height between head, shoulder, and rump, which may have made learning the model difficult.

Furthermore, Zhu et al. (2020) used a different computational model (ZFNet) to detect sow postures, selected different postures, and used a later fusion method on the images, which first used independent models to extract the feature map from RGB and depth images separately, and then the two maps were stacked and submitted to the classification model. Thus, the information from the two images was only merged after being submitted to a convolution layer of the classification model. In the current study, no later fusion method was studied, but the results obtained with CNN_{fcolor} were promising to highlight the main characteristics of the different images (RGB and depth) before submitting them to a computational model. As mentioned, the kneeling posture added a major challenge in training the model, which can be improved as the database grows by adding more samples of this class. In addition to increasing the database, different image fusion methods and computational models can be studied to improve the results. According to the potential of each model to classify certain postures, other models can be used to merge this information and improve the results even more.

Table 2: Confusion matrix between the predicted class by CNN_{fcolor} and the true label, obtained from the postural categories labeled manually

True label	Predicted label					Recall
	Kneeling	Lateral rec.	Sitting	Standing	Ventral rec.	
Kneeling	**38 (9%)**	0 (0%)	5 (1.2%)	5 (1.2%)	1 (0.2%)	77.60%
Lateral rec.	0 (0%)	**96 (22.7%)**	0 (0%)	0 (0%)	4 (0.9%)	96.00%
Sitting	1 (0%)	0 (0%)	**105 (24.9%)**	0 (0%)	2 (0.5%)	97.20%
Standing	0 (0%)	0 (0%)	0 (0%)	**99 (23.5%)**	0 (0%)	100.00%
Ventral rec.	1 (0.2%)	0 (0%)	0 (0%)	0 (0%)	**65 (15.4%)**	95.50%
Precision	95.00%	100.00%	95.50%	95.20%	90.30%	**95.50%**

Conclusions

This study investigated the use of different types of images as input to computer models to identify postures of lactating sows. The intention was to investigate whether different image fusion methods could highlight some parts of the images and help improve the results of the computational model to identify sow postures. The models that used the depth image (CNN_{depth}) and all the models that used merged images (CNN_{diff}, CNN_{blend} and CNN_{fcolor}) resulted in better accuracies than the model that used only the RGB image (CNN_{rgb}) as input. The "kneeling" category had the greatest difficulty in being classified correctly. Despite this challenge, CNN_{fcolor} presented good values of average accuracy, precision and recall for all classes. The results of this study illustrate the improvement in posture classification using depth or fused images. Other studies can contribute to the development of increasingly faster and more accurate models, using a larger database, evaluating different fused methods, computational models, systems, sow breeds, and also incorporating additional postures.

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Occlusion-resistant spatial analysis of pig distribution pattern in farrowing pens using center clustering network

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Abstract

The spatiotemporal distribution of animals in controlled housing systems is a good indicator of their physiological wellness and welfare. However, to monitor the pigs in farrowing pens for spatial distribution analysis, the existence of farrowing crates brings inevitable visual occlusions, leading to a need for occlusion-resistant computer vision methods. This study aims to use Center Clustering Network (CClusnet) to characterise pig distribution patterns in farrowing pens with closed and half-open crates. Three videos with crates closed and three with crates half-open were collected. A total of 4,600 images were extracted from the videos and labelled to train CClusnet, and the trained model was then used to analyse individual video frames. The model outputs, including centre points of individual piglets and semantic segmentation of the sow and piglets, were accumulated into piglet-position heatmaps (PPH) and bodily-space-usage heatmaps (BSUH) for spatial distribution analysis, respectively. The BSUH of sows revealed differences in sow space usage, e.g., the sow utilized 1.5 times more space in half-open crates than in closed crates in this study. In addition, the BSUH of sows showed different preferences in sow lying sides, e.g., five of the six sows had unbalanced lying side frequency. The BSUH of piglets demonstrated the most frequent area that piglets visited or stayed in, e.g., around the heat pad and the pen border. The PPH supplemented the missing information under occlusions, especially the suckling area of piglets. Our method could be further used for sow lying side preference analysis and thus precaution of lesions due to one-side lying.

Keywords: deep learning, space usage, animal welfare, farrowing crate, animal housing design

Introduction

In modern pig farrowing pen systems, crushing or overlying by the sow contributes to around 50% of the postnatal piglet mortality, which brings animal welfare concerns and a great economic loss to the pig industry (Andersen *et al*., 2005). To reduce piglet mortality, various farrowing pens with farrowing crates, which confine the sow during parturition and lactation, have emerged as the predominant farrowing environment during the last 50 years (Wackermannová *et al*., 2017; Robertson *et al*., 1966; Baxter *et al*., 2018).

Over the past decades, the welfare of pigs related to the adoption of farrowing crates has attracted increasing attention, and farrowing systems with less confinement have been suggested and adopted in some countries, such as the United Kingdom, Switzerland, and Finland (Baxter *et al*., 2018). There has also been voluntary uptake of loose-farrowing alternatives (King *et al.*, 2019). Farrowing pen with a hinged farrowing crate has been proposed to improve the welfare of lactating sows, in which the crate can be half-opened several days post-farrowing (Ceballos *et al.*, 2020). Ceballos *et al.* (2020) found that sows in half-open crates utilized the extra space and had fewer teat lesions than in closed crates. Nevertheless, piglet behaviour and welfare were not investigated in this study.

When analysing animal welfare, the spatiotemporal distribution of animals can be used as an important indicator of their physiological wellness and welfare status (Ross *et al.*, 2009; Estevez & Christman, 2006). An accurate spatial distribution analysis usually requires long-term and high frame-rate video monitoring, which is labour-intensive and cannot be done manually. Nowadays, deep learning methods have shown great power in analyzing animal videos automatically. However, when these methods are applied to monitor the pigs in farrowing pens, the existence of farrowing crates brings inevitable occlusions, which remains an unsolved challenge in deep learning (Wang *et al.*, 2018; Hafiz & Bhat, 2020). We previously developed Center Clustering Network (CClusnet) to count piglets in farrowing pens with occlusion problems (Huang *et al.*, 2021). CClusnet uses every visible pixel to predict the centre of an object, even if the object centre is occluded, which would be suitable for animal spatial distribution analysis in farrowing pens with occlusions. To the end, this study, using CClusnet, aims to analyse and compare the spatiotemporal distribution patterns of pigs in farrowing pens with half-open and closed farrowing crates.

Material and methods

<u>Experimental data</u>

Three videos from farrowing pens (Figure 1) with closed farrowing crates and three videos from pens with half-open crates were selected from a previously published study (Ceballos *et al.*, 2020). All animal procedures in this study were approved by the University of Pennsylvania's Institutional Animal Care and Use Committee (Protocol #804656). The six videos (Table 1) were taken by top-view cameras with a frame rate of 7 FPS and a resolution of 1024×768 pixels. Each video included one sow (DNA Genetics, Columbus, NE) and the number of piglets in each pen varied from 7 to 17. The farrowing pen dimensions were 2.1×2.0 m with a farrowing crate whose hinged sides had the dimensions of 0.64×1.73 m. Totally, 18,117 images were extracted from the six videos every 50 frames (7 s interval), among which 4,600 images were labelled for piglets centres, individual piglet masks, and sow masks as required by CClusnet (Huang *et al.*, 2021).

Figure 1: Image examples of farrowing pens. (a) a farrowing pen with half-open farrowing crates and (b) a farrowing pen with closed farrowing crates

Table 1: Summary of video details. The value in parentheses stands for the average. NA, not available

Description	Video 1	Video 2	Video 3	Video 4	Video 5	Video 6	Total
Days post farrowing	5	5	5	4	5	5	NA
Farrowing crates	Half-open	Half-open	Half-open	Closed	Closed	Closed	NA
Time period	08:45-15:20	07:45-15:27	08:30-14:46	08:46-14:35	08:10-13:53	08:50-12:57	NA
Extracted frames	3,307	3,899	3,188	2,928	2,726	2,069	18,117
Labelled images	1,100	1,000	1,000	500	500	500	4,600
Visible piglets per labelled image	7-13 (8.9)	7-9 (8.9)	7-13 (12.6)	10-17 (16.0)	11-17 (15.6)	9-11 (10.9)	7-17 (11.4)

<u>CClusnet training and its outputs</u>

CClusnet, a deep learning-based method initially developed for piglet counting under occlusion (e.g., occlusions from farrowing crates) (Huang *et al*., 2021), was adopted and trained using the labelled images (Table 1). The 4,600 labelled images were randomly divided into a training set and a validation set with a ratio of 4:1. Image augmentation, including flips and Gaussian blur, was performed five times for the original training set, resulting in a new training set with 18,400 images. The model with the best performance on the validation set was kept for further inference.

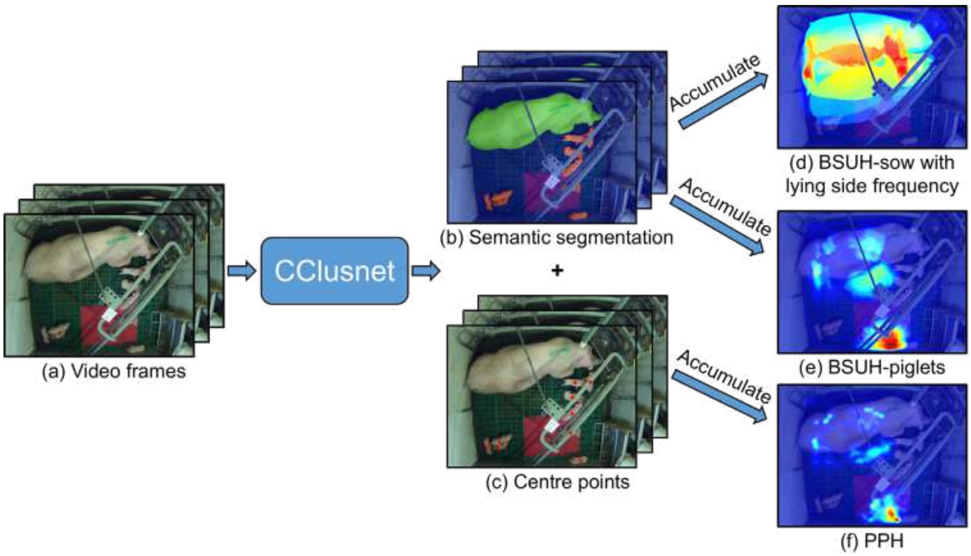

Figure 2: The flow of our method. CClusnet outputs a semantic segmentation map (b) and piglet center points (c) for each video frame. These maps and center points are further accumulated into two bodily-space-usage heatmaps or BSUH (with lying side frequency for sows) (d) and (e), and a piglet-position heatmap or PPH (f)

The trained CClusnet model was then used to predict the individual frames of the six selected videos and the flow chart is illustrated in Figure 2. CClusnet had two outputs for each frame, including a semantic segmentation (a three-dimensional one-hot matrix) for both sow and piglets (Figure 2b) and object centres for individual piglets (Figure 2c). These two outputs were further accumulated to generate two bodily-space-usage heatmaps (BSUH) and a piglet-position heatmap (PPH), respectively.

Bodily-space-usage heatmap (BSUH)

To show the spatial distribution of the sows and piglets, semantic segmentation results of extracted frames were accumulated to generate BSUH. Suppose there were *n* detected frames of a video, then the heatmaps for the sow and piglets were

$$BSUH^{(c)} = \frac{Seg^{(c)} - \min\left(Seg^{(c)}\right)\mathbf{1}}{\max(Seg^{(c)}) - \min(Seg^{(c)})} + \min\left(Seg^{(c)}\right), \tag{1}$$

where

$$Seg^{(c)} = \sum_{i=1}^{n} segmap_i^{(c)}, \tag{2}$$

and $segmap_i^{(c)} \in R^{384\times512}$ was a semantic segmentation map (a 0-1 matrix) for a class $c \in \{piglet, sow\}$. The functions *max*() and *min*() were the maximum and minimum value of a matrix, respectively, and $\mathbf{1} \in R^{384\times512}$ was a matrix with all elements equal to 1. Equation 2 meant the accumulation of segmentation maps, and Equation 1 meant the normalization.

From the BSUH, the space usage (in percentage) of the sow, represented by the proportion of all pixels ever occupied by a sow in all heatmap pixels, could be extracted by

$$Space\ usage = 100\% \times \frac{1}{m}\sum_{p=1}^{m} binary\left(Seg_p^{(sow)}\right), \tag{3}$$

where $m = 384 \times 512$ was the number of pixels in the semantic segmentation map and- *binary*() was a conditional function that

$$binary(x) = \begin{cases} 1, if\ x > 0 \\ 0, otherwise \end{cases}. \tag{4}$$

The sow lying side (if lying) in each frame was also extracted and accumulated to lying side frequency when generating BSUH. A minimum rotated bounding rectangle and a corresponding coordinate axis in its centre were generated for the sow mask (Figure 3). The sow mask centroid was calculated and a vector from the rectangle centre to mask centroid was formed. The detection rationality was that the sow mask centroid would be different from the bounding rectangle centre with an opposite direction towards the head and feet due to the lying shape of the sow, and this offset could be used to determine the lying side. Specifically, if the vector pointed to the second or the fourth quadrant of the coordinate axis, then this lying posture was classified as left-side lying and otherwise right-side lying.

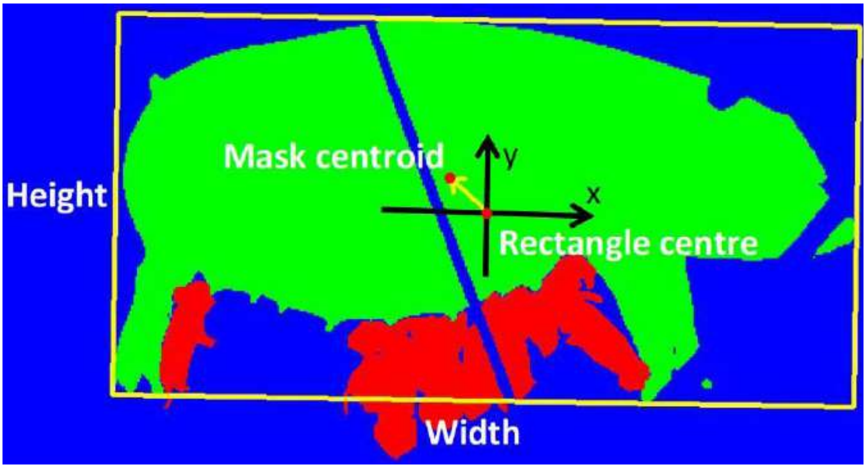

Figure 3: The sow lying side detection

Piglet-position heatmap (PPH)

Due to the occlusions from the farrowing crates, some body parts under the farrowing crates were invisible. Therefore, the information of these parts was missing in BSUH, which was more serious for small-size piglets. To compensate for the missing parts due to occlusions, the center points of piglets in each frame were accumulated to PPH, which gave more precise information of object locations. For each video, each center point was represented by a two-dimensional Gaussian distribution, so that the $PPH \in R^{384\times512}$ was defined as

$$PPH = \frac{PPH_{all} - \min(PPH_{all})\,\mathbf{1}}{\max(PPH_{all}) - \min(PPH_{all})} + \min\left(PPH^{(all)}\right), \tag{5}$$

where

$$PPH_p^{(all)} = \sum_{i=1}^{n} \sum_{cp\ in\ frame\ i} \frac{1}{\sqrt{(2\pi)^d|\Sigma|}} \exp\left[-\frac{1}{2}(p-cp)^T\Sigma^{-1}(p-cp)\right], \tag{6}$$

cp was a piglet center point in the frame i, $d = 2$ was the variable dimension for each pixel p, and

$$\Sigma = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{7}$$

was covariance matrix.

Results and Discussion

The BSUH and PPH results for each video are shown in Figure 4 and Table 2. The BSUH of sows could reveal the sow space usage differences (Table 2). In our study, the sow space usage ranged from 53.0% to 63.6% (58.6% on average) in half-open crates, while dropped in closed crates with a range from 36.3% to 38.8% (37.9% on average). The sow utilized 1.5 times more image space in half-open crates than in closed crates, which was consistent with the finding that sows utilized the additional space provided to them after opening the crates (Ceballos *et al*., 2020).

The BSUH of sows demonstrated the main and frequent lying side (Table 2). For example, most of the sows in this study showed unbalanced lying sides: the sows in Videos 1, 2, 4, and 5 lay more on the left side and the sow in Video 3 lay more on the right side, while only the sow in Video 6 lay equally on both sides (Table 2). These uneven lying sides were also consistent in the heatmap. For example, a right-side and a left-side sow lying posture were clearly seen in Video 3 (Figure 4c1) and Video 4 (Figure 4d1), in which the prominent lying side was 4-5 times more frequent than the opposite lying side.

Table 1: The image space usage and lying side frequency of sows in different farrowing pens. L, left, R, right

Farrowing crates	Video index	Space usage (%)	Lying side (%)
	Video 1	63.6	L: 62.5, R: 37.5
Half-open	Video 2	53.0	L: 62.1, R: 37.9
	Video 3	59.2	L: 20.8, R: 79.2
	Video 4	38.8	L: 83.6, R: 16.4
Closed	Video 5	38.7	L: 73.4, R: 26.6
	Video 6	36.3	L: 48.9, R: 51.1

The BSUH of piglets demonstrated the frequent area piglets visited or stayed in. For example, the piglets concentrated frequently around the heat pad and pen border in five video cases (Figure 4a2 and Figure 4c2, 4d2, 4e2, and 4f2), while there was an exception in Video 2, where the sow frequently lay with its udder against the heap pad (Figure 4b1).

The PPH supplemented the missing information in the BSUH where the object was invisible under occlusions. For example, in our three videos with closed crates, the piglet centres happened to locate frequently in the area where was occluded by crates (Figure 4d3, 4e3, and 4f3). As the centres output by CClusnet were hardly affected by the occlusion, the PPH could be a substitution for piglet spatial distribution analysis. In addition, the long bands, bounded by red boxes in PPH (Figure 4a3, 4b3, 4c3, 4d3, 4e3, and 4f3), were the area where piglets suckled frequently as we retrospected the videos. However, this information was not obvious in BSUH (e.g., Figure 4d2 and 4d3). Therefore, the PPH could reveal and complement some missing information in BSUH due to occlusions.

Our method could be further used for sow lying side preference analysis and thus precaution of lesions due to one-side lying. This is especially important during the period of lactation when lesions are commonly seen in sows (Rolandsdotter *et al.*, 2009). A long time one-side lying may cause heavy lesions (e.g., shoulder lesions and teats lesion, Rolandsdotter *et al.*, 2009; Rioja-Lang *et al.*, 2018). As our method could demonstrate frequent lying side of a sow, it could be further used to determine which side has a higher probability of lesions, with a longer monitoring period.

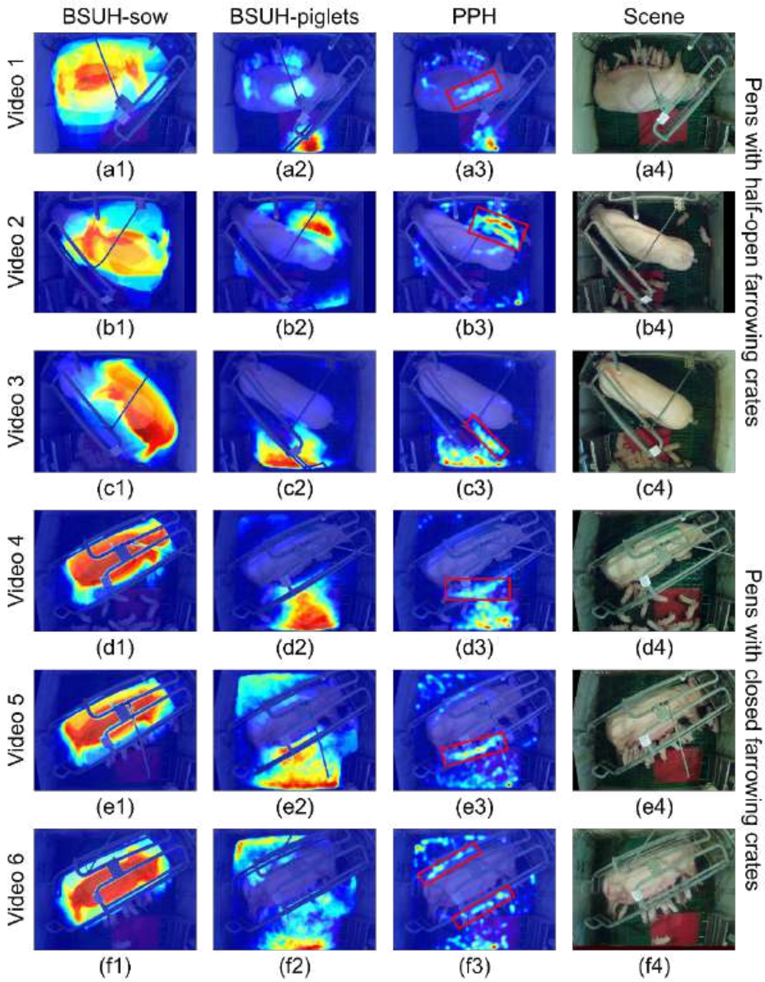

Figure 4: Bodily-space-usage heatmaps (BSUH) and piglet-position heatmaps (PPH)

Conclusions

This paper demonstrated a computer vision method for analysing spatiotemporal distribution patterns of pigs in farrowing pens. Two kinds of heatmaps, namely BSUH and PPH, were generated by accumulating the semantic segmentation maps and piglet centres, which were output by CClusnet. The BSUH of sow could reveal differences in sow space usage, e.g., the sow utilized 1.5 times more image space in half-open crates than in closed crates in this study. In addition, the BSUH of sows showed different preferences in sow lying sides, e.g., five of six sows had unbalanced lying side frequency in the videos. The BSUH of piglets demonstrated the frequent area piglets visited or stayed, e.g., around the heat pad and the pen border in most video cases. The PPH supplemented the missing information in BSUH due to occlusion (e.g., frequent suckling area of piglets). Our method could be further used for sow lying side preference analysis and thus precaution of lesions due to one-side lying.

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Lameness detection in sows using few-shot approach

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Abstract

Group housed sows have a higher occurrence of lameness. Continuous monitoring of lameness is necessary for high welfare standards. Some electronic sow feeders are designed with a corridor that holds the potential for continuous monitoring. The use of overhead 3D cameras (color + depth), along with state-of-the-art machine learning algorithms have shown promising results in gait analysis and detection of lameness in sows. However, sows don't always walk through these corridors at a regular pace or with uniform directionality. This adds complexity to model development that depends on gait cycle analysis. Therefore, detecting lameness from a few images, instead of longer video streams, is important.

In this study, the use of few-shot classification using top view depth images for lameness detection is explored. Few-shot classification is the machine learning technique of classifying and prediction based on limited training data. This study uses 2-way support set, lame vs non-lame and multiple shots 1,3,5 and 10 where each shot is a combination of multiple frames (1,5,10,15,30,60) of depth images derived from a 30 fps video streams. From a total of 1077 pigs, of which 34 had some level of lameness, a few shot classifier was modeled. The results show a worst-case accuracy of 33% at 1 shot with 1 frame. On the high end, an accuracy of 93% with both specificity (non lame) and sensitivity (lame) of 93% at 10 shots and 60 frames was achieved demonstrating the effectiveness of the few-shot approach.

Keywords: lameness, depth images, few-shot learning, meta learning

Introduction

Lameness in gestating sows is an agonizing condition that not only affects the welfare of the animal but also results in economic challenges to producers (Dewey et al. 1993, Heinonen et al. 2006). Studies (Heinonen et al. 2013, Conte et al. 2015) have shown early detection of lameness is important for treatments to be effective. Lameness is usually assessed by subjective visual gait scoring systems (Main et al. 2000, Deen et al. 2011). Such systems are time consuming, labor intensive requiring trained professionals and offer subjective variations in scoring (Main et al. 2000).

The use of technology and sensors to objectively detect lameness has seen tremendous growth in the last decade. Conte et al. (2014) measured and characterized lameness in sows using multiple measurements - force plates to analyze weight distribution of the legs, kinematics (stride, speed joint angles) and accelerometers to study time spent standing, frequency of stepping during feeding and time taken to lie down after feeding.

Meijer et al. 2014 used pressure mats, which provide both kinetic and kinematic data to assess the compensatory force distribution in lame versus sound sows. Amezcua et al. (2014) used infrared thermography to study temperature differences in the hind legs of sows of various gait scores (0-2 ranging from normal to non-weight bearing on at least one hind leg) at various anatomical areas (lower metatarsus, upper metatarsus, phalanges and tarsus) and reported observing significant mean temperature differences at low metatarsus and phalanges between the normal sow (gait score 0) and lame sow (gait score 2).

More recently computer vision techniques powered by machine learning and deep learning models and the use of 2d and 3d cameras have been used in various species to detect lameness. Van Hertem et al. (2014) evaluated three different classification methods – ordinal logistic regression, nominal logistic regression and linear regression on consecutive frames of 3D video to perform a 5-point classification on lameness in dairy cows. Jabbar et al. (2017) used Hilbert Transform on depth images of dairy cows to calculate height movements of hip joint, hooks and spine along with Support Vector Machine (SVM) based classifier and achieved 96% accuracy with 100% sensitivity and 75% specificity in lame/non-lame detection. Zhao et al. (2018) analyzed leg swings of dairy cattle and extracted motion curves to generate 6 features set (gait symmetry, speed, stride length, tracking up, stance time and tenderness) to train a decision tree classifier and achieved accuracy of 91% along with 90% sensitivity and 95% specificity in detecting 3 levels of lameness. Wu et al. (2020) used Long Short-Term memory (LSTM) derived step size characteristic vector and side view 2d color images for lame/non-lame classification in dairy cows with 98% accuracy. Condotta et al. (2020) explored the use depth images in sows and analyzed temporal changes in height measurements of various parts of the body along with estimated step parameters (stride, time) to detect lameness.

As promising as the computer vision techniques are, these approaches require video data stream of animals walking at a regular pace through a corridor or an alley and side/top view images/videos. Acquiring and analyzing data in a setting such as group housed pens is quite challenging. The movement of animals is not as fluid, mostly static, their strides/steps/speed are often irregular and lack consistent directionality. Animal movement within the pen may not yield consistent data needed for models that use gait analysis to make meaningful inference. The problem is further exacerbated in sows with some form of lameness whose movement is further restricted due to pain. A solution to this problem is to develop lameness detection models from limited data.

In this study, the use of few-shot classification to detect lameness using limited training data is explored. Few shot learning (FSL) is a meta learning task (Finn et al. 2017, Chen et al. 2021) where a classifier adapts to classify from an unseen small input/output set using prior knowledge gained from similar tasks. Different approaches to FSL such as matching networks (Vinyals et al. 2016), prototypical networks (Snell et al. 2017), model-agnostic meta learning (Finn et al. 2017) have shown great results in image classification. The FSL technique has been adapted to recognize actions/activities in humans. Bo et al.(2020) developed Temporal Attention Vectors (TAVs) to recognize human actions with a few labeled videos. Feng et al. (2019) used FSL with wearable sensors for human activity recognition by addressing negative transfer via the use of a metric that measure and increase cross-domain class-wise relevance. This study explores the use of FSL using temporal attention vectors developed by Bo et al. (2020), applying them to depth image frames, to perform lame/non-lame classification.

Materials and Methods

The video data for the study was collected at US Meat Animal Research Center (USMARC) at Clay Center, Nebraska over a nine-month period from November 2020 to July 2021. Data collection was performed in accordance with federal and institutional regulations regarding proper animal care practices and was approved by the U.S. Center for Animal Research Institutional Animal Care and Use Committee (2015-21) (IACUC 111.0). A total of 1078 Landrace x Yorkshire sows/gilts, 518 recently weaned sows/gilts and 560 sows at 110-day of gestation, were used in the study. An overhead camera system consisting of Microsoft Azure Kinect DK camera was installed at a height of 3 meters from the floor capturing both 2d (color) and 3d (depth) videos. The videos were recorded at 30 frames per second at 1080p resolution for color stream and 512x512 pixels for the depth stream. The depth camera was set to use the wide field of view (wfov) mode 120x120 degrees. The 1078 animals were visually assessed for lameness by trained professionals. Thirty-four sows were identified as lame. Since the number of non-lame animals were significantly larger than the number of lame animals, 34 non-lame animals were randomly selected to represent the non-lame class.

Preprocessing

The videos were preprocessed using MATLAB (v R2020b) and the Image Processing toolbox. Minimal preprocessing was required to isolate the only pig from the background and other unwanted objects in the frames. The use of binary thresholding and connected components to detect the largest object in the frame was enough to remove everything but the pig from the images. The depth images were further filtered using a median filter of window size 5x5 to smooth out discontinuities.

Overview - Few Shot Learning

The primary objective in Few Shot Learning (FSL) is to use limited labeled training data for classification. Few shot learning (FSL) is generally presented as a N-way-K-Shot classification problem where there are K labeled training data samples for each of the N classes and K is rather small. The goal for the model is to learn to detect classes from a just a few samples. The N classes and the K samples form a support set with N*K labelled samples. The task is to then classify samples from a query set Q among the N classes from the support set. An example case is shown in Figure 1 with a 3-way-2-shot image classification task where there are 2 images (k=2) for 3 dog breeds (N=3) and the task is to label Q=4 dogs from the query set as one of the 3 classes from the support set.

To solve such a problem, a meta-learning approach is used where FSL learns how to classify from other experiences/similar problems. The meta learning algorithms typically employ two methods 1) Metric Learning, such as Siamese Networks proposed by Koch et al. (2015) where the model learns to learn a distance function that can be used for comparison or 2) Model Agnostic (Finn et al. 2017) where a neural network model adapts to new examples in new task. The learning for image classification tasks starts by using a base dataset D with large sample size and typically does not contain data from the new unseen class that requires detection. The training happens in a fixed number of episodes E, where in each episode, K samples from each of the N classes in the support set along with Q query samples are chosen to train a model for classification. During each episode the models train to maximize the detection accuracy of the Q images from the query set.

Figure 1: 3-class 2-shot few shot learning. The model learns to classify the images from the query set by looking at 2 images from each of the 3 classes

<u>2-Class-K-Shot-M-Frame Selection</u>

This study uses a 2-Class-K-shot-M-Frame classification approach. The two classes are lame and non-lame. The K-shots are not individual images but rather M depth frames concatenated together. M will be referred to as frame length. For this study, multiple frame lengths M = 5, 10, 15, 30, and 60 were chosen to go along with multiple shots K=1,3,5, and 10. The frames were selected as two different groups – 1) Consecutive group where M consecutive frames at time intervals 1/30 seconds were collected and 2) Sampled group where M frames were sampled at 0.5 seconds. The base class data was represented by a total of 68 videos (34 videos for each class) and a 3-second window was extracted from them. At 30 frames per second, there were a total of 34*30*3=3060 depth image frames from both classes available for making the K-Shot-M-Frame base data and support and query sets.

Feature Extraction (TAV)

The temporal information of the frames was extracted using the Temporal Attention Vectors (TAV) approach developed by Bo et al (2020). Figure 2 shows the different stages. TAVs encode the temporal information from a sequence of frames into a smaller subset. The algorithms starts with video frames represented as $X = (f_1, f_2 .. f_M)$ where each frame f_M is just the depth image of dimension 512x512. These frames go through a Convolutional Neural Network (CNN) for feature extraction yielding $F=[p_1, p_2 \ldots p_M]$ where p_i is of dimension 1xD. The CNN feature extractor is the ResNet-152 network pre-trained on ImageNet and the parameters are frozen. The next step is to convert the M 1xD dimensional feature to an aggregate set of P TAVs (where $P < M$). Bo et al (2020) further trained an importance score learner but this study only uses the TAVs. Furthermore, the size of the aggregate set (P) was set to 3 i.e. the temporal information in the M frames are represented by 3 vectors. The TAV initialization and computation is done using the Dynamic Gaussian approach suggested by Bo et al. (2020).

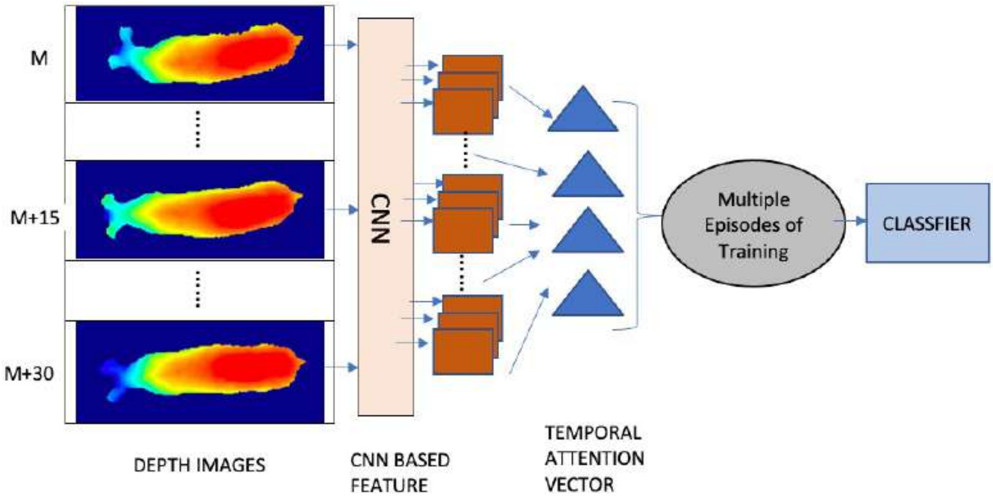

Figure 2: Using temporal attention vectors from depth images

Classifier

The classifier was trained using the Model Agnostic Meta learning (MAML) framework proposed by Finn et al. (2017). UCF101 (action recognition data set) was used as the base data and contains 101 classes of action categories. A 2 layer (each with 150 neurons) neural network with cross-entropy loss was trained. During the meta learning stage, the algorithm created multiple episodes, each episode containing 2 randomly selected classes from the UCF101 data set and K shots/groups of M frames from the two classes to form the support set and 2 groups of M frames to form the query set. The trained model was then used in the meta testing stage where the new data (lame/non-lame videos) are used for support/query set and the model adapts to predict the new data. The number of episodes used to build the classifier was set to 6000.

Results and Discussion

Tables 1 and 2 contain results of using multiple shots (1,3,5,10) and combinations of various frame lengths in the consecutive and sampled group respectively. The group "consecutive" refers to the shots being consecutive frames of length M and the group "sampled" refers to groups of frames at specific intervals. The two categories were investigated to understand how the selection of frames and the temporal evolution of the frames affect the detection accuracy. Frame length of 1 and shot size of 1 performs the worst at around 30% accuracy as expected. The K=1, M=1 setting is essentially asking the model to learn from just a single frame. For the M=1 setting, increasing the shots does not lead to improved accuracy in any of the groups. At M=1, K=10, the accuracy is 38% implying that single frames do not have the information needed to learn to distinguish between the two classes in focus. As the number of frames increase, the accuracy increases. Even at just 5 consecutive frames and 3 such instances/shots selected, the accuracy is 54% indicating the meta learning model has learned to exploit the similarity/dis-similarity to understand the difference by just looking at 3 occurrences of 5 frames. This is expected as more frames generally tend to have more information for the model to learn from. In some of the image classification studies using few shot learning, a 3-shot model performed well at almost 70% accuracy. However, the accuracy of 54% in this case seems to indicate that query set and support set might have similar elements in them for example frames of both lame sow and non-lame sow possibly just standing. A good accuracy of 91.67% accuracy was achieved at 10 shots and 30 frames. Further increase in frame lengths or the number of shots did not significantly increase the accuracy. For example in 30 and 60 frames, which correspond to 1 sec and 2 sec of consecutive frames, probably have redundant data that some of the earlier frames have already captured and hence does not improve accuracy. Another important observation from Table 1 is that both the sensitivity (lame sows) and specificity (non lame sows) at the best accuracy is around 93%.

For the "sampled" case (Table 2), however, the results did not have a consistent pattern except that the accuracies are lower than the consecutive frames counterparts. With 5 frames selected at 0.5 second interval and 3 shots, the accuracy is 43% compared to 54% for consecutive frames settings with the same M and K. Increasing the number of frames does not improve the accuracy and/or the sensitivity and specificity values. Even at 30 frames and 10 shots, the best accuracy was at 70%. This is probably caused by the sampling process that leads to grouping of frames that are out of sync and the temporal attention vectors cannot encode the motion as reliably as it can in the consecutive group case.

Table 1: Accuracy/Sensitivity (Lame)/Specificity Non-lame) values for Consecutive group

Shots (K)	Frame Length (M)	Accuracy	Sensitivity	Specificity	Shots (K)	Frame Length (M)	Accuracy	Sensitivity	Specificity
1	1	33.33%	26.67%	40.00%	3	1	36.67%	26.67%	46.67%
	3	35.00%	26.67%	43.33%		3	38.33%	30.00%	46.67%
	5	36.67%	30.00%	43.33%		5	53.33%	40.00%	66.67%
	10	36.67%	30.00%	43.33%		10	53.33%	40.00%	66.67%
	15	38.33%	30.00%	46.67%		15	58.33%	43.33%	73.33%
	30	38.33%	30.00%	46.67%		30	58.33%	43.33%	73.33%
	60	45.00%	36.67%	53.33%		60	63.33%	50.00%	76.67%
5	1	38.33%	26.67%	50.00%	10	1	38.33%	30.00%	46.67%
	3	41.67%	30.00%	53.33%		3	50.00%	40.00%	60.00%
	5	53.33%	40.00%	66.67%		5	66.67%	60.00%	73.33%
	10	63.33%	46.67%	80.00%		10	75.00%	66.67%	83.33%
	15	66.67%	50.00%	83.33%		15	80.00%	73.33%	86.67%
	30	73.33%	60.00%	86.67%		30	91.67%	90.00%	93.33%
	60	78.33%	66.67%	90.00%		60	93.33%	93.33%	93.33%

Table 2: Accuracy/Sensitivity (Lame)/Specificity (Non-lame) values for Sampled group S=0.5 seconds

Shots (K)	Frame Length (M)	Accuracy	Sensitivity	Specificity	Shots (K)	Frame Length (M)	Accuracy	Sensitivity	Specificity
1	1	33.33%	26.67%	40.00%	3	1	35.00%	26.67%	43.33%
	3	36.67%	23.33%	50.00%		3	43.33%	40.00%	46.67%
	5	38.33%	23.33%	53.33%		5	43.33%	33.33%	53.33%
	10	41.67%	26.67%	56.67%		10	45.00%	30.00%	60.00%
	15	41.67%	26.67%	56.67%		15	40.00%	30.00%	50.00%
	30	43.33%	26.67%	60.00%		30	50.00%	40.00%	60.00%
	60	46.67%	33.33%	60.00%		60	46.67%	40.00%	53.33%
5	1	30.00%	26.67%	33.33%	10	1	40.00%	30.00%	50.00%
	3	40.00%	26.67%	53.33%		3	53.33%	43.33%	63.33%
	5	53.33%	46.67%	60.00%		5	56.67%	40.00%	73.33%
	10	46.67%	33.33%	60.00%		10	56.67%	33.33%	80.00%
	15	50.00%	33.33%	66.67%		15	66.67%	46.67%	86.67%
	30	58.33%	36.67%	80.00%		30	70.00%	53.33%	86.67%
	60	58.33%	36.67%	80.00%		60	66.67%	50.00%	83.33%

Conclusion

In this study, lameness detection of sows using few-shot learning (FSL), which is a meta learning paradigm, was explored as a 2-class-K-way-M-Frame learning problem. This approach was chosen to address the issue of training models with limited data that is often the case in group housed pens. Depth images of various frame lengths were concatenated to form groups – some consecutive frames and others sampled at fixed intervals. A FSL model was trained to be able to classify the group of frames as lame or not-lame using just a few samples. The model achieved the best case accuracy of 93% at 60 consecutive frames (0.5sec) and 10 shots highlighting effectiveness of meta learning when training data is limited. Further study is warranted to study the lameness detection problem as a multi-class (multiple levels of lameness) few shot learning task.

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SESSION 7

Poultry:
Climate and Environment

Heat stress analysis of chickens in a mechanically ventilated broiler house using simulation

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Abstract

As meat consumption increases, the proportion of livestock industry to total agricultural production is increasing every year. Broiler production accounted for 12.5% of the livestock production in 2020. However, the breeding environment of broilers is gradually deteriorating due to heatwaves caused by recently global warming and high density of breeding. Also, broilers have difficulty regulating their body temperature, as they have high metabolic heat generation and are covered with feathers. Thus, broilers are vulnerable to high summer temperatures. To solve this, a tunnel ventilation which is a typical method is used in domestic broiler houses to effectively relieve heat stress in summer. However, heat stress was not evaluated under various broiler growth conditions, livestock ventilation conditions and thermal insulation. The purpose of this study was to validate and develop an energy model to quantitatively evaluate the heat stress of livestock using building energy simulation. In a mechanically ventilated broiler house, weather and internal micro-climate data were measured at various points in the house, and then a model validation was performed using the field data. The conditions for the simulation included the livestock age, breeding density, the thermal insulation of the wall, ventilation of the livestock, and the presence of a cooling pad. The results of the heat stress evaluation were derived and then analysed through the temperature humidity index. As a result, it was possible to reduce the damage to livestock because of climate change, by preventing mortality due to the heat stress of the broilers inside the house.

Keywords: Broiler house, Building Energy Simulation, Heat stress, Temperature Humidity Index

Introduction

Due to the increase in meat consumption, domestic livestock production continues to increase to 19.1 trillion won in 2015 and 20.3 trillion won in 2020, and the ratio of livestock to agricultural and forestry production is also increasing from 37.6% to 39.0%. (MAFRA, 2020). Among, the livestock industries, the poultry industry which is divided into broilers (raised for meat use), and laying hens (chickens raised to produce edible eggs) were considered to be one of the high-ranking sectors in livestock production. In 2020, the broiler industry alone accounts for 10.0%. (MAFRA, 2020). Moreover, meat consumption per capita in Korea is increasing from 13.4 kg in 2015 to 14.7 kg in 2020. (KREI, 2021)

The consumption of chicken has steadily increased, and the number of breeding animals per area has increased compared to the number of farms, which requires technology to control and operate the internal environment complexly. However, the current broiler facilities lack the production application of cutting-edge technologies such as ICT, and lack of production bases such as unlicensed chicken houses and outdated breeder farms and hatcheries. Under these circumstances, in the cold weather, they are suffering from killing due to viral infections such as Avian Influenza, and in the hot weather, abnormal climates and heatwaves caused by warming continues day after day.

Therefore, in this study, an energy model was developed to analyse the micro-weather environment inside the facility by inputting external weather data into the model to quantify the heat stress of livestock occurring in summer. Factors affecting heat stress were analysed through field experiments, and were used in the model to properly maintain the internal environment. If the weather forecast and the developed model are linked, it is expected that the heat stress index of livestock according to the abnormal climate will be analysed in advance to proactively respond to heat wave damage.

Material and methods

Broiler house selection and field experimental methods

The target livestock facility is located in Yeonggwang-gun (35.322, 126.467), Jeollanam-do, Korea. It is a forced ventilation type broiler house with a width of 18m, a length of 100m, and a peak height of 6m. From September 25 to October 28, 2020, a total of 34,000 chickens were bred per rotation production cycle for a month. A meteorological station was installed outside the house, and 12 air temperature and humidity sensors (3X4) were installed inside to measure and collect data at 5-minute intervals, and micro-weather analysis was performed for each section.

Tunnel ventilation is a representative ventilation method that is effective in minimizing heat stress in summer because the air velocity around the chickens. Under this type of ventilation method, air velocity is rapidly formed, the ventilation rate per hour is high, and the effective temperature is also reduced. It is necessary to measure the flow rate, a factor as important as air temperature and humidity. Therefore, 27 hot wire anemometers (3X9) were installed inside the building, one per 10m distance, and the internal velocity was measured by zone during tunnel ventilation and then uniformity was analysed. In addition, since the actual air volume of the ventilation fan installed in the livestock facility may differ from the designed air volume depending on conditions such as inlet conditions and fan aging, the actual air volume of the tunnel fan was measured. The broiler breeders control the number of tunnel fans operating according to the internal air temperature during the summer, so the relationship between air volume and static pressure was measured by changing the number of fan operations.

Development of dynamic energy model and validation

A heat stress model for broilers chicken was developed. The program for calculation used TRNSYS (University of Wisconsin-Madison. Solar Energy Lab., USA), a building energy simulation tool that numerically calculates the heat and energy flow of a building over time. Based on the energy balance equation, the temperature and humidity of the internal air was calculated by considering the heat loss and heat gain by convection, radiation, conduction, ventilation, infiltration, and internal heat sources on the wall surface as a whole building. The structure and covering of the livestock house were designed identical to the design of actual livestock house, and the actual ventilation amount measured through field experiments was entered. In addition, the age and breeding density of chickens were also considered by reflecting the amount of latent heat energy generated by broilers, which is an internal heat source, as boundary conditions as in equations (1) and (2). (CIGR, 2002) This is to more accurately simulate the internal thermal environment.

$$q_{tot} = \frac{10.62}{1000}(1.1678 \times d^2 + 11.137 \times d + 35.753)^{0.75}[1000 + 20 + (20 - t)] \quad (1)$$

$$q_s = \frac{10.62}{1000}(1.1678 \times d^2 + 11.137 \times d + 35.753)^{0.75}\{0.61 \times [1000 + 20 \times (20 - t)] - 0.228 \times t^2\} \quad (2)$$

where q_{tot} is total energy generation of broiler, q_s is sensible energy generation of broiler, d is number of breeding days and t is indoor temperature

In order to evaluate the reliability of the model for calculating the heat stress of livestock, the inside air temperature and humidity data of the house measured in the field and the calculation results were compared. The validation was performed using various statistical indicators such as coefficient of determination, RMSE, and MAPE.

Analysis of heat stress index for livestock

Table 1: Heat stress index previous research for poultry

Considered factor	Heat stress index formula	Reference
dry bulb temp., relative humidity	$THI = (1.8 \times T + 32) - [(0.55 - 0.0055 \times RH) \times (1.8 \times T - 26.8)]$	NRC (1971); Dikmen and Hansen (2009)
dry/wet bulb temp.	$THI = 0.85 \times T_{DB} + 0.15 \times T_{WB}$	Tao and Xin (2003)
dry/wet bulb temp., air speed	$THVI = (0.85 \times T_{DB} + 0.15 \times T_{WB}) \times V^{-0.058}$	Tao and Xin (2003)
dry/wet bulb temp., breeding age	$THI_{3-4WK} = 0.62 \times T_{DB} + 0.38 \times T_{WB}$ $THI_{5-6WK} = 0.71 \times T_{DB} + 0.29 \times T_{WB}$	Chepete et al. (2005)
dry bulb temp., relative humidity, area	$THI = 0.85 \times T_{DB} + \frac{RH(T_{DB} - 14.3)}{100} + 46.3$	Moraes et al. (2008)

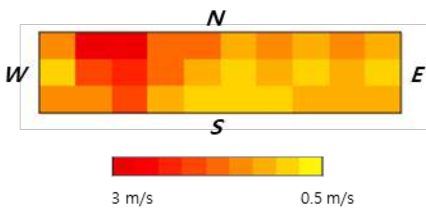
The heat stress of livestock can be defined as the result of a heat load in which livestock cannot maintain homeostasis. Its thermal balance is affected by various factors such as surrounding climate, livestock breeding, and environmental management. In order to apply the heat stress index to the model, a literature survey was first conducted, and then the heat stress index of the land system is shown in Table 1. The heat stress of chickens inside was evaluated by applying the air temperature and humidity calculated according to the results of the energy simulation model to this index.

Results and Discussion

The experimental broiler house structure had a door in the west, a tunnel ventilation fan in the east, and an inlet in the east and west direction respectively. Air temperature and humidity in broiler house were analyzed by evenly dividing the inner section and measuring it in a 3X4 section. As a result of analyzing the internal microenvironment along the longitudinal direction of the house, the closer to the ventilation fan, the more internal heat was accumulated in the air, and the temperature increased by about 1.57℃. However, there was no significant difference in air temperature and humidity according to the width direction. The average external wind speed on the day of the experiment was 2 m/s, and the southwest wind close to the west wind dominated, with the largest internal velocity of 3.15m/s near the entrance in the north. (Figure 1)

In addition, as a result of measuring the actual ventilation volume by changing the number of tunnel fans operated, it was found that fan performance decreased by about 30% compared to the maximum design flow provided by the manufacturer. (Table 2) This difference is analysed due to the difference between the standard test method and the field measurement environment of the fan performance curve. Since the internal high temperature stress may be underestimated when input to the calculation model according to the design performance of the fan, it seems that it should be applied to the model in consideration of the decrease in performance of the tunnel fan.

The energy model validation was conducted as data for a week from October 4th to 10th, and the time step was set to 5 minutes. Since there is a difference in air temperature and humidity for each internal area, it was analysed whether the calculation results were included within the minimum and maximum values of the experimental values. (Figure 2) As a result of analysis using statistical indicators, the MAPE of air temperature is 4.66% and the humidity is 5.69%, which is analysed to be more reasonable than the 10% error criterion of the 1-hour timestep model presented in the ASHRAE guideline.



1.69	3.37	3.06	2.03	1.98	1.51	1.71	1.47	1.76	1.45
1.12	2.22	2.56	2.07	1.42	1.19	1.31	1.03	1.38	1.19
1.75	1.73	2.34	1.41	1.30	1.28	1.27	1.46	1.38	1.49

Figure 1: Results of internal air velocity measurement by broiler house area

Table 2: Reduction rate of actual fan flow rate compared to design fan

Static pressure difference (Pa)	Tunnel fan flow (CMH)		Reduction rate (%)
	Design	Actual	
20	32,934	23,061	30
30	30,428	22,048	27.5
40	27,861	20,880	25.1

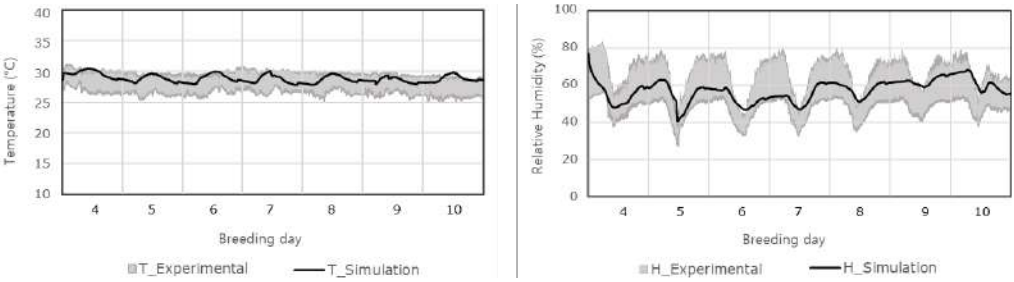


Figure 2: Comparison of experimental results and simulation results for air temperature and (left column) relative humidity (right column) inside the broiler house

Conclusions

In order to quantify the heat stress of chicken raised in the facility, a dynamic energy model was developed to calculate the internal microclimate environment. Through series of field experiments were conducted in the broiler house. The internal flow rate and actual ventilation amount were measured during tunnel ventilation, and the model was verified using the results of the internal air temperature and humidity experiment. The heat stress index was calculated using the developed model to compare and analyse the degree of risk. In future studies, the results of field experiments will be used to develop a temperature humidity velocity index calculation model rather than a temperature humidity index only.

Acknowledgements

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A dynamic model to precisely predict indoor air temperature and relatively humidity in laying hen houses

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Abstract

Precisely predicting the dynamic changes of indoor temperature and relative humidity is very beneficial to create a good indoor environment for laying hen houses. While, current models fail to consider the cooling efficiency variation of the evaporative cooling pad system, and its effect on indoor temperature and relatively humidity change of laying hen houses. In this paper, a new hourly model to predict the annual indoor temperature and relative humidity as well as its variation in layer houses was created and validated. In the proposed prediction, a mathematical model of the cooling efficiency was adopted to consider the quantitative influence of the evaporative cooling pad system on the indoor thermal and humid environment. Results showed the predicted values of indoor temperature and relative humidity were consistent with the field measurements. The overall average prediction error of indoor temperature was 0.67 °C, and average error of indoor relatively humidity was 3.1%. If the dynamic cooling efficiency variation of the evaporative cooling pad system was not taken into account, the accuracy of the prediction model would be reduced to some extent. Contrastively, when the cooling efficiency was fixed on 80%, the predicted temperature error would rise from 0.67 °C to 1.4 °C, and the relative humidity error was from 3.1% to 5.4%. This study can provide a technical guidance for animal building design and thermal environment control.

Keywords: temperature, humidity, laying hen house, thermal environment, evaporative cooling pad, cooling efficiency

Introduction

Appropriate indoor thermal and humid environment is very beneficial for laying hens to improve their health, production performance and egg quality under housing systems (Olgun *et al*., 2007; Freitas *et al*., 2017). Therefore, precisely predicting the dynamic changes and rules of temperature and relatively humidity (RH) in laying hen house throughout the year would be strongly helpful for the industry's development.

According to the calculation methods of enclosure heat gain, indoor thermal and humid model can be divided into steady state model and non-steady state model. The steady state model predicts the indoor thermal and humid environment by considering the heat transfer of the building enclosure as a two-dimensional steady state process. Several steady state models have been developed to predict the hourly change of average temperature and RH inside animal buildings based on heat balance, energy-mass balance and deep learning, by taking natural ventilation, thermal buoyancy, solar radiation and so on into consideration (Cooper *et al.*, 1998; Zhao *et al.*, 2013, Xie *et al.*, 2019). However, these models did not consider the influence of cooling efficiency variation of the evaporative pad system and its humidification effect. In fact, as a standard cooling method in laying hen houses (Malli *et al.*, 2011), the cooling efficiency of the pad system typically ranges within 30%~95% (Dağtekin *et al.*, 2009; Petek *et al.*, 2012; Rong *et al.*, 2017), which is significantly affected by surface wind speed, pad material and structure, and etc.

The non-steady state model is developed mainly based on the energy consumption simulation software of civil buildings (including DOE-2, EnergyPlus, TRNSYS, DeST, etc.) (Zhu *et al.*, 2012), which fully considers the non-steady state heat transfer process of the enclosure. Bantle *et al.* (1989) accurately simulated the annual energy consumption of chicken house with DOE-2 software, and Ahachad *et al.* (2008) used TRNSYS to estimate the changes of indoor temperature and cooling load of chicken house. However, these studies did not model the changes of indoor RH, nor did it consider the dynamic change of cooling pad efficiency. Moreover, there are also great differences between laying hen housing and civil buildings in the structure, indoor temperature and RH production, and ventilation requirements, etc., resulting in uncertainties of the prediction results by directly using the civil simulation software.

This study used MATLAB software to build and validate an hourly model for year-round temperature and RH environment prediction of laying hen houses to provide a reliable tool for animal building design and housing environment regulation.

Material and methods

Experimental laying hen house

Field test was carried out on a laying hen farm in Handan, China in July 2019. The layer house was in west-east orientation with a size of 100 m long, 12 m wide and 5 m high. The enclosure was 0.5 mm thick sandwich steel plate with 150 mm thick foam plate. The house was mechanically ventilated by 16 single speed fans installed on the west wall. Cooling pads was 1.75 m high, 9 m long and 0.15 m thick setting in the east, north and south walls. The stocking density, age, weight and egg production of laying hens were 19.6 hen m^{-2}, 55 weeks, 1.5 kg, and 50 g d^{-1} egg^{-1}, respectively.

Temperature and RH were continuously measured by T/RH data loggers (U23-001, HOBO, USA) at every 5 min. As shown in Figure 1, 26 T/RH data loggers were installed in the house, 2 loggers were close to gable walls, and other loggers were evenly located inside the 1st, 3rd, and 5th aisles at the cage bottom of the 2nd tier and 4th tier. Air velocity of each fan was measured by a hot-wire anemometer (model KA41 L, Kanomax, Osaka, Japan), and ventilation rate was calculated by multiplying air velocity and surface area of the fan. A weather station was installed on the roof of the house to continuously monitor the outdoor temperature and RH (accuracy: ±0.2 °C, ±2.5%). Sensors (accuracy: 2% reading) were installed on the east wall and roof to continuously detect the total solar radiation intensity at every 1 h. When the indoor temperature was higher than 28 °C, the cooling pad was operated, otherwise, it was turned off.

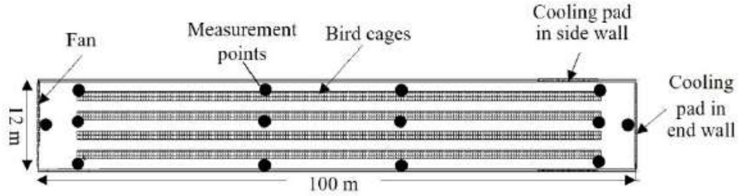


Figure 1: Top view of the indoor temperature and relative humidity measuring points

<u>Cooling efficiency of the evaporative cooling pad</u>

In laying hen house, the cooling pad system is usually used in conjunction with fans to cool the birds, and cooling efficiency of the pad system is usually variable (Dağtekin *et al.*, 2009; Petek *et al.*, 2012; Rong *et al.*, 2017). By analysing its heat and mass transfer process (Du *et al.*, 2003), cooling efficiency of a pad system can be modelled as:

$$\eta=1-\exp(-\frac{\alpha hL}{\rho v c_p}) \tag{1}$$

where η is cooling efficiency, %; ρ is air density, kg m^{-3}; υ is wind speed through the cooling pad, m s^{-1}; c_p is air specific heat capacity at constant pressure, J kg^{-1} $°C^{-1}$; α is specific surface area of cooling pad, m^2 m^{-3}; h is the heat transfer coefficient between air and water on the cooling pad surface, W m^{-2} $°C^{-1}$; L is the thickness of cooling pad, m.

Jiang (2006) considered the comprehensive influence of specific surface area and heat transfer coefficient as volume heat transfer coefficient h_υ, and fitted the h_υ of fiber paper, a typical pad material ($h_\upsilon=12.28305\nu^{0.69922}$). Then a new equation of η was obtained as:

$$\eta=1-\exp(-12.28305v^{-0.30078}\frac{L}{\rho c_p}) \tag{2}$$

Based on the definition of cooling efficiency, dry-bulb temperature t_c (°C) and moisture content d_c (kg kg^{-1}) of the air passing through the cooling pad could be expressed as:

$$t_c=t_0-\eta(t_0-t_s)=t_s+(t_0-t_s)\exp(-12.28305v^{-0.30078}\frac{L}{\rho c_p}) \tag{3}$$

$$d_c=d_s-(1-\eta)\frac{c_p(t_0-t_s)}{\gamma}=d_s-\frac{c_p(t_0-t_s)}{\gamma}\exp(-12.28305v^{-0.30078}\frac{L}{\rho c_p}) \tag{4}$$

where t_s is outdoor air wet-bulb temperature, °C; d_s is outdoor air moisture content at saturation, kg kg^{-1}; γ is latent heat of vaporization of water, J kg^{-1}.

<u>Hourly model for year-round temperature simulation</u>

The heat balance equation of large-scale laying hen house was shown in Equation (5).

$$\rho V c_p\frac{\partial t_i}{\partial \tau}=Q_s+Q_w+Q_h+Q_e-Q_v \tag{5}$$

where t_i is indoor air temperature, °C; τ is time, s; V is volume of laying hen house, m^3; Q_s is sensible heat production of laying hens in the house, W; Q_w is the heat gain of enclosure, W; Q_h is supplemental heat in laying hen house if there is, W; Q_e is heat of lighting and other equipment in laying hen house, which is usually ignored due to its small value; Q_υ is the heat loss due to ventilation and air penetration of the house, W.

For the caged laying hens, the total heat output (Q_t) can be calculated by equation (6), which is recommended by CIGR (1984).

$$Q_t=(6.28M^{0.75}+25Y)(4\times10^{-5}(20-t_i)^3+1) \quad (6)$$

where Q_t is total heat output of caged laying hens, W; M is the total weight of laying hens, kg; Y is egg production, kg d^{-1}.

Then, the Q_s, Q_w and Q_v can be calculated by equations (7)~(10).

$$\frac{Q_s}{Q_t}=0.67(1-0.02(20-t_i))-9.8\times10^{-11}t_i^6 \quad (7)$$

$$Q_w=\sum KA\,(t_{sa}-t_i) \quad (8)$$

$$t_{sa}=\frac{\rho_s I}{h_0}+t_0 \quad (9)$$

$$Q_v=mc_p(t_i-t_c) \quad (10)$$

where K is heat transfer coefficient of enclosure, W m^{-2} °C^{-1}; A is area of enclosure, m^2; t_{sa} is outdoor integrated temperature, °C; I is solar radiation intensity, W m^{-2}; ρ_s is absorption coefficient of solar radiation from enclosure surface; h_0 is heat transfer coefficient of outer surface of enclosure, W m^{-2} °C^{-1}; m is ventilation mass flow rate, kg s^{-1}; t_c is temperature of the air passing through cooling pad, which could be calculated by equation (3) when the system is operating; otherwise, it is equal to t_0. Data of the ambient air were obtained from the typical hourly meteorological data in China based on DeST.

By substituting equations (3) and (6)~(10) into equation (5), the prediction model of dynamic temperature in laying hen house could be given as equation (11). The model was built based on MATLAB, with 1 h as the time step.

$$\rho Vc_p\frac{\partial t_i}{\partial \tau}=\sum KA\,(\frac{\rho_s I}{h_0}+t_0-t_i)+(0.67(1-0.02(20-t_i))-9.8\times10^{-11}t_i^6)+(6.28M^{0.75}+25Y)(4\times10^{-5}(20-t_i)^3+1)-\ mc_p(t_i-t_s-(t_0-t_s)\exp(-12.28305v^{-0.30078}\frac{L}{\rho c_p})) \quad (11)$$

Hourly model for year-round relatively humidity simulation

Moisture balance equation of large-scale laying hen house is given in equation (12) as:

$$\rho Vc_p\frac{\partial d_i}{\partial \tau}=W_l+W_w-W_v \quad (12)$$

where d_i is indoor air moisture content, kg kg^{-1}; W_l is moisture production of laying hens, kg s^{-1}; W_w is moisture production of the enclosure surface, which is typically neglectful, kg s^{-1}; W_v is moisture emitted from the house to outside via ventilation, kg s^{-1}.

Then, the W_l and W_v can be calculated by equations (13)~(14).

$$W_l=\frac{Q_l}{\gamma}=\frac{Q_t-Q_s}{\gamma} \quad (13)$$

$$W_v=m(d_i-d_c) \quad (14)$$

where Q_l is latent heat production of laying hens, W; d_c is moisture content of air after passing the pad, which is calculated by equation (4); otherwise, it is equal to d_0.

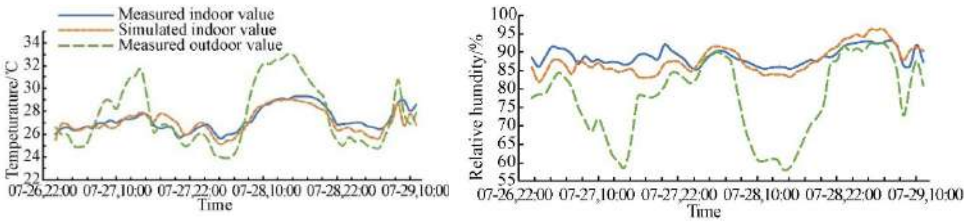
By substituting equations (4) and (13)~(14) into equation (12), the prediction model of dynamic RH in layer house could be given as equation (15) with 1 h as the time step.

$$\rho V c_p \frac{\partial d_i}{\partial \tau}=(6.28M^{0.75}+25Y)(4\times10^{-5}(20-t_i)^3+1)\times(1-(0.67(1-0.02(20-t_i))-9.8\times10^{-11}t_i^6))/\gamma-m$$
$$(d_i-d_s+\frac{c_p(t_0-t_s)}{\gamma}\exp(-12.28305v^{-0.30078}\frac{L}{\rho c_p})) \tag{15}$$

Results and Discussion

Model performance on year-round temperature and relatively humidity prediction

In this study, the average of 26 measuring points of temperature and RH was used as the measured values. Predicted values of indoor temperature and RH were compared with the measured ones as shown in Figure 2.



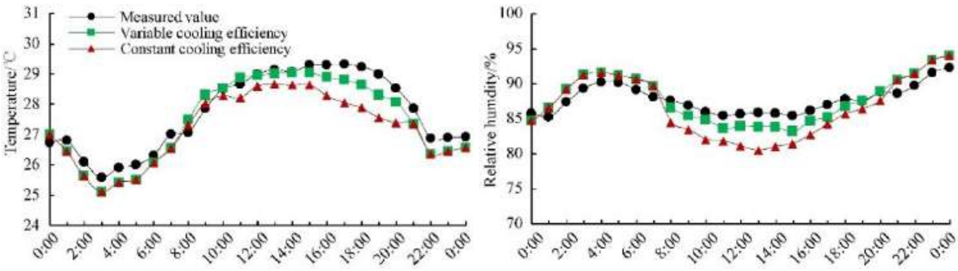
a. Temperature　　　b. Relatively humidity

Figure 2: Comparison of predicted and measured values of indoor temperature and relative humidity in the experimental laying hen house

Figure 2 illustrated that the predicted values of indoor temperature and RH had the same change pattern as the measured values. The average prediction error of temperature was 0.67 °C, and that of RH is 3.1%. Compared with other reported results, accuracy of the developed model to predict the dynamic change of indoor temperature and RH was improved, which can satisfy the control requirement of laying hen house environment. The prediction error might be caused by the deviation of the physical parameters of the enclosure and the cooling pad due to a long-time usage, and the influence of management activities such as air infiltration, disinfectant spraying, manure cleaning, workers' activities, etc, which were exclusive in the model.

Influence of cooling pad efficiency

Previous studies on thermal environment simulation simplified the cooling pad efficiency to 80% (Wang *et al.*, 2008), while, it practically varied with several factors (such as wind speed passing through the pad) (Dağtekin *et al.*, 2009; Petek *et al.*, 2012; Rong *et al.*, 2017). To illustrate effect of cooling efficiency variation, this study used fixed cooling efficiency of 80% and the calculated dynamic values (equation (2)) in the model to predict the indoor air temperature and RH in laying hen house, and compared with the measurements (July 28) in the field. The results were shown in Figure 3.



a. Temperature b. Relatively humidity

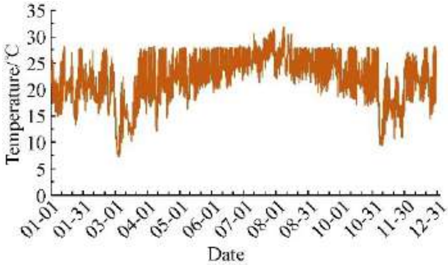
Figure 3: Effect of the cooling pad efficiency on the indoor temperature and RH prediction

Figure 3 showed that the predicted indoor temperature and RH by 80% and varied cooling efficiency were basically agreed during night, because the cooling pad was turned off for lower indoor temperature at night. In daytime (especially at noon and afternoon), along with the outdoor temperature and solar radiation rose, the cooling pad was operated, and differences of the predictions with fixed and varied cooling efficiency were observed. With a constant efficiency of 80%, the maximum difference between predicted and measured indoor air temperature was 1.4 °C, and that of RH was 5.4%, which were all greater than the errors (0.67 °C for temperature and 3.1% for RH) calculated with changed cooling efficiency. It is concluded that the cooling efficiency variations of evaporative pad system with different wind speeds should be considered into the indoor temperature and RH prediction models to improve its accuracy.

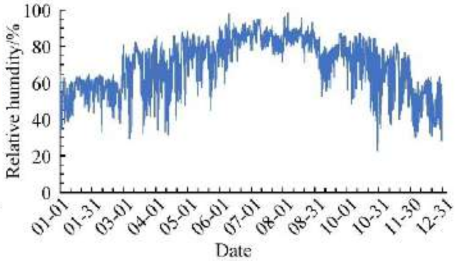
<u>Year-round temperature and relative humidity prediction in typical area in China</u>

To show its application potential, the developed model was used to predict the year-round indoor temperature and RH of laying hen houses in the cities of Wuhan and Harbin of China as an example. The input parameters of laying hen houses in two regions were supposed to be the same (Liang *et al.*, 2021). The hourly temperature and relative humidity predictions for the whole year in Wuhan (central China) and Harbin (northern China) as an example were shown in Figure 4.

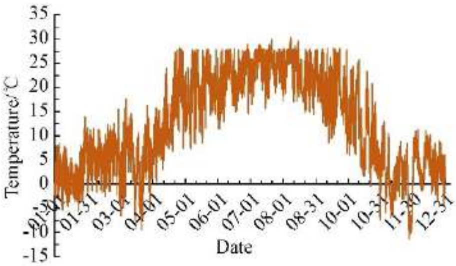
Figure 4 illustrated that indoor temperature of laying hen house in Wuhan was mostly between 10 °C and 25 °C, which could meet the basic requirements of thermal and humid environment in winter. However, indoor temperature can easily reach over 28 °C and RH was higher than 80% for most of time in July and August, showing a relatively poor cooling effect of the pad system for hot and humid weather. Therefore, in this areas, appropriately increasing ventilation should be considered to meet the requirements of heat and humid environment in laying hen houses during summer. As for Harbin, the house could basically meet the requirements of thermal and humid environment in summer, and the temperature in the house was mainly between 12 °C and 27 °C. However, the indoor temperature was usually lower than 13 °C, or even below 0 °C in winter. Therefore, in the cold region, integrated solutions including appropriate increasing of stocking density and insulation performance of house enclosure, as well as balanced ventilation could be taken to satisfy its thermal and humid environment of laying hens.



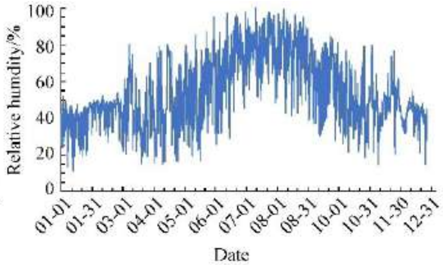
a. Temperature in Wuhan



b. Relatively humidity in Wuhan



c. Temperature in Harbin



d. Relatively humidity in Harbin

Figure 4: Hourly simulation values of the indoor temperature and relative humidity in the laying hen house in Wuhan and Harbin

Conclusions

An hourly model for year-round temperature and RH environment predictions in laying hen house in China was developed based on cooling efficiency mathematical models and heat and moisture balance equations, and the accuracy of the model was verified by field test. The main conclusions were as follows:

1. Predictions of indoor temperature and RH were well consistent with the field measured values. The overall average prediction error of indoor temperature was 0.67 °C, and that of indoor relatively humidity was 3.1%, showing the model had a good performance to predict the dynamic changes of environmental parameters in laying hen house.
2. If the dynamic variation of the cooling pad system efficiency was not taken into account, the accuracy of the prediction model would be reduced.

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Application of RNN model for predicting internal environments of poultry houses

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Abstract

Duck industry which is one of the fast-growing industries occupied 6th in the livestock industry in South Korea. However, there are few studies for quantitatively predicting the internally thermal and moisture environment of duck houses. In this study, the high-accuracy recurrent neural network (RNN) models for predicting the internal air temperature and relative humidity according to the type of duck houses, seasons, environmental variables were developed by learning the monitoring data of the internal and external environments of the mechanically and naturally ventilated duck house measured at field experiments. The optimal sequence length of learning data for the development of the RNN model was selected as 120 minutes. As a result of the validation, both air temperature and relative humidity could be accurately predicted within 1% error. In addition, the simplified RNN models were additionally developed by learning only from the data of external air temperature, relative humidity, and duck weight, which are relatively easy to acquire at the farms. The accuracy of the simplified RNN models was similar to the basic model for predicting the internal air temperature and relative humidity of duck houses in real-time.

Keywords: duck house, environmental monitoring, prediction of internal environments, machine learning, recurrent neural network

Introduction

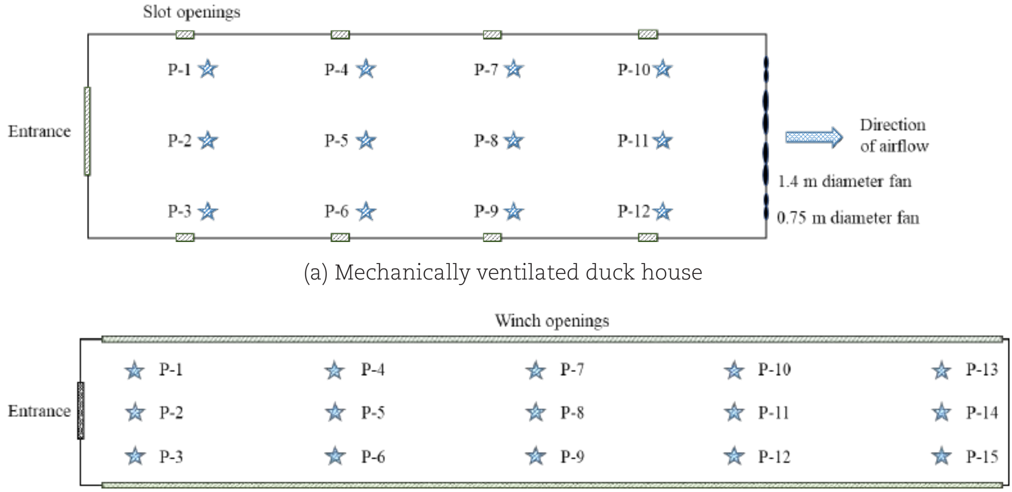
Recently, artificial neural network (ANN) has been actively used as a method to accurately predict the dependent variables from independent variables in the agricultural fields. The recurrent neural network (RNN) model, which is one of the ANN models, has been actively applied to the agricultural field due to the advantage of being suitable for dealing with time-series data. However, few studies focused on predicting the internal environment of livestock houses. The RNN model has the advantage of high accuracy and improving the model through continuous learning. Therefore, it is expected that the RNN model can be applied to develop the model for predicting the internal environments of duck houses in real-time.

In this study, the RNN models according to the type of duck houses, seasons, environmental variables were developed for predicting the internal air temperature and relative humidity of the mechanically and naturally ventilated duck houses. The internal and external environmental data of the duck houses monitored at field experiments such as external air temperature, relative humidity, solar radiation, wind speed, wind direction, ventilation rate of the mechanically ventilated duck house, and weight of the duck were used as learning data for RNN model development. Because ventilation is one of the most important factors affecting the internal environments of duck houses, the ventilation rates of the mechanically ventilated duck house were monitored and used as learning data. The data of wind speed and direction were used as learning data instead of the ventilation rate of the naturally ventilated duck house because it was hard to quantitatively monitor the natural ventilation rate at field experiments. The accuracy of the developed RNN models was evaluated according to the type of duck houses, seasons, environmental variables. In addition, the simplified RNN models were developed to improve the applicability of the RNN model to the field. The simplified RNN models were developed by learning only from external air temperature and relative humidity data, which is relatively easy to acquire at the farms. Finally, the accuracy of the simplified RNN models was compared with that of the basic model for predicting the internal air temperature and relative humidity of duck houses in real-time.

Material and methods

Data collection of environments of duck houses

A mechanically ventilated duck house and a duck house converted from a plastic greenhouse were used for developing the RNN model of mechanically and naturally ventilated duck houses, respectively. The internal environments of these duck houses could be directly compared with each other because these duck houses were located at the same farm (126°38’ E, 34°53´ N). To develop the RNN models for predicting the internal environments of duck houses, validate them, and then enhance their accuracy, the monitoring data of the external and internal environments observed during the field experiments were used. As shown in Figure 1, 12 and 15 sensors (HTX 75, Dotech Inc.) were installed to measure the internal air temperature and relative humidity of the mechanically and naturally ventilated duck houses, respectively. These sensors were installed at a height of 1.2 m at regular intervals to prevent breakdown by birds. When the exhaust fans were operated in the mechanically ventilated duck house, AC clamp sensors and an electrometer were installed for the monitoring of electric current flow. The data of the ventilation rates, air temperature, and relative humidity inside the duck house were monitored at 1 s intervals. However, the data averaged over 5 min were used to develop the RNN model. To observe the weather data, a portable weather station (Watchdog 2900ET, Aurora, IL, USA) was installed on the roof of the control room in the farm. Weather data such as the wind environments, solar radiation, air temperature, relative humidity, and rainfall were measured at 1 s intervals, and data averaged over 5 min were recorded.



(a) Mechanically ventilated duck house

(b) Naturally ventilated duck house

Figure 1: Sensor locations for air temperature and relative humidity in mechanically and naturally ventilated duck houses (P in figure means the measurement point)

Design of RNN model of duck houses

In this study, a single-layered LSTM model suitable for learning long-term data was used. As learning parameters, the learning rate was set to 0.01, and the tanh function, which is known to generally have high accuracy for the RNN model, was used as the activation function. The Adam optimizer was applied as the optimizer (Kingma & Adam *et al.*, 2014), and the loss was learned so that the mean square error was minimized (Esfa *et al.*, 2016; Rumelhart *et al.*, 1986; Wang *et al.*, 2017). For RNN learning, missing data were linearly interpolated. Detailed information of the dataset for development of the RNN model such as the monitoring period and the number of total dataset is presented in Table 1. Specifically, 70% of the data measured for each rearing period were used as the learning data for model development considering the time series, while 30% of the data for each rearing period were used as data to validate the developed RNN models. The data of external air temperature, relative humidity, and solar radiation, as well as ventilation rate and weight of the duck, were used as training data in order to develop the RNN model for predicting the internal air temperature and relative humidity of the mechanically ventilated duck house. Although it is hard to quantitatively monitor the ventilation rates of the naturally ventilated duck house, the external wind speed and wind direction are the main factors for natural ventilation. Therefore, when the RNN models of the naturally ventilated duck house were developed, the wind speed and wind direction data were used as training data instead of the ventilation rate.

Table 1: Identification results of the proposed algorithm

Monitoring Period	Seasons	Growing Days	Starting Date of Monitoring	Date of Shipment	Total Dataset
1st growing period	Summer	45 days	6 Aug. 2018	12 Sep. 2018	12,960
2nd growing period	Autumn	41 days	11 Oct. 2018	13 Nov. 2018	11,808
3rd growing period	Winter	30 days	9 Dec. 2018	7 Jan. 2019	8640

Validation of RNN models

The developed RNN model of the duck houses was validated by comparing the predicted data of the air temperature and relative humidity using the RNN model with the measured data of the air temperature and relative humidity data during the field experiments. The optimal sequence length was selected by comparing the accuracy of the RNN model developed according to sequence lengths of 30, 60, 90, 120, 150, and 180 min. Additionally, the accuracy and characteristics of the RNN model for the mechanically ventilated duck house were compared with those of the BES model developed in a previous study (Lee *et al.*, 2020). Statistical indices such as coefficient of determination (R^2), root-mean-square error (RMSE), and mean absolute percentage error (MAPE) were calculated to validate the RNN models by comparing the predicted data obtained using the developed RNN model with the data measured during the field experiments using Equations (1)–(3), respectively.

$$R^2 = \left(\frac{\sum_{i=1}^{n} (R_i - \bar{R}_i)(C_i - \bar{C}_i)}{\sqrt{\sum_{i=1}^{n} (R_i - \bar{R}_i)^2 \times \sum_{i=1}^{n} (C_i - \bar{C}_i)^2}} \right)^2 \quad (1)$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (R_i - C_i)^2}{n}} \quad (2)$$

$$\mathrm{MAPE} = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{R_i - C_i}{R_i} \right| \quad (3)$$

where R_2 is the coefficient of determination, RWSE is the root-mean-square error (°C, %), MAPE is the mean absolute percentage error (%), n is the total data according to time, R_i is the measured data at a specific time, $\bar{R}_l$ is the average of the measured data at a specific time, is the predicted data at a specific time, and $\bar{C}_l$ is the average of the predicted data at a specific time.

Comparison of accuracy of RNN models

In Analyses conditions for the developed RNN model were a total of 24 cases as shown in Table 2. The data of external air temperature, relative humidity, solar radiation, ventilation rate, and weight of the duck were used as training data in order to develop the RNN model of the mechanically ventilated duck house for estimating the internal air temperature and relative humidity. The data of external air temperature, relative humidity, solar radiation, wind speed, wind direction, and weight of the duck were used as training data in order to develop the RNN model of the naturally ventilated duck house for estimating the internal air temperature and relative humidity.

Considering the applicability of the RNN models to the field, simplified RNN models were additionally developed by learning only the data of the external air temperature, relative humidity, and duck weight, which are relatively easy to acquire at duck farms. It was generally difficult to quantitatively monitor the ventilation rate of duck houses at duck farms. Because most farms do not install their own weather stations, it is difficult to observe the external wind environment and radiation in real time. However, it is relatively easy to obtain the data of external air temperature and relative humidity from simple sensor installation and through the Meteorological Agency. The duck weight is an important factor affecting the internal environment of duck houses. These data could be calculated from growing days. The accuracy of simplified RNN models was then compared and analysed. Additionally, the accuracy of RNN models can be improved when time-series data are trained in reverse order according to previous studies (Srivastava *et al.*, 2015; Sutskever *et al.*, 2014; Vinyals *et al.*, 2015). Therefore, in this study, the RNN models were developed by learning time-series data in reverse to improve their accuracy.

Table 2: Experimental conditions of learning data for developing RNN model

Conditions		Conditions		Number of Cases
Learning data (Independent variables)	Mechanically ventilated duck house	Basic model	(1) External air temperature, external relative humidity, solar radiation, ventilation rates of duck house, and duck weight	4
		Simplified model	(2) External air temperature, external relative humidity, and duck weight	
	Naturally ventilated duck house	Basic model	(3) External air temperature, external relative humidity, solar radiation, wind speed, wind direction, and duck weight	
		Simplified model	(4) External air temperature, external relative humidity, and duck weight	
Dependent variable		Internal air temperature and internal relative humidity		2
Seasons		Summer (30 Jul. 2018–12 Sep. 2018), autumn (4 Oct. 2018–13 Nov. 2018), and winter (26 Nov. 2018–7 Jan. 2019)		3
Total		-		24

Results and Discussion

<u>Validation of RNN models</u>

The developed RNN model of the duck houses was validated by comparing the predicted data of the air temperature and relative humidity using the RNN model with the data of the air temperature and relative humidity data measured during the field experiments. For developing the RNN model, the accuracy according to several sequence lengths was compared to determine the sequence length of the training data. To quantitatively compare the accuracy of the RNN models, the statistical indices of R^2, RMSE, and MAPE were calculated, and the results are shown in Table 3. The sequence length should be at least 120 min to ensure that the deviation between internal relative humidity data predicted by the RNN model and measured during field experiments was within 1%. When the sequence length was 150 and 180 min, the accuracy of the RNN model was not significantly improved compared to other sequence lengths, but it took a long time to develop the RNN model. Therefore, the optimal sequence length was selected at 120 min, and it was applied to the development of RNN models. Additionally, the RNN model was able to predict more accurately compared with the BES model developed in the previous study (Lee *et al.*, 2020). The BES model was developed using the equilibrium equation of physical factors, and it was possible to apply it in changing conditions. Although the accuracy of the RNN model was high for the condition of the trained data, the accuracy of the RNN model was uncertain for untrained new data. However, the RNN models were expected to be highly applicable to the field because the RNN models could be continuously improved by learning the monitoring data in the future.

Table 3: Identification results of the proposed algorithm

Internal Air Temperature	Sequence Length for LSTM Model						BES Model (Lee *et al.*, 2020)
	30 min	60 min	90 min	120 min	150 min	180 min	
R^2	0.96	0.96	0.98	0.99	0.99	0.99	0.95
RMSE (°C)	0.61	0.51	0.35	0.23	0.25	0.22	0.70
MAPE (%)	1.50	1.22	0.85	0.45	0.47	0.44	1.71
Internal relative humidity	**Sequence Length for LSTM Model**						**BES Model (Lee *et al.*, 2020)**
	30 min	60 min	90 min	120 min	150 min	180 min	
R^2	0.91	0.95	0.96	0.98	0.98	0.98	0.92
RMSE (°C)	3.16	2.35	1.62	1.11	1.08	1.09	4.61
MAPE (%)	3.12	2.16	1.57	0.79	0.78	0.79	4.33

Analysis of accuracy of RNN model according to seasons and applicability of simplified RNN model

Ventilation operation, evaporation of litters, condensation at the wall, etc. were different according to seasons. However, the RNN models were developed by dividing the training data according to seasons because it was difficult to quantitatively monitor the data as these factors constantly changed. The accuracy of the RNN models trained in reverse order is shown in Tables 4 and 5. The accuracy of the RNN model of the naturally ventilated duck house was lower than that of the mechanically ventilated duck house. Because the internal environments of the naturally ventilated duck houses were operated through natural ventilation, there were several uncertainties such as non-uniformity of the internal environments. As a result of comparing the accuracy of the RNN model trained in reverse order according to seasons, the RNN models of both the mechanically and the naturally ventilated duck houses predicted the internal air temperature and relative humidity with errors of less than 1% in the summer. In summer, the accuracy of the RNN models was the highest compared with other seasons. In summer, the exhaust fans were maximally operated in the mechanically ventilated duck house, and the vent openings of the naturally ventilated duck house were maximally open. In the case of the simplified RNN model for applicability to the field, the accuracy of the simplified RNN models for both the mechanically and the naturally ventilated duck houses was similar to the accuracy of the basic RNN models. This is because the time factor included the changes over time of solar radiation, ventilation

Table 4: Accuracy of RNN model of mechanically ventilated duck house according to seasons and variables (reverse order)

Summer	Basic Model		Simplified model	
	Internal Air Temperature	Internal Relative Humidity	Internal Air Temperature	Internal Relative Humidity
R^2	0.988	0.980	0.987	0.981
RMSE (°C, %)	0.221	1.065	0.224	1.070
MAPE (%)	0.412	0.731	0.390	0.761
Autumn	**Basic Model**		**Simplified model**	
	Internal Air Temperature	**Internal Relative Humidity**	**Internal Air Temperature**	**Internal Relative Humidity**
R^2	0.998	0.998	0.999	0.998
RMSE (°C, %)	0.137	0.499	0.121	0.482
MAPE (%)	0.526	0.401	0.643	0.406
Winter	**Basic Model**		**Simplified model**	
	Internal Air Temperature	**Internal Relative Humidity**	**Internal Air Temperature**	**Internal Relative Humidity**
R^2	0.983	0.991	0.985	0.991
RMSE (°C, %)	0.487	0.647	0.403	0.728
MAPE (%)	2.317	0.332	1.654	0.463

Table 5: Accuracy of RNN model of naturally ventilated duck house according to seasons and variables (reverse order)

Summer	Basic Model		Simplified model	
	Internal Air Temperature	Internal Relative Humidity	Internal Air Temperature	Internal Relative Humidity
R^2	0.994	0.996	0.995	0.995
RMSE (°C, %)	0.414	1.103	0.390	1.313
MAPE (%)	0.813	1.254	0.891	1.512
Autumn	**Basic Model**		**Simplified model**	
	Internal Air Temperature	**Internal Relative Humidity**	**Internal Air Temperature**	**Internal Relative Humidity**
R^2	0.996	0.998	0.997	0.996
RMSE (°C, %)	0.385	0.914	0.352	1.496
MAPE (%)	1.891	1.048	1.701	1.819
Winter	**Basic Model**		**Simplified model**	
	Internal Air Temperature	**Internal Relative Humidity**	**Internal Air Temperature**	**Internal Relative Humidity**
R^2	0.997	0.984	0.997	0.989
RMSE (°C, %)	0.229	0.866	0.239	0.744
MAPE (%)	1.187	0.490	1.285	0.550

rate, ventilation configuration, etc. Therefore, the internal air temperature and relative humidity of the duck houses could be predicted by obtaining the data of external air temperature and relative humidity from installed sensors and the Meteorological Agency. In addition, the internal environments of duck houses could be more appropriately managed using these simplified RNN models.

Conclusions

The RNN models developed in this study have the advantage that they can be continuously improved by learning monitoring data in the future. The simplified RNN models with high accuracy are expected to be highly applicable to the field. They can be applied to control the internal environment of livestock farms and identify the occurrence of high-temperature stress for livestock. Furthermore, predicting the internal environments of livestock houses is important because the poor internal environment of livestock houses cause sensor corrosion or malfunction. In the future, for the convergence of ICTs and application of smart farms in duck houses, the RNN models of duck houses developed in this study can be applied to predict and control the internal environments of duck houses using the model predictive control (MPC) technique.

Acknowledgements

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SESSION 8

Over the Fence: Use of PLF in other Species

Uniting farms: Federated learning for sensor-based animal activity recognition

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Abstract

Automated animal activity recognition (AAR) has achieved great success due to the development of deep learning methods trained on large-scale datasets, providing rich insights into animal health and welfare and alleviating the workloads of animal caretakers and veterinarians. However, constructing centralised data across diverse sources (e.g., farms) faces two challenges: 1) data ownership and privacy issues when accessing farm data, and 2) limited storage and computational capabilities in a single central repository. Federated learning (FL), which allows data owners to collectively train a model while keeping their data stored locally, provides a privacy-preserving decentralised solution. This study introduced the FL-based framework for the first time to AAR fields and explored its feasibility and effectiveness in improving model performance by uniting sensor data from different farms. Three state-of-the-art FL strategies (i.e., FedAvg, FedProx, and FedBN) were compared against SingleSet (i.e., training an individual model within each client) based on two public datasets. These two datasets consist of 87,621 and 42,943 2-s motion data (tri-axial acceleration and tri-axial angular velocity) acquired from horses and goats, respectively. The results demonstrated that FedAvg, FedProx, and FedBN could accurately classify activities of horses and goats, outperforming the SingleSet with different increments in average accuracy (horses: 12.07%, 12.05%, 11.89%; goats: 4.05%, 4.07%, 4.16%). This proved the promising capability of FL to enhance AAR's performance without privacy leakage. In addition, empirical analyses were conducted to assess FL's performance from two aspects, including data sizes and clients numbers, providing rich insights into FL's appropriate applications in the future.

Keywords: animal welfare, wearable sensor, deep learning, privacy-preserving, distributed learning

Introduction

Automated animal activity recognition (AAR) with wearable sensors has attracted increasing attention, providing rich insights into animal health and welfare and alleviating the workloads of animal caretakers and veterinarians. In recent years, deep learning-based approaches have dominated this task due to their high performance with the help of large-scale training datasets. However, in reality, building a big dataset for one farm or institution is difficult, and limited training data easily cause the model's overfitting problem, yielding unsatisfactory performance. As shown in Figure 1, training models based on data within a single site always have low accuracies due to data limitations, whereas the accuracy significantly increases when using centralised data from both sites. Thus, data collaboration across diverse sources (e.g., farms) is increasingly desired to learn a global model. However, collecting large quantities of centralised data from different farms tends to face two challenges: 1) data access is often restricted due to data ownership, privacy concerns, and strict sharing policies, and 2) constructing and modelling all data samples in a single machine or central repository is impractical due to the high storage costs and limited computational capabilities. To this end, there is a need for a distributed learning paradigm that enables to build a collaborative model without privacy leaking and alleviates the burden on data gathering for a single entity.

Federated learning (FL), which is a new collaborative learning strategy, has emerged as an attractive solution to mitigate the aforementioned problems (Brendan McMahan *et al.*, 2017; Acar *et al.*, 2021). It allows learning from distributed clients (data sources) by aggregating the locally trained models without exchanging the client's data. Such a mechanism promotes privacy preservation between independent and decentralised data stores while producing trained models that leverage datasets of all participating clients (Deng *et al.*, 2020; Durrant *et al.*, 2021). Meanwhile, it enables us to train models under individual clients with less storage and computational capabilities. In recent years, FL has been increasingly designed for various applications due to its privacy-preserving nature, including mobile edge devices, industrial engineering, and health care (Li *et al.*, 2020a; Li *et al.*, 2020b; Li *et al.*, 2021a). However, as far as we know, no previous work employed FL models in AAR tasks based on decentralised data.

In this study, we introduced the FL-based framework for the first time to the AAR fields, and explored its feasibility and effectiveness of improving model performance using decentralised data. Three state-of-the-art FL strategies, i.e., FedAvg (Brendan McMahan *et al.*, 2017), FedProx (Li *et al.*, 2020c), and FedBN (Li *et al.*, 2021b), were compared against SingleSet (i.e., training an individual model within each client), based on two public datasets. These two datasets consisted of 87,621 and 42,943 2-s motion data (tri-axial acceleration and tri-axial angular velocity) acquired from horses and goats, respectively.

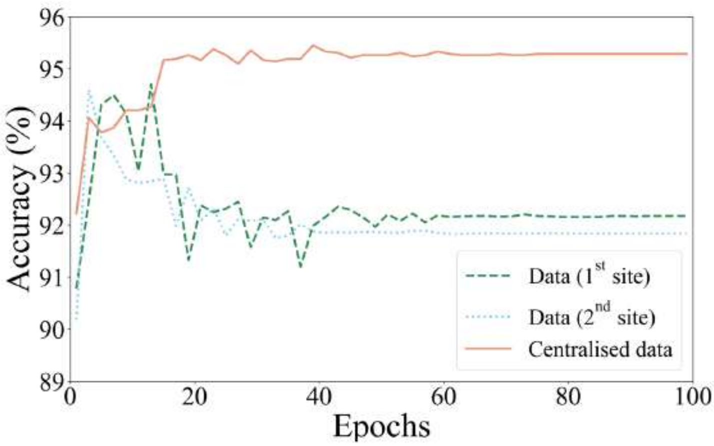

Figure 1: Testing accuracy based on data within a single site and centralised data

Material and methods

Data description

The data used in this study contained two public datasets collected from horses (Kamminga *et al.*, 2019) and goats (Kamminga *et al.*, 2018), respectively. They were denoted as horse-dataset and goat-dataset, respectively. The horse-dataset was a centralised dataset comprising 87,621 2-s samples acquired from six horses with neck-attached IMUs. It contained six activities, i.e., eating, galloping, standing, trotting, walking-natural, and walking-rider. The activity amount of these six horses, i.e., Happy, Zafir, Driekus, Galoway, Patron, and Bacardi, was 23,625, 11,071, 10,127, 24,602, 12,849, and 5,347, respectively. Amongst, the tri-axial motion data from the accelerometer and gyroscope were exploited as bi-modality data, forming up to two tensors ($1 \times 3 \times 200$) for each sample.

The goat-dataset was a real-world dataset consisting of 42,943 2-s motion data collected from five goats on two farms. Each goat's collar was attached to six sensors (i.e., tri-axial accelerometer and gyroscope) that were fixed with different orientations. Five main activities were included, i.e., standing, running, eating, trotting, and walking. The sample number of the five goats, i.e., three domestic pygmy goats from one farm and two larger and more wild goats from another farm, was 13,902, 5,321, 11,954, 7,523, and 4,243, respectively. Amongst, the tri-axial accelerometer and gyroscope data from all six sensors of the collar were utilised, forming up to two tensors ($1 \times 18 \times 200$) for each sample. Note that the sampling rates of the tri-axial accelerometer and gyroscope were set to 100 Hz in both two datasets. All these samples would be normalised before being fed into the network (Mao *et al.*, 2021).

Federated learning (FL) framework for AAR

Federated learning (FL) was initially proposed by Google (Brendan McMahan *et al.*, 2017), where a group of data owners collectively trained a model while keeping their data stored locally. Herein we adopted FL paradigms to achieve automated AAR where sensor data were located in different farms (clients), and presented the FL framework for AAR in Figure 2.

Let G and $L = \{l^k\}_{k=1}^{K}$ represented the global model and K local client models, respectively. $D^k = \{(x_i^k, y_i^k)\}_{i=1}^{N^k}$ represented a set of the dataset in the k-th client, where $y_i^k \in \{1, \ldots, C\}$was the corresponding label of the data instance x_i^k ($i \in \{1, \ldots, N^k\}$), C was the number of label categories, and N^k was the data number of the k-th client. Each communication round of the framework mainly consisted of three steps:

1) Local model update and upload. Each farm (k-th farm) trained the local model (l^k) based on its own dataset (D^k) for E local epochs, and then uploaded the updated model parameters to a trusted third-party (global server unit).

2) Global model update. The third-party randomly selected local models from several farms (here we selected all of the client models by default) and then aggregated their parameters to update the global model G. The most popular existing and easiest FL strategy is FedAvg, and its aggregation algorithm is defined as below:

$$w^G = \sum_{k=1}^{K} \frac{w^k}{K} \tag{1}$$

where w^G and w^k were the parameters of global model G and model l^k, respectively.

3) Gobal model delivery. Each farm downloaded the latest global model parameters w^G and used them as the updated weights for decision-making or the next model updating cycle. Note that the local model initialisation took place at the first delivery round.

Except for the FedAvg, as introduced above, FedProx and FedBN were further designed based on it. In reality, FedAvg often suffered from slow convergence and performance degradation in most non-iid contents(Deng *et al.*, 2020)we study communication efficient distributed algorithms for distributionally robust federated learning via periodic averaging with adaptive sampling. In contrast to standard empirical risk minimization, due to the minimax structure of the underlying optimization problem, a key difficulty arises from the fact that the global parameter that controls the mixture of local losses can only be updated infrequently on the global stage. To compensate for this, we propose a Distributionally Robust Federated Averaging (DRFA. Thus, FedProx was proposed to tackle the statistical heterogeneity by restricting the local updates to be closer to the initial (global) model. Specifically, the original loss function $L(w)$ within FedAvg was added by a new term, i.e, $\frac{\mu}{2}\|w - w^G\|^2$, where μ denoted the hyperparameters.

Considering the feature shift non-idd issue, i.e., local clients may store examples with different distributions compared to other clients, FedBN as an effective method was further presented. It kept the client BN layers updated locally without communicating and aggregating them at the global server. All these three FL strategies were implemented in this study to verify the effectiveness of FL under AAR tasks.

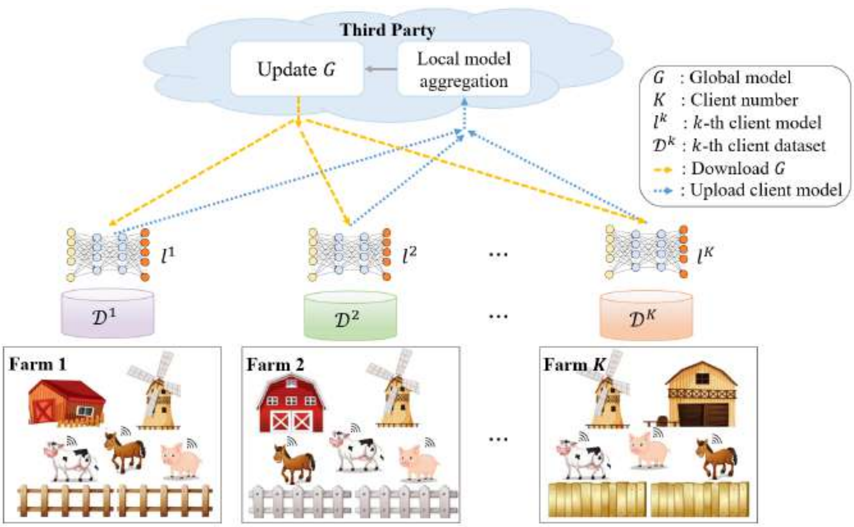

Figure 2: Federated learning (FL) framework for AAR across multiple farms

Implementation details

We employed the cross-modality interaction network, which has been previously validated in improving horse activity classification performance (Mao *et al.*, 2021), as the basic classification model to achieve AAR under the FL setting. Four common evaluation metrics were utilised: precision, recall, F1-score, and accuracy. To verify the model's generalisation ability, we performed the leave-one-out-based validation method where one individual's samples were separated as the testing set, and the data from the remaining subjects were used to be training set in each client. As for the horse-dataset, we reconstructed it into two clients, one containing training data from Happy and Zafir and testing data from Bacardi, and another containing training data from Driekus and Galoway and testing data from Patron. This matched the setup proposed by Li *et al.* (2021b), i.e., balanced sample numbers across clients. As for the goat-dataset, we constructed two clients corresponding to two farms.

During training, softmax cross-entropy loss with L2 regularisation (a weight decay of 0.15) was used. An Adam optimiser with an initial learning rate of 1×10^{-4} was employed, and the learning rate decreased by 0.1 times every 20 epochs. The number of local update epochs, communication rounds, and batch size was set to 1,100, and 256, respectively. The best model with the highest average testing accuracy across all clients was saved as the optimal model over the last five communication rounds. We performed three repeated runs for each experiment, and the final results were presented with format mean$\pm$std from the three-trial run. All experiments were executed using the PyTorch framework on an NVIDIA Tesla V100 GPU.

Results and discussion

Overall, experiments results demonstrated that FedAvg, FedProx, and FedBN exhibited superior performance to the SingleSet in terms of all evaluation metrics. In addition, a comprehensive investigation of the FL's performance was conducted on horse-dataset, concerning two practical aspects (i.e., local data sizes and clients numbers). It provided empirical insights into the appropriate applications of FL in AAR tasks in the future.

Performance on horse-dataset

To evaluate the effectiveness of FL strategies, we presented the comparative results of three FL methods and the SingleSet on horse-dataset in Table 1. It revealed that FedAvg, FedProx, and FedBN displayed promising capabilities for behavioural classification with increments of 11.42%, 11.49%, 11.62% in average precision, 13.51%, 13.51%, 13.33% in average recall, 13.75%, 13.79%, 13.73% in average F1-score, and 12.07%, 12.05%, 11.89% in average accuracy compared with the SingleSet, respectively. This was ascribed to the fact that FL enabled to access different clients' data implicitly to learn more pattern characteristics, whereas the SingleSet was only trained on the limited data within a single site. In addition, FL methods showed smaller variances than the SingleSet in values of all evaluation metrics over multiple runs, indicating FL methods' good stability and robustness. This was because that FL could discover more general and discriminative patterns effectively (Li *et al.*, 2020a). Figure 3 shows the training process of the two client models under three FL methods and SingleSet. We can observe that FedAvg and FedProx displayed approximate training curves and increased faster and smoother than FedBN, indicating that FedAvg and FedProx had larger convergence rates. These observations showed inconsistency with what was given by previous findings (Li *et al.*, 2021b), which might be due to the discrepancy of data characteristics between different datasets.

Performance on goat-dataset

To better understand the benefits of the FL mechanism in real-world scenarios, we further validated the effectiveness of FL approaches in comparison with the SingleSet on goat-dataset. As illustrated in Table 2, the FedAvg, FedProx, and FedBN exhibited superior performance for behavioural classification with increments of 1.55%, 4.98%, 3.02% in average precision, 8.46%, 8.38%, 9.10% in average recall, 8.03%, 8.13%, 8.19% in average F1-score, and 4.05%, 4.07%, 4.16% in average accuracy compared with the SingleSet, respectively. This demonstrated that the FL methods could also effectively improve the classification performance in a real-world application. Moreover, it is worth noting that the FedBN achieved better performance than FedAvg and FedProx with higher average values in recall, F1-score, and accuracy, which was inconsistent with the experimental results on the horse-dataset (Table 1). This might be explained by the fact that the goat-dataset existed feature shift non-iid issues due to the different behaviour patterns between two kinds of goats in two farms. And the issues could be effectively alleviated when applying FedBN that kept the local batch normalisation parameters not synchronised with the global model (Li *et al.*, 2021b). In addition, we presented the training process of two client models under three FL methods and SingleSet in Figure 4. It can be observed that FedAvg, FedProx, and FedBN showed similar convergence rates, although they fluctuated greatly with different degrees in the early training stage. Moreover, the testing accuracy showed overfitting phenomenons when SingleSet was applied, mainly because of the limited amount of data in a single client.

Table 1: Comparison (mean±std) of SingleSet and federated learning (FL) methods on horse-dataset

Methods	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
SingleSet	66.370.65	66.151.50	64.781.54	79.870.82
FedAvg	77.790.25	79.660.18	78.530.20	91.940.16
FedProx	77.860.19	79.660.19	78.570.15	91.920.09
FedBN	77.990.32	79.480.22	78.510.18	91.760.22

Table 2: Comparison (meanstd) of SingleSet and FL methods on goat-dataset

Methods	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
SingleSet	62.950.45	57.951.61	57.182.18	92.010.55
FedAvg	64.500.11	66.411.08	65.210.53	96.060.21
FedProx	67.935.48	66.330.63	65.310.33	96.080.22
FedBN	65.971.62	67.051.62	65.371.55	96.170.24

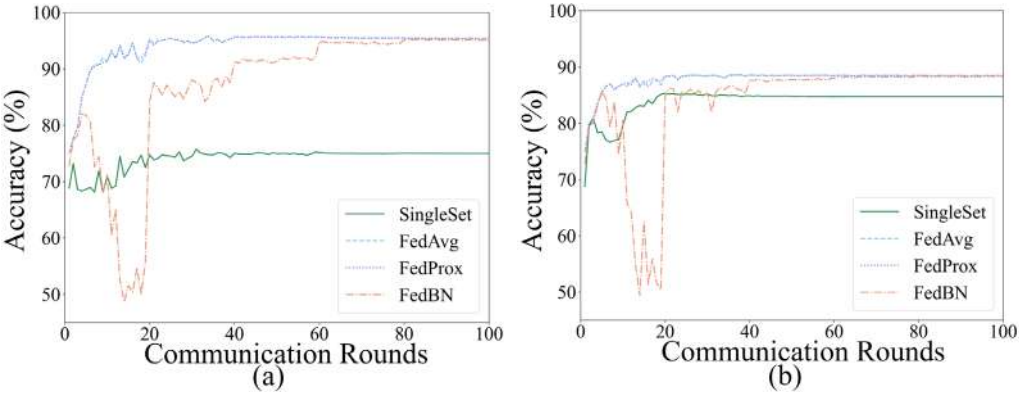

Figure 3: Testing accuracy of client 1 (a) and client 2 (b) on horse-dataset

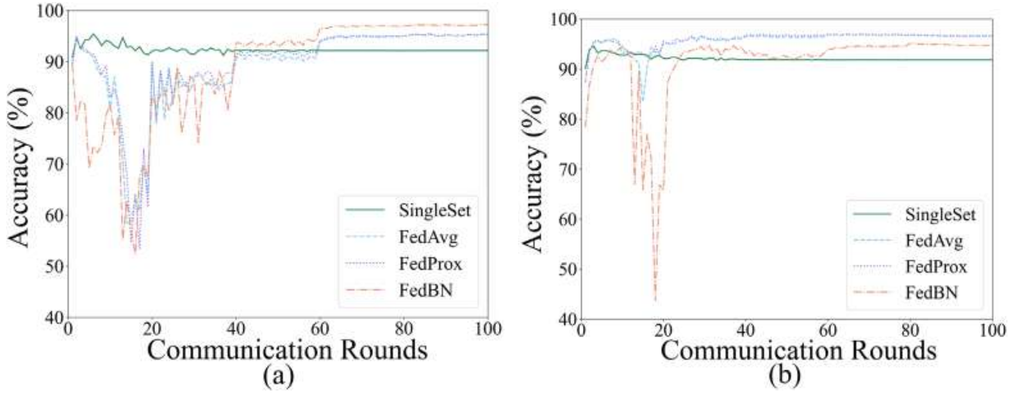

Figure 4: Testing accuracy of client 1 (a) and client 2 (b) on goat-dataset

Discussion and analysis

To observe the behaviour of FL methods over different data capacities, we presented the average testing accuracy of FL methods and SingleSet under various local dataset percentages (from 10% to 100%) in Figure 5(a). The variation of testing accuracy of FedAvg, FedProx, and FedBN showed approximate trends over various local data sizes and levelled off when each of the local clients was attributed more than 50% data from its original data amount. Moreover, the testing accuracy of SingleSet started to significantly drop from a local dataset size of 20%, whereas the FL methods conducted on 10% local data had comparable accuracy with the SingleSet performed on full-size local data. It indicated that FL methods could effectively mitigate the performance degradation due to the reduced data amount. Compared to the SingleSet, the improvement margin gained from FL methods increases gradually as data size decreases, indicating the good capability of FL under the scenarios with a small amount of data.

To further probe into the impacts of clients number on the model's performance, we displayed the experimental results under various numbers of clients (K = 2, 3, 5) in Figure 5(b). The results reflected that FL methods achieved substantially higher testing accuracy than the SingleSet under different clients numbers, especially in scenarios where very low testing accuracy was obtained when the model was trained under more than two clients. It demonstrated that FL methods could effectively benefit from collaborative training on distributed data and enhance the performance of AAR.

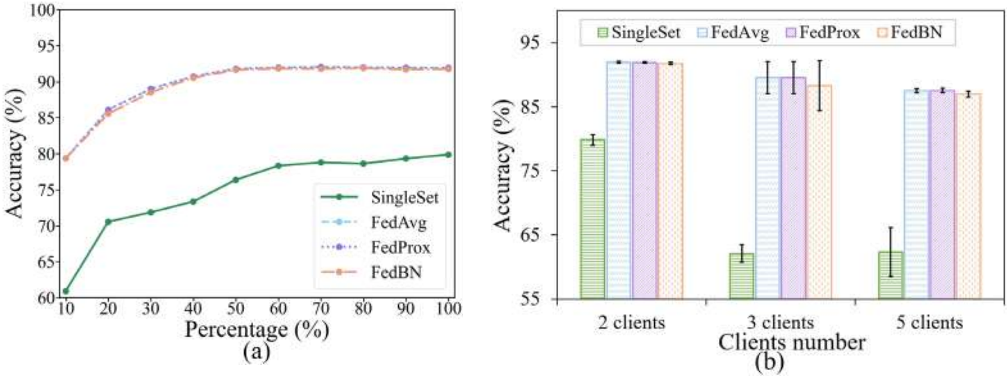

Figure 5: Testing accuracy over varying local dataset sizes (a) and clients numbers (b)

Conclusions

In this study, we first introduced the FL-based framework to AAR-based tasks, and explored the applicability and effectiveness of FL in automated AAR by uniting data from different farms. The results revealed that FL strategies (i.e., FedAvg, FedProx, and FedBN) exhibited superior performance to the SingleSet in terms of all evaluation metrics, proving the promising capability of FL to enhance AAR's performance without privacy leakage. In addition, empirical analyses were conducted to assess FL's performance on AAR from two practical aspects, including local data sizes and clients numbers, providing rich insights into the appropriate applications of FL in the future.

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Applications of hyperspectral imaging for documenting smoltification status and welfare in Atlantic salmon

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Abstract

In Norwegian commercial salmon farming more than 300 million Atlantic salmon are put to sea in net cages each year. A single net cage can contain up to 200 000 salmon, making management by direct human observation impossible. More than 15% of Atlantic salmon put out to sea die in the first three months, and this is partially attributed to suboptimal seawater acclimation (smoltification) and, consequently, management of fish welfare. Accurate, non-invasive and high-throughput methods are sorely needed to rapidly determine the smoltification status of individual salmon and their overall level of welfare. Recent advances in hyperspectral imaging systems have made it possible to rapidly image a large volume of fish at high speed with high spectral and spatial resolution. We sampled n=1834 fish in total, across four experiments, and developed methods for image analysis based on machine learning algorithms using the spectral data in the images. Automatic scores from the image analyses were compared to manual scores of operational welfare indicators for each fish to evaluate the correlation between the two methods. We found positive correlations in the range 0.5-0.8 between the quantitative trait estimates derived from image analyses and manual scores. Together these results demonstrate the feasibility of monitoring and consequently controlling for smoltification status before putting smolt out to sea and operational welfare between various operations such as delousing.

Keywords: operational welfare indicators, fin health, smoltification, hyperspectral imaging

Introduction

Norway is the largest producer of Atlantic salmon (*Salmo salar*), with more than 300 million salmon put out to sea each year (Sommerset et al., 2020). In 2020 it was reported that 1,701,347 Atlantic salmon were used for research in Norway, which accounted for 74.5 percent of the total number of reported research animals (Kristiansen et al., 2021; Mattilsynet, 2021). In both research projects and commercial salmon farming the overall welfare of the fish in a production unit is inferred through observation of operational welfare indicators (OWIs). These are manually assessed in individual fish of a sub-sample from the production unit. Examples of OWIs are fin damage, eye damage, skin ulceration and lice infection, among others. Each OWI is given a score 0, 1, 2 or 3 where 0 is perfectly healthy and 3 is a severe injury (Noble et al., 2018). The process of manually assigning these welfare scores is time consuming and prone to variations between observers due to the subjective nature of the method. This paper discusses the feasibility of hyperspectral imaging as a rapid and objective method of measuring a selection of OWIs.

Material and methods

Experimental data

The dataset presented here was collected over the course of 4 different experiments in the period from 2020 to 2021. For the purpose of this paper, one welfare indicator of interest was selected for each of these experiments in order to present a proof of concept for using hyperspectral imaging as an automated tool for OWI estimation.

In all experiments, hyperspectral images were taken on both the left and right side of each fish. The fish were presented to the camera on a conveyor belt moving at a speed between 10 and 20 cm/s. OWIs were recorded by trained manual observers for the same fish and used as reference data.

Trial 1 was a smoltification experiment performed in 2020 at the Nofima Centre for Recirculation Aquaculture at Sunndalsøra in Norway, and dorsal fin health was here chosen as the trait of interest. Trial 2 was a feeding trial done at the Tromsø Aquaculture Research Station in 2021, where the welfare trait of interest was smoltification state. Trial 3 was a disease treatment trial done at the same time and place, and the trait of interest here is the eye health. Trial 4 was a sea lice counting experiment in collaboration with Mowi and the Institute of Marine Research's research station in Matre in 2021, the aim of which was to develop an automated way of counting the lice. The fish were euthanized before imaging except for trial 2 where they were anesthetized in the sampling points throughout the trial and euthanized in the last sampling point.

For each OWI the correlation between the hyperspectral index and the manual OWI score was calculated. In trial 1, the dorsal fin was analyzed and compared with the manual OWI. The interrater agreement between 2 observers for dorsal injuries was calculated to be 0.66 in percentage agreement with a Spearman's correlation of 0.56 and a Cohen's kappa of 0.40. In trial 2, hyperspectral images of 120 fish, sampled before, during and after smoltification, were analyzed and correlated with smoltification status, assessed by quantifying plasma chloride levels after a 24-hour seawater challenge test. In trial 3, the use of hyperspectral imaging to evaluate eye haemorrhaging was tested. In trial 4, the potential of hyperspectral imaging to detect degrees of sea lice infection was assessed. Trial 2 is an exception in this case since the OWIs for smoltification are silvery colour, parr stripes and darkening of the fins, while the reference data used here is a laboratory-based welfare indicator (LABWI), namely blood serum chloride ion concentration after a 24-hour sea water challenge (Noble, et al., 2018).

Image analysis

An object detection model was developed for automatically detecting the various parts of the fish (figure 1). This model was trained on approximately 1000 images where the following features were labelled: eye, pectoral fin, pelvic fin, anal fin, dorsal fin, adipose fin, and caudal fin. The purpose of this was to be able to analyze the different parts of the fish individually.

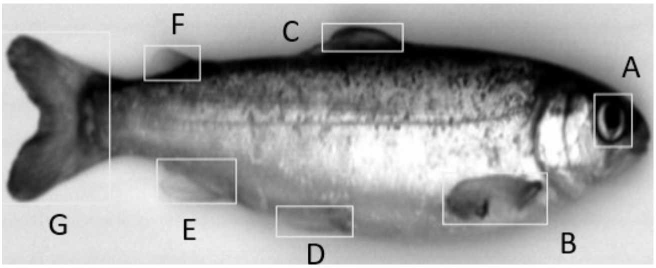

Figure 1: Example of an image segmentation with bounding boxes for the different parts of the fish: eye (A), pectoral fin (B), dorsal fin (C), pelvic fin (D), anal fin (E), adipose fin (F) and caudal fin (G).

Similarly, a separate model was developed for detecting sea lice in the images, the purpose of which was to establish a method for quickly counting the number of lice in an image. This model was used for pre-labeling the images, which were then manually approved.

Hyperspectral indexes (HSIs) based on the shape and spectral signature of the various features, partly based on Skjelvareid et al. (2017), were developed to comply with the manual OWIs. An exception is trial 2 where a supervised model between the spectral data and the reference data was developed. The image feature selected in trial 2 was an average light absorbance spectrum from the caudal fin pixels, which is hypothesized to indicate the degree of darkening of the fin edges.

Statistical analysis and modelling

For trial 1 the correlation between the discrete OWI scores and the continuous HSI scores was calculated according to Cox (1974), while the Pearson correlation (Pearson, 1895) was used for trial 2 and trial 4. The correlation in trial 2 was obtained by training a model that predicted plasma chloride levels from the spectral data, applying this model to a test set and then calculating the correlation between reference values and predicted values. For trial 4 the hyperspectral images were preprocessed to produce a contrast between the lice and the skin of the salmon, and a manual count from these images assisted by a machine learning object detection model was done. For trial 3 the agreement was taken to be the accuracy with which one can assign a discrete score from the HSI that agrees with the manual OWI scores.

Results and discussion

In trial 1 and trial 3 we found the OWIs for the dorsal fin and the eye to have the lowest correlation between the subjectively human scored OWIs and the hyperspectral scores (figure 2 and figure 3 respectively). This low correlation can be due to a phenomenon called ‘attenuation of error’ where correlations are generally lower between two variables if one or both is measured with error (Adolph & Hardin, 2007). Part of the error can be attributed to the OWIs scored by human observers. It was observed that different scorers weighted different aspects of an injury differently, despite training from a common scoring sheet and a standardized scoring scheme.

Table 1: Summary of the four trials and the agreement between manual welfare scores and the corresponding hyperspectral indexes.

	Number of fish scanned with HSI	Number of fish with manual reference	Indicator type	Feature	Agreement with manual WI
Trial 1	725	290	OWI	Dorsal fin injuries	0.54
Trial 2	849	120	LABWI	Plasma chloride	0.73
Trial 3	300	300	OWI	Eye injuries	0.55
Trial 4	1124	1124	OWI	Lice count	0.65

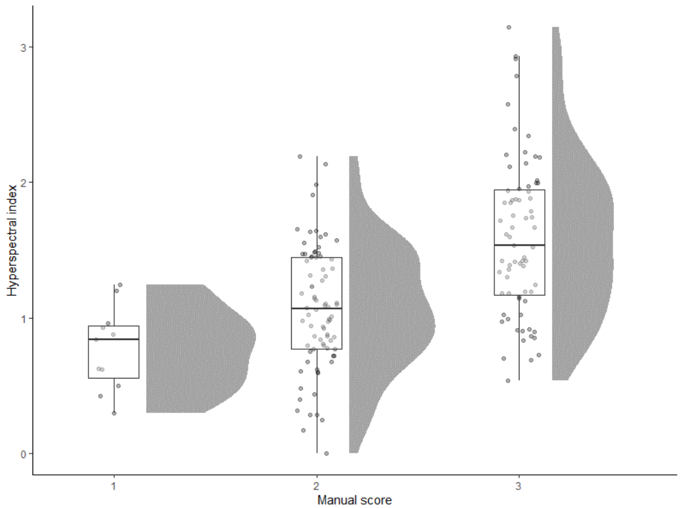

Figure 2: Raincloud plot (Allen et al., 2021) comparing manual OWI scores and hyperspectral index scores for active dorsal fin injuries in trial 1.

For instance, dorsal fin injuries are a complex trait comprising multiple aspects such as remaining surface area of the fin, presence and severity of split fins and the presence and intensity of haemorrhaging, and some observers place emphasis on different aspects of the injury.

This highlights the need for an objective method for measuring OWIs. The correlation between the HSI scores and manual OWI scores in trial 1 is on par with the interrater agreement between two human scorers, which demonstrates that the hyperspectral system agrees almost as well with a human observer as two human observers agree with each other.

Despite some of these challenges, clear differences are visible between eye measurements of the same fish before and after handling or stressful crowding events (figure 3).

For instance, in trial 3 one can clearly see that handling of fish for sampling increases the instances of eye injuries from the first sampling event to the second sampling event two hours later. Moreover, the effect of crowding shows as an increasing trend of eye severity with higher levels of crowding on the second sampling (figure 3). This agrees with findings that handling and crowding causes stress in Atlantic salmon (Basrur et al., 2010; McCormick et al., 1998), but for the first time we can objectively quantify and compare this effect on eye injuries.

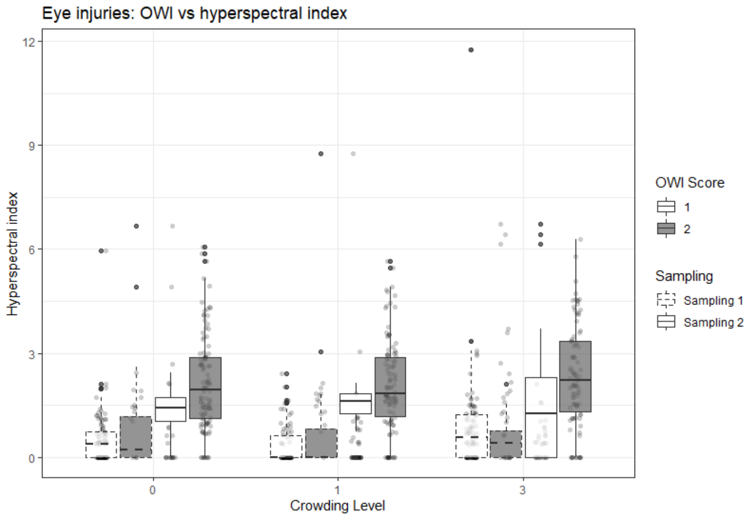

Figure 3: Box and whisker plot contrasting eye injury scores measured using a hyperspectral index variable (y axis) at different crowding levels (0, 1 and 3) for trial 3. The OWI scores for these fish were either 1 (white fill) or 2 (grey fill) of the boxes. There is a notable increase in HSI between sampling 1 pre-treatment (dashed line) and sampling 2 post-treatment (solid line) for all crowding levels.

The correlation between the hyperspectral measurement and plasma chloride levels was the highest (R2 = 0.73) and this may be due to the fact that plasma chloride levels are not prone to errors associated with human scoring. Of all the reference measurements, blood chloride levels, which is a LABWI that reflects the salmon's ability to regulate chloride ion concentrations in the blood as it transits from freshwater to saltwater (Stefansson et al., 2008), was the most accurate and reproducible. Furthermore, the characteristic morphological changes during the parr-smolt transformation, including fading of distinctive parr marks, silvering, and darkening of the fins (Folmar & Dickhoff, 1980), can be detected in the hyperspectral images. Yet, hyperspectral data needs to be validated by additional smoltification indicators and seawater performance in future studies as hypoosmoregulatory ability does not necessarily indicate completion of smoltification (Duston & Saunders, 1990). In general, the ability to regulate blood chloride concentration levels below 150 mmol/L has been used to demonstrated hypoosmoregularity (Noble et al., 2018). In the present study, serum chloride concetration was predicted from a non-invasive external hyperspectral measurement (figure 4). In this instance, HSI prediction correctly classified 11 out of 12 fish with measured

Cl-concetrations below a more conservative threshold of 140 mmol/L, demonstrating an accuracy of 97.5%, specficity 96.6% and sensitivity of 100%. These values are comparable but higher than those of Svendsen et al. (2021), who reported an accuracy of 90%, specificity of 97% and sensitivity of 73% in Atlantic salmon parr and smolt across multiple sites in Norway.

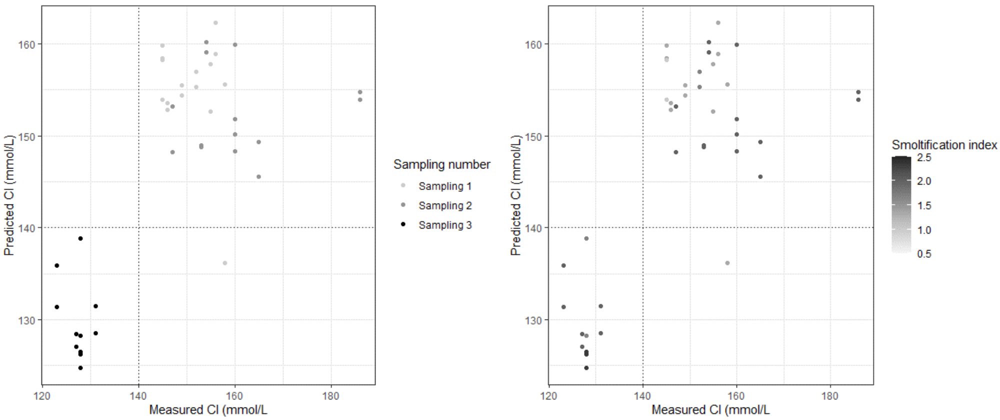

Figure 4: Scatter plots of the blood chloride model from trial 2 applied to a test set. The same plot has been coloured according to sampling date (left) and smoltification index (right). Samplings 1, 2 and 3 referred to in the figure legend are consecutive sampling points over 5 weeks during the smoltification period (15^{th} February, 8^{th} March and 22^{nd} March 2021 respectively). A Cl-concentraiont of 150 mmol/L or lower has been considered indicative of a seawater adapted salmon (Noble et al., 2018). This data suggests that a more conservative threshold of 140 mmol/L can be used to separate parr from smolt.

Conclusions

Hyperspectral index scores were compared to manual welfare scores for individual fish in order to evaluate the correlation between the two methods. These correlations were found to be in the range 0.5-0.8. For dorsal fin injuries this is on par with the interrater agreement between two manual scorers. One can hypothesize that the same would be true for the eye injury scores if two raters had been compared in trial 3. We also found a positive correlation between HSI scores and plasma chloride levels after a 24-hour sea water challenge, and between lice counts in the field and from hyperspectral images. Together these results demonstrate the feasibility for using hyperspectral imaging as a technique for automatically monitoring welfare in Atlantic salmon and quantifying traits such as fin and eye injuries, smoltification status and louse infection levels.

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Preliminary research on pain detection in horses: video based automated classification of the behaviour time budget

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Abstract

The objective of this research was to develop an automated method for image based monitoring of pain in horses. The purpose of application of computer vision was to enable automated extraction of behaviours of the horse from videos, which should reduce manual workload otherwise needed for human labelling, increase objectivity of behaviours labelling and quantify changes in behaviours too slight for the human eye to notice. The reason to do so was calculate the time budgets for each behaviour. Additionally, computer vision offered a possibility of continuous, 24/7 monitoring, which was not possible based on human observation. We recorded videos from 66 horses housed in a hospital of the University of Veterinary Medicine in Vienna. Most horses were in pain. A total of 16,816 key body points were labelled, including the nose, right and left ear, the wither, the tail and the hoofs. We detected key body points of 13 horses with Resnet 50 backbone in Loopy software. These were used as an input to Long Short-Term Memory (LSTM) model to estimate the time budget for different activity types: resting, feeding/foraging, alert and lying. The accuracy of the model was 95,65%. As pain can have a significant impact on the time budget of horses, these results could be a basis for video based pain detection in horses.

Keywords: pain in horses; behaviour time budget; image processing; computer vision

Introduction

The International Association of Study of Pain (IASP) defines pain as an unpleasant sensory and emotional experience associated with actual or potential tissue damage, or described in terms of such damage (Lipton, 1991). The unpleasant sensory and emotional experiences that constitute pain give rise to subtle or overt changes in behaviour that may offer the strongest indication of the presence, localization and severity of the pain.

Detailed knowledge of both normal and pain-related behaviours in equines is imperative to detect pain properly. However, subtle behavioural changes due to pain may become apparent if behaviour is analysed carefully. The time budget of basic behaviours (resting, feeding, lying and alert) can be an indicator of pain (Auer, 2021).

The Composite Pain Scale (CPS) described by Ask (2020), is regarded as a valid option to score pain and less operator-sensitive (e.g. less subjective) than other methods because of using multiple variables (behavioural, physiological or both) of well-defined parameters. For accurate pain assessment with CPS it is required to observe horses several times a day (Gleerup, 2016). These frequent assessments might tire a horse and require a lot of time for vets for its analysis.

Computer vision offers a possibility of continuous, 24/7 monitoring, which is not possible based on human observation. This can potentially help vets quickly detect unusual behaviours or detect pain in horses. A benchmark for animal pose estimation using computer vision is provided by Hu (2021). It can be useful for behaviour recognition and pose estimation in horses is recognized by Mathis (2021). Additionally, usage of video technology for recording of horses reduces some of the disadvantages of direct observation such as that, horses in the presence of a human tend to hide some behaviours like pain, as from a predator (Torcivia, 2020).

The objective of this paper is to use computer vision techniques and time series analysis in order to enable automated extraction of the key body points of the horse from videos and their basic behaviours. This should reduce manual workload otherwise, needed for human labelling, increase objectivity of behaviours labelling and quantify changes in behaviours too slight for the human eye to notice. In the follow up studies, automatically detected changes in basic activities are planned to be linked to pain state in horses.

Materials and methods

Animals and housing

Experiments were conducted at the clinic of the University of Veterinary Medicine Vienna. In total, 66 horses were recorded. The horses were admitted to the clinic with different pain levels and they were recorded at different stages of their recovery. All the horses were kept in pens individually (Figure 1).

Figure 1. Horses in individual pens.

Video recording

The videos for post hoc analysis were recorded with Gopro Hero 4 action camera (San Mateo, USA) in a time-lapse mode (TLM) in 2 frames per second (fps). The wide-angle lens allowed an overview of the whole box and a horse. The advantage of Gopro Hero 4 camera was that it could have been moved between pens easily. The camera was powered with battery packs that provided power sufficient for more than 24 hours. We decided to use TLM with 2 fps to limit the memory size of the videos and compress 24 hours of real duration in a video length of approximately 1 h. The quality of the video (2704x2028 pixels resolution) was verified in the pilot study and it was estimated as good enough to visually follow key points even with quick movements of the horse.

Dataset

The dataset consisted of 66 horses, with 24 hours of continuous recording for each one. Videos were recorded with a frame rate of 2 fps. This gave a total of 11.404.800 images. Nevertheless, this does not mean that all the images were usable to train a machine learning model. In the night images, because of the absence or low light, the horse was not visible. In addition, when horses were resting images were very similar and with little variance. In total 11.401.989 were discarded.

Key body points were manually annotated, these are the nose, withers, tail, right and left ear, right and left front limb and right and left hind limb. The key body points were selected as the most relevant body points of the horse to detect the basic behaviours of the horse. In total key body points of 13 horses were manually annotated out of 66 giving a set of 2,811 images (Table 1).

Table 1: Key body points.

Key body points	No. images labelled	No. horses
Nose	2100	13
Withers	2750	13
Tail	1842	13
Right ear	1626	13
Left ear	1654	12
Right front limb	1770	12
Left front limb	1854	12
Right hind limb	1732	12
Left hind limb	1845	12

Basic behaviours were also manually annotated (Table 2). These behaviours were ‘laying’, defined as the horse was on the ground; ‘resting’, defined as the horse was standing but not moving at all; ‘feeding/foraging’, defined as the horse was eating the feed located on the ground or in the feeder and head was moving; ‘alert’, defined as the horse was standing but some movements of the head and ears were observed, the horse was attentive and was looking around.

Loopy software (Loopbio, Vienna, Austria), was used for labeling of key body points. Loopy was also used to train a Resnet 50 model with an input of 740x480 and strides equal to 8 to automatically detect the key body points.

Table 2: Behaviour time budget.

Behaviour	Duration (s)	No. horses
Resting	44492	9
Feeding/Foraging	18936	9
Lying	247	1
Alert	16842	9

<u>Data analysis</u>

During the visual inspection of results of automated detection of key body points, it was observed that some key body points were detected in a wrong position or missed (Figure 2).

Figure 2: Key body point detection with Loopy software a) All key body points were correctly detected. b) Key body points associated with the front limbs were not detected. The same model was used for classification of key body points for both images.

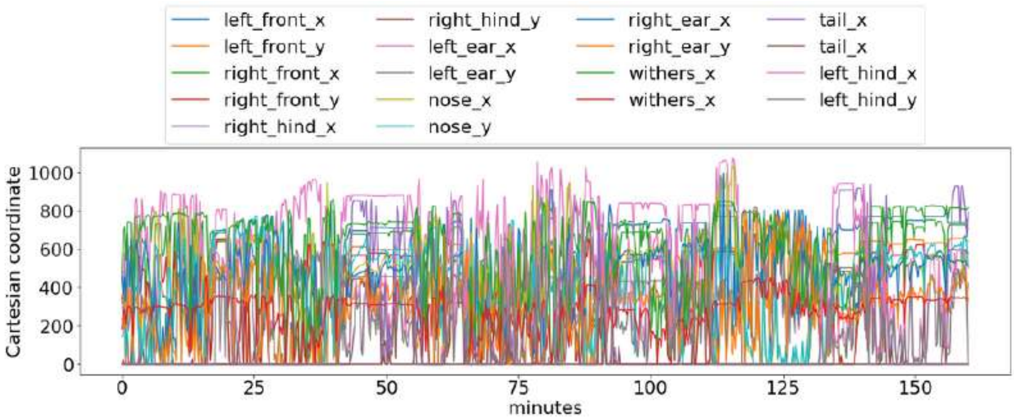

Figure 3: Average horizontal 'x' and vertical 'y' location of each key body point of one horse calculated on a 15-seconds interval.

To smooth the error of key points missing or in a wrong place, an average of each value of pixel position of detected key body points was calculated on intervals of 15 seconds (2 fps x 15 seconds = 30 key body points) (Figure 3). Interval of 15 seconds was considered a suitable interval to automatically detect the basic behaviours of horses.

Algorithm

Long short-term memory (LSTM) was used as a recurrent neural network (RNN) to train a model to detect the basic behaviours. The neural network was built with 16 units in the input layer LSTM, 8 units in the hidden layer LSTM and 3 units in the output dense layer, one layer for each basic behaviour. The optimal LSTM window value was between 2 minutes and 4 minutes meaning that the neural network needed as an input an interval of key body points coordinates of 2 or 4 min to predict the current basic behaviour. The rest of hyperparameters were: learning rate of 0.0001 with ADAM optimizer; a dropout of 0.5 to prevent an overfitting of the model; a decay rate of 0,97; sigmoid activation function; categorical cross entropy as a loss function and batch size equal to 12.

Tensorflow and Keras framework was used to create the model. Less than 2 minutes was necessary to converge a model using an Intel Core i7-1165G7 @ 2.80GHz CPU. The model was trained with different hyperparameters until the best result was found.

Results and Discussion

It has been shown that variation in basic behaviours such as lying, resting and feeding can be a promising indicator of pain and monitoring it can improve equine welfare (Auer et al, 2021). Moreover, Egan et al. (2021) concluded that behaviour variability might be a promising indicator of subtle pain. Behaviours such as playing, social interaction, tail biting or aggressiveness (Chen, 2019) in animals can reflect the health, welfare and growth status, e.g. in pigs (Larsen, 2021). Using traditional computer vision and deep learning methods it is possible to recognize behaviour in livestock (Chen, 2021).

On the other hand, facial expressions have been presented as a sensitive measure of pain in horses. Ly et al. (2021) proposed Deep Region and Multi-Label Learning (DRML) and AlexNet for face recognition in horses. Broomé et al. (2021) introduced a method to detect pain, which was induced, in horses with different facial expressions using Convolutional LSTM.

In our study, the pain was not induced. Horses were admitted to the clinic with different pain levels, giving us a very good representation of pain in horses. As a first step of our research on pain detection in horses, an attempt was made to classify the basic behaviour of the horse in 'resting', 'alert' and 'feeding/foraging'. The accuracy and confusion matrix of the developed model was presented in Table 3 and Figure 4.

Analysis of the confusion matrix revealed that the 'resting' and 'alert' classes got a higher error in their classification than 'feeding/foraging'. Considering this, 'resting ' and 'alert classes' were joined into a single 'resting' class and also the structure of the last layer (dense layer) was changed to two units, since only two behaviours needed to be detected.

Table 3: Accuracy for 3 labels.

Behaviour	Accuracy	Total Accuracy
Resting	78,37%	85,35%
Feeding/Foraging	92,45%	
Alert	50,00%	

The results of classification of two classes 'resting' and 'feeding/foraging' shown an accuracy of 95.65% (Table 4) and an improvement in the misclassification of basic behaviours (Figure 5).

Table 4: Accuracy with 2 labels.

Behaviour	Accuracy	Total Accuracy
Resting	98,33%	95,65%
Feeding/Foraging	93,58%	

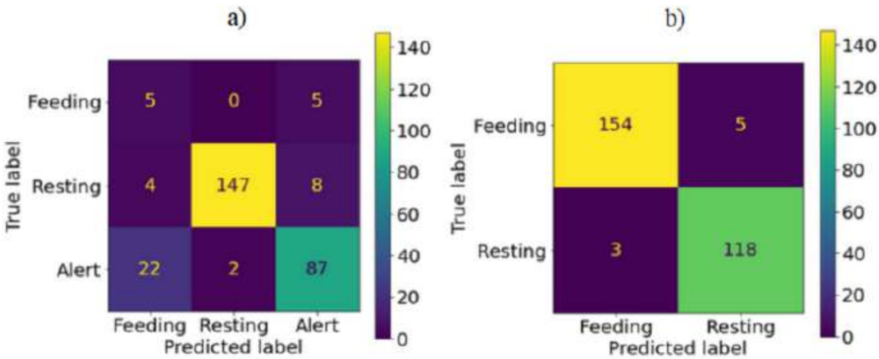

Figure 4: Confusion matrix a) 3 classes. b) 2 classes.

Additionally, a comparison is shown with the predicted behaviours in a horse and the behaviours that were annotated (Figure 6).

As shown in Figure 6a, the areas highlighted in blue are clearly, when the horse is resting, as seen more key body points have a constant value, but the area highlighted in red shows more movement of the key body points. This suggests the horse is not resting but rather in alert mode.

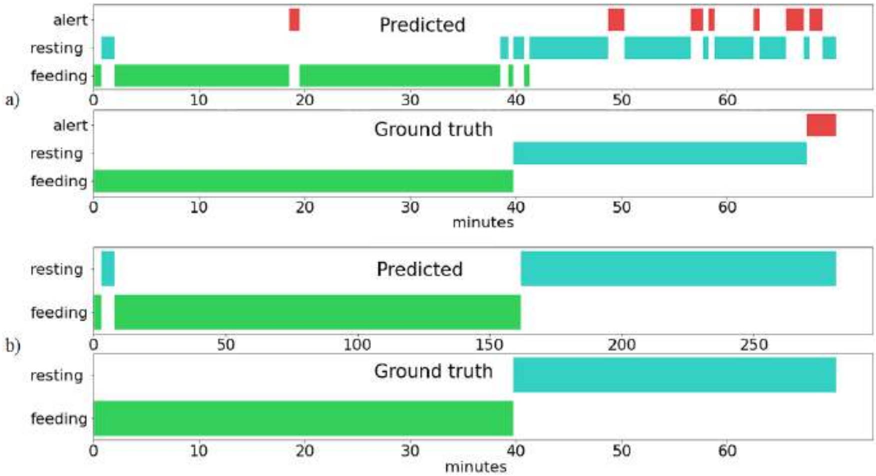

Figure 5: Comparison between the ground truth basic behaviours and predicted a) 3 classes. b) 2 classes.

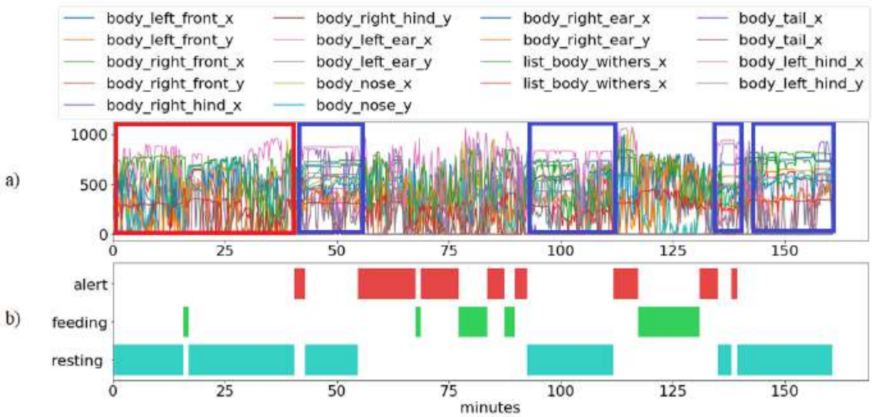

Figure 6: Location of key body points and basic behaviour of a horse a) Average horizontal 'x' and vertical 'y' location of each key body point of one horse b) Basic behaviour annotated.

Conclusions

The results of classification of basic behaviour with LSTM indicated that when only two classes were used (resting and feeding/foraging) a high accuracy was shown, but when a model with three classes was trained and validated (resting, alert and feeding/ foraging) the accuracy decreased by 10,3 %. It was challenging the second model to differentiate when the horse was 'resting' or it was in 'alert'. To improve the results of classification of three classes we propose to review the labelled data for 'resting' and 'alert' classes. In the next step, output of classification of basic behaviours will be used to detect changes in relation to pain in horses. The reference for pain will be CPS.

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SESSION 9

Cows:
Health and Production

Data-driven dairy herd management: An analysis of sensor-assisted health monitoring

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Abstract

On a research and demonstration dairy farm, 65 cows were equipped with a market available rumen bolus for continuous monitoring of activity and core body temperature. Based on individual, animal-specific decision algorithms, the sensor system issues messages in the case of abnormalities affecting health. The messages relevant to health (increase in core body temperature, decrease in core body temperature, decrease in activity, and decrease in the number of drinking cycles per day) are compared with veterinarian-documented disease diagnoses ('ProGesund') to assess sensitivities of disease detection by the bolus. Thus, a disease-specific assessment is calculated as the proportion of cases of a disease for which a health-related message was issued by the sensor system in a respective observation period. The results show a sensitivity of 61% for the detection of clinical hypocalcemia and 43% for the detection of mastitis. Considering reproductive diseases, sensitivities of 64% for retained placenta and 25% for metritis were determined. The sensor's potential for detecting diseases of the locomotor system was low (5%). Early detection of disease by the sensor system has been demonstrated in many cases. This suggests in a certain potential of the sensor system with regard to supporting health monitoring of a dairy herd, which however strongly depends on the disease. In the analyzed data set, only 20% of all health-related messages issued by the sensor system could be assigned to 'ProGesund' diagnoses.

Keywords: rumen bolus, activity, temperature, sensitivity, digital, smart farming

Introduction

Animal-specific sensor systems for dairy farming were initially focused on reproductive management but now also offer support for (early) detection of diseases and calving. In Germany, 20% of farmers have adopted such sensor systems to monitor animal behavior so far (Gabriel et al., 2021). The parameters activity (Nechanitzky et al., 2016, Chase et al., 2017) or core body temperature (Adams et al., 2013, Venjakob et al., 2016), which can be recorded by means of sensor systems, may show changes in case of disease. This fact raises hopes for an early detection of diseases (i.e., earlier than abnormalities would be detected by the farmer or veterinarian), potentially resulting in reduced spread of infectious diseases, milder courses of disease, and thus decreased performance losses and lower treatment costs. Dairy farmers are often exposed to a plethora of information when applying sensor systems (see Mollenhorst et al., 2012, Rutten et al., 2013). Thus, it is challenging to interpret health-related messages and, if necessary, initiate appropriate measures. Knowledge about the precision of commercially available sensor systems is still rare. Therefore, the aim of this study is to demonstrate the potential of a selected sensor system with regard to its contribution to health monitoring of a dairy herd.

Material and methods

Data

In the dairy herd of the 'Staatsgut Achselschwang', a state farm, 65 dairy cows of different breeds (mainly Simmental breed, also Brown-Swiss and Holstein) were equipped with a Classic rumen bolus (smaXtec animal care GmbH, Graz, Austria) in 2018. This version of the Classic rumen bolus continuously records activity and core body temperature including the number of drinking cycles (indirectly via core body temperature) and thus derives estrus, calving, and health status. The herein analyzed data stems from the period of July 2018 until the end of June 2020. It is thus an extension of the data set of the study by Pfeiffer et al. (2020).

The rumen bolus issues messages to the dairy farmer in case of abnormalities in the recorded parameters. Issuing of messages is based on individual animal-specific decision algorithms, taking into account the history of the individual animal. Health-related messages include the following categories: increase in core body temperature, decrease in core body temperature, decrease in activity, and decrease in the number of drinking cycles per day. In this process, no suggestion of a particular disease is given by the sensor system and the interpretation is up to the farmer.

In addition to the health-related messages issued by the rumen bolus, this study makes use of documentation on diseases whose diagnoses were made or confirmed by the farm veterinarian or hoof trimmer as part of the 'ProGesund' project. Although all diagnoses were confirmed by the farm veterinarian, no daily veterinary examination of all cows took place. Diseases for which no treatment was necessary were not included in the analysis. In this study, the diseases mastitis, clinical hypocalcemia, retained placenta, metritis, and diseases of the locomotor system are analyzed. All cases of mastitis were confirmed by pathogen detection in milk samples (including subsequent California mastitis test, bacteriological milk analyzing, and any necessary resistance test).

Sensitivity analysis of the sensor system

To determine the sensitivities of the sensor system with regard to a detection of disease cases, the documented diagnoses were compared with the health-related messages issued by the sensor system. A disease-specific assessment was made of the proportion of cases of disease in which a message was issued by the sensor system in the observation period from 6 days before (d-6) to one day after (d+1) the documented diagnosis (d0). For clinical hypocalcemia, the observation period was limited to d-2 to d+1 and for retained placenta to d1 to d+1. In this step, the assumption is made that the message assigned to a case of disease as correct-positive was actually issued due to the disease and not due to some other unknown cause. For each disease, the sensitivity of the algorithm implemented in the sensor system was determined for the respective observation period (number of correct-positive diagnoses / number of all diagnoses, in %). For each case of disease, the day of diagnosis and the day of the first health-related message issued by the sensor system were compared. Two diagnoses of the same disease in one animal had to be at least 14 days apart to be considered two independent diagnoses (see also Kim et al., 2019). This did not apply to diagnoses of different diseases.

Results and Discussion

The analysis includes a total of 70 cases of mastitis, 31 cases of clinical hypocalcemia, 11 cases of retained placenta, 24 cases of metritis, and 42 cases of diseases of the locomotor system. Table 1 visualizes the day of the first health-related message issued by the sensor system in each case of disease, relative to the day of the first diagnosis (d0).

Table 1: Day of first health-related messages issued by the sensor system for disease cases for all five analysed diseases

							diagnosis	
	d-6	**d-5**	**d-4**	**d-3**	**d-2**	**d-1**	**d0**	**d+1**
Mastitis (n=70), sensitivity[1] = 43%	xx	xxx	x	xxx	xxxxx	xxx	xxxxxxxxx	xxxx
Clinical hypocalcemia (n=31), sensitivity[1] = 61%	period not considered				xx	xxxx xxxx	xxx xxx	xxx
Retained placenta (n=11), sensitivity[1] = 64%	period not considered					xxxxx	xx	
Metritis (n=24), sensitivity[1] = 25%		x	x	x	x	x		x
Diseases of the locomotor system (n=42), sensitivity[1] = 5%	x					x		

X = in each case of disease only the first health-related message issued by the sensor system (correct-positive) in the respective observation period is considered, messages issued at a later day in the cases of disease are not shown or taken into account for determining the sensitivities

[1] sensitivity [%] = number of correct-positive diagnoses / number of all diagnoses, in the respective observation period

[2] pathogen: *E.coli, CNS, Strep. spp.* and others

[3] dermatitis digitalis, sole ulcer, panaritium, tyloma, paralysis and others

The sensitivity of the sensor system is highest for retained placenta (64%), followed by clinical hypocalcemia (61%), mastitis (43%), metritis (25%), and diseases of the locomotor system (5%). The cases of mastitis and metritis described here were detected primarily by an increase in core body temperature. Table 1 visualizes that the majority of all cases of mastitis and metritis recognized as correct-positive were already detected by the sensor system on days d-6 to d-1. When animals suffered from clinical hypocalcemia or retained placenta, the sensor system documented abnormalities related to all parameters monitored (activity, core body temperature, number of drinking cycles), with messages on decreased activity predominating in hypocalcemia. For these two diseases, a considerable proportion of messages was also issued prior to visual diagnosis. Thus, the analyzed data set demonstrated a certain potential of early detection of disease cases using sensor systems for certain disease.

Due to individual animal courses of disease and different severity of symptoms, the analyzed diseases differ in terms of their potential detection by the sensor system on the basis of changes in activity or core body temperature. When a cow suffers from mastitis, one of the decisive factors is the responsible pathogen. For example, acute mastitis is often accompanied by fever, which can be reliably detected by continuous recording of core body temperature. Studies thus also demonstrated that high sensitivities in the sensor-assisted detection of mastitis can be achieved (Adams et al., 2013, Kim et al., 2019). Increase in body temperature is also reported as a typical symptom of metritis (Benzaquen et al., 2007), explaining the dominance of issued messages of such type. When a cow suffers from clinical hypocalcemia, a decrease in activity and body temperature are typical symptoms (Venjakob et al., 2016, Chase et al., 2017), as they were responsible for the majority of messages issued by the sensor system. The literature shows that activity alone is not sensitive enough for early detection of diseases of the locomotor system and that additional indicators such as milk quantity, feed intake, and rumination need to be included for this purpose (see e.g., Ito et al., 2010, Van Hertem et al., 2013, Grimm et al., 2019).

Due to the circumstances, the herd managers of the dairy farm had access to the messages issued by the sensor system during the entire period analyzed and therefore included them in the herd management. As a result, the day of diagnosis (d0) may have been influenced by the sensor messages. It can be surmised that health management without the sensor messages would have resulted in a diagnosis at a later date for some cases of disease. However, such a shift of the date of diagnosis to the right would result in an even greater relative advantage of the sensor system for early detection. It also has to be considered that the health management and thus the detection of cases of disease of the dairy farm studied can be classified as above average.

In the analyzed data set, only 20% of all health-related messages issued by the sensor system could be assigned to documented disease diagnoses. However, as a limitation of this study, it has to be considered that no gold standard for disease diagnosis was applied. Therefore, only diagnoses that resulted in a treatment were included in the analysis. Thus, cases of disease without clinical symptoms (such as cell count increases or subclinical hypocalcemia) were not considered. For health-related sensor messages that could not be assigned to a documented disease diagnosis, possible causes were analyzed. Heat stress (temperature-humidity index ≥ 70), period around calving, oestrus (increase in core body temperature), vaccination (increase in core body temperature), and cell count > 200,000 were identified as possible causes for these messages.

The sensitivity of disease detection can be increased by including additional parameters such as feed intake or milk yield, for example. Indeed, the new version of smaXtec's rumen bolus also monitors rumination as an additional parameter. Thus, further positive effects regarding health monitoring of the herd can be expected. However, the results demonstrate that there are often several days between the first message issued by the sensor system and the diagnosis (d0). This shows that it is a challenge for farmers to identify causes for the sensor systems' messages on the one hand and to initiate appropriate measures at the right time on the other hand – even if more information is provided. Also, finding a balance between a high sensitivity and, at the same time, the highest possible specificity of the sensor system is not trivial (Mottram, 2016).

Conclusions and outlook

Sensor systems such as the rumen bolus can be a useful tool to support dairy farmers in herd health management. They give indications which animals require particular attention. However, cases of disease still need to be detected by the dairy farmer and diagnosed by the veterinarian. The results show that additional visual monitoring of herd health by the dairy farmer is still essential. In a next step, building on the analysis of this dataset, an economic evaluation of sensor systems for health monitoring will be pursued.

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Association between rumination patterns detected by an ear-tag-based accelerometer system and rumen physiology in dairy cows

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Abstract

Rumination is an essential part of the physiology of dairy cows. In this context, rumination activity is considered a useful indicator of stress, but also as an early detection of diseases and metabolic disorders.

The SMARTBOW accelerometer-based sensor system provides rumination alerts based on individual thresholds of rumination patterns in dairy cows. Detailed knowledge about the association between sensor-based rumination patterns and rumen physiology would help to detect conspicuous animals and to evaluate the success of treatments. The aim of this study was to investigate the association between sensor-based rumination alerts and rumen fluid parameters in Holstein-Friesian cows. For this, rumen fluid was collected from 50 pairs of cows with (ALRT) and without (NALRT) rumination alerts by the sensor system via stomach tube at the start and at the end of rumination alerts. Pairs were matched based on day of lactation. The parameters pH, redox potential, methylene blue reduction test and sedimentation/flotation time were examined directly after sampling and storage in a water bath at 38–39 °C for 5 min. Protozoa were analysed microscopically by counting chamber to evaluate number.

Results showed significant ($P < 0.05$) differences between both groups in rumen pH, redox potential, methylene blue reduction test, sedimentation/flotation time and number of protozoa at the first rumen fluid extraction. Furthermore, greater variations in rumen fluid parameters were observed for ALRT compared to NALRT cows.

Keywords: rumen fluid, rumination time, health alert, rumen disorders, accelerometer

Introduction

For the detection of changes in rumen function and associated disorders, rumen fluid evaluation has long been used as a diagnostic (Holtenius *et al.*, 1959; Leek, 1983; Dirksen & Smith, 1987; Dirksen *et al.*, 1990). Indicators of rumen health are: rumen pH, redox potential, methylene blue reduction time, sedimentation/flotation time and number of protozoa (Dirksen & Smith, 1987; Steen, 2001; Huang *et al.*, 2018).

Sensor systems (e.g., accelerometers, rumen bolus) provide detailed insights into rumen physiology, particularly the rumination time in dairy cattle. Accelerometers are commercial available for the detection of rumination and show good validated performance (Borchers *et al.*, 2016; Reiter *et al.*, 2018; Stygar *et al.*, 2021). The SMARTBOW (SB) ear-tag-based accelerometer system (Smartbow/Zoetis LLC, Weibern, Austria) provides additional health alerts based on the decline in rumination time.

The association between the time a cow spends ruminating and digestive disorders has already been investigated. Stangaferro *et al*. (2016) reported a sensitivity of 93% for detecting digestive disorders by the monitoring of accelerometer-based rumination time and activity. DeVries *et al*. (2009) investigated the relation between rumen pH and rumination time by challenging lactating dairy cows with repeated ruminal acidosis. A decline in rumination time was associated with diseases and digestive disorders, but no specific patterns were detected. The resulting challenge for dairy producers is to use the information provided by sensor technology in real time for the prevention or detection of diseases (Beauchemin, 2018).

To the best of our knowledge, no research has been carried out into the interaction between rumination alerts and changes in rumen fluid. The results could lead to a better interpretation of rumination alerts.

Material and Methods

All study procedures were approved by the State Office of Agriculture, Food Safety and Fisheries Mecklenburg-Vorpommern, Germany (7221.3-2-013/21) and noted by the Ethics Committee of the University of Veterinary Medicine, Vienna. The study was conducted between April and October 2021 on a conventional dairy farm in the north of Germany housing approximately 1900 Holstein-Friesian cows.

Animals, housing and feeding

Within the first 10 days of lactation animals were housed in a fresh cow pen equipped with cubicles with straw chalk bedding. Cows were milked twice daily in a 12-side-by-side milking parlour. After this period, cows were integrated into groups of approximately 200 animals according to reproduction status, lactation number and somatic cell count. The free-stall barns were equipped with cubicles supplied with straw chalk bedding or recycled manure solid. After day 10 of lactation, cows were milked in a 48-side-by-side milking parlour three times per day. The average energy-corrected milk yield (ECM, based on 4% butterfat and 3.4% protein) was 10,301 kg per cow in 2021. The feeding ration consisted of a total mixed ration (TMR) based on corn silage, grass silage and concentrates (rape seed as extraction meal and expeller, soy extract grist) and dietary supplements and was supplied every 4 h. During the study period, the diet composition was adjusted based on weekly analyses of the dry matter of the main components.

Rumination alerts

All cows were equipped with SB tags (size and weight 52 × 36 × 17 mm, 34 g). The ear tags recorded 3-dimensional acceleration data of head and ear movements at a frequency of 1 Hz. The data were sent in real time to receivers (SMARTBOW wall points), which were connected to a local server on the farm to process and analyse the incoming data. Algorithms provided an ‘acute rumination alert’ caused by an urgent rumination decline within the previous 24 h. Furthermore, a ‘long-time rumination alert’ was provided based on a decrease in rumination time over several days. The rumination alerts were presented in Smartbow software and sent to a mobile device.

Selection of animals

Cows with rumination alert (ALRT) were matched in pairs with healthy cows (NALRT) based on their lactation day and number of lactations. Healthy NALRT cows had to meet the criteria of rectal temperature less than 39.5 °C, a body condition score within the range 2.5–4 according to Edmonson *et al.* (1989) and a lameness score less than 3 according to Sprecher *et al.* (1997). A rumination alert was considered as valid if it persisted for at least 12 h, and the sample of rumen fluid was collected within the first 12 h of the alert.

Rumen fluid collection

Rumen fluid was taken twice using an oral stomach tube (SELEKT Rumen Fluid Collector, Nimrod Veterinary Products, Moreton-in-Marsh, UK). The first extraction (Ex1) was performed after the onset of the alert and the second extraction (Ex2) after the end of the alert. The sampling steps were performed according to the guidelines by the SmartCow consortium (Muizelaar *et al.*, 2020).

Rumen fluid examination

Rumen fluid samples were collected to study the parameters: rumen pH, redox potential, methylene blue reduction time, sedimentation/flotation time and protozoa numbers. The cows' status (ALRT vs NALRT) of each sample was blinded prior to examination by replacing the animals' identification number with a sample number randomly assigned by a second person. The pH and redox potential were measured using a portable electronic pH-meter (G1501 Serie, GHM Group Greisinger, Regenstauf, Germany; pH electrode GE 114-WD; redox electrode GR 175 BNC). Methylene blue reduction time and sedimentation/flotation time were determined according the methods described by Dirksen & Smith (1987). For the microscopic evaluation of protozoa, rumen fluid was placed in a counting chamber (Fuchs-Rosenthal, Paul Marienfeld GmbH & Co.KG, Lauda-Königshofen, Germany). All findings were documented on a worksheet and exported to an Excel file (version 16.0.5; MS Excel 2016, Microsoft Cooperation, Redmond, USA).

Statistical analyses

Data were imported into the SPSS statistical software package (SPSS version 27.0.0.0, IBM corporation SPSS Statistics, Armonk, NY) for analysis. Intra-observer agreement was calculated by the Spearman correlation coefficient (r_s). To investigate potential differences in rumen fluid parameters between ALRT and NALRT, the Mann–Whitney U-test was used. For the detection of changes in rumen fluid parameters within each group during the extraction period, the related-samples Wilcoxon signed-rank test was used. A *P*-value of ≤0.05 was considered as significant.

Results

During the study period, rumen fluid was collected from 60 pairs of animals. Of these, nine pairs were excluded from statistical analysis because the rumination alert was less than 12 h (n = 4), no possibility of a second rumen fluid collection (n = 4) and onset of a rumination alert in the associated control (i.e., NALRT) animal (n = 1). For each animal, rumen fluid samples were collected and examined twice (n = 204 samples in total). Based on 20 samples, the inter-rater agreement for rumen fluid parameter was calculated and ranged between $r_s = 0.89$ and 0.98.

Acute rumination alerts lasted on average 29 ± 21 h (n = 40), while an acute rumination alert followed by a long-time rumination alert showed a mean duration of 121 ± 52 h (n = 11).

The rumen parameters pH, redox potential, methylene blue reduction time and sedimentation/flotation time differed significantly between ALRT cows and their NALRT counterparts at Ex1 ($P < 0.01$), but not at Ex2. The mean and median values of the rumen fluid parameters for ALRT and NALRT cows at both extraction times, as well as the differences between the groups and within the extraction periods are presented in Table 1 and Table 2. The number of protozoa per mL presented in Figure 1 showed significant differences between groups at Ex1 and Ex2 ($P \leq 0.01$). No differences were apparent for the other parameters at Ex2. The rumen fluid parameters of ALRT cows reached alignment with the values of their NALRT partners during the extraction period, except for the number of protozoa. ALRT animals differed in all their rumen fluid parameters within the extraction period ($P < 0.01$) while those of NALRT cows remained constant.

Table 1: Rumen fluid parameters of cows with rumination alert (ALRT) and their healthy counterparts (NALRT) at the first extraction (Ex1) within 12 h of start of rumination alert and second extraction (Ex2) within 24 h of the end of rumination alert

			Ex1			**Ex2**		
Parameter	n	Status of Animal	Mean ± SD	Median	IQR	Mean ± SD	Median	IQR
Rumen pH	51	ALRT	6.87 ± 0.32	6.91	0.36	6.61 ± 0.29	6.56	0.38
	51	NALRT	6.57 ± 0.26	6.54	0.37	6.61 ± 0.23	6.61	0.38
Redox potential (mV)	51	ALRT	–352 ± 32	–349	38	–333 ± 39	–321	39
	51	NALRT	–336 ± 37	–326	32	–332 ± 35	–325	39
Methylene blue reduction	51	ALRT	104 ± 44	98	65	71 ± 28	65	47
time (s)	51	NALRT	73 ± 27	71	35	68 ± 29	63	22
Sedimentation/ flotation	51	ALRT	487 ± 234	416	250	306 ± 83	285	139
time (s)	51	NALRT	310 ± 80	294	74	306 ± 107	286	117
Number of protozoa	51	ALRT	99 ± 36	96	54	118 ± 42	117	64
($\times 10^3$ mL^{-1})	51	NALRT	136 ± 37	136	42	138 ± 34	141	40

Table 2: Differences in rumen fluid parameters (Mean ± SEM) between cows with rumination alert (ALRT) and their healthy counterparts (NALRT) at the first and second extractions (Ex1, Ex2) and within the extraction period in each group (ALRT, NALRT)

		ALRT *vs.* NALRT				Extraction period 1 *vs.* 2			
		Ex1				ALRT			
Parameter	**Pairs**	**Difference**	***P*-value**	**Difference**	***P*-value**	**Difference**	***P*-value**	**Difference**	***P*-value**
Rumen pH	51	0.38 ± 0.0	<0.01	0.25 ± 0.0	0.84	0.36 ± 0.0	<0.01	0.23 ± 0.0	0.30
Redox potential (mV)	51	25 ± 2.5	<0.01	21 ± 3.7	0.79	28 ± 3.2	<0.01	22 ± 2.7	0.66
Methylene blue reduction time (s)	51	44 ± 6	<0.01	28 ± 4	0.54	45 ± 5	<0.01	29 ± 4	0.12
Sedimentation/ flotation time (s)	51	214 ± 30	<0.01	79 ± 13	0.75	209 ± 31	<0.01	90 ± 14	0.64
Number of protozoa ($\times 10^3$ mL$^{-1)}$)	51	51 ± 46	<0.01	40 ± 4	0.01	32 ± 4	<0.01	27 ± 3	0.79

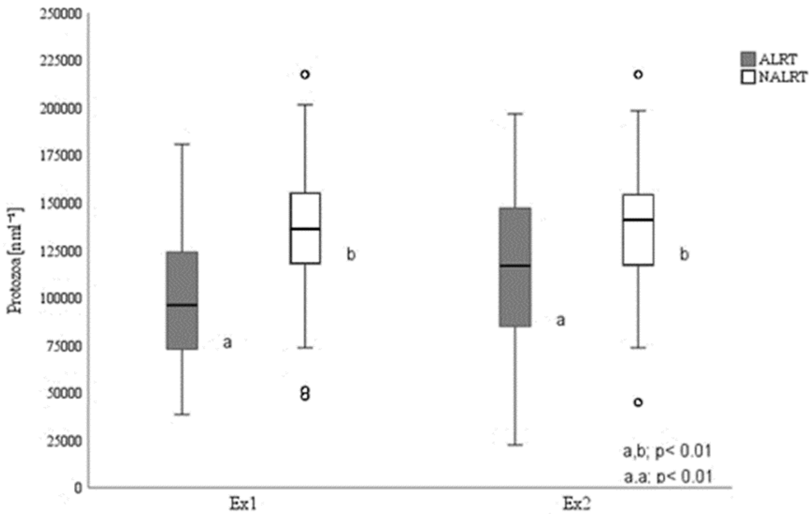

Figure 1: Total numbers (n) of protozoa per mL rumen fluid of cows with rumination alert (ALRT) and their matched partners without rumination alert (NALRT) at the first (Ex1) and second (Ex2) extraction times. Significant differences are presented by the letters a,a and a,b

Discussion

Health alerts are considered useful in supporting farmers in disease detection (Eckelkamp, 2019). The aim of this study was to investigate the relationship between rumination alerts in dairy cows triggered by a decrease in rumination time of SB and selected parameters of rumen physiology.

The physiological range of protozoa in rumen fluid is given as n = 10^3–10^6 per mL (Rings & Rings, 1993; Dehority, 2003). In this study the numbers of protozoa seen were within the reported range, but significantly lower number of protozoa were found for ALRT animals at Ex1 compared to their NALRT counterparts. A difference between groups remained after the end of alert at Ex2. Considering the regeneration of protozoa to be a continuous process, the protozoa in our study were not able to fully replicate themselves until Ex2, which justifies the difference existing between ALRT and NALRT animals at Ex2.

Although the rumen fluid parameters were within the physiological ranges for ALRT and NALRT cows at both extraction times, a higher variation for ALRT cows at Ex1 was found. Higher variations in rumen fluid parameter of cows with rumination alert could indicate a higher vulnerability to rumen health disorders. It should be considered that the collection of rumen fluid shows snapshots of rumen physiology in matched cows during and after rumination alert. Further research might focus on continuous measurement options for detecting rumen fluid parameters of cows at different health levels.

Conclusion

Cows with sensor-based rumination alert differed significantly from their healthy counterparts in all investigated rumen fluid parameters. These differences, however, were within physiological limits but showed greater variations for cows with rumination alert. Further research should consider continuous measurement options for recording rumen fluid parameters in order to correlate these variations to health events.

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Association of activity and time spent ruminating with subclinical and clinical ketosis in early lactation dairy cows

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Abstract

Ketosis and subclinical ketosis in early lactation are common production diseases in dairy cows. They negatively affect animal welfare, decrease milk performance and increase culling risk. Precision livestock farming as a rapidly emerging field can be useful for identifying cows at risk of developing ketosis. Thus, we were interested in investigating how activity and rumination time measured by a sensor system during 21 days prior until 16 days after calving are associated with subclinical ketosis in early lactation. 1,083 Fleckvieh dairy cows from 14 farms were equipped with collar-mounted sensors by Lely recording activity and rumination and data were recorded between October 2020 and August 2021. Data on subclinical and clinical ketosis were collected based on levels of β-hydroxybutyrate (BHB) in blood samples taken on day 7 and day 14 after calving. Predictions using the C5.0 decision tree algorithm yielded sensitivities between 0-14.3 %, specificities between 73.2-100 % and accuracies between 34.5-92.2 %. Based on these results further studies using larger data sets and additionally accounting for variations of cows within one herd should be conducted.

Keywords: ketosis; disease detection; precision dairy farming; activity and rumination sensor

Introduction

Ketosis and subclinical ketosis present a common production disorder in dairy cows in early lactation. Clinical ketosis manifests in symptoms such as loss of appetite and weight followed by a reduced milk production (Baird, 1982). Biochemical reactions to the negative energy balance are, amongst others, elevated concentrations of ketone bodies such as β-hydroxybutyrate (BHB). However, clinical signs of ketosis present one end of the spectrum whereas cows may suffer from a negative energy balance without showing clinical symptoms, commonly referred to as subclinical ketosis (Baird, 1982). Besides impaired animal welfare clinical and subclinical ketosis may lead to higher susceptibility to other diseases such as displaced abomasum, a reduced conception rate at first service, decreased milk yield and finally increase the risk of the cow being culled (McArt *et al.*, 2012). Sensor systems measuring cow behaviour (e.g. activity and rumination) are increasingly used on dairy farms aiming to improve herd management. Some studies investigated how these sensor measurements may be used for detection of ketosis or other postpartal health disorders. Stangaferro *et al.* (2016) for example showed that an automatic health-monitoring system combining rumination and activity was helpful in identifying cows with metabolic disorders in early lactation.

Other studies, which included data from up to three weeks before calving, found that cows with shorter rumination times are more likely to develop metabolic or other diseases postpartum (p.p. Calamari *et al.*, 2014; Kaufman *et al.*, 2016; Schirmann *et al.*, 2016; Soriani *et al.*, 2012). Besides using data from various time points before or after the detection of a disease, the informative value of sensor variables may vary depending on the aggregation method (Van Hertem *et al.*, 2013). The aim of this study was to asses if rumination and activity data provided by a sensor system for herd management are able to predict cows developing subclinical ketosis during 16 days after calving. For this purpose, approaches from other studies were combined using different aggregations of activity and rumination values or changes therein over varying periods. By application of a decision tree algorithm it was assessed, if the addition of sensor variables to a reference model improves predictions for subclinical ketosis events in dairy cows.

Animals, material and methods

The study was part of the D4Dairy project, which aims at integrating data from different sources such as national performance recordings, farm records, veterinary records, claw trimmings and different kinds of milking and sensor systems for dairy health herd management. Further information is provided under www.d4dairy.com.

Farms, animals and sensor system

Data used for the present analysis included 1,083 Fleckvieh dairy cows from 14 farms between January 2020 and August 2021, which were equipped with collar-mounted sensors by Lely International N.V. measuring activity and rumination. Sensor data were available at two-hour intervals with activity values for these two hours and the time (in minutes) spent ruminating during the last 24 hours. All farms were using automatic milking systems. Data on ketosis status were collected by farmers using the WellionVet BELUA device to measure BHB-concentration in the blood 7 and 14 days postpartum (p.p.). This test was validated by Khol *et al.* (2019), showing that more than 98% of the samples were correctly classified for subclinical or non-subclinical ketosis in capillary blood. Depending on the BHB-concentration, cows in this study were classified as either healthy (BHB ≤ 1.2 mmol L^{-1}), showing subclinical ketosis (BHB between 1.3 and 2.9 mmol L^{-1}) or clinical ketosis (BHB ≥ 3 mmol L^{-1}) for each test result (Benedet *et al.*, 2019). Additionally, cow specific data such as date of birth, parity, diagnoses and further health related information were available via the Austrian central cattle database (RDV).

Data preparation and sensor variables

Sensor data were checked for outliers and implausible observations such as rumination time exceeding 24 hours. Furthermore, cows showing retained placenta, milk fever, mastitis or lameness around calving were excluded to avoid confounded signals in sensor data due to other peripartal health issues. Data cleaning and merging left 421 animals from nine farms for further analysis. This was due to missing data on ketosis status (two farms) or the absence of any subclinical or clinical ketosis during the observation period (three farms). The number of cows per farm involved in the study ranged from 18 to 74. The following sensor variables were defined as potential predictor variables for ketosis:

— Mean daily rumination and activity as well as their standard deviation (s.d.) for the period consisting of three weeks before calving (rum_w, rum_sd_w, act_w, act_sd_w)
— Weekly mean daily rumination and activity and their s.d. for each of the three weeks before calving (rum_{w3}, rum_sd_{w3}, rum_{w2}, rum_sd_{w2}, rum_{w1}, rum_sd_{w1}, act_{w3}, act_sd_{w3}, act_{w2}, act_sd_{w2}, act_{w1}, act_sd_{w1})
— Rumination time and mean activity and its s.d. on the day of BHB-measurement (rum_{d0}, act_{d0}, act_sd_{d0})
— Mean daily rumination time and activity and their s.d. between day 4 and day 2 prior to the BHB-measurement (rum_{d4-d2}, rum_sd_{d4-d2}, act_{d4-d2}, act_sd_{d4-d2})
— The change in these variables from day 4 to day 2 before compared to the day of the BHB-measurement (rum_{delta}, rum_sd_{delta}, act_{delta}, act_sd_{delta})
— An index for this change defined as $rum_{index} = (rum_{d0} - rum_{d4-d2}) / rum_{d4-d2}$ and $act_{index} = (act_{d0} - act_{d4-d2}) / act_{d4-d2}$ similar to the Cow-Index for change in rumination time proposed by Paudyal *et al.* (2018)

Only cows with a BHB-measurement later than 6 days in milk were included to calculate sensor derived variables from four days before BHB-measurement to avoid bias due to the physiological decline in rumination around parturition. This time span was based on the findings of Schirmann *et al.* (2013) that lower rumination levels due to parturition go back to baseline 24-48 hours p.p.

Data analysis

Data were prepared and analysed using the statistical software R (R Core Team, 2019). Predictions if a cow was healthy (0) or if BHB-levels in the blood suggested subclinical ketosis (1) were made applying the C5.0 decision tree algorithm using the C50 package in R (Kuhn & Quinlan, 2018). Cases of clinical ketosis were not included in the data analysis because they were only present in two out of nine farms. For analysis of the weekly variables antepartum (a.p.) rum_w, rum_sd_w, act_w, act_sd_w, rum_{w3}, rum_sd_{w3}, rum_{w2}, rum_sd_{w2}, rum_{w1}, rum_sd_{w1}, act_{w3}, act_sd_{w3}, act_{w2}, act_sd_{w2}, act_{w1} and act_sd_{w1} cows were classified affected (1) if at least one of the two postpartal blood test results indicated subclinical ketosis. The remaining sensor variables were related to one specific BHB-measurement and thus the respective result was used for ketosis classification. To mimic a potential application with early detection of ketosis via sensor data, the last five calvings and the last ten BHB-measurements of each farm were used as validation for the weekly variables and the BHB-measurement related variables, respectively. All remaining data trained the decision tree models. For both groups of sensor variables (weekly and BHB-measurement related) different models were built to assess if the addition of sensor information improves predictive abilities of the model for subclinical ketosis. The reference model without sensor data included the variables farm, age class, calving year and calving season and days in milk in case of the BHB-measurement related sensor variables. Age class was derived from a combination of parity and age at calving for the first two parities. For cows in their first and second lactation, three classes were created, respectively: < 26, 26 - 28 and > 28 months for the first, and < 39.5, 39.5 - 42 and > 42 months for the second lactation. Further three age classes corresponded to animals in parity three, four and five or older, respectively. Calving years ranged from 2019 to 2021 and four seasons were defined according to quarters of the year. Adaptive boosting was applied limiting the number of separate decision trees to 10 (*trials = 10*). Furthermore, the 'cost' of missing a cow with subclinical ketosis (type 2 error) was set at four times the costs for classifying a healthy cow as sick (type 1 error). Sensitivity, specificity and accuracy were calculated based on predictions using validation data to assess whether adding sensor information improves predictions compared to the reference model. Corresponding sensor variables were added as features and four different classifiers were applied for the weekly variables a.p.:

1. Reference model including the features *farm, age class, calving year, calving season*
2. Full model I including the features from the reference model plus sensor variables rum_w, rum_sd_w, act_w, act_sd_w
3. Full model II including the features from the reference model plus sensor variables weekly means and standard deviations rum_{w3}, rum_sd_{w3}, rum_{w2}, rum_sd_{w2}, rum_{w1}, rum_sd_{w1}, act_{w3}, act_sd_{w3}, act_{w2}, act_sd_{w2}, act_{w1}, act_sd_{w1}
4. Full model III including all features listed above

Five different classifiers were applied for the variables prior to BHB-measurement:

1. Reference model including the features *farm, age class, calving year, calving season, days in milk (DIM) at BHB-measurement*
2. Full model I including the features from the reference model plus sensor variables rum_0, act_0, act_0, sd_0 and $rum_{d4\text{-}d2}$, $rum\_sd_{d4\text{-}d2}$, $act_{d4\text{-}d2}$, $act\_sd_{d4\text{-}d2}$
3. Full model II including the features from the reference model plus sensor variables rum_{delta}, rum_sd_{delta}, act_{delta}, act_sd_{delta}
4. Full model III including the features from the reference model plus the sensor index variables rum_{index}, act_{index}
5. Full model IV including all features listed above

Results and discussion

Weekly sensor variables prior to calving

The data set contained 429 ketosis data for 406 animals including 369 healthy (86.0 %), 55 (12.8 %) observations for subclinical ketosis and 5 (1.2 %) observations for clinical ketosis. Figure 1 shows how sensor variables vary at different weeks a.p. and within the later ketosis status. Training data for the decision tree included 379 observations from 361 animals from all 9 farms and validation data comprised 45 observations from 45 animals from all 9 farms. Proportions for healthy cows and cows with subclinical ketosis were 86.5 % (0) and 13.5 % (1) for training and 91.1 % (0) and 8.9 % (1) for test data. Results for sensitivity, specificity and accuracy for all four models are listed in Table 1.

Sensitivities were 0.0 % for all four models indicating that the model was not able to detect any cow with subclinical ketosis irrespective of addition of sensor information. However, ketosis was characterised by low frequencies in the current data set and thus the amount of training data in this study is clearly insufficient. The participating farms were well managed which may be the reason for the low frequencies of ketosis in this study. Furthermore, boxplots in Figure 1 indicate a potential negative association between rumination time one week prior to calving and clinical ketosis, which was also found in previous studies (Kaufman *et al.*, 2016; Schirmann *et al.*, 2016). With respect to herd management, these prepartal variables would be of particular interest because they could enable early identification of cows needing special attention during and shortly after calving by inclusion in predictive models. However, it was not possible to verify this association in the present study due to data limitations.

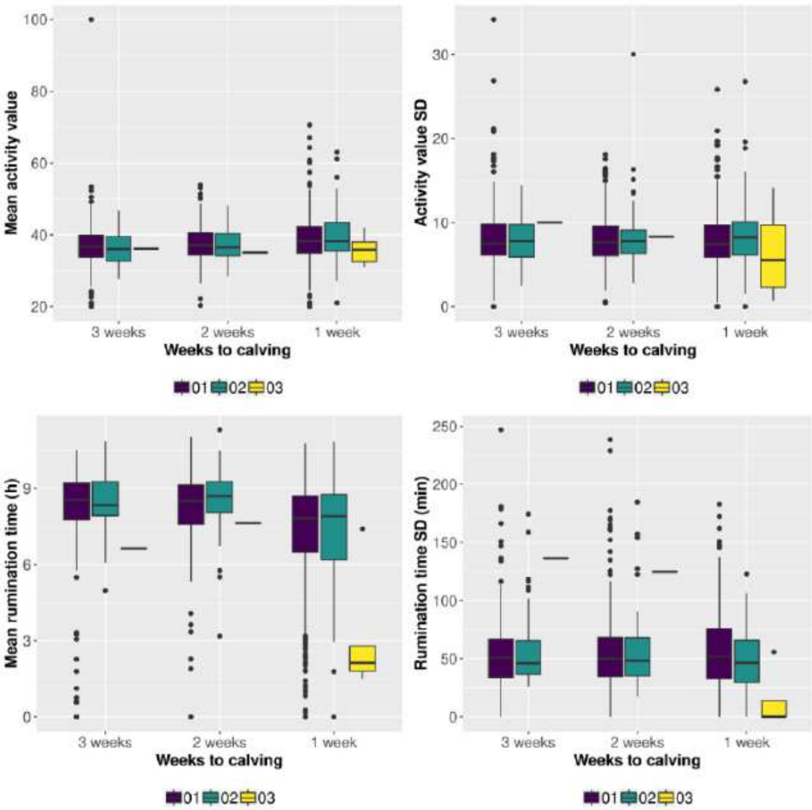

Figure 1: Mean daily activity value (top left), mean daily standard deviation for activity value (top right), mean hours per day spent ruminating (bottom left) and the standard deviation of rumination time per week in minutes (bottom right) in the third, second and one week before calving for healthy cows (01), cows developing subclinical (02) or clinical ketosis (03) during 16 days after calving.

Table 1: Sensitivity, specificity and accuracy using four different classifiers applied to weekly sensor variables antepartum (a.p.). RM = reference model, FM = full model, s.d. = standard deviation

Models	Features	Sensitivity	Specificity	Accuracy
RM	Farm, age class, calving year, calving season	0.0 %	73.2 %	66.7 %
FM I	RM + mean rumination and activity and activity s.d. over 3 weeks a.p.	0.0 %	75.6 %	28.2 %
FM II	RM + mean rumination and activity and their s.d. for weeks 3, 2 and 1 a.p.	0.0 %	73.2 %	27.3 %
FM III	FM I + FM II	0.0 %	92. 7%	34.5 %

Sensor variables prior to BHB-measurements

The data set contained 766 ketosis observations for 402 animals including 691 (90.2 %) healthy, 69 (9.1 %) observations for subclinical ketosis and 6 (0.7 %) observations for clinical ketosis. Figure 2 shows how sensor variables vary within ketosis status for different days prior to BHB-measurement. Training data for the decision tree included 670 observations from 359 animals from all nine farms and test data comprised 90 observations from 55 animals from all nine farms. Proportions for healthy cows and cows with subclinical ketosis were 90.7 % and 9.3 % for training data and 92.2 % and 7.8 % for validation data.

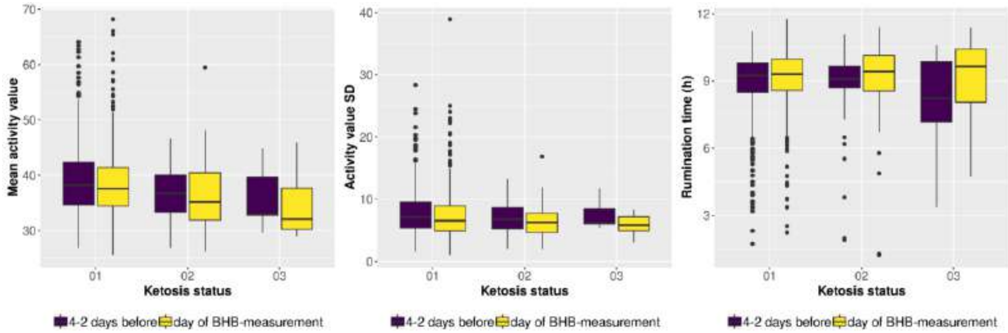

Figure 2: Mean daily activity value (left), mean daily standard deviation for activity value (middle) and mean hours spent ruminating per day (right) during 4-2 days prior to and on the day of BHB-measurement for healthy cows (01), cows developing subclinical (02) or clinical ketosis (03).

Table 2: Sensitivity, specificity and accuracy for predictions on the test data for the five classifiers built for the weekly sensor variables antepartum (a.p.). RM = reference model, FM = full model, s.d. = standard deviation

Models	Features	Sensitivity	Specificity	Accuracy
RM	Farm, age class, calving year, calving season, DIM BHB-measurement	0.0 %	86.7 %	80.0 %
FM I	RM + mean rumination and activity and its s.d. at BHB-measurement and 4-2 days before	14.3 %	94.0 %	87.8 %
FM II	RM + change in mean rumination and acitivity and its s.d. between day of BHB-measurement and 4-2 days before	14.3 %	84.3 %	78.9 %
FM III	RM + index for change in rumination and activity as in Paudyal *et al.* (2018)	0.0 %	100 %	92.2 %
FM IV	FM I + FM II + FM III + FM IV	0.0 %	100 %	92.2 %

Similar to the weekly sensor variables a.p. the sensitivities for the BHB-measurement related sensor variables did not perform well at predicting animals developing subclinical ketosis. This again may on the one hand be a result of limited data and low ketosis frequencies. On the other hand, within-cow variation alone may not provide enough information for disease prediction and thus additional comparisons to herd mates may improve results (Paudyal *et al.*, 2018). However, these comparisons require a clear definition of healthy herd-mates or herd averages to serve as reference value.

Conclusions

The current study investigated the potential of various variables derived from sensor data on rumination and activity to predict cows developing subclinical ketosis. The limited data and low frequency of cows with subclinical ketosis may explain why this study failed to detect predictive abilities of sensor information. Currently, work is being done on data validation of further farms to repeat the study on a larger data set. In addition, alternative sensor variables with the aim to assess between-cow variation will be investigated.

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Sensor-based detection of teat end hyperkeratosis with the help of the dielectric constant

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Abstract

The teat of a dairy cow is exposed to a large load during milking because it is the interface between the udder and the milking technique. A milking system that works improperly can damage the teat, resulting in the formation of teat end hyperkeratosis (HK). Currently, the severity of HK can only be assessed visually, and there is no way to detect the severity of hyperkeratosis on the bovine teat automatically. Thus, the aim of the present study was to test and evaluate the measurement of the dielectric constant of the teat skin as a method of automatic detection of hyperkeratosis. The study focused on surveying the occurrence of hyperkeratosis in a total of 241 teats of lactating dairy cows. A visual scoring system consisting of four categories was used to macroscopically assess the severity of HK using a four-level evaluation system. Additionally, the dielectric constant (DC) of all milkable teats was measured in a double iteration before the teat was prepared for milking. The Spearman rank correlation coefficient revealed a negative correlation between the DC value and HK score (rs = -0.55 to -0.36). The results of the regression analysis showed that the DC values differed significantly between healthy teat ends (score ≤ 2) and teat ends with HK (score ≥ 3). Thus, the non-invasive measurement of DC provides a promising method of objectively assessing the occurrence and severity of HK. However, further studies using more animals and repeated measurements are required to validate this method.

Keywords: dielectric constant, teat end hyperkeratosis, water content, dairy cow, udder health

Introduction

Teat end hyperkeratosis (HK) is defined as a thickened smooth keratin ring or as extending fronds of keratin around the teat canal orifice (Gleeson *et al.*, 2003). The occurrence of HK greatly impacts milk production. The severity of HK is an issue of importance because teat condition is connected with the capability to defend against mastitis pathogens (Sordillo & Streicher, 2002). Furthermore, serious HK as well as a relatively higher roughness of the teat end both increase the risk of udder diseases (Neijenhuis *et al.*, 2000; Neijenhuis *et al.*, 2001; Singh *et al.*, 2014). Milk from non-disinfected teats with an HK score higher than one had a larger content of somatic cells (Gleeson *et al.*, 2004). The prevalence of HK has been associated with many factors, such as season (Rudovsky *et al.*, 2011; Sandrucci *et al.*, 2014) and teat morphology (Graff, 2006; Rudovsky *et al.*, 2011) as well as milking traits such as milk flow (Rudovsky *et al.*, 2011), parity (Graff, 2006; Rudovsky *et al.*, 2011), and days in milk (Sandrucci *et al.*, 2014). Milking technique may also play a role in HK formation (Ryšánek *et al.*, 2001; Neijenhuis *et al.*, 2005; Haeussermann *et al.*, 2016).

Although HK is of substantial economic and animal health concern, there is currently no appropriate sensor-based method to objectively quantify the severity of HK. Until now the scoring systems of Mein *et al.* (2001) and those of Neijenhuis *et al.* (2001) were mostly used to evaluate the influence of biological or technical factors on HK.

This study was conducted to assess the use of the dielectric constant (DC) of the teat ends as a possible sensor-based method for monitoring HK. With the help of DC measurements, local changes in water content in the skin and subcutaneous fat could be measured for the early diagnosis of diseases that involve changes in tissue water content. The measurement of the DC provides an instantaneous and non-invasive measurement (Nuutinen *et al.*, 2004; Miettinen *et al.*, 2006).

Measuring the DC is often used to investigate lymphedema (Ferguson *et al.*, 2013; Birkballe *et al.*, 2014; Mayrovitz *et al.*, 2016), cutaneous edema, tissue fluid status (Palma *et al.*, 2015; Greenhowe *et al.*, 2017; Mayrovitz *et al.*, 2017), radiotherapy (Nuutinen *et al.*, 1998), burns, thermal injury (Papp *et al.*, 2006), wound healing (Forcheron *et al.*, 2012; Guihan *et al.*, 2012), and weight loss (Laaksonen *et al.*, 2003). The measurement of DC has been used in the field of agriculture as well. For instance, Hoffmann *et al.* (2013) used the measurement of DC to monitor the prevalence and severity of foot pad dermatitis in broiler chickens.

The aim of the present study was to validate the potential of measuring the DC of teat ends to evaluate the severity of HK in dairy cows. Therefore, the relationship between the measured values of the DC and the corresponding HK scores of the visual teat inspection was investigated.

Material and methods

Study design and data collection

The study was conducted within four weeks on a commercial dairy farm in Germany. On four non-consecutive measurement days, 241 teats of lactating Holstein cows were first assessed by visual observations to determine the HK score of each teat. Afterwards, the DC of the teat orifice was measured. The teats were scored once because it was assumed that no new HK would develop during the experimental period. At the time of this investigation, 52, 110, 66, and 13 of the examined teats had an HK score of 1, 2, 3, and 4, respectively.

Teat end condition was evaluated during the evening milking period using criteria established by Mein *et al.* (2001) as described in Table 1.

To measure the DC of the teat orifice the MoistureMeterD (Delfin Technologies, Kupio, Finland) with a probe (model XS5) of 10 mm in diameter and en effective measurement depth of 0.5 mm was used. The control unit of the device generates a high-frequency electromagnetic wave of 300 MHz, which is transmitted via an open-ended coaxial probe into the skin and subcutaneous tissues, where the majority of the electromagnetic wave energy is absorbed by water, while the rest is reflected (Figure 1). The DC is calculated from the information of the reflected wave, which is directly proportional to the tissue water content (Nuutinen *et al*., 2004). The higher the DC value, the higher the water content of the tissue.

Table 1: Four-level evaluation score of teat end hyperkeratosis according to Mein et al. (2001)

Score 1	Score 2	Score 3	Score 4
healthy teat without a ring at the teat end	slightly white ring at the teat end; no old keratin visible	raised and roughened keratin ring, extending up to 3 mm with visible old keratin	severely roughened keratin ring, extending more than 4 mm with clearly observable old keratin

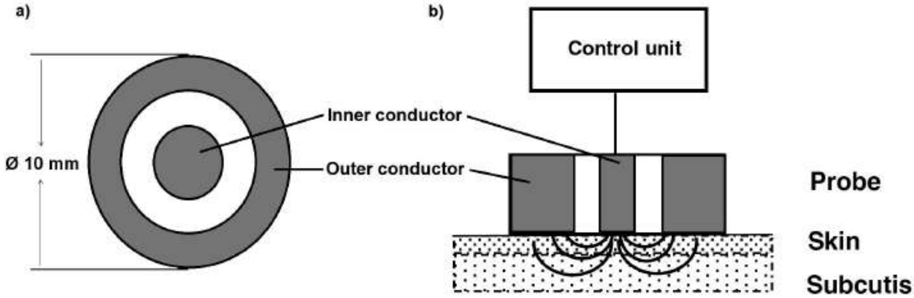

Figure 1: Magnified view of the measuring probe (a) and the measuring principle of the MoistureMeterD (b) according to Nuutinen et al. (2004)

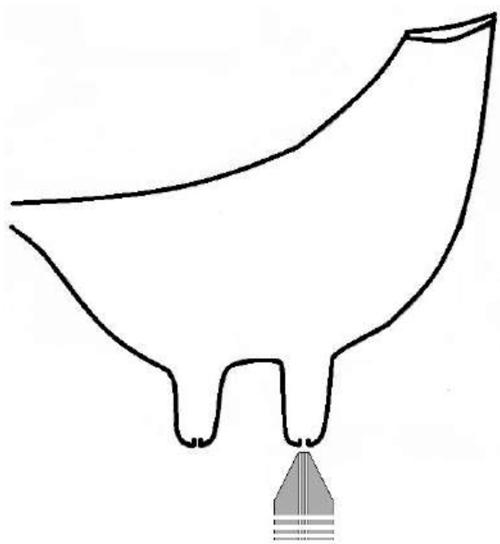

Figure 2: Schematic illustration of the measuring point on the teat orifice

During data collection, the circular probe was manually placed in contact with the skin of the teat orifice (Figure 2). Measuring was automatically started upon skin contact and lasted on average two seconds. Contact between the sensor probe and the skin was regulated by the person who was conducting the measurements, who produced so little pressure that the animals showed no painful reactions. The measurement was repeated two times per teat, except in cases of failed measurements, for which a third measurement was performed. Afterward, the probe was cleaned with a dry cloth. Before pre-milking teat preparation, the same person took all the measurements with the MoistureMeterD to ensure standardized conditions.

Statistical analysis

Data were analysed using the SAS 9.4 software package (SAS Institute Inc. Cary, NC, USA), and the Spearman rank coefficient (rs) was used to estimate the correlation between the DC value and the HK score. For the statistical analysis, the possible inference of the DC on the HK score was tested with a generalized linear model approach that assumed a binomial distribution with a logit link function. For this purpose, the median DC of the measurements on each teat was used. Therefore, a sequential logit model was used. Given the observed score y_{ijkms} for the ijkm-th teat with scores ranging from 1 to s, with s=4, binary responses were created as follows: (a) score = 1 versus score ≥ 2; (b) score ≤ 2 versus score ≥ 3; (c) score ≤ 3 versus score = 4. Models (a) through (c) examined the ratio between the probability of observing score r or lower and the probability of observing scores higher than r with logit Lr for a maximum r of s-1:

$$L_r = \ln\left(\frac{P(Y \le r)}{P(Y > r)}\right) = \ln\left(\frac{P(Y \le r)}{1 - P(Y \le r)}\right) = \theta_r + \eta_r \quad (1)$$

where θ_r is the threshold value for score r and η_r is a linear predictor. The linear predictor η_r is calculated as follows:

$$\eta_{ij} = \mu + ax + b_i + \varepsilon_{ij} \quad (2)$$

where μ is the general mean; a is the regression coefficient for DC value x; b_i is the random effect for cow i; ε_{ij} is the independent logistically distributed residual.

The GLIMMIX procedure was used to fit the model. The null hypothesis was that the DC would have no significant influence on the HK score, and all tests were carried out at a significance level of $\alpha = 0.05$.

Results and Discussion

The measured DC values ranged from 10.5 to 52.4. The values of DC decreased monotonically with increasing HK score. The Spearman rank correlation between the two traits was rs = -0.43 ($P = 0.005$), rs = -0.55 ($P < 0.001$), rs = -0.36 ($P = 0.001$) and rs = -0.39 ($P = 0.02$) on measurement day A, B, C, and D, respectively. Therefore, during all the measurement days, high HK scores were more likely to occur when the DC values were relatively lower, while low HK scores were more frequent when the DC values were high.

The results of the three models within the generalized linear model approach (Table 2) showed a significant influence of the DC value ($P < 0.0001$) on the HK score when the HK score ≤ 2. No significant influence of the DC value on the HK score was found when the HK score = 1 and when the HK score ≤ 3. The measured DC values showed overlaps among the investigated HK scores.

Table 2: Results of the three models within the generalized linear model approach for the tested effects

Model	Effect	Estimate	Standard Error	DF[1]	t-Value	P-Value
1 vs. ≥ 2	Intercept	7.64	1.97	97	3.88	0.0002
	DC[2] value	0.01	0.07	138	0.17	0.8638
≤ 2 vs. ≥ 3	Intercept	-3.47	1.16	97	-3.00	0.0035
	DC[2] value	0.19	0.05	138	4.16	< 0.0001
≤ 3vs. 4	Intercept	5.74	2.92	97	1.97	0.0520
	DC[2] value	0.17	0.11	138	1.53	0.1277

[1] Degree of freedom

[2] Dielectric constant

The comparison of DC values and HK scores of the investigated teat orifices indicated that the DC was higher in teat ends with lower scores and vice versa. This finding agrees with the results of Hoffmann *et al.* (2013), who found a negative correlation between DC values and the severity of foot pad dermatitis (FPD) in broiler chickens; specifically, the DC values were higher in foot pads with lower FPD scores and were lower in foot pads with higher FPD scores. Hashmi *et al.* (2015) found lower levels of hydration in hyperkeratotic than in normal foot skin. Alanen *et al.* (1999) reported that there was always some air between the probe and the skin due to the roughness of the skin. This result might be a reason for the association of lower DCs with severe HK scores, in which crusts covered the teat orifices of the cows. However, the DCs of the four HK scores demonstrated overlap. The results of the regression analysis revealed that DC values differed significantly between healthy teat ends (≤ 2) and teat ends with HK (≥ 3). This could be explained by the fact that the visual observation, which is the most commonly used method to assess HK, was used as a gold standard to find correlations between the HK scores and the DC values. The problem with this method is that it is very subjective and sometimes subtleties determine the assignment of the HK score. In an attempt to reduce the disadvantages of this method, the visual observation was always done by the same person. The different distribution of the HK scores in the examined herd may possibly explain this result.

In the present investigation, the measured DC values were on average 26.4 ± 7.0. The values for subcutaneous fat of human skin were approximately 36.0 ± 2.0 (Nuutinen *et al.*, 2004). The anatomical and physiological differences between human and bovine teat skin (e.g., thickness, tissue water content) could explain the different DC values. Another reason for this result could be the measurement depths. While the sensor probe used in the present investigation had an effective measurement depth of 0.5 mm, Nuutinen *et al.* (2004) used a probe with an effective measurement depth of 2.5 mm.

However, the diameter of this probe (23 mm) was too large to be used for measuring the DC on the teat orifice.

The DC values measured in the present investigation showed a high variability. There could be several reasons for this variability. First, the manipulation of the teat during the measurements could have resulted in a stimulation of the teat and milk flow could have started in some cows. The fact that not all teats may have been evenly dry as well as the different water content of the teat tissue of individual cows could result in a high variability of the DC values as well. Although the same pressure was attempted to be applied in each measurement, a slight change in this pressure could have changed the measuring depth of the probe and thus led to the high variation in the measured values.

Further studies are needed to validate the DC measurement to objectively assess the occurrence and severity of HK.

Conclusions

It can be concluded that measuring the DC of the teat orifice is a suitable and objective method for assessing the occurrence and severity of HK in dairy cows. This method is particularly suitable to distinguish between healthy teat ends (scores 1 and 2) and teat ends with HK (scores 3 and 4). Measuring the DC may be a helpful tool for detecting early teat end irritations; ultimately, this tool may help to improve the teat end condition of dairy cows. However, further studies are needed to validate this method and to define exact DC value ranges for the different HK scores.

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Systematic evaluation of different fresh cow monitoring procedures

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Abstract

Routine fresh cow monitoring procedures are considered beneficial for animal health, welfare and productivity. However, they are time-consuming and require the animals' fixation, which restricts their natural behaviour and, thus, might have a negative impact on herd health and performance. Automated monitoring by the use of 'precision livestock farming' (PLF) technologies is progressively used on farms to identify animals at risk of disease at an early stage and to reduce routine examination times.

In this study on a German dairy farm with approximately 1,900 Holstein Friesian cows, different methods of fresh cow monitoring procedures were compared against each other. These included, on the one hand, different routine examinations of fresh cows, on the other hand, three different workflows (systems) which differ in the order of examinations and treatments to evaluate in future whether management strategies can be improved with the help of PLF technologies.

Standard operating procedures were defined in advance for various examination steps, in particular the start and end points. To determine the individual examinations of the 3 veterinarians involved in the study as well as the fixation time of each animal, sixteen video cameras were installed in the fresh cow pen and video footage was analysed.

The different examinations lasted on average between 1 and 115 seconds. The animals were fixed in headlocks between 1 and 106 minutes. The resulting fixation time differed significantly between the three different fresh cow management systems ($P < 0.05$).

The study recorded the examination times for individual steps in fresh cow monitoring under practical conditions. Results should be used to optimize management strategies and to evaluate what contribution Precision Livestock Farming technologies can make to reduce fixation times and stuff working hours.

Keywords: dairy cow, health monitoring, transition period, accelerometer, fresh cow

Introduction

Intensive and well-structured monitoring of fresh cows is considered beneficial for the health and well-being of the cows and is an important factor for the success of the cows' further lactation (Guterbock, 2004; LeBlanc, 2010; Espadamala *et al.*, 2016). Due to the various metabolic and infectious diseases caused by a negative energy balance at the time of calving, fresh cow monitoring can become a very time-consuming task (LeBlanc, 2010; Silva *et al.*, 2021). However, currently it is necessary to lock up the animals for examinations and treatments, which restricts their natural behaviour and thus has a negative impact on the health and performance of the herd (Guterbock, 2004; Grant, 2007; Gomez & Cook, 2010). However, performing this important but time-consuming examination during the fresh cow period without excessively affecting the animals' natural behaviour is often a challenge.

The use of Precision Livestock Farming (PLF) technologies can further support animal monitoring. Among other parameters, automated and continuous monitoring of rumination activity can be achieved in real time. The use of sensors and animal-specific rumination alerts have the potential to detect animals at risk of disease at an earlier stage. By this, decision making is substantially supported (Silva *et al.*, 2021), allowing cost and time to be used in an efficient way. To our knowledge, there are hardly any studies on the duration of examination and treatment times that have been systematically recorded in practice. Many survey-based publications are based on farmers' perception of time (Couto Serrenho *et al.*, 2022; Espadamala *et al.*, 2016). For instance, Espadamala *et al.* (2016) described generalised examination and treatment times for animals between 1 to 46 seconds per animal. Determining the exact times that cows are fixed in headlocks for examinations and treatments under practical conditions can be used to evaluate existing and develop new management strategies. This is particularly important for practitioners that want to develop time- and cost-efficient management strategies while minimising the impact on the dairy cow's time budget. PLF technologies could be a support here to reduce the fixation times of cows in headlocks and stuff working hours.

In this study, a systematic analysis of video footage, recorded in the fresh cow pen of a commercial farm, was performed to determine (1) the duration of different animal-specific examination and treatment times and (2) the total duration of fixation time of cows in the headlocks.

Material and methods

All study procedures were approved by the State Office of Agriculture, Food Safety and Fisheries Mecklenburg-Vorpommern, Germany (7221.3-2-013/21) and noted by the Ethics Committee of the University of Veterinary Medicine, Vienna.

<u>Animals, housing, feeding</u>

The study was conducted from June 2021 to August 2021 on a commercial dairy farm in Mecklenburg-Vorpommern, Germany. The farm housed approximately 1,900 Holstein-Friesian dairy cows in free-stall barns. The average energy-corrected milk yield (ECM; based on 4 % butterfat and 3.4 % protein) was 10,301 kg per cow in 2021.

After calving, the cows were milked for colostrum harvesting and afterwards moved to the fresh cow pen. Cows were milked twice a day (at 05:30 and 17:30) in a 12 side-by-side parlour. Fresh cows remained in the fresh cow pen until approximately day 10 of lactation. The fresh cow pen was equipped with headlocks (Twist&Lock Headlocks, GEA Farm Technologies GmbH, Bönen, Germany), full concrete floors and cubicles with horse manure and chopped straw as bedding material. The headlocks had an additional feature allowing the fixation of individual animals by a 'twist and lock' system (TL) while releasing the other cows. Cows had ad libitum access to water and were fed a total mixed ration consisting of grass silage, corn silage, potato pulp, soya- and rapeseed extraction meal, wheat straw, soya hulls and minerals.

Accelerometer – based monitoring system

All animals were equipped with an ear-attached accelerometer SMARTBOW (SB; Smartbow/Zoetis LLC, Weibern, Austria) to monitor the animals' rumination activity. Data were sent in real-time to receivers and processed on the farm server. Based on individual data, the SB system generated rumination alerts (e.g., by urgent rumination decline), which were presented in the management software. At the beginning of the daily examination routine in the morning, all SB alerts were sighted, and the conspicuous animals were examined.

Video observation

The fresh cow pen was equipped with 16 digital observation cameras [network camera HYU-405, HYUNDAI Corporation, Korea] at a height of approximately 3.5 m. Mangold-Interact (version 17.1.0.0, Mangold International, Arnstorf, Germany), a specialized software for the visual evaluation of video footage, was used to analyse the time required for specific fresh cow management procedures. For this, the start and end times of each examination step (Table.1) as well as headlock time per cow were defined. The video footage was visually observed by one person in Mangold Interact (i.e., the principal author F.K.). Using a predefined and corresponding shortcut, the respective examination steps were assigned a start and end time, respectively, which was taken analogously from the video.

Examination and treatment procedures

The study was based on the herd health management strategy that was already implemented on the farm. Here, three veterinarians carried out health management in the fresh cow barn, two of whom were present on site at any one time. Accordingly, the animals were fixed daily in headlocks, for examination and treatment (between 7:00 and 9:00 am). The criteria for a more detailed examination after an initial check (taking rectal temperature, touching ears and skin) were as follows: existing SB rumination alert, signs of hypocalcaemia (cold surface temperature and -cold ears), rectal temperature ≥ 39.5°, retained foetal membranes or decreases in daily milk yield. One examiner was in the feed alley to manually check the temperature at the ear and to record the clinical findings, while a second investigator was in the cow alley measuring the rectal temperature and checking for retained foetal membranes. For ketosis prophylaxis, cows received 300 ml propylene glycol (1,2-Propandiol, Spezialfutter Neuruppin GmbH & Co. KG, Neuruppin, Germany) on days 1 and 2 of lactation.

Based on the criteria above, detailed examinations included: (1) rumen fill estimation and faecal examination (described by Zaaijer *et al.* (2001)) (3) percussion- and succession-auscultation (if a displaced abomasum (DA) was suspected), (5) rumen-auscultation, (6) rectal examination, (7) udder-examination. Examinations were described by Radostits *et al.* (2007).

Before the animals were examined and treated, all fresh cows were fixed in headlocks as quickly as possible. To compare the time budget of different examination strategies, three systems (S1–S3) were established. S1: one investigator measured the rectal temperature in the entire group in a row, while the second investigator in the feed alley permanently fixed all animals that had to be examined by use of the TL-System. After the measurement of all temperatures, only animals for prophylactic treatments and examination remained in the headlock. The remaining animals were examined and treated by both examiners; S2: one investigator examined and treated the animals one after the other from the cow alley. The second investigator at the feed alley documented all findings, handed over all treatment and examination utensils and immediately released the animals after the end of examination or treatment; S3: one investigator measured the rectal temperature in the whole group in a row, while a second investigator checked the animals from the feed alley at the same time. Then, both veterinarians examined and treated the animals. All animals remained in the headlock until the last treatment was completed.

Table 1: Standard operating procedures for various examination steps divided into start- and end points

Examination step	Definition	
	Start	End
Rectal temperature	the thermometer is inserted rectally	the animal is marked with a red/yellow marker
Rumen fill	the paralumbar fossa is palpated, cranial to the last rib	the hand is taken back
Percussion-auscultation	fingers touch the abdomen to perform the percussion	the succession starts by formation of a fist
Succession-auscultation	the succession starts by formation of a fist	a functional stethoscope is taken off
Faeces examination	the rectal glove is put on (shoulder protection over the head)	the rectal glove is removed (pull the shoulder protector over the head again)
Udder examination	Examiner squats down	Examiner stands again
Rumen auscultation	a functional stethoscope is put on	the examiner starts with percussion
Rectal examination	the rectal glove is put on (shoulder protection over the head)	the rectal glove is removed (pull the shoulder protector over the head again)

Statistical analysis

The results of the video analyses performed with Mangold Interact were exported into an Excel spreadsheet (version 16.0.5; MS Excel 2016, Microsoft Cooperation, Redmond, USA) for further statistical analyses with SPSS (version 27.0.0.0, IBM corporation SPSS Statistics, Armonk, NY). Data were tested for normal distribution using the Kolmogorov-Smirnov test. For comparison of the three different systems (S1–S3) as well as the examination steps, performed by the investigators, the Kruskal-Wallis test and, analysis of variance (ANOVA), respectively, were used. Intra- and inter-rater reliability was calculated by the use of Cohen (1960) Kappa (κ); the level of significance was set at p = 0.05. Results are presented as mean ± SD.

Results

Table 2: Duration of examination steps presented for each of the three investigators (Inv 1 – Inv 3) and differences among the investigators (Mean ± SEM).

Examination-step	Inv[1]	Duration (s)			Differences among Inv[1] (s)		
		n	Mean	SD[2]	1 vs 2	2 vs 3	1 vs 3
Temperature	1	831	16	3	<0.1 ± 0.2 (*P* = 1.00)	0.6 ± 0.2 (*P* < 0.01)	0.5 ± 0.2 (*P* = 0.02)
	2	847	16	3			
	3	561	15	3			
Rumen fill	1	84	1	0	0.2 ± 0.2 (P = 1.00)	0.9 ± 0.2 (P < 0.01)	1.2 ± 1.2 (P < 0.01)
	2	79	1	1			
	3	75	2	1			
Percussion auscultation	1	103	9	3	4.3 ± 0.5 (P < 0.01)	1.4 ± 0.5 (P = 0.02)	2.9 ± 0.5 (P < 0.01)
	2	136	4	3			
	3	90	6	4			
Succession auscultation	1	103	2	0	0.6 ± 0.1 (P < 0.01)	0.4 ± 0.2 (P = 0.03)	1.2 ± 0.2 (P = 0.96)
	2	127	1	1			
	3	95	2	1			
Faecal examination	1	38	22	7	8.3 ± 3.0 (P = 0.03)	6.8 ± 3.2 (P = 0.11)	15.1 ± 2.8 (P<0.01)
	2	22	31	14			
	3	27	37	12			
Udder examination	1	62	15	5	1.0 ± 2.0 (P = 1.00)	7.8 ± 2.0 (P < 0.01)	8.9 ± 2.1 (P < 0.01)
	2	75	16	12			
	3	67	24	15			
Rumen auscultation	1	42	115	38	4.2 ± 5.9 (P = 1.00)	31.7 ± 5.8 (P < 0.01)	35.9 ± 6.3 (P = 0.05)
	2	61	111	26			
	3	45	79	24			
Rectal examination	1	42	30	7	9.7 ± 2.3 (P < 0.01)	6.8 ± 2.3 (P = 0.01)	16.5 ± 2.5 (P < 0.01)
	2	62	39	12			
	3	44	46	13			

[1] Investigator
[2] Standard deviation

To test the accuracy, an intra- and inter-rater reliability was performed. The principal investigator (F.K, Inv.1) analysed the video sequences of one observation day twice (101 events). Here, a high level of agreement with κ > 0.89 was calculated for the intra-rater reliability. To compare the recorded parameters among the three different investigators, a joint but independent assessment of the animals was made at the beginning of the study (n=117). A high inter-rater agreement with κ from 0.89 to > 0.99 was detected. Examination procedures of 58 observation days and headlock times of 44 observations days were evaluated in the study. In total, 3,973 examination steps and 1,848 headlock times per cow were eligible for statistical analyses. Significant differences in the time needed to perform specific examinations were identified among the examiners (Table 2). The most frequent examination steps were as follows: (1) temperature measurement (n = 2,239, 56%), (2) percussion-auscultation (n = 329, 8.2%), (3) succession-auscultation (n = 325, 8.1%). Temperature measurement took on average of 16 ± 3 seconds and differed significantly among the three investigators in maximum 0.6 seconds ($P < 0.01$).

The succession- and percussion-auscultation took, on average 2 ± 1 and 6 ± 4 seconds, respectively. The maximum differences among the investigators were 1.2 s ($P = 0.96$) and 4.3 s ($P < 0.01$), respectively. The longest examination step was the rumen auscultation, which lasted 101 ± 40 seconds and differed most significantly among the investigators, with 35.9 s ($P = 0.05$).

Overall, 1848 headlock were used for statistical analyses (S1 (n = 562) vs S2 (n = 674) vs S3 (n = 612)).

Figure 1 shows the differences among the systems. Fifty percent of the animals left the headlocks after 11 minutes in S1, after 16 minutes in S2 and after 45 minutes in S3. Significant differences were found between all three systems (S1 – S3).

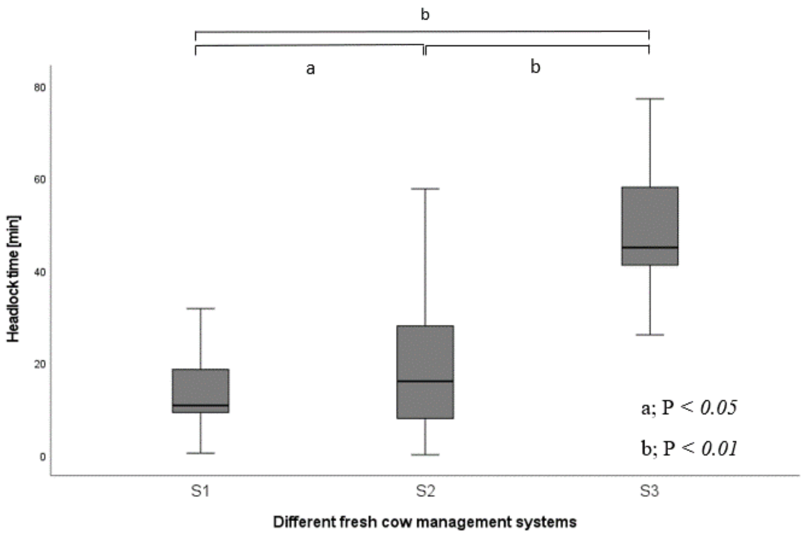

Figure 1: Distribution of headlock times per cow [min] for the different fresh cow management systems (S1–S3). Significant differences are presented by a and b.

Discussion

The objective of this study was twofold. First, the duration of individual examinations was determined. Second, three different fresh cow monitoring systems were compared.

One of the most commonly performed examinations is the measurement of rectal temperature in the first 10 days of lactation (Smith & Risco, 2005). Espadamala *et al.* (2016) and Heuwieser *et al.* (2010) reported that 36%, respectively 34% of the surveyed farms checked the temperatures in fresh cows. In this experiment, the measurement of the temperature was the most frequent (56 %) of all examination steps. It lasted on average 16 ± 3 seconds with a maximum difference of 0.6 seconds ($P < 0.01$). However, this difference among investigators can be neglected from a practical point of view. Guterbock (2004) assumed that it takes four times as much, namely 60 seconds per cow, to take and document the temperature. It should be noted that in our study, only the use of the thermometer, without documentation time was analysed.

Furthermore, fresh cows are frequently checked for DAs. Guterbock (2004) suggests that rumen motility should be determined with a stethoscope or by hand in the paralumbar fossa. In this study, succession- and percussion-auscultation took, on average, 2 ± 1 seconds and 6 ± 4 seconds respectively. Therefore, succession in combination with percussion-auscultation took only 8 seconds on average and are thus even shorter than measuring the temperature. Espadamala *et al.* (2016) described that 67% of the surveyed farms had functioning stethoscopes for rumen diagnostics. However, only 20% of them used a stethoscope when DA was suspected. In this context, it should be noted that the time-benefit ratio for auscultation is favourable, but it requires trained personnel who can diagnose a DA.

Furthermore, different fresh cow monitoring systems were compared. Here the management strategy S1 (by the use of the TL-system, only animals for prophylactic treatments and examinations remained in headlocks) with a median headlock time of 10.7 ± 9.0 minutes shows that this is the most effective one compared to S2 and S3. However, as a structural requirement, a TL system (or something comparable) must be in place to separate the animals. Aalseth (2005) described a fresh cow monitoring procedure where one person is in the feed alley and another person is behind the animals during the examinations one after the other. In our study, only a small difference between the mean fixation times between S1 and S2 was found. In S2, the animals stood in the headlock for an average of 5 minutes longer, but there was a significantly greater variation compared to S1. System 3 was performed according to the farm's procedure, with the animals staying in the headlocks the longest, i.e., 44.95 ± 17.00 minutes in median. It was thus shown that depending on the order of examinations and treatments, the headlock time per cow can be significantly reduced. In all systems, 50% of the cows left the headlocks within 1 hour. These systems must always be carried out by two investigators. However, for farms keeping more than 2,000 cows Espadamala *et al.* (2016) reported, that fresh cow checks are usually carried out by two or more employees.

Follow-up studies should evaluate to what extent different standing times of cows in the headlocks influence their time budget and restrict their natural behaviour. Based on this, optimal management strategies for fresh cows should be developed for different herd sizes, considering not only the cows' needs but also the number of available employees and economic aspects. PLF technologies could be a support to identify animals at risk of disease at an early stage, support decision-making and thus optimise workflows.

Conclusions

Although significant differences in the examination times of different investigators were identified, these can be neglected from a practical point of view. Significant differences in the fixation time of the animals in the headlocks were determined for the different fresh cow monitoring strategies. The results of this study can be used in the future to develop optimal management strategies that take into account cow needs, available labour and other economic factors. In this context, it will also be evaluated what contribution PLF technologies can make to reduce fixation times of cows in headlocks and stuff working hours.

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Validation of a heat detection system in different dairy management conditions

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Abstract
The automated activity monitoring (AAM) system for heat detection is an example of how animal sensor technologies and machine learning can improve heat detection while reducing labour costs. Nevertheless, customizing a heat detection algorithm to fit different management conditions is challenging. A new machine learning technique based on neural networks developed by Datamars SA seems to solve this issue. To develop this algorithm, a training dataset and heat labels were extracted from cattle managed in indoor and grazing conditions. Milk pro gesterone was used as a gold standard for developing the heat detection algorithm. The trained algorithm achieved an F1 score of 83%. The evaluation and commercial validation of the trained algorithm were performed across different farms in Europe, South America, and Oceania using a combination of farmer visual observation and a commercial AMM system as references. Finally, the proposed system was compared to a known commercial system (HerdInsight). The results showed that the final Datamars system outperformed the existing AMM system in both indoor and grazing conditions and achieved F1 scores greater than 90%. The results confirmed that the developed system is well suited to automatically detect heat (oestrus) events.

Keywords: heat detection, dairy, neural networks, AAM

Introduction
Optimal heat detection improves the reproductive life, productive life and welfare of dairy cattle (Rutten et al., 2014). Visual observation of standing heat is not only time-consuming but also suboptimal on most farms, which leads to low submission rates, extended calving intervals and a lower productive life of dairy cattle (Rutten et al., 2014). Research has shown that AAM systems can decrease days to pregnancy by 10 days compared with timed artificial insemination (AI) of cows and reduce labour costs (Stevenson et al., 2014).

Automatic heat detection by accelerometers has become mainstream in many parts of the world (Crowe et al., 2018; Lee & Seo, 2021). These systems outperform visual heat detection by 15 to 35% (Mayo et al., 2019; Nelson et al., 2017). Current leading commercial systems reach F1 scores of 65 to 87% depending on farm management conditions and other biological, environmental, and technical factors (Mayo et al., 2019; Brassel et al., 2018). For instance, the AMM sensitivity is higher during winter than in summer for indoor systems, 90 vs. 75%, and for grazing cows, 80 vs. 50% (Minegishi et al., 2019). Other AMM systems have lower sensitivity indoors than grazing systems, 78 vs. 82% (Roelofs et al., 2017). New knowledge on heat events and algorithm techniques can improve heat detection performance by using better gold standards and a larger number of subjects for the algorithm validation process (Homer et al., 2013; Wang et al., 2020). Moreover, neural networks should provide better performance than statistical algorithms, as they better account for the impacts of farm size, system, and management practices on heat expression.

The benefits of using machine learning for improving heat detection were highlighted in another study that combined different sensors to recognize behavioural changes associated with heat events, which achieved an 82% F1 score (Benaissal et al., 2020). Considering that the optimal time window for AI is 9 to 16 h after the alert is generated (Stevenson et al., 2014), any machine learning algorithm should have a short window to provide optimal AI in detected cattle (Benaissal et al., 2020).

In this document, a neural network algorithm conception, evaluation and validation are described in different farm management conditions. The modelling started with the initial descriptive and statistical analyses of heat events, continued with the comparison of the developed algorithm against a gold standard, and ended with the deployment of the commercial Datamars system on several farms worldwide. The commercial algorithm validation was performed against one leading AMM system. As a highlight, the proposed Datamars system outperformed the existing AMM system across different management conditions.

Material and Methods

Farms and animals

The data were collected on 5 different farms over more than a 3-year period. Except for farm C, all farms were commercial farms. The first two farms (A, B) were used for algorithm development, the third (C) farm was used for model evaluation, and the last 2 farms (D, E) were used for final model validation and for comparison against a leading AMM system (Table 1).

The observational study was conducted by the same team of researchers throughout all farms. The mounting of the sensors was not invasive and was usually conducted at the beginning of the trial. The numbers of animals and tags that were mounted for each farm are summarized in Table 2.

Farm A was a grazing seasonal farm in New Zealand. It had 146 cows in total. The trial lasted from October 2020 to January 2021.

Farm B was an indoor production farm with year-round calving. Cows were managed in three groups, and the voluntary waiting period was 6 weeks after calving. Two separate 5-month trials were run on this farm from July to November 2019 and January to June 2020. Both collar and ear tags were mounted in all cattle to compare data from both devices. Hormonal synchronization was used only on anoestrus cows.

Experimental Farm C has been managed by the Loire-Atlantique Chamber of Agriculture and the Institut de l'ELevage since its creation in 1973. The herd had 85 Holstein cows and 75 heifers. The monitoring period covered cows in all reproduction stages.

Farm D was in England and had year-round calving. The High group had a maximum of 123 cows, and the Fresh group had a maximum of 90 cows. Cows were mounted with Datamars collars and ear tags and HerdInsight collars.

Farm E was a grazing seasonal farm in New Zealand. There were 600 cows in total, mainly Friesians, split into 2 groups. Two hundred animals were mounted with both Datamars and HerdInsight devices and monitored for 4 months.

Table 1: Numbers of animals and heat events per farm and tag type

Farm	Tag	Farm type	Breeding	No. of Animals Tagged	No. of Heats	No. of Hours	No. of Heat Hours	Duration (months)
A	Collar	Grazing	Seasonal	13	212	245751	2922	3
B	Collar	Indoor	All year	101	119	269705	1515	5 + 5
C	Collar	Mixed	All year	58	162	131213	2441	5
D	Collar	Indoor	All year	131	224	393799	/	5
E	Collar	Grazing	Seasonal	200	458	590400	/	4
A	Ear	Grazing	Seasonal	30	36	46350	383	3
B	Ear	Indoor	All year	103	128	281948	1672	5
C	Ear	Mixed	All year	61	149	122950	2181	5
D	Ear	Indoor	Seasonal	141	229	412188	3333	4

<u>Description of the heat detection system</u>

The Datamars system consists of an accelerometer tag, with a gateway that collects the data and forwards it to the cloud where data are processed and alerts are generated. It was developed with two configurations: an ear tag and a collar tag with the estimated battery life of more than 3 and 5 years respectively (Figure 1). The tag records accelerometer data and derives different behaviours or activities, including feeding, ruminating, resting, and standing time, within one-hour intervals.

The system includes a gateway that will actively search for tagged cattle. Once the cattle are in range, all information stored will be sent from the tag to the gateway. The system can support several integrated gateways to ensure optimal data transmission. Most of the activities are processed internally, and the predictions are made on the cloud. The data from all cattle are saved and then processed, and the results are shown via a mobile or web application.

Before the development of the algorithm, all information was checked for data integrity and consistency (Table 1), and any data considered incomplete were removed from the analysis and the algorithm training process.

The machine learning (ML) algorithm was implemented as a multilayer perceptron with a web API so that the model could be called. The heat detection algorithm receives activity data from the cloud, looks at the historical values, calculates the averages for individual animals and the group behaviour, integrates information from other systems (if available), and creates additional features that are fed to the algorithm. The hourly probability of cows being in heat is produced and postprocessed to find the start and the end of the heat event. The best insemination time is estimated, and finally, an alert and other insights are produced to help farmers manage the herd.

Figure 1: Collar and ear tag design

<u>System evaluation and validation</u>

We focused our heat event analysis on nonpregnant cows with greater than 10 days in milk (DIM) (Chanvallon et al., 2014; Brassel et al., 2018; Minegishi et al., 2019). Only complete datasets were used for analysis and evaluation (Table 2). Furthermore, cows with unknown behavior, associated health issues or anestrus were removed from the trials. An event was considered true positive (TP) if the system produced an alert during the reference heat period. The reference heat period was set as a heat ± 12 h from a) visually observed heat (expert/farmer), b) heat detected by other AMMs (reference), c) heat estimated by milk progesterone (gold standard) or d) ovarian ultrasonography scan. The algorithm performance was evaluated by calculating and comparing the precision (PR), sensitivity (SE) and F1 score of the Datamars system in each trial and against another commercial AAM system (Table 2).

Farm C was used for an independent evaluation of the initial model. The researchers from Institut de l'ELevage cross-referenced the heat detection results from the training model with several systems running in parallel on the farm. The systems used were Herd Navigator (milk progesterone), DeLaval activity alarm – AAM collar device, Heat time SCR system – AAM collar device, Datamars ActiveTag – AAM collar and ear tag devices.

For the other selected farms, the heat reference was obtained by combining at least 2 different independent sources, usually visual observation and AAM systems. Each heat event on those farms was examined for activity patterns and cyclicity, and it was cross referenced against positive pregnancy scanning. Table 2 summarizes all heat events, devices, and farm management conditions.

Results and Discussion

Statistical analysis of the activities

Comprehensive knowledge of oestrus-related behaviours is fundamental to achieve optimal oestrus detection rates. During oestrus, cows are between 2.3 and 6 times more active; this change in behaviour lasts between 3 and 24 hours (16-hour average) and is detected by accelerometers (Valenza et al., 2012; Aungier et al., 2015; Silper et al., 2015; Roelofs et al., 2017). Cows in heat can also be identified by the decline in rumination time, and combining more behavioural activities can improve heat detection (Reith, 2018; Benaissa et al., 2020). Furthermore, the length and strength of visual heat depends on several external factors, such as housing type, flooring surface, ambient temperature and humidity, stock density, time of the day, nutritional factors or individual hormonal patterns, i.e., silent oestrus with little or no change in activity behaviour (Valenza et al., 2012; Aungier et al., 2015; Silper et al., 2015; Roelofs et al., 2017).

The acquisition of heat events used as a reference

To overcome the challenges of obtaining optimal references, the appropriate gold standard must be chosen. The gold standards for heat detection are milk progesterone, transrectal ovarian ultrasonography, and confirmed pregnancy (Nelson et al., 2017; LeRoy et al., 2018). However, these methods are expensive and difficult to implement on a large scale. Furthermore, ultrasonography might cause stress and delayed ovulation (Nelson et al., 2017; Roelofs et al., 2004). The use of AAM systems based on accelerometers, video recordings, and nosebands as gold standards to train the machine learning algorithms introduces the intrinsic bias already embedded in the solution. No algorithm can be better than the gold standard on which it is trained. Heat detection by visual observation is on average 50-60% accurate (Chanvallon et al., 2014). Furthermore, the event is not fully described, making it difficult to understand if the observation was made at the beginning, the peak or at the end of the heat period (Nelson et al., 2017). Defining the complete heat event is a prerequisite for developing machine learning models. Therefore, the proposed algorithm incorporates the idea of “expert advice” to cross-check the reference heat events from the AAM systems, visual observation, and pregnancy scans and to analyse the heat behaviour measured by the tags, as well as oestrus cyclicity. The goal of the cross-check was to produce a list with estimated beginning, peak and end times for all reference heat events. In cases where heat was only visually observed, the heat behaviour was examined to decide on the beginning and the end of a heat event.

One downside was that heat events with no clear behavioural signs (silent) could not be detected, except on farm C, where milk progesterone was used as the gold standard. Another downside was that some heat events were missed. Nevertheless, the chance of missing heat was low considering that all refence heat events were confirmed by at least 2 or more independent systems and verified that the activity patterns as well as cyclicity matched the known biological pattern (i.e., activity patterns 21 days before and after each heat event).

Methodological considerations

Animal and group behaviours were used to standardize the data recorded under different management and environmental conditions. This enabled the model to be resilient to different management conditions and unexpected group events. Data normalization significantly decreased the impact of this “group effect” on heat alert generation.

A wide range of factors influences the evaluation of heat detection systems, including methodological, environmental, technical, and biological factors. In some cases, activity data for the same brand of sensors under similar management conditions provide different results (Lee & Seo, 2021). Sadly, many experiments do not report the exact evaluation criteria, which makes it impossible to compare or ascertain which factor caused differences in performance. For instance, SCR Heatime scored from 95% (Nelson et al., 2017) to 71-72% in the F1 score (Holman et al., 2011; Chanvallon et al., 2014). Therefore, care was taken when using similar evaluation criteria for each experiment and AMM systems used as a reference. For instance, evaluating the F1 score was useful and less impacted by technical factors, while the precision and sensitivity were highly impacted by those factors, which was expected considering that there is a trade-off between the two. Therefore, to improve the consistency and reproducibility of the results, all trials were evaluated under the same technical conditions and using the F1 score as the benchmark.

The evaluation of AAM systems only on cows postpartum or after the voluntary waiting period (VWP) is used to exclude the first heat postpartum, as many are likely to be silent (Ranasinghe et al., 2010). For instance, Holman et al. (2011) considered only cows 20 days postpartum, Chanvallon et al. (2014) considered cows from calving to 90 days after calving, while Nelson et al. (2017) discarded all pregnant cows, as well as cows that had undergone any hormonal treatment. We decided to evaluate the systems on cows that were 10 or more days in milk.

Model evaluation

The 10-fold cross validation method was used to evaluate performance on each of the trials involved in the model training. The F1 score for the indoor farms was approximately 85%, while the F1 score for the outdoor grazing farms was approximately 90%. The performances for both the ear tag and the collar tag were similar (Table 2). The difference in performance between the farms can be explained by heat synchronization used in the indoor farm, which reduced the number of true events.

The trained model was evaluated on the blind data from farm C. The F1 scores were approximately 83% for both tag types (Table 2). It is important to note that the evaluation in this case included silent heat events, and the removed cases included a period where milk progesterone (gold standard) could not be recorded due to system malfunctioning. Nevertheless, for the Nedap AAM system, Roelofs et al. (2017) reported F1 scores of 82% and 85% for indoor and grazing farms, respectively, when compared against progesterone measurements. These results agree with the Datamars evaluation on farm C (Table 2).

Table 2: Model evaluation results. For farms A and B, 10-fold cross validation was used, as the model was trained on the data recorded on these farms.

Trial	Tag	Algorithm	TP	FP	FN	PR (%)	SE (%)	F1 (%)	Removed	Note
B	collar	DM	108	31	9	77.7	92.3	84.4	2	10-fold
B	ear tag	DM	103	16	22	86.5	82.4	84.4	3	10-fold
A	collar	DM	188	15	24	92.6	88.7	90.6	0	10-fold
A	ear tag	DM	32	4	4	88.9	88.9	88.9	0	10-fold
C	collar	DM	116	29	20	80.0	85.3	82.6	26	PG
C	ear tag	DM	113	25	20	81.9	85.0	83.4	16	PG

TP = True Positive, FP = false positive, FN= false negative, PR = precision, SE = sensitivity, F1 = F1 Score, removed= heat events removed, Note: 10-fold = 10-fold validation and PG = Milk progesterone (gold standard).

Validation against a commercial system

The model was retrained to include farm C data and then integrated into the Datamars final commercial system. Compared to previous farms where data were first gathered and then processed later, during validation on farms D and E, both Datamars and HerdInsight systems ran in parallel. On farm E, collar tags for both systems were mounted on the same animals. Due to a logistical problem, there was a delay in equipping all the tags on the same cows on farm D. Some cows had only Datamars tags, while others had only HerdInsight collar tags or had all three. As a result, the total numbers of heat events for collar and ear tags are slightly different. Additionally, some events were removed from the analysis, as the data for these events were not recorded (Removed, Table 3), or we could not determine if they were actual heat events (Unknown, Table 3).

The F1 scores for the Datamars system were 92% for collar tags on both farms. The performance of the Datamars ear tag was slightly lower, with an F1 score of 89%. The HerdInsight system had an F1 score of 84% on the grazing farm, while it underperformed on the indoor farm, with an F1 score of 70%. Our findings agree with a previous validation of the HerdInsight AAM system, which found an F1 score of 81.4 on grazing farms (Brassel et al., 2018). Nelson et al. (2017) assumed that different management conditions would impact the performance of standard heat detection algorithms. Our results with HerdInsight seem to confirm that assumption (Table 3). The use of the machine learning algorithms seems to reduce that effect, as in both management conditions, the Datamars algorithm performed similarly (Table 3).

The difference in the Datamars system performance during evaluation on farm C (83%) and validation on farms D and E (collar 92% ear 89%) could be explained by silent heat events that were included in the evaluation on farm C. Similarly, the initial model was trained on events from farms A and B only, while the final model that was validated on farms D and E also included events from farm C (Tables 2 and 4). The slight difference between collar and ear tag F1 performance (92% vs. 89%) of the Datamars system could also be explained by the number of heat events on which the model was trained: 412

events for the collar against 248 events for the ear tag (Table 2). It is worth exploring whether training on more events would improve the system performance and what would be the limit of such improvement.

Table 3: Model validation results. DM – Datamars, HI - HerdInsight

Trial	Tag	System	TP	FP	FN	PR (%)	SE (%)	F1 (%)	Removed	Unknown
D	collar	HI	167	105	35	61.4	82.7	70.5	14	10
D	collar	DM	180	20	12	90.0	93.8	91.8	32	14
D	ear	HI	167	114	41	59.4	80.3	68.3	13	10
D	ear	DM	165	13	27	92.7	85.9	89.2	37	11
E	collar	HI	397	92	58	81.2	87.2	84.1	10	8
E	collar	DM	421	28	37	93.8	91.9	92.8	7	8

TP = True Positive, FP = false positive, FN= false negative, PR = precision, SE = sensitivity, F1 = F1 Score, Removed= heat events removed and Unknown =unknown heat events.

Conclusion

The validation of the presented algorithm that is integrated into the Datamars system suggests that different farm management conditions can be overcome by a machine learning-based approach to heat detection. The results of our 3-year development and evaluation suggest that the Datamars system improved the performance of heat detection throughout different management conditions, outperforming the current commercial AAM system. Moreover, it provided optimal heat detection capabilities compared to visual observation by farmers. Using the Datamars system to automate heat detection on dairy farms will free up labour and reduce costs while improving the reproductive and productive performance of dairy cattle worldwide.

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SESSION 10

Pigs:
Computer vision in Gilts, Weaners and Growers

Automatic extraction of gilt gait pattern using computer vision technologies

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Abstract

Sow productive lifetime or sow longevity is a complex trait, and is determined by many genetic and environmental factors. A previous study found that feet and leg soundness, lameness, or leg problems represent the second most identifiable reason that sows leave commercial breeding herds. Gait status is often visually assessed by an experienced gilt manager, which requires significant amount of human labor and is inherently subjective. Therefore, automating this assessment is important for improving sow productive longevity. In this study, a total of 155 gilts were captured by a side-view camera as they passed through the alley and individual gait scores were visually estimated. To capture the gait pattern, the YOLOv3 object detection model was applied to isolate gilts from the background. Then, a pose estimator which stacks a Convolution Neural Network with three deconvolution layers was used to extract the locations of 19 body landmarks with a mAP (Mean Average Precision) of 99.1%. Guided by empirical metrics in manual assessment, static features (Stride Length, Leg Angle) and dynamic features (Lagging Indicator, Skeleton Energy Image) were extracted and evaluated. The result shows that the combination of Leg Angle and Lagging Indicator provide the best performance, by which the worst and best gait animals are linear separable.

Keywords: Gilt lameness, gait analysis, pose estimation, computer vision

Introduction

Sow productive lifetime or sow longevity is a complex trait and is determined by many genetic and environmental factors. A previous study found that sow feet and leg soundness, lameness, or other leg problems represent the second most identifiable reason for sows leaving commercial breeding herds (Stalder et al., 2004). Therefore, identifying and (if possible) rectifying such issues can help the producer to achieve better efficiencies with his breeding herd. However, in current commercial practice determining the gait status often involves a subjective assessment made by the gilt manager.

In human applications, computer vision based pose estimation is done by predicting the location of specific keypoints like hands, head, elbows, etc. With rapid development of computer vision technology, such advanced pose estimation algorithms are now able to provide new inspirations for monitoring gilt gait (Fang et al., 2017; Cao et al., 2018).

The objective of this study is to apply the-state-of-the-art pose estimation model to gilt gait assessment so that gait pattern features can be related to leg robustness of the gilts in future data analysis.

Material and methods

Experimental data

A total of 155 gilts were filmed from a side view perspective while they were passing through an alley (length of 5m and width of 1.8m). To accurately capture the motion of the walking gilts, the action camera GoPro HERO 9 (https://gopro.com/) was used, as its properties of faster shutter speed, larger aperture, and higher ISO speeds allowed for video capture with minimal motion blur. The raw video was captured at the resolution of 2704 * 1520 pixels with 120FPS as shown in Figure 1. The front and rear leg of each gilt was scored by experts at PIC according to the criteria associated with structure, quality of movement, and physical defects (Stalder et al., 2004). A histogram summary of the gilt leg scores is shown in Figure 2, where it can be seen that the score ranged from 4.0 (poor leg) to 8.0 (strong leg). In a well-managed gilt farm, gilts outside this range are very rare.

Figure 1: An example of raw data

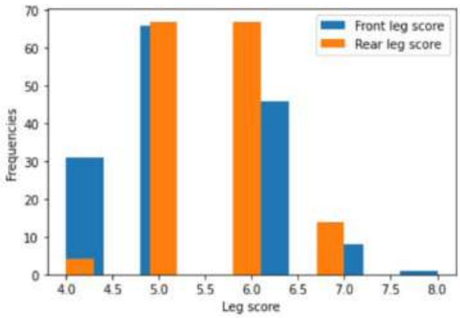


Figure 2: Front and Rear leg score histogram

Image annotations

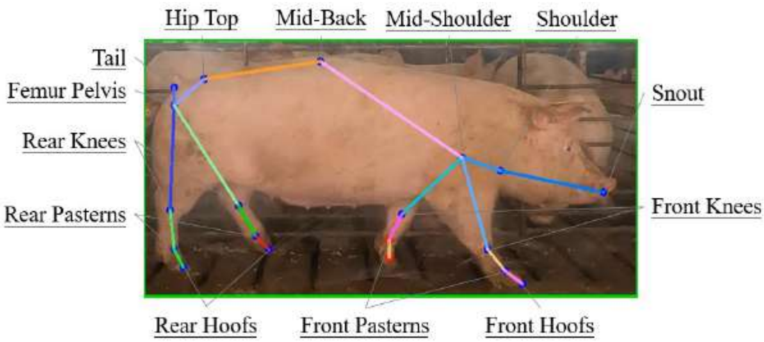


Figure 3: Pre-defined 19 body landmarks in *PigPoints* dataset

To isolate gilts from the background (object detection task) and locate body landmarks (keypoints detection task) using deep learning techniques, two datasets were created for training and evaluation - ***PigDet*** and ***PigPoints***, respectively. ***PigDet*** consisted of 1448 images, in which a bounding box is assigned for each gilt. ***PigPoints*** consisted of 1100 images, in which a total of 19 body landmarks were pre-defined as shown in Figure 3. Both ***PigDet*** and ***PigPoints*** were labelled by COCO annotator tool (https://github.com/jsbroks/coco-annotator) and divided into a training set and a validation set with a ratio of 4:1 to evaluate the model performance.

Development of the pose estimation model

Existing pose estimation methods can be categorized into top-down and bottom-up approaches. Our study aimed to build a robust top-down approach that incorporated a bounding box detector followed by estimating the parts and calculating the posture of each pig.

For the object detection model, YOLO v3 was employed for isolating gilts from the background by a bounding box (Redmon et al., 2018). As a one-stage object detector, YOLO v3 is famous for its fast-inferencing speed and flexible architecture, which can be adapted for, e.g. YOLO NANO or precision, e.g. YOLO Large.

For the pose estimation model, we propose a simple architecture that stacks a Convolution Neural Network (CNN) with three deconvolution layers, as shown in Figure 4. Such architecture provides most flexibility to replace the backbone (CNN part) with either a deeper backbone to pursue higher accuracy or a lighted-weighted backbone to improve inferencing speed. We tested the performance of two different CNN backbones: ResNet-50, ResNet-101 and ResNet-153.

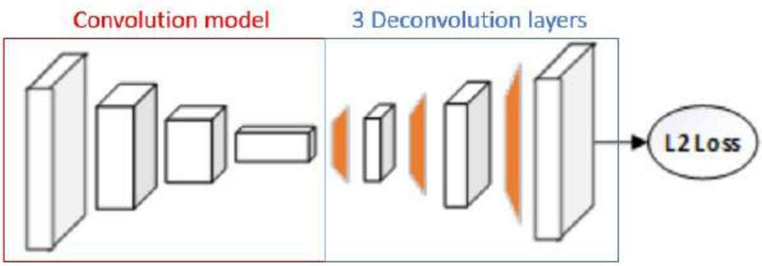


Figure 4: Architecture of the pose estimation model

Since the model predicts 19 body landmarks (Figure 3), the last deconvolution layer has 19 channels. Each channel outputs a heatmap that considers only one key point. To train the pose estimation model, 19 heatmaps should be generated as ground truth, as shown in Figure 5. L2 loss was used to minimize the error, which was the sum of the all the squared differences between the ground truth heatmap and the prediction heatmap. The pose estimation network is trained by the following hyper-parameters:

— Stochastic gradient descent with a momentum of 0.9, a weight decay of 0.0005.
— The network is trained for 150 epochs with a batch size of 64.
— The learning rate schedule follows the cosine annealing from 0.0001 to 0.0005.

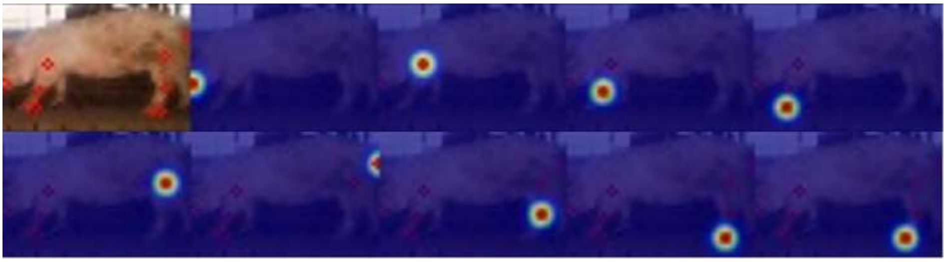


Figure 5: Generated ground truth heatmap for body landmarks

<u>Gait features exploration</u>

Static gait feature – Leg angle as stride length indicator. Guided by empirical metrics in manual assessment, Stride Length is a generally accepted metric. However, distance measurement by image processing is significantly affected by geometric distortion and perspective effect. Therefore, we used the angle of two front legs to approximate the stride length (as shown in Figure 6). Angle features also has the property of scale invariance.

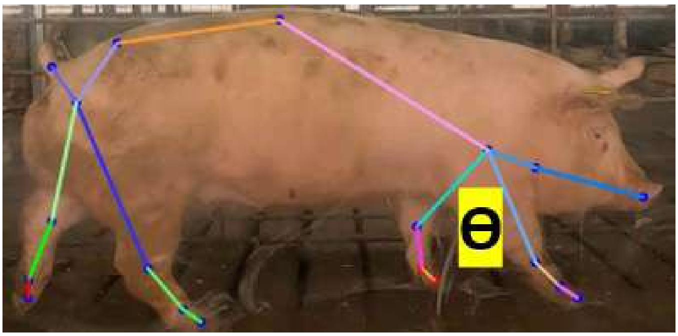


Figure 6: Static gait feature – front leg angle

Dynamic gait feature - Lagging Indicator is designed to quantify the walking coherence, based on the observations: 1) For stronger front legs, gilts can support their body weight on single front leg, so they usually lift the rear leg before landing on both front legs; 2) Conversely, for weaker front legs, gilts only dare to lift their rear leg when ensure that both front legs are firmly on the ground. Periodic changes in the angle of front legs and rear legs when gilts pass through the alley are shown in Figure 7, the Lagging Indicator is calculated by formula (1), where and are illustrated in Figure 7(b), which actually measures the offset of blue curve and green curve.

$$LI = 2 \times \frac{A}{B} \tag{1}$$

Dynamic gait feature – Skeleton Energy Image (SEI) is a data driven method which was proposed for representing different types of pathological gait (Loureiro et al., 2020). The way humans walk can also be used for identification purpose and is usually known as gait recognition. Given its success in human gait study, we also tested its performance on representing different leg scores. The SEI for a gait cycle corresponding to a set of N images, I_t (x, y), can be computed by averaging the skeleton of those images:

$$SEI(x,y) = \frac{1}{N}\sum_{t=1}^{N} S_t(x,y) \quad (2)$$

Where, S_t (x, y) is the skeleton by linking the key points. In this study, we evenly sample 15 images in a stride cycle. Some examples of generated front leg SEI and rear leg SEI is shown in Figure 8. In total, we generated 176 SEIs per gait score and employed a CNN (ResNet-50) as image classifier.

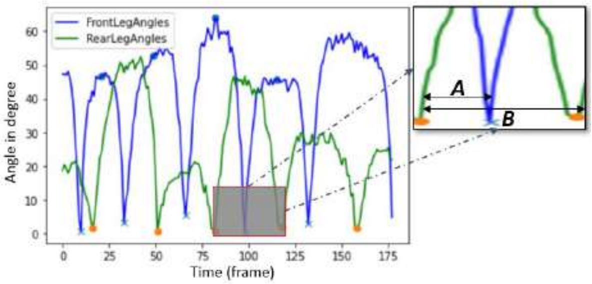
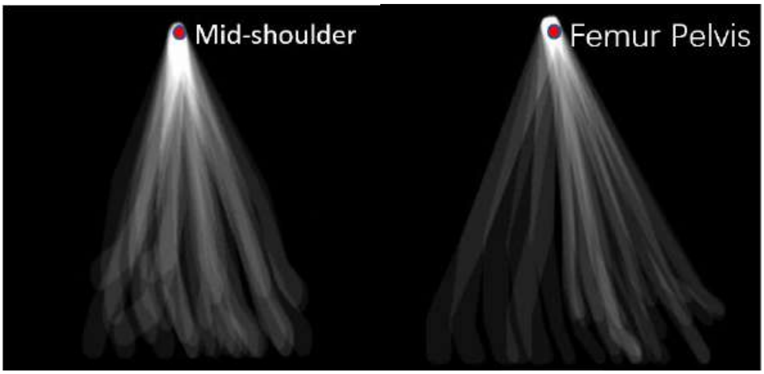


Figure 7: Periodic changes in the angle of front legs and rear legs when gilts pass through the alley



(a) (b)

Figure 8: Generated Skeleton Energy Images. (a) SEI of front leg is generated by fix the Mid-shoulder point; (b) SEI of rear legs is generated by fix the Femur-Pelvis point

Results and Discussion

The performance of YOLO v3 is summarized in Table 1. We finalized YOLO v3 small as the object detector whose inferencing speed is around 150 frames/s with NIVIDIA GTX3090 GPU device.

Table 1: Performance comparison of different YOLO v3

Model	mAP @0.5:0.95	Params(M)	FLOPs @640*640
YOLOv3 small	0.954	7.2	16.5
YOLOv3 medium 0.973		21.2	49.0
YOLOv3 large	0.975	46.5	109.1
YOLOv3 xlarge	0.988	86.7	205.7

The performance of proposed pose estimation model is summarized in Table 2. Balancing the speed and mAP, ResNet-50 was finalized as CNN backbone in this study.

Table 2: Comparison of pose estimation model with different CNN backbone

Keypoints	Average Precision		
	ResNet-50	ResNet-101	ResNet-153
Snout	0.94	0.95	0.97
Shoulder	0.89	0.88	0.91
Mid-Shoulder	0.87	0.92	0.91
Mid-Back	0.94	0.96	0.96
Hip-Top	0.91	0.95	0.98
Tail	0.95	0.94	0.97
Femur Pelvis	0.89	0.92	0.97
Rear Knees	0.97	0.99	0.98
Rear Pasterns	0.98	0.95	0.95
Rear Hoofs	0.96	0.97	0.97
Front Pasterns	0.97	0.98	0.97
Front Hoofs	0.96	0.96	0.96
Front Knees	0.96	0.95	0.98
mAP	0.95	0.96	0.96

Figure 9 visualizes the gait pattern by plotting the distribution of the extracted gait feature and training recordings of Skeleton Energy Image (SEI). The results show that the stronger legs (with higher leg scores) had larger leg angles (or larger stride lengths). The trend was evident even if their distributions overlapped heavily (as shown in Figure 9a). The Lagging indicator is more distinctive (Figure 9b). The combination of Leg Angle and Lagging Indicator provided the best performance, by which the worst and best gait animals are linear separable (Figure 9c). However, the SEI is not as useful as was expected. There are two possible reasons, one is overfitting problem since the limited dataset, another one is the collected data is not optimal due to the difficulty of controlling gilts passing through the alley in a consistent way.

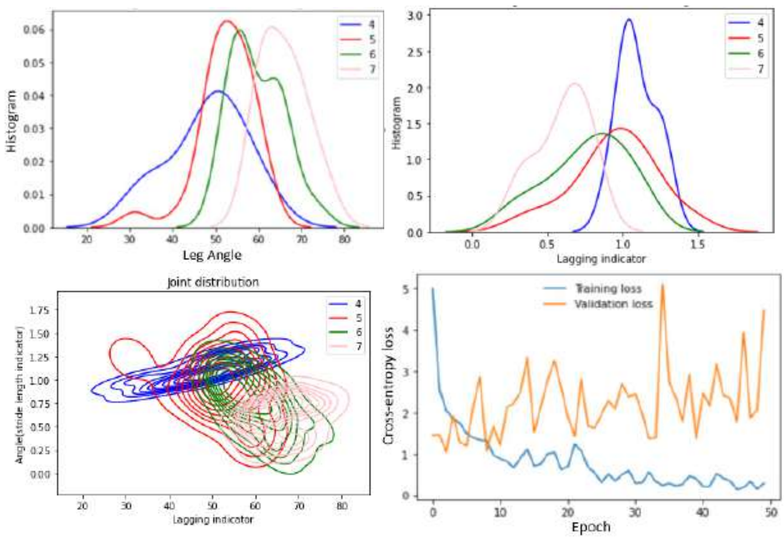


Figure 9: Gait pattern visualization and analysis. (a) Leg Angle as the stride length indicator; (b) Lagging indicator; (c) Join distribution of Leg Angle and Lagging indicator; (d) Skeleton Energy Image classification

Conclusions

This paper proposed a method to analysis gilts' gait pattern by a pose estimation model. We proposed three different graphic features to quantify/measure the leg quality. A preliminary result showed that the combination of Leg Angle and Lagging Indicator provide the best performance, by which the worst and best gait animals are linear separable. More gait analysis will be performed in the future, expecting to distinguish gilts with different level of leg quality.

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Automatic phenotyping of activity traits utilizing NUtrack to enhance gilt selection

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Abstract
A major decision of a sow operation lies in the identification of which gilts to retain given the importance of sow longevity. Automatic computer vision allows producers to classify animals without human interference of natural behaviors. This investigation studied overall activity of replacement gilts and the use of these activities to aid in gilt retention. Beginning around 20 weeks of age, video on gilts (n = 2,374) was collected for nine consecutive d and processed using the NU*track* System, which tracks distance travelled (m), average speed (m/s), angle rotated (degrees), and time standing (s), sitting (s), eating (s), and laying (s). NU*track* is a deep learning-based multi-object tracking system that has been shown to achieve >92.5% precision and recall when tracking the long-term location and identity of individual pigs in group-housed settings. Gilts (n = 1,049) were culled based on structural unsoundness as determined by an experienced herdsman. Data were analyzed using logistic regression (RStudio V1.2.5033) with farrowing group, pen, and on-test date included in the model. Angle *($P < 0.01$)*, avg speed *($P < 0.001$)* and standing *($P < 0.001$)* were significantly associated with gilt retention. Heritabilities were estimated in ASReml 4.1 using an animal model with a two-generation pedigree. Heritabilities are 0.32 ± 0.048, 0.32 ± 0.049, 0.23 ± 0.044, 0.34 ± 0.051, 0.26 ± 0.046, 0.31 ± 0.049, and 0.21 ± 0.044 for average speed, distance, stand, sit, eat, angle, and laying respectively. These data suggest that animal activity and movement, as measured by NU*track*, can enhance herdsman efforts in making culling decisions of breeding animals.

Keywords: Computer-supported measurement, PLF, sow longevity

Introduction
Sow lameness and conformation is the number two reason for sow culling and death (Boyle *et al.*, 1998; Lucia *et al.*, 2000). Previous literature has noted that an increase in the average parity of the U.S. sow herd by a tenth of a parity would result in an annual revenue increase of $15 million in the United States alone (Mote *et. al.*, 2009). The high economic and animal welfare importance of the issue has drawn attention to sow longevity. Manual observations are commonly used in commercial settings; however, it has been shown that manual observations can be inaccurate due to subjectivity, fatigue, and animals responding to a foreign object in their environment (Martin & Bateson, 1993). This leads workers to only see the obvious and/or significant signs when they walk through the barn and that is only if the pig is showing them at that moment. Schlooser (2001) reported that, on average, there is one nursery caretaker per

4,000 pigs in the nursery, meaning that certain injuries or lameness may be overlooked if an individual pig is not actively moving in that moment. It is also important to note that an animal may respond to a foreign object in the environment in a fearful manner via 'fight', 'flight', or 'freeze' (Weimer *et al.*, 2014). This leads animals to mask or hide things from caretakers, meaning that the observation will be missed. This poses a question for producers on how to observe the animals most accurately to obtain their true phenotype in order to catch lameness and other symptoms sooner to treat, care for, and select individuals most effectively. The two main subjective scoring systems used in assessing lameness of livestock are visual analog scores (VAS) and numerical rating scores (NRS). A VAS is composed of either a 100 mm or 150 mm line that is defined by two extreme definitions of sensation, either extremely painful sensation or no sensation at all, located at the two endpoints (Chaput *et al.*, 2010). Observers place a mark on the area of the line that corresponds to their perception of the severity of that sensation, which is then quantified by evaluating its distance from both ends of the line. NRS systems have been designed for many species to evaluate lameness by using broad groups or scores with descriptive scales and definitions that apply varying clinical signs of pain and/or lameness (Quinn *et al.*, 2007). Groenevelt *et al.* (2014) described the four- point NRS scale developed by Zinpro that defines sound as 0, mildly lame as 1, moderately lame as 2, and severely lame as 3. It has been used in swine herds as a tool to quantify and evaluate lameness prevalence on a herd level. Both VAS and NRS are difficult to implement on farm as agreement within subjective scoring is low unless lameness is severe (Quinn *et al.*, 2007). Precision livestock farming (PLF) provides an avenue for individuals to observe and monitor livestock through nonobjective measures more accurately. For these reasons and in order to best select for lameness and longevity, it is in the producer's best interest to identify the precision livestock farming technology that would work best for their operation (Benjamin & Yik, 2019). A noninvasive technology that accurately and precisely monitors animals over long periods of time is ideal for the swine industry. This will allow producers to know the true state of the animal as they cannot hide anything from a system that is monitoring them constantly.

With precision livestock farming, remote sensors such as cameras, microphones, thermometers, and accelerometers are utilized to monitor and/or capture various forms of information that can include images, sounds, heat, and motion all in real time (Benjamin & Yik, 2019). This data is then either stored in an external drive or sent directly to a processing node and processed by specialized algorithms composed of formulas used to solve a desired problem. More specifically, a computer algorithm tells the computer exactly how to perform specific operations to solve a desired problem (Benjamin & Yik, 2019). While researchers have introduced a variety of methods and technologies that fall under precision livestock farming, there has yet to be a system truly fit for modern, commercial livestock operations.

Our group at the University of Nebraska-Lincoln began addressing this gap by presenting a system through the Mittek *et al.* paper (2018) that utilizes depth images to continuously track individual nursery pigs in a group-housed setting. More specifically, the tracking method takes an assumed set of targets that all have a known shape and fits a fixed number of ellipsoids to three-dimensional points obtained from depth images using expectation maximization. This does require an initial one-time user annotation to identify the corner points of the pen, the feeder, and the waterer. Lancaster (2018) evaluated the system of Mittek *et al*. utilizing 28 newly weaned pigs over the course of 42 days. Based upon 10,311 data points, overall accuracy was determined to be 96.2%, with accuracy classification of the activity of walking and lying at a rate of 99.3% and 99.1%, respectively, and close proximity to the feeder and in close proximity to the waterer at a rate of 86.4% and 73.6%, respectively (Lancaster, 2018). These accuracies and specifics on activity data show that a PLF system can be effectively used to further study group-housed pigs. This led us to the hypothesis that the NU*track* system (Psota *et al*., 2020), an advanced PLF method that utilizes 2D cameras and deep learning, can be used to identify and track various activity traits. This investigation aims to estimate NU*track's* ability to aid in selection decisions by analyzing the various activity traits of selection eligible gilts in a group-housed setting.

Materials and Methods

Animals:

All procedures involving animals were approved by the University of Nebraska Institutional Animal Care and Use Committee protocol number 2089. The group-housed replacement gilts (n = 2,374) used in this study were housed at the United States Meat Animal Research Center in Clay Center, NE. The gilts are York by Landrace maternal females. The USMARC swine resource population is managed as a rotational crossbreeding herd alternating between Landrace and Yorkshire semen, sourced from four different commercial genetics suppliers. All replacement gilts are produced on site and animals are managed in facilities similar to commercial production with newly constructed breeding, gestation (group-housed) and farrowing barns. Gilts are penned in groups of 12-16. The pens in the finishing barns are 2.438x7.01m. Gilts were observed and either kept for use as a replacement female or culled to market by an experienced herdsman primarily based on conformation.

NU*track*:

FLIR/Lorex NVR Systems (Lorex Corporation, Linthicum, Maryland) utilizing 4K (8MP) IP cameras (IP67 rated to better withstand the harsh environments in swine facilities) with added infrared capability for nighttime recording were used to collect video at 5 frames per second. Given the resolution of the video and the frame capture rate, data storage requirements are approximately 1 terabyte per six cameras for a week's worth of video. Researchers installed a single camera in each pen where it was placed on the ceiling as close to the center of each pen as possible while avoiding feed lines and any water piping that may obscure the image of the gilts in the pen. The captured video was sent to the Network Video Recorder (NVR) and then pushed to a Dell Alienware desktop computer with NVIVIA Graphics Processing Unit (GPU) running NU*track*. Researchers at the University of Nebraska-Lincoln (UNL) procured, installed, managed, and analyzed video output on an individual animal basis from group-housed pigs in finishing. Utilizing the proprietary data capture and analysis system developed at UNL, data collected on individual pigs included the time/day associated with walking, standing, at feeder, at water, and lying down; distance walked/day; and coordinates of head and tail of each pig within pen associated with activity.

NU*track* is a deep learning-based multi-object tracking system that has been shown to achieve >92.5% precision and recall when tracking the long-term location and identity of individual pigs in group-housed settings (Psota *et al.*, 2020). NU*track* uses Bayesian multi-object tracking where the points of reference on each individual gilt are the ear, point of shoulders, and rump as seen in Figure 1. To correctly identify the individuals in each pen, 16 individual Allflex ear tags per pen were used in this study. The specific color and alpha-numeric tags were specifically generated to maximize tag identification in research barns. The ear tags are non-barcoded and non-RFID. The system identifies individual animal identification probabilities with a deep classification network. This allows the tags to be obscured from view while still allowing the system to correctly identify the location and orientation of individual pigs within a group-housed environment. This system has shown an accuracy to automatically maintain individual pig identity in pen settings at greater than 97% when pigs are standing and can automatically annotate the pig's current activity to greater than 95% accuracy (Lancaster, 2018).This study focused on the activity traits of distance travelled (m), avg speed (m/s), angle rotated (degrees), and time standing (s), sitting (s), eating (s), and laying total(s). Angle is the circular rotations that an individual makes while it is in motion. These activity traits can be indicators of an animal's ability to move about freely without pain. An example is that an animal that is in pain while standing will limit its mobility when compared to its contemporaries.

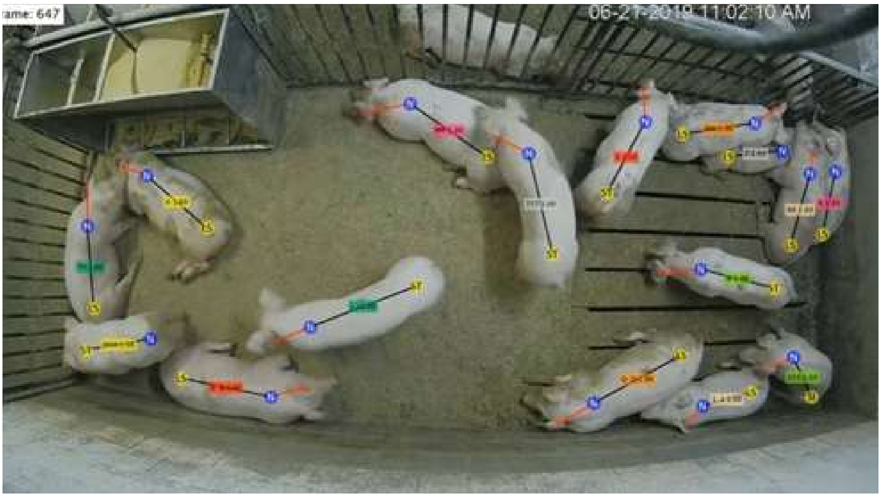

Figure 1: This is a screen capture of the NU*track* system used to validate the animal identification and activity. The activity is denoted as standing (ST), lying lateral (LL) lying sternal (LS), or sitting (SI) being displayed in the yellow circle on the posterior of the pig. The identification that NU*track* assigns to each pig is noted in the colored blocks shown in the center of each individual pig along with the probability that it is the correct identification. The classification of a pig engaged (E) at the feeder or not engaged (N) at the feeder is noted in the blue circle at the anterior of the pig.

Data Management

Beginning at 20 weeks of age, video recorded data of approximately 75 gilts per week for a total of 2,374 gilts was collected for nine consecutive days, with the first partial day and ninth partial day removed from analysis as they are not complete 24-hour time segments. The twentieth week of age was chosen as it represents the time at which most gilts are identified as either replacement females in a breeding operation or sold as market females. A complete seven day analysis period captured of an animal represents a truer status of the animal when compared to the single snap-shot in time which is what the on-site selectors would see during the normal selection process. Animals that did not make the full test period were dropped from analysis. The final values used for analysis were the average daily values for each individual trait on each individual gilt.

Statistical analysis:

Heritability analysis was done using an animal model with a two-generation pedigree in ASReml 4.1. (Gilmour *et al*., 2014). For association with gilt retentions, data were analyzed using mixed models in RStudio (V 1.2.5033) including fixed effects of birth farrowing group, pen and on-test date combination, and random effects of the activity traits distance travelled (m), avg speed (m/s), angle rotated (degrees), and time standing (s) and laying (s). The model used was:

$$y_{ijkl} = \mu + An_l + Av_l + D_l + S_l + L_l + fg_i + p_j d_k + e_{ijkl} \tag{1}$$

where y_{ijk} is equal to gilt retention or removal for gilt l, μ is equal to the intercept, An_l is equal to the angle observation for gilt l, Av_l is equal to the average speed observation for gilt l, D_l is equal to the distance travelled observation for gilt l, S_l is equal to the time standing observation for gilt l, L_l is equal to the time laying observation for gilt l, fg_l is equal to the fixed effect of birth farrowing group with i = 1–54 levels, p_j is equal to the fixed effect of pen with j = 1-23, d_k is equal to the fixed effect of on-test date with k = 1-30, and e_{ijkl} is the random residual.

Results and Discussions

Heritability

Listed in Table 1.1 are the variance components and heritability estimates calculated in ASReml 4.1 using a two-generation pedigree and the average daily standardized values for the activity traits. Genetic variance is the result of the varying genotypes of the individuals in a population, residual variance is the non-genetic variation between the individuals observed, and phenotypic variance is the total variation observed, which is the summation of the genetic and residual variances. These components are then used to calculate the heritability, which is found by taking the genetic variance divided by the phenotypic variance. The heritabilities for the activity traits range from 0.23 to 0.34 and can be seen in Table 1.1. Angle had an estimate of 0.31 and is of intrigue as it is a more novel trait with a strong behavior component going beyond the basic necessities of life such as resting and moving to feed and water. Further research on the eating measurement needs to be elucidated to more precisely identify when the individual is actively eating or simply just standing at the feeder. While the importance of actively eating at the feeder is obvious, time standing at the feeder is also of importance as the animal may be exhibiting dominance behavior precluding additional pen mates from eating. Taken as a whole, these nine activity traits identify as moderately heritable, which means that they can be used to aid in selection decisions. Knauer *et. al.* (2011) measured growth and composition traits on gilts at puberty and again at 114 kg (n = 1,225). Locomotion was found to have a heritability estimate of 0.36, which aligns with the moderate heritability estimates of the seven activity traits in the current study. To our knowledge, this is the first time these specific traits have been analyzed in this capacity as well as the first time the heritabilities of these activity traits have been calculated on pigs, especially in a group-housed environment. Additionally, these activity trait heritabilities are calculated utilizing a multi-hole feeder that allows competition versus a single-hole electronic feed recorder.

Table 1: Genetic variances, residual variances, phenotypic variances, and heritability estimates of the seven activity traits.

Activity Trait	Genetic Variance (σ_g^2)	Residual Variance (σ_e^2)	Phenotypic Variance (σ_p^2)	Heritability Estimate (h^2)
Angle	0.19 ± 0.033	0.42 ± 0.27	0.61 ± 0.020	0.31 ± 0.049
Average Speed	0.17 ± 0.029	0.37 ± 0.023	0.54 ± 0.018	0.32 ± 0.048
Distance	0.19 ± 0.034	0.41 ± 0.027	0.60 ± 0.020	0.32 ± 0.049
Eat	0.12 ± 0.023	0.35 ± 0.020	0.47 ± 0.015	0.26 ± 0.046
Lie Total	0.11 ± 0.024	0.41 ± 0.022	0.52 ± 0.016	0.21 ± 0.044
Sit	0.20 ± 0.034	0.39 ± 0.026	0.59 ± 0.020	0.34 ± 0.051
Stand	0.12 ± 0.025	0.42 ± 0.023	0.54 ± 0.017	0.23 ± 0.044

Gilt Retention

Investigation into these activity traits and their association with gilt retention was warranted given the phenotypic variation observed. After analysis, angle *($P<0.01$)*, average speed *($P<0.001$)* and time standing *($P<0.001$)* were significantly associated with gilt retention. These results align with a study reported by Stock *et al.* (2018) where the feet and legs of replacement females (n=319 females) were evaluated at the industry standard time when replacement females are selected (approximately 150 d) and again post first parity (n=277 females). The Stock *et al.* (2018) investigation measured joint angles obtained via image analysis of still images of the carpal joint (knee), metacarpophalangeal joint (front pastern), metatarsophalangeal joint (rear pastern), tarsal joint (hock), and rear stance. Significant differences were observed for all joints between selection and first parity ($P < 0.05$) while heritability estimates were low to moderate (0.04-0.35) for all traits measured across time points. This observation showed that conformation is directly related to sow longevity. The traits analyzed by Stock *et al.* (2018) are singular and rely on images taken at a single time point but make sense as animals that are more correct in their conformation tend to not be lame or hindered in their locomotion. However, the traits we analyzed are not singular given the wide range of reasons beyond simply conformation that can affect an animal's desire and ability to stand and move.

Further research is warranted to truly understand what angle is telling us as it can be considered a composite trait combining both the animal's ability and comfort when moving but also a behavioral trait that has the animal moving in less of a straight line than its pen mates. The distance an animal travels per day was found to not be significantly associated with gilt retention. While an animal is assumed to be sound that travels a greater distance each day, the underlying behavior that motivates an animal to move about also is a contributing factor in its phenotype. Further analysis of distance traveled per day as well as time sitting and standing, should consider models beyond a simply linear model as the trait could have more of an intermediate optimum.

Conclusions

These data suggest that animal activity and movement, as measured by NU*track*, can enhance herdsman efforts in making retention decisions of breeding animals. The moderate heritability estimates of the activity traits provides an opportunity for them to be utilized in multiple tiers within the swine industry. The swine industry is a three-tiered structure denoted as a breeding pyramid (Bichard, 1971) with the most elite nucleus animals at the top of the pyramid and working our way down the pyramid with the commercial animals. While genetic resources flow from top to bottom, economic signals flow from the bottom to the top (Nikkilä *et al.*, 2013). The nucleus level drives genetic change where the activity traits analyzed herein may be utilized as indicator traits for longevity in a selection index, however, genetic progress is not going to be seen in full at this level. The multiplier and commercial levels are set up better to benefit from increased longevity as sows are typically retained longer at these two levels and can be enhanced with the ability of NU*track* to be utilized in direct phenotypic selection. The data reported herein only considers data through gilt selection for breeding. A continuation of this study will be following these females past parity three, the point at which females recover their investment costs. Further advancements in the NU*track* system aim to improve selection of replacement females and decrease economic and welfare concerns associated with current industry standards.

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Utilizing imaging methodologies to classify sow characteristics for optimized selection

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Abstract

Structural assessment is essential to select robust sows for welfare and production efficiency. Structural problems, such as abnormal knee and pastern angles, are the 2nd most common reason for early culling. Incorrect knee and pastern angles are detrimental to locomotion and longevity, whereas intermediate values are considered ideal. Currently, sow structural scoring relies on subjective classification and is time-consuming, inconsistent, and prone to error. This study aims to develop an image processing model to extract representative sow body structural traits from RGB images and identify body structural traits contributing to sow longevity using principal component analysis and supervised machine learning approaches. Ten body structural traits (length, height, depth, angles) from 480 sows at parity 1 mid-gestation were measured from side profile images. For these sows, front knee angles (n = 478) ranged from 138.0 to 163.7 degrees (148.4 ± 6.7°) with a heritability (h^2) of 0.35 ± 0.099, indicating potential to respond to selection. A non-linear principal component analysis demonstrated that sow body length increased with shoulder and flank dimensions, whereas hock angles negatively associated with flank measurements. A feature importance score analysis performed with a light-weight machine learning model demonstrated that sow body depth at the flank was the greatest contributing variable to sow longevity, and all leg angle-based traits contributed more to sow longevity than other length-based body structural traits. This approach demonstrated that PLF tools are of merit to provide efficient datasets and can be utilized in analyzing genetic correlations between body structural traits and sow longevity.

Keywords: structural traits, pig, swine, longevity, conformation

Introduction

The longevity of a sow (productive lifetime) is of high economic and well-being importance to the swine industry. Over the last two decades, sow mortality and early culling rates have increased, resulting in a shorter average lifespan in commercial farms (Supakorn et al., 2019). To cover the gilt development and maintenance costs, a sow must produce at least three parities to become profitable (Stalder et al., 2003; Mote et al., 2008). In addition, reproductive throughput (e.g., litter size at birth) is not maximized until parities 3 to 6 (English et al., 1978, as cited by Friendship et al., 1986). Therefore, culling or mortalities prior to this instance result in lower farm efficiency and productivity. Consequently, there has been a recent push for the development of methodology to select for increased sow longevity directly and/or utilizing genetically correlated traits.

Suboptimal structural conditions (e.g., abnormal knee and/or pastern angles) are the 2nd most common reason for culling prior to parity 4, the time point where development costs are covered. Lameness associated with these structural issues accounted for 22% of all early removals (culling for any other reason than age) in three commercial farms in the United States (Mote et al., 2008) and 16% in three commercial farms in Mexico (Segura-Correa et al., 2011). Conformation assessment is essential when selecting robust gilts as breeding herd replacements. As an example, larger knee (KA) and front pastern (FP) angles are associated with inferior locomotion and consequently longevity, whereas intermediate values are considered ideal. At present, sow structural scoring relies on subjective assessment of breeding herd replacement gilts carried out by trained workers. This scoring method has been reported to be inconsistent, labor intensive, and prone to error.

This study aims to develop light-weight machine learning models to 1) develop an image processing model to quantify sow body structural traits from RGB images and 2) identify important body structural traits contributing to sow longevity using machine learning approaches.

Material and methods

This research was conducted at the Eastern Nebraska Research and Extension Center (ENREC) swine farm located near Mead, NE, USA. All following procedures were approved by the UNL Institution of Animal Care and Use Committee protocol 1859.

Data Collection

A portable action camera (SJ4000, SJCAM, Shenzhen, China) was used to collect side profile images for this study. The camera has a wide angle of view (170°) and an effective resolution of 3.15 megapixels. An open-top customized enclosure (measured 50.8 cm wide and 254 cm long) was built to temporarily halt the animals for imaging. A feeder was placed at the front of the enclosure to ensure sows would stand in a consistent position directly aligned with the cameras. The left side profile images of 480 first parity sows were taken at mid-gestation (day 57) and were processed to quantify structural trait measurements. Ten structural traits that could be objectively measured from the side profile of a sow were selected for this analysis, including body length (BL), body depth at the shoulder (BDS), body depth at the flank (BDF), height at the shoulder (HS), height at the flank (HF), front knee angle (KA), front pastern angle (FP), hock angle (HA), rear pastern angle (BP), and rump slope (RS). An example of a side profile image and the depictions of these ten structural trait measurements can be found below in Figure 1. The life on test (number of days between entry into gilt development and removal) for each sow was recorded and used as the predicting variable.

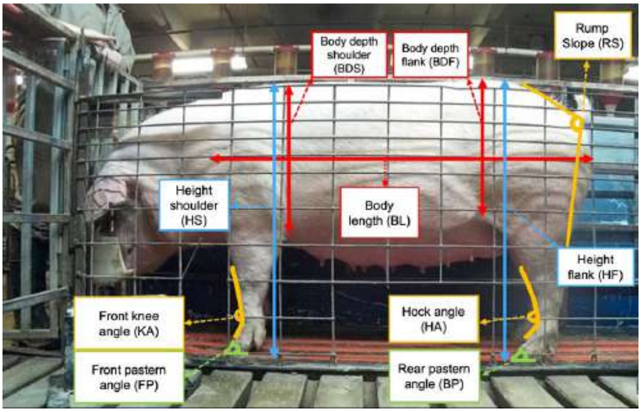

Figure 1: An example of a sow's side profile image and the ten structural trait measurements quantified for analysis. Each measurement and its corresponding description are annotated in the figure.

<u>Image processing for sow profile extraction</u>

Twenty representative sow images from various first parity mid-gestation cohorts were randomly selected to classify color groups and train the designed software to extract sow profiles. The image processing utilizes Mahalanobis distance method (Md) to extract sow from the image. Because of the unique surface color of the sows (light pink) and its obvious contrast to the surrounding backgrounds, the Mahalanobis distance (Devroye et al. 1996), a classification method for analyzing colors, can be used to extract sow profiles from RGB images. The Mahalanobis distance method (Eqn. 1) measures the similarity between an unknown sample group and a known sample group and has been used to determine canopy cover (Liang et al., 2018; Liang et al., 2021) and separate grape and vine (Diago et al., 2012).

$$Md = \sqrt{(X-Y)^T S^{-1} (X-Y)} \tag{1}$$

where X is a three-dimensional vector (R, G, B), which represents pixels from the image to be processed. Y is a three-dimensional vector ($\bar{R}$, $\bar{G}$, $\bar{B}$) that represents the average of reference pixels (reference group) for each class to be identified.

The Mahalanobis color distance (S) standardizes the influence of the distribution of each feature considering the correlation between each pair of terms. In the case of RGB color images, S is computed as (Eqn. 2):

$$S = \begin{bmatrix} \sigma_{R_{ref}R_{ref}} & \sigma_{R_{ref}G_{ref}} & \sigma_{R_{ref}B_{ref}} \\ \sigma_{G_{ref}R_{ref}} & \sigma_{G_{ref}G_{ref}} & \sigma_{G_{ref}B_{ref}} \\ \sigma_{B_{ref}R_{ref}} & \sigma_{B_{ref}G_{ref}} & \sigma_{B_{ref}B_{ref}} \end{bmatrix} \tag{2}$$

and as an example, the elements of S are calculated as:

$$\sigma_{G_{ref}R_{ref}} = \sigma_{R_{ref}G_{ref}} = \frac{\sum_{i=1}^{n}(R_i - \bar{R})(G_i - \bar{G})}{n-1} \tag{3}$$

where σ is covariance of R, G, B reference group colors, R_i, G_i, B_i are the values of the i^{th} match (i=1, 2, 3, …, n), and $\bar{R}$, $\bar{G}$, $\bar{B}$ are the mean color values for R, G, B in the given image, respectively.

In the proposed methodology of this work, six reference groups of pixels were selected to generate the classification, in which every group represented relevant characteristics of sow body classes and background classes. The six groups identified were: sows (white, pink) and background (shadow, feeder, floor, and panels). If any of these classes were not present, or a new class appeared on the image, the number and/or the group labels were automatically modified in the program.

Each reference group was randomly selected from a set of 20 sow images and a set of 20-30 colors in each reference group was chosen. The 20 sow images were used to train software to determine the color group that each pixel belongs to. After training, Md was computed over a set of 480 images in our software and each pixel was assigned to the class with the lowest distance to calibrate and test the accuracy in the determination of sow image. To implement the classification and provide a graphical interface to the user, the software was developed using Visual Basic 2017. Details of the identified pig were shown as pink color and background were shown as black color in the output figures.

From the processed images, five length-based structural trait measurements (BL, BDS, BDF, HS, and HF) were estimated from RGB images using pixel conversion to length, while the other five angle-based traits (KA, HA, FP, BP, and RS) were measured using ImageJ. A generic conversion equation (Eqn. 4) was used to convert pixels to meters.

$$l_m = 2 \times \tan\left(\frac{FOV}{2}\right) \times l_{px} \times Res^{-1} \tag{4}$$

where l_m = dimension (in metric unit), FOV = camera field-of-view (in degrees), l_{px} = measured dimension (in pixels) and *Res* = image resolution (in pixels).

<u>Data and statistical analysis</u>

Principal component analysis (PCA) and nonlinear PCA were conducted to study the relationship between numerical data (BL, BDS, BDF, HS, HF, RS, HA, KA, FP, BP, life on test) and categorical data (last parity achieved). The PCA approach was used to simplify the structure of a set of variables by replacing those with a smaller number of linear combinations from the original variables (Wold et al., 1987). The linear combinations are expected to explain above 70 or 80% variability in the dataset modeled by the variables. Linear combinations with eigenvalues greater than 1 will be selected (Dunteman et al., 1989), and correlations greater than |0.6| indicate significant correlations between the variable and the extracted linear combinations (Dunteman et al., 1989). This approach allows the linear combinations to effectively explain the variability associated with the numerical data. In this study, PCA and non-linear PCA were used to examine the relationship of key numerical variables with numerical and categorical data. The last parity achieved was grouped as categorical variables (0, 1, 2, 3, 4); thus, nonlinear PCA was used to incorporate those nominal and ordinal variables and to discover nonlinear relationships between numerical and categorical variables. PROC PRINQUAL procedure in

SAS (v9.4) was used to fit a principal component model with nonlinear transformation of the variables and plot the results, where all sow body structural measurements were taken as input variables, and sow longevity was the categorical variable for the nonlinear PCA. All numeric variables were specified with a MONOTONE transformation using SAS, so their original values were optimally rescored to maximize fit of a two-component model.

To further explore the contributing features on sow longevity, robust regression models leveraged the open-access Python-based machine learning library, Scikit-learn (Pedregosa et al., 2011), to conduct a feature importance score analysis for the proposed multiple-feature regression to predict sow longevity based on body structural trait input variables. The feature importance scoring is an impurity-based method and critical for reducing unnecessary or redundant features (Nembrini et al., 2018). A light-weight machine learning model, XGBoost Regressor (Chen and Guestrin, 2016), was selected as the best model to perform the feature importance score analysis. All ten structural traits were ranked and plotted based on the calculated feature importance scores. A feature with a greater score plays a more significant role in predicting sow longevity, and lower scores indicate little importance of that input feature on the prediction.

Results and Discussion

Depending on actual computer hardware capacity (e.g., CPU and GPU), it takes 1-2 seconds to process one image using designed software. An example of processed sow image by Md method is shown in Figure 2. Most shadow pixels, floor pixels, and feeder pixels were properly filtered. The proposed classifiers for 6 reference groups performed well without requiring any additional adjustments of contrast, brightness, or color.

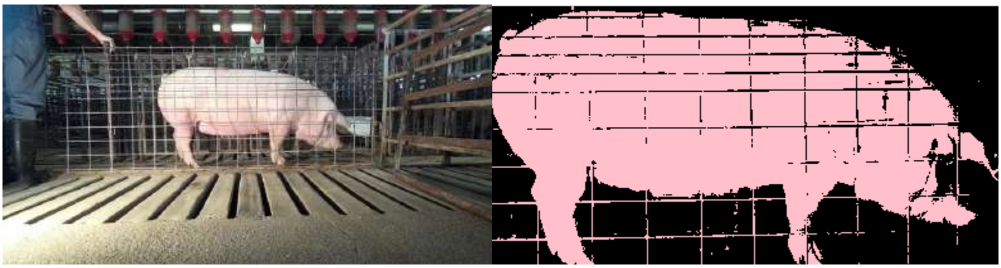

Figure 2: An example of an original (left) and a processed (right) sow image using designed software.

Table 1 lists the summary statistics of the ten measured body structural traits for 480 sows. At parity 1 mid-gestation, KA (n = 478) ranged from 138.0 to 163.7 degrees (148.4 ± 6.7°) with a heritability (h2) of 0.35 ± 0.099, indicating potential to respond to selection (Trenhaile-Grannemann, 2021). Trenhaile-Grannemann (2021) summarized heritability analysis of additional pertinent structural traits.

Table 1: Summary statistics for ten body structural traits from 480 sows first parity, mid-gestation females.

Summary Statistics	Sow Body Structural Trait Measurements									
	BL (cm)	BDS (cm)	BDF (cm)	HS (cm)	HF (cm)	RS (deg)	KA (deg)	HA (deg)	FP (deg)	BP (deg)
Minimum	84.6	33.7	27.8	56.7	64.4	104.3	138.0	124.5	40.0	35.8
Maximum	116.8	48.8	43.1	80.7	83.9	131.3	163.7	163.7	90.0	84.3
Average	98.6	41.0	35.6	68.3	74.1	116.9	148.4	148.4	61.5	60.7
Standard deviation	5.98	2.83	2.69	3.58	3.75	6.68	6.68	6.78	9.16	7.30

Principal component 1 (PCA1) explains 30.4% variance, principal component 2 (PCA2) explains 29% variance and principal component 3 (PCA3) explains 17% variance. In total, the three components explain 76% variance. Total variance explained how much of the data variability was modelled by the extracted factors. PCA1 demonstrated that sow body length increased with depth (BDS, BDF) and height (HS and HF) measurements. PCA2 was associated with high values of RS, whereas HA negatively associated with BDF and HF. PCA3 distinguished that for 17% of the variables, sow longevity increased with KA and decreased with FP and BP angles. However, since PCA3 can only explain a small portion of the dataset, the results generated from PCA3 should not be extensively generalized.

Fig. 3 shows the transformed numerical variables projected into the two-dimensional plane. The green line is perpendicular to sow longevity. The last parity achieved (right panel) with 0 values tend to have less longevity achieved.

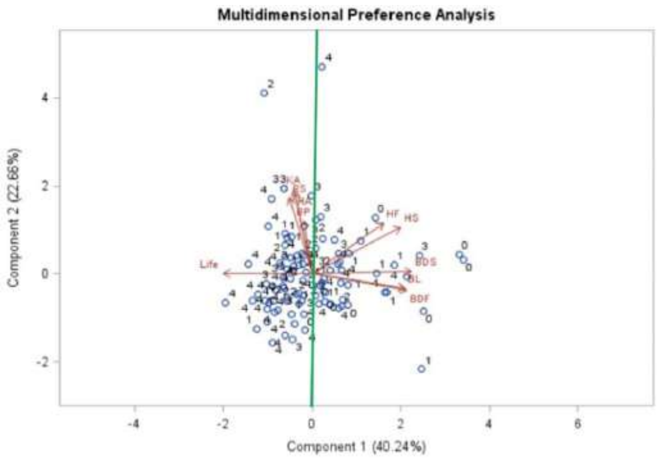

Figure 3: Biplot image displaying the linear and nonlinear variable transformations (PRINQUAL procedure in SAS) for last parity achieved.

The results of feature importance scores are depicted in Fig.4. The sorted features for the most important input variables were BDF (0.1602), FP (0.1283), HA (0.1066), BP (0.1012), and KA (0.0858). Although not statistically significant, Fig. 4 demonstrates an interesting fact that the BDF was the most featured contributing variable, and all leg angle-based body structural traits contributed more to sow's longevity than other length-based body structural traits. This suggests that leg angle-based body structural traits can be used as weighted input variables for future machine learning model training.

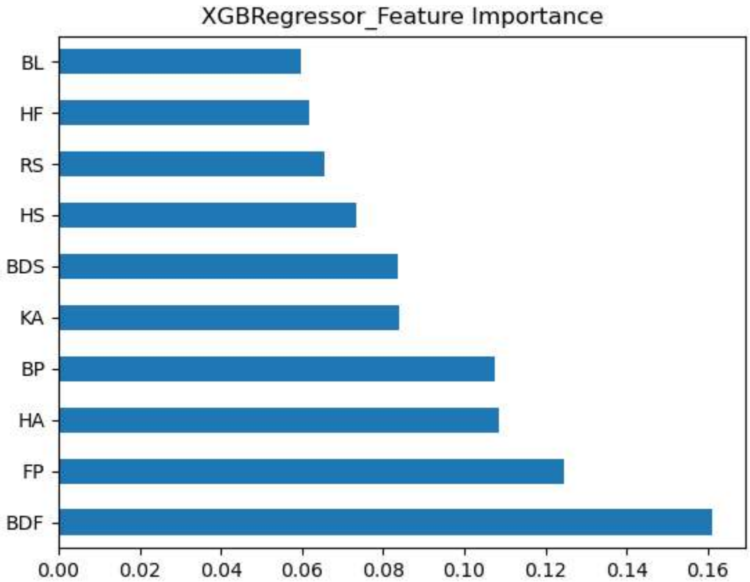

Figure 4: Feature importance score performed by the best-selected machine learning model XGBRegressor for multiple input variables to predict sow longevity (expressed as days on test).

Conclusions

Image processing utilized the Mahalanobis distance method to extract the sow from the RGB images in the current study. Ten sow structural traits were estimated from these images. Principal component analysis demonstrated that sow body length increased alongside shoulder and flank dimensions, whereas hock angles were negatively associated with flank measurements. A feature importance score analysis leveraged a light-weight machine learning model and demonstrated that sow body depth at the flank was the most featured contributing variable, and all leg angle-based structural traits contributed more to sow's longevity than other length-based structural traits. This suggests that leg angle-based structural traits can be used as weighted input variables for future machine learning model training. Refined image analysis and PLF tools should be developed for optimizing routine genetic evaluations and selection indices as well as selection of commercial replacement females.

Acknowledgements

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Investigation and application of tracking algorithm on behaviour analysis for weaners housed in two-climate pens

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Abstract

Computer vision based methods for tracking animals such as pigs have recently been studied. However, most studies focus on algorithm development and not on its application for behaviour analysis. The current study explores how a developed tracking algorithm could be applied in the monitoring of short-lasting event behaviours in weaners, including locomotor play and aggression, wherein the need to retain identity of the performing pig for the full duration of the behaviour is a key contsraint. The involved videos were collected from weaners housed in two-climate pens, which include a cover to provide a resting place with higher temperature. This type of housing presents a challenge when developing tracking algorithms due to pigs disappearing and reappearing from the cover, which typically happens when they perform locomotor play and aggression. To deal with such a senario it is necessary to engineer features beyond Intersection over Union (IoU) to achieve sufficient re-ID information for tracking the pigs. This study focused on extracting features for short-time animal tracking of pig agression and playing by designing re-ID features and utilizing these in combination with IoU to improve the tracking. Twenty video clips including locomotor play and aggression behaviours were selected to test the tracking algorithm. The tracking percentage per individual was 75.15% and 54.62% and the ID switching frequency per individual was 0.23 and 0.41 for locomotor play and aggression respectively. The results indicate that the algorithm is more applicable to one involving short-lasting behaviour rather than multiple pigs with the case of reappearance.

Keywords: tracking, animal behaviour, animal welfare, locomotor play, aggression, two-climate pens

Introduction

Due to the increasing demand for animal products, commercial pig production is continuously intensifying towards larger industrialized farming units, which results in critical challenges for continuous monitoring of animal health within big groups (Berckmans, 2017). On the other side, the development of computer-vision-based algorithms brings lots of new opportunities to animal research (Redmon et al., 2016; Wojke et al., 2017). As such, the development of state-of-the-art approaches for tracking group-housed farm animals is becoming a more widely studied topic. However, most of the studies thus far focus on the development of detection and tracking algorithms (Cowton et al., 2019; Psota et al., 2019), while little work has been devoted to learning the requirements for these tracking algorithm to be accurately in welfare-related behaviour analysis (Wutke et al., 2021). Play behaviour has been suggested as a potential indicator of an animal's welfare (Held & Špinka, 2011) and it is most often observed in young animals that have their primary needs satisfied (Newberry et al., 1988). For pigs in the age of 2 to 6 weeks, locomotor play is considered the most dominant play type (Newberry et al., 1988). Another important welfare indicator for young pigs is aggression behaviour, which usually occurs when piglets are mixed/regrouped at weaning and this is a harmful and costly behaviour, impacting both welfare and feed efficiency (Peden et al., 2018). Thus, a contactless video-based system that can automatically track pigs have the potential to transform pig monitoring into addressing issues in welfare for farming system.

Young weaner pigs are often housed in two-climate pens, in which a roof is provided for covering part of the pen to obtain a thermal comfort zone for resting (Pedersen, 2018). As pigs will go under the cover and thereby disappear from the field of view of the camera, the challenge of tracking a specific behaviour in such a system is to re-identify the pig reappearing from the cover.

The aim of this study is to investigate the capability of computer vision based a tracking algorithm to accurately and continuously monitor the pigs during playing and aggressive behaviours in two-climate pens, with a specific aim of minimizing occurrence of track drop-out and maximizing pig re-identification when it re-appears in a scene (e.g. after emerging from the covered area). To our knowledge, this is the first attempt to track pigs performing specific behaviours (locomotor play and aggression) in the scenario of partly covered pens.

Material and methods

Data collection and selection

The included data were obtained from an experimental study conducted at the pig research facilities at the Department of Animal Science, Aarhus University, Denmark. The study was conducted in accordance with the Ministry of Food, Agriculture and Fisheries, The Danish Veterinary and Food Administration under act 474 of 15 May 2014 and executive order 2028 of 14 December 2020, and under consideration of the Arrive Guidelines (Du Sert et al., 2020).

The videos involved in the study were collected on weaners who were weaned on average at 26 days of age (range: 22-30 days old). The pigs were from the Danbred sow hybrid and a total number of 22 were included in the experiment. At the date of weaning, the pigs were moved into the conventional weaner pen (5.4 × 2.45 m), where approximate 1/3 of the floor was slatted, 1/3 drained (wider slats) and 1/3 solid. The solid floor was covered with a manually adjustable fiber panel (Jyden A/S, Denmark) which was positioned 87 cm above floor level, providing a warmer and darker resting area under the cover (two-climate pen). There were two feeders (Rotecna, type: TR4) placed next to each other (56 × 18 × 2 cm openings), and one pig water trough (Aqua-Level system with hinged trough, Jyden Denmark, 31 × 17 × cm) in the pen. Chopped wheat straw (approx. 260 g) and sawdust (approx. 800 g) were provided on the drained and solid floor daily, respectively. Pigs were fed *ad libitum* post-weaning with a pelleted standardized weaner diet (Prime Midi Piller, DLG, Fredericia, Danmark, 14.8 MJ ME/KG, 19.3 % crude protein). Artificial light was provided from 0700-2300 h.

A 2D camera (HIKVISION, model DS-2CD2145FWD-I, 2.8 mm lens) was placed 2.8m above the pen to provide a top-down view for the entire pen area. The collected video recordings had a frame dimension of 1270 × 720 pixels with 15 fps. Twenty test videos (Mean ± SD: 82.50s ± 53.96s) containing locomotor play and aggression were selected for the study. Besides, another 1605 frames were labeled for training the tracking model, with each pig being labelled by a bounding box and the ID of each pig being annotated.

Tracking model

The tracking model followed the common architecture of multi object tracking, which has a detection branch followed by a tracking module. The detection branch was built based on FairMOT (Zhang et al., 2021) due to its state-of-the-art performance for pedestrian tracking. The model was composed of a backbone network and four parallel heads. The backbone network extracted the features for each object and then four parallel heads were added on top of the backbone network, estimating the heatmap, object center offsets, the size of the bounding box, and extracting re-identification (re-ID) features. Each head was comprised of a 3×3 convolution followed by a 1×1 convolutional layer, generating the final features for tracking. The overview of the training architecture is illustrated in Figure 1.

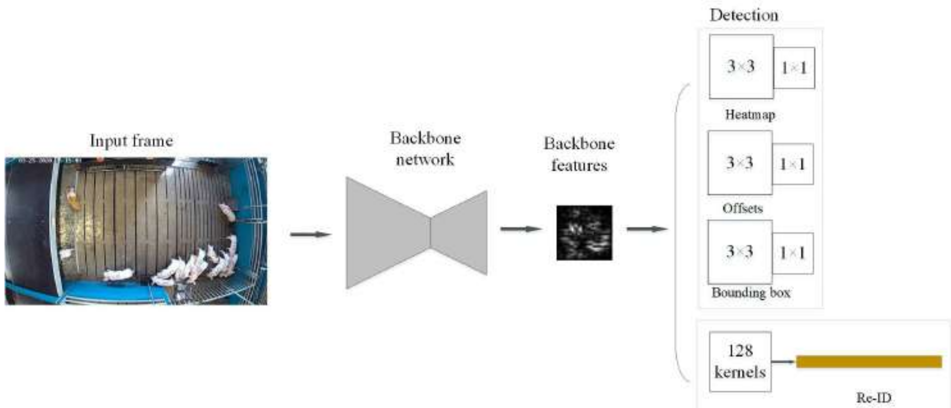

Figure 1: Graphical overview of the training architecture

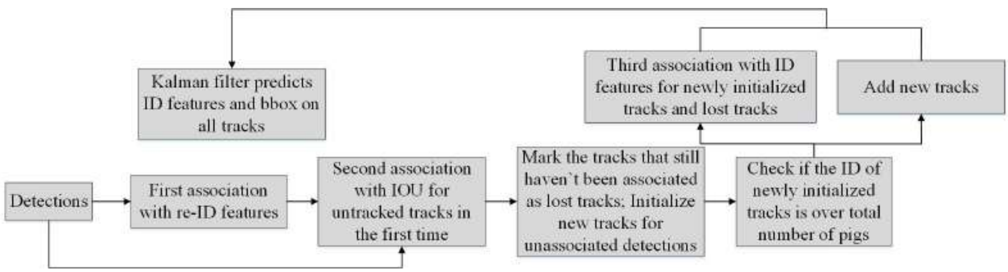

Figure 2: Workflow of tracking

The tracking module used Kalman filter and Hungarian for matching the ID for pigs. The tracks were first initialized by the detections in the first frame, then three associations were adopted to match the existing tracks with the detections in subsequent frames. Specifically, the first association was based on re-ID features and the second one was made by IoU. The third association was presented to address the special case where pigs disappear from the field of view. In that case, the pig is very likely to be assigned a new ID when it reappears from the cover. Thus, to deal with that, the third association based on re-ID features was added to enhance matching the correct ID for the pigs. Additionally, the total number of pigs were set as a constraint parameter to avoid introducing too many ID numbers. Note that the third association is only made when the ID of the newly generated track is over the number of pigs. The workflow of tracking is illustrated in Figure 2.

Model evaluation

The study focuses on tracking of specific behaviour (locomotor play and aggression) in pigs. The performance of the tracking model was evaluated on 20 videos (82.50s ± 53.96s) by the following metrics: Detection Percentage per Performing Individual (DPPI), Tracking Percentage per Performing Individual (TPPI), ID Switching per Performing Individual (IDSPI), which are defined in below.

$$\mathrm{DPPI} = \sum \frac{N_d}{N * f} \tag{1}$$

$$\mathrm{TPPI} = \sum \frac{N_t}{N * f} \tag{2}$$

$$\mathrm{IDSPI} = \sum \frac{IDS}{N * f} \tag{3}$$

Where N_d is the number of detected performing pigs per frame, N_t is the number of tracked performing pigs with the right ID per frame, N is the number of performing pigs in ground truth per frame, IDS is the number of switched ID per frame, and f is the number of frames in one video.

Results and Discussion

<u>Tracking results on test videos</u>

Twenty videos (Mean ± SD: 82.50s ± 53.96s) were included in the test, so the results showed in Table 1 were averaged over all videos. About three quarters of pigs in locomotor play can be tracked, and for aggression the tracking percentage for the individual pig is about one half. Locomotor play and aggression are both behaviours involving fast motion. For pigs housed in two-climate pens, locomotor play is more involved with pig reappearance as pigs need more space to perform this forward moving behaviour. The test results (Table 1) show that the overall tracking performance for locomotor play is better than aggression, including DPPI, TPPI and IDSPI. This indicates that the tracking algorithm performed better in re-identifying single pigs reappearing from the cover, but on the other hand, it performed worse when two or more pigs were involved in an aggressive interaction. Particularly, the IDSPI showed the ID switching frequency for aggression is almost twice as that of locomotor play, meaning that the tracking model has a good performance in matching the right ID based on re-ID features, as the association for reappearing pigs mainly relies on re-ID features rather than IoU. While for aggression, the association mostly relies on IoU. When pigs are involved in aggressive interactions, they are close to each other and move fast. Thus, IoU may match the bounding box with another pig's if the position of the bounding box changes a lot.

Table 1: Tracking performance for specific behaviour (↑ denotes the higher the better, while ↓ denotes the lower the better)

Specific behaviour	Locomotor play	Aggression
Number of specific behaviours	1.60	1.90
Number performing pigs	2.45	4.25
Number of reappearances	2.30	0.55
DPPI (%) ↑	98.71	96.29
TPPI (%) ↑	75.15	54.62
IDSPI (%) ↓	0.23	0.41

Compared with DPPI, evaluators (TPPI and IDSPI) related to tracking are much worse. If a pig is not detected, it cannot be tracked neither. However, it is obvious that the unsatisfactory performance in TPPI and IDSPI is more related to the mistakes in association, i.e., ID switching problem. As mentioned earlier, both locomotor play and aggression are fast movements, which can sometimes make it difficult to recognize the pattern on the back of the pig. Figure 2 (a) shows when a pig goes under the cover and reappears along with another pig within a short period, re-ID features extracted from the blurred patterns cannot match the correct ID. Another ID switching example (Figure 2 (b)) is from an aggressive interaction: one pig was pushed in the corner and not detected, while the pattern of another one was not very clear. In this case, the IoU-based association matched it with the ID of the undetected pig. In most cases, the ID switching problem is caused by blurred patterns, and essentially by fast movements. Due to the limitation of neural network models in image/video analysis, adopting other technologies, e.g., sensors and transmitters, could help increase the performance in tracking.

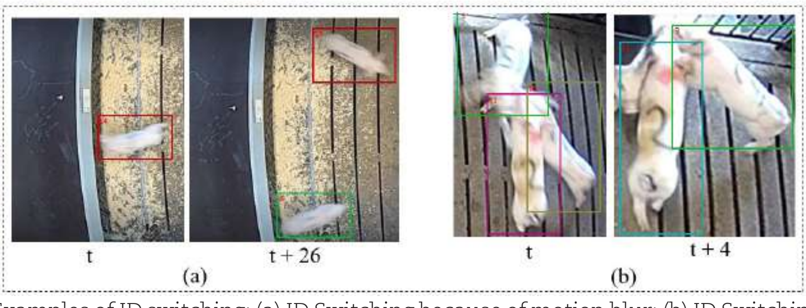

Figure 3: Examples of ID switching: (a) ID Switching because of motion blur; (b) ID Switching because of missed detection. (t is in frames)

Conclusions

This paper investigated and tested a tracking algorithm on weaner pigs performing locomotor play and aggression while housed in two-climate pens. The algorithm was developed specifically with consideration for the reappearance case. For locomotor play where pigs are likely to reappear from the cover, the tracking percentage reached about three quarters.For aggression where two or more pigs turn and move fast but are not frequently involved in the reappearance case, the tracking percentage is about one half. The results showed that the algorithm could be applicable to track and analyze the behaviour of single pig reappearing from the field of view. Regarding fast movement behaviours involving multiple pigs, e.g., recognizing pigs in aggression by tracking, integrating with other technologies (e.g., sensors and transmitters) could be helpful.

Acknowledgements

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Potential of depth images to monitor feeder access in growing pigs: a methodological study

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Abstract

Unobstructed access to the feeder is important for animal welfare and to avoid behavioural problems such as tail biting in pigs. The current study aimed to monitor access to the feeder by exploiting commercially available data and using methods requiring low computational power to monitor floor space available around the feeder. This paper presents the concepts and potentials of the methodology on a small sample of the data. Data included depth images, pig bounding boxes and pig weights. The feeder access area was defined as a half circle around the feeder with a radius corresponding to the average pig length for the average pig weight on the previous day. Within the feeder access area, the number of pixels representing standing pigs, lying pigs and flooring were counted based on depth value thresholds. This was calculated for one pen of pigs, with depth images captured every 10 s across two production rounds (99 days of data). With increasing weight, the available floor space in the feeder area decreased, while the proportion of lying pixels increased. The diurnal pattern also changed: at first the floor space available varied across the day depending on the activity in the area, while later, the floor space available were at a lower and more constant level with proportion of lying and standing pig pixels interchanging. The growth trends and changes in diurnal pattern indicate that pigs were filling up the pen and had no choice but to use the feeder area for resting.

Keywords: animal behaviour, animal welfare, camera, technology, segmentation,

Introduction

In modern commercial pig production, growing pigs are housed on limited space and often with limited access to the feeder, not allowing the pigs to eat in synchrony. As pigs are motivated to synchronise their behaviour (Špinka, 2009), limited space at the feeder can create frustration and competition among the pigs. The space allowance per pig in a pen will become lower as the pigs grow, which may also limit the pigs' access to eat as pigs performing other behaviours may take up more and more of the space necessary to access the feeder. Frustration and competition for resources may lead to abnormal and damaging behaviour such as tail biting and lesions due to aggression, lowering the welfare of the pigs (Botermans et al., 2000; 2016; Kobek-Kjeldager et al., 2022; Valros et al., 2016). To be able to limit the effect of eating restrictions on the welfare and health of the pigs and their production parameters, the pig's access to the feeder should be monitored across the production period to define thresholds for when to act on such restrictions e.g. by increasing the space allowance or feeder space per pig in a pen. The current study aimed to monitor access to the feeder by exploiting commercially available data and using methods requiring low computational power making it possible to implement the algorithms in a commercial farm environment. This paper presents the concepts of the methodology on a small sample of the data and presents preliminary results to indicate the potential of the methodology.

Material and methods

Data and concept

Data of the current study were collected by dol-sensors A/S as part of the validation of their pig weighing technology (iDOL 65, www.dol-sensors.com/products/idol-65-camera). The pig weighing technology uses 3D camera technology and produces depth images and pig bounding boxes to estimate the weight of the pig; all three data sources were made available to the authors for the current methodological study.

The subsample of data used in this paper includes one pen of growing pigs monitored during two production rounds (see Table 1). This pen had an open feed trough with room for two pigs eating at a time and access to the trough from all sides except against the pen wall. The pig weighing technology were placed above the feed trough providing a top-view depth image above a limited area around the feed trough (see Figure 1). Approximately every 10 sec throughout the day, a depth image was taken. The pigs in the image were first identified by a bounding box and those identified as standing were weighed. Thus, the methodology developed in the current study resembles behavioural observations made by 10-sec instantaneous sampling.

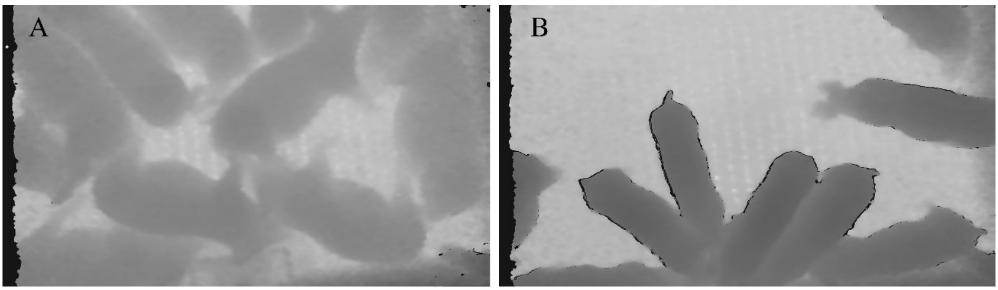

Figure 1: Depth images illustrating the two scenarios causing obstruction of feeder access: (A) no available floor space around the feeder due to the pigs lying in the feeder area, (B) crowding at the feeder.

Access to the feeder can be obstructed in two ways: (1) no available floor space around the feeder due to the pigs lying in the feeder area, (2) crowding at the feeder. The two scenarios are illustrated in Figure 1. The current methodological study will focus on the first scenario and will take advantage of the obvious depth difference between the flooring, lying pigs and standing pigs to calculate the proportion of available floor space in the feeder area. The second scenario will be investigated in the future in a second methodological study including the same data sources.

Table 1: Number of days in each production round, number of days with data and the weight range within each production round for the included pen.

Round	Days	Days with data	Weight range (kg)
1	65	49	41-106
2	60	50	33-94

Feeder access area

To define the feeder access area in the depth image, three masks were created: (1) inventory mask, (2) feed trough mask, (3) feeder access mask. These masks will differ from pen to pen and from herd to herd, depending on the setup of the sensor and the type of feeder. In the current case, the sensor was angled so pen walls were in the field of view; these parts were removed with the inventory mask. The feed trough mask removed the feed trough from the depth image as the feed trough does not count as floor space. The feeder access mask removed the part of the field of view not needed to gain access to the feed trough. In the current case, the pigs could get access to the feed trough from all sides except for the side of the pen wall. Thus, the feeder access area was defined as a half circle with the feed trough in the centre. The radius of this half circle was defined based on the average length of the pig bounding box calculated from the average weight of the pigs in the pen on the day before by the following 2nd degree relationship (equation 1):

$$\text{Radius} = -0.0137 * Weight^2 + 4.374 * Weight + 271.955 \qquad (1)$$

Thus, the radius and area of the feeder access area will increase as the pigs grow larger. Illustrations of the three masks applied to the depth image can be seen in Figure 2.

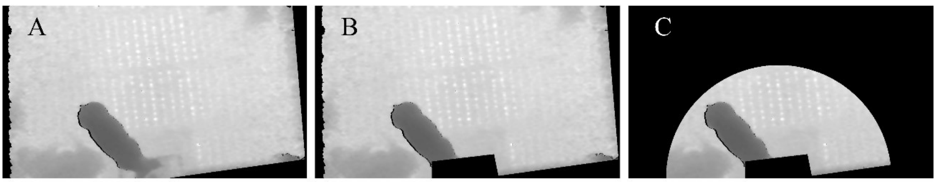

Figure 2: Illustration of the masks applied to the depth images: (A) inventory mask, (B) feed trough mask on top, (C) inverse feeder access mask on top. The masks are represented by black.

Available floor space around the feeder

To evaluate the floor space available around the feeder in each depth image, the masked image was segmented based on depth values and the following rules:

Standing pig: $0 < \text{depth} \leq 1900$

Lying pig: $1900 < \text{depth} \leq 2200$

Flooring: $2200 < \text{depth} \leq$

After segmentation into the three classes, the number of pixels representing standing pigs, lying pigs and flooring were counted and the proportion of pixels representing each class was calculated. An example can be seen in Figure 3.

The above described method of depth image masking and segmentation and calculation of proportion of pixels representing standing pigs, lying pigs and flooring were applied to all depth images of all days of the two production rounds for the included pen. Finally, the average proportion of each class per hour and per day was calculated.

Results and Discussion

The described method took on average 4.54 min (range: 3.32-6.51 min) to run per day of data on an 11th Gen Intel i5, 8-core 2.40GHz processor (CPU) with a 64-bit operating system and 16 GB RAM, indicating that the developed method requires low computational power to run.

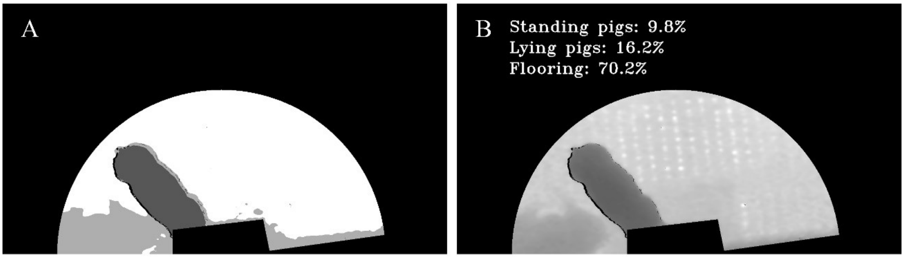

Figure 3: Illustration of (A) the segmentation of the depth image into standing pigs, lying pigs and flooring, (B) the calculation of the proportion (percentage) of pixels within the feeder access area representing standing pigs, lying pigs and flooring.

Figure 4 presents the daily average of the proportion of pixels in the feeder access area representing flooring, lying pigs and standing pigs within the feeder access area across the days of the two production rounds. The two rounds show a similar growth trend in the three parameters with the proportion of flooring pixels decreasing, the proportion of lying pig pixels increasing and the proportion of standing pig pixels being relatively stable across the round. At some point in each round, the proportion of flooring pixels and lying pig pixels cross each other indicating that from this point in time, on average the feeder access area has less available floor space than lying pigs in the area. Around day 55 in both rounds, a change in pattern is seen with an increase in the proportion of flooring pixels and a decrease in proportion of lying pig pixels. While the authors do not have evidence on the reason for this change in pattern, a possible explanation could be removal of the larger pigs of the pen, which is supported by the fact that a slight decrease in average pen weight is seen on the day of the change. If this is the reason, this change in pattern could indicate that pigs prefer to lie in another location of the pen than the feeder access area if given a choice, thereby indicating overcrowding in the pen when pigs lie in the feeder access area.

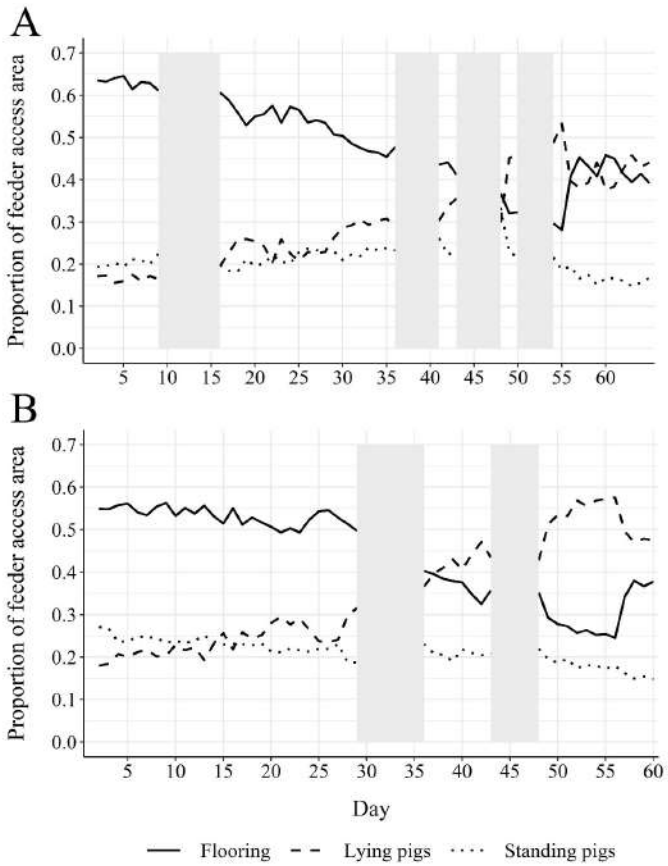

Figure 4: Daily average proportion of pixels in the feeder access area representing flooring, lying pigs and standing pigs across the days of round 1 (A; pigs from 40-106 kg) and round 2 (B; pigs from 33-94 kg). Light grey areas represent days with missing data.

Figure 5 presents the diurnal pattern in average proportion of pixels in the feeder access area representing flooring, lying pigs and standing pigs for each production round on one of the first days of the round, a day close to the change in pattern and a day shortly after the change in pattern. It is seen that in the beginning of the round where the pigs are relatively small, the amount of available floor space seems most to depend on the pigs being active in the feeder access area (e.g. eating). Towards the end of the round where the pigs are relatively large, the amount of available floor space in the feeder access area seems stable and at a lower level across the day, while the amount of pigs standing and lying in the feeder access area seems to be interchanging. This could indicate that the pigs may be disturbed in their resting by pigs eating or opposite that pigs may be limited in their access to the feeder by pigs lying in the area, again indicating overcrowding in the pen. Therefore, identifying when this correlation between lying and standing occurs could be used when indicating an increased risk of compromised welfare to the farmer.

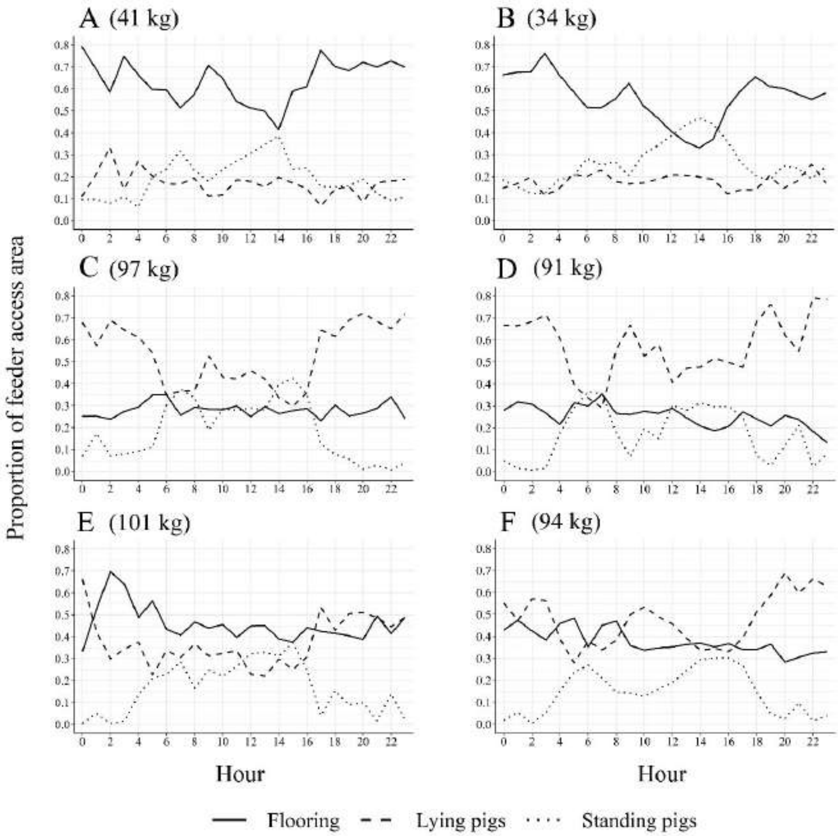

Figure 5: Diurnal pattern in average proportion of pixels in the feeder access area representing flooring, lying pigs and standing pigs in round 1 (A, C, E) and round 2 (B, D, F) at day 2 (A-B), day 55 (C-D) and day 60 (E-F).

The above explanations of trends seen in the data are only speculations and should be investigated further in future studies. However, the current methodology study highlights the potential of how to use already commercially available data to extract even more information with relatively simple methods. The current methodology will in the near future be applied to multiple farms with different feeding systems, while the same data will be used to also develop a method for describing the second mean to feeder access obstruction: crowding at the feeder.

Conclusions

This paper presents the concept and potential of a methodology to monitor access to the feeder by exploiting commercially available data and using methods requiring low computational power. The methodology monitors the amount of available floor space around the feeder and how much of this area is taken up by lying and standing pigs. Data include depth images taken every 10 sec and the method developed could process a full day of data in less than 5 minutes. When applied to one pen in two production rounds, the growth trends and changes in diurnal patterns found followed the expectation of pigs filling up the pen as they get larger and thus, having no choice but to rest in the feeder area.

Acknowledgements

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Conflict of interest

The authors declare that no conflict of interest exist in the development of the current methodology. The data were provided by the company dol-sensors A/S, but the company had no influence on what the data was used for and what methodology was developed.

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SESSION 11

General:
Sustainability and Environment

Why Precision Livestock Farming will generate a more sustainable livestock sector

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Abstract

On 25 September 2015, the 193 Member States of the United Nations adopted the 2030 UN Agenda for Sustainable Development. The agenda has generated 17 aspirational objectives, the Sustainable Development Goals (SDGs). About half of them are related to livestock.

Livestock is positioned at the interface of the world's human and natural systems, which has been at the basis of the Global Agenda's understanding of sustainability. In agriculture we use natural resources (land, water, biodiversity, forests, fish, nutrients, and energy) and environmental services and transform them into agricultural products (food, feed, fiber, fuel). Agriculture does not only serve immediate needs, but also provides economic and social services (food security, economic growth, poverty reduction, health, and social and cultural value). Because of the increasing population growth and welfare, the conventional meat industry cannot follow consumer-increasing demands worldwide. In Europe, we see a trend that makes choices and realization of European policy in relation to livestock, animal welfare and environmental impact even more challenging.

This paper aims to think about how PLF can help the livestock sector to fulfill the worldwide increasing demand of animal products, and at the same time become more sustainable. This by explaining the concept of continuous monitoring of the metabolic energy balance of animals. It shows that PLF offers the technology to monitor each component of the most fundamental biological process in the livestock sector. This approach is about monitoring and managing an improved efficiency of the different components of the metabolic energy balance when transforming feed into animal products.

Keywords: Precision livestock farming, sustainability, metabolic energy balance.

Introduction

On 25 September 2015, the 193 Member States of the United Nations adopted the 2030 UN Agenda for Sustainable Development. The 17 aspirational objectives, the Sustainable Development Goals (SDGs), which will serve governments, international organizations, the private sector, and civil society to shape the path of human advancement over the next 15 years.[1] Five out of 17 SDGs received significantly higher priority from all perspectives: SDG 1 (no poverty), SDG 2 (zero hunger), SDG 13 (climate action), SDG 15 (life on land) and SDG 17 (partnership for the goals). When asked as individuals, partners also prioritized SDG 12 (responsible consumption and production).Livestock is positioned at the interface of the world's human and natural systems, which has been at the basis of the Global Agenda's understanding of sustainability). 5 out of the 17 SDGs are strongly connected to livestock production and received significantly higher priority from all perspectives in relation to livestock: SDG 1 (no poverty), SDG 2 (zero hunger), SDG 13 (climate action), SDG 15 (life on land) and SDG 17 (partnership for the goals) (UN, 2022 Keeling et al., 2019).

In agriculture we use natural resources (land, water, biodiversity, forests, fish, nutrients, and energy) and environmental services and transform them into agricultural products (food, feed, fiber, fuel). Agriculture serves not only immediate needs but also provides economic and social services (food security, economic growth and poverty reduction, health, and cultural value). Approaches to sustainability must therefore address the interactions and trade-offs occurring within and between the human and natural systems because of farm production and decide how best to reduce their impact. Because of the increasing population growth and welfare, the conventional meat industry cannot follow consumer-increasing demands worldwide. Expectations show an increase of over 60 % by 2050 in the worldwide demand for animal products. In Europe we see another trend which makes choices and realization of European policy in relation to meat and livestock even more challenging (EU, 2019).

Problems to be solved

Domestication of animals by human started over 13.000 years ago and can only be considered as a revolutionary step in the evolvement of mankind (McHugo et al., 2019, Childe, 1928). Today, the position of livestock within a worldwide efficient and economic means of food production is challenged. Concerns are expressed on several issues, notably: *Lack of increasing efficiency in animal production, especially beef; criticism on the guarantee of animal welfare for several reasons; environmental pollution by intensive animal production, absence of and so far no successful identification of appropriate technologies to improve this; Risk for disease transfer from livestock to humans. More questions are raised by the society such as: Are lab-meat and plant-based protein a threat for livestock producers? Can we reduce food loss and create food waste recovery as animal feed? Do livestock of the rich eat the grain of the poor?*

Moreover, excessive consumption of animal protein is considered to exert pressure on the global food system. Consequently, in the EU, consumption trends indicate increase in alternative plant-based diets, which could change the future balance of protein consumption. A gradual shift towards alternatives, including novel plant-based meat alternative products, and in the future lab-grown meat, could have a significant impact on agricultural production in the EU, over the next 10-20 years (EU, 2019). The worldwide COVID19 pandemic does not help to improve people's perception regarding the contribution of the livestock sector in the food chain due to the risk for pandemics. Health issues and diseases can decrease production efficiency of livestock by up to 33% (McHugo et al., 2019). The trend towards more and more intensification of livestock farming systems increases productivity but can also have adverse effects on animal health and welfare and increases the risk of rapid and far-reaching disease outbreaks. It is not realistic to think that, with an increasing demand for animal products of around 60 %, we can solve this by getting 60 % more animals. When considering the efficiency of producing animal protein in relation to environmental impact, then namely beef is under criticism.

It is obvious that the livestock sector and related stakeholders must come up with solutions and answers to create a more sustainable protein production by livestock. *The objective of this paper* is to show that we must act now on implementing the appropriate technology in the field in a realistic way to fulfil the huge increasing worldwide demand for animal products in a sustainable way. We believe that, although yet a lot of work needs to be done, the science behind a very useful technology is available: "PLF".

What is Precision Livestock Farming (PLF)?

Precision livestock farming (PLF) aims to create a tool for farmers to help them managing their animals based on continuous automatic real-time monitoring and control of production/reproduction, animal health and welfare, and the environmental impact of livestock production. The automated monitoring is realized by using cameras, microphones, sensors etc. PLF assumes that continuous monitoring of animals will enable farmers to detect and control the health and welfare status of their animals at any given time during the production process. Ultimately, an animal enjoying good health and welfare might provide a better guarantee of product quality in the long term. Nowadays, the farmer can use modern technologies to measure different parameters on the farm, such as ventilation rate, feed supply and heating/cooling inputs, but few of the tools available up to now have directly focused on monitoring the most important part: the animal.

How can the use of PLF create a more sustainable livestock production?

Most of the increase in animal products in the last decades has come from an increase in animal numbers rather than from an increase in individual-animal productivity. When considering what we are doing for many decades in the livestock sector, the whole biological process in the animals can be rationally summarized in it's essential components as follows:

$$\text{Total Energy}_{\text{intake}} = \text{Energy}_{\text{basal metabolism}} \text{ (including Energy}_{\text{immune system}}\text{)} + \text{Energy}_{\text{movement}} + \text{Energy}_{\text{thermal}} + \text{Energy}_{\text{mental}} + \text{Energy}_{\text{production}} \quad (1)$$

It is all about managing and supporting the animal to help it transfer the energy, delivered from feed intake, in the most efficiency in the Energy production term (meat, eggs, milk and fibre). It is not a matter of focusing on a specific term of this equation 1. It is not a matter of optimizing OR this term OR another term in the energy equation. It is about working on AND this term AND all other terms to maximize the Energy production with minimal Total Energy intake. In other words, we need "more with less": more animal products from less feed intake and consequently with less manure production, less emissions, less infections, and less losses.

PLF has already developed several techniques and offers many more possibilities to work on each of the terms of the energy equation-1.

Total Energy$_{intake}$: There are several opportunities to improve feeding management. There is a difference between the amount of feed fed to animals and the real feed intake. In research stations feed delivery or feed intake are measured since many years but the used technology is too expensive for large scale applications in livestock houses in the field and for sure for small family farms. PLF has shown techniques for very accurate measurements of feed intake by broilers using sound analysis with a simple microphone integrated in the feeder pan. The algorithm detects the number of peckings where feed is taken in. The average feed intake per pecking was found as 0.025 g. The amount of feed intake and the pecking frequency were highly correlated (R^2 0.985) (Aydin et al., 2016). The amount of feed consumed was measured with mean absolute and square errors (MAE and MSE) of 0.127 kg, and 0.034 kg respectively (Ran Bezena et al., 2020). For grazing cattle an initial pasture intake algorithm was established for time spent grazing: pasture DMI (kg day(-1)) = -4.13 + 2.325 x hours spent grazing (P = 0.010, r(2) = 0.53, RSD = 1.65 kg DM day (Greenwood et al., 2017). There are several unused opportunities to improve feed management such as feeding in meal packages, adapt the composition of the feed, appetite regulation, post-ruminal nutrient absorption, and cellular energetics and metabolism to the efficiency of feed utilization in cattle (Kenny et al., 2018).

Energy$_{\text{basal metabolism}}$: The basal metabolism is the absolute minimal amount of energy that an individual body needs to keep all organs functioning. This is a totally individual characteristic depending on species, age, weight, health condition, production phase, etc. So far, the individual feeding strategy is depending on the Energy $_{\text{production}}$ term in milking cow but the real estimation of the basal metabolism term is not yet realized, although feasible as we see later. Genetic selection has accomplished huge advantage in working on this Energy basal metabolism and has consequently played a huge role in producing more animal product. More efficiency in terms of feed conversion, growth rate, less infections will result in less manure, less emissions.

Today, PLF technologies can offer the advantage of collecting data from animals to study the efficiency of phenotypes in the field at very large scale. If one is for example interested in analyzing the aggressive behavior of a specific species and want to collect data from e.g. 500.000 animals, PLF can make it happen. Knowing this, new breeding opportunities can be defined for the potential of livestock species to acquire plasticity for adaptation to for example current climate changing conditions or improved emission results.

Energy$_{\text{immune system}}$: Animal health is of course crucial in realizing a more efficient energy equation-1. PLF offers many possibilities for real-time health monitoring from which most of them are yet not implemented in operational field systems. It is now possible to monitor animals using normal cameras with an image speed of up to 25 images per second. Moreover, we can have many different monitoring algorithms that are easy to implement using top-view cameras placed in operating livestock houses. In broiler chickens, for example, the eYeNamic system has been developed for continuous automatic monitoring of the behavior of housed birds (Aydin et al., 2010). The EU specifies that a broiler farmer must carry out a visual inspection of the birds at least twice a day, the eYeNamic system does this continuously in a fully automated way. Lameness problems often are related with inflammation and infections. An abundance on lameness literature exist that shows the different risk factors related with lameness for milking cow and other species.

Continuous health monitoring by image systems

Such example of PLF technology is an automated camera analysis to detect lameness in milking cow (Viazzi et al., 2013). Lameness is a major health and welfare problem in modern dairy cows, where up to 25% may be badly affected. In literature over 200 possible causes are described. It is a matter of detecting as soon as possible when the first sign of lameness can be noticed to start treatment immediately. A camera is filming the individual cow each time she leaves the milking robot. By an algorithm that does a gait analysis based upon the video a gait score is given. By carrying out image analysis and calculating model parameters from the image information, it was possible to develop an algorithm for automatic detection of lameness problems in dairy cows (Viazzi et al., 2013). Such techniques provide frequent and fully automatic monitoring of each individual cow (Figure 1), a process that the farmer can no longer carry out easily. As soon as the calculated individual gait parameters change, a warning alerts the farmer. The objective was to detect the first sign of upcoming lameness problems by focusing on the variation in gate analysis when a come transfers from a sound gait to a first score of lameness in a scale of 5 as scored by experts. It was shown that the individualizing of the algorithm is an important asset to make the monitor up to 10 % more accurate in detection animals with problems (Viazzi et al., 2013). To make the principle applicable in the field, a simplified prototype of the lameness monitor was developed based upon only a top view image in which the main feature variable is the back arch of the cow. When a cow has pain in one of the feet or legs, it will use the back muscles to reduce the weight on that leg which is seen in the back arch of the animal (Figure 2). The prototype tested in field conditions measures the back arch by using a top view image (Figure 3). But so far also this technology did not turn yet into a commercial product for large scale implementation.

Continuous health monitoring by sound analysis

Respiratory pathologies are widespread in intensive livestock farms like pig farms (Ferrari et al., 2010) their incidence and prevalence are high, and their principal clinical sign is coughing. The importance of these diseases must be viewed from an economic as well as a hygiene perspective; veterinary intervention can be expensive and farmers can experience substantial profit losses due to high mortality rates in growing/fattening pigs (which can be as high as 15%) (Islam et al., 2013) or to a drop in production as a result of reduced feed conversion and a lower growth rate. It is very unlikely that a pig will reach the slaughter weight without having respiratory problem (Baumann and Bilkei, 2022). With the Covid-19 pandemic the importance of continuous health monitoring is demonstrated once more. Over 60 % of the diseases that humans get are zoonoses: transferred from animal to human. It is also known that detecting illness in individual animals and providing individual care or group-by-group mass treatment in response to illness are not very effective and are also costly. It is therefore beneficial to investigate animal sounds with the aim of both understanding respiratory diseases and using bioacoustics for real-time monitoring purposes. The importance of coughing as a predictor of respiratory disease applies to animals as well as to humans. It has been shown that pig vocalization is directly related to pain and classification of these sounds has been attempted (Marx et al., 2003, Chedad et al., 2001). It is also common practice among veterinarians to assess cough sounds in livestock houses for diagnostic purposes. In this regard, there have been attempts to identify the characteristics of coughing in animals like bovine and pigs and to automate the identification of cough sounds from field recordings for e.g. detection of bovine respiratory disease (Figure 4) (Vandermeulen et al., 2016). The detection of infection by sound analysis and related production loss due to reduced feed intake is visible from Figure 5 (EU-PLF, 2016). Also, for calves it is possible discriminate cough sounds from other sounds and that cough sound can be used as a non-invasively diagnostic tool for respiratory diseases in youngstock groups (Aydin et al., 2010).

Energy$_{movement}$: All physical or mental performances of animals or humans take metabolic energy. So far, we are not yet taking into account the effect of the movement of animals in the management of the energy equation. Many solutions are described in the scientific literature to monitor movement continuously mainly for cows, pigs, and bigger animals by using 3D accelerometers and gyroscope technology. The wearable technology is making fast progress in terms of accuracy, dimensions, weight, price, and energy use. For lameness detection several solutions have been proposed for several species and position and gait analysis become standard techniques for milking cow (Aydin et al., 2010).

The potential of technology for active management of the Energy$_{movement}$ component however is not yet explored. When combining such technology with heart rate monitoring, interesting opportunities become available for active management of this component. Do we get more happy animals when they move more like has been shown for humans when doing sports? What is the effect on body composition, meat quality, feed conversion, etc.? For large animals like cow, beef cattle, horses, etc. the metabolic energy for moving the body is not neglectable which does not mean that active movement management would not be a good option for health management or animal welfare.

Another example of using movement information is the automated continuous monitoring of cows to detect problems during delivery. When farmers with cow and sheep are in the period of deliveries the follow up takes a lot of man hours. In collaboration with the Teagasc research institute in Ireland we developed a system that reduces the complex animal to 10 dots (Figure 6). The real-time monitoring of the position of the simplified model allows to detect when the delivery does not proceed as can be expected and the algorithm can give an alert to the farmer that human help is needed.

Energy$_{thermal}$: What we do for many decades is to work on the Energy$_{thermal}$ term by housing livestock in structures to protect them from the varying outside weather conditions. With climate change there are new problems to be solved. With genetic engineering many possibilities are still unexploited in relation to phenotypes of livestock where PLF can collect many data. There are several candidate genes that are associated with adaptation of ruminants, monogastric and poultry to heat stress (Rovelli et al., 2020). Also, the use of new technologies and materials in climate control of livestock houses has many unexploited opportunities when combining with let animals more decide for themselves by using PLF technologies with camera's, microphones, sensors etc.

Energy$_{mental}$: Energy$_{mental}$ includes animal welfare as a central element for several reasons. It is important to note that animal welfare is not only required for ethical reasons but also for reasons of efficiency of the animal production process. As said higher it is a challenge to work on each term of the energy equation-1. Animal welfare or the Energy mental term is the term that is related to most other terms in equation-1. Animal welfare is also the part that is related to many SDG's (Sustainable Development Goals) (Keeling et al., 2019).

A first way to improve the efficiency in animal production is to reduce the number of health issues since these always generate production losses. Animal welfare is closely connected to animal health since stressed animals are using the feed energy for mental stress instead of bringing this amount of energy into production (meat, milk, eggs, fiber). Moreover, stressed animals depress the immune system with increasing risk for infections. How many of the 70 billion livestock animals, slaughtered this year for the worldwide demand, are not stressed? All the energy, used for the mental component when stressed, is not available for the basal component, the immune system, the thermal or the production term in the equation.

What we expect to become a real disruptive technology for the livestock sector is the continuous real-time monitoring of the Mental energy term or animal welfare based upon physiological variables. The technology is available for humans (Viazzi et al., 2013) and will become available for animals as soon as the appropriate sensor is realized (Joosen et al., 2019, Luwei et al., 2020).

In the past, Darwin has already shown that there is a dynamic relationship between the central nervous system and the expression of emotions and that physiological variables offer potential for monitoring stress (Darwin, 1872, Porges, 1995). When an animal produces metabolic energy within the aerobic zone, the inhaled air is brought into the blood in the lungs. Then the heart is pumping the blood to the cell level where the metabolic energy is produced. This means that the level of heart rate is a measure for the possible total production of metabolic energy. This means that equation-1 can be written in the form of a heart rate equation.

$$HR_{TOTAL} = HR_{BASAL} + HR_{MOV} + HR_{THERM} + HR_{MENTAL} + HR_{PROD} \qquad (2)$$

The decomposition of heart rate components in mental and physical components remains a challenge on moving subjects, which leads to the consequence that most methods for stress monitoring based on heart rate are limited to non-moving subjects, like heart rate variability.

The mental component in the energy equation can be monitored based upon physiological measurements (heart rate and movement) in combination with individualized algorithms that adapt to each individual animal. It has been shown on pigs that it is possible to monitor the response of animals in real-time by measuring heart rate and movement in real-time in a synchronized way. We stressed pigs 6 times with a sound-signal to induce a negative mental response, and we gave them 6 times a toy to induce a positive mental response. The algorithm picked up both types of responses in real-time (Figure 7). We could also show the agreement between the output of the real-time algorithm with the blood hormone response of noradrenaline (Figure 8) (Joosen et al., 2019).

To introduce this technology in the field we need a sensor that can accurately measure heart rate and movement for example in an ear tag. A candidate technology to monitor heart rate in livestock is the meanwhile well know ppg technology standing for photoplethysmography (Luwei et al., 2020). It can be expected that such an ear tag, monitoring heart rate and movement, will come soon and it seems obvious that the first species will be the more expensive individual animal such as milking cow, beef cattle, racehorses etc. We can expect that miniaturization with soon also bring it to pigs. Such objective and continuous monitoring of animal welfare based upon objective physiological measurements will be a huge step in creating a more efficient production process. It finally will create the possibility to give animals in the production system a life worth living (Wathes, 2010, Yeates, 2011).

The PLF solutions are mostly built upon the combination of one or more sensors (e.g. 3D accelerometer, temperature sensor,…) or sensing systems (sound, image, …) in combination with an algorithm to calculate the so called target variable aimed for e.g. like lameness detection.

Conclusions

While the worldwide demand for animal products is increasing, the livestock sector is challenged to answers several questions from the society Today there is an inadequate demonstration of how livestock can play a key role in the development of sustainable agriculture in different agri-ecosystems, and a failure to transfer appropriate technologies to the field.

To come up with solutions an important step is to improve the efficiency in animal production rather than once again increasing the number of animals to fulfil the demand. From the few examples, we can see that PLF has a high potential to play a role in the more efficient management of producing animal products.

And yet there are some other issues to be looked at: Lab-meat, food losses and grain use by livestock. Europe aims for eating less meat and dairy products and looks for alternative protein solutions. This might make livestock producers nervous. The possibilities of lab-meat and plant-based protein should not be considered as a treat since the worldwide demand for animal protein is expected to increase with over 60 % by 2050 (Gerhardt et al., 2019, Deloitte 2017). Less feed must generate more animal products. Alternative solutions are welcome to contribute to the increasing demand. The use of insects as food for humans and animals is an alternative for the increasing demand for heat and has environmental and social advantages over intensive production of livestock. However, an issue that might compromise the success of insect rearing is the outbreak of insect diseases and virus transmission. More understanding is required of the different factors that interact in insect mass rearing.

At the same time, we struggle with several serious food loss and food waste. We must consider whether we can use food wastes as animal feed to collaborate with waste management processes and food security challenges. Animals also consume food that could potentially be eaten by people. FAO has published that 86% of livestock feed is not suitable for human consumption. If not consumed by livestock, crop residues and by-products could quickly become an environmental burden as the human populations grows and consumes more and more processed food. Grains account for 13% of the global livestock dry matter intake.

PLF research has started in the 90's with experimental laboratory work (Wouters et al., 2018) but so far, 30 years later not many systems have been successfully implemented in the field at large scale. There is a lack of successful identifications of appropriate technologies that proven to work in the field at large scale. It is now time to start implementing PLF technologies, developed at lab-scale to bring them to commercial livestock applications. Although the high number of animals per farm, we need to bring the animals closer to the farmer (Norton et al., 2019).

We must wonder whether the need today is to develop more new systems, rather than finally putting focus on implementing developing systems in real field applications. To come up with real solutions, a collaboration between different research disciplines (animal scientists, veterinarians, engineers, etc.) is needed as well as a strong collaboration between researchers and industry.

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Using LCA to estimate the potential reduction of the environmental impact by PLF technology

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Abstract

Every year over seventy billion animals are slaughtered to fulfil the worldwide demand for animal products (meat, eggs, milk) and a further increase is expected by 2050. The livestock sector, like other sectors, has a high environmental impact and we must find solutions to reduce it. Normally an evaluation by experimental work in field conditions becomes very expensive in monitoring techniques and in labour.

This paper shows a method to evaluate the effect of PLF technology on the environmental impact by using simulations of Life Cycle Assessment (LCA). We use an example on dairy cows by evaluating the use of pedometers for the detection of oestrus events. The results show that the application of LCA can work as a feasible approach to get insight in the significance of the environmental benefit of applying PLF tools on farms.

Keywords: environmental sustainability, dairy cows, monitoring, efficient management

Introduction

It is widely known and recognized that the livestock sector has both positive and negative impacts on the environment. These latter are especially related to emissions caused by animals such as methane from enteric fermentation of dairy cows and to emissions from slurry storage and field application practices (Opio et al., 2011). Considering the big growth of the sector of the last decades and that it is continuing to expand to respond to the growing demand for animal products, the livestock sector needs a critical reflection (Pelletier & Tyedmers, 2010; Steinfeld & Gerber, 2010; Bellarby et al., 2013). A possible trade-off between the positive and negative effects of livestock production can be identified with an enhanced holistic efficiency and performance, partially made possible by technology (Opio et al., 2011; Steinfeld & Gerber, 2010). Measures to reduce emissions have been widely studied and proposed, and often mitigation strategies introduced on farms (Herrero et al., 2016). Realizing accurate measurements on field is very expensive in equipment, time required for several seasons and manpower when we want to evaluate technologies to reduce the environmental impact. For some cases like emissions from naturally ventilated buildings there are even no accurate monitoring techniques. The error might be bigger than the positive effect of technology.

In this context, the Life Cycle Assessment (LCA) approach might be helpful, because it allows to have a holistic view on the system and evaluate possible side effects on the environmental perspective of different mitigation strategies (Kiefer et al., 2015; Pirlo &

Lolli, 2019). However, also the effect of ecosystem services and territory maintenance need to be mentioned (Chatterton et al., 2015; Kiefer et al., 2015). Evaluations on the effect of global warming are widely increasing, due to its important role in current and future policies (Opio et al., 2011; Steinfeld & Gerber, 2010).

To achieve the primary goal of a farmer (i.e. production of milk, meat, eggs, fiber, etc.) high productivity in an economically sustainable way is fundamental. Growing healthy animals, with good performances, welfare, and a balanced use of inputs (e.g., feed) is very important (Brito et al., 2020). These aspects have also an environmentally sustainable façade, since a balanced use of inputs in respect to the outputs, good performances, efficiency, high yields, and high welfare and health indicators are positive aspects for an environmentally sustainable livestock system (Lovarelli et al., 2020). In addition, considering that farms are reducing in number while increasing the number of farmed animals, monitoring all individuals within the herd for a farmer is becoming more challenging and automatic systems can be of help (Pezzuolo et al., 2017). Technologies able to support farmers in monitoring big herds and single animals and in the decision-making process are spreading widely. They also bring benefits to the monitoring of variables that have become impossible to be continuously monitored by humans, such as the identification of night-time or silent oestrus events (Arcidiacono et al., 2020; Zebari et al., 2018), variations in behaviour (Cairo et al., 2020), but also the monitoring of other variables that help improve welfare, such as the microclimate in the barn (i.e. temperature, relative humidity, wind speed) and the air quality (i.e. pollutants concentration in air). Furthermore, until now farmers, researchers and policy makers have focused their attention on animals in their production stages, but it is important to provide enhancements to the non-productive phases as well, which represent the future of the herd: animals growing in healthy conditions will be more robust and resistant to illnesses or stresses during their productive stages. Paying attention to young animals also influences the environmental perspective. In fact, heifers not adequately farmed (i.e. fed and monitored) will postpone their first calving, thus prolonging their unproductive age. Measuring the potential environmental advantage of new PLF technology in comparison with the absence of technology is quite complex. Setting up experimental studies that compare this condition (with PLF) with the one prior to the installation of PLF tools entails the difficulty of not having specific data in that previous period. Collecting accurate data during several seasons is expensive, takes a lot of time and manpower and is often not accurate enough to come up with reliable results. For example, to measure the possible effect of a low cost PLF technology for dairy cows on the emissions from a naturally ventilated barn is today quite impossible. Ammonia concentrations can be measured with expensive techniques, but measuring methane is challenging. Even more difficult is the absence of an available measuring technique to monitor the ventilation rate through the barn with required accuracy.

The example that we use aims to show the potential of LCA to evaluate environmental impacts on dairy cows, thus comparing the environmental sustainability of a farm equipped or not with PLF, in particular with pedometers. In this condition, both the age of the first calving and the efficiency of the heat detection are evaluated. A simulation is carried out for a traditional dairy cattle farm, modelling the effect of PLF installation.

Material and methods

Farm description

To evaluate the environmental performance of a dairy cattle farm in which pedometers or other similar technological support is introduced to detect heat events, a dairy cattle farm of average dimensions located in Northern Italy was identified. A survey was carried out to collect data useful for the inventory phase of the Life Cycle Assessment (LCA) study. This farm has no technological support, since it is a traditional farm where the farmer is still evaluating the potential benefit of introducing sensors/tools (Traditional Scenario, TS). In Italy, in fact only about 30% of farms have PLF tools for heat detection (Abeni et al., 2019). This farm has the characteristics reported in Table 1 regarding herd dimension, average dry matter intake (kg DMI d^{-1}) and milk production (kg milk d^{-1}) in the different phases of the lactation. Considering the lack of technological support in the herd monitoring, the cows farmed in these conditions show an average age at first calving equal to 28 months, and the pregnancy rate and fertilization success are quite unsatisfactory, on average with 3 months of failed inseminations. This is quite common in Italian dairy cattle farms of this type (Holtz & Niggemeyer, 2019). The lactation lasts longer than theoretical, reaching 395 DIM before drying which creates unnecessary environmental impact.

Table 1: Farm characteristics in the traditional scenario.

Variable	Unit	TS
Dairy cows	n.	180
Dry cows	n.	28
Heifers	n.	82
Calves	n.	70
Dairy cows	kg DM d^{-1}	23.0
Dry cows	kg DM d^{-1}	12.0
Heifers	kg DM d^{-1}	12.0
Calves	kg DM d^{-1}	8.0
Total lactations	n.	3
Milk prod. at 0-90 DIM	kg d^{-1}	45
Milk prod. at 90-210 DIM	kg d^{-1}	37
Milk prod. at 210-305 DIM	kg d^{-1}	26
Milk prod. at 305-365 DIM	kg d^{-1}	22
Milk prod. at 365-395 DIM	kg d^{-1}	21

Evaluated scenarios

Beside these traditional farm characteristics, two improved situations are modelled and tested on their environmental impact consequences:

— "Best Scenario" (BS): in this case, the farmer adopts the best technologies that can support the heat events detection, such as the measurement of the progesterone level in milk. In this case, the farmer properly grows heifers and promptly identifies the oestrus window, even when it occurs at night-time, or it is silent. Then, the first calving takes place at 23 months, which is a proper timing for not encountering parturition problems (Pirlo et al, 2000). The subsequent calving-conception interval (CCI) is minimized since monitoring progesterone in milk can allow identifying at best the oestrus events and defining when to inseminate the cow. This implies that the lactation proceeds in its optimal theoretical duration and the cow is dried off after 305 DIM;
— "Intermediate Scenario" (IS): in this case, the farmer installs common technology solutions like accelerometer sensors on the cows. This allows the detection of heat events with a better accuracy than humans but with possible errors. In this case, the heifers are properly grown, but insemination and the subsequent calving take place later than in BS (calving at 25 months). This condition is quite common in Italian livestock farms of Northern Italy, where 25 months represents the average age of the first calving (CLAL, 2022). Due to not identifying all of the estrus events, some failures in the fertilization of cows are considered, therefore the cows are dried off after 365 DIM, which is also a common practice.

Table 2 reports the differences in the age at first calving and the duration of lactation of TS (traditional scenario), IS (intermediate scenario) and BS (best scenario).

Table 2: Age at first calving and duration of the lactation in the three scenarios (traditional, intermediate and best, respectively for TS, IS and BS).

Variable	Unit	TS	IS	BS
Age at first calving	months	28	25	23
Duration of lactation	days	395	365	305

LCA and climate change

After a literature survey and previous experience on the assessment of the environmental sustainability of dairy farms in Northern Italy, a linear equation that relates dairy efficiency with climate change was defined (Lovarelli et al., 2019; Pirlo and Lolli, 2019; Zu cali et al., 2017). This equation permits to quantify the environmental impact for the category of Climate Change (CC; kg CO_{2eq}/kg_{milk}) based on the dairy efficiency (DE; kg_{milk}/kg_{DMI}) of each farm, and was used in each scenario (TS, IS and BS) to predict CC. The variable DE was calculated based on the collected/modelled data.

Results and Discussion

Table 3 reports the average dry matter intake (DMI; kg DM) per scenario of farmed animals during the early growing stages and, for dairy and dry cows, for each lactation. Table 4, instead, shows the milk production of the 180 dairy cows in the 3 scenarios, depending on the length of their lactation period. Here, IS and BS show a lower total ingestion for dairy cows because of the shorter duration of the lactation compared to TS, and because of the shorter duration of the diet as a heifer (i.e. different age at first calving).

Table 3: Dry matter intake of the entire herd per lactation per scenario.

Variable	Unit	TS	IS	BS
Dairy cows	Mg DM	1635.3	1511.1	1262.7
Dry cows	Mg DM	13.4	13.4	13.4
Heifers	Mg DM	275.5	246.0	226.3
Calves	Mg DM	67.2	67.2	67.2
Total ingestion	Mg DM $lact^{-1}$	1991.5	1837.7	1569.7

Similarly, for milk production it is observed that IS and BS produce less milk than TS, due to the shorter duration of the lactation period. In this period, however, the lactation curve is decreasing, therefore milk production is lower. Both aspects of feed intake and milk production contribute to the quantification of DE (i.e. the amount of milk produced per amount of feed ingested) that results higher in BS and lower in IS and TS.

Table 4: Milk production of the farmed dairy cows (n. 180) per lactation per scenario, and the calculated average dairy efficiency (DE; kg milk/kg DMI).

Variable	Unit	TS	IS	BS
Milk prod. 0-90	Mg d^{-1}	729	729	729
Milk prod. 90-210	Mg d^{-1}	799.2	799.2	799.2
Milk prod. 210-305	Mg d^{-1}	444.6	444.6	444.6
Milk prod. 305-365	Mg d^{-1}	237.6	237.6	
Milk prod. 365-395	Mg d^{-1}	113.4		
Total milk production	Mg $lactation^{-1}$	2323.8	2210.4	1972.8
Dairy efficiency	$kg_{milk}\ kg_{DMI}^{-1}$	1.17	1.20	1.26

A literature search and analysis on Dairy Efficiency (DE) and Climate Change (CC) data resulted in the values as reported in Table 5. The linear regression among these values is reported in Eq. (1) and shows quite satisfactory results, with R^2=0.69:

Table 5: Mean and standard deviation of DE and CC from literature for calculating Eq.(1).

n. farms	DE	CC	Authors
33	1.35 (0.26)	1.38 (0.32)	Lovarelli et al. (2019)
102	1.19 (0.25)	1.51 (0.53)	Zucali et al. (2017)

The application of Eq. (1) results in CC (kg_{CO2eq} kg_{milk}^{-1}) values for the 3 scenarios as: 1.65 (TS), 1.60 (IS) and 1.50 (BS), respectively. This is a simplification in the quantification of CC, because it assumed that the composition of the animals' diet and milk quantity and quality are not affected by any difference in the 3 scenarios. Instead, the different CC values are caused by the duration of one diet instead of the other and of one lactation duration instead of the other. For a more detailed assessment, additional considerations could be done to include the possible effects of different productivity, milk quality and mastitis due to the different management opportunities and technological equipment. In this case, these differences were excluded to avoid additional variability.

Some further considerations can be made by making equal lifetimes for the cows. Both a longer and a shorter lifetime have been tested as follows: (a) if cows in BS live longer, reaching equal levels of IS and TS (i.e. 66 or 72 months) and (b) if cows live shorter (i.e. also IS and TS have lifetime equal to 58 months as in BS). Of course, this is an assumption based on the need to compare all scenarios based on the common productive duration, set equal to 3 lactations. When changing the lifetime to make it comparable in the 3 scenarios, the lifetime becomes equal, while the number of lactations changes. In this condition, the cows in IS and TS need 8 and 14 months more, respectively, than cows in BS to conclude the 3rd lactation. Therefore, if cows in BS had a prolonged productive period, they would eat (with a diet for dry and dairy) and produce more, as reported in Table 6 (they would add one dry period and one lactation – partial in BS-66 or complete in BS-72). Conversely, if the cows in TS and IS had a shorter productive period to compare them with cows in BS, then the results would be as reported in Table 7, with a common lifetime equal to 58 months, thus not being able to start (TS) or conclude (IS) the 2nd lactation.

Table 6: Results for prolonged lifetime of BS.

Variable	Unit	BS-66 months	BS-72 months
Lifetime	months	66	72
Additional milk prod.	Mg	1328.4	1972.8
Total milk prod. (*)	Mg	7247	7891
Additional feed	Mg	765.4	1323.7
Total feed (*)	Mg	5474	6033
Dairy efficiency	kg_{milk} kg_{DMI}^{-1}	1.32	1.31
Climate Change	kg_{CO2eq} kg_{milk}^{-1}	1.39	1.42

(*): referred to lifetime.

Table 7: Results for shortened lifetime of TS (-14 months) and IS (-8 months).

Variable	Unit	TS-58 months	IS-58 months
Lifetime	months	58	58
Lowered milk prod.	Mg	-2324	-1238
Total milk prod. (*)	Mg	4647.6	5392.8
Lowered feed	Mg	-9.1	-5.6
Total feed (*)	Mg	5965.3	5507.6
Dairy efficiency	$kg_{milk}\ kg_{DMI}^{-1}$	0.78	0.98
Climate Change	$kg_{CO2eq}\ kg_{milk}^{-1}$	2.31	1.97

(*): referred to lifetime.

The results of CC reported in Table 6 and 7 were calculated based on the different DE values that results from the modelled assumptions. Both DE and CC result better in BS in all the modelled options (i.e. BS, BS-66 months and BS-72 months), followed by IS.

Conclusions

The example used in this case study shows that using a PLF technology that permits a more accurate identification of oestrus events and that avoids missed inseminations in dairy cows, finally leads to relevant reductions in the Climate Change impact category. Therefore, LCA can work as a feasible approach to understand the significance of an environmental benefit when applying a certain PLF technology on farms. It is clear that a more comprehensive LCA study can be done by considering more environmental impact categories for a better and more detailed understanding of the system.

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A UAV-based system for greenhouse gases and particulate measurement in livestock farms

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Abstract
Livestock production is a relevant anthropogenic source of gaseous and particulate pollutants. The increasing regulatory pressure to reduce emissions requires their systematic assessment. However, current methodologies for accurate GHGs, ammonia and particulate measurements at farm level demand extensive field and laboratory work, with high costs in terms of equipment and skilled personnel. In this context, the development of cost-effective methods for rapid and systematic monitoring of emissions is a key element. A UAV-based system was developed to measure gas (CO_2, CH_4, NH_3) and particulate matter ($PM_{2.5}$, PM_{10}) concentrations in the bottom atmospheric boundary layer. The system is founded on a flexible architecture and can be adapted to different operating environments. Prototype measuring units equipped with low-cost sensors were designed and implemented with the aim to identify emission hotspots. The units are designed to be employed both for ground measurements and for in-flight data collection on board of a customised UAV. Two flight missions were carried out in a dairy farm to evaluate the feasibility of ground and in-flight measurements. Ground units were positioned both inside and outside the building where dairy cows were housed, while simultaneous measurements were collected by the UAV. The results obtained showed that the prototype units are able to provide ground and in-flight measures of gases and PM, however further research is required to embed additional sensors and validate data across multiple state of the art methods.

Keywords: drone, sustainable livestock farming, GHG emissions, dairy farming

Introduction
Current environmental policies are targeting a green transition, which involves the reduction of greenhouse gases and air pollutants emissions. In this context, a key issue will be to develop cost-effective techniques ensuring a rapid and continuous assessment of air quality and of the distribution of pollutants in the atmosphere.

Atmospheric particulate matter (PM) is classified into inhalable particles, with an aerodynamic diameter less than or equal to 10 μm (PM_{10}), and in fine particle matter with an aerodynamic diameter lower than 2.5 μm ($PM_{2.5}$). Livestock production can emit considerable amounts of PM, which is a cause for air quality issues inside, but also outside livestock houses. Fine particles are known to be responsible for respiratory and cardiovascular diseases (Losacco & Perillo, 2018), thus a systematic assessment of particulate pollution is crucial for the protection of human and animal health.

Farming activities and livestock breeding cause also the emission of several gases, as CH_4, CO_2, N_2O, NH_3, especially during the digestive process and excreta decomposition. The emissions of greenhouse gases contribute notably to global warming, while NH_3 can cause respiratory diseases, damage terrestrial vegetation and be a precursor of secondary $PM_{2.5}$. Obtaining punctual and regular measures of gas concentrations at farm scale represents a crucial goal to assess the efficacy of mitigation practices and, ultimately, to improve the management of GHGs emissions.

In the last decade, UAV-based monitoring systems have emerged as an alternative or complementary technique to traditional ground-based detectors. UAVs represent a new frontier for atmospheric chemistry research; moreover, they are being increasingly applied in the fields of industrial emission monitoring and precision agriculture (Burgués & Marco, 2020). Drones equipped with gas and/or PM sensors have been employed to measure the emissions at point sources or to investigate the vertical profile of pollutants concentrations in the atmospheric boundary layer. Examples of the assessment of emissions at pollutant sources with drone-based measurements regard the quantification of methane emissions from oil and gas infrastructures (Smith *et al.*, 2016) and landfills (Emran *et al.*, 2017) or multipollutant determination in open burnings (Aurell *et al.*, 2017). Vertical profiles were assessed using multicopters equipped with particulate (Kuuluvainen *et al.*, 2018) and gas (Cabassi *et al.*, 2022; Gu *et al.*, 2018) sensors both in urban and in rural environment. A variety of small and low-cost gas sensors (amperometric gas sensors, metal oxide semiconductor sensors, non-dispersive infrared sensors, and photoionization detectors) were used on UAVs to detect or measure leaks, concentrations or flux of a wide array of gases (e.g. CO, CO_2, NO_x, N_2O, O_3, NH_3) and VOCs. In the field of precision agriculture, however, research is still pioneering. Drones equipped with environmental sensors have been proposed as an option to automate certain agricultural tasks, such as monitoring climate variables in greenhouses (Roldán *et al.*, 2015) or evaluating fruit maturity (Valente *et al.*, 2019), but their potential use for gas pollutants and particulate monitoring has still to be assessed. In this framework, the research aimed to develop and test a UAV-based system to assess PM, GHGs and ammonia hotspots in the context of livestock farming. The goal is to provide a rapid and real-time system for emission monitoring of livestock buildings, manure and feed stores. A prototype UAV-based and ground measurement system was developed, implemented and tested to assess the feasibility of ground and in-flight measurements.

Material and methods

System design

The project is based on a modular design with flexible architecture and can be adapted to a wide range of operational fields. The design is structured in four layers (Figure 1). Layer 1 (sensor layer) concerns the sensors and the collection of all measurements; layer 2 (network layer) regards the transmission of data collected by the sensors towards the storage system; layer 3 (service layer) represents the storage system where measurements are collected and analysed; layer 4 (application layer) provides a tool for data presentation where measurements can be visualised through a dashboard.

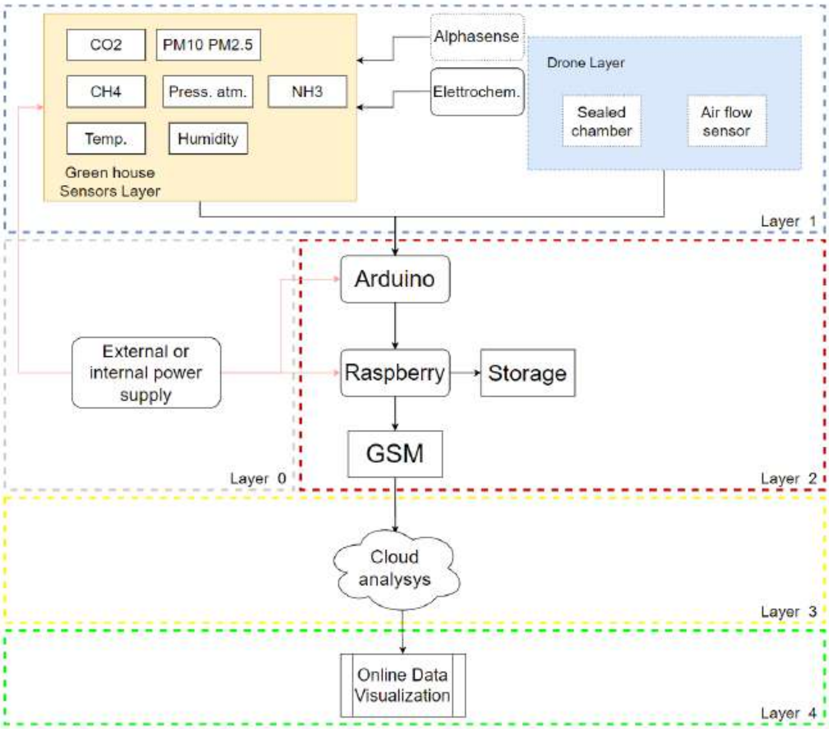

Figure 1: Layer organisation of the system architecture

The whole project design comprises four modules: gas and particulate measurement units, a UAV, a server and a dashboard. For the purposes of this research, aiming to assess the feasibility of ground and in-flight measurements, the first two models were developed and tested. The sensor layer and network layer were embedded in a prototype ground-based measurement unit and in a miniaturised version on board of a drone (Figure 2). The measurement unit on the UAV was deployed on a tube to prevent the effects of the airflow and turbulence generated by the rotors on gases and PM measurements. The drone (3DR Solo; 45.7 x 45.7 x 25.4 cm; weight: 1.5 kg) was a quadricopter. The units were provided with multisensor boards with ARM Cortex M0+ processor, ATM2560 microcontroller for data processing and transmission and Raspberry Pi Compute Module. They integrated data from all onboard sensors, tagged data with timestamp and, for the UAV module, geolocation in real time, while ground-based units were manually georeferenced with a GPS-GNSS receiver.

Air pollutant sensors

Low-cost commercial sensors were selected to meet the goal of air quality monitoring in a livestock farming environment, according to a Life Cycle Assessment (LCA) procedure. Target pollutants were particulate matter ($PM_{2.5}$, PM_{10}), NH_3, CH_4 and CO_2. Additionally, temperature, relative humidity and atmospheric pressure sensors were embedded in each unit. Detailed technical characteristics of the sensors are summarised in Table 1.

Field tests

The ground and the UAV measurement units were tested in a commercial dairy farm located in Tuscany, Central Italy, where 450 Holstein Friesian cows were housed.

Table 1: Name, type, measurement and operative range of the tested sensors

Target measurement	Sensor name	Type of sensor	Measurement range	Operative range: Temperature (°C)	Operative range: Relative humidity (%RH)
$PM_{2.5}$,PM_{10} (µg m^{-3})	SDS011	Optical	0 to 999.9	- 20 to 60	0 to 90
NH_3 (ppm)	MICS 6814	Electrochemical	0 to 100	- 30 to 50	15 to 95
CH_4(ppm)	IRC-AT	Electrochemical	200 to 10000	- 20 to 50	0 to 95
CO_2 (ppm)	SCD30	NDIR	400 to 10000	- 40 to 70	0 to 95
Temperature, %RH	SHT40	CMOSens	- 40 to 90 0 to 100	- 40 to 125	0 to 100
Atmospheric pressure (hPa)	BMP280	CMOSens	300 to 1100	- 40 to 85	0 to 100

The field tests on the ground and on the UAV unit were conducted during two days in March and July 2021. In each session, the ground station was deployed in five locations: inside (I) the cubicle barn, in the central feeding alley, and outside (O) the barn, at the four sides of the building. Environmental, gas and particulate measurements were recorded for on average 20 minutes at each location; overall, 788 records were collected. Two flights were conducted at 31.3 ± 0.9 m a.g.l. over the farming site; the first measurement session (March 2021) was carried out during a 7 minutes non-stop flight, where 175 records were collected while the drone was moving along the chosen path (Figure 3). In the second measurement session (July 2021) the flight mission was planned to obtain static measurements: the drone stopped at each waypoint where measurements were taken. To cover the same area over the farm, two consecutive flights were conducted for 24 minutes in total, and 451 records were collected.

Figure 2: The '3DR Solo' drone equipped with the miniaturised prototype measurement unit

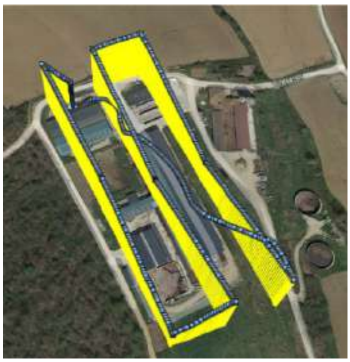

Figure 3: Path followed by the UAV during the 1st field session

At the same time of ground and in-flight measurements, representative samples of air inside and outside the main building were collected in sample bags selected to ensure good stability of the target gases. Sampled air was analysed by Gas Chromatography (GC) to determine methane and carbon dioxide concentrations. The results were used to assess the adequacy of measures from the prototype units.

Results and Discussion

Table 2: Gas and PM measurements (minimum, maximum, average ± standard deviation) collected by the prototype UAV unit and ground unit (O: outside the cubicle barn; I: inside the cubicle barn).

	UAV (March 2021)	UAV (July 2021)	Ground (March 2021)	Ground (July 2021)
Min - Max CO_2 (ppm)	-	0 - 40000	O: 3.10 - 30.34 I: 4.56 - 37.00	O: 401.00 - 475.00 I: 442.00 - 504.00
Ave ± S.D. CO_2 (ppm)	-	3187.49 ± 7440.68	O: 6.92 ± 4.08 I: 15.88 ± 12.02	O: 426.20 ± 22.31 I: 467.81 ± 15.38
Min - Max CH_4 (ppm)	0.75 - 4.44	0.12 - 26.8	O: 1.62 - 11.40 I: 1.64 - 10.69	-
Ave ± S.D. CH_4 (ppm)	2.48 ± 0.87	5.24 ± 5.77	O: 2.52 ± 1.50 I: 4.49 ± 3.26	-
Min - Max NH_3 (ppm)	-	0.47 - 1.10	O: 0.22 - 0.65 I: 0.20 - 0.43	-
Ave ± S.D. NH_3 (ppm)	-	0.99 ± 0.21	O: 0.42 ± 0.10 I: 0.27 ± 0.04	-
Min - Max $PM_{2.5}$ (µg m^{-3})	4.60 - 327.60	2.00 - 249.30	O: 1.50 - 4.60 I: 1.30 - 2.90	O: 4.10 - 10.40 I: 5.00 - 14.00
Ave ± S.D. $PM_{2.5}$ (µg m^{-3})	153.16 ± 126.83	96.41 ± 70.47	O: 2.82 ± 0.77 I: 1.65 ± 0.27	O: 5.10 ± 0.89 I: 6.43 ± 1.99
Min - Max PM_{10} (µg m^{-3})	7.56 - 327.48	3.30 - 715.70	O :2.00 - 14.70 I: 1.60 - 21.20	O: 4.50 - 71.00 I: 5.60 - 98.80
Ave ± S.D. PM_{10} (µg m^{-3})	123.50 ± 100.07	206.81 ± 197.43	O: 5.03 ± 1.87 I: 4.45 ± 3.83	O: 10.30 ± 8.61 I: 17.38 ± 20.32

The first field tests on the ground and UAV measurement units demonstrated the technical feasibility of the prototype modules. The gas and particulate concentration measurements collected during the two surveys with UAV and ground units are summarized in Table 2. Data collected in March 2021 by the CO_2 sensor in the first ground unit prototype (O: 6.92 ppm; I: 15.88 ppm) were not plausible compared to the concentration measurements obtained with GC analysis of sampled air (O: 448.38 ppm; I: 525.34 ppm). Thus, a different commercial sensor was selected for the second version of the prototype unit (July 2021). The new sensor revealed concentration values (O: 426.20 ppm; I: 467.81 ppm) that were comparable to those measured with GC (O: 486.01 ppm; I: 608.80 ppm), although lower. The same sensor was deployed on the UAV, however results were not reliable due to technical reasons related to the sensor placement on the unit. The methane electrochemical sensor on the ground yielded plausible, yet lower, values (O: 2.52 ppm; I: 4.49 ppm) compared to those measured in sampled air (O: 3.24 ppm; I: 8.50 ppm). With the aim of improving the accuracy of the system, the CH_4 and NH_3 sensors were removed from the second version of the prototype unit and newer commercial options will be evaluated. Measurements collected at 30 m a.g.l. with the UAV unit yielded values that were consistent with those measured by the ground unit, suggesting that in-flight gas and particulate assessment is a promising technique.

Conclusions

The prototype system described in this work represents a first attempt to evaluate the feasibility of a low-cost and real-time air quality monitoring in livestock farms. Technical adjustments will be needed to optimize costs, accuracy of measures and size of the units; moreover, further laboratory and field trials will be necessary to select the best available sensor options on the market, calibrate the sensors in a lab environment and to assess the accuracy of measures in the field. Despite improvements are required before its use for research or farm management, the results confirm the feasibility of the system and set the basis for a rapid and smart tool to monitor GHGs, ammonia and particulate emissions in livestock farms.

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Physically grounded causal modeling for PLF

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Abstract

We propose an approach for efficient, robust learning and reasoning under realistic conditions. Our approach emulates the way students acquire prior knowledge from the combination of practical and theoretical training. This prior knowledge then informs the interpretation of observations on the farm, and provides a causal model for the prediction of future events and the outcome of actions. Grounding the causal model in physical modeling fusing all sensors, enables future sensor data to be predicted. Recognition and segmentation of materials and objects is done on the physical model. This provides descriptions that are definitive, enabling one-shot, and zero-shot learning. Flow of mass, energy, momentum and force, facilitate recognition of actions and causes. Objects and actions are input to abstract causal model search. This allows tangible concepts of anatomy and physical examination to be linked to abstract concepts of physiology, nutrition and disease. The abstract causal model provides explanation in terms of counter-factuals, actions that would alter the outcome. Unlike deep networks, all the components are examinable and explicable

Keywords: causal, physical modelling, segmentation, one-shot, zero-shot

Introduction

We consider what is possible in machine perception for precision livestock farming (PLF), from evidence in cognitive science, information theory and computer vision. This leads to an approach for efficient, learning and reasoning under realistic conditions.

<u>Problems with existing approaches</u>

PLF sensors (Gómez et al., 2021) can be broadly classified as either point sensors or imaging sensors. The interpretation of point sensors depends on where they are, and the significance the signal in that location. This leaves important tasks to the user including (a) ensuring that the instrument is measuring what is intended, and (b) integrating the sensor data with other information about the farm, to arrive at useful actions.

The use of imaging sensors depends on interpreting the scene. Advantages of imaging sensors are that fewer are needed, and that they last longer than sensors in contact with livestock. At present interpretation of image data in PLF is predominantly done with neural networks, with PLF as an end-user of techniques developed in computer vision research. Previously 'industrial vision' techniques relied on controlling causes of variation in the image, so that simpler measures could be used.

Limitations of big-data/deep-learning inference for PLF

Deep-learning (DL) from big-data has been the dominant paradigm in artificial intelligence and computer vision since AlexNet in 2012, (Oliveira et al., 2021). However, the quantity of data and processing required for Deep Learning techniques to solve real-world problems can be extreme. For example, in 2021 Tesla announced (CNBC, 2021) that they are building a custom ExaFLOP computer to process billions of kilometers of driving videos, in the hope of making their autonomous driving system safe to use without a human supervisor. The fact that humans learn this task from a few hundred kilometers of driving shows that much more efficient algorithms are possible.

Obfuscation: DL systems are 'black boxes' that are prone to making errors that appear bizarre and obviously wrong to humans, (Geirhos et al., 2020). This tendency to make types of errors that a human would not is a major barrier to using DL in automation of any critical task. In particular, DL tends to short-cut recognition, by correlation with characteristic patches of texture and absolute value of image pixels, without consideration of how the image is caused by a scene of objects with 3D structure, illumination and material properties.

Limited transfer-ability: Lack of understanding makes DL systems sensitive to irrelevant changes, and unable to interpret novel scenes or events. Consequently, the training data must include many examples of every irrelevant cause of variation in the sensor data, for each thing that must be recognized. DL systems often need extensive retraining on each farm, if there are differences in breed of animal, illumination, cameras, or scenery, especially where superficially similar objects or actions need to be distinguished. Where rare events must be reliably recognized, under all conditions, it can be challenging to obtain adequate training data. For novel scenes and events, there is by definition no training data available.

By comparison non-neural network methods can be two orders of magnitude faster on the same task e.g. (Yu et al., 2021), and do not require a 'black box' stage. We now consider what is necessary to build a system with human-like causal understanding of PLF tasks.

Cognitive science of livestock management

It is worth considering the tasks required in livestock farming and how it is possible for humans to perform these. When we unpack the complexity of skills we take for granted, this can provide a guide as to what component problems must be solved, to produce a system with human-like competence. When a farm manager, consultant, or vet inspects a farm and its livestock they integrate information from many sources:

1. senses: vision, hearing, smell, and touch
2. prior knowledge
   1) geographic: layout of buildings, the farm, its surroundings
   2) ecological: soil types, biomes, field condition
   3) procedural: farm routines, feeding methods, feed composition
   4) medical: anatomy, physiology, nutrition, pathology, epidemiology

Fig 1 sketches the sources of information that a farm manager or veterinarian would be expected to draw on when deciding what actions to take. This context is critical to the significance of the data from any sensory sample.

Figure 1: Information leading to actions.

Desiderata of a PLF system

We need a general purpose system that:
— makes optimal inference with limited data
— transfers correctly between farms
— is quick to train in new skills
— explains its reasoning
— reliably arrives at the correct answer
— does not require hand-coding knowledge

Prior information

A critical insight from information theory is the "No-Free-Lunch" theorems, which show that for an algorithm to be efficient at solving a given problem it must contain relevant prior information about the problem (Wolpert, 2012).

To understand how this applies in agricultural decision making, consider an altered form of the Turing Test thought experiment: require competent farm manager or vet to perform their normal work via a data link. The sensors and data that must be sent, tell us the "*data sufficient to perform*" for a skilled person. A layperson without relevant expertise would not be able to interpret this data to perform the work of the skilled person. This indicates "*professional prior knowledge*" implied by competence.

Next, require a new student to attend agricultural or veterinary college via the data link. The sensors and data required tell us the "*data sufficient to learn*". This is the interaction required to acquire the prior knowledge of a competent professional. This is both more and different information from the "*data sufficient to perform*". Note that if we present topics in random order, then student will fail to understand critical parts of them. Likewise, if we omit key parts of practical training, then the student will not be able to relate their textbook knowledge to reality on the farm. Conversely, it would be prohibitively slow to leave the student to rediscover agricultural and veterinary science from personal experience.

If in the thought experiment we replace the student with a baby, we can consider the "*data sufficient to learn*", for the perceptual skills and "*common sense*" understanding of the physical world that we expect the student to already possess. Chief among these are (i) the ability to perceive materials, objects and actions as the cause of the data coming from all their senses (sensor fusion), (ii) to predict physical consequences (simulation) and (iii) to reason about causes of past and future events (causal inference). It is the ability to reason about causal relations abstractly, that enables the student to learn and apply theoretical knowledge.

Components

Causal inference

Causal inference has been an increasingly active field of research since the 1990s (Spirtes et al., 2000a). Most researchers will be familiar with the maxim "*Correlation does not imply causation*". While this maxim is true in itself, idea that purely observational (non-experimental) correlation cannot be used to obtain information about causation is false (Spirtes et al., 2000b). What is true is that some initial causal information is required. This may be the ability to manipulate just one variable in the system, or confidence in the direction of causality between one pair of variables (e.g. sunrise wakes the rooster and not the other way around). Given this initial causal axiom, it is then often possible to infer a great deal of the causal structure from observational data, and also to define a minimal set of experiments for determining the unresolved causal relations.

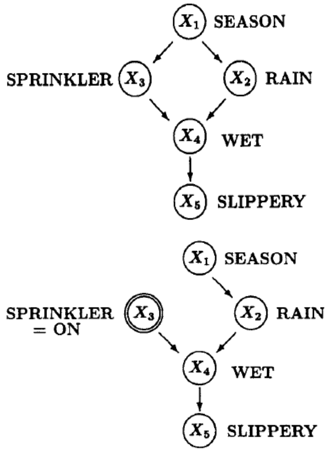

Figure 2: The Do operator : P(A|set_B,C) != P(A|B,C) Observation vs action "set_Sprinkler" modifies the graph (Pearl 2009, fig1.2&1.4)

Key insights include (i) the distinction between observing versus setting the value of a variable (fig 2), (ii) the use of graphical models to represent causal relations between variables, (NB a causal edge implies a "*counterfactual*" hypothesis about what would occur if the values of variables were changed) and (iii) the concept of dependence-separation "*D-separation*" between variables (Pearl, 2009). Together these enable propagation of causal relations and effects across a causal model, even to variables that can neither be manipulated nor directly observed.

Causal model search

Of particular importance for PLF is the ability to discover the correct causal model for a system of interest. Glymour et al., (2019) reviewed of causal model discovery algorithms. The Tetrad library (Ramsey et al., 2018) provides implementations of many published algorithms. There are also algorithms such as PC-MCI (Runge et al., 2019) which model time-lagged relations between variables. The PC-MCI family of algorithms are implemented in the Tigramite software library (Runge et al., 2016).

Physical grounding

Abstract causal inference algorithms require input of semantically meaningful variables, measurements of observed objects and actions. Relating abstract concepts to the tangible world is physical grounding. Modeling the physical world from sensor data is physical perception. These are a crucial part of the "*common sense*" skills expected of the new student, and applied in practical training to ground the abstract models taught in lectures and textbooks.

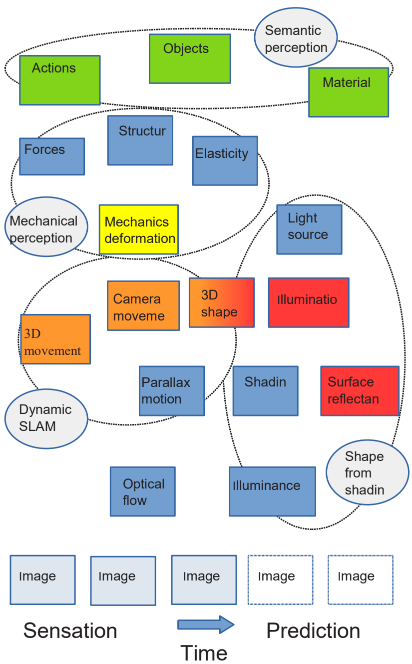

Figure 3: Causal relations in physically grounded visual perception

For visual perception (fig 3) physical grounding can be broken into four subsidiary problems (i) dynamic SLAM, and (ii) shape-from-shading, (iii) mechanical perception, and (iv) semantic perception, for which nearly complete 'white box' solutions are available. From image data to mechanical perception, the causal relations derive from the physical laws of geometry, optics and mechanics. Conversely, semantic perception is a lossy compression of the physical model to produce a much more compact representation, that retains predictive accuracy.

Dynamic SLAM/SFM

In *dynamic SLAM* the sensor can move and the object(s) can move and deform e.g. animals. The source of information in *passive visual SLAM* is parallax motion in the image sequence of a camera. For reconstruction from conventional video cameras "*passive dense monocular dynamic SLAM*" is required. A monocular algorithm provides the advantage markerless auto-calibration e.g. (Mahmoud et al., 2017). *Real-time passive dense monocular SLAM* algorithms have been available since DTAM (Newcombe et al., 2011), however extension is required to accommodate dynamic scenes.

Shape, illumination and reflectance from shading

People perceive 3D scenes from single photographs. Single image 3D reconstruction is a strictly ill posed problem (fig 4). By including *prior information* about *natural scene statistics*, it is possible to find the 3D reconstruction that represents the most probable cause of the image. Such algorithms are known as "*shape from shading*" algorithms. When people describe the color of an object in a scene, they refer to the constant material property of reflectance. Knowing the reflectance, the appearance can be predicted under different illumination, hence it is possible to recognize an object having seen it under only one illumination. Algorithms and code have been published for *single-image shape illumination and reflectance reconstruction from shading*, e.g. (Barron & Malik, 2014). Combining dynamic-SLAM and SIRFS algorithms would be particularly useful in PLF. Modeling reflectance and illumination would improve the robustness of the SLAM algorithm. This is particularly true for specular (shiny) materials, e.g. the fur and skin of animals, wet surfaces, glass, metals and plastics.

Mechanical perception

Perceiving and predicting forces and motion in the world is a critical part of the "*common sense*" skills that enable a student to learn from practicals. In particular it is critical to understanding the anatomy and mechanics of animals, machinery and all materials of importance in PLF (e.g. feed, bedding, soil, flooring).

If the moving visible surface is tracked then a mechanical model can be fitted under the surface using a *differentiable soft matter physics simulator* e.g. (Hu et al., 2020). From the observed deformation it is possible to infer the relative density, elasticity, viscosity and mechanical structure of objects. The mechanical simulation also provides constraints on plausible reconstruction of the moving surface. It is possible integrate force sensing and calibrate the absolute values of the parameters of the model. Multi-physics can fuse different classes of sensors, e.g. heat, sound and olfactory/chemo sensors.

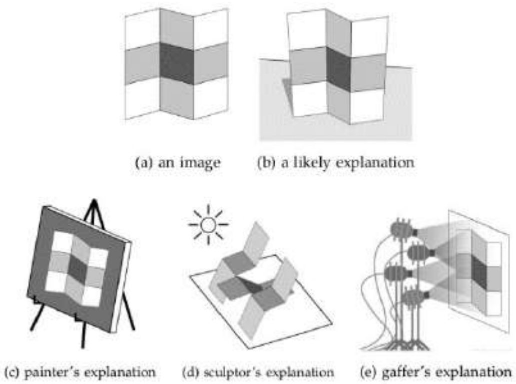

Figure 4: Adelson and Pentland's "workshop" metaphor for different possible causes of the same image, from (Curtis & Baker 2011).

Semantic and instance segmentation

Distinguishing and tracking individual animals in a herd, and distinguishing what part of the scene belongs to each animal, require instance segmentation and semantic segmentation.

In physical perception, objects are described in terms of their mechanical structure, topology of parts, material properties, and 3D geometry. This is sufficient to predict how they will behave and how they will appear. 3D geometry and topology facilitate instance segmentation. Mechanical simulation and SLAM provide robust tracking.

This physical causal definition of objects (1) is invariant in changing scenes, (2) enables classification to be completed with non-black-box methods, (3) "one-shot" learning from a single example, (4) "zero-shot" learning from description[1], and (5) retains end-to-end differentiability[2].

Action, cause and agent recognition

Mechanical perception provides a model of the forces, accelerations, and the flow of mass, momentum and energy in the scene. These provide a causal basis for recognizing actions and power sources. Agents (animals, people, and machinery) standout because they are power sources, whose behavior is more complex than inanimate objects. Agents can be modeled as having purposeful actions, selected based on goals and limited perception. Physical perception allows the sensory stimuli and behavior of other agents to be predicted via *perspective transform*, e.g. livestock may refuse to walk forwards because they perceive something nearby as threatening.

1 These correspond to (i) the learning from minimal examples in student practicals and first encounters of new object classes, and (ii) learning from verbal information in textbooks or professional communication

2 This enables (i) learning scene specific priors for SIRFS and SLAM and (ii) top-down refinement of physical reconstruction from recognition, e.g. completion of partially obscured objects.

Interface between physical perception and abstract causal inference

Instance segmentation of objects and actions from physical perception provides the ability to learn and recognize high level semantic concepts that link abstract causal reasoning to sensor data. Together these provide the perceptual skills needed to learn professional knowledge.

Acquiring information

Sensors

The sensors needed for the system would also provide "*data sufficient to perform*" for remote consulting. Applying them in this role is a good way to acquire some of the training data. Eye tracking glasses capture what the wearer sees and where they focus their attention (Tobii, 2022). Force sensing is important for learning material properties and mechanical structure. If tools can be used to perform the handling work, then strain and vibration sensors can be added to them, and their motion tracked visually, to infer forces applied in the scene.

Prior knowledge

The required knowledge has sequential dependencies, so requires a similar syllabus to human learning. Much of the learning can be done passively and in parallel from recordings of student interaction in existing practicals. Theoretical knowledge would be initially acquired by parsing textbooks to generate abstract causal models, which are then linked to recognition and physical simulation from the practical learning. The abstract model can be inspected by the human trainer. It can also be used to find edge cases in its predictions and generate questions to verify and refine its understanding.

Application in service

Monitoring from fixed cameras and point sensors, taking account of professional and farm-specific knowledge, would (i) produce a warning and prediction system that is transferable between farms, and (ii) able to learn production systems and diseases in a human-like way.

The causal model can predict the outcome of potential actions (counterfactuals). This can be used (i) to recommend optimal plans of action for farm management, or treatment of individual animals, and (ii) combined with prediction of sensor data from physical simulation, to automate control of machines to do the work. The system would have the ability to learn the 'what, how, why and context' of manual tasks. Physically grounded causal modeling would enable the system to understand the tangible and meaningful risks and consequences that are crucial to "common sense" behavior.

Conclusions

Causal models predict the outcome of interventions. This allows optimization of planned actions. Physically grounded causal modeling provides a fully explicable system, capable of efficiently acquiring professional prior knowledge, to interpret sensory perception, and produce justified diagnoses and plans. The necessary components are nearly complete in the published literature, but need particular extensions and integration into a coherent system. Such physically grounded, causal AI systems, with human-like common sense, have become a focus of research in computational cognitive science, as solution to the shortcomings of deep-learning, (Zhu et al., 2020).

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Precision Livestock Farming: from where we come, to where we go

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Abstract

Precision Livestock Farming (PLF) is a tool for management of livestock by continuous automated real-time monitoring of production/reproduction, health & welfare, and environmental impact. A "tool" means that PLF does not replace experts like farmers, veterinarians, feed experts, etc. but that it supports people in their decision taking by offering objective measurements. The paper aims to give an overview of where it started, where we are and where to go.

When starting this research in 1991 with a more fundamental question on predictability of the responses of living organisms, we started on insects and mussels. It soon became clear that animals, like humans, are so called C.I.T.D. systems: Complex, Individually different, Time-varying in their responses and Dynamic. We did experiments on bees, fish, mice, rats, chicken, pigs, cow, horses, dogs to from 2001 also work on humans. Results are shown in videos and graphs. The research trajectory showed principles on how to develop the technology and to implement it in products.

The pickup in the field however goes far too slowly and that is where we must put more efforts. Finally, we will show where to go with this technology to create a real impact for many people and animals worldwide.

The PLF concept takes off worldwide and can help us to create a more sustainable livestock sector which is so much needed. We need to deliver more animal product with less feed input, less manure and environmental impact and improve animal welfare and health. PLF shows high potential to help us create these solutions.

Keywords: Precision livestock farming, overview of what has been accomplished, where we go.

Introduction

PLF is perceived by many as digital technology for continuous monitoring and automated management of livestock. We like to define it as "a tool for management of livestock by continuous automated real-time monitoring of production/reproduction, health & welfare and environmental impact". A "tool" means that PLF does not replace experts like farmers, veterinarians, feed experts, etc. but that it supports people in their decision taking by offering objective measurements. PLF is realized by using digital technology like cameras, microphones, sensors on or sensing technologies around the animal combined with digital networks, internet of things, databases in digital environments, general software and a lot of PLF-specific software.

In 1991, there were three arguments that made us start with rather fundamental research projects for continuous monitoring of animals. *The first reason* resulted from a research project from 1980 – 1990 where we followed 100 fattening pig houses for ten years (Goedseels et al., 1987). These pig houses had totally different systems like naturally versus mechanically ventilation, heated versus unheated, different types of inlets, floorings, feeding systems, climate controllers, etc. But they were all built by the same materials and equipment for each system, used at the same moment the same feeder composition, same genetic line of pigs, same advisors, etc. They were all contract farms with a same follow up. The question was which factor (type of flooring, feeding system, ventilation system, heating system, etc.) has most effect on the production results (feed conversion, growth rate, mortality and diseases). All farms were visited each in fattening period over 10 years and all results from over 2500 fattening periods were analyzed. The big conclusion was that the farmer has the highest impact on how the animals were producing in the different production systems. Farmers with the best production results used as a main tool more audio-visual observation of the animals several times a day (Goedseels et al., 1987). We then realized that we were busy trying to optimize the thermal environment for the animals with working on the ventilation system, heating system with different technologies, the climate control system (Berckmans et al., 1988), but that we did not pay enough attention to the core of the whole process: the animal. Having experienced as a twelve year old boy how my grandfather observed his animals, I realized the importance of continuous monitoring. My grandfather had more kids than cows and they all had a first name, and he checked the animals several times a day. Being in a creative team at the KU Leuven, led by Professor V. Goedseels and with my colleague Dr. R. Geers, I was submerged in the vision of looking directly to the animal. That's when the idea originated to monitoring animals continuously during the production cycle and to focus on which technology could make this happen.

The second reason was to notice that animal welfare was subjectively and 'manually' observed and this only once at or near the end of the production period. The first general animal protection law, called the Protection of Animals Act, was introduced by UK in 1911 and updated several times since. In US since its inception in 1966, the Animal Welfare Act (AWA) has been shaped and expanded upon by political and social influences. In 1965 the Irish professor Brambell had published the 85-page "Report of the Technical Committee to Inquire into the Welfare of Animals Kept under Intensive Livestock Husbandry Systems" (Rogers Brambell, 1965), later known as "the Five Freedoms". The Farm Animal Welfare Advisory Committee in UK was created in response to Brambell and colleagues' report to monitor the livestock production sector. In 1979, the name was changed to the Farm Animal Welfare Council (since 2011 Committee) (Wathes, 2009). The field implementation of systematic monitoring animal welfare was mainly based upon visual checkups after the production period with the so-called iceberg indicators. Like the top of an iceberg hides a bigger obstacle under the water, some indicators (e.g., a bitten tail) in the slaughterhouse indicated a problem in that farm. The visual observation happened in the slaughterhouse, after the production period, too late to solve the problem for these animals. The visionary approach by observers in the field of the Welfare Quality (Blokhuis et al., 2003) concept was described in 2003 and the project started in 2004. It generated a detailed protocol for human observers to observe and score the animal welfare for different species in European farms. But also, this approach was based upon scoring once a year a farm and yet near or at the end of the production period.

Seeing around 1989 that a lot of sensor technology and software was under development, research was started to develop technology for continuous monitoring of livestock (Figure 1).

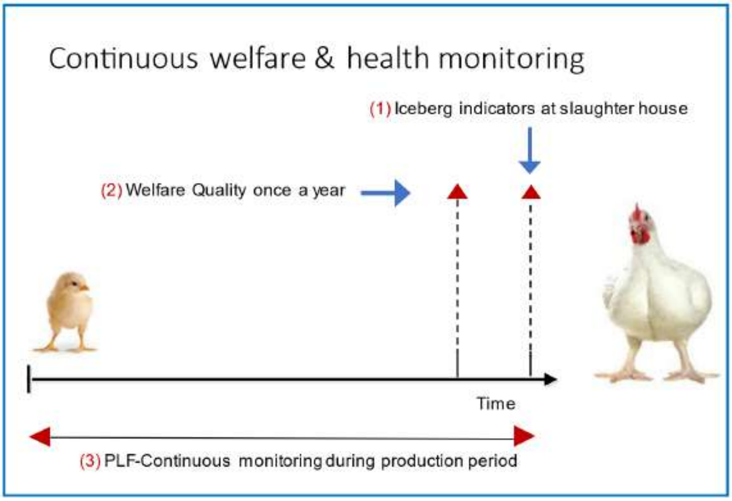

Figure 1: Continuous objective PLF-monitoring during the whole production period versus once scoring at or near the end of the production period.

Problems to be solved

Society and everybody connected to the livestock sector knows for sure the big challenges that we are facing. The worldwide demand for animal products is increasing till 2050. Recent facts show how animal health is of crucial important since zoonoses coming from animals remain a serious issue. Tuberculosis for example goes from elephants to dairy cows and from cows to humans. Looking to the fundamentals of the biological core process in the livestock sector, it is about transferring feed energy into animal product. All the metabolic energy, coming from feed and lost in the lack of animal welfare or health, is not available for animal product (meat, milk, eggs, fiber, etc.,). This shows that animal welfare is not only an ethical issue but is in the middle of a more sustainable production. We need higher efficiency to produce more animal product with less feed input to reduce the environmental impact (manure, emissions, odor, etc.) (Figure 2).

In September 2015, 193 Member States of the United Nations agreed in the General Assembly to adopt the 2030 Agenda for Sustainable Development that includes 17 Sustainable Development Goals (SDGs). We must realize that SDG 1, 2, 3, 6, 11, 12, 13, 14 and 15 are related to the livestock sector and that all of us, have the responsibility to contribute in transforming to a more sustainable world (Figure 3) (UN, 2015).

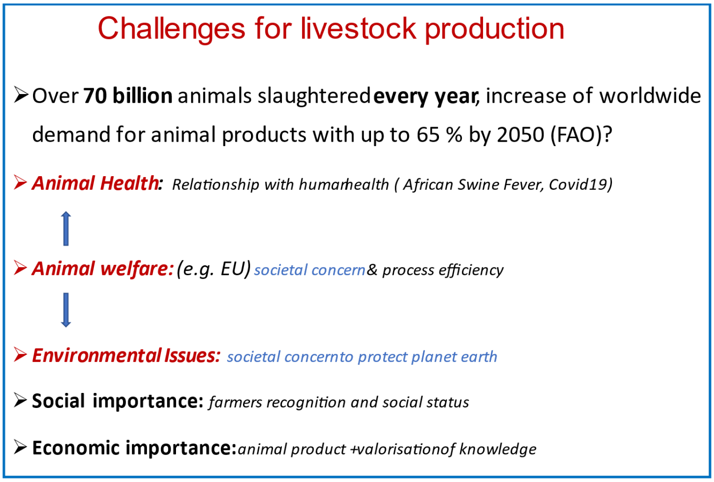

Figure 2: From metabolic energy viewpoint, animal welfare is in the middle of the biological process to transfer feed energy into animal product.

Figure 3: Half of the 17 Sustainable Development Goals by the United Nations are related to the performance of the worldwide livestock sector.

Today, the position of livestock within a worldwide context with climate change and available economic means of food production is challenged. Concerns are expressed on several issues, notably: *Lack of increasing sustainability and efficiency in animal production; criticism on the guarantee of animal welfare for several reasons; environmental pollution by intensive animal production, absence of or so far no successful identification of appropriate technologies to improve this; risk for disease transfer from livestock to humans. More questions are raised by the society and the sector such as: are lab-meat and plant-based protein a threat for livestock producers? Can we reduce food loss and create food waste recovery as animal feed? Does livestock of the rich eat the grain of the poor?*

Objective

The objective of this paper is to show where we came from in the research trajectory to come to basic principles of PLF technology and to give a vision on where we will go to.

Where we came from

Around 1990,great explorative research was done on analyzing possibilities to monitor variables on animals, but not yet with the idea to have a continuous monitoring technology for field applications (Scott and Johnson, 1982, Leidl and Stolla, 1976). When in 1991 we focused research on continuous monitoring living organisms, we realized that the detection of animal problems is based upon understanding the normal behavior. The more fundamental question was whether it was possible to predict normal responses of living organisms. Research was started using well controlled laboratory experiments with living organisms which we naively thought were simpler to do experiments with and for sure cheaper in experiments. This first research for continuous monitoring of living animals, was done with contactless technology to make sure not to influence the animal response by the used monitoring technology.

In those pioneering years, developing the PLF concept, several efforts were done with *image analysis* on different species to develop model-based monitor techniques on living animals and their behavioral responses. It showed that digital image analysis is an accurate technique for the quantification of the behavioral response of Tubificidae to pollutants (Vanhoof et al., 1994). A biological early warning system was developed based on the phototactic swimming behavior of Daphnia Magna in relation to the reproducibility of its response and sensitivity towards potential pollutants in water (Leynen et al., 1999). Research was done on continuous monitoring of animals like on poultry (Aerts et al., 1997, Sergeant et al., 1998, Bloemen et al., 1997, Leroy et al., 2006), pigs (Geers et al., 1991, Wu et al., 2004, Shao et al., 1997), cows (Herlin and Drevemo, 1997, Choi et al., 2001, Leroy et al., 2005), horses (Audigie et al., 2001, Schofield et al., 2003, Jansen et al., 2009), fish (Ruff et al., 1994), mice (Leroy et al., 2009), etc. With *sound analysis* many trials were done with applications on pigs (Chedad et al., 2001, Van Hirtum and Berckmans, 2002, Guarino et al., 2008), chicken (Silva et al., 2010, Tong,et al., 2015), cows (Jahns et al., 1998, Laca and Wallis DeVries, 2000, Ikeda et al., 2003), fish (Nordeide and Kjellsby, 1999), bees (Ferrari et al., 2008), One of the first attempt with *sensors* was to monitor the so crucial heart rate in the production of metabolic energy in a living organism, that was on embryos in chicken eggs (Aubert et al., 2000). Due to the cost of sensors it cannot surprise that most research with sensors on animals was on higher value animals like cows (At-Taras and Spahr, 2001, Mottram et al., 2000).

Around 2005, several researchers were working on the development of technology for continuous monitoring of farm animals, but still there was doubt about the feasibility to develop systems than can monitor animals continuously 24/7 working with the required accuracy and reliability within the harsh farm conditions (Carpentier et al., 2018).

A living organism is a C.I.T.D. system

Lesson learned from the early research and mainly from laboratory work under well controlled environments is that living organisms are very different from other physical, mechanical, electrical or digital systems. All animals, as all living organisms, are Complex, Individually-different, Time-varying and Dynamic (CITD). We did bring this concept in the first ECPL2003 conference in Berlin and published it in 2006 (Berckmans, 2006). When looking to the data transfer in a single cell of an animal body, it becomes clear that animals are very *complex systems*. No way to describe such systems in real-time with mechanistic models. Another fact is that animals respond in a complete *individually different* way to experienced environmental events or interactions with other animals or humans. This contrasts with the general classical approaches where animals are considered as "an average of a population". The average of a population and the standard deviation are made to compare groups, like e.g., the treated group versus the control group. But population statistics is not the best method to analyze results from individually different animals. In each variable considered, the standard deviation of the group is much bigger than the standard deviation of an individual (Figure 4).

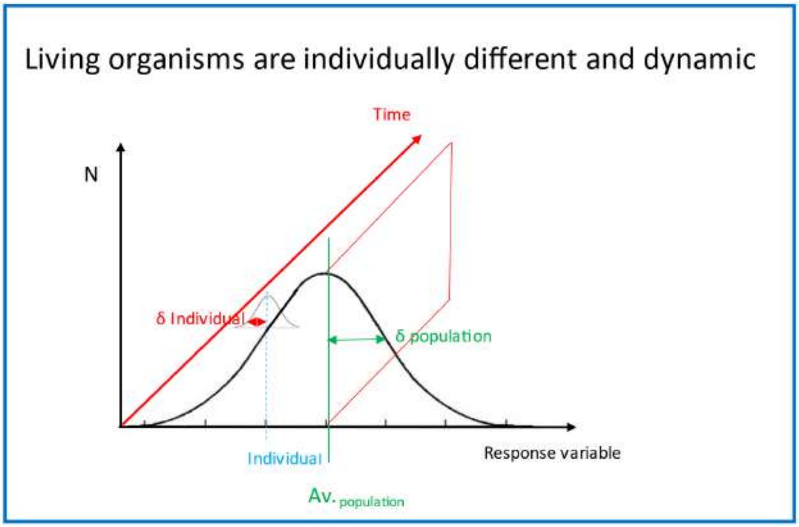

Figure 4: Animals are individually different and dynamic. They are CITD systems (Berckmans, 2006).

The fact that animals are individually different has consequences on the required accuracy of sensors or sensing techniques. The sensor now needs to be accurate enough in relation to the much smaller individual standard deviation of variables over time, than the population standard deviation. That is also why many sensors for animals or wearables for humans are yet not bringing the required accuracy. As shown in Figure 4, animals have variations over time in all physiological variables and behaviors. Depending on the variable measured, sensors or sensing techniques must have the appropriate sampling frequency.

Even more interesting is to notice that animals, like all humans, are *time-varying* systems. This is a different thing than being dynamic. Time-varying responses means that every time an environmental event or stressor happens, the animal might respond in a different way. For example, a horse is happy when receiving the feed, and next time it is frustrated because the feed was not given fast enough. It is like humans, a Monday morning might to the same question give different responses than a Saturday morning.

Of course, animals are very dynamic which needs the appropriate analysis tools to catch the information. Humans and animals act individually different, whether we like it or not. The concept of an animal being a CITD system has huge consequences on the appropriate technology to monitor animals and to improve the management to create more sustainability.

Where we go

In 2022 we can notice that there is more research than ever before on precision livestock farming which started in Europe and is worldwide more than just being picked up like in US and China, but yet we are far away from enough implementation and proof in the field. We see that a lot of researchers repeat work being done in the past not being eager enough to make the very challenging step from research to application. Though several efforts happen in precision livestock applications (Halachmi, 2015), more field application is what we need. If we do not bring efficient applications to the field with demonstrated return on investment for the farmer and all stakeholders, we will not be able to produce more animal product with less feed input, and that is what we need.

In history, most of the increase in animal products has come from an increase in number of animals rather than from an increase in individual-animal productivity, beside the huge advantage in genetic lines of farm animals. This year over 70 billion animals will be slaughtered, it is unthinkable that we will solve the increasing demand for animal products with 65%, by keeping more animals. When considering the fundamentals of the process to be managed in the livestock sector, we have to look to it's essential components as given in Figure 5.

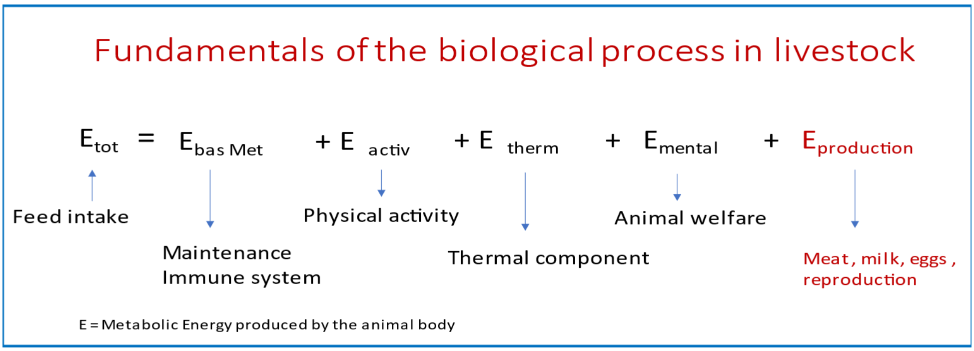

Figure 5: The fundamental process of transferring feed energy into animal product.

Where we go-1: Focus on each term of the fundamental equation (Figure 5)

It is all about managing and supporting the animal to help it transferring the feed energy with highest efficiency in the $Energy_{production}$ term (meat, eggs, milk and fiber). It is not a matter of focusing on a specific term of this equation in Figure 5. It is not a matter of optimizing OR this OR another term in the energy equation. It is about working on AND this AND all other terms to maximize the $Energy_{production}$ with minimal Total $Energy_{intake}$. In other words, we need "more with less": more animal products from less feed intake and consequently with less manure production, less emissions, less infections, and less losses in lack of health or animal welfare.

The good news is that PLF has the potential to develop and implement more techniques and to offer more possibilities to work on each of the terms of the energy equation (Figure 5).

Total $Energy_{intake}$: There are several opportunities to improve feeding management. There is a difference between the amount of feed fed to animals and the real feed intake. In research stations feed delivery or feed intake are measured since many years but the used technology is too expensive for large scale applications in livestock houses in the field and for sure for small family farms. PLF has shown techniques for very accurate measurements of feed intake by broilers using sound analysis with a simple microphone integrated in the feeder pan (Aydin et al., 2014, Ran Bezena et al., 2020, Greenwood et al., 2017).

$Energy_{basal\ metabolism}$: The basal metabolism is the absolute minimal amount of energy that an individual body needs to keep all organs functioning. This is a totally individual characteristic depending on species, age, weight, health condition, production phase, etc. So far, the individual feeding strategy is depending on the Energy production term in milking cows, but the real estimation of the basal metabolism term is not yet realized, although feasible. Genetic selection has accomplished huge advantage in working on this Energy basal metabolism and has consequently played a huge role in producing more animal product. More efficiency in terms of feed conversion, growth rate, less infections will result in less manure, less emissions.

Today, PLF technologies can offer the advantage of collecting data from many animals to study the efficiency of phenotypes in the field at very large scale. If one is for example interested in analyzing the aggressive behavior of a specific species and wants to collect data from e.g., 500.000 animals, PLF can make it happen. Knowing this, new breeding opportunities can be defined for the potential of livestock species to acquire plasticity for adaptation to for example current climate changing conditions or improved emission results.

$Energy_{movement}$: All physical or mental performances of animals or humans take metabolic energy. So far, we are not monitoring the effect of the animal movement on the management of the energy equation. Many solutions are described in the scientific literature to monitor movement continuously mainly for cows, pigs, and bigger animals by using 3D accelerometers and gyroscope technology. The wearable technology is making fast progress in terms of accuracy, dimensions, weight, price, and energy use. For lameness detection several solutions have been proposed for several species and position and gait analysis become standard techniques for milking cow. The potential of technology for active management of the $Energy_{movement}$ component however is not yet explored. When combining such technology with heart rate monitoring, interesting opportunities become available for active management of this component. Do we get more happy animals when they move more like has been shown for humans when doing sports? What is the effect on body composition, meat quality, feed conversion, etc.? For large animals like cow, beef cattle, horses, etc. the metabolic energy for moving the body is not neglectable which does not mean that active movement management would not be a good option for health management or animal welfare.

$Energy_{thermal}$: What we do for many decades is to work on the $Energy_{thermal}$ term by housing livestock in structures to protect them from the varying outside weather conditions. With climate change there are new problems to be solved. With genetic engineering many possibilities are still unexploited in relation to phenotypes of livestock where PLF can collect many data. There are several candidate genes that are associated with adaptation of ruminants, monogastric and poultry to heat stress (Rovelli et al., 2020) Also, the use of new technologies and materials in climate control of livestock houses has many unexploited opportunities when combining with the concept where animals decide for themselves by using PLF technologies with camera's, microphones, sensors etc.

<u>Where we go-2: Continuous real-time physiological measurements to manage the mental component</u>

$Energy_{mental}$: the mental component includes animal welfare as a central element in the metabolic energy equation. Animal welfare is not only required for ethical reasons but also for reasons of efficiency of the animal production process. How many of the 70 billion livestock animals, slaughtered this year for the worldwide demand, are not stressed? All the energy, used for the mental component when stressed, is not available for the basal component, the immune system, the thermal or the (re)production term in the equation. What we expect to become a real disruptive technology for the livestock sector is the continuous real-time monitoring of the $Energy_{mental}$ term or animal welfare based upon physiological variables. In the past, Darwin has already shown that there is a dynamic relationship between the central nervous system and the expression of emotions and more recent literature shows that physiological variables offer potential for monitoring stress (Darwin, 1872, Porges, 1995). When an animal produces metabolic energy within the aerobic zone, the inhaled air is brought into the blood in the lungs. The heart is pumping the oxygen rich blood to the cell level where the metabolic energy is produced in the mitochondria. This means that the level of heart rate is a measure for the possible total production of metabolic energy. The decomposition of heart rate components in mental and physical components remains a challenge on moving subjects, which leads to the consequence that most methods for stress monitoring based on heart rate are limited to non-moving subjects, like heart rate variability. However, the technology is available for humans and animals and will also become available for animals as soon as the appropriate sensor is realized (Joosen et al., 2019, Luwei et al., 2020).

Where we go-3: real-time infection monitoring

Energy$_{immune\ system}$: Animal health is of course crucial in realizing a more efficient energy equation (Figure 5). PLF offers many possibilities for real-time health monitoring from which most of them are yet not implemented in operational field systems. PLF might become the most important One Health Technology to detect infections in wildlife, livestock and humans. Tuberculosis for example goes from elephant or deer to dairy and next to humans. A 24/7 real-time infection monitoring system for humans and animals is possible. For humans, several algorithms have been developed based upon using heart rate or heart rate combined with activity (Mishra et al., 2020). To introduce this technology in the field we need a sensor that can accurately measure heart rate and movement for example in an ear tag. A candidate technology to monitor heart rate in livestock is the meanwhile well know ppg technology (photoplethysmography) (Luwei et al., 2020). It can be expected that such an ear tag, monitoring heart rate and movement, will come soon and it seems obvious that the first species will be the more expensive individual animal such as milking cow, beef cattle, racehorses etc. We can expect that miniaturization can also bring it to pigs and poultry but the existing infection monitoring with sound analysis will be more economic (Mishra et al., 2020).

Conclusions

This paper was not aiming to be a review paper since it is far too incomplete in covering the work of many colleagues worldwide who contribute with fantastic work to the PLF field. A great overview of existing PLF technology is made by Halachmi et al (2018). The objective was to show where we came from in the field and based upon lessons learned where we should go. It is clear that PLF has a huge potential in bringing solutions for the enormous challenges the livestock sector is facing. We need focus on the core energy equation that runs in each livestock application to turn feed energy into animal product. PLF offers solutions to focus on each of the components of the equation to generate more animal product with less feed input. The way to go is by using the new sensor technology to measure 24/7 physiological variables on the animals with totally new possibilities for higher efficiency that will generate a more sustainable livestock sector. Such objective and continuous monitoring of animal welfare and infection, based upon objective physiological measurements, will be a huge step in creating a more efficient production process. We will finally create the possibility to give animals in the production system a life worth living (Wathes 2010, Yeates, 2011). Bringing a worldwide 24/7 infection monitor for animals will not only help the animal and the sector but all people on planet earth and specially people in developing countries. more implementation in the field is a first priority. To come up with real solutions, a collaboration between different research disciplines (animal scientists, veterinarians, engineers, etc.) is needed as well as a strong collaboration between researchers and industry.

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SESSION 12

Consortia Presentations

DiLaAg - digitalisation and innovation laboratory in agricultural sciences

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Abstract

Sustainable production and development in livestock sectors are critical to meeting the growing requirements placed on it, increased production, efficiency and reduced labour, along with the various political declarations and societal claims. Digitalisation is increasingly seen as a prerequisite to achieving the goal of sustainable agriculture and reduced labour. Therefore, it is the aim of the DiLaAg project to bring together scientists from different fields of expertise to work interdisciplinary on the complex topic of digitalisation in agriculture. In the DiLaAg consortium, PhD students and their supervisors from the University of Natural Resources and Life Sciences, Vienna (BOKU), the University of Technology Vienna (TU) and the University of Veterinary Medicine Vienna (VETMED) build the scientific core. The project was initiated and is funded by the Federal State of Lower Austria and the private foundation 'Forum Morgen'. The PhD students work in the fields of robotics, image-based plant classification, agronomic analyses of crops, impact of technologies, digital twinning, livestock management on pasture and sustainability assessment as well as on interdisciplinary topics such as computer vision, application of digital sensor technologies, machine learning, complexity science, remote sensing, data integration, precision agriculture and precision livestock farming. Apart from this scientific nucleus, the DiLaAg consortium aims to act as a platform for innovation and exchange, by continuously expanding its network and collaborations in order to continue working on current challenges in agriculture.

Keywords: digitalisation, smart farming, agriculture, sensor technology, precision farming, sustainability

Introduction

Vision of DiLaAg

The DiLaAg project aims to connect the expertise in the field of Precision Farming at the University of Natural Resources and Life Sciences, Vienna (BOKU), the University of Technology (TU) and the University of Veterinary Medicine (VETMED) for scientific cooperation. Interdisciplinary collaboration between experts is a promising approach when tackling the complex problems found in agriculture, leveraging the various insights, methodologies and research topics, novel solution can be developed. The main objective of DiLaAg is to form a scientific nucleus in the area of agricultural digitalisation and educate young researchers in this interdisciplinary field. It shall also serve as a platform for consultation, development, education, exchange, and knowledge transfer.

Innovation platform

The Innovation platform of DiLaAg consists of the 'Applied Farming Network' and the 'Company Network'. The basis of the 'Applied Farming Network' is built by the two experimental sites of BOKU and VETMED in order conduct studies on agronomic production ('Groß-Enzersdorf') as well as on livestock farming ('VetFarm') in the frame of DiLaAg. Further expansion of the 'Applied Farming Network' is planned to enable research on digitalisation in agriculture on commercial farms in the crop and livestock sector.

DiLaAg partners

In addition to the three partner universities, which are responsible for the scientific in- and output, there are two partners, who support DiLaAg with funding: the Federal State of Lower Austria and Forum Morgen Private Foundation. In terms of networking and knowledge transfer, DiLaAg is collaborating with 'Smart Agri Hubs' (https://www.smartagrihubs.eu/) and 'DIH Innovate' (https://www.dih-innovate.at/). Moreover, a valuable input is the recent inclusion of Prof. Holzinger, Prof. Stampfer and Prof. Roth into DiLaAg due to their expertise in agronomy, forestry, livestock and artificial intelligence.

PhD projects

The common aim of the individual PhD projects is to facilitate everyday farming, to optimise production and to promote sustainability in farming by using digital sensor technologies under agricultural conditions. Interdisciplinary collaboration is necessary to deal with topics that play a role in several PhD projects, such as computer vision, remote sensing, resilience analysis, sustainability assessment and machine learning.

A) Data-based networked process management in agricultural engineering

In the project 'Data-based, networked process control in agricultural engineering', a 'digital field' at the experimental farm in Groß-Enzersdorf should be used to demonstrate robotic integration into agricultural process engineering, generating data for a wide variety of crop production models, and its integration into corresponding working processes. In order to achieve this, a mobile robot platform (Supper *et al.*, 2019) is being used to collect the data during systematic field experiments. Beside the pure data collection, the focus of this project is on autonomous cultivation using an autonomous field robot platform. Possible fields of applications are numerous, such as data acquisition of the plant stocks, weeds, soil condition, and autonomous performance (e.g., of the weeding process). To achieve that, the robot will be equipped with sensors to detect the environment and an attachment will be developed to carry out an application in the field. Connectivity with the robot's higher-level systems should enable data storage and data exchange. A user interface is used for direct communication with the user. To make this possible, the robot is equipped with long-term evolution

(LTE), wireless-fidelity (WiFi) and bluetooth communication systems. The free platform ROS (Robot Operating System) is used as software. This enables sensors and actuators to be integrated flexibly into the robot application. To fulfil the previously mentioned demands, a set of experimental procedures have been established and performed, defining the required autonomous working parameters e.g., indoor navigation, as well as the investigation and evaluation of the main performance parameters in the outdoor field working tasks e.g., slip, traction performance and electrical energy consumption. Above mentioned findings should represent a solid ground for the future upgrades of the autonomous robot system, e.g., integration of the computer vision system on robotic platform.

B) Integration of plant parameters for intelligent agricultural processes

The project 'Integration of plant parameters for intelligent agricultural processes' aims to identify plant parameters on a single plant basis for smart crop farming. These plant parameters serve as a base for decision support, offline creation of application maps, or online actions on the field. The goal of the work is to combine colour and shape information in deep neural networks for image classification and semantic segmentation tasks in the context of plant parameter identification. One use case is to implement a semantic segmentation of different plant species in crop images that can be used for smart weeding concepts like precision hoeing or spot spraying. For the creation of a red-green-blue-depth (RGB-D) training database, we performed field trials, captured images with a ground-based measurement system equipped with a red-green-blue (RGB) stereo camera pair and a global navigation satellite system with real time kinematic (GNSS RTK) module, and annotated the images adding plant species information on a pixel level. In comparison to satellite data or even drone images, a ground-based image capturing system offers high-resolution information from single plants that can reflect the heterogeneity in the field. Based on the RGB-D dataset of various crop and weed species, different deep neural networks will be trained to segment the images based on the colour and depth information. We expect our method to improve the state-of-the-art plant classification performance by adding depth information, as shown in other domains by Wang & Neumann (2018). Other research interests focus on the potential of image-based automated crop and weed estimation and data augmentation techniques for RGB-D images.

C) Strategic collection and provision of field crop data

The objective of this PhD project is to perform agronomic analyses and the estimation of canopy parameters using remote sensing technologies in wheat (*Triticum aestivum* L.). Experimental data were collected in a two-year field experiment, which was conducted at the experimental farm in Groß-Enzersdorf. In agronomic analyses, the effects of experimental factors, e.g. environment, sowing date and nitrogen fertilization, on canopy parameters are examined. Investigated parameters include developmental stage, above-ground dry matter, leaf area index, nitrogen content, protein yield, grain yield and yield components. These parameters are analysed based on state-of-the-art techniques for statistical analysis, e.g. quantitative mixed model analysis and principal component analysis. In addition, agronomic analysis was performed on experimental data of autumn- and spring-sown triticale (Koppensteiner *et al.*, 2021). Furthermore, canopy parameters, e.g. leaf area index and nitrogen content, are estimated based on remote sensing data. Therefore, various devices were used to collect remote sensing data in the two-year field experiment including a handheld hyperspectral sensor and multispectral satellite images (Sentinel-2, ESA). Different techniques are applied to process spectral data and setup models, e.g. vegetation indices and radiative transfer modelling. Preliminary agronomic analysis on yield and yield components showed that grain yield was higher for autumn-sowing than spring-sowing, the increase in grain yield with nitrogen fertilization was higher for autumn-sowing and yield components were highly affected by sowing date, nitrogen and environment. Preliminary estimations of leaf area index and nitrogen content were performed using radiative transfer model inversion, which showed promising results (Koppensteiner *et al.*, 2021b). In the future, agronomic analysis on growth and nitrogen uptake as well as the estimation of canopy parameters based on remote sensing techniques with a focus on radiative transfer modelling will be published.

<u>D) Identifying novel approaches for socio-environmental technology assessments and their implications for managing complex agricultural systems</u>

This PhD project addresses the following core area:

— Finding methods that render the complexity of agricultural environments quantifiable and thus capture the impact of the technologies in terms of sustainability and resilience.

For this purpose, geochemical soil data sets were processed and a code test infrastructure was built that enables the application of individual complexity metrics. Initial results of defining the system state through probabilistic measures (e.g., Fisher information) showed promising applications for capturing the systemic stability of agricultural soil environments. For this purpose, a conglomerate of geochemical parameters (calcium, magnesium, sodium, pH, etc.) collected over a twenty-three-year period was used. By capturing the probabilistic properties of the individual variables and their progression over time, conclusions can be made about systemic soil equilibrium and the evaluation of agricultural practices to multivariate soil properties. The next steps mainly concern the expansion of the quantitative test environment of geochemical soil properties and the recording of resilience and sustainability aspects. In this context, different methods (e.g., stochastic interpolation methods, mutual information acquisition, entropy measures) will be applied to analyse and improve data properties (uniformity, completeness, increase of informative value) in order to enable the fine-tuning of individual complexity metrics. Concepts for fusing metrics will be developed and tested.

<u>E) A deep-learning based approach for the Digital Twinning of biological entities and systems</u>

The announcement of 'Agriculture 4.0' in academia and industry has brought the promise of digitalisation to agriculture, by leveraging advancements in data analysis, decision support and the adoption of data collection technology, to increase sustainability (Zhai *et al.*, 2020). Initiatives such as Climate Smart Farming and technological adoption in the form of Precision Agriculture (PA), Precision Livestock Farming (PLF) and more recently the Digital Twin (DT) show a shift toward these allusive goals, however, extracting actionable information from heterogeneous agricultural systems remains difficult (Neethirajan & Kemp, 2021). The DT is a real-time synchronized virtual representation of a product, process, or environment. It provides a novel means to achieve digitalisation through high-fidelity modelling, simulation, and consolidation of data streams (Wright & Davidson, 2020). Since its inception and early classification, the DT has evolved, in terms of requirements, capabilities and applications, growing beyond its original focus on manufacturing (Grieves, 2015; Jones *et al.*, 2020). PLF, the closest area of research, has seen extremely promising results. However, requirements for PLF in Austrian agriculture are often ambiguous and suffer from isolated views of systems, processes, or applications, with current implementations consisting of bespoke technologies applied to individual use cases and tasks (Mahmud *et al.*, 2021). Therefore, the goal of the Digital Twin project has been to go beyond the state-of-the-art examples found in research, with the goal of developing the requirements, methodologies, and technical approaches necessary to leverage the Digital Twins' benefits for the agricultural domain, with a specific focus on dairy cows. Utilizing a variety of internet-connected sensors, animal and environmental data is used to develop a Digital Twin for the modelling and monitoring of temperature effects on behaviour and rumination, leveraging cutting edge Deep learning techniques to extract and model the complex features associated with these effects, allowing the current animal state to be assessed in near real-time.

F) Using digital sensors to monitor dairy cows on pasture

The project 'Using digital sensors to monitor dairy cows on pasture' aims to investigate sensor-based parameters to assess health and welfare of dairy cows at pasture and to display differences between indoor housing and grazing conditions. For dairy farming, different types of technologies have been validated for supporting animal health and welfare monitoring (Chapa *et al.*, 2020; Stygar *et al.*, 2021), mainly for the use in indoor housing. Therefore, the first step of this project was the evaluation and practical testing of different sensor systems for their use on pasture. Indirect visual observation using a drone-mounted camera served as gold standard for the sensor-based classification of behaviour of lactating dairy cows (standing, lying, rumination) with restricted access to pasture. In the second use case, prior tested technologies were employed to monitor the time budget of dairy cows before, at and after dry-off, under indoor housing and full grazing conditions. Apart from on-cow sensor systems, digital technologies to collect environmental parameters were included to this project, as they can play an important role in pasture management. Clinical examinations and laboratory parameters served as reference for animal health and welfare. We expect the outcome of this project to be a contribution to the application of reliable sensor systems for monitoring grazing dairy cows, to yield insights regarding the effects of pasturing and dry-off management and to contribute to the assessment of cow comfort using sensor-based parameters. Sensor data and video footage collected in the frame of this study can also provide a basis for further interdisciplinary collaboration.

G) Sustainability assessment with LCA

According to the latest IPCC (Intergovernmental Panel on Climate Change) report, there is high confidence that climate change will make some areas no longer suitable for crop production. Consequently, the necessity to produce more food with fewer inputs without causing environmental impacts is more latent than ever. Agricultural digitalisation can be one of the solutions to maximise food production while minimising environmental degradation (Biermacher *et al.*, 2006; Pedersen *et al.*, 2006; Diacono *et al.*, 2013). However, most of the studies present their results in terms of input efficiency without showing evidence of reducing critical environmental impacts. Life Cycle Assessment (LCA) is a scientific-based decision support tool that quantifies environmental impacts during the life span of a service or product. The objective of this research project is to quantify the environmental impacts of smart farming technologies using the LCA as the main method of assessment. Moreover, to have a more holistic and comprehensive evaluation of these technologies other methods to quantify environmental emissions are being used together with the LCA methodology. For instance, the Denitrification-Decomposition soil model (DNDC) (Li *et al.*, 1992), which assists to quantify site-specific soil emissions. Positive environmental impacts results have already been revealed by implementing smart farming technologies for crop production. Preliminary results of this study showed that using an optical crop sensor for variable rate nitrogen application (VRNA) in comparison to a conventional application scheme can reduce 8.8% the global warming potential. Furthermore, additional primary results of another LCA comparison study of several smart farming technologies – remote and proximal sensors, automatic steering, and automatic section control (ASC) – show that remote sensing is the most environmentally friendly technology. It is of great relevance to assess emerging technologies in order to enable decision-makers to place more resources on technologies with better performance and less damage to the environment.

Discussion

Interdisciplinary approach

The use of similar or the same sensors, data and techniques in different projects is one aspect that connects the three Universities with each other. For instance, computer vision techniques are useful both for animal classification as for crop and weed characterisation. There are ongoing overlaps between the PhD projects as well as future collaboration possibilities: Using the field robot, the derived information of computer vision can be applied for online action on the field (e.g., precision hoeing). Image-based plant parameters and strategically collected remote sensor data on crops can be analysed together in combined models. The assessment of sustainability and the impact of agricultural technologies as well as resilience analysis are based on experimental data from other projects. With regard to machine learning and digital twinning, sensor data from the experimental farms (e.g., on-cow sensors, environmental sensors, remote sensing) yield data for more complex analyses, which are in turn necessary for research questions on modelling and decision support. It becomes clear that these overlapping topics require close collaboration. Regular meetings between the PhD students take place to guarantee an exchange on the status of the projects and to discuss arising challenges as well as future ideas. In the course of the DiLaAg project, students from different fields of expertise were able to develop a better understanding of mutual research areas and strategies. To deepen interdisciplinary collaboration and to expand the network of doctoral students, DiLaAg is currently being extended with two associated PhD students. One study at BOKU, Institute of Agricultural Engineering, is focusing on the subject of 'Life Cycle Assessment of innovative agricultural systems with a focus on multi-output processes'. Another student at VETMED, Clinical Unit of Herd Health Management, is working mainly on sensor-based monitoring of the development of pre-weaned calves, but also on the assessment of grassland by using digital devices for pasture management. The inclusion of these additional PhD students strengthens interdisciplinarity and broadens the horizons of all students, as new topics and approaches are being added to the consortium.

Future – DiLaAg II

Ideas for future projects are based on the holistic approach to agricultural digitalisation that has been established within DiLaAg. The currently existing network between the Universities enables inter- and transdisciplinary research to be built upon a solid basis. As climate change poses rising challenges for agriculture, the focus on sustainability and food security is gaining importance rapidly. This consortium has expertise to tackle both the approach to plant-based human nutrition as well as keeping ruminants to convert grassland into valuable human-edible protein in a viable agriculture without impairing environmental resources.

Conclusion

The DiLaAg consortium consists of experts from three different Universities, who are connected by the topic of digitalisation and the aim of promoting sustainable production in agriculture. At the core of DiLaAg are the PhD projects, which are closely interlinked and therefore allowed the students to deepen their expertise in their own field as well as to gain insights into other fields of expertise. A planned consortium and future network of collaboration can bring DiLaAg and its technological development closer to local farmers. In the frame of workshops and conferences, the PhD students can present their work to a broader audience. This collaboration between the Universities builds the basis for interdisciplinary and even transdisciplinary research.

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SESAM sensor technology for milk producers

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Abstract

Sensors dominate modern agricultural technology more and more, also could milk recording organisation benefit from this. Sensor assisted Alpine milk production (SESAM) project is an Interreg Alpine Space project. The main aim was to promote in the Alpine region intelligent, sustainable and integrative growth. The objective was to develop a tracking system for dairy cows based on an existing system that integrates the data from the milk performance test and the health monitoring systems. The SESAM tracking system at final stage will monitor: walking, lying, eating and ruminating dairy cows and can localize the animals. By integrating animal health data with activity data, it is possible to identify emerging health problems in dairy cows (ketoses, acidosis, mastitis, etc.). A central, multi-lingual server, record the sensor information, perform the integration with the health data and run the second level algorithm. Since August 2020 the system is subjected to performance and validation tests and in addition, all events relating to animal health will be recorded in order to identify behaviour patterns in cow's health events. These behavioural patterns are the source for development of 2nd level algorithm, which is relevant to automate the classification in order to produce a fast database in case the cow behaviour deviates from normal. The new and holistic (due to integration of milk recording data with the data on animal behaviour) data recording leads to an easy and understandable decision-support system for farms in the Alpine area.

Keywords: sensor, tracking, health, milk recording organization, dairy cow, dairy farming

Introduction

The SESAM project was starting in 2018, true different milk recording organisations in the Alpine space, the project was funded by the INTERREG Alpine Space program, with a budget over 2 million euros. SESAM provides all framework conditions to enable farms to realize innovative, integrated monitoring: introduction of an easy-to-use tool that allows remote monitoring of individual animals through holistic, real-time assessment of their activity and connection to existing health data from milk recording organizations. The project work was carried out by a total of 9 partners from 6 countries in the Alpine region - France, Germany, Austria, Italy, Slovenia and Switzerland. Among them are 4 milk recording organizations, university, and chambers of agriculture, technological institute and livestock breeders organizations. In the main and final phase of the project, it was collected and analyze data from about 26 pilot farms with over 1000 dairy cows - 5 Germany, 7 in Austria, 4 in France, 7 in Slovenia and 3 in Italy. Although it was planned and prepared sensors and infrastructure for a minimum of 40 pilot farms, due to pandemic constraints, two of our partners were unable to equip and launch their pilot farms.

Material and methods

SESAM is a system of sensors, infrastructure equipment and software tools that provide a remote monitoring of individual animals through holistic, real-time assessment of their activity and connection to existing health data from milk recording organization. SESAM aims at introducing an innovative IT-sensor based framework for innovative decision-support, tailored to family farm (SME) needs, that enables them to improve competitiveness, animal wellbeing, decrease calf-loss through real-time monitoring while preserving the traditional & culturally relevant role in the regional socioeconomic structure. SESAM work via the transnational existing partner network of milk recording organizations (reaching out to 80.000 farms & more than 3 M cows), in cooperation with key research organizations and farms themselves, to implement an Alpine wide solution through pilots and market roll out.

Experimental data – infrastructure equipment and technology used

Sensors - The SESAM sensor uses a 3-axis MEMS acceleration chip to measure the movements of the cow. It records the sensor measurements, perform buffering, processing and transmitting the data to the next component – the base station/amount: 10 – 200 (number of cows). The raw acceleration data needs to pass through multiple devices and programs before the cow activities can be visualized on a web page (Figure1).

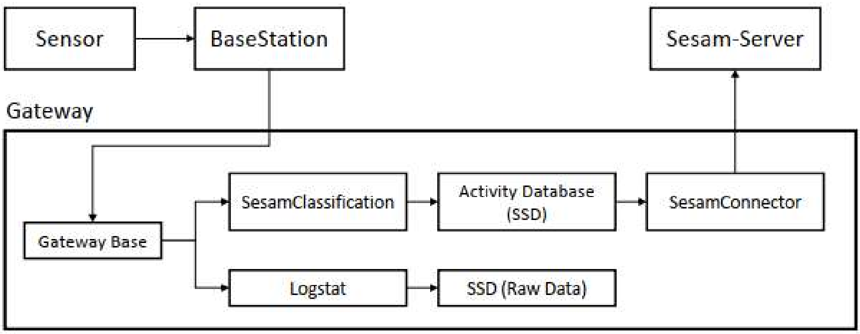

Figure 1: The sensor data is transmitted to the base station(s) over Bluetooth (low energy) and processed on the SESAM Gateway. The classification results (cow activities) are sent to the SESAM Server.

Radio Base station

The base stations build the connection with the sensor using Bluetooth. The base stations consist of a raspberry pi 3 and receive commands from the gateway (gateway base). Up to 20 base stations can be placed in a barn. The base stations use the WIFI network of the gateway (SesamBarnWIFI) to connect and transmit data to the gateway, amount: 1 – N (depending on barn size and localization accuracy necessary). Only two programs/services are running on the base stations. The program “basestation_up” makes sure that the base station reconnects with the SesamBarnWIFI network, in case the connection is interrupted. The "base station" program/service receives commands from the gateway, connects to the sensors over Bluetooth, and sends the received data back to the gateway.

Barn Gateway

The SESAM gateway consists of a Jetson Nano Computer from Nvidia, WIFI Access Point, USB-SSD, and in some cases an LTE-Modem, if a connection with an Ethernet cable is not possible in the barn. The main responsibility of the gateway is to send commands to the base stations, store the received data to the SSD, process the sensor data using the build-in classification model (First level algorithm) and send the results to the SESAM server. The gateway base software decides which base station should connect to a particular sensor, receives the data from the base stations and transmits the data to other program for post-processing. The Logstat program/service receives the raw sensor data from the gateway base program (using a pipe file/Fifo buffer under Linux) and saves the data into a binary raw file into the SSD. The saved sensor data can be processed manually later on, if necessary. The SesamClassification service (aka SesamGatewayServer) receives the raw sensor data from the gateway base program and estimates the cow activities. First, some features are calculated from the acceleration signal and then a classification model is used to get the cow activities. The results are saved into a SQL database on the SSD. The "SesamConnector" program/service reads out the SQL database on SSD every 5 minutes and sends the classification results (cow activities) with timestamps to the SESAM server.

SESAM Server

The SESAM server receives the cow activities from the SesamConnector program and saves the data. The classification results can then be visualized using a web browser. On the SESAM server is deployed the Second level algorithm, which purpose is to predict important events based on the activity data of each cow.

Feature calculation

As input for the classification algorithm data of an accelerometer is used, measuring the acceleration along the X, Y and Z-Axis. Additionally, the derivate and the integral of each axis was calculated. Based on this data a feature set consisting out of 345 features was created. These features consist out of time-domain features, such as different statistical measures like the mean and the standard deviation but also frequency-domain features to capture activities with repetitive nature like e.g. walking. These features were calculated over a window size of 250 samples, which corresponds to a window size of 25 seconds with a sampling frequency of 12.5Hz of the accelerometer. To prevent overfitting a smaller set of features was selected, consisting out of 40 different features, which were determined to be the most influential ones. The resulting features were used as input for a decision tree ensemble consisting out of multiple decision trees (see Figure 2). Each decision tree calculates the probability for a given class (Eating, Lay, Ruminating, Standing, Walking). These probabilities get averaged across the trees and the output of the model will be the class that yields the highest probability. This way we get a predicted class for every 250 Samples of accelerometer data.

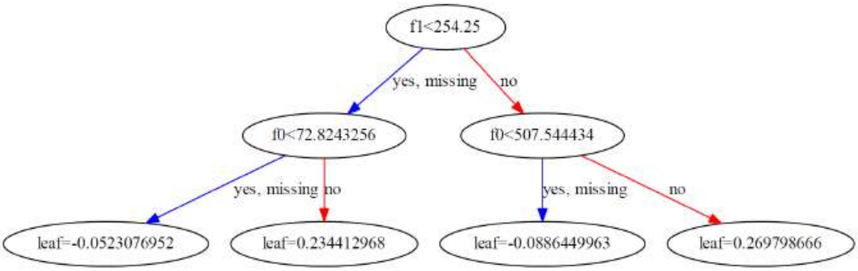

Figure 2: Singular decision tree used for the classification

Algorithm optimization results

The final analysis was carried out with an independent test set.

Collected data from a new farm for testing showed good results for Eating and Walking but some difficulties with correct detection of Rumination. Decent results for laying and standing.

Comparison with specification (Figure3):

Walking > 90% (Prio 1) met

Rumination > 90% (Prio 2) not met

Eating > 90% (Prio 3) almost met

Average > 88% not met

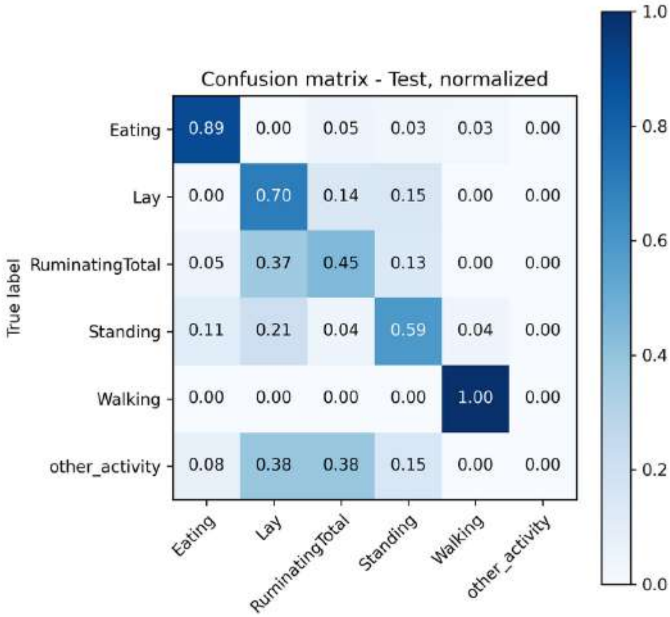

Figure 3: Final results from sensor data classification

Results and Discussion

<u>“AliBaba” platform for data analysis</u>

We have our pilot farms from which we receive sensor information classified by the 1st level algorithm in 5 main activities - Walking, standing, lying, eating, and ruminating. From MRO through a standardized interface, we receive health information about the same animals - diagnoses, major events, information about milk production, milk quality, etc. The main events are marked in the activity graph with the help of symbolic icons (on the top right corner of the screenshot). With the help of the visualization tool, we have the opportunity, with the active participation of the pilot farms, to analyze the activity of animals during, before and after the events marked in the MRO data - insemination, birth, disease diagnosis, hoof manipulation or other manipulations. Observation of individual activities in a day interval, brings useful information about the routine of the farm and whether and to what extent the animal fits into it. Any deviation from the mean values or from the manifestation of the same within the day, can be interpreted and investigated further - it can only be a social manifestation, but it can also be an indicator of a disorder or problem. A tool for working with experts and decision support - using visualization and comparison features, experts can analyze animal behavior, identify “normal” conditions, and track changes indicating abnormalities - potential health problems. By the time the project was completed, information had been accumulated from nearly 1,000 cows over an interval of more than a year. This information was analyzed in combination with the data on the health status of the observed animals, their diagnoses during the observed period as well as the performed manipulations. Those analysis serve as a guide line for the development of the second level algorithm that will eventually send back to the farmers alerts for major events or abnormalities in the animal activities.

Second level algorithm – concept and application

The working group dealing with the second level algorithm developed the main parameters of the model. Subsequently, each partner‘s experts made their own versions using data collected from the pilot farms.

Within the project, two developments of a second-level algorithm were made. The first, is from the experts of LKV BW, with an emphasis on the ability to predict a wide range of events and diagnoses like oestrus, milk fever, ketosis, mastitis, cysts, cycle disruption, liver fluke, Mortellaro claw disease, Limax claw disease, Sole ulcer claw disease, and White Line Defect (WLD) Claw disease. For the model, behavioral parameters comprising lying, standing, walking, eating, and ruminating were collected from the 6 LKV BW pilot farms over a 13-month period. These parameters were used as predictive feature attributes and combined with observational data on previous events and diagnoses from the corresponding time period, to train support vector machines with the aim of detecting them prior to onset.

The second, under the supervision of Prof. Dr. Hubert Pausch and Peter von Rohr, focused on the possible prediction of calving and oestrus, published in Jessica Gaering’s master thesis in 2022. Behavioral parameters comprising lying, standing, walking, eating, and ruminating were collected from the 4 Slovenian pilot farms over a 13-month period. These parameters were used as predictive feature attributes and combined with observational data on previous oestrus and calving events from the corresponding time period, to train support vector machines with the aim of detecting oestrus and calving in the 24 hours prior to onset.

The most appropriate for the needs of this material is the description given by Jessica Gearing in her Master’s Thesis at ETH on “Exploring the potential of machine learning to predict oestrus and calving in Alpine dairy cows” using the Slovenian data from the SESAM project. Due to limited space, we will mention a brief description of the method and the conclusions from the results of the model.

The data set for Ms. Goering‘s model has been cleared of other health problems and comprises 9079 „no event“ cases, 22 cases of oestis and 19 cases of calving. A two-sample t-test was used to analyze the potential relationship between behaviors and the occurrence of oestrus and calving compared to periods of no reproductive or health events (J. Gearing, (2022)). Separate models are designed for oestrus and calving using the support vector machines method.

For SVM classification each data point in the training set was allocated a 5-dimensional vector consisting of each of the five behavioral attributes. The SVM model was thus built to discriminate between the two classes (no event vs pre-oestrus or pre-calving) by attempting to define a hyperplane decision boundary that maximized the margin of separation between the data points of the two classes (J. Gearing, (2022)).

With a sensitivity of 100% and specificity of over 90%, the model was effective for the prediction of calving 24 hours before onset. For the oestrus detection, the model yielded a sensitivity of 83.3%; however, the low specificity of 43.4% means this would not be applicable in practice.

Conclusions

In the process of analysis, we found that clearly expressed samples of activity are not always available, or they do not carry useful information for the needs of forecasting. With a number of udder or hoof problems, there is a slow or sharp decrease in activity, reduced mobility or, of course, reduced productivity. This means that a number of health problems have similar patterns of changes in the activities we observe. But over time, thanks to the large amount of data, we will be able to train our algorithms to recognize specific diagnoses that are most common in our sample of pilot farms. With the accumulation of data, more and more new and interesting opportunities are opening up: at the moment we start processing data from the first pilot farms, which are already in an interval of more than a year - we will have the opportunity to compile a detailed picture of the activities during the whole lactation, or seasons and type of feeding. To compare the patterns of activities between lactation cycles, or animal breeds, of breeding systems. Farm experts and advisers are already beginning to accumulate their ideas for comparing annual activity data, drawing conclusions about food and farming efficiency.

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D4Dairy – Interdisciplinary network for creating added value out of different data sources

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Abstract

A large amount of different data already exists in partly isolated databases of various stakeholders, but are generated by different hardware and software products on the farms every day. As automation increases, so does the amount of data recorded. In order to derive maximum benefit from these data and to optimally support farmers in their herd management and genetic improvement, it is necessary to create structures to collate these data sources.

The COMET project D4Dairy unites 44 partners, among them experts and researchers from universities and other domestic and international research organisations, professionals from national and international company partners along the dairy value chain, stakeholder organisations and national and international technology providers to exploit the opportunities offered by new technologies and analytical methods.

In various pilot studies with 305 participating farms, numerous cow specific parameters (e.g. automation, performance recording, genetic and genomic information, health information) as well as environmental factors (housing, feeding, management, climate) are recorded.

D4Dairy aggregates data into a central platform in compliance with data protection requirements and specific agreements. Analyses within D4Dairy include identification of risk factors and early predictors of health problems using big data approaches, use of mid-infrared spectra, genetic and genomic studies, mycotoxin detection and information about the impact of housing climate on animal health and welfare and the development of data-based strategies to reduce the use of antimicrobials.

The overall objective is that D4Dairy aims to benefit the farmer and the community by improving health, welfare and sustainability in dairying.

Keywords: interdisciplinary network, welfare, animal health, advanced data technologies

Introduction

New technologies are revolutionising the dairy industry and as automation increases, so does the amount of data produced. According to a survey within D4Dairy in 2019, 30% of the farms keeping more than 50 cows are equipped with a milking robot and animal sensors in Austria with further expected increase. This means that large amounts of data are generated by different hardware and software products, but also other sources, on and off the farms every day, but many systems are still stand-alone solutions with no or a low level of communication and integration between different data sources (Rutten *et al.* 2013). Hence, data exist in partly isolated databases of various stakeholders. An Austrian survey among farmers and veterinarians (Perner *et al.* 2016; Weissensteiner *et al.* 2018) revealed the importance of linkage of data.

In order to derive maximum benefit from data and to best support farmers in their herd management and genetic improvement, it is necessary to create structures to bring data sources together.

D4Dairy

The transdisciplinary, cross-industry COMET project D4Dairy (Digitalisation, Data integration, Detection and Decision Support in Dairying) started on 1.10.2018 with 4 years duration and a budget of 5.5 million Euro. It aims to develop further digitally supported management and breeding tools for dairy farms that contribute to improvements in animal health, animal welfare and product quality through data-supported and integrated information systems. Cooperation between various partners and integrating different data is a prerequisite for that.

Figure 1: D4Dairy Consortium

D4Dairy unites 13 scientific and more than 30 industrial partners in an internationally competitive, transdisciplinary network. It includes universities, competence centres and research institutes in Austria and abroad, companies along the milk value chain, including farmers, breeding organisations, milk processors, animal health services and interest groups and national and international technology providers in the areas of sensor technology, feeding, housing climate measurement and data processing (Figure 1).

Data collection

In the nine projects of D4Dairy research is done on different topics (Figure 2).

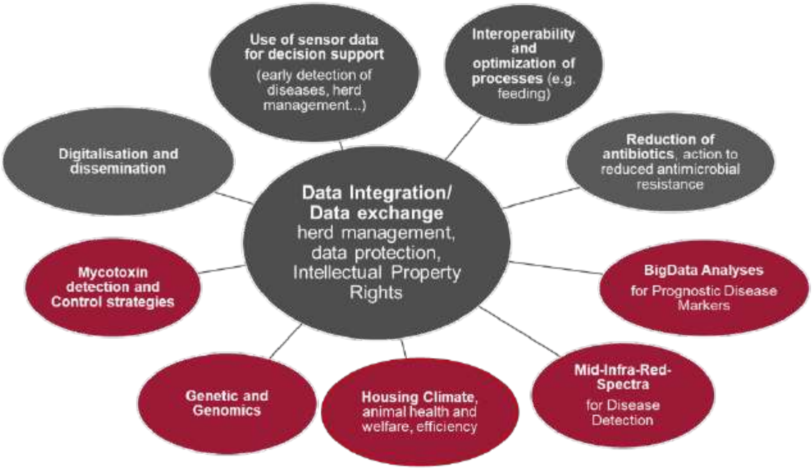

Figure 2: Focus of research within D4Dairy

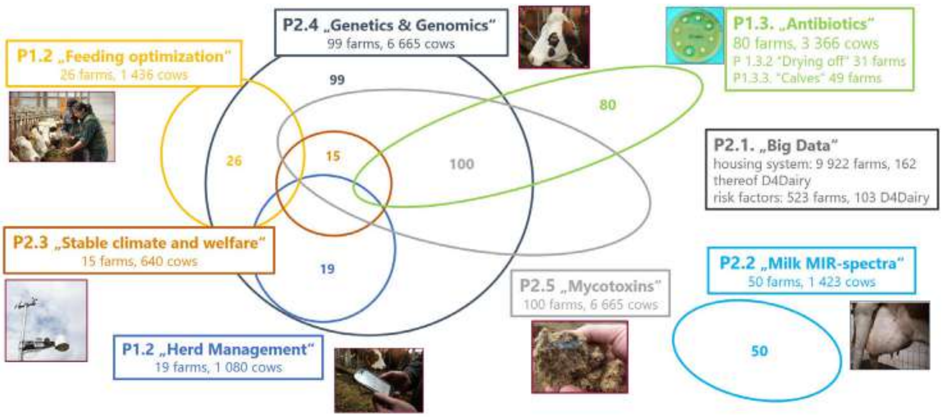

Figure 3: D4Dairy project farms

Data collection was set up in a way to minimize the effort for data recording and use as many synergies and cooperation between the projects as possible.

Data were collected on the project farms between October 2019 and June 2021. In total, 305 farms participated in the projects as shown in Figure 3.

Digital tools developed in other projects of Rinderzucht AUSTRIA or already available within the different applications within the Central Cattle Database (RDV) could be used for data collection. Harmonised protocols for recording were elaborated taking into account already existing international standards (www.icar.org) and different needs within the various projects within D4Dairy. Comparability and joint use of data was considered. Strategies to record directly and electronically as much as possible were set up. This includes Application Programming Interfaces (API) to the automatic milking systems and sensors, routine interfaces (e.g. with the feed laboratory, milk laboratories), as well as the electronic recording by mobile APPs. Farmers, veterinarians, claw trimmers and technology providers were motivated to participate or collaborate in the project. The huge data set comprises data from performance recording, data from automatic milking systems, activity and health data from animal sensors, lab data, like feed analysis, milk MIR spectra or bacteriological milk tests, genetic and genomic data, environmental and housing climate data, data on housing, feeding and management and health information of the individual animals, for example veterinary diagnoses, claw trimming data, ketosis tests, lameness and body condition scores and daily milk yield.

D4Dairy developed standards for data sharing e.g. harmonised the antimicrobial susceptibility testing or feeding rations. New interfaces to automatically submit results from feed analysis, antimicrobial susceptibility testing, sensor and automatic milking systems to the Central Cattle Database (RDV) were established (Egger-Danner *et al*. 2021). This is important to reduce the workload for the farmer by avoiding multiple entries of data. Data integration is also the base for added value out of different data sources. Beside technical aspects, the legal background had to be elaborated and agreed between partners.

<u>Monitoring data quality</u>

To ensure high data quality all data recorders were trained and the inter observer reliability was evaluated. We found good agreement (values of weighted Kappa of 0.6 and above) between all participating LKV-employees recording the body condition and lameness scores on the project farms. The received data was monitored continuously, missing data and outliers were identified and investigated and an automatic feedback to the data recorders and partly farmers was established.

<u>D4Dairy data</u>

The newly developed D4Dairy data platform provides an interface to project partners for data collection. It is a platform for data integration, harmonization, quality assurance, data exchange and offers the possibility for evaluation (e.g. algorithm for predictions). Anonymized research data sets are made available to the research groups in D4Dairy directly out of D4Dairy data following legal agreements on the use of the data between data providers and researchers.

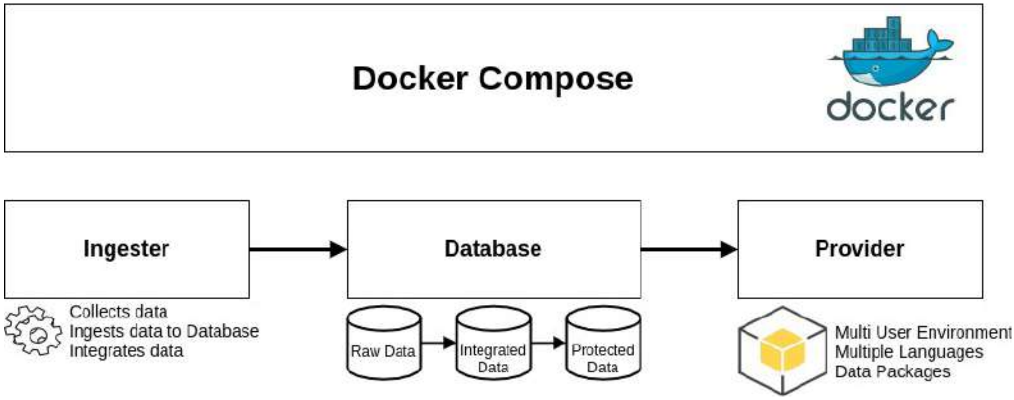

Figure 4: D4Dairy data platform developed within the project (Papst *et al.* 2021)

<u>Data-sharing concept</u>

Another challenge of data integration from different sources is compliance with legal data protection regulations. A detailed D4Dairy data-sharing concept (Figure 5), which regulates data exchange, data use and ensures data protection with various agreements was established between all participating partners. For each research question a Material Transfer Agreement is signed, that lists the specific data, the purpose they can be used for, who works with the data and specifies the conditions for the use of data. To date (February 2022) 32 Material Transfer Agreements exist in D4Dairy. Additionally, all participating farmers signed their agreement to use data from his/her farm in D4Dairy and all D4Dairy partners agreed to an Agreement pursuant to Art. 26 General Data Protection Regulation (GDPR) and the Consortium Agreement.

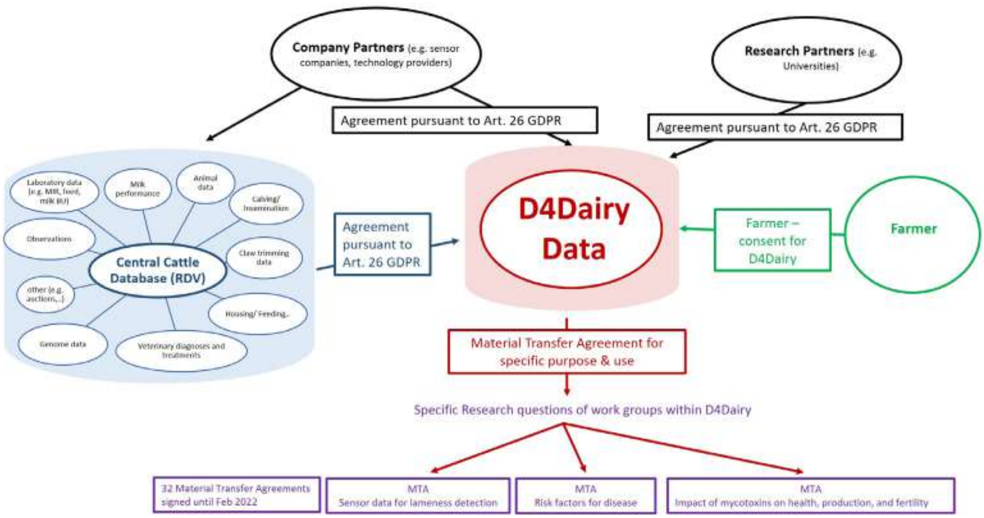

Figure 5: D4Dairy Data Sharing Concept

Decision support tools – added value out of data integration

The focus in D4Dairy is on data analysis and tool development. Integrated datasets are the precondition that different animal-, farm- and environment specific data can be used for big data analyses to explore the impact of and dependencies between different risk factors for development of diseases (Matzhold *et al.* 2021). Models to predict individual diseases using a selection of features and the best performing methods are being developed (Lasser *et al.* 2021). In the first step a comprehensive already existing dataset from the project Efficient Cow (Egger-Danner *et al.* 2017) was used to predict disease risks. The F1 Score e.g. for lameness was 0.72 and for ketosis 0.70. Presently, models that also integrate data from automatic milking systems and sensors are being developed. The overall aim is to provide an alarm for farmers if diseases are developing using integrated relevant data.

Further areas of research and development of decision support tools are mid-infrared spectra for health monitoring (Rienesl *et al.* 2019, Christophe et al 2021, Köck *et al.* 2019, Dale *et al.* 2021) genetic and genomic studies, mycotoxin detection (Penagos-Tabares *et al.*, 2021), information about the impact of housing climate on animal health and welfare and the development of data-based strategies to reduce the use of antimicrobials.

Some further examples of the numerous results that can be expected out of D4Dairy are a decision support tool for drying off strategy to support a targeted use of antimicrobials, a herd management decision support tool to analyse reasons for health problems, enhanced risk predictions by means of routine MIR milk spectra or merging of different data sources and new breeding values for health traits to make it easier to breed healthier cows.

Farmers want better tools that are more effective for prevention of diseases or genetic improvement of health and welfare (Palluch *et al.* 2021).

Conclusions

With the collaboration within the D4Dairy consortium uniting various expertise in an interdisciplinary network with one common goal, a big step towards generating added value through data integration and applying advanced research was taken. The key to success are multi-actor approaches and a win-win cooperation with shared benefit. D4Dairy brought many players along the dairy value chain together in one project to develop structures together, which enable transparency in data sharing and trustful cooperation. Major challenges in creating added value out of different data sources are different standards and parameter definitions, different data formats and data quality, data privacy concerns or competing business interests. An approach to overcome these challenges is by means of data sharing platforms (Papst *et al.* 2021) with a transparent data-sharing concept. Comparability of results, standardisation and harmonisation, data validation, data privacy, transparency and data protection concerns were addressed in the project.

The overall objective is that digitalisation aims to benefit the farmer and the community by improving health, welfare and sustainability in dairying. Expected results are the reduction of the workload of farmers, better tools that are more effective for prevention of diseases, the early detection of health problems, the use of new data for breeding allowing increased genetic improvement of health and welfare and overall leading to healthier animals and a more sustainable and efficient production.

Acknowledgements

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SESSION 13

Cows:
Health and Production II

My sensor beeped: The economic and animal welfare gains

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Abstract

Precision livestock farming (PLF) is expected to add value in both economic and animal welfare domains. Sub-optimal mobility (SOM; syn. lameness) in dairy production is a costly health condition with negative animal welfare effects. Implementing PLF technologies to help manage SOM may prove beneficial in both domains by reducing SOM costs and increasing animal welfare. While many PLF technologies apropos SOM are documented in the literature, few of them are available in practice. This contributes to a lack of empirical data available to quantify whether these PLF technologies add value to the economic and welfare domains. To circumvent the lack of available information, our objective was to quantify herd-level SOM costs and welfare impacts with stochastic simulation modelling. SOM was described by 5 mobility scores. SOM costs were quantified with a partial budgeting approach. Animal welfare was quantified by multiplying mobility score durations with welfare compromise weights per mobility score. We simulated 9 different scenarios for a farm with automatic SOM detection sensors (ASDS) and compared them with a without ASDS scenario. Scenarios differed by SOM management and alert notification intervals. Results from 5/9 scenarios showed added value in both economic and welfare domains; the optimum scenario obtained a 45% reduction in SOM costs and a 93% improvement in animal welfare. The remaining 4/9 scenarios showed added value in only the welfare domain. We conclude that PLF can add value to both economic and welfare domains, albeit altered SOM management strategies and improved sensor performance are required.

Keywords: Sub-optimal mobility, sensor detection, animal welfare, simulation.

Introduction

Precision livestock farming (PLF) is expected to add value in both economic and animal welfare domains. Sub-optimal mobility (SOM; syn. lameness) in dairy production is a costly health condition with negative animal welfare effects. Using PLF technologies, such as automatic SOM detection sensors (ASDS) to manage SOM, are expected to add economic and welfare value to the farming operation (Banhazi et al., 2012; Berckmans, 2017, 2014)particularly in Asia, India, and South America, are getting more financial possibilities to buy animal protein. This fact, combined with the changing diets of these people in those countries, will result in an increase of the worldwide demand for animal products (meat, eggs, and milk. Research quantifying the economic value of PLF technologies in relation to SOM are sparse. For ASDS, only Van De Gucht et al. (2017)information about their economic value is lacking. In this paper, a conceptual and operational framework for simulating the farm-specific economic value of automatic lameness detection systems was developed and tested on 4 system types: walkover pressure plates, walkover pressure mats, camera systems, and accelerometers. The conceptual framework maps essential factors that determine economic value (e.g., lameness prevalence, incidence and duration, lameness costs, detection performance, and their relationships and Kaniyamattam et al. (2020) showed that an economic value exists. On the other hand, no research quantifying the animal welfare value in managing SOM with ASDS exists. The objective of this study was to quantify the economic and welfare gains of ASDS when used to manage SOM. This was done via bio-economic simulation modelling. In the economic context, this research adds to the work of Van De Gucht et al. (2017)information about their economic value is lacking. In this paper, a conceptual and operational framework for simulating the farm-specific economic value of automatic lameness detection systems was developed and tested on 4 system types: walkover pressure plates, walkover pressure mats, camera systems, and accelerometers. The conceptual framework maps essential factors that determine economic value (e.g., lameness prevalence, incidence and duration, lameness costs, detection performance, and their relationships and Kaniyamattam et al. (2020) by considering different SOM management strategies with ASDS and includes alert notification intervals for mild SOM. In the animal welfare context, this research is the first to simulate the impact of SOM on animal welfare and to assess the animal welfare gains of ASDS when used to manage SOM.

Material and methods

Simulation model

A stochastic daily time-step bio-economic simulation model was used for this study (Edwardes et al., 2022). The model simulates a Dutch dairy herd of 125 cows that are housed in cubicle housing with concrete slatted floors during Autumn and Winter while cows have pasture access for >6h per day during Spring and Summer.

The cows' actual state of mobility, either optimally or sub-optimally mobile, is simulated by the model. This is achieved by simulating the incidence and duration of hoof disorders at hoof-level. The occurrence of hoof-disorders are then modelled as the mechanisms responsible for SOM. Cow mobility is modelled using the Sprecher 5-point mobility scoring scale where 1 = optimal mobility and 5 = severely impaired mobility (Sprecher et al., 1997). If a cow is scored with mobility score ≥2, she is considered as SOM. Mild and severe forms of SOM are represented by mobility scores 2 – 3 and 4 – 5, respectively.

SOM management is defined by a simulated management scenario. These scenarios include SOM (mild and severe) treatment by either the farmer, veterinarian, or hoof-trimmer. Further explanation on SOM management is provided in the Scenarios section.

In each time-step, (re)productive events were simulated. These (re)productive events are milking, feeding, culling, estrus detection, insemination, and calving, and are all affected per mobility score 1-5.

Economic module

Economic computations are based on production events (unaffected and affected by SOM), and management actions for non-SOM specific events (i.e., culling for non-SOM reasons and inseminations) and SOM specific events (i.e., treatment). Associated input parameters are found in Edwardes et al. (2022). Economic variables include gross milk returns and costs of milk losses, discarded milk, feed, inseminations, culling, farmer labour, veterinarian, hoof-trimmer, treatment. These variables were summed for each cow over a one-year time period to obtain the annual total of each economic variable. An annual (ASDS) sensor depreciation was included as the annual (ASDS) sensor cost (€1553.75 based on Nedap (2021) and (Sleurink, 2018)). The difference between the annual total gross milk returns and the sum of the annual total costs obtained the net economic farm results. Subtracting the net farm economic results for a scenario where SOM was present from the net farm economic results for a scenario where SOM was not present obtained the annual cost of SOM (Rushton, 2009).

Welfare module

Table 1: Welfare impact weights per mobility score.

Aspect	Mobility score				
	1	2	3	4	5
Feed and water intake	0.00	0.00	0.57	1.14	1.14
Functional impairment	0.00	0.42	1.01	1.46	2.06
Body condition score	0.00	0.00	0.39	0.67	0.67
Behavioural change	0.00	0.00	0.42	0.75	0.75
Cow-human interaction	0.00	0.00	0.20	0.20	0.20

Quantifying the welfare impact of SOM was done in a two-step procedure. First, welfare impact weights per mobility score were derived via adaptive conjoint analysis (ACA; Orme, 2006). In brief, ACA allowed us to elicit welfare impact weights due to SOM that experts placed on the multi-aspect concept of animal welfare (Mellor, 2017) per mobility score. Five welfare aspects that SOM affects were included in the ACA. These aspects were: feed and water intake (Norring et al., 2014), functional impairment (Sprecher et al., 1997), body condition score (O'Connor et al., 2019)economic, and environmental consequences that have yet to be extensively quantified for pasture-based systems. The objective of this study was to characterize mobility quality by examining associations between specific mobility scores, claw disorders (both the type and severity, behavioural change and cow-human interaction (Welfare Quality®, 2009). Second, the welfare impact weights $\beta_{j,l}$ for welfare aspect j and mobility score l were then used as parameter inputs to compute the welfare impact of SOM per SOM incident per cow that occurred in a one year period. These inputs are tabulated in Table 1. Per SOM incident, the duration of mobility scores within the incident were respectively weighed by the welfare impact weights as follows:

$$W_{h,i} = \sum_{j=1}^{4} \beta_{j,l} \times \alpha_{h,i,l} + \sum_{h=n}^{N} \beta_{j=5,l} \times \gamma_{h,i,l} \quad (1)$$

where $W_{h,i}$ is the total welfare impact score of SOM incident h for cow i, $\beta_{j,l}$ is the welfare compromise weight for welfare aspect j and mobility score l, $\alpha_{h,i,l}$ is the duration (days) of mobility score l during SOM incident h for cow i, and $\gamma_{h,i,l}$ is the number of cow-human interactions directly related to SOM (i.e. treatments) for mobility score l during SOM case h for cow i. Cow-human interactions were separated from the summation of the 4 other welfare aspects to limit the indirect effects of SOM on cow-human interaction that may occur during daily farming activities. The welfare impact scores were analysed at SOM incident level and normalised to the maximum welfare impact score to obtain welfare impact scores between 0 and 100 across all SOM incidents. These normalised welfare impact scores were then summed to obtain an annual herd-level welfare impact score.

<u>Simulation scenarios</u>

Table 2: Description of simulated scenarios

Aspect	**Scenario**					
	0[a]	**1**	**2**	**3**	**4**	**5**
ASDS[b] on farm	No	Yes	Yes	Yes	Yes	Yes
Mobility score ASDS threshold value for SOM	NA	Mobility score ≥3	Mobility score ≥3	Mobility score ≥3	Mobility score ≥2	Mobility score ≥2
Routine hoof trimming at start of pasture and housing period	Yes	Yes	No	No	No	No
SOM cow treated by:						
	At routine hoof trimming		At alert notification			
Mild SOM[c]	Hoof trimmer	Hoof trimmer	Farmer	Hoof trimmer	Farmer	Hoof trimmer
	At alert notification					
Severe SOM[d]	Farmer/ veterinarian	Farmer/ veterinarian	Farmer/ veterinarian	Farmer/ veterinarian	Farmer/ veterinarian	Farmer/ veterinarian
Alert notification interval in day(s)	NA	1	1; 7	1; 7	1; 7	1; 7

[a] Baseline simulation scenario: visual detection as per Edwardes et al. (2022).
[b] ASDS = automatic SOM detection sensor.
[c] In Scenarios 2and 3 mild SOM is defined by mobility score 3 and in Scenarios 4 and 5 mild SOM is defined by mobility scores 2 – 3.
[d] Severe cases of SOM with mobility score 5 are treated by the veterinarian.
[e] See Equation 2.

Management scenarios were defined and simulated for a farm with an ASDS that had a sensitivity of 68% and a specificity of 88% (Van Hertem et al., 2016). These scenarios were compared to a farm without ASDS (Scenario 0). This was done to assess the economic (reduced SOM cost) and welfare gains of using ASDS in the management of SOM. The management scenarios are described in Table 2. In Scenario 0 and 1, mild SOM is treated twice yearly at routine hoof trimming as a preventative measure for severe SOM. In Scenario 2 – 5, routine hoof trimming no longer occurred. Mild SOM was treated by either the farmer or the hoof trimmer. Severe SOM was either treated by the farmer or a veterinarian in all management scenarios (Scenario 0 – 5). In Scenario 1 – 3, the mobility score ASDS threshold value for SOM was mobility score ≥3 meaning that the ASDS classified cows with these mobility scores as SOM (Van Hertem et al., 2016), else they were non-SOM. In Scenario 4 – 5, the ASDS classified all cows with mobility scores ≥2 as SOM.

In Scenario 1, alerts were generated daily. Whereas in Scenario 2 – 5, 2 sub-scenarios concerning alert notification interval scenarios of 1 and 7 days for mild SOM were simulated, respectively. At each alert notification interval, alerts were generated for cows that were classified with mobility score 3 (Scenario 2 – 3), or mobility scores 2 or 3 (Scenario 4 – 5) for more than 50% of the notification interval. Thus, notification intervals of 1 day represent an ASDS that cannot distinguish between mild and severe SOM. In total, nine with ASDS and one without ASDS scenarios were simulated.

Results and Discussion

Absolute results from the nine with ASDS (Scenario 1 – 5) and without ASDS (Scenario 0) simulated scenarios are presented in Table 3. Mean results from the nine with ASDS scenarios are plotted in Figure 1 relative to the without ASDS scenario. Overall, 5/9 with ASDS scenarios resulted in a reduction in SOM costs (i.e., economic gain) and welfare gain, while 9/9 showed a reduced welfare impact (i.e., welfare gain) and 4/9 showed increased SOM costs.

Table 3: Absolute results (95% CI) apropos the annual cost and welfare impact of SOM.

Management scenario	Alert notification interval	SOM cost in € ‘000	SOM welfare impact in ‘000
0	NA	14.65 (1.76; 27.52)	30.44 (22.10; 38.83)
1	1	18.76 (6.3; 31.34)	28.77 (17.29; 38.01)
2	1	14.23 (1.48; 27.06)	14.84 (13.02; 16.13)
3	1	10.00 (-2.18; 22.58)	15.12 (13.21; 16.81)
4	1	21.91 (9.71; 34.22)	1.38 (0.24; 0.49)
5	1	16.5 (4.59; 28.64)	1.4 (0.44; 10.33)
2	7	13.08 (0.72; 25.46)	17.47 (15.12; 19.66)
3	7	8.45 (-4.25; 21.06)	17.38 (14.76; 19.66)
4	7	14.8 (2.58; 26.85)	2.1 (1.16; 2.9)
5	7	8.13 (-4; 20.22)	2.28 (0.66; 3.2)

Scenario 1 with an alert notification interval of 1 day showed an increase in SOM costs (28%). This was mostly due to the additional annual sensor depreciation and cost of labour required to check false alerts or alerts generated for cows with mobility score 3 that were to be trimmed at routine hoof trimming. The additional labour related costs apropos alert checking may be an overestimation as Eckelkamp and Bewley (2020) found that farmers tend to ignore alerts if too many are generated at one time. A welfare gain of 5% was obtained due to severe SOM cows being detected and consequently treated sooner compared to severe SOM cows in management scenario 0.

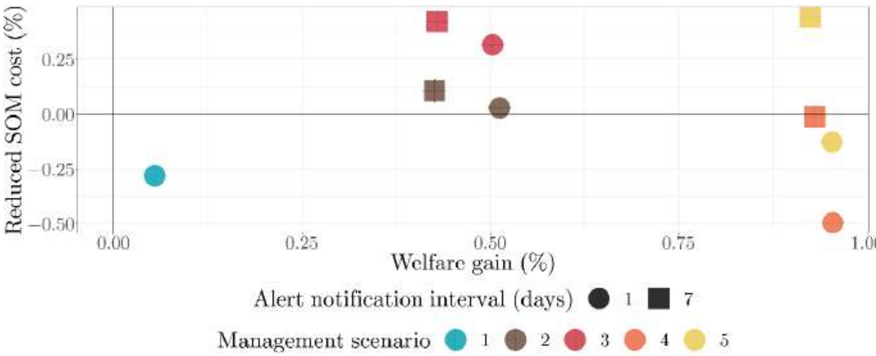

Figure 1: Mean reductions in SOM costs and animal welfare gains for a farm with an automatic SOM detection sensor respective of notification interval and management scenario. Mean SOM costs and animal welfare results per scenario are compared relative to a farm without an automatic SOM detection sensor.

Detecting and treating cows with mobility score 3 sooner, as in Scenario 2 with an alert notification interval of 1 day, showed a reduction in the cost of SOM by 3%. While large reductions in production losses costs (i.e., milk and culling) occurred, they were offset by the increases in labour for treatment and alert checking, treatment, and sensor costs. However, with sooner treatment of cows with mobility score 3 a welfare gain of 51% was achieved. Increasing the alert notification interval to 7 days reduced the SOM cost by 11%. The alert notification interval reduced the number of false alerts and thus the associated labour costs. A welfare gain of 43% was achieved.

Larger reductions in SOM costs in Scenario 3 for both notification intervals of 1 (32%) and 7 (42%) days were achieved. This is due to the hoof trimmer hourly rate being cheaper than the farmer labour apropos the cumulative time to treat cows with mobility score 3. These results may overestimate the reductions in SOM costs because we did not consider different hoof trimer fee structures that may occur as they become more frequently required. The welfare gains for alert notification intervals of 1 and 7 days were 50% and 43%, respectively.

Interestingly, an alert notification interval of 1 day in Scenario 4 and 5 when cows with mobility score ≥2 were detected and treated, the cost of SOM increased by 50% and 13%, respectively. A large contributor to both increases in the SOM costs was the increase labour cost apropos alert checking since the frequency of alerts was higher with alerts being generated for mobility scores ≥2. On the other hand, welfare gains of 95% were achieved due to treating mobility scores ≥2 as soon as possible, which affects cow welfare.

Similar welfare gains (93%) were achieved when the alert notification interval was 7 days in Scenario 4 and 5. However, in Scenario 4 the cost of SOM increased by 1%. Although costs related to alert checking farmer labour reduced due to an alert notification interval of 7 days, the costs related to farmer treatment labour were high and offset the reductions in costs related to alert checking farmer labour. In management scenario 5 when mild SOM was treated by the hoof trimmer the cost of SOM reduced by 44%.

Overall, results from the simulated scenarios show that using ASDS to manage SOM can achieve animal welfare gains because of sooner intervention of mobility scores 2 and 3. However, using ASDS does not always result in economic gains when treating mobility scores 2 and 3. This is largely due to the increased labour costs associated with alert checking and treatment. Increased costs due to alert checking reflect the costs associated with false alerts and show the economic importance of sensor performance. Better economic gains can be achieved apropos mobility score 2 and 3 intervention by limiting the number of false alerts with alert notification intervals of 7 days while this change in alert notification interval reduces the welfare gains marginally.

Conclusions

This research concludes that economic gains cannot always be achieved with ASDS due to the high labour costs associated with high frequencies of SOM intervention for mobility scores 2 and 3. Introducing an alert notification interval apropos mobility scores 2 and 3 helps prioritise mild SOM cases and reduces the labour costs associated with mild SOM intervention. On the other hand, managing SOM with ASDS can achieve welfare gains because intervention for cows with SOM can be performed sooner.

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Forecasting chronic mastitis using milking machine data on using online somatic cell counts and random forest classification

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Abstract
Knowing which mastitis cases are at risk of becoming chronic as early as possible during a (subclinical) episode would be helpful in limiting transmission of chronic mastitis, and unnecessary culling. The Online Cell Counter (OCC) enables the collection of data on Somatic Cell Count (SCC) at each milking. The aim of this study was to develop a forecasting model of mastitis chronicity after the initial increase in SCC and to examine predictive performance of such a model. We used sensor data from 14 European and North American dairy farms with an automatic milking system (AMS) and an OCC (DeLaval International AB). Chronicity was defined as the lack of a structural decrease below 200,000 SCC/ml in 50 days after the day at which the prediction was performed. This prediction was performed using OCC data from 30 days prior to the day where the forecast was made. The label (i.e. to-be-predicted status) indicates whether the cow would recover or turn chronic. A random forest classification model was trained on data from seven randomly selected farms and the data of the remaining seven farms were used to estimate the predictive performance. These results were compared with a default approach that approximated how farmers would diagnose chronicity with monthly SCC data. On average, the model outperformed the default approach on all farms based on accuracy, Matthew's Correlation Coefficient, sensitivity, and specificity. This study shows that it is possible to predict the mastitis chronicity status with high accuracy using past SCC data from the OCC.

Keywords: chronic mastitis, udder inflammation, automatic milking system

Introduction
Chronic subclinical mastitis causes substantial costs through increased risk of pathogen transmission within the herd, increases the risk of clinical mastitis, and prolonged milk loss in affected cows (Bonestroo et al., 2022). Knowing which cases run the risk of becoming chronic at an early stage of a subclinical mastitis episode would be helpful in planning appropriate interventions and limiting cow-to-cow transmission of the pathogen. Automatic milking systems can employ sensors that can measure somatic cell counts (SCC) regularly. These measures can be performed more often than the commonly used monthly Dairy Herd Improvement (DHI) SCC measurement. The benefits of more frequent sampling would include a higher diagnostic performance to forecast whether the case would recover or become chronic. This forecast could serve as decision support tool on treatment, dry-off, or culling decisions. The aim of this study was, therefore, to develop a prediction model based on online cell counts that forecasts

chronic mastitis status based on past sensor data after an initial increase in SCC. The model, based on SCC and using random forest classification, was compared to a default approach representing the performance achieved with monthly sampled SCC data.

Materials and Methods

We used data from 14 herds from Belgium, Canada, France, Sweden, and the Netherlands, with herd sizes of lactating cows ranging from 55 to 638 cows. The data was retrieved from a central database of DeLaval International AB (Tumba, Sweden). Herds with an online cell counter (DeLaval OCC, DeLaval International AB, Tumba, Sweden) and an automatic milking system (DeLaval VMS series, DeLaval International AB, Tumba, Sweden) were selected. The data included SCC and days in milk for each milking, and the cow identification number. The SCC data was aggregated from a "per milking" frequency to a "daily" frequency by taking the daily mean SCC. All days with missing SCC data were imputed using a forward fill procedure. To create a training and a validation dataset, we randomly divided the herds in our dataset. Half of the herds were selected for the training set and the other half of the herds entered the validation set. Validation herds were identified as herd 1 to 7 while herds 8 to 14 were designated as training herds. The data from the training herds were used to fit a prediction model, all at once (i.e. the model was trained once using data from all training herds), and data from the validation herds were used to test the model's performance.

A prediction day (i.e., a day on which a prediction of a future mastitis state was made) was defined as a day in the lactation with a) a daily mean SCC higher than or equal to 200,000 cells/ml (International Dairy Federation, 2013); b) 30 days of preceding SCC data, since the model used 30 days of data as input for the prediction (i.e. the lagged variables); and c) 50 days of subsequent SCC data, since 50 days of SCC data were used to derive the chronic mastitis status.

A cow was labelled as chronic when the rolling 20-day mean SCC did not decrease below 200,000 SCC/ml at any time during the 50 days after the prediction day. As most cases tend to recover within 3-4 weeks (Bonestroo *et al.*, 2021), we see that most cases would recover within the 50-day window. We used the random forest classification algorithm, as implemented in sci-kit learn (Pedregosa *et al.*, 2011), to create a prediction model that forecasted whether the cow would recover (=0) or turn chronic (=1). This random forest classifier used the default settings for all parameters. A random forest classifier was chosen as they can be quite robust to outliers by binning them.

The predictive performance of the random forest classifier was compared to that of a default approach: the monthly sampling approach (monthly sampling approach mimicking DHI sampling frequency, but using OCC data). To mimic a monthly sampling frequency, we used 2 SCC measurements in the 30 days preceding the prediction day. This approach labelled the cow as chronic when the SCC was higher than 200,000 SCC/ml in the SCC measurement closest in time to the prediction day and the SCC evaluation as early as possible within the preceding 30-day window. If both SCC samples were higher than 200,000 SCC/ml, chronic mastitis was predicted. A comparison between the monthly (default) sampling approach and the predictions of the random forest classification model on the basis of sensitivity, specificity, accuracy, Matthew's correlation coefficient, and accuracy metrics (see Equations 1 to 4) allowed us to approximate whether there is an increase of predictive performance of using online SCC relative to using SCC in a non-sensor setting.

$$Matthew's\ correlation\ coefficient = \frac{tp \times tn - fp \times fn}{\sqrt{(tp + fp)(tp + fn)(tn + fp)(tn + fn)}} \quad (1)$$

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn} \quad (2)$$

$$Sensitivity = \frac{tp}{tp + fn} \quad (3)$$

$$Specificity = \frac{tn}{tn + fp} \quad (4)$$

Results and Discussion

Table 1 presents the sensitivity, specificity, Matthew's correlation coefficient, and accuracy of the model predictions and monthly sampling approach. All performance measures varied slightly between the different validation herds. Overall, the chronic mastitis prediction model outperformed the default approach on all farms for all performance indicators. We were also able to see that the accuracy does not majorly differ between the herds, apart from herd 7. This is interesting as this hints to the limited influence of herd-specific factors in chronic mastitis prediction.

On average, if we would have 100 mastitis cases for which chronic mastitis is forecasted, 27 cases would be wrongly forecast under the default approach, while 19 cases would be wrongly forecasted using the forecasting model. The difference in wrongly forecasted cases would lead to unnecessary culling and treatment when chronic mastitis is falsely forecasted, and unnecessary transmission of pathogens when recovery is falsely forecasted. In both cases, it would lead to extra economic costs for the dairy farm. Another factor to consider is that the prediction can be made more frequently using daily sensor data. This would result in more moments of evaluation and henceforth allowing for more moments to intervene in chronic mastitis.

The results show that a random forest classifier based on frequent SCC values would have value for farmers in the activity of forecasting chronicity, assuming that farmers currently use the default approach as provided in the study. This point is strengthened by the fact that farmers may not need to invest in extra sensor technology to gather these forecasts, as all sensors are already available on commercial dairy farms. Chronic mastitis forecasting has not obtained substantial interest in the literature. Bartel *et al.* (2019) created two chronic mastitis prediction models for healthy cows and unhealthy cows, respectively, using non-sensor DHI data and generalized additive models. However, this two-model approach cannot be directly compared with our results due to the usage of non-sensor SCC measures. Kristula *et al.* (1992) also used DHI SCC to predict chronic mastitis, in which they concluded that chronic mastitis prediction is challenging. However, sensor data from milking machines is more frequent than monthly sampled SCC measurements and hence can potentially contain more information regarding the chronic mastitis status. This can potentially explain the difference in predictive performance between the default approach and the model.

Table 1: The predictive performance of the model predictions and default approach over 7 validation herds

Herd	Sensitivity	Specificity	Matthew's correlation coefficient	Accuracy
		Forecasting Model		
Herd 1	0.84	0.73	0.58	0.79
Herd 2	0.85	0.74	0.59	0.80
Herd 3	0.83	0.76	0.58	0.79
Herd 4	0.84	0.74	0.56	0.78
Herd 5	0.86	0.78	0.64	0.82
Herd 6	0.85	0.79	0.62	0.81
Herd 7	0.86	0.89	0.70	0.88
All herds	0.85	0.78	0.61	0.81
		Default approach[1]		
Herd 1	0.70	0.70	0.40	0.70
Herd 2	0.75	0.65	0.40	0.71
Herd 3	0.69	0.68	0.36	0.68
Herd 4	0.76	0.69	0.44	0.72
Herd 5	0.76	0.72	0.48	0.74
Herd 6	0.73	0.72	0.43	0.72
Herd 7	0.72	0.83	0.51	0.81
All herds	0.73	0.71	0.43	0.73

[1]The default approach is using 2 SCC samples, approximately 1 month apart.

We expect that the performance of the forecasting model would increase further when additional mastitis indicators recorded are included as input in the model These mastitis indicators would be able to measure different markers related to different biological processes tied to udder inflammation (Viguier *et al.*, 2009). Additionally, data on the general health state of the cow (e.g., the rumination, the activity of the cow) could be added to the model to capture the severity of the mastitis. Including more markers containing predictive information on the severity of mastitis could improve model performance and enable a more complete sensor-based evaluation of the disease. The combination of the markers would potentially enable to correct for possible measurement errors of a single inflammation marker by using the rest of the inflammation markers. Nevertheless, these markers would still need to be relevant to the chronic mastitis forecasting problem to increase the predictive performance.

We used SCC data to define a prediction day and define the future chronic status, as SCC is a common way to measure and define subclinical mastitis (Smith *et al.*, 2001; International Dairy Federation, 2011). However, different markers of inflammation may be used to perform these activities. Electrical conductivity is available for all AMS systems, while the inflammation marker lactate-dehydrogenase (Nyman *et al*., 2016) is increasingly available using sensors on-farm. However, one could also use a non-mastitis-specific indicator such as milk yield, which could serve as an indicator for the consequences of a mastitis case on animal production. Using milk yield, one may forecast a chronic status based on the milk yield loss that would come with a mastitis case (Bonestroo et al., 2022) and see whether the amount of milk yield would return to a level similar to other healthy cows. In this case, it is vital to have some mastitis-specific indicators as otherwise the predicted milk loss could be due to other diseases. Even though the approach used in this study focused on SCC, it could be applied on a broader scale of mastitis or disease indicators.

Conclusions

This paper shows that a machine learning approach based on data of an SCC sensor attached to an AMS outperformed a default identification approach that approximates common non-sensor-based decision-making. These results indicate that it is possible to improve the identification and forecasting of chronic mastitis using on-farm SCC and machine learning methods. In the future, forecasting chronicity and thus improved recovery of a mastitis case could help farmers to make better decisions based on online SCC. This could result in targeted antibiotic treatment, culling, and dry-off protocols that take consideration of cows that will not recover.

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SESSION 14

Pigs:
Sound, Computer Vision and Automated Weighing in Finishers

Environmental risk factors influence the frequency of coughing episodes in finisher pigs: a case study on a farm free of respiratory disease

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Abstract

Coughing in response to environmental irritants can detrimentally affect pig health and performance even in the absence of disease. This study aimed to characterize the influence of temperature, relative humidity, and ammonia concentrations on the frequency of coughing on a farm free of respiratory disease.

Six replicates were conducted (690 pigs in total). A cough monitor (SoundTalks®) and an ammonia sensor were installed, issuing a daily Respiratory Distress Index (RDI: average number of coughs/pig/24h), average temperature and relative humidity values; and ammonia concentrations for an average of 78 days per replicate.

A cross-correlation analysis was performed and lags of the predictor variables were carried forward for multivariate regression analysis when significant and showing $r > 0.25$. Results show that coughing frequency was overall low. In the first replicate, coughing was best predicted by exposure to higher ammonia concentrations that occurred with a lag of 1, 7 and 15 days ($P = 0.003$, $P = 0.001$ and $P < 0.001$, respectively). While in the sixth replicate coughing frequency was best predicted by the exposure to lower relative humidity and higher ventilation rates with a lag of 7 and 15 days ($P < 0.001$ and $P = 0.003$, respectively).

Guidelines on coughing levels in healthy pigs, and calibration of the alarm systems of tools that measure coughing frequency can be extrapolated from this study. Environmental risk factors are associated with the respiratory health of finisher pigs. A better understanding of these effects can help determine when to implement appropriate preventive measures.

Keywords: Ammonia; Air quality; Coughing frequency; Porcine Respiratory Disease

Introduction

Respiratory disease remains a major economic and health concern in the pig industry worldwide (Nathues et al., 2017). Although there are several primary and opportunistic pathogens involved in the Porcine Respiratory Disease Complex (PRDC) (Brockmeier et al., 2002), inappropriate thermal and gaseous environments in pig buildings can exacerbate transmission and spread of these pathogens, triggering and/or increasing severity of clinical outbreaks (Brockmeier et al., 2002). Furthermore, unfavourable environmental conditions act as a stressor and may damage the pigs' respiratory tract (Brockmeier et al., 2002). Therefore, they have a detrimental effect on pig health, welfare and performance (Brumm, 2019).

Ammonia (NH_3) is the most common health threatening gas in animal buildings (Cargill et al., 2002). Like several respiratory pathogens, NH_3 depresses ciliary activity and mucus flow (Stombaugh et al., 1969), impairing the mucosal clearance system, thus predisposing the respiratory tract of pigs to infections (Yaeger & Van Alstine, 2019). Temperature and relative humidity can also influence pigs' respiratory health by disrupting the normal respiratory and thermoregulatory behaviour of the animals, while contributing to the survival of pathogens (Brumm, 2019). Environment-oriented data, specifically data on air temperature and relative humidity, are routinely collected and used to regulate ventilation systems in most intensive pig farms. Unfortunately, the potential of such data to add value to pig health management on farm is rarely exploited (Pineiro et al., 2019). Measurements of NH_3 concentrations on-farm largely rely on portable sensors that give intermittent and short-term readings (Dennier, 2019; Pineiro et al., 2019).

With on-going technological developments, a variety of PLF tools are available (Larsen et al., 2021; Norton et al., 2019). In recent years, research efforts developed a tool to help monitor and control respiratory disease on-farm by performing continuous and automated measurements of coughing through the analysis of sound collected within pig buildings using a microphone (Hemeryck et al., 2015). A recent study employing such technology identified the need to classify patterns of coughing according to environmental risk factors, and to verify the baseline coughing frequency in healthy pigs (Pessoa et al., 2021).

Combining animal- and environment-oriented sensor data for the purpose of strategic decision-making is a promising area of future research (Pineiro et al., 2019) and could help address the challenge of the respiratory disease syndromes in pigs (Chantziaras et al., 2020).

Therefore, the objectives of this study were 1) to assess baseline levels of coughing on a respiratory disease-free farm, and 2) to assess the relationship between environmental conditions (ammonia, temperature, and relative humidity) and levels of coughing.

Material and methods

Experimental design

This study took place at the Teagasc Pig Research Facility in Fermoy, Co. Cork, Ireland from March 2019 to January 2020. The farm operates as a farrow-to-finish facility with a three-week farrowing batch system. The farm was negative for Porcine Reproductive and Respiratory Syndrome virus, Influenza A virus, *Mycoplasma hyopneumoniae*, and *Actinobacillus pleuropneumoniae*. Pigs were housed in rooms with 10 pens with fully slatted concrete floors, containing a wet-dry feeder (MA37, Verba, Netherlands) and one nipple drinker. Water and pelleted feed were provided *ad libitum*. Temperature was controlled with a temperature-based mechanical ventilation system (Big Dutchman 135pro, Vechta, Germany). Three production batches of pigs (690 pigs in total) were each housed in two rooms (rooms A and B; 115 pigs per room) from 11 weeks of age, thus encompassing six replicates. All pigs were identified with ear-tags such that they could be monitored until reaching the target slaughter weight of 110 kg. All seasons within a year were covered. The first batch was reared from March to May (spring), the second from July to September (summer), and the third from October to January (autumn/winter).

Data collection

Data on environmental parameters and respiratory health were collected resulting in several datasets originating from different sensors. Moreover, lung lesions were scored at slaughter.

Environmental data

Environmental sensors were used to record daily measurements (average, minimum, and maximum values) of temperature and relative humidity. Sensors were placed in the center of each room. Temperature sensors were placed at a height of approximately 1.5m and the relative humidity sensors were placed at approximately 2m. These sensors were part of the cough monitor (SoundTalks NV, Leuven, Belgium) system.

The ammonia sensors (Dräger Polytron C300 with DrägerSensor NH3-Al, Lübeck, Germany) used in this study were electrochemical sensors that perform continuous long-term ammonia measurements. One NH_3 sensor was placed in each room, following manufacturer's guidelines. It provided data points for ammonia concentrations every 30 seconds. Data on ventilation rates were recorded for the whole duration of this study.

Respiratory health data

The cough monitors (SoundTalks NV, Leuven, Belgium) used in this study perform continuous and automated measurements of cough sounds, issuing a Respiratory Distress Index (RDI) that corresponds to the average number of coughs per pig per twenty-four hours. They also generate an automated warning, which is set according to a patented Statistical Process Control algorithm using the history and the variation of the RDI from a specific room. One cough monitor was installed in each room, following the manufacturer's guidelines. All data collected during this study were stored and accessed using the associated pig respiratory distress monitoring (RDM) software.

Statistical analysis

R version 4.0.2 was used for the statistical analyses. Descriptive statistics are presented for all variables assessed.

For all variables (temperature, relative humidity, ammonia concentrations, ventilation rates and the respiratory distress index), mean, standard deviation, median, minimum and maximum values were calculated for rooms A and B in each batch.

Daily averages of NH_3 concentrations and of ventilation rates were used.

To assess the relationship between the time series corresponding to temperature, relative humidity, NH_3 concentrations, ventilation rates (the predictors), and the RDI (response variable), variables were first tested for stationarity using the Dickey-Fuller test. If non-stationary, differencing was applied.

Because respiratory health can depend on the exposure to the currents day's environmental conditions (lag 0), but also on exposure on previous days (negative lags), a cross-correlation analyses was carried out in order to gain insight into the relationship between these variables, and to identify lags that may be useful predictors of the RDI. For biological reasoning, only negative lags and lag zero were considered. Lags of the predictor variables were carried forward for multivariable regression analysis when significant and showing $r > 0.25$.

Models were constructed using a backward stepwise elimination based on the Akaike information criterion (AIC). Residuals' autocorrelation was assessed using the Breusch-Godfrey test. Only models where no residual's autocorrelation was detected are presented. Bonferroni correction was applied to correct for multiple testing.

Results and Discussion

The duration of each finisher period was on average 78 (±1) days. Lung lesions were scored on 506 pairs of lungs (84 ± 22 pairs of lungs per replicate). In general, no gross pathology was observed in the lungs. However, the prevalence of pericarditis in pigs reared in the first batch in room A was 10%; moreover, 3 ± 2% of the trial pigs presented liver milk spots. Table 1 shows descriptive results for all sensor-based variables.

Overall, the respiratory distress index remained low throughout the six replicates assessed, with the exception of room A during the 1st batch where the RDI reached 31.9 at the end of the finisher stage (Figure 1). Daily variation for all sensor-based variables can be seen in Figure 1. In general, higher daily values of NH_3 concentrations were recorded in autumn/winter (3rd batch), followed closely by spring (1st batch).

The multivariable models fitted for the RDI in room A during the 1st batch and in room B during the 3rd batch are presented in Table 2 and were able to explain 47 and 39% of variability, respectively. In room A during the 1st batch the RDI was best predicted by exposure to higher ammonia concentrations that occurred with a lag of 1, 7 and 15 days ($P = 0.003$, $P = 0.001$ and $P < 0.001$, respectively). While in room B during the 3rd batch the RDI was best predicted by the exposure to lower relative humidity and higher ventilation rates with a lag of 7 and 15 days, respectively ($P < 0.001$ and $P = 0.003$, respectively).

Table 1: Multivariable regression models of lagged environmental parameters from the Respiratory Distress Index.

Models	Predictors	Estimate (SE)	P-value
	Intercept	-0.01 (0.426)	0.976
Respiratory Distress Index	[NH3][1] lag -1	0.58 (0.184)	0.003 *
(1st batch – room A)	[NH3] lag -7	0.70 (0.209)	0.001 *
	[NH3] lag -8	0.51 (0.210)	0.020
Adj. R^2 = 47%	[NH3] lag -15	0.98 (0.240)	<0.001 *
	RH[2] lag -3	-0.32 (0.127)	0.014
Respiratory Distress Index	Intercept	-0.00 (0.033)	0.982
(3rd batch – room B)	RH lag -7	-0.07 (0.016)	<0.001 *
	RH lag -8	0.03 (0.016)	0.028
Adj. R2 = 39%	Ventilation flow lag - 15	0.01 (0.004)	0.003 *

[1]Ammonia concentrations

[2]Relative humidity

*Indicates significant variables after Bonferroni corrections

The findings of our study show that the frequency of coughing were mostly low. Several studies measured the RDI in farms with a high prevalence of lung lesions (Hemeryck et al., 2015; Pessoa et al., 2021) and/or in farms positive for different pathogens associated with the Porcine Respiratory Disease Complex (Pessoa et al., 2021; Polson et al., 2018). When compared to our study, others generally reported higher values of the RDI, where it reached ≈ 10 (Hemeryck et al., 2015; Pessoa et al., 2021) and ≈23 (Polson et al., 2018). However, these studies also report low coughing levels throughout the finisher stage. Indeed, Polson *et al.* (2018) associated an increase in coughing with positivity to Influenza A virus.Although more research is needed to understand how different coughing patterns associate with different pathogens, our study indicates that RDI values between 0 – 4 can be considered normal for intensive, indoor commercial farms.

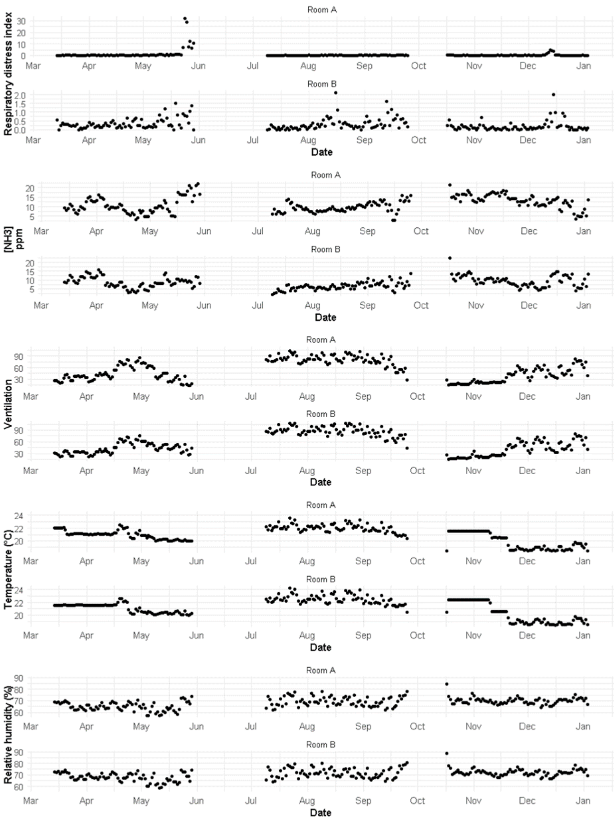

Figure 1: Daily averages of the respiratory distress index, three environmental parameters, and ventilation flow.

However, we also recorded RDI values of ≈ 32 at the end of finisher stage in one batch (1st batch in room A). When exploring the relationship between environmental risk factors and coughing frequency, our model was able to explain 47% of the variability. Interestingly, in this case, the RDI was best predicted by the exposure to higher concentrations of ammonia occurring with a lag of 1, 7, and 15 days. In Figure 1, we can see that, by the end of finisher stage, a steep increase in NH_3 precedes an increase in the RDI. To our knowledge, this is the first study evaluating the relationship between continuous measurements of coughing frequency and NH_3 concentrations. However, in 1969 Stombaugh *et al.* reported that at 100 and 150 ppm, pigs coughed three times more than those exposed to lower ammonia concentrations (10 and 50 ppm). Still, several other studies showed that 1) NH_3 concentrations over 35 ppm induce inflammatory reactions in the respiratory mucosa of animals (Johannsen et al., 1987); 2) pleurisy is positively correlated with NH_3 concentrations above 25 ppm (Donham, 1991); 3) pigs exposed to NH_3 concentrations varying from 0.6 – 37 ppm show small pathological changes in their respiratory tract (Done et al., 2005); and that pigs show a preference for clean air when compared to air with varying NH_3 concentrations (Jones et al., 1996; Jones et al., 1999; Smith et al., 1996). Moreover, high concentrations of NH_3 are relevant not only to animal health and welfare, but also to occupational health and safety of farm staff (Cole et al., 2000; Lühken et al., 2019). Although there are no legal requirements regarding concentrations of ammonia in pig buildings, studies recommend that levels should be kept below 25 ppm, and ideally below 10 ppm (Donham, 1991; Michiels et al., 2015). In our study, maximum daily averages reached 22.5 ppm, with mean daily averages varying between 6 – 13 ppm. Furthermore, for the trial pigs reared during Autumn/Winter (3rd batch in room B) we also found that the RDI was best predicted by the exposure to lower relative humidity and higher ventilation rates with a lag of 7 and 15 days, respectively (adjusted R^2 = 39%). As reviewed by Boyle et al. (2022) there is strong evidence that high ventilation rates, i.e. draughts are risk factors for respiratory disease. Indeed, draughts are associated with in-creased frequencies of coughing and sneezing (Scheepens et al., 1991), and with the prevalence of pleurisy (Fablet et al., 2012). Conflicting with our results, high relative humidity is associated with respiratory disease (Done, 1991).

Ultimately, our results suggest that coupling continuous environmental-oriented data and animal-oriented data may be useful to better understand pigs' respiratory health, and as suggested by Chantziaras *et al.* (2020) could help to elucidate the complexity of the Porcine Respiratory Disease Syndrome.

Conclusions

Results of this study can be used as guidelines on coughing levels in healthy pigs, and to calibrate the alarm systems of tools that measure coughing frequency, such as the cough monitor used in this study. Furthermore, we show that environmental risk factors are to some extent associated with the respiratory health of pigs, thus we suggest that information collected on these risk factors should be used to help with decision-making processes on farm. We highlight the importance of continuously measuring ammonia concentrations, and urge for the integration of sensor technology and ventilation systems.

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The impact of respiratory health status on production losses in commercial pig farms

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Abstract

Constraints such as respiratory infectious diseases can cause significant economic losses to the pig industry worldwide and these are also the main reason for high antimicrobial use in growing-finishing pigs. As antimicrobial resistance has become a worldwide problem, threatening both livestock and public health, measures must be taken to reduce the use of antibiotics. (Aarestrup *et al.*, 2008; Holmer *et al.*, 2019).

Continuous monitoring of the respiratory health status of pigs based on automated detection of respiratory symptoms offers a solution to treat animals in an early stage of disease development, and consequently reduce the use of antimicrobials (Berckmans *et al.*, 2015; Chung *et al.*, 2013; Ferrari *et al.*, 2008; Genzow *et al.*, 2014; Guarino *et al.*, 2008; Gutierrez *et al.*, 2010; Polson *et al.*, 2018).

The aim of this on-going study is to assess the relationship between a sound based Respiratory Health Status score (ReHS) which represents the respiratory health status in the farm, and the production performance in different commercial farms spread over 4 European countries.

In each farm, sound monitors were placed in all rooms (1 device per 200 pigs), resulting in a current data base of over 60 production rounds for fattening pigs and 97 production rounds for piglets with complete sound data. In all farms, records were kept in logbooks concerning the used medical treatments.

Data analysis showed a strong correlation between the ReHS and the performance metrics average daily growth and mortality as well as the number of treatments in piglet farms. In fattening farms, a correlation was also found between ReHS and average daily growth.

Based on the results of this study, we could evaluate the effect of (early) detection of respiratory diseases on the reduction of medication use in pig production.

Keywords: respiratory health, production results, treatments

Introduction

Respiratory infectious diseases are an important problem in the pig industry worldwide. They can cause significant economic losses and they are the main reason for high antimicrobial use in growing-finishing pigs. As antimicrobial resistance has become a worldwide problem, threatening both livestock and public health, measures must be taken to reduce the use of antibiotics (Holmer *et al.*, 2019). In addition, one infection with a pathogen may lead to an easier infection of another (Schagemann *et al.*, 2016). Often more than one pathogen can be acting concurrently in the respiratory system.

Because of the limited physical presence of caretakers in the barn, technological solutions detecting the health status of the animals in a continuous way are considered in this study.

Precision livestock farming (PLF) offers a real-time monitoring and managing system for farmers. This is fundamentally different from other approaches that tried to monitor the animal welfare by human experts scoring (Norton *et al.*, 2019).

In that regard, SoundTalks has developed the SoundTalks® surveillance system to monitor the respiratory health status of the pigs by sound analysis (Genzow *et al.*, 2014; Polson *et al.*, 2018). The sound in the barn is monitored 24/7. Sound data are analysed using Artificial Intelligence providing a trustworthy and objective way of detecting respiratory problems. Based on this, automatic warnings and alerts are generated. That way the farmer knows when respiratory health issues occur in the barn and when and where to intervene or call a vet.

Material and methods

Data collection

Since the start of a research project funded by the Flemish Government within SoundTalks, sound monitors (1 device per 200 pigs) were installed at 6 commercial fattening pig farms and 9 commercial nursery farms spread over 4 European countries: Belgium, The Netherlands, Germany and Spain. Besides sound data, the monitors also collect climate data themselves in real-time such as temperature and relative. In addition to the data collected by the monitors, other sensor data such as temperature (in the barn and outside), relative humidity, ventilation rate, CO2-concentration, NH3-concentration and feed and water supply is collected when they are available on the specific farm. Farmers fill in a logbook every day. It contains information about daily mortality (and cause), technical issues, medical treatments and used antibiotics. Also, manual assessments are done by the farmers. These reveal a score between 1 and 5 related to number of coughs and sneezes, the activity of the pigs and the general health status of the animals.

Respiratory Health Status

The Respiratory Health Status (ReHS) is a A.I.-processed, sound-based metric that objectively reflects the respiratory health status of a monitored group of pigs in real time. The score is calculated based on the detection of respiratory symptoms, such as coughs during the course of the day. The score is presented on a scale from 0 to 100. A certain color is assigned to different categories of the respiratory health status. A ReHS between 0 and 40 is presented as a red colour; it means that the respiratory health status of the pigs is in an alarm phase. A ReHS between 40 and 60 results in a yellow colour; it means that the respiratory health status of the pigs is in a warning phase. A ReHS between 60 and 100 is an indication that the respiratory health status of the pigs is good.

Data analysis

The average ReHS calculated over all days of a production round can be used to represent the overall respiratory heath status in one metric. In this paper, the health performance of a production round is often expressed in this way. Another way to represent the respiratory heath performance of a round in one metric is using the **alarm score**. For this alarm score, points are given over each day. A day when the respiratory health status of the pigs is optimal gets a score of 0. A day when the respiratory health status of the pigs is in a warning phase (yellow color) gets a score of 1. A day when the respiratory health status of the pigs is in an alarm phase (red color) gets a score of 2. The sum of these numbers over a production round is presented as the overall alarm score for that production round.

To determine the relationship between the Respiratory Health Status (ReHS) and the production performance in commercial pig farms, correlations between the ReHS and production numbers were examined. To check the performance of a round, 4 Key Performance Indicators (KPI's) were investigated: mortality (expressed as percentage of the number of animals), Feed Conversion Ratio (i.e. FCR, no unit), Average Daily Growth (i.e. ADG, expressed in g/day) and treatments (expressed in percentage treated animals during a round).

Results and Discussion

Fatteners

A total of 60 fatteners rounds were analysed from October 2020 till December 2021. The relationship between the average ReHS and the alarm score is shown in Figure 1. It shows that both numbers are significantly correlated ($R^2=0.892$; $P<0.001$). This means that the average ReHS also gives information about the days in warning (monitor in yellow) and days in alarm (monitor in red). In the studied relationships, average ReHS was used. Similar relationships can be expected when using the alarm score.

There was no significant correlation between the Respiratory Health Status (average ReHS) and Feed Conversion Ratio (FCR; $R^2=0.021$; $P>0.05$) as shown in Figure 2. This can be explained by the fact that both feed consumption and growth are reduced during periods with respiratory symptoms and therefore the feed conversion will not change significantly. The clustering of rounds of a farm (shown in figure 2) are due to different duration of production periods between farms. However, there is not yet enough data to do farm-specific analysis in terms of FCR. Also the relation between average ReHS and mortality in the fattener groups (Figure 4) is not significant ($R^2=0.001$; $P>0.05$). A reason for this can be that mortality has many causes and is not limited to respiratory infections. On the other hand, a positive significant correlation ($R^2=0.196$; $P<0.001$) was found between Respiratory Health Status and pig growth (i.e. ADG) (Figure 3). The better the pigs score on respiratory health, the higher their growth will be. Also, the number of treatments and the use of medication is significantly negatively correlated ($R^2=0.183$; $P<0.001$) with the ReHS. For this relationship, information of less rounds was available because only 1 farm could be analysed so far (figure 5).

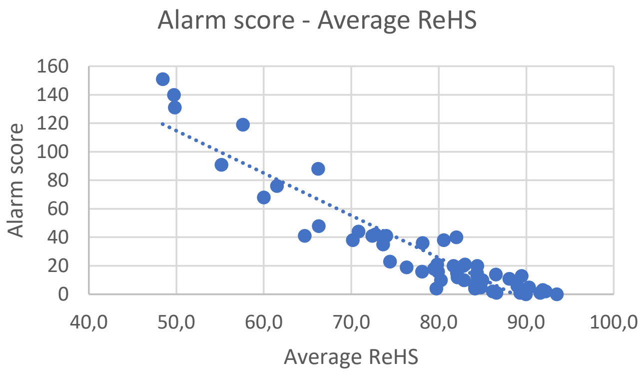

Figure 1: Relationship between the Average ReHS and the alarm score (Fatteners)

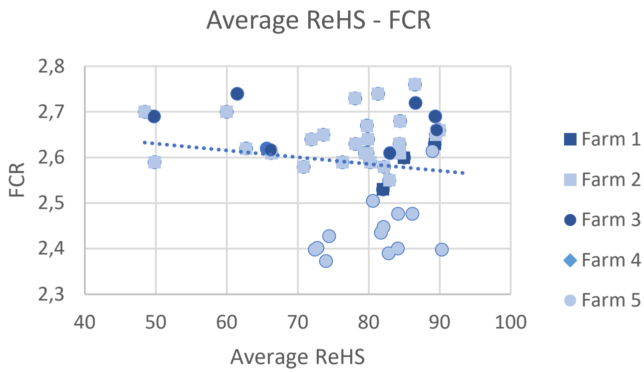

Figure 2: Relationship between the average ReHS and the Feed Conversion Ratio (FCR) (Fatteners)

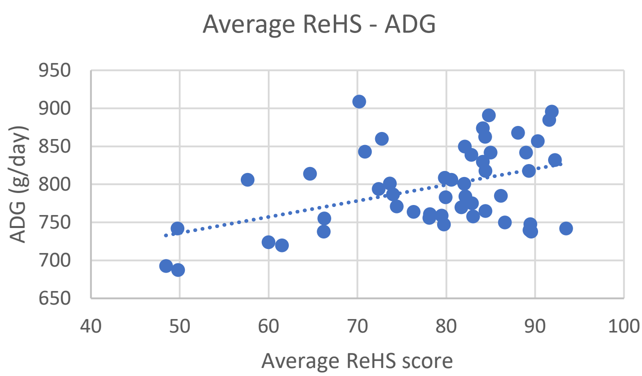

Figure 3: Relationship between the average ReHS and the Average Daily Gain (ADG) (Fatteners)

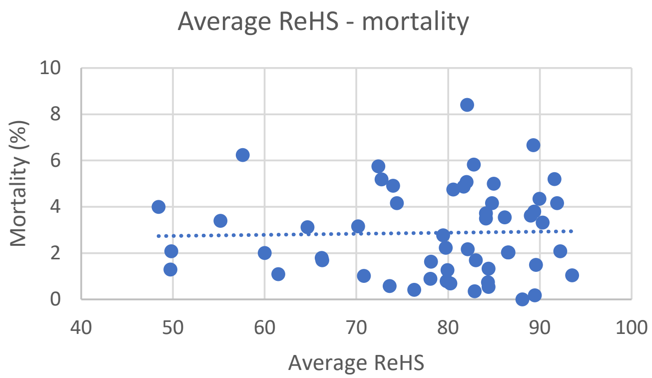

Figure 4: Relationship between the average ReHS and mortality (Fatteners)

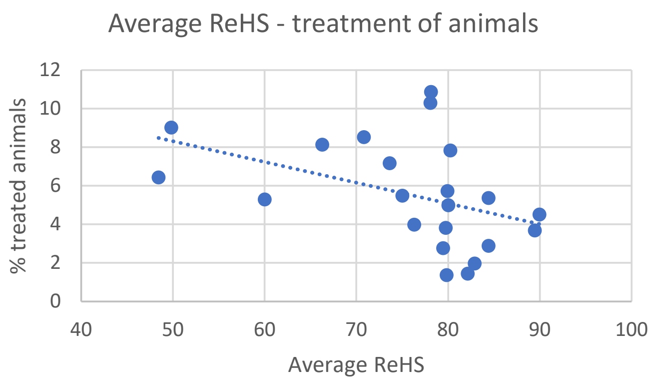

Figure 5: Relationship between average ReHS and treatments of animals (Fatteners)

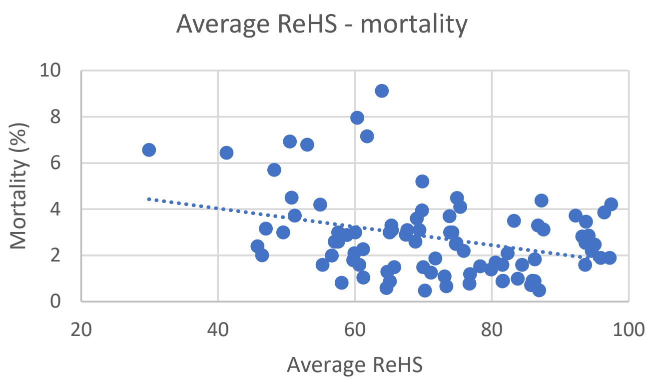

Figure 6: Relationship between average ReHS and mortality (piglets)

Piglets

A total of 97 weaned piglets rounds were analyzed from October 2020 till December 2021. Figure 6 shows that there is a significant negative correlation (R^2=*0.114; P<0.01*) between average ReHS and mortality. In contrast to fattening pigs, respiratory symptoms in piglets cause higher mortality rates. Also the daily growth (i.e. ADG) is positively correlated with the average ReHS (R^2=*0.292; P<0.001*) (Figure 7). The better the respiratory health, the better the growth. Figure 8 shows that there is no significant correlation (R^2=*0.142; P>0.05*) between the average ReHS and Feed Conversion Ratio (FCR). To confirm this conclusion, more production rounds should be present with an available FCR to have a better insight on the relationship between those two variables.

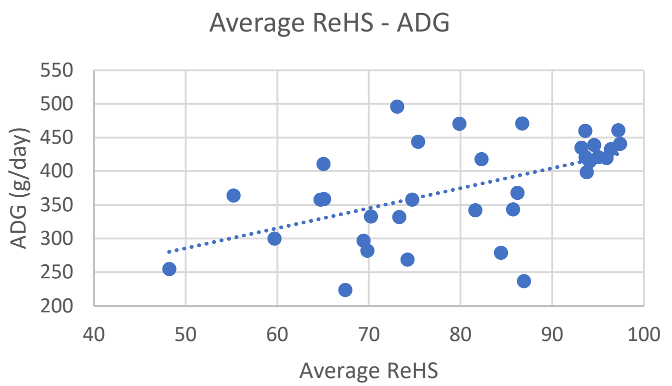

Figure 7: Relationship between average ReHS and Average Daily Gain (ADG) (piglets)

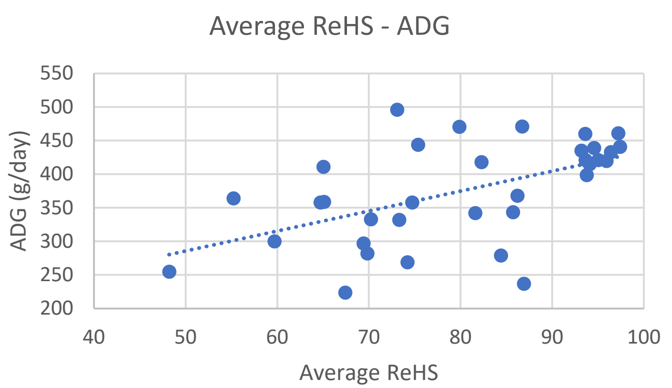

Figure 8: Relationship between average ReHS and Feed Conversion Ratio (FCR) (piglets)

Conclusions

This study showed that the sound based respiratory health status (ReHS) measured by SoundTalks® has a significant relation with the production performance parameters during the growth and finishing phase of the pig.

For the finishing phase (fatteners), the association of the ReHS with pig growth (i.e. ADG) was strong, similar to the relationship between a good respiratory health and reduced use of medication. The impact of ReHS on FCR and mortality seems rather limited, but further investigation on more production rounds is needed.

For piglets, different from fatteners, a negative correlation was found between ReHS and mortality. A positive correlation was found between ReHS and average daily growth rate. The relationship between ReHS and FCR needs some more investigation since the available data was limited at the moment this study was done.

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Assessment of the economic value of early intervention triggered by an audio-based technology (SoundTalks) following experimental seeder pig dual-challenge in a large research barn

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Abstract

An audio-based Precision Livestock Farming (PLF) technology, SoundTalks, continuously records and processes sounds in pig facilities. generating algorithm-based alerts when respiratory problems are detected. These alerts enabled earlier caregiver awareness of the onset of respiratory clinical episodes than via caregiver observations alone. However, for tangible value to be derived from early detection, timely and appropriate intervention actions must be taken. The purpose of this experimental study was to evaluate the performance and economic differences resulting from earlier intervention following the onset of clinically detectable respiratory disease episodes as measured by SoundTalks using a standardized economic index (SEI) method. Eleven week old pigs (n=1655) were allocated to 72 pens across two rooms, with three SoundTalks zones covering 12 pens per zone. Sets of treatment groups (G0, G5 and G10) were randomly allocated within each zone. In every pen, three randomly selected seeder pigs were challenged seven days apart with Mycoplasma hyopneumoniae and PRRS virus. The number of days to the onset of treatment after the first SoundTalks alerts was defined: day zero (G0), day 5 (G5) and day 10 (G10). All groups received the same post-SoundTalks-alert treatment. Economic differences between groups were calculated using a Standardized Economic Index (SEI) model. Throughout the 120 month SEI data period the mean monthly B:C Ratio was 4.59, ranging from 2.80 to 8.12 and exceeding 2:1 for 120 of 120 (100%) months (G0:G5). Further, the 48 month rolling B:C Ratio ranged from 3.55 to 5.27, exceeded 2:1 for 120 of 120 (100%) intervals (G0:G5).

Keywords: pig, cough, seeder challenge, economics

Introduction

Respiratory disease outbreaks continue to be a major pig production problem, impacting antibiotic use, welfare, productivity and profitability (Lopes et al, 2019). SoundTalks is an audio-based technology that continuously identifies and quantifies respiratory problems in pigs, generating alerts (yellow warnings, red alarms) when respiratory outbreak onset is detected. These alerts have enabled triggering earlier caregiver awareness than caregiver observations alone (Polson et al., 2018). However, further research is needed to quantify the economic impact of this technology. The objective of this study was to evaluate the performance and economic differences resulting from earlier detection and intervention following the onset of a clinically detectable respiratory disease episode measured by SoundTalks.

Materials and Methods

Eleven-week-old pigs (n=1655) were placed in 72 pens throughout two rooms (airspaces). Each room contained three SoundTalks monitors, one monitor per 12 pens. Study groups were randomly allocated within each zone. In every pen, three randomly selected seeder pigs were challenged with Mycoplasma hyopneumoniae for two consecutive days followed by a PRRS virus challenge seven days later.

Continuous sensor data was recorded at the zone level (e.g., audio, temperature) and pen level (e.g., water use, temperature). Performance was measured at both the individual pig and pen levels. Individual pigs were weighed at the beginning of the study and every four weeks through the end of the study. Feed disappearance was recorded weekly for every pen. Daily individual pig treatments and mortality were also recorded.

There were three study groups, defined as: SoundTalks (ST) alert day zero (G0), day 5 (G5) and day 10 (G10). Alert day 0 was defined as the day that the first ST yellow/red alerts were reported post-challenge. All pigs received the same treatment protocol – differentiated only by the date the treatment protocol was started. Group ST-G0 received the intervention beginning the day of the first actionable SoundTalks alert. Subsequently, groups ST-G5 and ST-G10 received the same intervention at ST alert day 0 + 5days and ST alert day 0 + 10 days, respectively.

Linear regression mixed models were used to study the association between the production parameters and treatment groups after controlling for other independent variables. Economic differences among treatment groups were calculated using a "Standardized Economic Index" (SEI) based on a partial budget spreadsheet model.

The SEI is a function of finished pig performance measures, historical feed ingredient costs, historical market pig prices, historical inflation rates and the calculated cost-to-operate (CTO) of the technology being evaluated. Pig performance measures utilized in the SEI were average daily gain (ADG), feed conversion rate (FCR), average daily feed (ADF), mortality, and individual pig treatment cost. Historical monthly market prices and feed ingredient costs were obtained for a 30 year period from January 1992 through December 2021. The most recent 12 year (144 month) time period (January 2010 through December 2021) was used as the focus of the economic analysis. In addition to hardware installation costs (labor and materials), a weighted SoundTalks hardware lifespan of 48 months was used to calculate the hardware cost on a per pig marketed basis for inclusion in the CTO.

To represent the impact of a more natural (contact) exposure and infection dynamic under routine operational conditions, performance data for contact challenged pigs that did not experience exceptional handling (e.g., did not experience individual snaring, bleeding, tracheal catheterization) were used to model the SEI.

A sensitivity analysis was conducted by constructing a 3 x 3 table (nine combinations) where the X-axis was pig live market price (USD per kg live body weight) and the Y-axis was diet cost per metric ton (USD per 1000 Kg complete diet). The pig price middle value was the calculated average of the 144 historical monthly market price values from January 2010 through December 2021. The pig price lower and higher sensitivity matrix values used were calculated as the 99% lower control limit (LCL) and 99% upper control limit (UCL) from the 144 months of historical data for the same period.

The diet cost per metric ton middle value was the calculated average of the 144 historical monthly cost values from January 2010 through December 2021 for:

— Number two yellow corn as the primary dietary energy source
— 44% soybean meal as the primary dietary protein source

Non-energy and non-protein ingredient cost estimated were obtained (Dr. Mike Tokach, Kansas State University, personal communication) and were adjusted across the 12 year period using monthly US inflation rate data. The fee for finished diet preparation and delivery (GMD) was obtained (Jon Hoek, Summit Smart Farms, personal communication) and was also adjusted across the 12 year period using monthly US inflation rate data. Typical grower-finisher pig diet formulations were obtained (Dr. Mike Tokach, Kansas State University, personal communication), and utilized the aforementioned ingredient and GMD costs to calculate an average diet cost per metric ton representing the 144 month period. The diet cost lower and higher sensitivity matrix values used were calculated as the 99% lower control limit (LCL) and 99% upper control limit (UCL) from the 144 months of historical data for the same period.

The resulting calculated sensitivity matrix values for three levels of pig market price and three levels of diet cost with the nine combinations are shown in Figure 1.

12 year (2010-2021) Standard

	MKT$$/Cwt>	UCL(99%)	Middle	LCL(99%)
Diet$/1000kg		$1.353	$1.300	$1.247
UCL(99%)	$264.59	3	6	9
Middle	$249.34	2	5	8
LCL(99%)	$234.09	1	4	7

Figure 1: Values utilized for a sensitivity analysis comparing combinations of pig market price per Kg and diet cost per 1000 kg and observed performance differences between experimental study Groups SoundTalks alert day zero (ST_G0) SoundTalks alert day 5 (ST_G5).

Results

After the seeder pig dual challenge (Mycoplasma hyopneumoniae followed by PRRS virus), two respiratory outbreaks caused by swine A influenza virus (IAV-S) were documented during the study period. All pigs and pens were treated accordingly to study design.

Contact challenged pigs from G0 had 12,7 and 20,4 grams higher ADG compared to those from G5 and G10 respectively. Similarly, contact challenged pigs from G0 had a 23.4% and 10.1% decrease in individual treatments when compared to G5 and G10 respectively. Contact challenged pigs from G0 had a 0.26% higher and 1.22% lower percent mortality compared to those from G5 and G10 respectively. All production variables were introduced into the SEI model and the resulting Benefit:Cost (B:C) ratio 10 year time series is shown in Fig 1.

Figures 2 and 3 show the 12 year (144 month) time series and overall frequency distribution of the estimated benefit:cost ratio based on the aggregate performance differences observed in the study; as well as monthly market price, diet cost and inflation data. Throughout the 144 month period from January 2010 through December 2021, based on a CTO of USD $0.254/pig marketed (inclusive of installation, hardware and software subscription for a single barn 4800 head grow-finish site) the mean monthly B:C ratio was 4.59, ranging from 2.80 to 8.12 and exceeding 2:1 for 144 of 144 (100%) months (G0 vs G5). For the same 144 month period, the 48 month rolling B:C Ratio ranged from 3.55 to 5.27, exceeded 2:1 for 144 of 144 (100%) intervals (G0 vs G5).

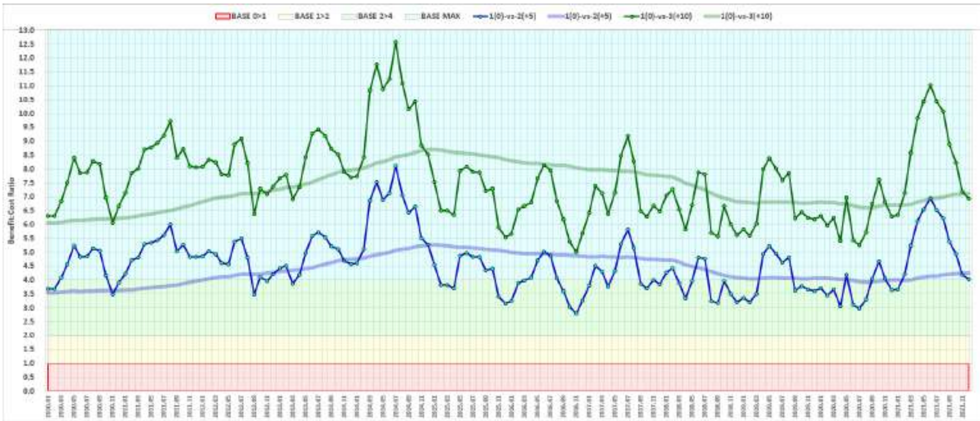

Figure 2: Twelve year (January 2010 through December 2021) monthly Benefit:Cost ratio (green and blue dotted lines) as well as its 48 month rolling average (green and blue lines) for SoundTalks investment based on performance group differences.

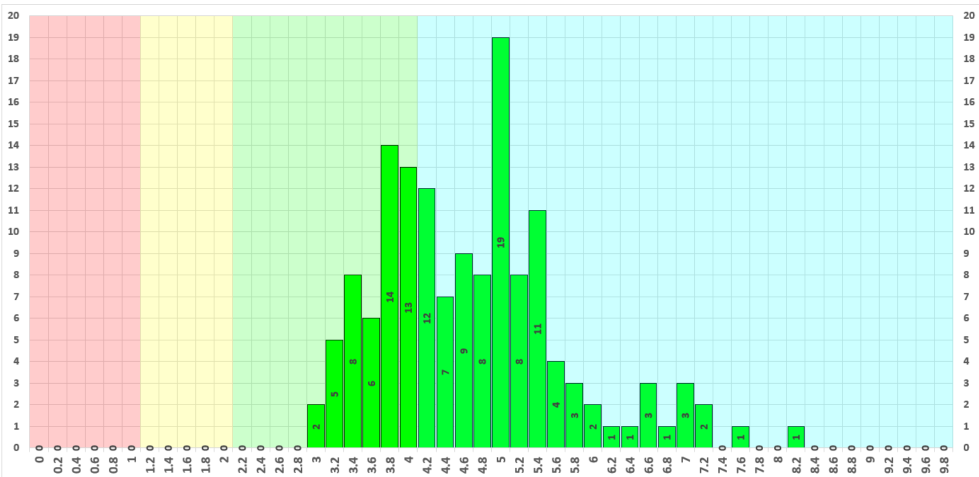

Figure 3: Twelve year (January 2010 through December 2021) monthly Benefit:Cost ratio frequency distribution for SoundTalks investment based on performance differences between Alert Day 0 and Alert Day +5 intervention groups.

When a higher CTO of USD $0.303/pig marketed (inclusive of installation, hardware and software subscription for a smaller single barn 1200 head grow-finish site) is used for the same 144 month period, the mean monthly B:C ratio was 3.84, ranging from 2.35 to 6.82 and exceeding 2:1 for 144 of 144 (100%) months (G0 vs G5). For the same 144 month period, the 48 month rolling B:C Ratio ranged from 2.98 to 4.42, exceeded 2:1 for 144 of 144 (100%) intervals (G0 vs G5).

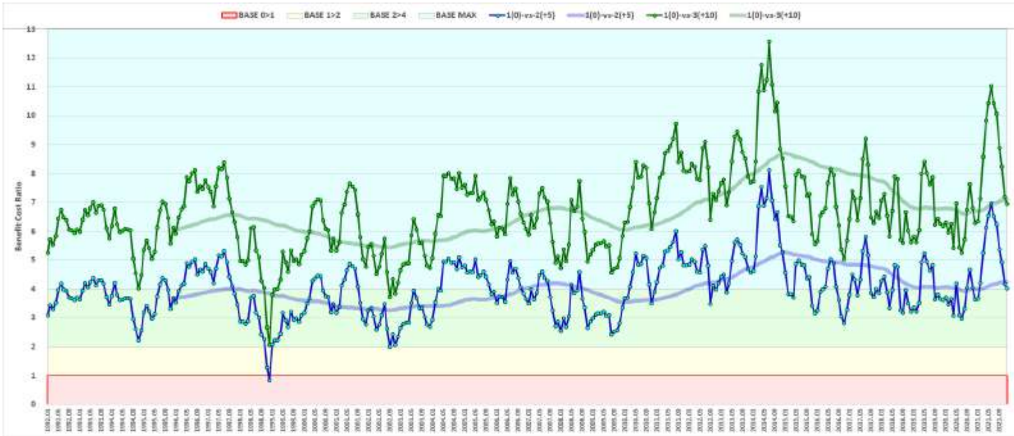

Figure 4: Thirty year (January 1992 through December 2021) monthly Benefit:Cost ratio (green and blue dotted lines) as well as its 48 month rolling average (green and blue lines) for SoundTalks investment based on performance group differences.

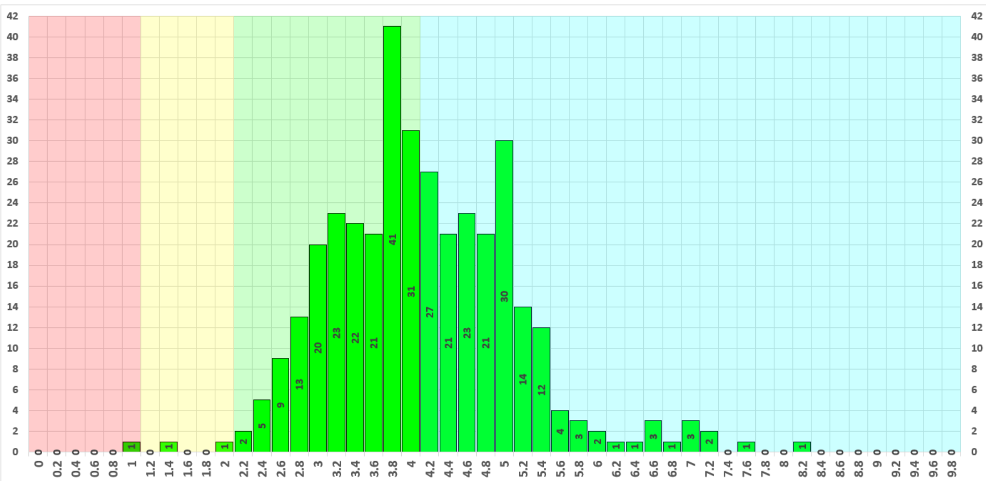

Figure 5: Thirty year (January 1992 through December 2021) monthly Benefit:Cost ratio frequency distribution for SoundTalks investment based on performance differences between Alert Day 0 and Alert Day +5 intervention groups.

Figures 4 and 5 show a 30 year (360 month) time series and overall frequency distribution of the estimated benefit:cost ratio based on the aggregate performance differences observed in the study; as well as monthly market price, diet cost and inflation data. When examining the entire 30 year (360 month) period for which monthly market price, diet cost and inflation rate data was available, (January 1992 through December 2021), and based on a CTO of USD $0.254/pig marketed (inclusive of installation, hardware and software subscription for a single barn 4800 head grow-finish site) the mean monthly B:C ratio was 4.03, ranging from 0.84 to 8.12 and exceeding 2:1 for 357 of 360 (99.2%) months (G0 vs G5). For the same 144 month period, the 48 month rolling B:C Ratio ranged from 3.26 to 5.27, exceeded 2:1 for 360 of 360 (100%) intervals (G0 vs G5).

Figure 6 shows the results of the sensitivity analysis for the nine combinations of pig market price and diet cost. The middle market price ($1.300) and diet cost ($249.34) generated a benefit:cost estimate of 4.56 where a denominator cost of $0.254 for SoundTalks was used, reflecting the technology and installation cost per pig marketed for a single-barn 4800 head grow-finish site. As would be expected, the lowest benefit:cost (4.19) occurred where the market price was lower ($1.247) and the diet cost was higher ($264.59), and the highest benefit:cost (4.93) occurs where the market price was higher ($1.353) and the diet cost was lower ($234.09). When a denominator cost of $0.303 was used (reflecting the cost per pig marketed for a single-barn 1200 head grow-finish site), the middle market price ($1.300) and diet cost ($249.34) generated a benefit:cost estimate of 3.83, with the lowest benefit:cost (3.52) occuring where the market price was lower ($1.247) and the diet cost was higher ($264.59), and the highest benefit:cost (4.14) occuring where the market price was higher ($1.353) and the diet cost was lower ($234.09) (Figure 7).

12 year (2010-2021) Standard				
	MKT$$/Cwt>	UCL(99%)	Middle	LCL(99%)
Diet$/1000kg		$1.353	$1.300	$1.247
UCL(99%)	$264.59	4.71	4.45	4.19
Middle	$249.34	4.82	4.56	4.30
LCL(99%)	$234.09	4.93	4.67	4.41

Figure 6: Sensitivity analysis of the Benefit:Cost for a 4800 pig site* comparing combinations of pig market price per Kg and diet cost per 1000 Kg and performance differences between experimental study Groups SoundTalks alert day zero (ST_G0) SoundTalks alert day 5 (ST_G5).

*NOTE: This matrix is based on a denominator cost of $0.254 for SoundTalks, reflecting the technology and installation cost per pig marketed for a single-barn 4800 head grow-finish site.

12 year (2010-2021) Standard				
	MKT$$/Cwt>	UCL(99%)	Middle	LCL(99%)
Diet$/1000kg		$1.353	$1.300	$1.247
UCL(99%)	$264.59	3.96	3.74	3.52
Middle	$249.34	4.05	3.83	3.61
LCL(99%)	$234.09	4.14	3.92	3.70

Figure 7: Sensitivity analysis of the Benefit:Cost for a 1200 pig site** comparing combinations of pig market price per Kg and diet cost per 1000 Kg and performance differences between experimental study Groups SoundTalks alert day zero (ST_G0) SoundTalks alert day 5 (ST_G5).

**NOTE: This matrix is based on a denominator cost of $0.303 for SoundTalks, reflecting the technology and installation cost per pig marketed for a single-barn 1200 head grow-finish site.

Conclusions and Discussion

A 48 month rolling average was used to allow evaluation of the B:C ratio across the estimated average lifespan of SoundTalks hardware.

The results of this study and the economic analysis suggests that there can be a consistent and long-term favorable economic impact based on aggregate performance differences using a technology that enables earlier detection and treatment intervention.

Earlier alerts of the onset of clinical disease episodes, in and of themselves, do not have a direct positive impact on the course of disease in affected pigs. Alerts can only provide the producer the opportunity to take the most appropriate action to mitigate and resolve the developing clinical disease episode, i.e., knowledge requires informed action to generate value. As soon as meaningful alerts are observed, only immediate and optimal interventions taken by the pig producer will enable capturing the value potential enabled by any detection technology that provides early alerts of disease episode onset.

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Are image analysis based weight prediction systems precise enough for on-farm applications?

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Abstract
There are a number of instruments available commercially or semi-commercially to obtain weight information frequently, including the Weight-Detect™ instruments (one of the available contactless monitoring devices developed and produced by PLF Agritech Pty. Ltd). However, the adoption rates of these tools are limited due to the unavailability of reliable verification of their precision. Thus, a study was implemented to reliably assess the precision and reliability of Weight-Detect™ instruments under commercial conditions over an extended period of time. The Average Pen Weights (APWs) were predicted in a number of pens on commercial farms in Australia and in Europe using Weight-Detect™ instruments. At the same time, on these farms, manual weight-scales were used to obtain measurements of APWs. The predicted and measured APWs were compared using various statistical methods. Results from these long-term monitoring events demonstrated that the Weight-Detect™ instruments have average predictive errors lower than 3% that makes it possible to routinely monitor APWs on commercial farms. However, a number of factors, such as animal behaviour, camera placement and farm management will influence predictive precision.

Keywords: PLF tools, machine vision, farm management, livestock weight estimation

Introduction
The main objectives for the management of modern farms housing meat producing animals such as pigs, are to convert feed to meat efficiently (as the main output) while ensuring welfare friendly conditions for the animals and environmental suitability for the whole farm (Doeschl-Wilson *et al.*, 2005; Backus *et al.*, 1995; Krystallis *et al.*, 2009). As farming is a business activity, efficiency is a key consideration. The amount and the speed of weight gain or the average daily gains (ADGs) achieved by pigs are the primary indicators of their growth efficiency (Honeyman *et al.*, 2001; Hicks *et al.*, 1998; Losinger, 1998). Thus, frequent monitoring of the average pen weights (APWs) and corresponding ADGs are desirable under commercial conditions. Normally, on commercial farms pigs are only weighed a handful of times (2-4 times, depending on specific farm conditions) during their growth phase (as spot-checks) to gain an understanding of the shape of their growth curve (Banhazi *et al.*, 2019)2019. However, more frequent measurements of APWs and ADGs would be desirable to identify periods of inefficiencies. Banhazi *et al.* demonstrated that on commercial farms there could be short periods of inefficiencies that can easily go undetected if pigs are only weighed occasionally as spot-checks (Banhazi *et al.*, 2012a). These short periods of inefficiencies can significantly undermine the efficiency of the whole growth period, as their combined effects can be substantial (Banhazi *et al.*, 2019)2019. Without continuous monitoring, the reasons for these short periods of inefficiencies will remain a mystery and

thus opportunities for improvements will never be identified (Hartung *et al.*, 2017). Black *et al.* calculated that if ADGs are predicted reliably with an error margin of 5% or less, that could be used to improve the financial performance of pig production (Black *et al.,* 2016).

A number of so-called Precision Livestock Farming (PLF) technologies, including the eYeGrow system (Fancom BV, Panningen, The Netherlands), ProGrow (Skov, Roslev, Denmark) and OptiSCAN (Hölscher, Emsburen, Germany) are available commercially. PLF Agritech Pty Ltd., an Australian company that has developed the Weight-Detect™ weight prediction technology over the years demonstrated that such continuous weighing technology could potentially decrease the production related costs of pig farms by up to 30% (Black and Banhazi, 2013). However, the adoption rates of these tools are limited due to the unavailability of reliable verification of their precision. Thus, the need for a proper precision verification study was identified. As a result, a study was implemented to reliably assess the precision of the PLF Agritech's Weight-Detect™ instrument under commercial conditions. It was hoped that a methodological evaluation of the predictive precision that can be achieved by such instrumentation, would enhance the adoption rate of similar PLF technologies as well.

Material and methods

Long-term weight monitoring was carried out in five different grower/finisher buildings on two farms in Queensland, Australia and in three different grower/finisher buildings on three farms in Eastern Europe. The average number of pigs per study pens varied widely between approximately 15 to close to 200 pigs. The average pen weights (APWs) were predicted in a number of pens on these commercial farms using Weight-Detect™ instruments. Further information about the inner workings of the Weight-Detect™ instrument can be found in previous publications and relevant patents (Banhazi and Dunn, 2016; Banhazi *et al.*, 2012b). At the same time, manual weight-scales were used on the same pens to obtain measurements of APWs. The pens monitored were located in traditional grower-finisher building with natural ventilation systems installed. All experimental pigs were fed mash or pelleted feed and were kept on partially slatted floors. One building in Europe had straw bedding that was changed in every 2-3 days. On each farm a number of pens were selected and in each pen, Weight-Detect™ (PLF Agritech, Toowoomba, Australia) equipment was installed approximately in the middle of the pen at 2m height (Banhazi *et al.*, 2011). Corresponding manual weighing procedures were undertaken on the farms in the same pens at varying intervals based on normal on-farm management procedures. The functionally of the Weight-Detect™ instruments has been described previously, so no additional description will be given here (Banhazi *et al.*, 2012a; Banhazi *et al.*, 2012b; Banhazi *et al.*, 2011). All calculations were completed in ADAMS (Automated Data Analysis and Management System) which is a commercially operated, secure database maintained in Amazon cloud by PLF Agritech Pty. Ltd (PLFAg). The features of ADAMS enable PLFAg to automatically analyse the collected information and automatically generate and email periodic reports to selected users.

Automated reports were emailed to the producers in a PDF format reporting on growth rate and environmental conditions of individual pens. In these reports, descriptive statistics have been used to convey the average, maximum, minimum values to producers and other important parameters, such as ADG. The predicted and measured APWs were compared using descriptive statistical methods in this study.

Results and Discussion

APWs data predicted by the Weight-Detect™ instruments and corresponding manual data are shown in Figure 1. The descriptive statistics associated with the dataset is displayed in Table 1.

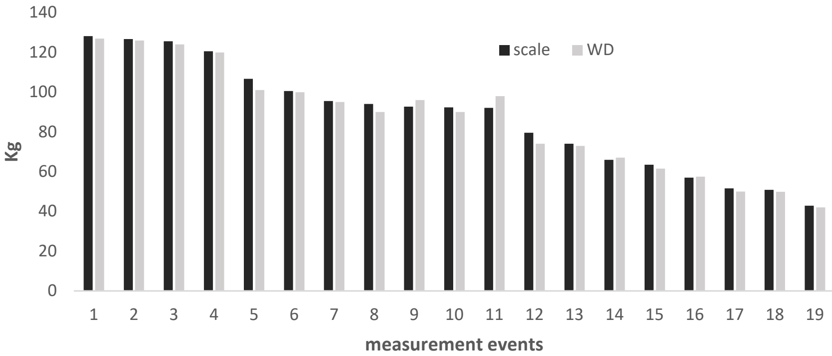

Figure 1: Average Pen Weights (kg) recorded on the farms (combined dataset) during the period between 06/03/18 and 23/03/20. Manual scale measurements are depicted by the black bars while the corresponding Weight-Detect™ measurements are represented by the grey bars. During this study period 19 comparative measurements were undertaken.

Table 1: Descriptive statistics associated with the measurement errors of Average Pen Weights (kg) recorded on the farms (combined dataset) during the period between 06/03/18 and 23/03/20.

Descriptive statistic	Error (kg)[a]	Error (%)[b]	Comments
maximum	5.96	7.57	Largest difference (between the measured and predicted weights) observed was above 7.5%
minimum	0.5	0.50	Extremely small differences were observed that were below the expected 1-1.5 kg differences (i.e. that is normally due to feed, water consumption and due to the timing of faeces, urine release).
average	2.11	2.55	Average and median values were quite different indicating a greater level of fluctuation in the differences
median	1.2	1.89	

[a] Difference between measured and predicted weights expressed in kilograms

[b] Difference between measured and predicted weights expressed as percentage of body weights of pigs

Good results have been obtained generally over an extended period of time, indicating the reliability of the Weight-Detect™ instrument (Black *et al.*, 2016). However, throughout the trial it was recognised (often anecdotally and not necessarily directly connected to the current study) that there are a number of factors influencing the precision of the weight predictions on farms generally. These influencing factors are discussed below.

Limiting factors of achieving the best precision

A number of factors, such as (1) animal behaviour, (2) camera placement and (3) farm management will influence predictive precision. *Animal behaviours* will have influence on predictive precision as the precision is based on even sampling of the animals in the pen. If smaller or larger animals are disproportionally represented in the images, obviously the obtained APWs will be skewed in some way (Tscharke and Banhazi, 2013; Lind *et al.*, 2005). Therefore, correct *camera placement* will be important in terms of ensuring appropriate and even visual sampling of the animals. Contrary to the general belief this is not best achieved by placing the camera above the feeder, as previous studies demonstrated that placing the camera close to the feeders can actually increase sampling skewedness (Tscharke and Banhazi, 2013). The best camera placement should be specific for each given pen. Therefore, the experience and practical knowledge of installers will be crucial for ensuring even sampling of pigs. The *management of farms* is also very important in terms of influencing the precision of the instruments. It is important that the team undertaking the monitoring is routinely informed about any management changes, such as removal/addition of pigs in the pens, any work tasks undertaken in the pens, as the disturbance of pen population could have a detrimental impact on precision (Korthals, 2001; Doeschl-Wilson *et al.*, 2005). The disturbance of pigs in the pen will change the sampling rate and sampling distribution and thus will have an influence on precision. Thus, these matters will need to be taken into consideration when explaining sudden changes in weights. Obviously, the addition or removal of pigs to the pen will have a very significant influence on the APWs generated by image analysis based systems, such as the Weight-Detect™ instruments.

The importance of realistic expectations and correct interpretations of the results

In addition, the correct interpretation of results obtained will influence their usefulness on farms. For example, if the animals are sold in a number of smaller batches at the end of the growth period, the associated sudden changes at the very end of the growth curve should not be interpreted as the 'fault' of the monitoring system or as a 'fault' of the management but as a normal consequence of disturbed pen population. In well managed pens we often seen a stabilization of weight after a number of pigs are sold and a sudden and significant weight gain that corresponds with the compensatory growth displayed by the animals that were perhaps disadvantaged by larger animals. Once the larger animals are removed, a good growth rate is often displayed by the remaining pigs in the pen. However, in other pens, stability might not be achieved immediately after the partial removal of the pen population, so obtained data should be viewed and interpreted with caution. This does not mean that the weight prediction system is wrong, but this reflects the natural consequences of population disturbance that yet remains to be fully understood.

The importance of communicating realistic expectations to end users cannot be overemphasised (Artmann, 1999). For example, it has been demonstrated before that even the timing of the release of urine and faecal materials can account for as much as 0.5-0.7 kg fluctuation in body weight per grower pig (Banhazi, unpublished). In addition, the timing of feed and water intake can add another fluctuation in body weight. Thus, 1-2 kg differences in body weight are absolutely acceptable, indeed expected.

Any claims suggesting a greater level of precision that can be achieved consistently should be treated with caution and might be instead the result of fortunate coincidences. However, the main benefit is definitely not the simple measurement of the body weight, but the documentation of the shape of the growth curve that gives producers an understanding of periods of inefficiencies.

Other on farm experiences

Most problems encountered on farms were related to the unreliability of internet connections. It was surprising to see that in Australia and also in Europe the reliability of internet connection on most farms were variable (Gray *et al*., 2017). Internet problems were especially obvious in Australia and not just because the considerable distances and remoteness of many farms. In Australia, most livestock buildings are built using metal building components such as metal roofing and building frames. These metal building components tend to significantly reduce and interfere with internet signal strength within livestock buildings. In Europe, interference caused by metal building components are less of a problem, because more livestock buildings are built from bricks and mortar. Internet and connectivity issues on farms are serious problems and unfortunately not discussed extensively on public forums. Recent studies in Europe demonstrated that even larger companies struggle with maintaining reliable internet connections consistently in livestock buildings (Banhazi, 2021, unpublished). However, the lack of open discuss about these issues resulted in the development of unrealistic expectations by many PLF technology users. Open discussions about connectivity problems on farms would results in achieving better connectivity on farm generally. For example, discussing issues around appropriate antenna use on farms would potentially benefit PLF technology developers, providers and users. The most efficient antenna configurations that are not complicated to install, cost effective and able to enhance the reliability of on-farm connectivity are yet to be widely adopted. Due to the previously mentioned and serious connectivity problems experienced on farms; new Weight-Detect™ installations are only set up on farms that are able to guarantee locally enhanced internet connections or internet 'hot-spots'.

Conclusions

The Weight-Detect™ instrument proved to be able to collect information reliably on farms, but of course a number of other factors, such as placement of the camera, management of the farm and animal behaviour can all influence the results generated. In addition, proper interpretation and use of collected data cannot be overemphasised. However, if PLF tools, such as continuous monitoring of pen weights, are properly introduced on commercial farms, the financial return on using such technologies could be significant.

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Validation of body weight monitoring by a 3D camera in finisher pigs

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Abstract

Automated recording of body weight (BW) can be a useful tool for continuous health, performance, and welfare monitoring in commercial pigs. Hence, we aimed to validate a three-dimensional (3D) camera (iDOL65, DOL-sensors A/S, Aarhus, Denmark) for monitoring BW in conventional finisher pigs on two farms (F1:131 Yorkshire×Landrace pigs, 10-18 pigs/pen; F2:107 Landrace×Large White pigs, 9-11 pigs/pen). On each farm, BW data was recorded on one day. The camera was placed above the multi-partitioned feeder (F1) or individual feeding station (F2) and combined with a radio frequency identification system. Whenever a pig visited the feeding site, 3D images were taken and used to estimate BW. The individual estimated BW was calculated as the median of the outcome of all daily images. For each farm separately, the individual estimated BW was compared against the individual scale-based BW (F1 (average±SD):36±5 kg; F2:74±8 kg) in R. On Farm 1, concordance correlation coefficient (CCC) (0.85) and coefficient of determination (R^2=0.95) were high. The root mean square error (RMSE) was 1 kg. On Farm 2, CCC (0.92) and R^2 (0.94) were very high, and the RMSE was 1.9 kg. The camera's BW estimation performance was high for both farms, especially in F2. Differences in camera set-up potentially influencing body boundary detection, and differences in body shape arising from different breeds may explain the better camera performance on F2 over F1. A further validation including a larger sample size and pigs at various development stages is necessary to confirm the use of this system in commercial farms.

Keywords: *Sus scrofa*, precision livestock farming, depth sensor, image analysis, animal welfare

Introduction

In pig production, the body weight (BW) of pigs is a crucial indicator of growth, conversion efficiency, and readiness for market (Schofield *et al.*, 1999; Wang *et al.*, 2008). Typically, in commercial farms, pig weighing is performed manually, constituting a labour-intensive and relatively stressful procedure to both pigs and stockmen (Brandl & Jørgensen, 1996). Alternatively, based on the high, positive correlation between body dimensions and body mass (Brandl & Jørgensen, 1996), earlier studies retrieved pigs' body dimension from manual measurements (e.g., girth size, withers height; Petherick *et al.*, 1983; Brandl & Jørgensen, 1996) and digital images (e.g., Schofield, 1990; Wang *et al.*, 2008; Kashiha *et al.*, 2014) to indirectly determine the BW of pigs. Whereas the image-analysis-based BW estimation can be an efficient, non-invasive method, the outcome can still be affected by the room lighting and the status of the pig skin (e.g., dark, stained, or dirty) (Condotta *et al.*, 2018). To deal with these potential sources of errors, recent studies explored the use of depth sensors based on a structured infrared-light system, which provide three-dimensional (3D) images. As 3D images can account for animal height, they may lead to more accurate BW estimates than two-dimensional (2D) images (e.g., Kongsro, 2014; Condotta *et al.*, 2018; Pezzuolo *et al.*, 2018; Fernandes *et al.*, 2019). Yet, the methods proposed by the cited studies required physical changes in the farm, such as modifications in the feeding site or pen corridor, to accommodate the equipment. We therefore aimed to validate a commercially available 3D camera for continuous BW monitoring of individual finisher pigs kept under conventional husbandry conditions requiring minimal physical intervention on-farm.

Materials and Methods

Animals, housing, and management

This study included 238 finisher pigs, of which 131 Danbred Yorkshire × Landrace pigs kept on the experimental farm of Department of Animal Science, Aarhus University, Foulum, Denmark (Farm 1; F1), and 107 Landrace × Large White pigs kept on a commercial farm in Gronau, Germany (Farm 2; F2).

On F1, pigs were housed in a finishing pig unit including 8 identical pens (15 to 18 pigs/pen in 7 pens and 10 pigs in 1 pen; ≥ 0.73 m^2/pig) with the floor divided between one-third solid, drained, and slatted flooring. Pigs were fed *ad libitum* with a commercial dry feed (14.8% crude protein; Svin Struktur E, DLG, Denmark), and the feeder containing three partitions were filled four times daily at 07:00 h, 11:00 h, 16:00 h and 20:00 h. Water was accessible *ad libitum* in two drinking cups. All pens were equipped with wooden sticks and a rubber ball as minimum pen enrichment in compliance with European Union and Danish animal welfare legislation and enriched with 100 g straw/pig delivered at 08:30 h daily to ensure permanent access of unsoiled straw in the pen for 24 h after delivery (Pedersen *et al.*, 2014). Artificial light was on from 0600 to 2100 h (182 lx).

On F2, pigs were housed in 10 identical pens (9 to 11 pigs/pen; ≥ 1.03 m^2/pig) spread across five rooms, on fully slatted floors. Pigs were fed *ad libitum* with acommercial dry feed (15.3% crude protein, Select Delta 4, Royal Agrifirm Group, the Netherlands) using an IVOG® electronic feeding station (Hokofarm Group, The Netherlands). From a separate feeder, pigs could obtain fibre-rich feed *ad libitum* by manipulating a chain (chopped straw mixed with straw pellets, in compliance with German animal welfare legislation). Water was available *ad libitum* from two drinking nipples, and enrichment consisted of a wooden block, a chain with plastic rings and in some pens one or more hosepipes. Pens were naturally illuminated through windows.

Body weight recording

Two types of BW data were recorded at individual level: scale-based BW (gold standard) and BW estimated by a 3D camera (iDOL65, DOL-sensors A/S, Aarhus, Denmark; technical information available on https://www.dol-sensors.com/documentation/).

On F1, the scale-based BW was recorded on one day in September 2021, in the morning between 0800 and 1000h. Per pen, all pigs were moved into the corridor of the pig unit and individually walked into a calibrated digital weighing scale (MTW2-STACON, Schauer Agrotronic GmbH, Germany; accuracy: ±0.3 kg) once, which scanned the pigs' radio frequency identification (RFID) ear tag and recorded the individual BW (average ± standard deviation (SD): 36 ± 5 kg) in an Excel document. On F2, the scale-based BW was recorded on one day in October 2021, in the afternoon between 1230 and 1600h. All pigs per pen were moved into the corridor of the farm, near a calibrated digital weighing scale (Welvaarts Weegsystemen type W-2000; accuracy: ±0.5 kg), individually weighted once, and data was entered by scanning the pig's RFID ear tag and typing the BW (74 ± 8 kg) into the scanner.

Each pen was equipped with one 3D camera placed horizontally above the three-partitioned feeder (F1) or individual feeding station (F2) at an approximate height of 2.2 m and worked in combination with a RFID system installed in the feeding sites (F1: one RFID antenna per feeder partition; F2: one RFID antenna per feeding station). After being mounted, the camera self-calibrated as specified in its technical user guide (DOL-sensors A/S, Aarhus, Denmark; https://www.dol-sensors.com/documentation/). On F1, the RFID was configured to randomly switch between the three partitions and read once every second, hence each position could only be read once every 2 s. On F2, due to the feeding station's construction, only one pig could eat, and consequently be detected by the RFID system, at a time. Throughout the day, the camera took a 3D image every 10 s. A YOLO-based algorithm developed and trained by DOL-sensors detected whether a pig was present in the image and, if so, segmented out the individual pig. Segmented images were retained only if the pig was in standing position, close to the RFID reader and in full view (determined with the YOLO-based algorithm), and if there was no dirt on the image. For selected segmented images, a regression neural network developed and trained by DOL Sensors used the head-to-tail distance as well as the width and curve of the pigs' ribs to estimate pig BW. Using the time stamps of the 3D camera and RFID system, each measurement could be prescribed to an individual pig. The median was taken of the weight estimates of all the images taken on each experimental day (≥ 30 images/pig, otherwise measurement would be discarded due to unreliable estimation) to obtain an estimation for daily weight (in kg). The number of images per pig ranged from 34 to 1107 on F1, and from 50 to 535 on F2. If multiple pigs were detected in a frame, only the BW estimated for the pig closest to the RFID antenna (F1: the pig with the head in the feeder partition; F2: the pig in the feeder) was automatically maintained. If the closest pig to the antenna could not be determined, a dummy pig was recorded and the respective sample was manually discarded. Samples were also discarded if only an RFID reading or only a BW estimate was obtained, or if two pigs were registered to be in the feeder partition (F1) or feeding station (F2) simultaneously. Image acquisition, segmentation and selection, weight estimation, and removal of outliers, if any, were conducted by DOL-sensors using their confidential algorithm.

Statistical analyses

Statistical analyses were performed for each farm separately in R v.4.1.1 (R Core Team, 2021). The agreement between the estimated BW and scale-based BW was assessed at individual level with concordance correlation coefficient (CCC) and Bland-Altman analysis (library *SimplyAgree* v.0.0.2; Caldwell, 2021), both controlled for pen. The interpretation of CCC values was based on the criteria proposed by Hinkle *et al.* (2003), indicating the level of agreement: negligible (0.0 to 0.3), low (0.3 to 0.5), moderate (0.5 to 0.7), high

(0.7 to 0.9) or very high (0.9 to 1.00). The Bland-Altman analysis indicates the mean differences (bias) between the individual paired estimated weight and scale-based weight, as well as the lower and upper 95% limits of agreement (LoA; calculated as ±1.96 × SD from mean difference). The normal distribution of the differences was confirmed using histogram and QQ-plot. We prespecified an acceptable LoA of 10% of the average BW (Barrios *et al.*, 2016) of each farm population (F1: ±3.6 kg; F2: ±7.4 kg). Additionally, the relationship between the two types of weight data was assessed with a mixed-effects linear regression (library *glmmTMB* v.1.1.2; Brooks *et al.*, 2017) including the estimated BW as dependent variable, the scale-based BW as fixed effect, number of daily images per pig as covariate and pen as random effect. We prespecified an acceptable root mean square error (RMSE) of maximum 5% (Schofield, 1990). Model assumptions of normality and homoscedasticity were confirmed through graphical inspection of the residuals.

Results and Discussion

On F1, we found a high agreement between the individual estimated BW and the individual scale-based BW (CCC: 0.85; 95% Confidence Interval (CI): 0.81 to 0.88). The Bland-Altman analysis (Fig. 1) revealed that BW was overestimated by the 3D camera in comparison with the scale with a mean difference of 1.2 kg (approximately 3.5% of the average BW) (95% CI: –0.3 to 2.8 kg). The LoA were outside the prespecified acceptable range with a lower LoA of –3.6 (95% CI: –8.2 to –1.6) kg and an upper LoA of 6.1 (95% CI: 4.1 to 10.7) kg. Moreover, the coefficient of determination was very high ($R^2 = 0.95$), with an RMSE of 1 kg or 2.8%.

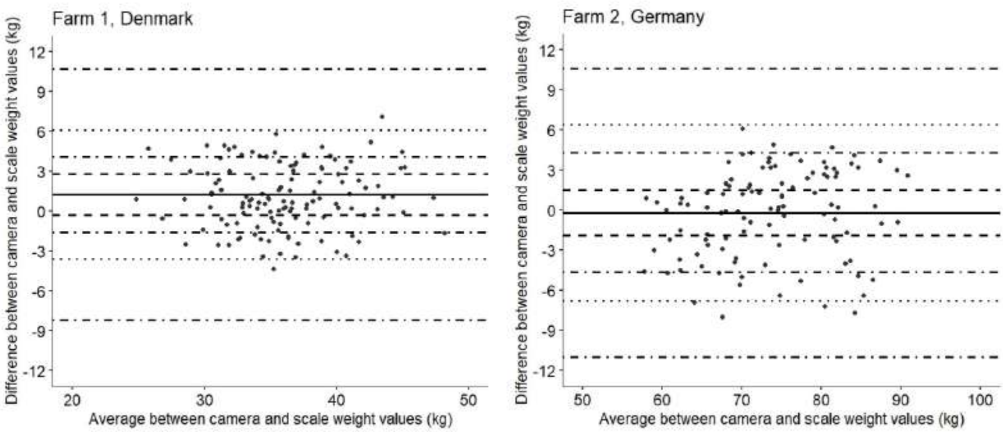

Figure 1: Bland-Altman plot of pairwise differences between 3D camera estimated BW values and scale BW values vs. the mean of the two methods on each farm. In each plot, the solid line indicates the mean difference, the dashed lines indicate the mean difference's 95% confidence interval, the dotted lines indicate the upper and lower limits of agreement, and the dot-dashed lines indicate the limits of agreement's 95% confidence intervals.

On F2, we found a very high agreement between the individual estimated BW and the individual scale-based BW (CCC: 0.92; 95% CI: 0.90 to 0.94). The Bland-Altman analysis

(Fig. 1) revealed that BW was underestimated by the 3D camera in comparison with the scale with a mean difference of –0.2 kg (approximately 0.3% of the average BW) (95% CI: –0.2 to 2.9 kg). The LoA were within the prespecified acceptable range with a lower LoA of –6.8 (95% CI: –11.0 to –4.7) kg and an upper LoA of 6.4 (95% CI: 4.3 to 10.6) kg. Moreover, the coefficient of determination was very high (R^2 = 0.94), with an RMSE of 1.9 kg or 2.7%.

The performance of the 3D camera was high on both farms and was similar to or better than the BW estimation reported in earlier studies using alternative 3D cameras. For instance, Kongsro (2014) and Condotta *et al.* (2018) reported a higher R^2 (0.99) than F1 and F2. However, they also found higher RMSE (Kongsro, 2014: 3.38 kg, 4.8%; Condotta *et al.*, 2018: 3.01 kg, 4.9%) than our farms. In Kongrso (2014), 71 finisher pigs (37 Duroc and 34 Landrace) with a BW ranging from 29 to 139 kg were used, whereas Condotta *et al.* (2018) used 234 finisher pigs (78 Landrace, 78 Duroc and 78 Yorkshire) sampled at four different development stages (approximate BW: 17.6 ± 2.9, 44.7 ± 4.8, 72.0 ± 7.5 and 100.6 ± 9.8 kg). Additionally, using finisher pigs (unknown breed) with an average BW of 120 kg, Fernandes *et al.* (2019) reported a R^2 of 0.88 and a RMSE of 4.36 kg (3.6%), both values poorer than F1 and F2.

The indicators used in this study revealed that the 3D camera better estimated BW on F2 than on F1. We propose the following explanations for the reduced performance of the 3D camera on F1 compared with F2. First, the different feeding sites where the 3D camera was mounted could have influenced the identification of individual pigs and estimation of their BW. On F2, the camera was mounted in an individual feeding station, so that the eating pig was well separated from other pigs and the respective image solely belonged to the eating pig. Whereas on F1, multiple pigs could have tried to access the same feeder partition and the camera may have had issues to take images of the actual eating pig (closest to the RFID antenna) and detect the respective pig body boundary without the presence of another pig's body part. Such a challenge was reported by Buayai *et al.* (2019) using a semi-automatic machine vision approach in commercial finisher pigs whose 2D images were also taken from the top view of the feeder. Second, each farm used different pig breeds leading to potential differences in body conformity and consequent requirement for different algorithms for BW estimation (Schofield *et al.*, 1999). Third, the digital weighing scale used on F1 had a lower accuracy compared with the weighing scale used on F2, which could have negatively influenced the comparison between the scale-based BW and the BW estimates.

Our findings indicate that the iDOL65 can estimate BW of finisher pigs with high precision and accuracy. Yet, the performance of the camera may be affected by equipment set-up and pig breed. Future work is needed to confirm the use of this system in commercial farms and should involve the inclusion of a larger sample size, and pigs at different development stages within farm and set-up.

Conclusions

We conducted a validation of 3D camera that automatically monitors BW of conventional finisher pigs. Our findings indicate a high agreement between the estimated BW and a gold standard represented by the scale-based BW. A further validation including a larger sample size and pigs at various development stages within farm and set-up is needed to confirm the use of this system in commercial farms.

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Individual management of health in weaned piglets using precision livestock farming technology

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Abstract
The growth rate and feed consumption of piglets are significant indicators for the health of the animal and are of economic importance in pig production. New approaches, such as continuous automated real-time monitoring of animal behaviour and health, aim to meet the increasing requirements in pig production on productivity, profitability as well as animal health and welfare. The Asserva System PigInsight is unique for automated feeding and weighing of small piglets at weaning age. Using RFID (radio-frequency identification) ear chips, the system permits individual recognition and monitoring of daily feed consumption and body weight for each animal without causing any stress and extra labour. The aim of this study was to compare individual data recorded by the system with traditional pen-based feed consumption and manual individual weighing of the animals on 6 occasions over a 7-week trial period. Therefore, 84 healthy weaned piglets were allocated to 6 slatted floor pens with balanced mean body weight, sex ratio, age and relatedness among pens. All animals were fitted with RFID ear-tags. Feed (*ad libitum*, 12 g per demand) and water (*ad libitum*) were provided through two automated feeders and drinkers per pen. We verified that the system estimated body weight reliably (R^2 = 0.986). During our verification period, a mean deviation of 0.2633 kg +/- SE 0.1609 (n = 6 weighing occasions) between manual and automated weighing was recorded. The individually monitoring of body weight and feed consumption can be further developed for an early and automated detection of animal health issues.

Keywords: piglets, production monitoring, health monitoring

Introduction
The Food and Agriculture Organization of the United Nations (FAO) expects a globally increasing demand for food and feed by 70 % in the first half of this century. Crops, used for industrial purposes, will parallel this demand. At the same time, animal health (European Commission (EC) Directorate-General for Health & Consumers, 2011, e.g., transmissionable diseases, use of antibiotics and resistances) and animal welfare have become topics of concern and public attention (European Food Safety Authority (EFSA), 2012). While farmers aim for a decent economic return, they are expected to manage a wide range of processes including animal health as well as animal welfare, product quality, biosecurity, and reduction of greenhouse gas emissions. The increasing requirements in animal production on productivity, profitability as well as animal health and welfare can only be accomplished by using new technological approaches related to precision livestock farming and the continuous automated real-time monitoring of animal behaviour and health.

The growth rate and feed consumption of piglets are significant indicators for the health of the animal and are of economic importance in pig production. The traditional approach to measure body weight and weight gain by repeated manual weighing, which is labour intensive, can induce stress to the animals that may impair the growth rate and in extreme cases even cause mortality (Grandin & Shivley, 2015; Faucitano & Goumon, 2018). New approaches, such as computer vision systems or automatic scales are alternatives that enable continuous automated real-time monitoring of animals, to gain insights in the growth rate and feeding behaviour with minimal human intervention (Kongsro, 2014, Fernandes *et al*., 2019).

The aim of this study was to validate a commercially available system that incorporates automatic scales, drinkers and feeders for piglets and fattening pigs (PigInsight by Asserva, France). The PigInsight system is especially unique for automated feeding and weighing of small piglets at weaning age. RFID (radio-frequency identification) ear-tags permit individual recognition of each animal. The system allows for individual monitoring and digital recording of an animal's feed consumption and thus helps to control the feed quantity during a day based on an individual feeding curve. Additionally, animals are automatically weighed whenever entering the drinking station and their weight is recorded without any extra manual labour and handling stress for the animals.

The aim of this study was to compare individual data recorded by the system with traditional pen-based feed consumption data and manual individual body weight measurements on six occasions over a seven-week trial period.

Methods

The study was conducted in a commercial farm in Austria over a period of seven weeks. In total, 84 healthy weaned piglets were included in the study. The piglets (Austrian genotype Ö-HYB-F1) originated from a cross-bred dam (Landrace x Large White) and a pure-bred sire (Pietrain) and were four weeks (range: 26-28 days) old at weaning. The sex ratio was 50:50 and the body weight at trial start ranged from 6.07 kg to 8.75 kg.

The weaned piglets were allocated to six slatted floor pens (3.02 x 2.30 m) in groups of 14 animals with balanced mean body weight, sex ratio, age and relatedness among pens. Additional to the regular ear-tags, all animals were fitted with RFID ear-tags to automatically monitor the feed consumption and body weight of the animals over the trial period in the digital system PigInsight (Asserva, France).

Each pen contained two connected drinkers with an automatic weighing station and two automated feeders (PigInsight, Image 1).

The two feeders were located parallel to the corridor wall and the two drinkers were placed parallel to the exterior wall. Mash feed based on a commercial diet suitable for this age and mass (*ad libitum*) and water (*ad libitum*) were provided whenever the animal entered an automated feeder and drinker. Side panels surrounded each weighing station and feeder to prevent disturbance by other animals. When an animal entered the weighing stations, the RFID ear-tag was recognized by the radiofrequency identification antenna and the weight was recorded using two force sensors (precision ± 10 g). Each automated feeder was composed of a trough with a specific sensor at the bottom to detect remaining feed and a motor in the elevated feed hopper to provide the feed. The feed hopper was filled daily by the Spotmix feeding system (Schauer Agrotronic GmbH, Prambachkirchen, Austria), which also recorded the daily amount of feed provided per pen.

Image 1: Photo of the two PigInsight drinking/weighing stations (on the left) and the two feeding stations (on the right) per pen. At each station, two piglets can be served at a time.

When an animal entered the feeding station, the RFID ear-tag was recognized by the radiofrequency identification antenna and the feed distribution was triggered based on the recognition of the sensor inside the trough. When no feed was detected by the sensor, a new feed portion 12 g (± 2 g) was delivered to the trough. When remaining feed was detected by the sensor, no further portion was provided until the portion was consumed. The amount of feed recorded includes real feed consumption of the animal and wastage, which is considered part of the natural feeding behaviour of pigs.

Each pen contained organic and commercial pig toys for enrichment. Climate conditions were computer-regulated according to standard recommendations for weaning piglets and recorded daily. Pigs were exposed to both natural light (via doors and windows) as well as artificial light (12:12 light-dark cycle).

In order to validate the system, the individual body weights of the animals were measured manually on days 1, 7, 21, 28, 35 and 49. The precision of the manual, mobile scale was 0.1 kg. Additionally, the feed consumption determined by the PigInsight system was compared with the daily amount of feed provided by the Spotmix system.

Data evaluation

Clinical observations regarding animal health issues (such as diarrhoea and lameness) as well as mortality were recorded daily. Body weight of each single animal was manually measured and recorded on day 1, 7, 21, 28, 35 and 49. The amount of feed provided per pen was daily recorded by the Spotmix feeding system.

Trial data was subjected to statistical analysis using RStudio version 1.3.1093. Boxplots and individual value plots were used to visually inspect the data distribution, variability and outliers.

Results and Discussion

During the study, four animals were excluded from three different pens within the first week of the trial, due to health issues. All remaining animals were included in the validation study. The animals visited the digital weighing stations on average 30 ± 10 times per day (mean ± SD). Compared to the first half of the trial, the number of visits were 2.29 times higher in the second half of the trial. The raw data can be highly variable, due to animals not standing on the scale entirely or in case of more than one animal entering the scale at the same time. The PigInsight system determined valid and invalid individual body weight measures per animal automatically based on formulas incorporated in the software. All body weight measures per day and animal were additionally visually examined prior disregarding invalid data (i.e., unrealistically high or low values). For our validation, we calculated the daily individual body weight per animals based on the median of all valid individual body weight measures on the specific day. Hence, the automated measurements provided a value derived from multiple weighings during a 24-hour period, whereas manual weighings represented only a single sample. Daily individual body weight determined by the PigInsight system during the study period and manually measured body weight on the six weighing occasions are depicted for four piglets in Figure 1.

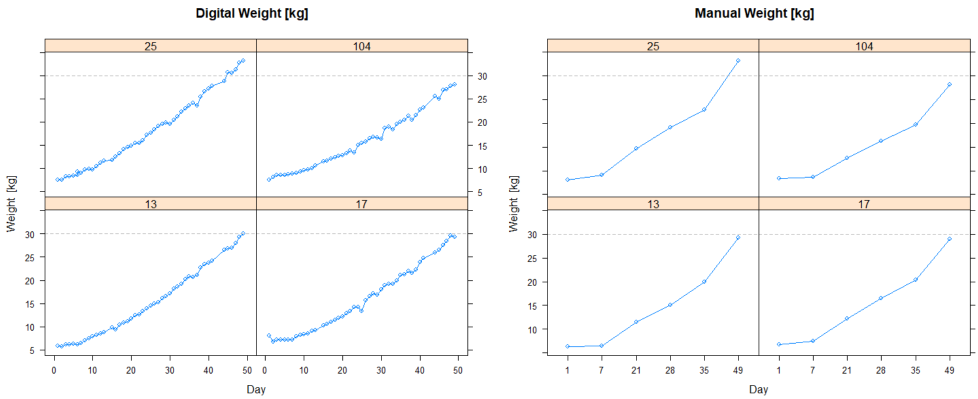

Figure 1: Exemplary depiction of the digital capture of daily individual body weight (left) and the manually measured body weight on the six weighing occasions (right) of 4 piglets (ID 13, 17, 25, 104) in one pen, housing a total of 14 piglets.

On all weighing occasions, the data derived by daily automated voluntary weighing was highly correlated to the manual weighing data ($R^2 = 0.986$, $p < 0.001$). During our validation period, a mean deviation of 0.2633 kg ± SE 0.1609 (n = 6 weighing occasions) between manual and automated weighing was recorded, however, there was a different pattern across the six manual weighing occasions (Figure 2, Figure 3).

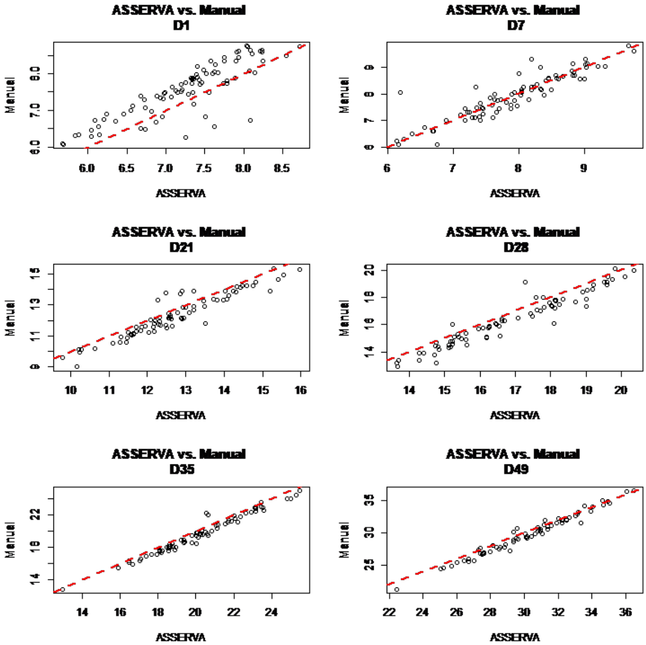

Figure 2: Relationship between the digital (ASSERVA) and manual capture of daily individual body weight [kg] on the six manual weighing days (D) 1, 7, 21, 28, 35 and 49. The red slashed line represents equality on which all points would lie if the two meters gave exactly the same reading every time, to help gauging the degree of conformity between measurements.

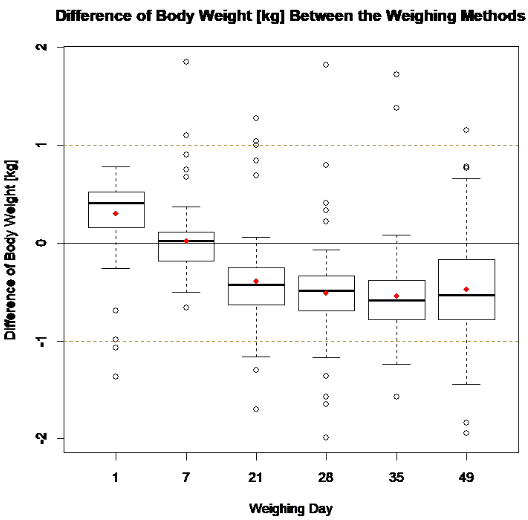

Figure 3: Boxplots presenting the differences in the manual vs. digitally captured individual body weight of the piglets at the six manual weighing occasions.

The box represents the interquartile range (IQR: 50% of data are found between Q1 to Q3). A line within the box indicates the median. The lines/whiskers outside the box extend by Q1 - 1.5 × IQR (25% of data) and Q3 + 1.5 × IQR (25% of data), respectively. Values that exceed this range are indicates as dots. The red rhombus indicates the mean of the group.

On the first day of the trial, the digital capture of daily individual body weight was on average 3.98 % higher than the manual body weight measurement. On day 7, the mean difference between the digital captured body weight and the manual body weight was only 0.25 %. On the remaining days, the digital capture of daily individual and body weight was on average 1.60 % to 3.14 % lower than the manual body weight measurement. The observed deviations in manual and automated weighing can be attributed to the time of the manual body weight measurement and differences in feed and/or water intake as well as defecation during the day. As outlined by Stygar *et al.* 2018, body weight can fluctuate during a day from 0.9 to 1.4 kg in grower-finisher pigs. Automated systems that record frequent body weight measures per pig over the day are able to capture these daily fluctuations, whereas manual weighings at a certain timepoint are not. Automated measurements are considered superior to manual measurements due to important parameters for pig production, such as the average daily weight gain, being true measures and are not calculated values between manual weighing occasions.

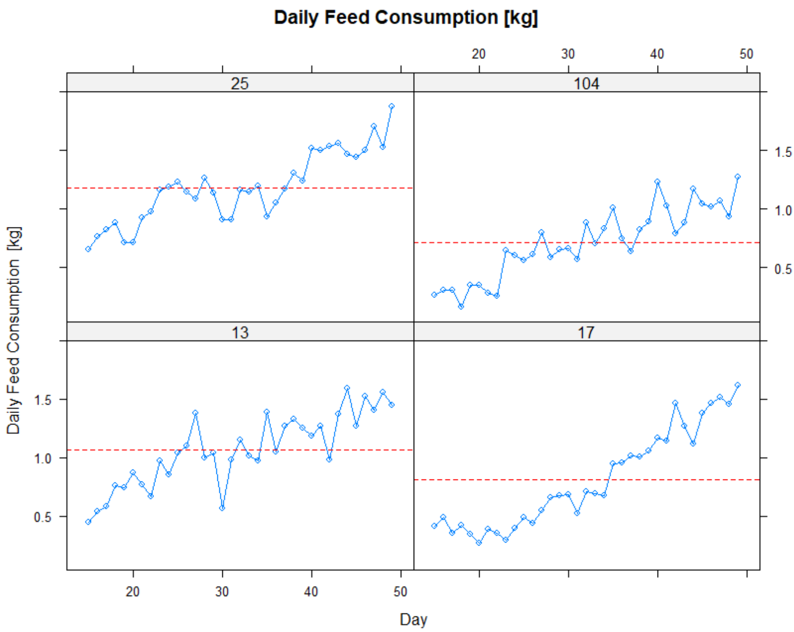

Figure 4: Exemplary depiction of the digital capture of daily individual feed consumption of 4 piglets (ID 13, 17, 25, 104) in one pen, housing a total of 14 piglets. The individual average daily feed consumption (ADFI) per animal is shown as red dotted line.

During the study, the animals visited the feeding stations on average 23 ± 5 times per day (mean ± SD). Compared to the first half of the trial, the number of visits were twice as high as in the second half of the trial. Daily individual feed consumption represents the sum of feed delivered to the animal throughout the day in the specific number of portions. Exemplarity daily individual feed consumption data for four piglets are depicted in Figure 4 and traditional pen-based measures are depicted in Figure 5.

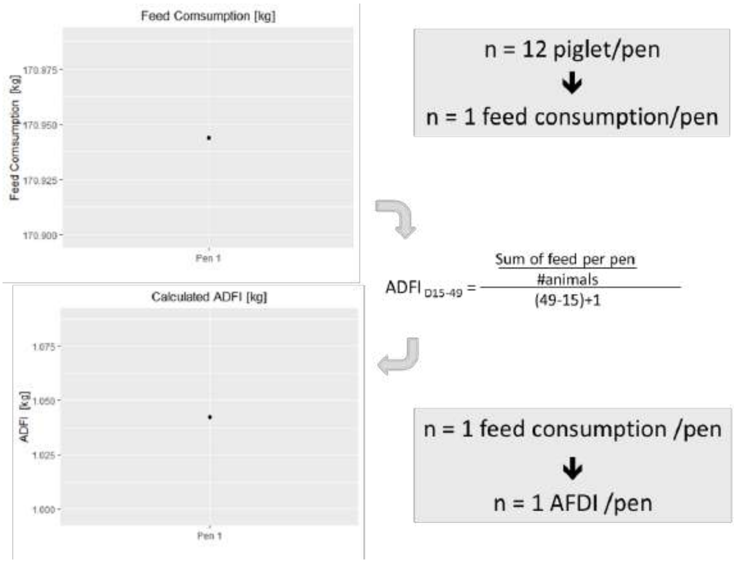

Figure 5: Depiction of pen-based feed consumption, as provided by Spotmix, together with the calculated respective average daily feed intake (ADFI)

Using data derived from the automated PigInsight feeding stations, feed derived calculations, such as ADFI (average daily feed intake / consumption), is available on an individual level. The traditional pen-based data on feed consumption cannot take into account the individual variation of the animals held within a pen. Important economic parameters, such as average daily feed intake, can only be considered on a pen-level. Taking into consideration the feeding pattern per animal, early alerts that indicate potential health issues could be integrated in automated monitoring of the individual feeding behaviour of the animals.

Conclusions

We verified that the system estimated body weight reliably. We conclude that digital captures of body weight and feed consumption can be considered superior due to several reasons. Firstly, voluntary weighing quantifies the animals' weight during the whole day without causing any stress and extra labour. Secondly, important parameters, such as ADFI, are true individual measures and not calculated values. Thirdly, with the single animal being the experimental unit instead the pen, we can increase the statistical power. Finally, the bias of an animal being excluded from a pen during a trial is erased. The individually monitoring of body weight and feed consumption can be further developed for an early and automated detection of animal health issues.

Acknowledgements

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SESSION 15

General: Adoption and Barriers of PLF

Digital technology adoption on Canadian beef feedlot farms

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Abstract

While anecdotal evidence suggests that adoption of digital precision livestock farming (PLF) technologies in the beef sector lags behind other livestock sectors, such as dairy, in Canada, few formal studies exist on PLF adoption and use on Canadian beef farms. To address this research gap, a study was conducted involving Canadian beef feedlot farmers and veterinarians to understand their perceptions and experiences with PLF technologies. Data from 11 interviews and 24 web-based surveys were collected. Qualitative analysis was conducted to identify key themes in the data. The study found little adoption of recent real-time individual animal health and welfare monitoring technologies, and a general perception that these technologies were cost prohibitive for the beef industry. Instead, participants were more likely to adopt mature software and hardware technologies like productivity, data entry, and record-keeping software, and digital weigh scales and feeding systems. One feedlot-specific cloud-based software application was being used by some participants. Study results highlight the need for feasible pricing models that reduce barriers of entry for reluctant adopters and the need for user-centric technology design to ensure PLF technologies better meet the needs and expectations of Canadian beef producers.

Keywords: technology adoption, digital technologies, beef industry, survey study

Introduction

Due to increasing world population, the demand for beef and other meat-based proteins is increasing (Thomson, 2003). At the same time, beef farmers are facing ever higher operating costs, forcing many of them to increase their herd sizes to meet increasing demands and to ensure a higher return on investment (Berckmans, 2014). Precision livestock farming (PLF) promises to increase animal health and welfare outcomes, as well as optimize farm productivity (Banhazi *et al.*, 2012). Although there has been wide adoption of certain PLF technologies, such as automated handling of feed, excrement, bedding, and ventilation (Hostiou *et al.*, 2017), the adoption of other PLF technologies has been slower in certain livestock sectors. While studies have been done on technology adoption in some Canadian farming sectors, such as crop (Duncan, 2018; Mitchell *et al.*, 2020) and dairy (Duncan, 2018; Tse *et al.*, 2018), to our knowledge, no studies have focused on the beef industry. Thus, little is known about adoption or use of PLF technologies in this livestock sector in Canada.

There is a similar dearth of beef-focused PLF adoption studies outside of Canada. A study conducted in Brazil in 2011, found that beef farmers avoided technologies that lacked strong relevance and compatibility with their needs and goals, or did not provide significant overall advantages over alternatives (de Aragão Pereira & Woodford, 2011).

A recent Swiss study on technology adoption on ruminant farms, including beef cattle, found little uptake of technology on Swiss beef farms, with transponder collars (14%), automated calf feeders (13%), data transfer into herd management systems (11%), and digital weigh systems (9%) the most commonly used technologies (Groher *et al.*, 2020).

Interestingly, the Swiss study found only 1% adoption of electronic ear tags, which is in stark contrast to Canadian beef operations where, due to government traceability regulations, all cattle must be fitted with radio frequency identification (RFID) ear tags when leaving their farm of origin (Canadian Food Inspection Agency, 2016). Since most cattle in Canada are born on a calf/cow (breeding) operation and then sold to a feedlot operation for the last 6-18 months of their lives to grow to market weight, most will be fitted with RFID ear tags before arriving at a feedlot. Many PLF technologies are designed to leverage RFID ear tags (e.g., digital weigh scales, activity tracking ear tags); thus, there seems to be significant opportunity in Canada to utilize this existing, mandated technology in the beef industry.

To fill the research gap in PLF adoption on Canadian beef farms we conducted a study involving online surveys and phone interviews of feedlot farmers and veterinarians in the province of Ontario, Canada's third largest beef production region. The study findings revealed little adoption of real-time 24/7 individual animal monitoring technologies, but some adoption of digital technologies that support record- keeping and reporting, animal weighing, feed mixing and measuring, and herd management was found.

Materials and Methods

An online survey and phone interviews were conducted with beef farmers and veterinarians of Ontario, Canada between January and March 2020. Note, data collection was cut short when the COVID-19 pandemic hit Canada to respect the tremendous stress farmers were under to meet new public health mandates; however, findings still provide key insights into the needs, constraints, and expectations of feedlot farmers. The study methodology was reviewed and approved by our university's research ethics office.

Study Context

Beef producers and veterinarians in the beef feedlot sector were recruited for the study. This beef sector was chosen because feedlot operations in Canada are highly controlled. Feedlot cattle are housed in indoor or outdoor pens, provided controlled high-yield diets, and monitored regularly for health and dietary issues. The controlled nature of these operations aligned well with current PLF capabilities, making them potentially viable for PLF adoption.

Different definitions of "technology" are used in the PLF literature. For clarity, this study focused on digital technologies, including desktop and laptop computers, mobile phones, software applications used for animal or farm management, automated or robotic feeders, weight scales that read RFID ear tags, and automated environment controls.

Participant Recruitment

Farmers were recruited for the online survey through email, postcards distributed at beef industry conferences, weekly bulletins from a beef industry association, and social media channels (Twitter and LinkedIn). Survey participants had a chance to win one of five $40 random prizes. Twenty-four valid survey responses were received (demographics presented below). Nine farmers who completed the survey participated in follow-up interviews and received $20 for participating. Two beef feedlot veterinarians who worked for large veterinary services that specialize in feedlot animal care in Ontario were recruited for interviews. They received $20 for their participation.

Survey Design and Implementation

The survey aimed to understand farmers' perceptions of PLF technologies, their experiences with these technologies, their needs and pain points, their current awareness of PLF technologies, and potential factors hindering their adoption of PLF technologies. The survey was designed in collaboration with industry and academic beef experts. The survey was implemented in the online survey tool Qualtrics[1]. Participants completed an informed consent section on the survey landing page before beginning the survey.

Interview Design and Implementation

Interviews were used to provide deeper insights into survey data collected from farmers, and to gather additional perspectives from veterinarians. Farmer interviews focused on the same themes discussed above for the survey design but used open-ended questions to allow for in-depth answers. Veterinarian interviews focused on perceived value, awareness, and perceived usability of PLF technology used on feedlots in Ontario. Interviews were conducted over the phone after participants had submitted a consent form via email. Interviews lasted 20 to 30 minutes. Interview audio data were first transcribed and imported into the NVivo[2] qualitative analysis software tool. These data were coded using an open coding method (Corbin & Strauss, 1990), whereby the data were reviewed for key themes and then coded based on identified themes.

Results and Discussion

We received 52 online survey submissions. After filtering for completeness, eligibility, and logical responses, we obtained 24 valid survey responses for analysis. Seventeen participants were male and 7 were female. Most participants (16/24) reported they were farm owners/operators, five reported they were herdsman/lead hand, two reported they were farm employees, one did not specify. Participants worked on a range of farm sizes: four had less than 100 cattle/year, six had 100-500 cattle/year, seven had 500-1000 cattle/year, five had 1001-3000 cattle/year, and one had over 5000 cattle/year. Most participants (13/24) had more than 10 years of beef farming experience, six had 5-10 years experience, and four had 2-5 years experience, one did not specify.

Technology Currently in Use

The survey probed the types of technologies farmers were using at a high-level, focusing on the technological capabilities and perceived values of the technologies, rather than specific technologies or brands being used. Eighteen (18/24) farmers reported

1 https://www.qualtrics.com/

2 https://www.qsrinternational.com/nvivo/

using technology on their farm. These farmers were further asked to select from a set of predefined benefits in response to the question, "*How has technology improved the efficiency of your farming operations?*". Figure 1 shows the responses from the 15 farmers who responded; six producers selected all four benefits. As shown, farmers reported a variety of benefits from adopted technologies, with improved animal health as the most commonly reported benefit.

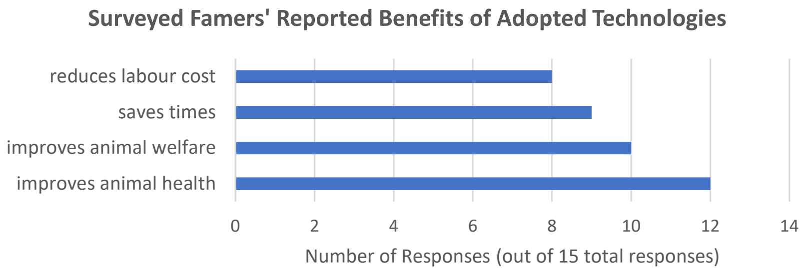

Figure 1: Reported benefits of adopted technologies. Farmers could select multiple benefits; six farmers selected all four benefits.

The survey provided opportunities for farmers to identify general or specific technologies used on their farms in free-form comments. Farmer interviews revealed additional technologies. Table 1 summarizes the reported technologies. Business productivity and accounting software and general computing tools were reported most often, followed by specialized software for feedlot and herd management and hardware and software systems for feeding and weighing cattle.

Table 1: Summary of PLF technologies farmers' reported using on their feedlots.

Reported Technologies in Use	No. of responses	Exemplar comments
General purpose computer, business software, mobile apps	8	*"MS Excel", "Excel for record keeping", "Quickbooks", "Quip smart phone app", "software", "smart phone", "computer system", "Bluetooth", "USB stick", "laptop"*
Specialty software for feedlot management	6	*"Performance Beef", "Performance Livestock Analytics", "data based for cattle", "cattle management system"*
Feeding software, systems	6	"TMR" (total mix ration feed mixer system), "feed software", "feeding"
Chute system w/ digital scale system that scans RFID tags	5	*"digital scale TSI", "chute system…ear tags automatically gets read", "weigh system … has an RFID scanner", "RFID readers and weight scales"*
Animal identification and traceability technologies	3	*"RFID reader and computer system"* (RFID: Radio frequency identification), *"Gallagher"* (*HR3 hand-held RFID reader*)
Crop / Planting technologies	2	*"Precision planting technologies", "GPS on tractors for planting", "Autosteer"*
Environmental controls	1	*"thermostat fans"*

Interviewed veterinarians revealed additional technologies used on Ontario beef farms, including "bunk scoring" camera systems used to manage the feeding trough (bunk) and smart ear tag systems that monitor cattle temperature (rarely used as discussed below).

Overall, the data analysis found a gap between technologies being used on beef feedlots and more advanced PLF capabilities used in other livestock sectors in Canada. Most technologies reported by participants are mature software and hardware technologies. Few beef producers in the region use any 24/7 individual animal monitoring technologies. Only one producer, a client of an interviewed veterinarian, was reported to use such technology (smart ear tags). One veterinarian and one farmer reported these technologies were currently not cost effective for the beef industry, as Farmer 9 commented, "*There's lots of technology the dairy industry is using, like tracking animals in the pens or measuring feed per animal. I don't think we are there yet. … it's cost prohibitive.*" (F9).

<u>Usability</u>

The survey found that many farmers required some type of expert assistance to use their technologies (10/18; 55.5%). One farmer, who uses an automatic RFID ear tag reading system, reported during their interview, "*[M]anaging the data is where you need the expert assistance … The actual tool is easy to use but capturing the data and effectively making use of the data requires assistance.*" (Farmer 4).

Some surveyed farmers reported they stopped using a particular technology due to its poor usability or "*lack of tech support*" (Farmer 2). The importance of technology usability was underscored by the veterinarian interviews, as evidenced by the comment, "*Ease of use is a big one… there are a lot of older generation farmers. If it is not intuitive and easy to use and implement, then it won't get used.*" (Vet A).

To motivate farmers' use and adoption of a technology, its usability must be continuously improved. User-centred design methods from the field of human-computer interaction would help to create products that meet users needs and expectations (Sharp *et al.*, 2019).

<u>Farmers Needs and Challenges</u>

To understand farmers' needs and pain points survey participants were asked to select from a list of potentially difficult aspects of their job. Figure 2 shows the list options and summarizes farmers' responses (18 responses). As shown, record-keeping and reporting was the most reported pain point (16/18 farmers). It was selected by *three times* more farmers than any other aspects of their job, with individual cattle health monitoring (5/18) the next most reported pain point. Pain points identified by farmers in free-form text include marketing fed cattle and dealing with packers (slaughterhouses).

Farmer interviews revealed additional pain points, including marketing related tasks (4/9), barn chores (2/9), feeding related tasks (2/9), processing cattle (1/9), managing herd health (1/9), dealing with weather (e.g. flooding, freezing) (1/9), and meeting regulatory requirements (1/9). A distinction was made between time-consuming and stressful tasks. Everyday barn chores, such as feeding and cleaning were reported as time consuming, whereas dealing with marketing and financial aspects were generally reported as stressful.

The data analysis found that while most farmers find record-keeping, reporting, and other business aspects of farming (e.g., marketing) difficult, there were also a wide variety of reported challenges and pain points. This finding underscores the need to consider feedlot farmers' unique and varied needs in PLF technology development. There was strong alignment between the reported pain points and capabilities of reported technologies in use. However, despite several farmers reporting animal health monitoring being a challenge, no farmers reported using any technologies to facilitate with this task. This is consistent with previously mentioned reports of such technologies being cost prohibitive for beef farmers.

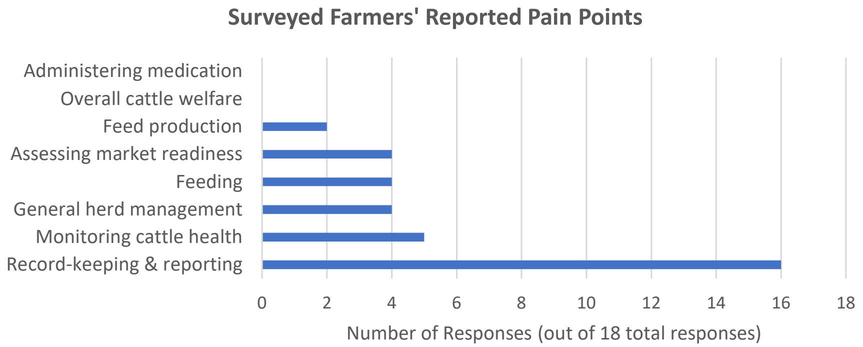

Figure 2: Farmer responses to survey question, "*What are the most difficult aspects of your job?*".

Barriers to Adoption

To understand potential barriers farmers face in addressing their needs using technology adoption, the survey asked farmers to select from a list of options in response to the question, "*What are the barriers stopping you from automating or using technology to help manage the operations?*". Figure 3 shows the listed barriers and farmers' responses (19 responses). These findings are discussed below along with related data from the interviews.

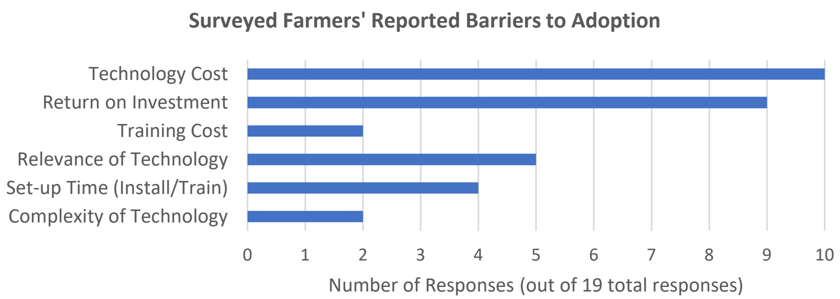

Figure 3: Survey responses to the question, "*What are the barriers stopping you from automating or using technology to help manage the operations?*"

Costs and Return on Investment. Finance-related barriers were the most commonly reported barriers on the survey. Fifteen of 19 farmers reported at least one of the three cost/money related barriers (technology costs, training costs, and/or return on investment). Veterinarian interviews highlighted the financial stress regional beef farmers were facing, both from profits being less than they used to be and from the closure of a large local processing plant (due to public health concerns) that was having wide-scale impacts on the local beef industry.

Despite farmers and veterinarians agreeing that cost was an adoption barrier, some farmers reported several large technology expenditures (e.g., $150,000 (CAD) for a new total mixed rations (TMR) feed mixer), suggesting that cost effectiveness (return on investment) may be the actual factor in some cases limiting technology adoption. The interviews supported this assertion through discussions of whether a farmer would "*get back*" (Vet A) a technology investment over time or whether a technology cost would "*outweigh the cost of labour and probably maintenance and repair.*" (Farmer 3).

The interviews revealed other financial factors related to technology adoption, including the relatively short time cattle remain on a feedlot (commonly 6-18 months) and the relatively small size of Ontario feedlots (compared to feedlots in western Canada). These factors underscore the need for feedlot farmers to minimize up-front and per animal costs.

Relevance of the Technology. Five surveyed farmers reported relevance of the technology as a barrier to adoption. The interviews revealed some technologies do not meet Ontario farmers' needs due to regional climate or farming practices, as illustrated by the comments,

"*Technology seems to come out with … a trial and you invest in it and then you find it's either not safe, not cold safe, or winter safe. Then they upgrade it and the second or third evolution of the technology is … when it would be wise to buy … [when it] is more 'farm ready'*". (Farmer 4), and

"*There is a lot of research [on technologies for the beef industry] out there, a lot of it comes from the West and sometimes it doesn't fit in Ontario.*" (Vet B).

One veterinarian reported some dairy PLF technologies are not relevant due to different animal handling practices in beef farming that lead to different health and welfare concerns. Overall, this highlights the need to design PLF technologies to suit the unique, and varied farming practices within each farming sector, and across farming regions.

Other Factors. Four surveyed farmers reported set-up time (to install/train/etc.) and two farmers reported complexity of technology as barriers that prevented them from adopting certain technologies. Both responses support the importance of the usability of PLF technologies. An additional barrier reported in free-form comments was "*Access to internet*", referring to the lack of reliable cellular or high-speed internet services in some rural areas, limiting the relevance of some internet-based technologies.

Conclusions

Our study of digital technology adoption in the Canadian beef industry revealed the use of mature business and general-purpose computer technologies and mature feedlot technologies (e.g., precision feed mixers and digital weigh scales), that have been around for many years. Only a few participants reported using more recent PLF technology, including a feedlot-specific cloud-based precision record-keeping and reporting mobile application that supported herd and feed management. Cost and return on investment were revealed to be key factors in technology adoption on beef farms. Feasible pricing models, such as monthly subscription services, were found to be attractive to feedlot farmers. The findings also underscore the need for more usable, relevant technologies that better meet the unique and varied farming practices of feedlot farmers.

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Factors associated with the adoption of different clusters of precision livestock farming technologies in pasture-based dairy systems

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Abstract

Precision livestock farming (PLF) technologies have been identified as important tools to improve the sustainability of dairy production systems due to perceived economic, social and environmental benefits. However, there is still limited information regarding the level of adoption of PLF technologies and the factors associated with PLF technology adoption in pasture-based dairy systems. The current research aimed to address this knowledge gap by using a nationally representative survey of dairy farms in a pasture-based dairy system. Firstly, we established the adoption rates of nine PLF technologies, and secondly, we determined the factors associated with the adoption of different PLF technology clusters (reproductive, grass, milking management technologies and automatic calf feeders). Four binomial logistic regressions were conducted to determine the factors associated the adoption of each PLF technology cluster. The results found that adoption rates varied widely, with the most adopted PLF technologies being those related to the milking process. Overall, PLF technology adoption is mostly influenced by herd size, proportion of hired labour and the age of farmers. However, the magnitude and direction of the influence of the factors in technology adoption differ depending on the type of PLF technology being investigated.

Keywords: precision livestock farming technologies, technology adoption, pasture-based dairy systems

Introduction

Livestock farmers are currently facing several challenges. On the one hand, it has been estimated that the worldwide demand for animal products will increase by 70% by 2050 (Berckmans & Guarino, 2017). On the other hand, consumers have shown an increased concern in animal production system practices related to animal welfare, zoonotic disease transmission, use of medical treatments and environmental impacts (Bewley, 2017). To satisfy current market demand, livestock farmers are urged to increase productivity but in a sustainable manner (Cavaliere & Ventura, 2018). Additionally, increasing herd sizes and decreasing workforce availability is challenging dairy farmers and their capacity to monitor and manage their herds efficiently (Hostiou *et al.*, 2017; Gargiulo *et al.*, 2018). In this context, Precision livestock farming (PLF) has been widely identified as an important approach to improve the economic, social and environmental sustainability of dairy production systems (Lovarelli *et al.*, 2020). This arises from the expectation that PLF technologies will increase farm efficiency, reduce costs, improve product quality, improve animal health and welfare and reduce the environmental impacts of dairy farms (Bewley, 2017). Additionally, PLF technologies are expected to improve the quality of life of farmers by reducing labour needs or increasing the time they spend with their families (Stone, 2020). Despite PLF technologies potential benefits, there are still doubts about their actual value to dairy farmers (Steeneveld *et al.*, 2015), especially on pasture-based dairy systems, where there are less specialised PLF technologies available and perceived demand for technologies compared to indoor dairy systems (Shalloo *et al.*, 2021).

Estimating adoption rates and understanding adoption decision making constitutes the first step to evaluate the impacts of PLF technologies on all aspects of dairy farms and to explore the limited adoption rates in some contexts. Previous studies have investigated the adoption of precision livestock farming technologies on pasture-based dairy systems (Edwards *et al.*, 2015; Gargiulo *et al.*, 2018; Dela Rue *et al.*, 2020; Yang *et al.*, 2021) and indoor dairy systems (Borchers & Bewley, 2015; Jelinski *et al.*, 2020), finding varying levels of adoption. However, these studies are mostly based on voluntary online surveys, which suggest a selection bias towards dairy farmers that already use computers and internet (Gargiulo *et al.*, 2018), or phone surveys that are not representative at the national level.

Additionally, previous studies of the factors associated with PLF technology adoption on pasture-based dairy systems have focused on labour-saving (or automation) and data-capture technology groups (Dela Rue *et al.*, 2020; Yang *et al.*, 2021). There is limited published evidence on the factors affecting the adoption of PLF technology clusters related to areas of dairy farm management such as dairy cow reproduction, grassland management or milking management. The current paper contributes to filling these knowledge gaps by using a nationally representative survey of dairy farms in a pasture-based system to first, establish the adoption rates of PLF technologies, and secondly, to determine the factors associated with PLF technology adoption.

Material and methods

<u>Data</u>

The analysis was based on farm-level data collected from the 2018 National Farm Survey (NFS). The NFS is conducted annually in Ireland by Teagasc, as part of the Farm Accountancy Data Network (FADN) of the European Union. A statistically representative sample of approximately 900 farms is selected randomly each year (Dillon *et al.*, 2018). Each farm is assigned a weighting factor so that the results of the survey represent the national population of farms (approximately 93,000 farms). Farms are categorised into one of six farming systems based on dominant farm enterprise: dairy, cattle rearing, cattle other, sheep, tillage and mixed livestock (Dillon *et al.*, 2018).

The 2018 NFS included an additional survey that asked dairy farmers about their use of different PLF technologies. The PLF technologies included in the survey were individual cow activity sensors, rising plate meters, automatic washers, automatic cluster removers, automatic calf feeders, automatic parlour feeders, automatic drafting gates, milk meters, as well as use of PastureBase Ireland (an Irish grass management decision support tool).

Additional to the 2018 NFS original variables, we created four PLF technology clusters variables by grouping technologies based on their level of associations with each other, and the area of dairy farm management in which they are used. The PLF technology clusters were reproductive management technologies (grouping adopters of individual cow activity sensors, automatic drafting gates or both), grass management technologies (grouping adopters of rising plate meters, PastureBase Ireland or both), milking management technologies (grouping adopters of automatic washers, automatic parlour feeders, automatic cluster removers, milk meters, or altogether) and automatic calf feeders in a separate group by themselves.

Statistical analysis

Adoption rates of PLF technologies were retrieved from the 2018 NFS data and are presented as percentage of adoption.

Four binomial logistic regression models were applied to determine the factors associated with the adoption of each PLF technology cluster. The outcome binary variables in each situation were the adoption of the reproductive management technologies cluster, grass management technologies cluster, milking management technologies cluster and automatic calf feeders. The explanatory variables were herd size, farm family income (FFI), proportion of hired labour, age, number of household members, agricultural education (categorical variable of three levels, “no agricultural education” as reference category, “medium agricultural education” and “high agricultural education), region (categorical variable of three levels, “north-west region” as reference category, “mid-east region” and “south-west region”) and discussion group membership (categorical variable of two levels, with “no discussion group membership” as reference category). We also included squared herd size, squared farm family income and squared age in the model to test for a non-linear effect of these variables. Significance was determined if $P < 0.05$.

Results and Discussion

PLF technologies adoption rates

Table 1 shows the percentage of adoption of each PLF technology. The results showed that adoption rates varied widely depending on the type of PLF technology, ranging from 6% of rising plate meters to 52% of automatic parlour feeders.

Irish dairy farmers most commonly adopted PLF technologies around the milking process (automatic parlour feeders, milk meters, automatic washers and automatic cluster removers). Similar results were reported in other countries with pasture-based dairy systems (Edwards et al., 2015; Gargiulo et al., 2018; Dela Rue, 2020) and indoor systems (Borchers & Bewley, 2015), although with differences in technology adoption rates. This might be because the milking process is physically demanding and time-consuming, accounting for the majority of labour required on pasture-based dairy systems (Deming et al., 2018). Therefore, the benefits of using this type of precision technology are greater (Edwards et al., 2015) and quickly perceived by dairy farmers (Groher et al., 2020) in an environment of scarce and costly labour.

Table 1: Adoption rates (%) of PLF technologies in Irish dairy farms

PLF technologies	PLF technology cluster	Adoption rates (%)
Rising plate meters	Grass management technologies	6
PastureBase Ireland (PBI)	Grass management technologies	24
Individual cow activity sensors	Reproductive management technologies	7
Automatic drafting gates	Reproductive management technologies	8
Automatic washers	Milking management technologies	27
Automatic clusters removers	Milking management technologies	25
Milk meters	Milking management technologies	29
Automatic parlour feeders	Milking management technologies	52
Automatic calf feeders	Automatic calf feeders	8
No technologies		30

Factors associated with the adoption of different PLF technology clusters

Table 2 shows the results of four binomial logistic models, one per PLF technology cluster. As reported by other studies of precision technology adoption in pasture-based dairy systems (Gargiulo *et al.*, 2018) we found that herd size is positively associated with the adoption of all PLF technology clusters (*P<0.01*). Additionally, we found age has both a negative association with the odds of adopting reproductive and grass management technologies and a positive association with the odds of adopting milking management technologies and automatic calf feeders. Specifically, for a one unit increase in age, the odds of being a technology adopter of reproductive and grass management technologies decreased by 10% (*P<0.01*) and 19% (*P<0.01*), respectively; while the odds of being an adopter of milking management technologies and automatic calf feeders increased by 7% (*P<0.01*) and 18% (*P<0.01*), respectively. This might be explained because milking management technologies require significant capital investments (Yang *et al.*, 2020) and for younger dairy farmers this capital may be more difficult to access. Additionally milking management technologies have been commercially available for longer than reproductive and grass management technologies, therefore older dairy farmers may be more familiar and aware of the benefits of these technologies.

Dairy farms with higher proportion of hired labour have higher odds of being adopters of grass management technologies, milking management technologies and automatic calf feeders, but lower odds of being adopters of reproductive management technologies. Specifically, for a one unit increase in the proportion of hired labour, the odds of being a technology adopter increased about 5 fold (*P<0.01*) for grass management technologies, 83% (*P<0.01*) for milking management technologies, and 61% (*P<0.01*) for automatic calf feeders. This may be explained because labour has been identified as the second highest costs on pasture-based dairy systems (Deming *et al*., 2018). Additionally, improving labour efficiency and reducing hired labour are one of the most important drivers for technology adoption, with farmers investing more in automation (or labour saving technologies) than others (Gargiulo *et al*., 2018; Dela Rue *et al*., 2020; Yang *et al*., 2021).

Table 2: Results of the binomial logistic regression models by PLF technology cluster

Variables	PLF technology clusters			
	Reproductive management technologies	**Grass management technologies**	**Milking management technologies**	**Automatic calf feeders**
Herd size	1.05***	1.03***	1.05***	1.05***
Herd size ^2	1.00***	1.00***	1.00***	1.00***
FFI	1.00***	1.00***	1.00***	1.00***
FFI ^2	1.00***	1.00***	1.00***	1.00***
Hired labour	0.63**	4.94***	1.83***	1.61**
Age	0.90***	0.81***	1.07***	1.18***
Age^2	1.00***	1.00***	1.00**	1.00***
Household	1.13***	1.03	0.92***	0.84***
High ag. edu.	3.69***	1.15	0.99	1.25**
Medium ag. edu.	1.44**	1.22***	1.01	0.30***
Mid-east region	0.68***	1.20**	1.65***	1.48**
South-west region	0.23***	1.87***	1.21***	6.88***
Discussion group	2.62***	7.22***	0.89**	0.65***
Constant	0.04***	2.43**	0.01***	0.00***
Log likelihood	- 3,188.9	-5,944.9	-7,182	-2,987.6
AIC[1]	6,405.8	11,917.8	14,392	6,003.2

*** $P < 0.01$, ** $P < 0.05$

The number of household members has a significant negative association with the odds of being an adopter of milking management technologies and automatic calf feeders, while it has a positive association with the odds of being an adopter of reproductive management technologies and no association with grass management technologies adoption. Specifically, for a one unit increase in the number of household members the odds of being an adopter of milking management technologies and automatic calf feeders decreased by 8% ($P<0.01$) and 16% ($P<0.01$), respectively. This suggests a greater availability of household members to work on milking tasks and calf care, and thus less need to invest on these labour saving technologies.

1 AIC = Akaike Information Criterion

As reported by other studies (Pierpaoli *et al.*, 2013), farmer's education is an important factor associated with precision technology adoption. The results showed that dairy farmers with high-levels of agricultural education are about 4 times ($P<0.01$) more likely to adopt reproductive management technologies compared to farmers without agricultural education, however this association is smaller on automatic calf feeders' adoption and there is no association with grass and milking management technologies adoption. This may be explained due to this type of technologies requiring users to have a greater knowledge to interpret data (Dela Rue *et al.*, 2020).

There are also geographic regional differences in the adoption of PLF technology clusters. Dairy farmers of the south-west region of Ireland have higher odds of adopting grass management technologies, milking management technologies and automatic calf feeders. This might be explained because the south-west region of Ireland has a greater proportion of dairy production with free draining soils, therefore an advantaged region in terms of productivity and profitability compared to the mid-east and north-west regions (Lapple *et al.,* 2012; Shalloo *et al.*, 2004; Hanrahan *et al.*, 2018).

Finally, we found discussion group membership has a positive and significant association with the odds of adopting reproductive and grass management technologies, however a negative association with the odds of adopting milking management technologies and automatic calf feeders. This may relate to the age of discussion group members, who are on average younger than non-members (Hennessy & Heanue, 2012) and more willing to adopt new precision technologies (Pierpaoli *et al.*, 2013), such as individual cow activity sensors, rising plate meters or PBI.

Conclusions

The current study reports the first assessment of PLF technology adoption rates on pasture-based dairy farms in Ireland, which can be used as a baseline for future research on PLF technology adoption trends. Additionally, the study determined several factors associated with the adoption of PLF technology clusters in pasture-based dairy systems. Overall, we found that herd size, proportion of hired labour, and age influenced the adoption of all PLF technology clusters; while factors such as number of household members, agricultural education and discussion group membership influenced the adoption of some PLF technology clusters. However, the magnitude and direction of the influence of the factors in technology adoption differed between PLF technology clusters. Thus a more nuanced understanding of PLF technology adoption in specific farm management areas, which we have provided in this study, is likely to be important in understanding the broader ongoing transformation of the dairy sector.

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Cooperative Livestock Farming: a chance for a breakthrough for PLF?

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Abstract

Economic viability is a fundamental precondition for the practical adoption of innovations in livestock farming. While precision agriculture bears the potential for a drastic reduction of manual labour and resource use, the economic potential of precision livestock farming (PLF) is limited by biological, ethical and ecological boundaries. At the same time, PLF solutions often require complex sensor systems and evaluation methods that increase their cost and lead to long amortisation times. A paradigm shift - from incorporating animals as passive factors that just have to tolerate management procedures to actively collaborating agents - could help to overcome this dead centre. Farm animals have sensory and cognitive abilities that are not matched by current technical systems. Their inclusion could reduce the cost and complexity of technical solutions and thereby may open up new areas for process automation. The key to unlocking these abilities is the establishment of bidirectional communication between animals and machines using automated learning procedures. This would enable the animals to indicate their needs in a way that is better discernible by machines and inversely would allow them to better adapt their behaviour in response to signals given by machines. As a side effect, this more cooperative livestock farming would occupy the animals with biologically relevant tasks and simultaneously improve the controllability and predictability of their husbandry conditions. It could thus directly improve animal welfare and therefore has the potential to increase the revenue per animal if it becomes an element of welfare product labels.

Keywords: operant conditioning, cooperative livestock farming, animal welfare, PLF adoption

Introduction

The economic gains from cost reductions due to increased efficiency, increased product quality and reduced manual labour can be assumed to be the driver for the practical adoption of solutions from precision agriculture. Selective spraying has the potential to reduce the use of pesticides by 80% and more (Oberti et al., 2016). New weed detection systems that guide autonomous mechanical weeding robots may eliminate the need for herbicides altogether and at the same time reduce manual labour (McAllister et al., 2019). New technologies open up the opportunity to automate the handling of special crops and fruits with autonomous harvesters and autonomous pruning robots (Tinoco et al., 2021). This technology also enables selective harvesting to ensure optimal ripeness and size of the products (Kootstra et al., 2021).

Does precision livestock farming bear the same potential? Existing examples for successful applications of PLF usually generate much lower economic benefits. Reductions reported from improved ventilation control are about 30% of the heating costs (Van Wagenberg and Vermeij, 1998). Increased productivity from improved pig health due to air filters is in the range of 4% for the farrowing rate and 2% from reduced sow mortality (Alonso et al., 2013). Automatic milking systems can increase milk yield by 5-10% (Veysset et al., 2001) and reduce workload by more than 30% (Shortall et al., 2016). Devices for oestrus detection increase net return in the range of 1-2% (Rutten et al., 2014). Devices for lameness detection in cattle (which are not practically relevant by now) could increase the net return by 4% to 25% depending on the prevalence and severity of lameness (Kaniyamattam et al., 2020). Selective feeding depending on body condition can reduce feed costs by 6% in pigs (Monteiro et al., 2017) and 7% in broilers (Moss et al., 2020).

Amortization times reported in the literature cited here are in the range of 3 to 10 years. Given the limited lifespan of electronic devices in a farm environment, this amortization time seems to represent an upper limit for the economic feasibility of PLF solutions. Hence, the main inhibiting factor for the adoption of new PLF applications in practice appears to be that they are too complex and costly compared to the economic gains that can be achieved. The prospects for economic gains in livestock farming are limited in various ways. They are limited by biology as feed conversion efficiency and growth rates may already be close to their biological maximum. For example, the increased metabolic activity required for faster growth leads to increased bodily heat production which already resulted in a higher susceptibility to heat stress in poultry (Gous, 2010). Similar results were found for milk yield in cattle (Jones and Stallings, 1999). Likewise, the litter size in pigs grew already beyond biological limits especially with regard to sufficient milk supply of the piglets (Rutherford et al., 2013). Therefore, solutions aiming to increase productivity cannot be expected to create large economic effects.

Economic gains are also limited by ethics. As long as the animals are affected, there is not much room for cost reductions. The main animal-related cost factors space, feed supply and heating or cooling are already subject to economic optimisation. Drastic cost reductions in this area can be expected to give rise to similarly drastic animal welfare issues (Dawkins, 2017). There is also not much room for productivity increase e.g. by genetic methods. Breeding for high productivity and fast growth can lead to severe welfare issues in the parent generation of breeding animals. This already led to trimming practices in fowl (Fiks and De Jong, 2007) and higher prevalence of abnormal bone development in pigs (Kadarmideen et al., 2004). Therefore, solutions aiming to reduce production costs at the expense of the animals or increase productivity cannot be expected to be socially accepted. Economic gains are furthermore limited by ecology. Cost factors like manure, air pollution and land use are to a large extent externalised and represent a major issue in climate change and the preservation of biodiversity (Bowles et al., 2019). Therefore, solutions aiming to intensify livestock farming cannot be expected to be socially accepted.

The present work discusses other options for how PLF solutions can become economically viable and how this may create synergy effects with regard to animal welfare. This conference paper is partly based on hypotheses previously published in Manteuffel et al., (2021).

Reducing cost and complexity of PLF

The fundamental approach of PLF is to use sensors, automata, artificial intelligence, and robots to monitor the state of the animals at the level of individuals and to automate management tasks by utilizing methods from systems engineering (Wathes et al., 2008). This is supposed to “create innovations replacing the eyes, ears, and nose of the farmer” (Norton and Berckmans, 2018). These solutions incorporate animals mainly passively, e.g. by measuring their health status or by predicting their biological status in terms of growth or oestrus and so forth.

Allowing the animals a more active role by enabling bidirectional communication between animals and machines opens up opportunities to reduce the cost of PLF solutions and to significantly enhance the automation of management procedures. Through communication, the animals could be enabled to indicate their inner states and current needs in a way that is more easily discernible by technical equipment. This bears the potential to reduce the cost and complexity of technical solutions because it may render sensors and evaluation logic unnecessary if the animals can provide their own sensory information and evaluation results. At the same time, communication may make the ‘intention’ of the equipment easier to interpret for the animals so that they are better able to react appropriately. This could facilitate process automation because it enables the animals to cooperate in the realisation of this intention and may make manual intervention by humans unnecessary.

Stimulus-controlled operant conditioning is a method that enables such bidirectional communication. Numerous studies show that many captive animals can be automatically conditioned to perform operant behaviour. Animals can be conditioned to use joysticks (Croney and Boysen, 2021) touch a screen (Rivalan et al., 2017), push levers (Ernst et al., 2005), perform simple movements such as approaching or avoiding a target (Horback and Parsons, 2019), but also more complex action sequences (Poddar et al., 2013). At the same time, animals can identify various stimuli. They are able to recognize and react to olfactory signals (Erskine et al., 2019), abstract visual cues (Langbein et al., 2009), individual acoustic signals (Ernst et al., 2005), temporally related events (Balsam and Gallistel, 2009), and even their own bodily signals (Dirksen et al., 2021).

Here, conditioning should not be misunderstood as a sort of deterministic programming. The procedure must provide a clear motivation for the animals to behave in the intended way and it is the animal that decides whether this motivation is sufficient in comparison to other motivating factors. Therefore, operant conditioning can be interpreted as a behaviour economic preference test (Dawkins, 1983), for the strength of an animal’s motivation <u>not</u> to behave as intended. This has to be taken into account in any practical application especially if not reacting as intended involves negative consequences for animal welfare.

CLF and animal welfare

The ability to perform positively motivated behaviour (Bracke and Hopster, 2006) and an environment that is both predictable and controllable (Bassett and Buchanan-Smith, 2007) are considered to be major factors for good animal welfare - besides fundamental requirements such as good health conditions and adequate basic services. Cooperative livestock farming may contribute to animal welfare if it enables the animals to occupy themselves with biologically relevant tasks that are positively motivated.

For example, sows do selectively choose between cooling systems (Barbari and Conti, 2009). Hence, cooling is under hot conditions sufficiently motivating for sows to perform operant behaviour. This could be used in a PLF solution to make the animals autonomously operate cooling devices in order to achieve a cooling rate that is aligned to the animals' individual needs on the one hand and enables cognitive occupation on the other hand. Furthermore, the number of activation attempts provides information about the severity of the heat stress as perceived by the animals. This could be a guiding parameter for a demand-driven activation of barn-wide cooling mechanisms which would then require no rumen boluses, ear-tags or cameras (Islam et al., 2021). Similarly, animal operated actuators that improve air quality (Jones et al., 1998) may be a cost-effective alternative to solutions based on dust and ammonia sensors (Banhazi, 2009).

Once CLF solutions are accepted as measures that improve animal welfare, their installation could become an element of product labels for animal-friendly housing conditions and thereby could generate additional revenue for the farmers.

Paths to practical applications

The concept of cooperative livestock farming dates back to Kilgur (1978). Early examples of stimulus-controlled operant conditioning in livestock farming are electronic feeding stations and automated milking systems (Jago and Kerrisk, 2011; Vier et al., 2016). Recent examples for practical use cases are virtual fencing (Lomax et al., 2019), latrine training in pigs (Tillmanns et al., 2022) and cattle (Dirksen et al., 2021) as well as signal feeding (Kirchner et al., 2012). So far, these recent examples are mainly pilot studies that were performed in experimental settings using improvised equipment. Their broad application requires an automation of the conditioning procedures.

In general, two main scenarios have to be considered for the training. In the first case, the stimulus is motivating itself. In this case, the training only needs to create a link between the reward and the operant behaviour. Examples are electronic feeding stations or future animal operated cooling systems. In the second case, the stimulus is not motivating to perform the intended operant behaviour. A link between an additional motivation and the behaviour has to be learned. An example is latrine training. Here, the latrine use is rewarded by additional food and the animal has to learn that the urge to urinate means that food is available at the latrine. To perform the training, the system must know the ground truth for the parameter that the animal is ought to distinguish. This is not different from any other supervised learning procedure. Thus, the latrine training requires sensors to identify the animal and the urination behaviour. It has to be performed in multiple steps. One option is to associate the reward with an individual signal (similar to Manteuffel et al., 2011). In a second step, a sensor must detect the discharge and immediately initiate the emission of the reward signal. This creates an association between the urge to urinate and the availability of the reward. An open hypothesis is that the animal are then able to approach the latrine before urination by anticipating the reward. After the training is finished, it should be no longer necessary to identify the animal or emit a signal. All that is needed would be to detect the discharge at the latrine and provide a reward in return. This example shows that CLF does not eliminate the need for sensors altogether. It merely restricts the need for complex sensor systems to the training period.

The practical utilisation of rewards in group-housed animals requires a sufficient number of devices and protection mechanisms to ensure the accessibility of the reward for animals of low social rank and to avoid stress from increased resource concurrence (Manteuffel et al., 2010). In addition, a universal method for assessing the learning progress is required to make the training procedure universally applicable under different conditions. This aspect of CLF is discussed in Manteuffel et al. (2021).

Conclusions

CLF may increase the economic viability of PLF solutions by reducing their cost and technical complexity through the incorporation of animal abilities. In result, control mechanisms may be adjusted more directly to the individual needs of the animals and thus bear the potential to create more adequate husbandry conditions at reduced costs. At the same time, CLF could enable the animals to occupy themselves with biologically relevant tasks that make their environment better predictable and controllable. In result, CLF could become an accepted way to improve animal welfare and thereby additionally increase the revenue from process automation. However, this requires the restriction to positive motivations and means to safeguard equal feasibility of all behavioural options for all animals in a group. In addition, CLF solutions have to incorporate the fact that the animals may decide not to perform the intended operant behaviour if they are sufficiently motivated.

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SESSION 16

Cows:
Tracking

Are GPS sensors and density-based classification suitable to ensure the traceability of dairy cows on pastures? Part I: Development and validation on experimental farms

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Abstract

Since 2007, the 'pasture milk' recommendation has grown further in Europe. It requires the cows to spend a minimal duration on pasture (> 6h). Our objective was to develop and test an algorithm that estimates the time dairy cows spend outside the barn (T-Out) thanks to an automatic detection of the barn and therefore of the pastures. With an analysis of cows' locations local density distribution, we identified a local density threshold to discriminate the cows' locations that are on pasture from the cows' locations that are in the barn. By using the DBSCAN algorithm (Hahsler et al., 2019), which allow to identify clusters of arbitrary shape from noises, we identified a unique "barn" cluster. We defined T-Out as the sum of locations labelled "on pastures" multiplied by the time interval between location acquisitions (11 min). We tested the solution (GPS sensors + algorithm) on 2 experimental farms in 2019 (2 datasets) and 2020 (1 dataset). Farms were equipped with 8 and 9 GPS sensors. The T-Out reference was recorded by a RFID antenna at the barn entry or manually by the farm staff. On experimental farms the estimations of the T-Out were accurate with RMSEs between 17 min/d to 53 min/d regarding the dataset. The estimation of the T-Out using GPS sensors seems promising to objectify the "pasture milk". However, the solution (GPS sensors + algorithm) needs to face on farm conditions to evaluate its reproducibility with a variety of farm systems and quality of GPS data.

Keywords: grazing time, geo-tracking, dairy cattle, density-based clustering

Introduction

Naturalness has been identified as a key request formulated by citizens worldwide (Schuppli *et al.*, 2014; Delanoue *et al.*, 2018) about their expectations regarding dairy cattle production. They ask for more transparency about livestock production (Frewer *et al.*, 2005). To face the reduction in dairy products consumption, several actors of the dairy branch across Europe developed a label, which certifies that cows spend enough time outside the barn. This specification asks to reach a minimum daily and yearly duration of access to pastures with a minimal accessible land area for a minimal percentage of the herd. This specification is variable across dairies in France and is commonly verified with farmers' manual notes and audits made by independent organisms.

Different sensors are already providing animals' locations to farmers. They are based on a global navigation satellite system (GNSS) coupled with a telecommunication technology. Those sensors are mainly used to monitor the animals' locations and to track them in large area. From this locations data, different services have been created like alerts when animals are leaving a delimited grazing area or virtual fencing (Aquilani *et al.*, 2022). Studies have indicated that those sensors can also be used to monitor animals' health and welfare when coupled with other technologies as accelerometers (Aquilani et al; 2022) but have not been developed so far. Those sensors seem to have the potential to provide data all along the production chain with the development of new applications.

For analysing locations' data, density-based classification seems promising to detect location clusters. DBSCAN is one of the most used density-based clustering and is implemented on R (Hashler *et al.*, 2019). The DBSCAN algorithm classifies in a same cluster points that are density-reachable, i.e., that the number of points in an *Eps* neighbourhood is superior to a minimum number of points chosen, *minPts* (figure 1). DBSCAN classification results in points classified as core or border of a cluster or noise (figure 1). The DBSCAN algorithm have been used to detect hikers' stop area and their impact on the wildlife (Kerouanton *et al.*, 2017). The use of this algorithm to detect automatically when cows are in the barn seems promising.

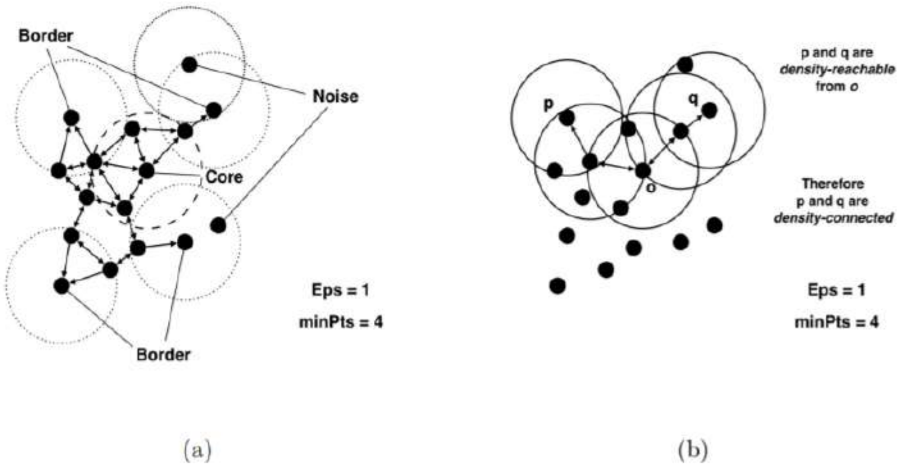

Figure 1: (Hashler et *al.*, 2019): Concepts used in the DBSCAN family of algorithms. *Eps* = a user-specified radius, *minPts* = a user-specified density threshold. (a) shows examples for the three-point classes. A point p is classified as: a core point if at least *minPts* points are within a radius *Eps* around p, a border point if p is not a core point but is within the *Eps* radius of a core point, and a noise points otherwise; (b) illustrates the concept of density reachability and density-connectivity.

The aim of this project was to develop an algorithm able to discriminate when cows are on pastures from when they are inside the barn to ensure the grazing time traceability. This paper presents the algorithm developed, and its performance to predict grazing time.

Material and methods

<u>Experimental design</u>

To ensure the traceability of dairy cows on pastures, we monitored the time spent outside by dairy cows on 2 farms. Three trials were performed, one in 2019 in the farm A and two in 2019 and 2020 in the farm B (Table 1). The farm A is the Derval experimental farm (Chambre d'agriculture Pays de la Loire, Derval, France) located in western France (Latitude: 47.69; Longitude: -1.68). The cows are milked by an automatic milking system (AMS). Among the 70 lactating cows, 8 were equipped with GPS sensors. The cows had a free access to the pastures most of the day. They were pushed back in the barn at 6:00 pm and were able to leave after their milking from 9:00 pm on: one cow left the barn after milking on average every 6 min after 9:00 pm. The grazing system of the farm A was composed of 7 paddocks with an average of 4-5 days spent per paddock (figure 2). The farm B is the Poisy experimental farm (Chambre d'agriculture Auvergne-Rhône Alpes, Poisy, France) in the French Alps (Latitude: 45.93; Longitude: 6.07). On the 85 lactating cows, 9 cows were equipped with GPS sensors for the trial B-2019 and 9 others for the trial B-2020. The cows' access to pastures was controlled by farmers on the farm B regarding the grass growth and weather conditions, and was therefore changing from day to day. On the farm B cows had a day paddock and a night paddock with 3-4 days spent per paddock (figure 2).

Table 1: Description of the experimentations

Trial Name Farm Name	A-2019 A	B-2019 B	B-2020 B
Trial period (dmy)	03/04/2019 – 05/05/2019	19/07/2019 – 31/08/2019	22/07/2020 – 16/09/2020
Number of cows in the herd	70	85	85
Number of cows equipped with GPS sensor	8	9	9
Trial duration (days)	37	36	48
Access to pastures	Mostly free	Limited	Limited

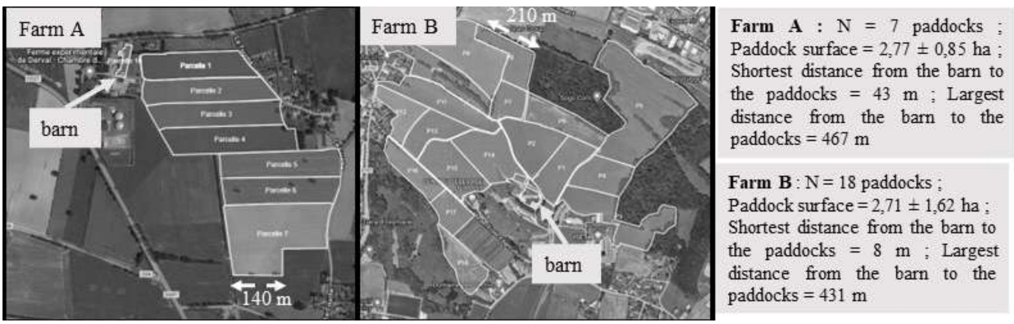

Figure 2: Grazing system of the farm A (left) and the farm B (right). Each white polygon represents a paddock. The scale is provided by the dashed white arrow.

GPS data and gold standard acquisition

In all trials, a part of the herd (table 1) was equipped with a GPS mounted collar (DigitAnimal, Spain). The GPS sensors recorded the locations and transmitted them by the Sigfox network every 11 minutes in average. The GPS sensors have no cash memory, the locations are sent on time or lost if there is no network coverage.

In trial A-2019, the 8 cows equipped with GPS sensors were also equipped with an RFID pedometer (Nedap, the Netherlands). An antenna placed in the corridor between the barn and the exit to pastures recorded the passage of each cow equipped with a pedometer and was used to calculate the reference T-Out (T-Outref). In the trials B-2019 and B-2020, the farm staff have recorded manually the time the cows spent outside (T-Outref).

Estimation of the time spent outside from the gps data

An algorithm has been developed to automatically detect the barn, based on the hypothesis that when processing all the data of a sufficient time window, the density of geotracking positions of the cows would be higher when cows are in the barn than on pasture. This clustering method was developed with the DBSCAN package available in R (Hahsler et *al*., 2019). The DBSCAN algorithm was used to identify a unique "barn" cluster. For this reason, we hypothesized that within a radius called *Eps* and for an appropriate time window called *T*, there will be a binomial distribution of the local density of the geotracking positions (figure 3). Thus, the step 1 of the algorithm defines a threshold which discriminates the local density of the geotracking positions from pastures (left peak in the figure 3) to those from the barn (right peak in the figure 3). This threshold will be the *minPts* parameter of DBSCAN in the next step. Data are divided in segments of *T* days, and the step 1 is replicated on each segment. Thus, the algorithm has 2 parameters to be defined: *Eps* and *T*. They were defined after testing a combination of Eps (from 0.0001° to 0.0008° every 0.00005°) and T (7, 14, 21, 28 days) and selected on the RMSE of the algorithm's estimation.

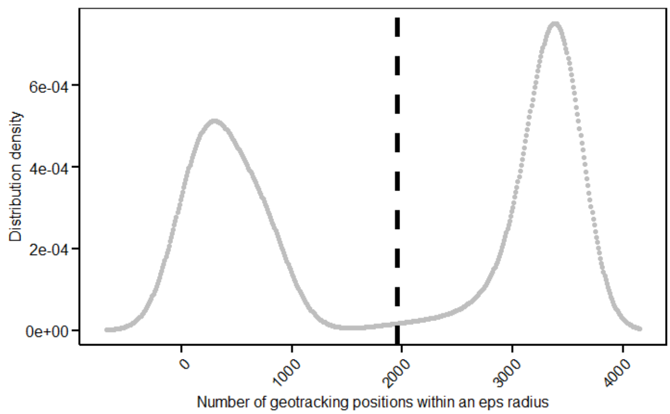

Figure 3: Binomial distribution local density of the geotracking positions within an eps radius. eps = 0.0005° on the plan latitude/longitude. Data are from 8 GPS sensors from the farm A on a segment of 7 days. The dashed line represents the local density threshold defined by the algorithm to discriminate pasture local density to barn local density.

Figure 4: Representation of the geotracking positions after labelling as “barn” (black dots) or as “pastures” (white dots). Data are from 8 GPS sensors from the farm A on a segment of 7 days (same data than in the figure 3).

Parameters were defined in the farm A as *Eps* = 0.0005° and *T* = 7 days and in the farm B as *Eps* = 0.0003° and *T* = 14 days. Then in the step 2, for every segment of *T* days, the algorithm uses the DBSCAN algorithm to identify the barn cluster with the *Eps* chosen by the user at the previous step and *minPts* = the local density threshold identified by the step 1. The geotracking positions are then labelled “barn” if they are in the cluster or “pastures” if they are not (figure 4). In the step 3, the algorithm applies kinetics corrections to missing data: if there was more than 17 minutes and less than 36 minutes between two successive geotracking positions labelled as “pastures”, new data were added as “pastures” positions. This step is based on the hypothesis that most of the time a cow will not have time for making the round trip to the barn in less than 36 min. The time spent outside (T-Out) was then estimated daily as the number of positions labelled as “pastures” per the day multiplied by the theoretical interval between two successive GPS records that is 11 min.

Statistical analysis

The quality of T-Out estimation was characterized by the estimation of the root mean squared error (RMSE). The concordance between the estimation by the algorithm and the reference method were assessed with a bland Altman plot.

Results and Discussion

In the farm A (A-2019), the average T-Out estimated with the algorithm (675 ± 221 min/d) was similar to the average of the reference T-Out (T-Outref, 676 ± 217 min/d). In the farm B, the daily average T-Out estimated with the algorithm was slightly higher in 2019 than the reference and slightly lower in 2020 (figure 6): T-Out = 1156 ± 58 min/d vs. T-Outref = 1132 ± 31 in 2019 (B-2019); T-Out = 829 ± 349 min/d vs. T-Outref = 835 ± 377 in 2019 (B-2020). The estimation of T-Out on a daily scale was achieved with RMSE of 17 min/d (A-2019), RMSE of 53 min/d(B-2019), and RMSE of 50 min/d (B-2020). The T-Out estimation was worse when cows spent more than 800 min/d outside and less than 250 min/d (figure 7). At the full experimental period, the estimation of the T-Out is very accurate because the over-estimation of the T-Out when cows spent a lot of times in the barn balanced the under-estimation of T-Out when cows spent a lot of times outside (figure 7). Moreover, the estimation difference averaged zero between 250 min/d and 800 min/d of time spent outside (figure 7). The over-estimation when cows spent a lot of time inside the barn could be explained by a lower geotracking position accuracy indoor. This lower accuracy would create false positive “pastures” labelled positions and would increase the estimated T-Out. In the other hand, little time spent in the barn might break the binomial distribution seen in the figure 3. Indeed, without a peak of distribution relative to the barn (high local density peak, figure 2), the cluster detection in the algorithm would be less specific to the barn. This issue happens when there is more missing GPS data within the barn than outside the barn. In the B-2019 dataset, the small variability of T-Out could explain the slope bias of the linear regression (figure 6) while having a similar RMSE than the dataset B-2020.

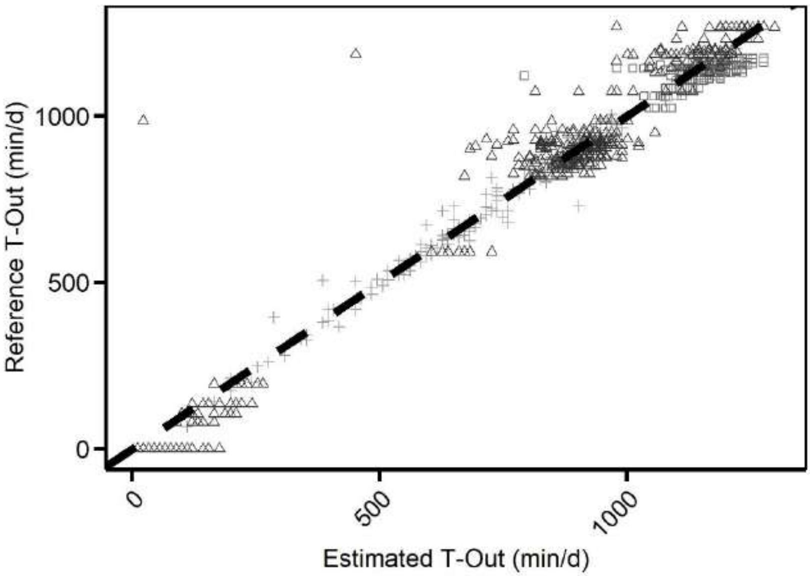

Figure 5: Correlation between the estimated and reference time spent outdoor (T-Out). One point represents the T-Out estimated for one collar for one day in the dataset A-2019 (N= 143, black triangle), in the the dataset B-2019 (N= 252, dark grey square) and in the dataset B-2020 (N= 432, grey plus). The black dashed line is the first bisector (Y = X).

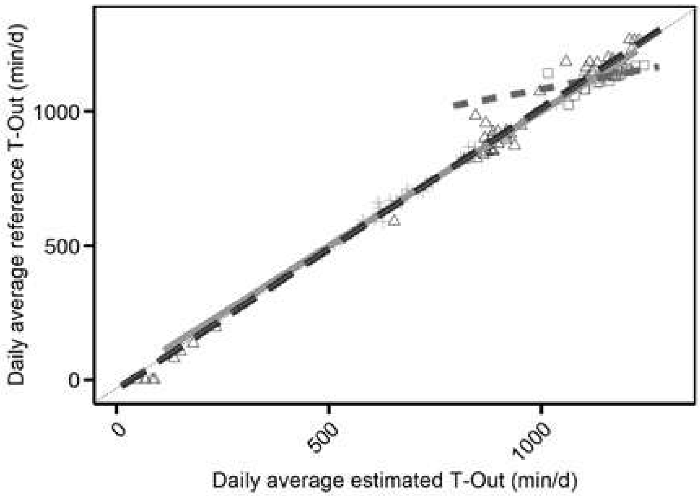

Figure 6: Correlation between the daily average estimated and the daily average reference time spent outdoor (T-Out). One point represents the average T-Out per day in the dataset A-2019 (N= 37 d, black triangle), in the the dataset B-2019 (N= 36 d, dark grey square) and in the dataset B-2020 (N= 48 d, grey plus). Linear regressions are the black dashed line for the A-2019 dataset, the dark grey dashed line for the B-2019 dataset, and the grey line for the B-2020 dataset. The thin grey dotted line is the first bisector (Y = X).

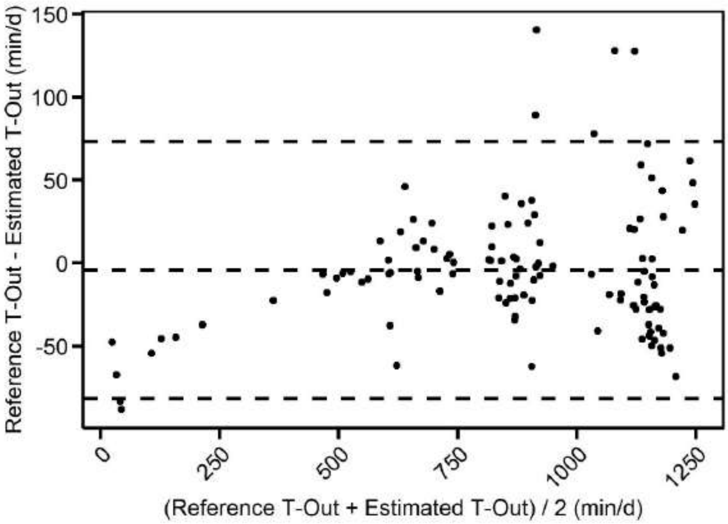

Figure 7: Bland-Altman plot of the time spent outside (T-Out) between reference T-Out and estimated T-Out on the combination of the three datasets. The middle dashed line indicates the average difference between the reference method and the estimation by the algorihm, the bottom and the top line represent 2 SD from the average difference.

The density-based classification is accurate on these datasets. Due to the variety of barns, grazing systems and its stocking rates more research is needed to study its reproducibility. Our algorithm is based on the optimization of 2 parameters (*Eps*, *T*), trade-offs of the parameters should be found regarding the stocking rates and the shortest distance to the barn from the paddocks. Other kinetics corrections (trajectory corrections) might increase the estimation by correcting the location bias. Our methodology seems particularly dependent of GPS accuracy and signal coverage, particularly when the sensors are indoor. The deployment of the solution (GPS sensors and density-based classification) in 22 commercial farms will be presented in the part II of this communication by Nicolas et *al*. (2022). It seems that in many French farms there are too many missing data due to poor connectivity to apply this algorithm (Nicolas et al; 2022).

Conclusions

A GPS embedded sensor combined with a density-based classification can be used to automatically identify the number of days dairy cows spend on pasture. The estimation is less accurate when cows spend very short time in the barn or very short time in pastures. Further validation on different systems and with more cows will be required prior to a commercial use, as well as the development of complementary services to make it useful for farmers.

Acknowledgements

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OpenCattleHub: A portable reference system for indoor tracking in livestock farming

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Abstract

In recent years, the application of sensor systems in livestock farming has increased noticeably. Tracking systems for dairy barns are of great interest in the context of smart farming to enable a continuous digital monitoring of the cows' movements, their individual behavioural patterns and the derived health status. In order to assess and validate the various number of different commercial systems, the CattleHub team specified a portable reference system for indoor tracking in livestock farming: *OpenCattleHub*. The system is defined to work in a 'plug and play' manner with portable, battery-powered UWB-based 'satlets' that can be freely arranged in a new environment. Besides easy handling by non-engineers, the focus is on high accuracy in x-y-coordinates and update frequency with full data availability including covariance matrices. Thereby, battery life is subordinate as it suffices to run the system for trials of approx. 1 – 2 weeks duration. The application lies in the scientific area: Apart from evaluating commercial systems, new applications of tracking systems can be identified and demonstrated. The *OpenCattleHub* tag is open for possible attachments of further sensors and has high scalability with an almost unlimited number of active tags.

Different trials have been conducted with a preliminary functional prototype to validate the systems specified properties and behaviour in a sports hall and under barn conditions with static and dynamic experiments. The results presented are promising with a high precision in the static trials (3.7 cm / 7.0 cm) and an overall accuracy of 67.0 cm (sports hall) and 75.3 cm (barn).

Keywords: tracking, indoor locating, dairy cow, reference system, validation

Introduction

In the context of Agriculture 4.0 and growing herd sizes, assistance systems gain increasing importance in livestock farming. Sensor systems used for animal monitoring have the potential to support farmers in their daily caretaking by providing meaningful data. They allow a continuous surveillance leading to a larger database for decision making. Besides taking a burden of the farmers' workload and responsibility, also animal welfare benefits from advantageous decisions. Indoor tracking systems are of special interest as they monitor the animals' movements and behavioural patterns together with a spatial component. Thus, saving time while searching for individual animals, but also enabling more sophisticated data analysis and derived information. The resulting applications are manifold.

In cattle farming, various indoor tracking systems (e. g. CowLocator[1], CowView[2], and CattleData[3]) are available for dairy barns. They apply different radio technologies and methods for deriving positions which differ in localization accuracy, power consumption as well as functionality. In order to assess and validate these systems, the CattleHub team specified a portable reference system for indoor tracking in livestock farming: *OpenCattleHub*. To meet the requirements of a comprehensive and objective evaluation of tracking systems, *OpenCattleHub* focusses on high accuracy of x-y-coordinates and easy handling by non-engineers. Literature studies have shown that such a reference system for comparative analyses of commercial tracking systems in barn environments is not yet available.

In the following, the concept of *OpenCattleHub* will be introduced together with validation results of a preliminary functional prototype. Different trials have been carried out in a sports hall and under barn conditions without animal presence. Thereby, static and dynamic measurement series have been conducted.

Material and methods

<u>OpenCattleHub</u>

The specified *OpenCattleHub* tracking system consists of anchors (‘satlets’) with known positions and mobile transponders. The satlet infrastructure shall be mounted at a height of around 3.5 m. With that, the antenna beam covers a maximum area and the satlets can be distributed sparsely in the environment (up to 20 – 25 m distance between the satlets). The satlets do not need any special geometric order or specific points of installation. Also the height can be varied and does not need to be uniform, so that the system can be adapted to any indoor setting, for example a barn or a hall. The transponders can be located inside the area spanned by the satlets.

The localization technique is reverse TDoA (Time Difference of Arrival). That means the satlets transmit their timing data to the transponder – like GPS satellites to GPS receivers. Instead of satellite signals, *OpenCattleHub* uses ultra-wideband signals (UWB) for indoor localization. The transponders are configured to calculate their location onboard based on the received timing data with a resolution of 10 cm. Similar to GPS, the timing information can be delivered to uncountable devices. At the moment, the only restriction is the backlink, i. e. the data transmission from the transponders to a data collection centre. For the functional prototype, this backlink is implemented via Bluetooth and its limitations in range and data rate. A RaspberryPI single board computer was used as data collection centre. The data collection centre supervises the infrastructure’s behaviour. In addition, it collects and saves the position data transmitted by the transponders for further analysis.

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1 Nedap Livestock Management, https://www.nedap-livestockmanagement.com/dairy-farming/solutions/nedap-cowcontrol/cow-locating/

2 GEA Farm Technologies, no longer distributed

3 CattleData GmbH, www.cattledata.de

A test design for static and dynamic transponder localization was developed, which was initially evaluated in an empty sports hall that can be easily characterized in terms of radio frequency properties. These experiments were used to study the handling, the potential influencing factors and the performance limits of *OpenCattleHub*. In a second series of experiments, the system was tested in a dairy barn.

During the trials, the transponders' software was specified to calculate more detailed data. In the beginning, the position estimation was updated as often as possible (7.5 – 11.5 Hz). This was changed for the barn trials to synchronize the calculation of the position with the infrastructure's transmit rounds at 4 Hz. Moreover, a threshold of 40 cm was introduced to suppress jumping locations without transponder movement. This functionality was deactivated for the barn trials.

The functional prototype satlets used for the experiments were supplied with energy by rechargeable power banks. With this concept, the satlet infrastructure runs autarchic for several days, long enough for the performed measurement series and trials of 1 – 2 weeks.

<u>Conducted trials</u>

The trials have been conducted first in a sports hall (SH) and second in barn environment (BE). Both sports hall and free-stall barn were located at the Saxon State Office for Environment, Agriculture and Geology in Köllitsch (Germany). The sports hall had an area of 20.00×10.54 m² of which a trial field of 12.00×5.00 m² and later the whole area was equipped with six satlets. Inside the barn, the pen of one performance group (22.80×10.20 m²) was used as experimental site. Six satlets span an antenna field of 24.50×18.05 m² as shown in Figure 1. The barn trials have been conducted without animal presence in order to keep disturbing factors low.

At both experimental sites, static and dynamic experiments were carried out. For the static measurement series, 65 (SH) resp. 24 (BE) measuring positions were selected covering the whole antenna field and all functional areas of the pen. At each measuring point an *OpenCattleHub* transponder was positioned immobile for a specified duration. In the sports hall, the satlets were installed at a height of 0.50 m and the transponder was placed on ground level for 30 – 120 s resulting in 225 – 1380 location estimations. In the barn, the satlets were installed at a height of 2.74 – 3.57 m. The transponder was positioned on two tripods adjusted at a height of 0.75 m and 1.45 m corresponding to the transponder height when mounted on the collar of lying and standing cows respectively. The duration was increased to 210 s due to rougher conditions resulting in 840 location estimations.

Each static measurement series was repeated at least three times on three different days. In addition, trials have been conducted in the sports hall with different arrangements of the satlets in order to investigate the effect of the satlets and their environment. To this end, four satlets were successively rotated clockwise in one experiment while keeping the measurement positions unchanged. In a further experiment, the whole antenna field including measurement positions was turned by 180° inside the sports hall.

For the dynamic measurement series, the *OpenCattleHub* transponder was attached to a baseball cap and carried by a human along predefined routes. Different vertical and horizontal routes were investigated at three velocities: slow (approx. 0.7 m s^{-1}), medium (approx. 1.0 m s^{-1}), and fast (approx. 1.5 m s^{-1}). Each route was repeated at least three times consecutively during one measurement series. In the sports hall, the satlets were moved to a height of 2.47 m for these trials.

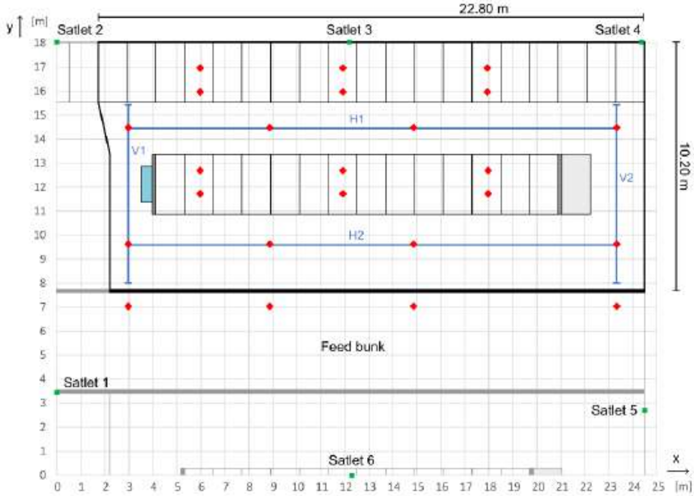

Figure 1: Experimental setup of the barn trials (left). Static measurement positions are indicated with red diamonds, routes of the dynamic measurement series with blue lines. The functional prototype transponder and its dimensions are depicted on the right.

<u>Statistical analysis</u>

For each static measurement series, the parameters Difference Root Mean Squared (DRMS), precision, and offset were calculated following Maalek & Sadeghpour (2013). Thereby, the precision measures the spreading of the obtained locations (2D standard deviation) whereas the offset characterizes the difference between the average measured location and the actual location. Finally, DRMS combines both aspects. In expectation, 63.2 % of the measured locations lie in a radius of 1 DRMS around the actual location and 95.0 % in a radius of 1.73×DRMS (R95).

For the dynamic measurement series, the sideways deviation and offset (orthogonal to the direction of movement) was calculated as well as the percentage of measured locations inside a band of ± 10, 30 and 50 cm.

ANOVA with post hoc Tukey tests were performed to compare different measurement groups. The statistical analysis was carried out with Python at a significance level of $p < 0.01$.

Results and discussion

Static measurement series

The results of the static trials are similar for both settings. In the sports hall, the overall accuracy is 67.0 ± 36.6 cm (DRMS) with a precision of 3.7 ± 8.6 cm and an offset of 66.4 ± 36.4 cm. For the barn trials, the overall accuracy is 75.3 ± 39.0 cm (DRMS) with a precision of 7.0 ± 3.2 cm and an offset of 74.8 ± 39.4 cm. In either case, the precision is high (< 10 cm deviation) and the DRMS is dominated by the offset. The precision values of the measurement series in the sports hall are significantly smaller compared to the barn. This may be due to the threshold of 40 cm for new positions that was active during the sports hall trials and fewer disturbance factors in the empty hall.

In the sports hall trials, the offset in x- and y-direction differed for each measurement series with a restart of the system. This difference between measurement series (SD 44.7 cm in x- and 46.2 cm in y-direction) was greater than the difference between the measurement positions (SD 7.4 cm in x- and 6.1 cm in y-direction). Therefore, there was no effect of the transponder's location inside the antenna field.

Apart from the varying offset, there was no significant difference found when rotating the satlets. The mean measured locations for the rotation trials – corrected by the mean offset of the respective measurement series – are depicted in Figure 2. The turn of the experimental setup by 180° had no effect either.

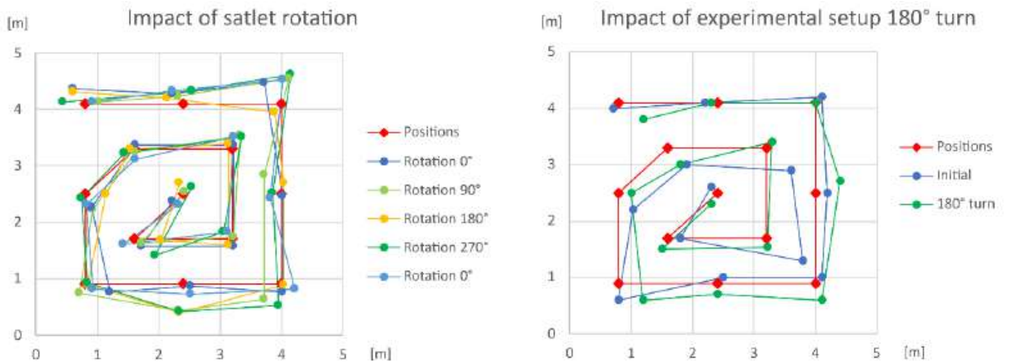

Figure 2: Impact of successive clockwise satlet rotation (left) and turn of the experimental setup by 180° (right). Depicted are the mean measured locations (corrected by offset in the left diagram) for 13 consecutive measurement positions each.

In the barn, the offset was more stable but differed significantly in y-direction for trial 2 causing a significant difference in offset and DRMS, too. The parameters DRMS, precision and offset for the trials in barn environment are listed in Table 1. Figure 3 shows the mean measured positions.

Table 1: Parameters DRMS, precision and offset for the trials in barn environment. Different letters indicate significant differences.

Parameter [cm]	Tag height		Trial		
	0.75 m	1.45 m	1	2	3
DRMS	74.4	75.8	66.6[a]	93.1[b]	65.7[a]
Precision	7.7	6.7	8.1	6.1	6.3
Offset	73.7	75.3	65.5[a]	92.7[b]	65.3[a]
Offset (x)	-36.7	-42.8	-44.8	-58.2	-19.4
Offset (y)	38.8	24.0	11.7[a]	47.1[b]	26.1[a]

Figure 3: Mean measured positions in the static barn trials.

No significant differences have been found for the parameters tag height, functional area and precision. The reproducibility of the trials is high and the precision is similar in all three trials. There is a significant difference within the offset in x-direction in all three repetitions which decreases from left (44.2 cm) to right (-145.6 cm) inside the pen. Consequently, the offset and the DRMS also differ significantly.

The experiments show that in the pen the position estimations in the middle of the antenna field are more accurate than at the edges as can be seen in Figure 3. So far, the authors did not find an appropriate explanation for this effect yet.

Similar results for static measurement series have been achieved at a different research station under barn conditions with the same version of *OpenCattleHub* used in this study (DRMS 50.7 cm, precision 4.6 cm, offset 50.5 cm; Sporkmann et al., 2022).

<u>Dynamic measurement series</u>

The movement of each route could be tracked with the system.

In the dynamic sports hall trials, the average sideways deviation was 15.7 cm on average for vertical and 21.4 cm for horizontal routes. Although the deviation was higher at a velocity of 1.5 m s^{-1} this difference was not significant. The offset varied between -64.1 and 14.5 cm (mean: -19.0 cm). The percentage of the measured locations inside the ± 50, 30 and 10 cm band around the actual routes is listed in Table 2 for the different velocities. Figure 4 shows the measured positions for the vertical routes.

Table 2: Percentage of measured locations inside a ± 50, 30 and 10 cm band at the different velocities for the dynamic sports hall trials.

band	slow velocity	medium velocity	fast velocity	all
± 50 cm	97.1	95.0	84.1	92.1
± 30 cm	83.8	76.6	67.4	76.0
± 10 cm	41.3	41.1	29.0	37.1

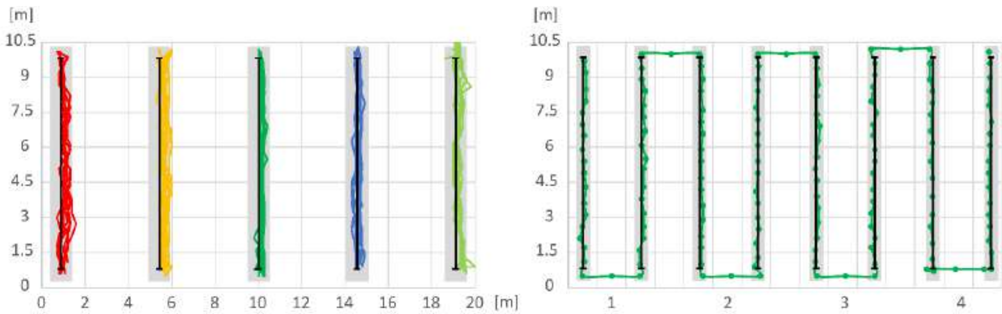

Figure 4: Measured locations for dynamic measurement series in the sports hall. Five vertical routes at low velocity are shown with their ± 50 cm band and four repititions each (left). On the right, the third route is depicted in a shifted representation so that the measured positions of each repitition (1 – 4) are visible.

In the barn, the sideways deviation of the movement was 28.8 cm on average. This deviation increased slightly with increasing velocity from 26.8 cm (slow) to 32.5 cm (fast) but not in the same extent for the four routes. The sideways deviation was highest for the two routes H1 and V2 traversing the pen's upper right corner (as shown in Figure 5). The offset varied between the four routes. For the horizontal routes it amounts to 29.6 cm. The vertical routes show the same varying offset in x-direction found in the static barn trials: 74.3 cm for route V1 at the pen's left side and -106.6 cm for route V2 at the pen's right side. For the horizontal routes, 90.3 % of the measured locations lie inside the ± 50 cm band around the actual route (30 cm band: 63.9 %, 10 cm band: 15.7 %). Due to the high offset in x-direction, only 18.3 % of the measured locations of the vertical routes lie inside the ± 50 cm band around the actual route.

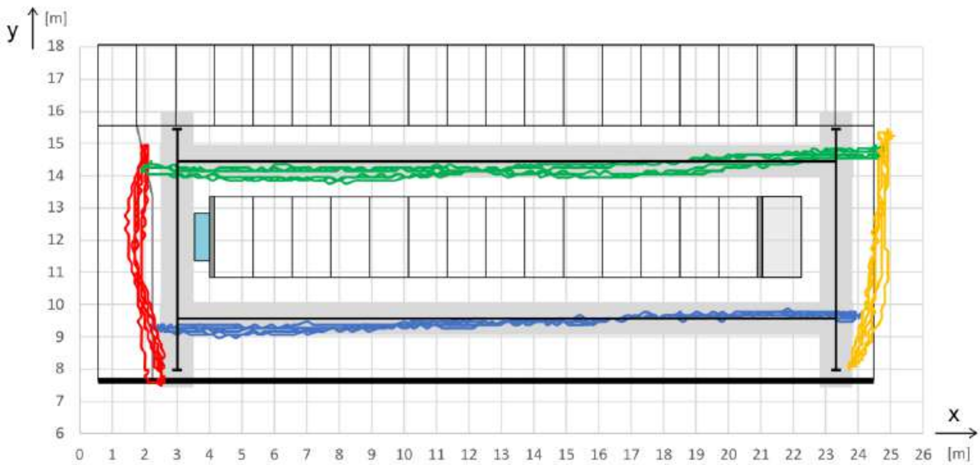

Figure 5: Measured locations for the dynamic measurement series at medium velocity in the barn with three repetitions each. Actual routes and ± 50 cm bands are indicated in black and grey respectively.

Conclusions

The conducted trials show that the *OpenCattleHub* tracking system is very stable as the low precision values indicate. The high and varying offset is a problem as it dominates and increases the DRMS. When this challenge can be solved, the resulting system is very precise and therefore suitable for comparative studies of commercial tracking systems. Such systems for dairy cows have accuracies of 0.5 – 1.2 m according to the manufacturers and confirmed in studies (CowView: < 0.50 m, Veissier et al., 2017; SmartBow: 1.22 – 1.80 m, Wolfger et al., 2017).

The dynamic measurement series show that movements can be tracked with the system with few deviations to the side. This enables the possibility to open up further new use cases for practical applications apart from validation.

As a next step, trials will be conducted with *OpenCattleHub* tags attached to the collars of dairy cows.

Finally, cows will be equipped in comparative studies with both a commercial tracking system and *OpenCattleHub*. In analysing the differences between the measured locations, the accuracy of the commercial tracking system can be derived when taking into account the accuracy parameters of *OpenCattleHub*.

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Is it possible to identify individual animal faces with state-of-the-art computer vision algorithms?

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Abstract

Individual animal identification allows producers to keep records on an animal's health history, geographical origin, dietary background, and a host of other important management information. In the field of computer vision the identification and verification of human and faces are two major issues where Deep Learning models have proven to be successful. The question remains: how performant these methods when trained on animal images? This study focused on the development of a Deep Learning based algorithm for this task. Using photos of cattle faces a similar procedure developed for human face recognition was developed. The algorithm comprised of (1) face detection, which allowed the models to focus on the bounding box around the cattle's head, (2) face alignment based on facial landmarks, to standardize the position of the head, and (3) a CNN model (called Arcface), which employs L2-regularization of the feature vector and a loss function designed to maximize of the angular margin between classes and thus separating individuals in the feature space. The resulting pipeline can be used for animal verification when a current picture of the animal and another picture from an alike animal are compared. When there is no prior knowledge on the identity of the animal, the same pipeline can be utilized to rank images based on similarity and therefore match with the closest result. To train the models involved in the cattle face recognition, a dataset of 9182 pictures of 3200 individual cattle was collected with the help of CattleTracs® software. This method can lead to a faster way to track down the outbreak of a disease or facilitate verification of intentional or unintentional miss-labelling of the animals.

Keywords: face recognition, cattle identification, arcface loss, deeplearning, precision livestock

Introduction

The accurate and reliable identification of individual animals is required in many precision livestock farming applications. From animal breeding and selection to precision feeding and disease control, animal identification can be considered a fundamental technology. In the field of animal identification, there have been different proposed solutions, which can be grouped into three categories: body modification, attached hardware and software based. The first method consists in modifying the animal body in a unique way so that it can be recognized in the future and includes practices like hot iron branding (Adcock et al., 2018), ear notching and ear or lip tattooing. These practices are by far the most invasive and can lead to severe medical issues for the animal. The fact that they're considered in violation of the animal welfare legislation in different countries, makes them obsolete and not suitable for being adopted across borders. Identification using attached hardware, such as ear tags and RFIDs, is by far the most used method for recognizing individuals, as they are generally less invasive. One of the major drawbacks of this approach is the fact that what is identified is the piece of hardware itself and not the animal and this can leave room for fraud, replication and lost ids. These inconveniences are being addressed by an increasingly popular method in the world of precision livestock and modern-day farming, known as animal recognition via software applications and in particular computer vision models. The fast-paced development in deep learning models and technologies has enabled the deployment of online pipelines able to perform a wide range of tasks. With respect to animal identification, researchers have investigated different algorithms to study and recognize different features on the animal body, the iris pattern the retina vascular network, and in the case of cows the muzzle print. Just recently an analogue to human face recognition has been applied to cattle faces (Xu et al., 2022) although to a limited dataset. Similarly, this study aims to leverage the work done in the field of human face detection, alignment and recognition to build and train a deep learning pipeline using our own dataset. This will allow us to answer the question if it's possible, and within which limits, to identify the same cow using a picture of its face without relying on special equipment like in the case of the iris recognition or on a specific type of cow like in the case of the muzzle print.

Material and methods

Experimental data

The dataset has been collected throughout different farms in Oklahoma and consists of 9182 images of 3200 different cows. Each animal has one to three pictures of its face, and when possible, from different angles. This dataset has been gathered by farmers via the CattleTracs® smartphone application that guides the user on how to take the pictures to produce a well-defined image. This dataset has also undergone a cleaning step in which we removed images from different cows that were labelled as being the same.

Labelling

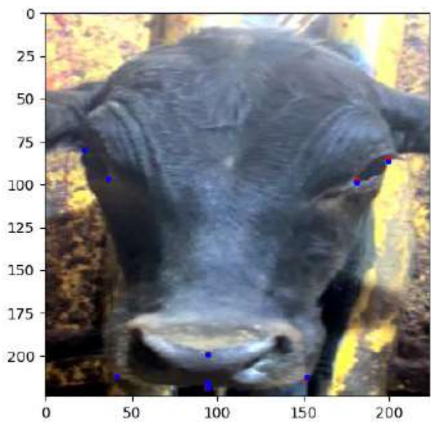

Figure 1: Example of key points on the cattle face. Key points include inner and outer corner of both eyes, nose tip, mouth corner, upper and lower lip. In blue the ground truth and in red the model prediction.

To train the face recognition model, images have been structured in different folders, one corresponding to each animal, with the id label was set as the folder name. The face recognition model used 2038 images for training and 908 to validate the model. A dataset with labelled key points has also been created for the face alignment model. The labelling has been done using COCO Annotator[1] producing JSON annotation files. We used 277 images in the training dataset and 152 in the testing dataset.

Face Alignment

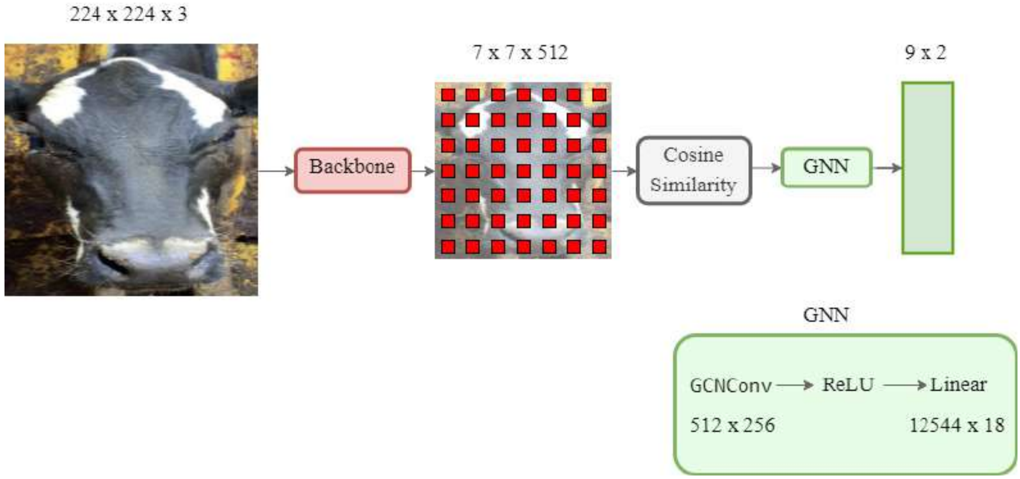

Figure 2: The architecture of the model used to regress the key points on the cow's face.

To align the face of the cow in a standard position we used a model to regress key points on the cattle face. This model is composed by a backbone, for which we used a ResNet34 and a graph neural network that outputs the regressed points. A resized image (224x224) of the cattle face is passed through a ResNet34 to extract a 7 x 7 x 512 feature tensor. To construct the graph every vector of dimension 512 is considered as a node and it is connected to its most similar vectors. This graph pass through a graph convolutional layer with a ReLU activation function, then flattened and passed through a linear layer that output the regressed coordinates of the nine key points. The idea behind this architecture is to create a 7 by 7 grid of vectors, with similar vectors referring to similar areas in the image. The vectors are then used as nodes of a graph and each of them is connected with the 10 most similar vectors. The graph convolutional layer then aggregates information amongst similar areas of the image e.g., the eyes. The resulting features are flattened and passed through a fully connected layer to output the x and y coordinates of the nine key points. To optimize this neural network, we used a loss function composed by two terms the smooth L1 loss from each point to its target and the smooth L1 loss of the 9 by 9 matrix of relative distance between the points. This last term was added to have a faster convergence and robustness to mislabelling.

1 Coco Annotator, author Justin Brooks, https://github.com/jsbroks/coco-annotator/, 2019.

Face Recognition

We used a deep convolutional neural network (DCNN) to extract feature vectors corresponding to the cattle face. The architecture of this feature extractor is MobileNet, and the output vector is compared with vectors from the same cattle and from different ones to calculate the loss. To maximize the margin between classes and minimize intra-class distance we used an Additive Angular Margin Loss (ArcFace)(Deng et al., 2018). To calculate this loss we first apply L2 normalization to the vector and the weights of the last fully connected layer. All feature vectors are projected on the unit hypersphere, such that the dot product between weights and the vector give the cosines θy that are then used in the ArcFace loss function:

$$L = -\frac{1}{N}\sum_{k=1}^{N} log \frac{e^{s\left(cos\left(\theta_{y_k}+m\right)\right)}}{e^{s\left(cos\left(\theta_{y_k}+m\right)\right)} + \sum_{j=1,j\neq y_k}^{n} e^{s\,cos\theta_j}} \tag{1}$$

Results and Discussion

The training of the recognition model presents a couple of challenges that need consideration. The first challenge was studying the false positives (FP) and false negatives (FN) rates testing the model in a range of similarity thresholds, that impose how similar two feature vectors must be to be considerate as originated from the same animal. We used a FP-FN plot (Figure 3) with different thresholds to see their rate of change and their optimal combination at a threshold of 0.18.

The second challenge is given by the fact that we have a heavy imbalanced set of pictures of different cows with respect to pictures of the same cow. This would lead the model to be biased and classify any picture as a different cow (Huang et al.). This is overcome by validating on a random number of cows each epoch and balancing same-cattle comparison and different-cattle comparison. Once we have minimized the ArcFace loss over this balanced subset of the validation dataset, we apply early stopping. The validation is done over the whole validation dataset. In Figure 4 and 5, the histograms of cosine similarity of the feature vectors in the random subsample, and on the whole validation set respectively.

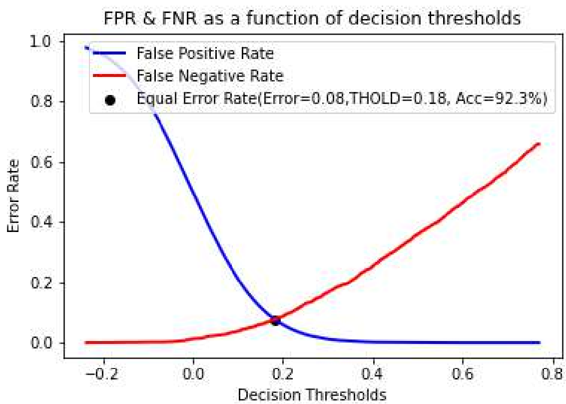

Figure 3: False positive and false negative plot using different similarity threshold.

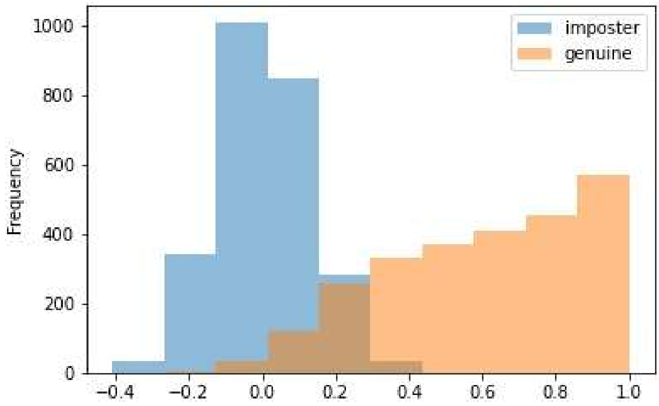

Figure 4. Distributions of cosine similarity between same cow images (genuine) and different cow images (imposter) in the random subset of the validation set.

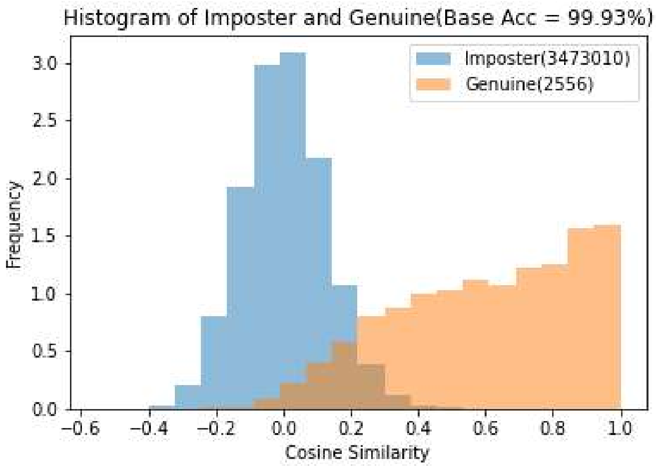

Figure 5: Distributions of cosine similarity between same cow images (genuine) and different cow images (imposter) in the entire validation set.

The results on this dataset are encouraging. Using different similarity threshold, we constructed plots to analyse different metrics like F1-score, precision and recall.

Further study is needed though as recent testing on this model showed like training on smaller datasets with fewer animals leads to severe overfitting or again training using only animals with the same uniform colour impacts the results. It will be interesting to use 3-D information to see if this lack of variation in colour can be compensated by the three-dimensional structure of the face and include this feature in the identity vector. This could be accomplished by taking different pictures from different angles to construct a key-point mesh or point cloud representation of the animal face.

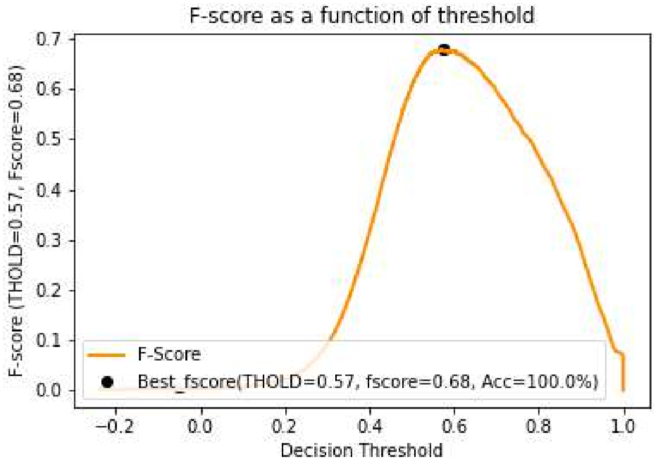

Figure 6: F1-Scores corresponding to different thresholds, maxing out at 0.57.

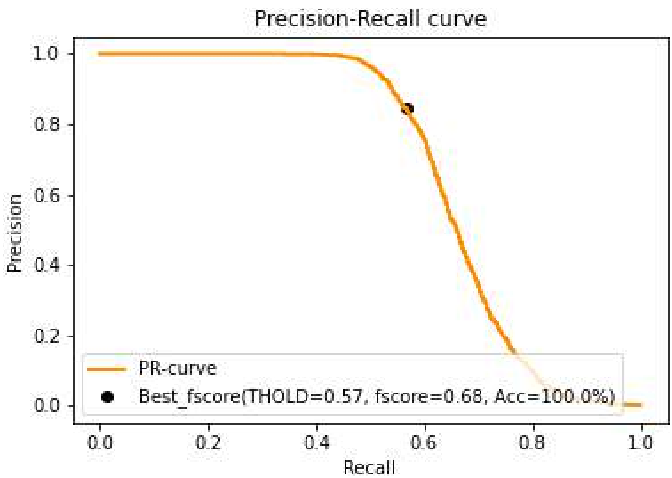

Figure 7: Precision-Recall curve with marked the 0.57 threshold derived by the F1-Score curve.

Conclusions

This paper proposes an automatic and non-invasive method of identification for cattle faces. Based on the work done for human face recognition, we developed a similar pipeline and trained on a large dataset collected by farmers. Future improvements for this research will be to use 3-D features of the cattle face, using pictures from different angles to construct the feature vector, this can provide important information in cases where the cows are uniformly coloured and don't present any distinctive feature.

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SESSION 17

Cows: Heat Stress

Heat load THI thresholds based on physiological parameters of lactating dairy cows

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Abstract

Physiological parameters of high-yielding dairy cows react sensitively under heat stress conditions. However, the severity of heat stress is difficult to quantify. The present study aimed to determine the critical threshold of the temperature-humidity index (THI) based on physiological parameters of lactating Holstein-Friesian cows under a continental climatic zone in Germany. Data were collected from 139 cows (1st to 8th lactation) housed in a loose naturally ventilated barn, on three randomly chosen measurement days per week. The following physiological parameters were measured: respiration rate (RR), measured hourly in standing and lying cows; heart rate (HR) and rectal temperature (RT), both measured twice daily. In addition, the ambient temperature and relative humidity of the barn were recorded every 5 min to calculate the current THI. The data of the physiological parameters were linked to the THI, and the heat load thresholds were determined using the broken-stick model. Considering the increases in the physiological parameters, our study provided reliable data to determine heat load thresholds for lactating high-yielding dairy cows in a moderate climatic zone. The heat load threshold could be determined for RR in standing (THI = 70) and lying cows (THI = 65) as well as for HR (THI = 72) and RT (THI = 70) in standing cows. According to the study, measures should be taken to reduce heat stress in high yielding dairy cows when THI is above 65.

Keywords: heat stress, respiration rate, heart rate, rectal temperature

Introduction

The issues regarding the sensitivity of high-yielding dairy cows to high temperatures, associated with negative effects on their performances, have been frequently reported in the literature (Galán *et al.*, 2018). The heat load of cows is commonly assessed using the temperature-humidity index (THI), determined with a combination of ambient temperature and relative humidity (NRC, 1971; Schueller *et al.*, 2013). Although most studies consider THI 72 to be a reliable heat stress threshold (Armstrong, 1994; Bohmanova *et al.*, 2007), a THI between 70 and 74 is reported by Mader *et al.* (2006) to be a potential heat stress condition for cattle. Several studies have shown that THI predictions are currently underestimating the severity of heat stress on physiological responses in dairy cows (West *et al.*, 2003; Zimbelman & Collier, 2011). Physiological parameters, such as respiration rate (RR), heart rate (HR) and body temperature, have been demonstrated as adequate and timely indicators of heat stress in dairy cows (Costa *et al.*, 2015a; Hoffmann *et al.*, 2020; Kadzere *et al.*, 2002; Moallem *et al.*, 2010). Among which body temperature have long been used as a heat load indicator (Brown-Brandl *et al.*, 2005; Galán *et al.,* 2018; Gaughan *et al.*, 2000).

The aim of the present study was to determine the heat load threshold of THI in relation to physiological parameters, such as respiration rate (RR), heart rate (HR) and rectal temperature (RT), of lactating Holsteins-Friesian cows under moderate climatic zone conditions. Thus, it is assumed that the body postures of the cows have an effect on the heat load thresholds based on physiological parameters in dairy cows.

Material and methods

Animals, Housing and Management

The present study was conducted on a dairy experimental farm in Groß Kreutz, Germany (coordinates: 52°23'47.4"N, 12°46'02.8"E, approximately 56 km west of Berlin, 32 m above sea level). The climate of this region is predominantly continental. The measurements were carried out in a naturally ventilated barn with loose housing system. The detailed barn design is described by Heinicke *et al.* (2018) and by Hempel *et al.* (2018).

The data were collected from June to September 2015 and from January to December 2016. The herd in the experimental barn consisted of 51 Holstein Friesian dairy cows from the first to eighth lactation. They were milked by an automatic milking system (Lely Astronaut A4, Maassluis, the Netherlands) and had an average daily milking production of 41.08 ± 6.72 kg.

Physiological parameters

The physiological parameters (RR, HR, RT) of the cows were carried out between 0700 h and 1500 h (GMT + 0100 h). The RR was visually observed hourly by counting right thoracoabdominal movements for 30 seconds and multiplying the value by two (i.e., breaths per minute, bpm). Cow body posture (i.e., standing vs. lying) was documented during the data collection. The HR was measured in standing cows twice a day using a stethoscope (Littmann, 3M, Neuss, Germany) between the fourth and sixth intercostal space in the breastbone region for fifteen seconds and multiplying the value by four (i.e., heartbeats per min, hpm). Immediately after the HR counting, the RT was measured in standing cows using a veterinary digital thermometer (Microlife VT 1831, Microlife Corporation, Taipei, Taiwan) and measurements were obtained directly from the rectal wall.

The datasets were collected during the experimental period with up to three measurement days per week. Every measurement day, the same group of 30 cows were randomly selected from the herd. Occasionally, some cows were replaced by others among the week measurements due to management decisions (e.g., health status, low milk yield, dry period stage). Therefore, a total of 139 lactating cows were included during the entire experimental period.

Environmental data

Ambient temperature (AT) and relative humidity (RH) of the air in the barn were recorded every 5 min with eight data loggers (EasyLog USB 2+, Lascar Electronics Inc., Whiteparish, England) positioned at eight locations inside the building at 3.4 m above the floor. The temperature-humidity index (THI) was calculated according to NRC (1971) as follows:

$$THI = (1.8 \times Tdb + 32) - (0.55 - 0.0055 \times RH) \times (1.8 \times Tdb - 26), \quad (1)$$

where Tdb is the dry bulb temperature in °C, and RH is the relative humidity in %.

The THI of all measurement points was averaged afterwards with one average THI value of the barn per time unit (every 5 min).

Statistical Analysis

In order to determine the heat load thresholds for each physiological parameter we used a broken-stick regression model. The physiological parameters were linked to the THI values from the start of every five-minute interval for the analysis. The broken-stick regression of the THI indicated a specific breakpoint at which the physiological parameters begin to change. We classified each physiological parameter over a THI breakpoint range of 42 to 77 in steps of one and identified the best predicted broken-stick regression according to the Akaike information criterion (AIC) (Akaike, 1974). The THI breakpoint was determined as the threshold regarding the AIC of “smaller is better”. All analyses were performed using SAS 9.4 (SAS Institute Inc., Cary, NC, USA).

Results and Discussion

The heat load threshold of THI for RR was determined for each body posture (standing or lying) during the data collection. Figure 1 shows the AIC values of the broken-stick regressions from the THI breakpoint 42-77. The results showed two different heat load thresholds for RR regarding the body posture. The best fit for the RR of standing cows was found at a THI threshold of 70, while the model fit for cows in lying position resulted in a lower heat load threshold at a THI of 65. The RR values of these breakpoints were 37 bpm and 39 bpm for standing and lying cows, respectively (Fig. 2).

This THI threshold for lying cows is in accordance with Spiers *et al.* (2004), who used Holstein cows and considered thermoneutral conditions within the range of 62.5 – 65.8 THI conditions. The THI threshold determined for lying cows in our study is lower than the threshold found by Heinicke *et al.* (2018) with a THI of 67 regarding the activity traits in dairy cows. In addition to the influence of THI in cows, individual animal factors, such as body posture, influence the response to heat load (Kadzere *et al.*, 2002; Pinto *et al.*, 2019) and suggest that lying cows may develop heat stress earlier and at a lower temperature threshold than standing cows, as also mentioned in a previous study by Berman (2005).

According to Wang *et al.* (2018), the lying cows decrease approximately 42% of their body surface area in dissipation; hence, standing cows are more exposed to airflow and increase the wind convection.

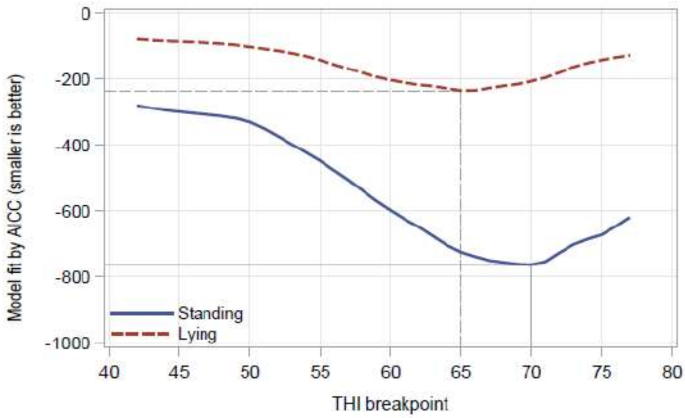

Figure 1: Relation between the Akaike information criterion (AIC) values of the broken-stick models for respiration rate of cows in a standing (solid line) or lying position (dash line), with a temperature-humidity index (THI) between 42 and 77. The predicted broken-stick model according to AIC (smaller is better) indicates a THI breakpoint of 70 for standing and of 65 for lying cows.

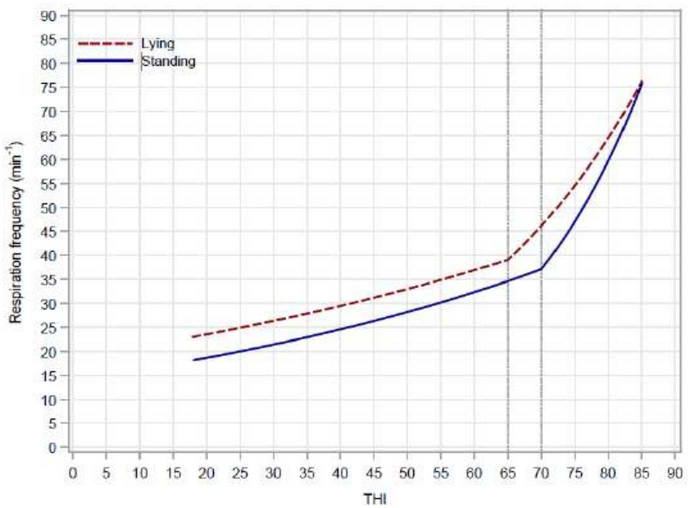

Figure 2: Determined broken-stick model for respiration rate of dairy cows in a standing (solid line) or lying position (dash line) dependent on temperature-humidity index (THI).

Following the same procedure as for RR, the HR and RT were examined as follows: the estimated model showed the best fit for a heat load threshold of 69 THI for HR, at which the HR started increasing linearly from 81 hpm. In a previous study carried out in Brazil with Holstein dairy cows, the HR (mean 76, values range: 62 to 91 hpm) demonstrated an increase point at 72 THI (Dalcin *et al.*, 2016), higher than that observed in our present study. The fact that the animal may be highly nervous directly affects the HR during the measurement (Costa *et al.*, 2015b; Dalcin *et al.*, 2016). In addition, cows under chronic heat stress tend to decrease the HR due to the internal heat generation reduction (Kadzere et al., 2002).

The model with the best fit for the determined heat load threshold for RT was at a THI of 70, and the RT of the cows tended to increase with THI > 70 (breakpoint) starting at 38.4 °C.

Our results demonstrated a distinctly lower RT on the broken-stick of the THI threshold in comparison with the data observed (39.0°C) by Spiers *et al.* (2004) in cows under thermoneutral conditions (THI ≤ 65). Heat stress conditions lead to an increase in the RT from 38.5 to 40.4 °C with THI values of 55 and 84, respectively (Garner *et al.,* 2017; Wheelock *et al.*, 2010). The THI threshold 70 for RT in the present study is in accordance with Du Preez (2000), who assessed body temperature and RR in dairy cows with THI 70 as the heat stress threshold. In contrast, the results of Dalcin *et al.* (2016) demonstrate a THI threshold of 72 for RT in high-producing dairy cows. This different effect of the latter study may be related to the different climate, in which this experiment was performed (mesothermal), with a THI between 72 and 87.

In further studies, more animal individual effects, especially the lying body posture, should be considered in the analysis of RT to assess heat load. Lying cows may have a heat load earlier than standing cows (Berman, 2005), and straw bedding increases the thermal discomfort of the animals (Angrecka & Herbut, 2017; Pinto *et al.,* 2019).

Conclusion

Based on the present study, it is recommended that heat protection measures should be initiated in high-yielding dairy cows at a THI of 65. The lowest observed THI threshold was 65, indicating changes in cows' physiological responses. In addition, it is strongly recommended to consider animal individual differences in the analysis in further studies evaluating heat load thresholds.

Acknowledgments

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Application of a respiration rate sensor in dairy cows to detect heat stress

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Abstract

A common method to measure the respiration rate (RR) in cows is to count the flank movement visually. This method is time-consuming and labor-intensive. Thus, we developed a sensor device to measure the RR continuously and automatically. The present investigation was a pilot study to test the usability of the new developed RR sensor in dairy cows. Data were continuously collected from six lactating Holstein Friesian cows. The system consisted of a differential pressure sensor, a microcontroller and software to analyze the data. A halter positioned the sensor on the jaw and a flexible silicone tube connected one port of the pressure sensor with the left nasal cavity. The experiment was carried out on two days and one night. During the data collection cow body posture (standing vs. lying) was documented and videos of the flank movements were made for the visual counting of RR. The results showed a positive correlation between visual and automatic counted RR (in breaths per minute, bpm) in lying (r=0.98) and standing cows (r=0.99). Ongoing studies with an evolved RR sensor (n=20) during summer showed the influence of heat stress on RR. With increasing temperature and temperature humidity-index (THI≥68) the RR increased from 35±0.99 to 75±1.39 bpm (MW±SE). The RR of lying cows was higher than that of standing cows. In conclusion, the results of the study showed that a continuous RR measurement is possible without disturbing the cows. In addition, the investigation of RR is a suitable method to detect heat stress in cows.

Keywords: heat stress, respiration rate, sensor, cow, THI

Introduction

The measurement of the respiration rate (RR) is an essential tool to monitor the health or stress status of individual animals. Therefore, it is an important method in research and veterinary practice. There are different influencing factors on the RR value like excitement, forced activity, pregnancy, high milk yield and pathological conditions (Gaughan *et al.,* 2000; Knickel *et al.*, 2000), but especially heat stress is known to lead to an increase in RR (Hoffmann *et al.*, 2020; Pinto *et al.*, 2019). If changes in RR can be detected early, targeted measures can be taken to alleviate the stress load on the animal and thus increase the animal welfare on the one hand and prevent performance losses on the other hand.

The most common method to measure the RR in calves and cows is to count the flank movement visually (Milan, 2016). However, this method is time-consuming, labor-intensive and not constantly possible. The continuous measurement of the RR is difficult to implement and can be physically strenuous, what can lead to miscounts. Furthermore, the constant presence of a person can cause additional stress and hence unintentionally affect the RR of the animal. Such disturbances as well as non-specific flank movements, which are not caused by respiration, can falsify the measurements (Eigenberg *et al*., 2000). Different methods have already been developed in the past to measure the RR automatically, but so far without satisfactory results regarding continuous measurements. One method is a device that monitors temperature changes near the nostrils with a thermistor (Milan, 2016). Another system consists of a belt, which is attached around the chest of animals and measures thoracic movements (Eigenberg *et al*., 2000), and one more idea is a system to measure RR via a laser distance sensor during milking (Pastell *et al*., 2007). The objective of this study was to develop a device and mounting hardware for continuous RR measurement in cows. Therefore, the sensor data were compared with the reference method of visual counting in order to evaluate whether the sensor was able to count the RR reliably.

Material and methods

Animals and Housing

The study was conducted during two days at the Educational and Experimental Center for Animal Breeding and Husbandry (LVAT Groß Kreutz, Germany, coordinates: 52°23’47.4”N, 12°46’02.8”E) during January 2018. Six Holstein Friesians cows were used in this study. On the first day, data were taken during the day and night (one cow 0800 h to 0800 h the following day and two cows 0800 h to 1800 h) and on the second day during the day (three cows 0800 h to 1800 h). For each examination day, three different cows were used for data acquisition. The dairy cows were housed in a free-stall barn, equipped with 51 lying cubicles (straw-lime mixture) and were part of an existing herd of 51 cows on average. The animals differed in their stage of lactation (1st to 5th lactation) to ensure that the sensor device works at different ages and lactation stages. The animals were able to move freely in the barn during the experimental study so as not to restrict their natural behavior. Water and a total mixed ration were freely available. The State Office for Occupational Safety, Consumer Protection and Health (LAVG Brandenburg, Germany) approved the experimental animal study under the study number 2340-1-2018.

Respiration rate sensor

The prototype of the new developed device to measure RR (Figure 1) consisted of a differential pressure sensor, a microcontroller and software to analyze the data. A halter positioned the sensor on the jaw, fixed on the right side of the head. A flexible silicone tube connected one port of the pressure sensor with the left nostril and ended in the nasal cavity. The other port of the sensor was left open and hence exposed to ambient pressure. Through a flexible silicone tube, the nasal exhalation pressure was transmitted to the pressure sensor, and the microcontroller converted the incoming analog signal from the pressure sensor to a digital signal. Thus, the incoming pressure (mbar) at the sensor increased at the beginning of the exhalation, which was characterized by an increase in the breathing curve (sampling rate 100 Hz). At the beginning of the inhalation, the pressure at the sensor decreased and a negative pressure was generated, which resulted in a drop of the breathing curve (Figure 2). A power bank (capacity 2600 mAh) secured the power supply and the data transmission to a server occured via a wireless local area network (WLAN).

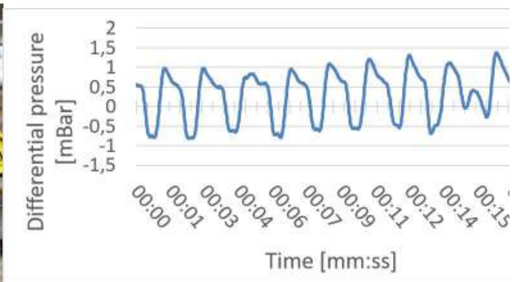

Figure 1: Respiration rate sensor (prototype)

Figure 2: Pressure difference curve measured with respiration rate sensor

Data collection

At the beginning, the test animals were stationed at the feeding fence to be equipped with the sensor. After a short acclimatization time of 30 min, the data were recorded. The RR data were logged continuously over the investigation period without interruption. During the observations no restrictions on the behavior of the animals were obvious. Cow body posture (standing vs. lying) was documented during the data collection and video recordings (Samsung Galaxy Note 10.1, Seoul, South Korea) were made regularly for the visual counting of RR afterwards. For each body position and each cow, at least two data flows with a total duration of one minute each were used and included in the validation. A Light Emitting Diode (LED) fixed to the sensor signaled the beginning of each minute during the video recordings. The LED signal was also used as a marker in the data flow so that the recordings could be assigned. In addition, the time of the recordings was synchronized with the time of data acquisition. The generated data were saved and graphically displayed in Excel. The breathing pattern was counted visually (peak counting method) for a fixed period of one minute each. An increase and subsequent decrease of the curve corresponded to one breath (Figure 2). Independent of the sensor data, one person counted the RR visually by use of the videos. For this purpose, according to the time stamp of the sensor data, the RR was counted from the video recordings for one minute. The flashing LED indicated the beginning and end of counting. One breath was defined as the right-sided or left-sided lifting and compression of the abdomen.

Further development for heat stress measurements

In ongoing trials, we already developed the RR sensor further, so that it can be fixed on the nose of a cow without the halter (Fig. 3). A battery gave the power supply here. This evolved RR sensor was used in 20 dairy cows from April to September 2019 to measure the influence of heat stress on the RR over a longer time period. The LAVG Brandenburg (Germany) approved the heat stress study with dairy cows under the study number 2340-8-2019. During the trial period, the ambient air temperature and relative humidity were recorded every 5 min using eight data loggers (EasyLog USB 2+, Lascar Electronics Inc., Whiteparish, UK) positioned 3.4 m above the floor in the barn.

Based on these values, the temperature humidity-index (THI) was calculated according to NRC (1971) as follows:

$$THI = (1.8 \times Tdb + 32) - (0.55 - 0.0055 \times RH) \times (1.8 \times Tdb - 26),$$

where Tdb is the dry bulb temperature in °C and RH is the relative humidity in %.

Figure 3: Further developed respiration rate sensor

<u>Statistical analyses</u>

The statistical evaluation was performed by JMP (12.0.1, Cary, North Carolina) with a significance level of α=0.05. To assess the strength of the statistical relationship between the RR generated by the sensor data and the visual observation data, a Bravais-Pearson correlation analysis was conducted. To describe the agreement between the visual observation and the sensor data, a matched pairs analysis was performed, which includes a Tukey mean-difference plot and the results of a paired t-test. The results are presented as mean-difference plots, also known as Bland-Altman plot (Bland & Altman, 1999).

Results and Discussion

The test animals had an average RR of 29 bpm during the pilot trial period with a standard deviation of 10 bpm. This is in accordance with Knickel *et al.* (2000), who give 25-35 bpm as the reference range for adult cows. The difference between the two paired measurements (sensor data and visual counting data) are shown in Figure 4. The horizontal line illustrates the mean difference, with the 95% confidence interval (CI) above (dotted line).

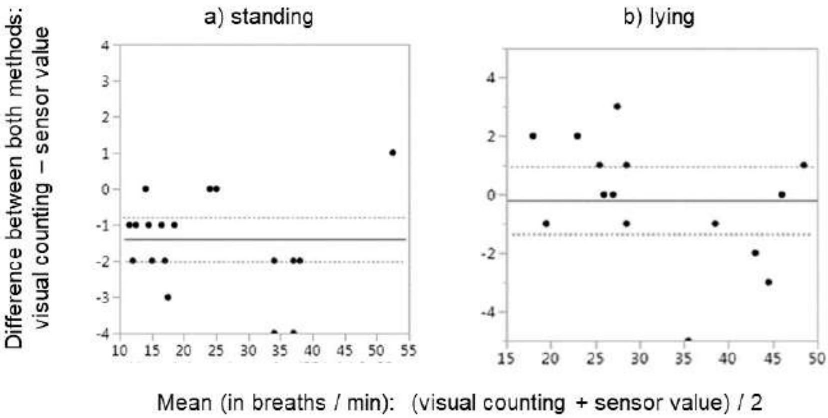

Figure 4: Difference between respiration rate (RR) during standing (a) and lying (b) counted by the RR sensor and visual observation compared with the mean of both methods. Data (each in RR/min) represent recordings of 1 minute each (95% confidence interval of a: -2.01 to -0.78; b: -1.35 to 0.95; mean difference of a: -1.4; of b: -0.2)

The correlation analysis for RR during standing showed a high correlation coefficient (*r*) and a high coefficient of determination (R^2) (r=0.99, R^2=0.99, n=20). The differences plotted were not homogeneous and normally distributed (Figure 4a). The differences represent a strong one-sided shift. The mean difference of -1.4 during standing showed that the sensor counted 1.4 breaths more per minute than the visual counting. The CI of the mean difference was -2.01 and -0.79 breaths ($P < 0.0001$). The results during standing showed that there is a significant difference between automatic and visual counting.

During lying the results of the correlation analysis showed a high correlation coefficient (*r*) and coefficient of determination (R^2) for the RR (r=0.98, R^2=0.96, n=15), as well as a homogeneous and normal distribution of differences during lying in the mean-difference plot (Figure 4b). The mean difference of -0.2 during lying showed that the sensor counted 0.2 more bpm than visual counting. The CI of the mean difference was -1.35 and 0.95 breaths (P=0.71). The results for lying showed no significant difference between the automated and visual counting methods.

However, in this context it is important to clarify that the one-sided shift of the differences, mainly in the standing position, should be considered. This is probably due to shallow breathing or difficulties in counting due to short-term limb movements during standing, which may have resulted in a partial counting of the RR. With repeated analysis of the video recordings or direct observations beside the animals, these missing breaths could be identified. In accordance, Milan *et al.* (2016), who also used the nasal cavity to measure RR, showed both fewer breaths (n=4) and more breath (n=1) counted by the sensor (thermistor) in comparison to visual counting, whereby no differentiation between lying and standing position was done. It should also be considered that counting inhalations and exhalations may be a more precise approach compared to counting flank movements, which can be triggered by other causes.

Ongoing studies with the evolved RR sensor during summer showed the influence of heat stress on the RR. With increasing air temperature and temperature humidity-index (THI ≥ 68) the RR increased from 35 ± 0.99 to 75 ± 1.39 bpm (MW±SE). The RR of lying cows was higher than that of standing cows. Our own research confirmed findings of previous studies that various factors in addition to THI, such as body position and milk production, can influence the susceptibility of dairy cows to heat stress (Gaughan *et al.*, 2000; Berman, 2005).

The animals of the pilot study (n=6) and of the ongoing trial (n=20) showed a high level of acceptance to the sensor. There was no obvious outward impairment in behavior and health.

Conclusion

The investigations for the validation of the RR sensor have shown that the measurement of the RR by a pressure difference sensor provides reliable data. Continuous measurements are possible and can replace visual observations. Overall, it was found that the RR sensor did not disturb the animals' behavior during the study and their health was not affected. Abnormal behavior, such as a violent defensive reaction or restlessness, could not be detected. RR is well suited as a heat stress indicator because it is very sensitive as well as timely in indicating a stress response and can be measured individually. The measurement results have also shown that with rising THI the RR increased. In addition, lying cows had a significantly higher RR under heat stress than standing cows.

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Thermodynamic prediction of heat stress in dairy cattle

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Abstract

Heat stress in dairy cattle is an ongoing challenge that is expected to be exacerbated by climate change and continual selection for higher yield. Numerous studies have attempted to develop heat stress indices based on regression of meteorological parameters and animal responses or to select the "appropriate" index from the literature. Despite these efforts, a universal index remains elusive and many of the existing induces have been shown to be inadequate for precision farming in times of climate change. Recently, mechanistic heat-balance models for assessing the thermal balance of the animal with its surroundings have seen a resurgence of interest. Nevertheless, little effort has been made so far to apply such models systematically to identify conditions of potential heat stress. The present work adopts an existing model from the literature to identify conditions of heat accumulation (thermal imbalance) and heat strain (body-core temperature rise) for typical Holstein dairy cows. It is shown that the onset of heat accumulation and heat strain strongly depends on the air temperature and speed, but hardly on humidity.

Keywords: heat stress, thermoregulation, mechanistic model, critical temperature

Introduction

Heat stress remains a challenge to both productivity and animal welfare in dairy farming, particularly in precision farming of high-yield cattle in times of climate change. Most studies of heat stress in dairy cattle focus on statistical relations between meteorological parameters such as temperature, humidity, wind speed, solar radiation, and animal responses such as body temperature, respiration rate, milk yield. The typical result through regression analysis of such relations is a "heat stress index" and corresponding heat stress criteria. A recent review Ji *et al.* (2020) lists as many as 20 such indices for dairy cattle. Nevertheless, and despite more than 60 years of research, a versatile index remains elusive.

An alternative, possibly complementary, approach to statistical indices is the use of mechanistic models of heat generation and dissipation for assessing the thermal balance of animals and identifying conditions of potential stress. Examples include the work of McArthur (1987), Ehrlemark and Sällvik (1996), Turnpenny *et al.* (2000a,b), McGovern and Bruce (2000), Thompson *et al.* (2014), Li *et al.* (2021). Despite its fundamental robustness, the heat-balance approach has attracted much less attention than the statistical approach and its application remains limited. Very few studies deal with the application and assessment of heat-balance models. The papers by Bloomberg and

Bywater (2007) and van der Linden *et al.* (2019) are two examples. Even fewer attempts have been made at systematic application of a heat-balance model to identify conditions of potential heat stress and to develop relevant indices and/or thresholds accordingly. Furthermore, aside from the simplified general model by Turnpenny *et al.* (2000a,b), no effort has been made to address the implementation gap, particularly to facilitate implementation in predictive-model control of the barn climate.

A general shortcoming of the heat-balance models is lack of validation against experimental data. Turnpenny *et al.* (2000b) observed that the limited data available on the partition of heat loss, heat generation and the thermophysical characteristics of the livestock hinders further development and refinement of heat-balance models. Two decades later, that limitation remains the case, although some recent studies (Yan *et al.*, 2021; Zhou *et al.*, 2021) have attempted to address the validation gap. Mechanistic models have also been criticized as unsuitable for use in precision farming due to complexity and presence of many parameters that often need to be re-evaluated or adjusted for each application (Wathes *et al.*, 2008). Nevertheless, the present day's computational power has removed practical barriers to wider application of mechanistic models.

The present paper proposes a framework for systematic application of mechanistic heat-balance models to predict conditions of potential heat stress in dairy cattle and derive improved heats stress criteria. An existing model from the literature is utilized to identify the onset of heat accumulation and heat strain in terms of the standard meteorological parameters. Recommendations for further establishment and wider application of mechanistic models are presented.

Model description

The general heat-balance model by (Turnpenny *et al.*, 2000a) was adopted. In this model, the total heat dissipation from the animal, G_e, is estimated based on the thermodynamics of heat and mass transfer between the animal and its environment, and compared with the thermoneutral metabolic heat generation rate, M. Thermal balance, i.e. $G_e=M$, is assessed as a prerequisite of thermoneutrality.

Cattle dissipate bodily heat through respiration and from the skin. The total heat dissipation rate on a flux (per unit skin surface area) basis can be written as:

$$G_{\mathrm{e}} = \frac{\rho c_{\mathrm{p}}}{r_{\mathrm{H}}}(T_{\mathrm{c}} - T_{\mathrm{a}}) + \frac{\rho c_{\mathrm{p}}}{r_{\mathrm{R}}}(T_{\mathrm{c}} - T_{\mathrm{r}}) - S_{\mathrm{abs}} + E_{\mathrm{r}} + E_{\mathrm{c}}$$

The first term on the right-hand side represents convective heat transfer from the haircoat to the ambient air while the second term represents the net long-wave radiant exchange at the external surface of the haircoat, with in both terms denoting the resistance to heat transfer in [s/m] and ρc_p J/(m^{3}K) a constant; S_{abs} is the absorbed solar radiation; E_r is heat loss through respiration; and E_c is the latent heat loss from the skin, normalized by the skin surface are, A_s.

The sub-models for heat transfer from the animal and thermoregulatory responses were also adopted from Turnpenny *et al.* (2000a,b), with a few exceptions, as outlined below. More details about the model implementation and the sub-models are available in a recent publication (Foroushani and Amon, 2022).

Ambient conditions

Ambient conditions are defined in terms of pressure, p [kPa], temperature, T_a [°C], mean radiant temperature, T_r [°C], relative humidity, RH [%], wind speed, u [m/s]. Since heat stress in naturally ventilated barns is of main interest to the present study, the direct solar irradiation was assumed to be zero (S_{abs}=0). For simplicity, it was assumed T_r=T_a.

Thermoregulation

The thermoregulatory responses are iteratively adjusted to find the conditions of thermal balance, i.e. G_e=M, following the "principle of least metabolic cost" (Mount 1974; Turnpenny *et al.* 2000a). This means that, for given boundary conditions (T_b, T_a, RH, u), thermoregulation is simulated by:

— Decreasing the tissue resistance to heat transfer (vasodilation) until thermal balance is achieved (Ge=M).
— If the minimum tissue resistance is not sufficient for thermal balance, i.e. Ge<M, the cutaneous latent heat loss (sweating) is increased until thermal balance is achieved.
— If the maximum sweating rate (physiological or environmental) is not sufficient to maintain G_e=M, heat will accumulate in the body and the body-core temperature will increase. The corresponding ambient conditions signify conditions of potential heat stress.

As discussed below, the respiration rate is independently calculated as a function of the ambient conditions (T_a, RH), using empirical correlations.

Convective heat loss

The convective resistance, r_H, was estimated using an empirical correlation for cattle (Wiersma & Nelson 1967). Since air is hardly ever still in naturally ventilated barns, only forced convection was considered.

Latent heat loss from skin

Heat loss through the evaporation of sweat on the skin is a crucial thermoregulatory mechanism. The maximum latent cutaneous heat flux is a major determinant of the onset of heat stress. There is a physiological limit on the sweating rate, dictated by water availability and the activity of sweat glands. Moreover, as discussed by Turnpenny *et al.* (2000b), extremely high humidity may suppress E_c below the physiological limit due to low evaporation potential. In other words, there is also an *environmental* limit on E_c. As pointed out by McArthur (1987) $E_{c,max}$ is normally physiologically limited. Here, the a phsysiological limit of $E_{c,max}$ =120 W/m^2 was assumed, in accordance with Turnpenny *et al.* (2000a), which in the conditions of interest to the present study ($T_a \leq 40$°C, RH < 60%) prevails over the environmental limit.

As suggested by McArthur (1987), the evaporation of moisture from an animal's body can take place below the skin surface. In cold, for instance, when the sweat glands are inactive and the skin surface is dry, there is water vapour loss by diffusion through the skin, i.e. $E_{c,min}>0$. Following McArthur (1987), it was assumed $E_{c,min}=0.04E_{c,max}$. This baseline was implemented in the model by initializing E_c at $0.04E_{c,max}$.

Respiratory heat loss

The inspired air was assumed to be at the ambient conditions and the expired air was assumed to be saturated at a temperature calculated based on the empirical correlation proposed by Stevens (1981). Notably, Stevens' results show that the exhaled air is not at the body temperature, contrary to the assumption made in many studies, e.g. McArthur (1987) and Turnpenny *et al.* (2000a,b). The respiration rate and tidal volume were similarly calculated using correlations proposed by Stevens (1981). Respiratory heat loss was then calculated based on an energy balance between the inspired and expired air with the enthalpy of air calculated using the standard psychrometric relation for moist air and the density of dry air estimated using the ideal gas model.

Animal shape and size

The size characteristics were chosen to represent a typical, high-yield Holstein cow: $m = 670$ kg, $A_s = 7.04$ m^2, $d_t = 0.5$ m. A haircoat length of $l = 9$ mm was chosen to represent the summer conditions. Given that l is small, the difference between the skin surface area and the haircoat surface area as well as the effect of the haircoat on the curvature of the outer surface were ignored.

Metabolic heat generation and body temperature

The metabolic heat flux, M [W/m^2], was calculated based on the regression proposed by van Knegsel *et al.* (2007) for daily heat production in lactating cows, converted to an average flux based on the skin surface area. Metabolic heat generation was assumed constant at the thermoneutral rate. In reality, the metabolic rate declines with prolonged exposure to heat, thereby increasing the animal's tolerance to heat stress. This decline is associated with a decrease in food intake and in thyroid gland activity. See the paper by McArthur (1987) for details.

The thermoneutral body-core temperature was assumed constant at $T_b = 39$°C.

Heat stress threshold

As pointed out by West (2003), the term "heat stress" is used rather loosely to signify the climate, climatic effects or the animal's response. A relatively concrete definition has been suggested by Lee (1965), where heat stress is defined as "the conditions that displace the animal's thermoregulation system out of the thermoneutral zone", and heat strain as "the displacement or deviation of the physiological, behavioral or productive parameters from the corresponding base values in the thermoneutral zone". Nevertheless, Lee's definitions are still qualitative; in order to adopt the definitions in a numerical framework, critical thresholds must be established for heat strains, e.g. rise in the body-core temperature or respiration rate or drop in the daily milk yield. The establishment of those thresholds, ideally based on independent physiological or productive considerations, is a challenging, multifaceted task that calls for dedicated studies in the future. Here, an increase of 1°C in the body-core temperature was assumed as critical heat strain.

In order to apply the present steady-state model to identify this threshold, experimental data on the relation between T_b and T_s were used. As shown in Figure 1, past a certain threshold, T_b increases linearly with T_s in order to maintain a minimal temperature difference (in this case ~3 °C) and allow heat dissipation through the body tissue. Therefore, the critical strain ΔT_b=1°C was approximated as an identical rise (1°C) in T_s above equilibrium (see Results).

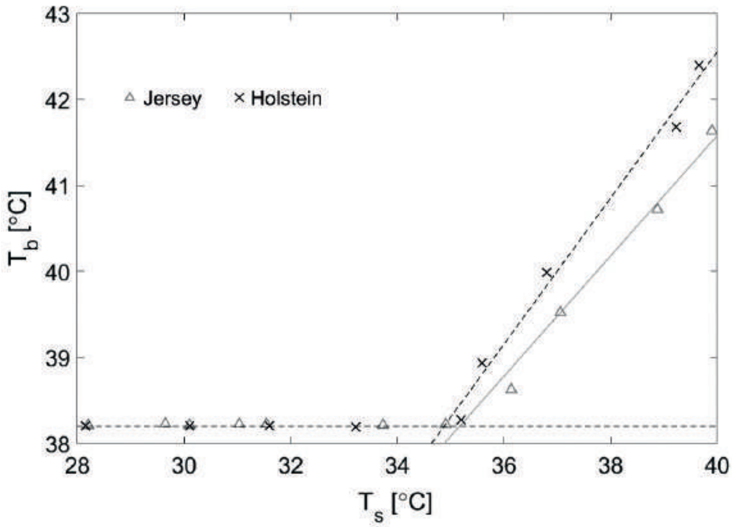

Figure 1: Body-core temperature vs. mean skin (trunk) temperature. Data from Worstell and Brody (1953)

Results and discussion

Figure 2 shows sample results obtained from running the heat-balance model at constant u and RH, and for various values of T_a. Two main outputs are to be observed: 1) G_e and specifically its magnitude relative to M; $G_e<M$ means the endogenous heat cannot be fully dissipated and will start to accumulate in the body, eventually causing stress, and 2) T_s and specifically its intersection with the T_s=34°C line, which represents the elevated T_s corresponding to ΔT_b=1°C (the horizontal segment of the T_s curve corresponds to equilibrium at maximum vasodilation).

Figure 2a, for instance, suggests that, for u=2 m/s and RH=40%, the thermoregulatory responses are sufficient to maintain the heat balance up to $T_a \approx$ 20°C. In other words, increasing T_a to ~20°C, vasodilation and sweating can reduce the overall heat transfer resistance between the body core and the ambient to compensate for the reduction in $T_b - T_a$. Beyond that point, it takes roughly another 6°C increase in T_a for critical heat strain (ΔT_b=1°C) to occur, as indicated by T_s=34°C.

The effect of air speed can be seen by comparing Figure 2a, 2b and 2d; higher air speed enhances convective heat loss from the skin, thus shifting the onset of heat accumulation to a higher T_a. In other words, vasodilation (reflected by the rise in T_s) and sweating (reflected by the rise in E_c) are triggered, and therefore exhausted, at higher T_a, meaning G_e=M can likewise be maintained at higher T_a. Consequently, critical heat strain also occurs at higher T_a.

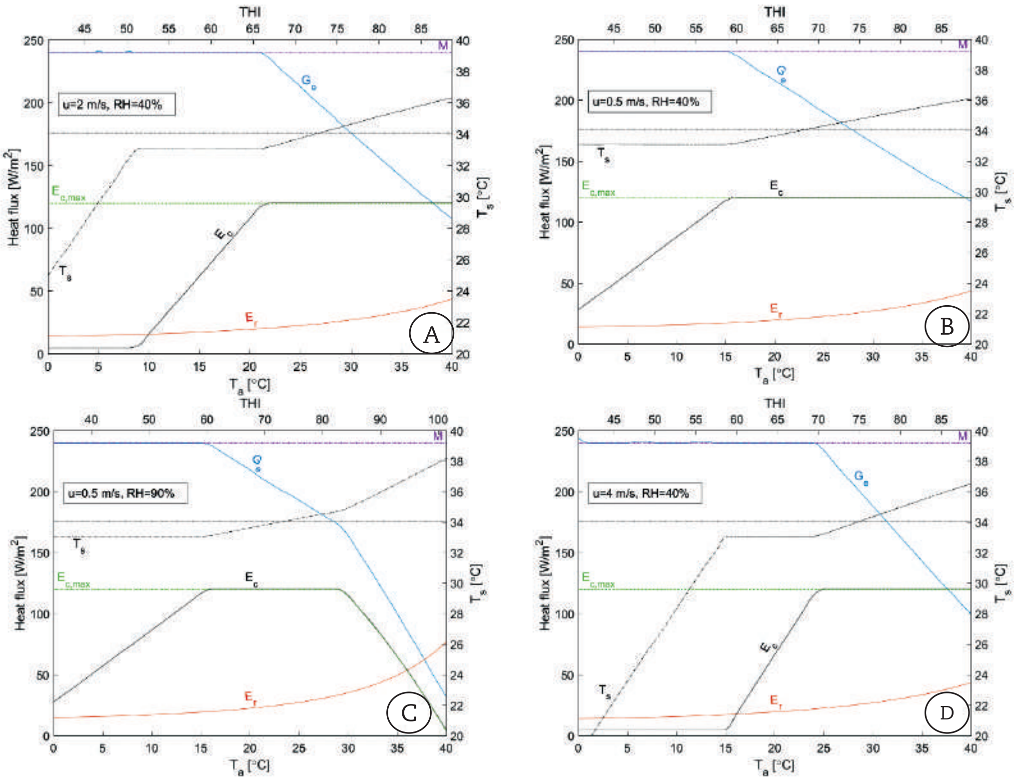

Figure 2: Equilibrium heat fluxes and skin temperature of a typical Holstein dairy cow (m = 670 kg, dt = 0.5 m, l = 9 mm) as a function of the ambient temperature at various air speeds and relative humidity, estimated based on the heat-balance model of Turnpenny *et al.* (2000a,b) [M: metabolic heat generation, G_e: total heat dissipation, E_c: cutaneous latent heat loss, E_r: respiratory heat loss, T_s: skin temperature.]

Most notably, Figure 2 suggests that humidity has little effect on the onset of heat accumulation and critical heat strain. Comparing Figure 2b and 2c, representing moderate (RH=40%) and extremely high (RH=90%) relative humidity, the various heat fluxes are virtually identical up to T_a27°C, well beyond the onset of heat accumulation (T_a15°C in both cases). The adverse effect of excessive humidity (RH=90%; Figure 2c) on heat dissipation becomes apparent only at T_a27°C, some 12°C above the onset of heat accumulation and 4°C above the onset of critical heat strain. This observation is in agreement with the conclusion by Turnpenny *et al.* (2000b). The thermodynamics of thermoregulation can explain this seemingly surprising result. The ambient humidity could affect the latent components of heat loss, namely latent heat loss through respiration and though the evaporation of sweat. Nevertheless, as discussed above and shown in

Figure 2, heat loss through the evaporation of sweat is usually physiologically limited, i.e. not suppressed by RH. Moreover, although E_r is a function of RH, it is by far dominated by E_c. Therefore, the adverse effects of RH are not a determinant of the onset of heat stress.

Finally, Figure 2 shows how reliance on indices such as the temperature-humidity index, THI (NRC, 1971), as predictors of heat stress/strain is inadequate and possibly misleading. Comparing Figure 2a, 2b and 2d, it is seen that the THI thresholds for the onset of heat accumulation and critical strain both depend on, *u*. Note that THI is shown on the upper horizontal axes.

Figure 3 shows thresholds for heat accumulation and critical heat strain at RH=40% and as function of *u*. The onset of heat accumulation was calculated as the ambient temperature at which G_e falls to 99% of *M*. The onset of critical heat strain was calculated as the ambient temperature at which T_s=34°C. As discussed above, RH does not influence the onset of heat accumulation or critical heat strain. The results shown in Figure 3 therefore represent general trends, regardless of RH.

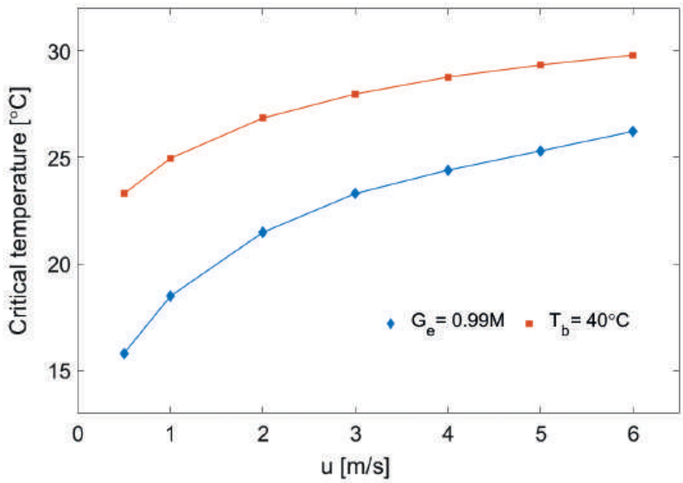

Figure 3: Critical temperature for the onset of heat accumulation (G_e = 0.99M) and critical heat strain (ΔT_b = 1°C) [RH = 40%]

Conclusion

Mechanistic heat balance models are an alternative, and possibly complementary, approach to the statistical heat stress indices that have dominated dairy science for the past six decades. In the present work, an existing model from the literature was used to assess the thermal balance of a typical high-yield Holstein cow under various combinations of temperature, humidity and air speed. The results highlight the effect of air speed on heat dissipation from the body and consequently on the onset of heat strain. It was shown that, depending on the air speed, bodily heat accumulation can start at temperatures as low as ~15°C or as high as ~25°C. Also depending on the air speed, critical heat strain, here defined as 1°C increase in the body-core temperature, occurs at ambient temperatures 5-8°C above the onset for heat accumulation. Notably, the onset of heat accumulation and critical heat strain does not depend on humidity. In order to further establish the mechanistic approach, future work will focus on validation against experimental data, refining thermophysiological definitions for heat stress/strain and the incorporation of productivity (lactation) and diurnal metabolic heat cycles in the model.

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A machine learning approach for the assessment of heat stress in dairy cows

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Abstract

PLF devices are being increasingly adopted in the dairy sector, including automatic milking systems and monitoring tools for animals and environmental conditions. As a consequence, a great amount of data concerning individual animals are available and could be effectively used for the calibration of numerical models for the prediction of production trends. Besides, the machine learning approaches represent extremely promising solution in PLF and their application in dairy cattle farming would increase the sustainability and the efficiency of the sector. The study aims to define, train, and test a model developed through machine learning techniques, adopting a Random Forest algorithm, with the main goal to assess the trend in daily milk yield of individual cows in relation to environmental conditions. The model has been calibrated and tested on the data collected on 91 lactating cows of a dairy farm, located in northern Italy, and equipped with an automatic milking system and thermo-hygrometric sensors during the years 2016–2017. In the statistical model, the daily milk yield is evaluated as a function of the days in milk and daily average temperature-humidity index in the same day and in the previous five days. In this way, extreme hot conditions inducing heat stress effects can be considered in the yield predictions by the model. The average relative prediction error of the milk yield of each cow is about 2% of the total milk production.

Keywords: livestock sustainability; precision livestock farming; heat stress; random forest; machine learning method

Introduction

PLF devices are being increasingly adopted in animal production and in particular in livestock farming, including monitoring tools for animals and environmental conditions (Tassinari et al., 2021). As a result, a large amount of data on individual animals is accessible, which may be efficiently used to calibrate numerical models for forecasting production trends. The availability of data recorded in real time about the environmental conditions of the barn and the production performances of individual cows in the dairy cattle sector represents a quantitative knowledge base with a huge potential for further informatics and electronic tools development, able to achieve optimal conditions of animal welfare and more sustainable productions, in addition to improvements in milk quality and production efficiency (Lovarelli et al., 2020). Automatic Milking Systems (AMSs), in particular, are becoming increasingly popular since they give farmers with extensive information about health conditions and characteristics related to the milk produced, which is useful for optimizing output (John et al., 2016). Moreover, in technological farms, data concerning different parameters of behavior and activity of cows, animal health, and welfare are collected from different sensors (e.g., individual cow data recording system, activity tags such as pedometers or neck collars, ear tags for rumination monitoring, automatic concentrate feeders), and used for the ordinary management (Halachmi et al., 2019), management of systems (Vitali et al., 2021) and for design or retrofitting of livestock buildings (Bovo et al., 2022).

Several studies have indicated that properly storing collected data in structured databases is a vital first step in developing numerical models that can define individual cows' circumstances and performance (Bonora, Benni, et al., 2018) and to quantify the effects of particular thermo-hygrometric conditions on milk production (Bonora, Pastell, et al., 2018). The welfare of dairy cows exposed to heat waves is becoming increasingly relevant in a climate change scenario. Furthermore, the response of cow activity to heat load was recently studied (Heinicke et al., 2021). Heat load was found to be more sensitive in advanced lactation cows than in early lactation cows. Furthermore, multiparous cows had weaker activity responses than primiparous cows. Individual cow-related characteristics and heat load amount were found to be major contributors in prediction models based on animal vulnerability to heat stress (Benni et al., 2020). Applied statistical methods used in the literature (Piwczyński et al., 2020) showed that milking frequency, lactation number (parity number), the month of milking, and type of lying stall represent important factors responsible for the monthly milk yield of dairy cows in farms with AMS. In this context, Machine Learning (ML) algorithms have already been used in some areas of dairy research, particularly to predict data, and they represent a promising tool for developing and improving decision support for farmers (Cockburn, 2020) in order to increase milk yield and animal welfare while reducing the resources required, thereby increasing the sector's sustainability (Strpić et al., 2020).

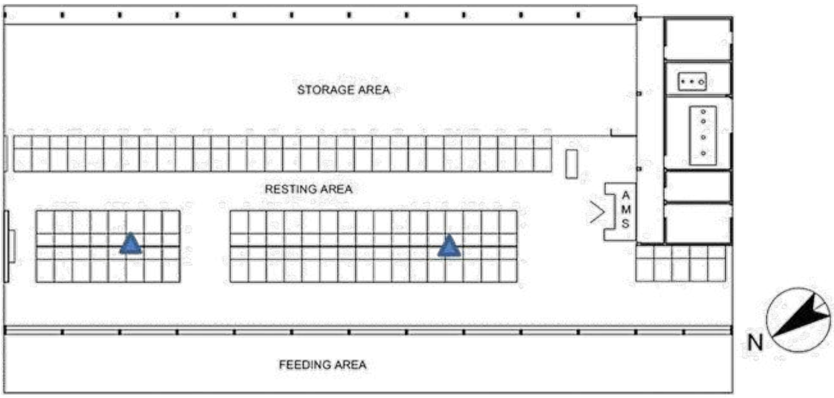
More research is needed to determine how elements affecting animal welfare and cow performance might be integrated with barn interior conditions. To this end, continuous and real-time monitoring of the animals and the barn's environmental parameters contributes to an understanding of the individual cows' welfare conditions (Bovo et al., 2020): it can provide valuable information for barn management and the prevention of problems related to the cows' longevity, productivity (Bovo et al., 2021) and milk quality.

The study aims to define, train, and test a model developed through machine learning techniques and, in particular, by adopting a Random Forest (RF) algorithm, having the main goal to assess the trend in daily milk yield of a single cow in relation to environmental conditions. The model can be applied as a regression tool or as a predictive tool.

Materials and methods

The case study

The model has been developed based on the data collected on 91 lactating cows of a dairy farm, located in northern Italy and equipped with an AMS and two thermo-hygrometric sensors acquiring information on the environmental conditions, during two entire years—i.e., 2016 and 2017. The study dairy farm is located in the municipality of Budrio, about 15 km NE of Bologna (Italy). The region is characterized by hot summer seasons with a high percentage of humidity;, considering the warmer months of the year (i.e., June, July, and August), the average of the daily maximum temperature typically ranges from 27 to 29 ◦C, with daily average relative humidity, for the same period, from 75% to 85%. The rectangular layout of the barn is 51 m long and 23 m wide, with the longitudinal axis SW–NE-oriented, a ridge height of 8.52 m, and gutter heights of 4.95 m on the NW side and 6.65 on the SE side. It consists of a hay storage area on the SE side, a resting area in the central zone of the building, and a feeding area with a feed delivery lane on the NW side (see Figure 1). The resting area has a partially slatted floor and hosts 78 cubicles with straw bedding. Two blocks of head-to-head rows are in the central part of the resting area, while another row runs along the entire length of the barn close to the storage area. Milking is performed by an AMS "Astronaut A3 Next" (Lely, Maassluis, The Netherlands) placed at the SW extremity of the barn. Mechanical ventilation is controlled by three high volume low speed (HVLS) fans with five horizontal blades which were activated by a temperature-humidity sensor situated in the middle of the barn at about 3 m of level. Lactating cows are fed with a total mixed ratio kept available along the feeding lane.



(a)

(b)

Figure 1: Plan layout (a) and picture (b) of the milking area of the cattle barn adopted as the study case. The triangles represent the locations of the temperature-humidity sensors.

During the period of the study, the robot was programmed to ensure a particular number of daily visits for each cow depending on her productivity and her expected optimal milk yield per visit, with a minimum of two and a maximum of four daily visits as constraints. Animals with fewer than two visits in one day were signaled by a warning, while the cows which have been milked four times in one day can only pass through the AMS box without being milked and fed further.

The data of the various milking events recorded by the AMS were downloaded, together with the cow tags and the DIM in a large dataset. Then, the daily milk yields were calculated for each cow. The dataset was then filtered by eliminating the exceptional events (e.g., daily milk yields of cows with mastitis or other factors that can influence animal production). This allowed us to create a cleaned dataset for each cow, collecting the time series of the milk yields during the monitored period. The cow datasets considered in the study ranged from 100 to about 550 milk daily yields.

Statistical Model

The general statistical model used to determine the effect of environmental conditions on milk yield at the single animal level has the general form of Equation 1:

$$y_{i,j} = DIM_{i,j} + THI_{i,j} + THI_{i,j-1} + THI_{i,j-2} + THI_{i,j-3} + THI_{i,j-4} + THI_{i,j-5} + e_{i,j} \quad (1)$$

where $y_{i,j}$ is a test-day milk yield for cow i at day j; $DIM_{i,j}$ denotes the effect on milk yield of the DIM of cow i at day j; $THI_{i,j}$ is the effect on milk yield for cow i of the daily average THI at day j; $THI_{i,j-1}$—$THI_{i,j-5}$, respectively, represent the effect on milk yield for cow i of the daily average THI at day from j–1 to j–5; e_{ij} represents the random residual effect, a priori assumed to be independently and identically distributed as $N(0,s_e^2)$, where s_e^2 is the residual variance. In particular, several statistical models have been tested also considering a longer period, starting from 10 days before testing. Then, it was gradually reduced to 5, removing one day at a time with the value of the average relative error that remained almost unchanged (modifications lower than about 0.1%). Only with the removal of the THI value of the fifth day before testing did the average error increase significantly, thus leading to the decision to consider a preceding period of 5 days. To predict the heat stress effects at the level of a single cow, seven different features (i.e., predictors) have been used as input data to the Random Forest algorithm and the dataset of each animal has been divided into data for the training phase and data for the testing phase.

The Random Forest technique, an ensemble learning method that creates predictions by averaging over the predictions offered by numerous separate random models, was used to do regression analysis on the acquired data. In this work, the algorithm was adopted for regression purposes by using the Scikit-Learn Python library to establish the random forest model (RFM) best fitting the data values of each cow.

A significant advantage of the RFMs is the possibility of assigning a score to each feature composing the input of the statistical model. The scores are representative of the importance of the different features in the model output (i.e., the prediction). A function of the *scikit-learn* library allows users to produce the ranking of the features and the evaluation of various scores.

Two of the most important parameters for the application of RFMs are the size of each tree (i.e., number of nodes) and the number of trees adopted. If the parameters are too large, overfitting problems could appear, while if the values are too small for the complexity of the data, the model is not able to converge to a suitable solution. In this work, for the first parameter, a self-expanded criterion, it was assumed that the nodes number expand by itself when the number of samples is bigger than 2, while the number of trees has been set equal to 1000.

The dataset of each selected cow was divided into two portions: one used for the training phase and the other for the validation, and a specific RFM was obtained for each animal. The RFM has been developed for the assessment of the daily yield (the dependent variable) starting from the values of the independent variables.

Numerical analyses

The numerical analyses adopted have been realized with the objective to train and test a RFM for the assessment of continuous time series values, with the main aim to obtain a model for the assessment of future productive trends of cows under different climatic conditions. In this scenario, the dataset of each cow was divided into two groups: the initial 80% of the data were used for the training while the last 20% were used to test the model accuracy and reliability (see Figure 2). In this case, for each cow, a continuous series of daily milk yields was obtained from the model and compared to the real one.

Figure 2: Division of the datasets for the numerical analyses

Results and Discussion

In this paper, the Random Forest model was used to assess future milk yields. As far as the average accuracy related to single cow is concerned, in Figure 3, the median accuracies ± standard deviation of the 91 cows are reported in ascending order. The figure highlights that for the 91 cows considered in the study, having data numerousness higher than 100 days, the median accuracy for the different animals ranges between 62% and 91%. For 74 cows out of 91, i.e., 81% of the considered animals, the median accuracy is higher than 75%. the average (out of the cows) median accuracy of the predictions is equal to 81.91% (equivalent to a relative error Er = 18%), whereas the standard deviation of the median accuracy is 13.02% confirming a generally good accuracy, even if it is rather scattered.

As a confirmation of the good accuracy of the models, Figure 4 displays the distribution of the relative error Er on the sum of the daily yields over the period of tests. For 80% of the animals, the Er value is included in the range ±10%, with an average value of the cows equal to 1.85%. This means that, if we sum the daily yield of each cow for the test days (68 days on average), the relative error in the assessment of the total milk production is lower than 2%.

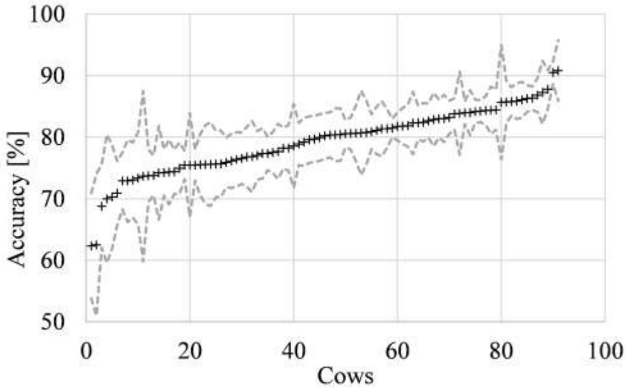


Figure 3: Median accuracy ± standard deviation for each of the 91 cows of the study. The values are sorted ascendingly.

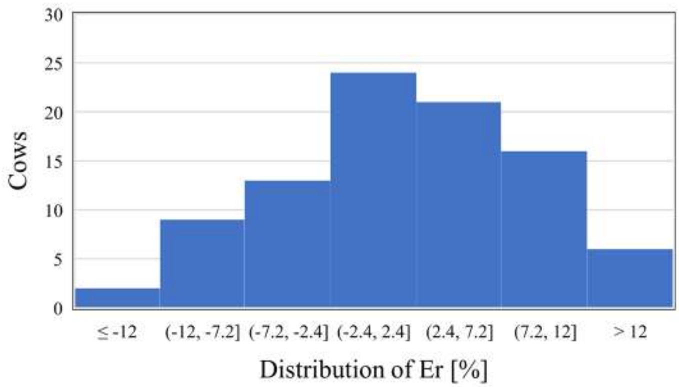


Figure 4: Distribution of the relative error Er on the sum of the daily yields over the test days.

Lastly, the boxplot diagram of the different importance scores is reported in Figure 5 for the whole dataset containing the 91 investigated cows. The DIM has the highest importance scores, with a median score of 0.29. Then, THI_0, i.e., the average THI of the day to predict, has a median of score equal to 0.13, whereas the other features (THI_{-1}–THI_{-5}) have comparable median scores ranging from 0.093 to 0.11. Moreover, the feature with highest median importance score value (DIM) is affected by the highest variability in the score values, i.e., it presents the highest values of Coefficient of Variation (CoV).

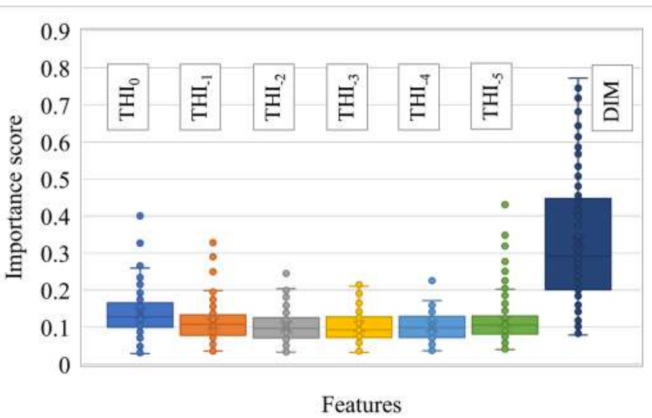


Figure 5: Boxplot diagram of the importance score of the different features for the whole dataset.

Conclusions

The study aimed to define and test a Random Forest-based model for the assessment of the daily milk yield of a single cow. The model has been applied to the data collected in 2016 and 2017, in a dairy farm, located in northern Italy, and collected both productive data from the automatic milking system and environmental data from two thermo-hygrometric sensors. The results in the paper showed that the model can detect the drop in the cow's milk yield due to extreme hot conditions inducing heat stress effects. In fact, the average relative error of the predictions, is about 18% on a single daily yield, whereas it becomes just 2% if the total milk production in the test days is considered. The results confirm the RFM can represent a reliable and viable tool for the evaluation of productive scenarios of dairy cows in presence of heat stress. This could help to develop decision support for farmers to increase both milk yield and animal welfare and, on the other hand, to reduce the resources needed, so to increase the sustainability of the dairy sector.

Acknowledgements

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SESSION 18

Pigs:
Water, Climate and Emissions

Evaluation of zone-level ambient temperature and pen-level water usage in a large swine research barn

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Abstract

Two key measurement goals of precision livestock farming (PLF) are capturing continuous real-time data and maximizing the granularity of measurement to the most detailed level possible to support optimal operational decision-making. Two disease challenge studies were conducted in a single research barn from September 2020 through July 2021. All pens were equipped with individual water meters to measure daily water usage and ambient temperature. From September through December 2020, the coolest zone was Fan_Out with a -3.6oC temperature deviation from the warmest Middle_In zone, with deviations staying consistent throughout the period.

Keywords: ambient temperature zones, pen level water

Introduction

Most measurements tracked in growing pig production are done at the group level and represent the entire feeding period. In contrast, two key measurement goals of precision livestock farming (PLF) should be capturing continuous real-time data and maximizing the granularity of measurement to support optimal operational in-process decision-making.

Two potential influences on post-weaning live pig performance are ambient temperature and water availability/quality. Temperatures levels and fluctuations within the direct animal environment can impact pig performance (Rauw et al., 2020). Water usage can be an indicator of both animal related problems (e.g., sickness during detected and undetected disease events), water quality problems, water availability problems and water wastage problems (Brumm, 2006).

Typically, indicators of both internal environment ambient temperature and water usage are measured at the barn level or room (airspace) level. However, measurement at these high levels – while certainly of some usefulness (versus not measuring) – do not support sufficient problem detection timing, sensitivity and precision.

Continuous water usage measurement at the barn/room level is useful for detecting deviations from the expected range. While useful, barn/room-level water usage measurement does not direct the barn manager to the pens and drinkers that are the source of the problem(s). Further, substantial detection sensitivity can be lost when the unit of data is a barn or room value to the extent that any specific pens where the water usage is abnormally high or abnormally low go undetected because their abnormal deviations are offset by the aggregate normal variation in all of the other pens that comprise the barn or room data values.

An even greater value can be captured from continuous measurement of water usage at the pen level. Pen-level water usage measurement can be used not only to identify when unusual water usage deviations are occurring (either too high or too low) in a barn or room, but it can also clearly direct the barn manager to the specific pens where those water use deviations originate. This increased level of detailed information enables faster and more precise detection of a problem's location, leading to a faster and more accurate diagnosis of the cause(s), and an active and more precise resolution of the problem(s) that are more easily identified.

In similar fashion, continuous ambient temperature measurement at the barn and room level are useful for detecting when there are deviations from the expected range of air temperature that is expected for pigs at a particular age/weight during various seasons and their corresponding external environment characteristics (e.g., temperature, relative humidity, wind speed, wind direction). However, rather than presuming a single value adequately represents an entire airspace or barn, continuous ambient temperature measurement at a more granular zone and pen level hold the potential to provide substantially richer information, substantially better (earlier, more specific and precise) problem (abnormal deviation) detection and clearer diagnosis – thus enabling greater effectiveness of intervention, problem resolution; as well as prevention.

To describe and characterize both water usage and ambient temperature at more granular (pen and zone) levels, the occasion of two consecutive disease challenge studies was used to incorporate a layer of pen-level water usage and ambient temperature monitoring on top of the study primary protocol execution.

Materials and Methods

The research barn is located in the upper Midwest region of the US and has a South (inlet curtains) to North (tunnel fans) orientation. A schematic of the research barn's interior layout and external directional orientation is shown in Figure 1. The outside walls are solid with built in windows (i.e., not curtain-sided). Ceiling air inlets located over the alleyway in each room and outside pit wall fans provide air flow during periods of minimum-to-low ventilation. Tunnel ventilation is generated using a curtain-style inlet on the South wall and a bank of large tunnel fans on the North wall during periods requiring higher ventilation rates. Manure is stored in a dep pit under a fully slatted floor. The pits are pumped (emptied) approximately twice per year – once in the late fall (after crop harvest) and once in the spring (prior to crop planting).

As part of two different disease challenge studies spanning from September 2020 through July 2021, 72 pens across two rooms were equipped with individual water meters to measure pen-level daily water usage, water temperature and ambient temperature. This full array of temperature sensor-equipped water flow meters enabled the capture of daily data values with pen-level data granularity. The water meters stored the data in built-in memory and on a weekly basis the data were read wirelessly and uploaded to a central database.

For the ambient temperature analysis, the research barn was partitioned into 12 distinct zones (six zones per room). Each zone covered six pens per zone. Zones represented varying combinations of proximity to inside walls, outside walls, tunnel air inlet curtains, tunnel exhaust fans and room (airspace). To create separate and distinct zones in the barn, there were 13 animal pens left empty (i.e., contained no pigs) plus one alleyway and the floor scale area (Figure 1).

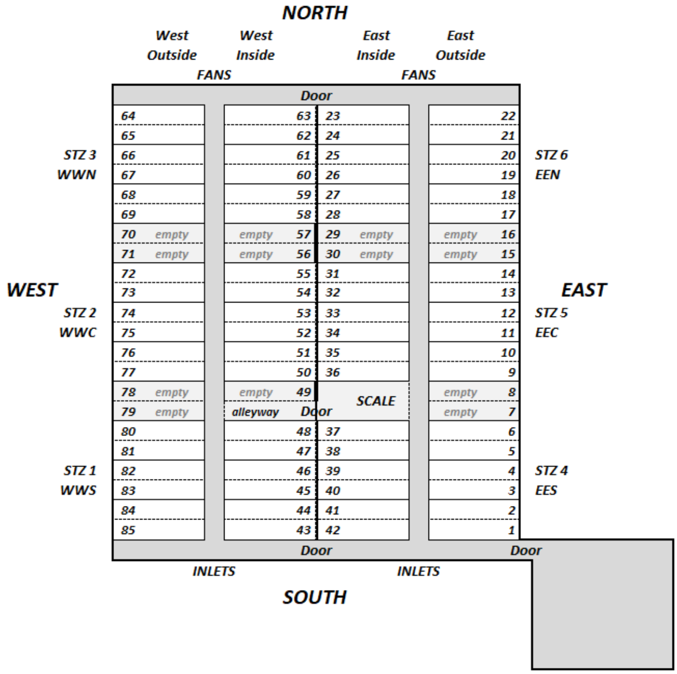

Figure 1: Detailed schematic of the large research barn layout and directional orientation.

For the water usage analysis, water data from each of the 72 pens were recorded by the water meters continuously and stored as a daily value (liters per pen per day). To account for changes in the number of pigs over time in each pen throughout the two studies (e.g., from mortalities and removals), a continuous pen-level inventory was calculated and used as the denominator to calculate a standardized measure of "Liters per Pig per Day" (LPD) for each pen.

Continuous external environmental data (e.g., temperature, relative humidity, wind speed, wind direction) were also obtained from the nearest US national network weather station. External weather station data was recorded approximately four times per hour.

For the first study, the average starting pig weight was 40 kg on September 22, 2020 and the average study ending pig weight was 116 kg on December 22, 2020.

Results and Discussion

Ambient Temperature

The external weather environment was typical for the Upper Midwest US. Figure 2 shows the daily average external temperature (Celsius) and average percent relative humidity based on data from the weather station nearest to the research barn from September 1, 2020 through December 31, 2020. Figure 3 shows the daily average wind speed (kilometers/hour) and wind direction.

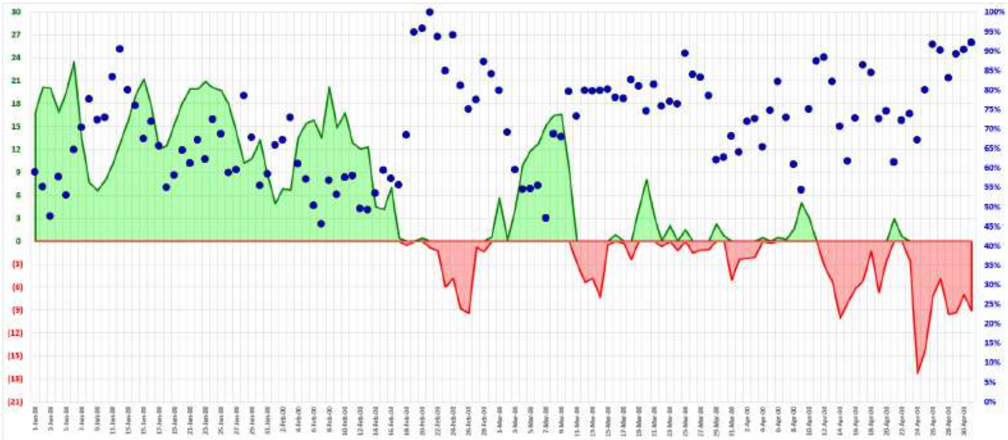

Figure 2: Daily average external temperature and average percent relative humidity from the weather station nearest to the research barn from September 1, 2020 through December 31, 2020.

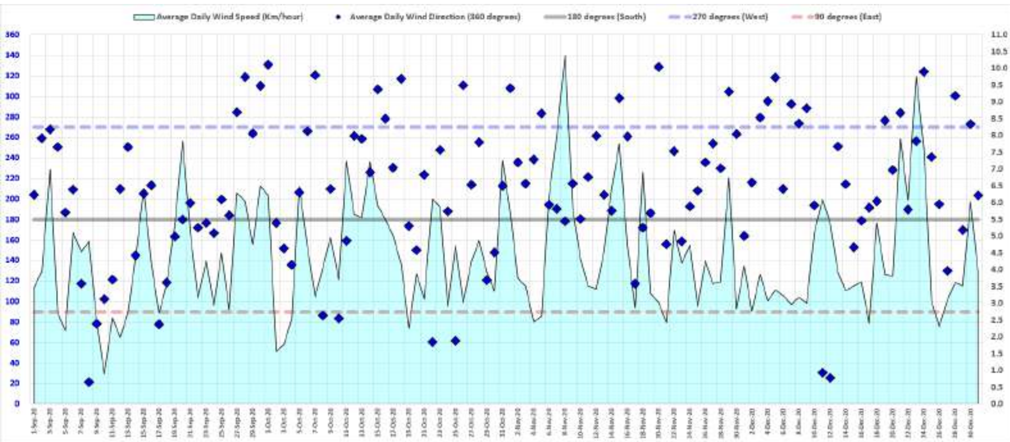

Figure 3: Daily average wind speed (kilometers/hour) and average wind direction (360 degrees*) from the weather station nearest to the research barn from September 1, 2020 through December 31, 2020. (*NOTE: North = 0 & 360, East = 90, South = 180, West = 270)

The daily average external temperature generally trended downward throughout the period of Study 1 with several cycles of falling and rising temperatures as weather patterns moved through the area (Figure 4). The inside temperature also trended down over the study period as the study pigs aged and gained weight, showing a much less variable inside temperature average, maximum and minimum throughout the study period – an indication that the barn ventilation management was relatively consistent.

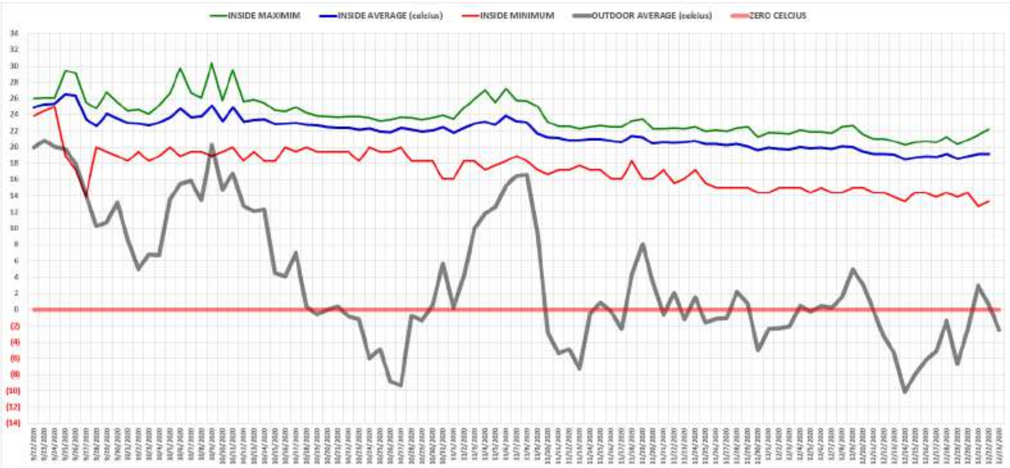

Figure 4: Daily average external temperature (Celsius) from the weather station nearest to the research barn compared to daily inside temperature average, maximum and minimum from September 22, 2020 through December 22, 2020.

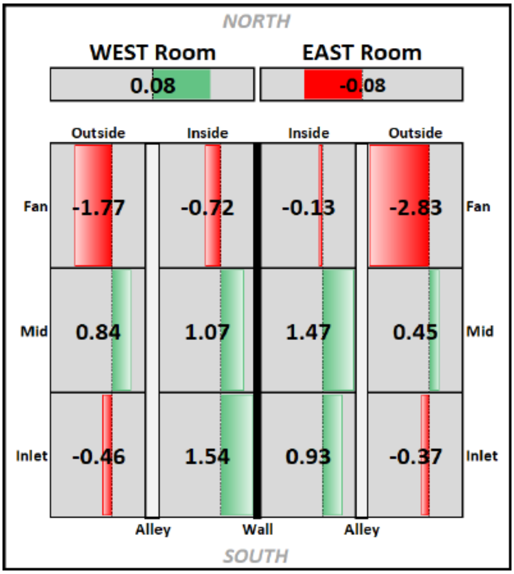

Figure 5: Average temperature deviations from the overall barn average inside temperature for the entire period of Study 1 from September 22, 2020 through December 22, 2020.

From September 22, 2020 through December 22, 2020, deviations of the average temperature from the overall barn average were calculated for each of the 12 Zones (Figure 5). The coolest zones were the Fan_Outside zones of both the East and West airspaces, with the warmest zones being the Middle_Inside and Fan_Inside zones. When comparable zones from both airspaces were combined (Figure 6) the coolest zone was the fan end/outside wall (Fan_Outside) with a -3.6°C temperature deviation from the warmest Middle_Inside zone. Relative ambient temperature deviations held relatively consistent over the period (Figure 7).

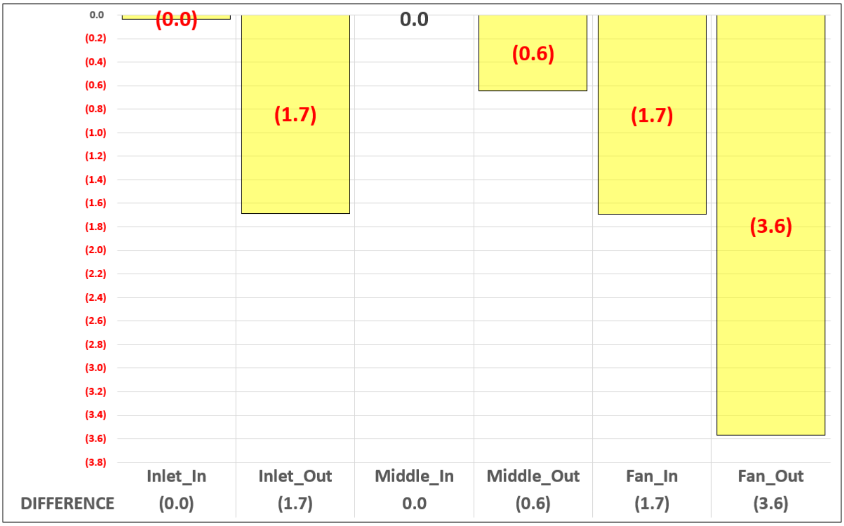

Figure 6: Average temperature deviations of Zone Types from the warmest Zone Type, Middle_In for Study 1 from September 22, 2020 through December 22, 2020.

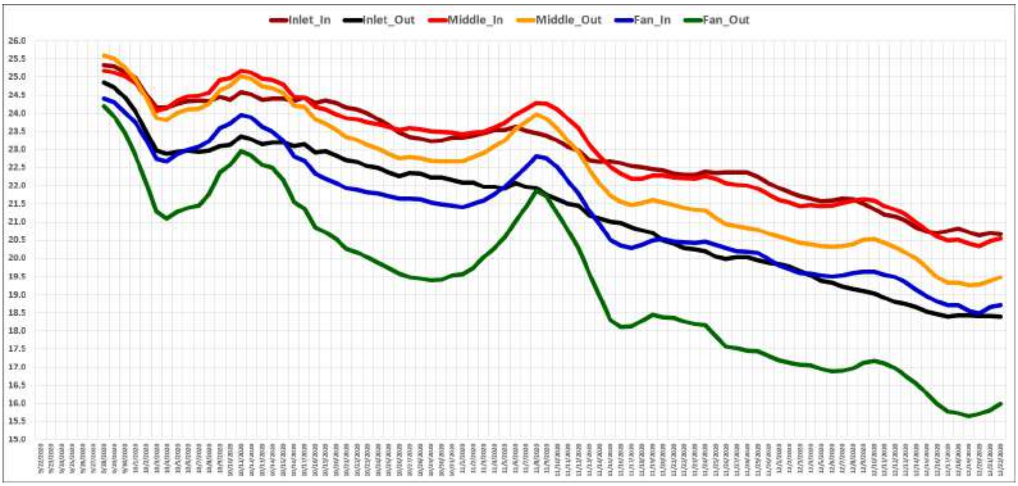

Figure 7: Time series of ambient temperature (Celsius) among six Zone Types (7 day rolling average) from September 22, 2020 through December 22, 2020.

Based on this ambient temperature analysis, it is evident that use of an array of ambient temperature sensors assigned to all defined zones in a swine barn enable the continuous monitoring and assessment of ambient temperature variation throughout the rooms and barn. Further work and analysis are needed to assess to what extent that these zone temperature deviations may affect growing pig health, welfare and performance.

Water Usage

Figure 8 displays the time series of pen-level daily water usage (liters per pig per day) for the 72 pens in Study 1 over the 90 day study period. During this period, pigs grew from a starting average weight of 40 kg to an average ending weight of 116 kg and would be expected to consume an increasing volume of water per pig over that same period. This was generally the case, although the impact of the controlled disease challenges can be seen (as expected) in the first one-third of the study period.

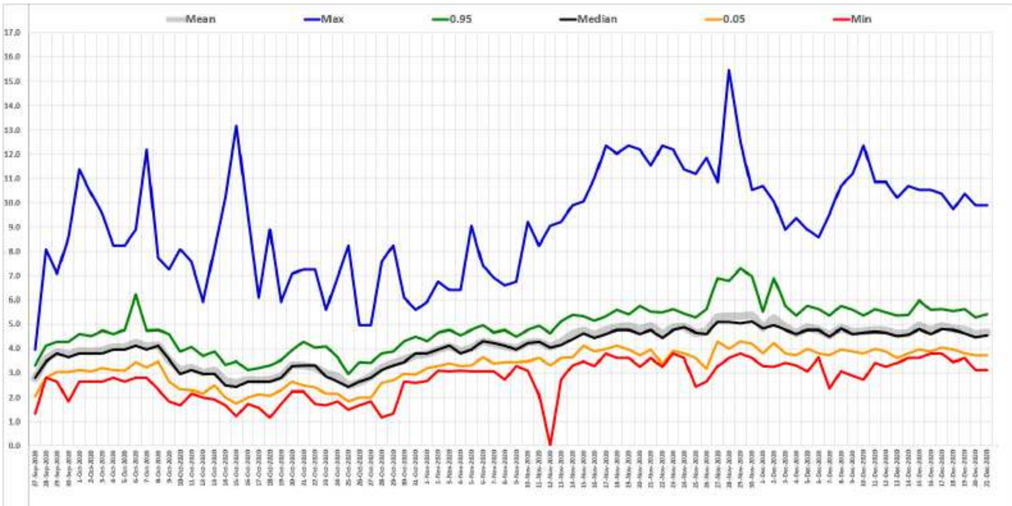

Figure 8: Time series of descriptive statistics of pen-level daily water usage (liters per pig per day) across 72 pens over a 90 day period for pigs from 40 kg to 116 kg body weight.

Figure 8 shows a substantial deviation of the maximum pen-level water usage above not only the mean and median for the barn, but also shows surprising deviations from the 95th percentile throughout the 90 day period of Study 1. Examining a time series of frequency distributions of water usage (Figure 9) it is evident there are several outlier pens where the water usage is unusually high, suggesting water wastage. Figure 10 displays a time series of pen-level daily water usage of four selected outlier pens in the West Room – two pens with unusually high water usage (66, 72) and two pens with consistently low water usage (47, 80).

Based on this water usage analysis, it is evident that use of water meters in individual pens throughout a swine barn enable the detection of unusual water usage deviations that may indicate pig-origin causes (e.g., diseases, vices) and/or faulty equipment (e.g., leaky or plugged drinkers) that can adversely affect growing pig health, welfare and performance.

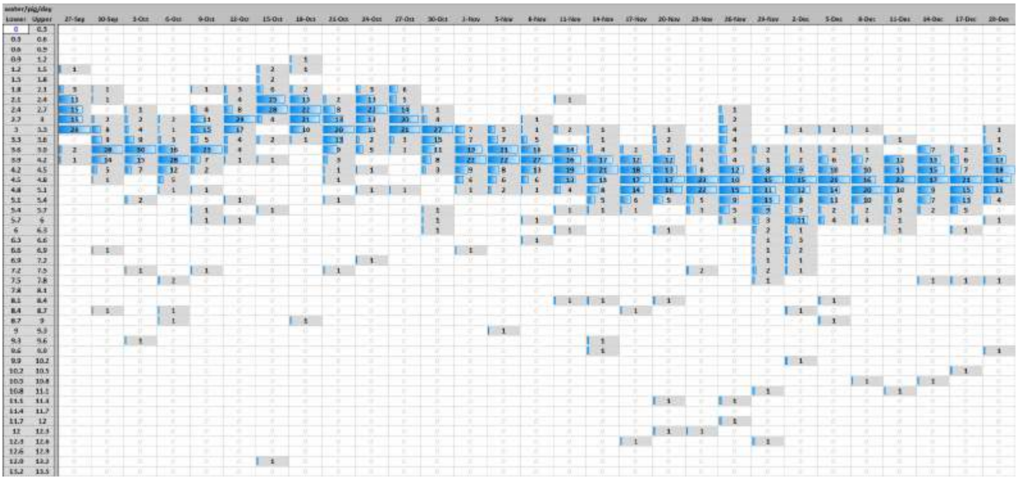

Figure 9: Frequency distribution time series of pen-level water usage (liters per pig per day) across 72 pens at 3 day intervals over a 90 day period for pigs from 40 kg to 116 kg body weight.

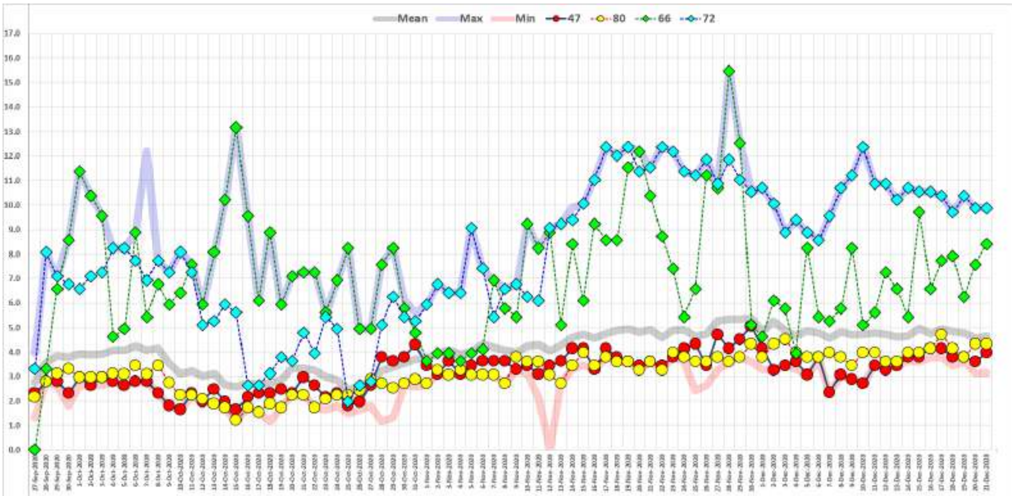

Figure 10: Time series of pen-level daily water usage (liters per pig per day) for selected outlier pens in the West Room over a 90 day period for pigs from 40 kg to 116 kg body weight.

Conclusions

Further research must be conducted to better assess the relationship of of zone-level ambient temperature variation and pen-level water usage variation with measures of pig health, welfare and performance. As these relationships are further evaluated and better documented, the cost-effectiveness of operating pen-level water usage meters and ambient temperature sensors can be defined. Obviously important to the benefit:cost (specifically as the denominator) is the overall cost of purchasing, installing, connecting (to the cloud) and maintaining these meters/sensors. To be scalable and sustainable as a precision livestock monitoring method, it will be important that the per unit cost of cloud-connected combination water meters/temperature sensors decrease substantially.

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Predicting diarrhoea events and event levels in finisher pigs with sensor data on water usage

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Abstract

Timely diagnosis of disease is essential for managing swine enteric diseases. In this study we investigate if diarrhoea events in finisher pigs can be detected based on water usage measures collected by sensors. Data used in the study originate from four farms of finisher pigs raised from 30kg till approximately 110 kg. Each farm consisted of several sections with several batches per sections. Batches with less than 60 days of observations were removed, and the maximum number of observation days was 102. A combination of Dynamic linear models and Random Forests are used for developing the prediction model. The effect of different parameters of the models were studied, e.g. the inclusion of a day and night pattern for drinking behaviour, the number of days back in time data was included, and different event sampling strategies. Results show a higher accuracy of the model when day and night drinking patterns and more days of data in the model were included. The test data shows best per-farm accuracies between 50 % and 63 % for the best performing model. This study shows that it is possible to predict diarrhoea events based on water usage measures, but performances seem not good enough for practical purposes. Further research should aim towards improving these performance further.

Keywords: water usage, dynamic linear model, random forest, swine enteric diseases

Introduction

Timely diagnosis of disease is essential for managing swine enteric diseases. Early detection and diagnosis of enteric disease are particularly critical in the nursery-through-finisher phase because of the significance of economic effects. One important sign of disease is diarrhoea, which in many cases can be present in pigs without the farmer being able to tell from looking at the pigs (Weber et al., 2015).

Monitoring pig behaviour is important for detecting problems with pig health, but is challenging given the large scale of many farms. Surveillance of pig diseases and behaviour often involves human observations, by either farm staff or veterinarian assessments. With the development of sensors, data collection on pig behaviour has been automated, which enables routinely collection of data and detection and tracking of the movement of (individual) pigs over an extended period of time (Martínez-Avilés, 2015). This provides opportunities for the early detection of potential health or welfare problems.

Several studies already looked at how various types of routinely collected data can be used for the early detection of diseases or undesired behaviour in pigs. Pen level temperature was used for the early detection of diarrhoea and pen fouling (Jensen and Kristensen, 2016). This study showed that temperature data contained meaningful information for predicting diseases, but in combination with other variables or by using more advanced models the predictive power was expected to improve. Combining pigs' water usage and pen temperature showed that predicting tail biting events was possible with an AUC of more than 0.80, but many false alerts on tail biting were generated due to the algorithm also flagging events other than tail biting (Larsen et al. 2019). Regardless, these predictions can still be useful for farmers to point out pens that need extra attention. Pigs' water usage is an interesting variable for detecting health issues, because pigs generally have a stable drinking patterns and typically does not deviate unless they are affected by a disease outbreak (Jensen et al., 2017). Madsen and Kristensen (2005) showed that a deviation in water consumption in weaned pigs can provide a warning for diarrhoea. Thus, sensor data on water usage may hold predictive value for detecting health events in finisher pigs as well.

The aim of this study was to investigate if diarrhoea events in finisher pigs can be detected based on water usage measures collected by sensors. This was tested by describing the patterns in the water usage data with a dynamic linear model (DLM), developing and optimising a Random Forest (RF) on a learning set and testing the predictive performance of the RF on the remaining test set.

Material and Methods

Data

Data used in this study were provided by IQinAbox (Værløse, Denmark). The data had been recorded between 2019 and 2021, and originated from three pig finisher farms, raising pigs from 30 kg to approximately 110 kg. Each farm had between 4 and 6 sections, delivering between 25 and 49 batches of finisher pig. Two of the farms used liquid feed. On the third farm, half of the sections were given liquid feed and the other half dry feed. The raw data consisted of sensor data on water usage aggregated to hourly sums per batch of finisher pigs. The water usage in this study does not include the water intake from liquid fed. In addition, the farmers had been instructed to record the number of health events (i.e. diarrhoea) per batch. These farmer records were also available to us. A total of 37 batches were removed because of missing water usage recordings at the start or middle of the growing period (23 batches), or because less than 60 days of observations were removed (14 batches). Table 1 presents the final dataset that was used for this study.

Table 1: Final dataset used for the prediction of diarrhoea

Farm	Feed type	Sections total	Batches total	Diarrhoea (1) events	No diarrhoea (0) events
1	Liquid	6	49	14,777	49,785
2	Liquid	8	48	34,985	22,791
3	Liquid	4	25	24,407	12,096
3	Dry	4	26	17,216	3,912

The data were split for each farm into a learning set (70 %) and a test set (30 %), stratified by section. The learning set was used to model the drinking pattern and estimate the parameters of the DLM, as described below. The test set was subsequently used to assess the performance of the trained RF models, as described further below. Separate models were made per farm for Farms 1 and 2, while separate models were made for each feed type for Farm 3. All data processing, modelling, and various calculations were done using the statistical language and environment R (R Core Team, 2017).

Modelling drinking pattern

The water consumption of growing pigs have a diurnal pattern and a uniform water consumption pattern is required for assessment of changes in pig health and well-being (Madsen and Kristensen, 2005). Therefore, the drinking pattern of the growing pigs was described in the DLM as a linearly increasing mean plus the sum of three harmonic waves, following the example of Madsen and Kristensen (2005).

Dynamic linear model

In general, a DLM will start with a certain set of assumptions, which in our study were defined by the parameters learned from the learning set. When applied to a new time series of data, the DLM will gradually learn the specific patterns of the new data through via the Kalman filter (West and Harrison, 1997). In this study, the DLM was used to make a one-step-ahead forecast on water usage, with each step corresponding to one hour. The forecast errors, i.e. the differences between the forecast from time t-1 and the observation Y_t is standardized by dividing it by the square root of the forecast variance, which is estimated continuously as part of the Kalman filter. The standardized forecast error is then used as a measure of the deviation from the "normal" level of water intake; so long as the system is normal or "in control", the standardized forecast errors will follow a standard normal distribution. If, on the other hand, the pigs change their drinking behaviour, data will no longer conform to the model predictions, and the absolute value of the standardized forecast errors will increase.

Forecast error transformation

The farm and feed-type specific DLMs, which had been optimized on the learning set, were subsequently applied to their respective learning and test sets, and the standardized forecast errors saved. The standardized forecast errors were transformed by calculating the summary statistics (min, 1st quarter, mean, medium, and 3th quarter max) for a set number of hours back in time, relative to each observation. The exact summary transformation varied with respect to several different conditions, i.e. (1) whether the summary statistics were naively calculated for all observations in the set number of hours relative to the observation, or if separate summary statistics were calculated for day hours (07:00 – 18:00) and night hours (19:00 – 06:00); (2) the number of observations (hours) that were included in the summary statistics, i.e. t-24h, t-48h, t-72, and t-96

All 8 combinations of these two variations were used, in order to identify the most important features for predicting diarrhoea in pigs on batch level. Thus, in total 16 new datasets (8 learning and 8 test sets) per farm were created and used as input for the RF.

Data balancing

Since the data were highly imbalanced with relatively few positive diarrhoea events, two different methods of data balancing were applied to the data: (1) random over-sampling which populates the data set with copies of randomly selected data points of the minority class (diarrhoea); and (2) random under-sampling where the data points from the majority class (without diarrhoea) are removed at random.

Random forest

To predict diarrhoea at batch level, this study applied a RF. A RF is a classification model that generates a set of different decision trees and combines their predictions into a single final prediction. For each farm, the learning data (70 % of the full per-farm data set) was split into a validation set consisting of one section and a training set consisting of the remaining sections.

First the RF was trained on the training set and the number of trees was set to 500. This trained model was then used to make prediction on diarrhoea occurrence, using the validation dataset. In total 64 sets of RF predictions were made (i.e. 4 farms/feed types x 2 (under/oversampling) x 2 (day/night pattern) x 4 (t- 1 to 4 days)), and model performances were evaluated based on the major-mean accuracy, and the 95 % confidence interval (CI) with bootstrap resampling. The best performance model per farm where identified and we used these best set of parameters to train the final model for each farm using the full learning balanced set for each farm. Finally this trained model was tested on the test data (30 % of the full per-farm data set).

Statistical analysis

The accuracies achieved from the 64 different sets of RF predictions were analysed with a linear mixed-effects model, using the *lmerTest* package in R. The mixed-effects model was made to describe the accuracies given whether or not day/night distinctions were used, whether under-sampling or over-sampling were used, and the number of days back in time, relative to a given observation (t-days) was used in the summary statistics transformation of the forecast error data. All variables were included as factors. The farm was included as a random effect, with farm 3 (liquid feed) and farm 3 (dry feed) being considered as separate values. Effects were considered statistically significant if their corresponding *p*-values were less than 0.05.

Results and Discussion

Table 2 presents the accuracy of each RF model when evaluated on the validation datasets, while Table 3 shows the results of the statistical analysis, i.e. the estimated effects of the various values of the different factors on the accuracy of the RF, along with the corresponding *p*-values for the effects under the null-hypothesis of no effect.

It is seen from Table 3 that the data balancing method (over-sampling or over-sampling) does not significantly affect the performance. This is also evident by the fact that no balancing strategy consistently yields the best performance for any of the farms (Table 2).

Table 2: Predictive performance Random Forest on validation datasets. Bold numbers indicate the best performance for a given farm.

Farm (feed type)	Day-night pattern	t-days[a]	Under sampling Accuracy (95% CI)		Over sampling Accuracy (95% CI)	
Farm 1 (liquid)	YES	1	0.61	0.56-0.67	0.52	0.49-0.55
		2	0.64	0.59-0.69	0.55	0.52-0.58
		3	0.64	0.59-0.69	0.55	0.51-0.58
		4	**0.68**	0.64-0.73	0.55	0.52-0.59
	NO	1	0.49	0.46-0.52	0.49	0.44-0.54
		2	0.65	0.60-0.69	0.48	0.43-0.53
		3	0.50	0.50-0.50	0.63	0.58-0.69
		4	0.66	0.61-0.71	0.66	0.61-0.71
Farm 2 (liquid)	YES	1	0.62	0.57-0.68	0.60	0.55-0.66
		2	0.62	0.57-0.67	0.63	0.58-0.68
		3	0.63	0.57-0.68	0.61	0.56-0.67
		4	0.61	0.55-0.67	**0.65**	0.60-0.70
	NO	1	0.63	0.58-0.69	0.64	0.58-0.69
		2	0.63	0.58-0.69	0.63	0.58-0.69
		3	0.64	0.58-0.69	0.64	0.58-0.69
		4	0.61	0.56-0.67	0.64	0.58-0.69
Farm 3 (liquid)	YES	1	0.63	0.58-0.68	0.66	0.61-0.71
		2	0.65	0.60-0.70	0.64	0.59-0.70
		3	0.66	0.61-0.71	0.67	0.62-0.72
		4	0.68	0.64-0.73	**0.68**	0.63-0.73
	NO	1	0.59	0.53-0.64	0.59	0.54-0.64
		2	0.60	0.54-0.65	0.60	0.55-0.65
		3	0.60	0.55-0.65	0.60	0.55-0.65
		4	0.61	0.55-0.66	0.60	0.55-0.65
Farm 3 (dry)	YES	1	0.71	0.65-0.77	0.70	0.63-0.76
		2	0.73	0.67-0.79	0.74	0.68-0.80
		3	0.70	0.64-0.76	0.75	0.68-0.81
		4	0.73	0.67-0.80	0.76	0.70-0.83
	NO	1	0.50	0.50-0.50	0.76	0.71-0.82
		2	0.50	0.50-0.50	0.71	0.67-0.75
		3	**0.79**	0.73-0.84	0.71	0.67-0.75
		4	0.71	0.67-0.75	0.77	0.72-0.83

[a] The number of days (24 hour periods) back in time, relative to a given observation, was used in the summary statistics transformation of the forecast error data.

Table 3 shows a statistically significantly positive effect of distinguishing between day and night hours, when performing the summary transformation of the standardized forecast errors of the DLM, compared to naively calculating the summary statistics on the whole included time window. In Table 2, this is evident by the day/night strategy yielding the best performance in 3 out of the 4 farms. Even in Farm 3 (dry), where the best performance is achieved without the day/night strategy, the day/night strategy still yield higher performance than the naïve strategy in 5 out of 8 cases, when comparing these two strategies stratified by both balancing method and t-days.

A statistically significantly positive effect of using the 4 days (96 hours) up to a given observation in the summary transformation, compared to only using one day (24 hours). The effects of using 2 and 3 days are not statistically significantly different compared to 1 day, although using 3 days comes close with a *p*-value of 0.06. Furthermore, there is a clear trend towards the positive effect increasing with more days being used, suggesting that this is indeed a real effect. The fact 4 days yields the best performance in 3 of the 4 farms suggests that using even longer retrospective time windows for the summary transformation should be explored in future studies.

It is also worth noting that for Farm 3 (dry) the performances were no better than random guessing when only 1 and 2 days of observation data was used for the summary transformation. However, for farm 3 (dry) using three days of observations for the summary transformation yielded an accuracy which was significantly higher than the best accuracies for any of the liquid fed farms. This higher accuracy might be because changes in drinking behaviour are more clearly seen when using dry feeding compare to liquid feeding (Meunier-Salaün et al, 2017; Zoric et al., 2015).

Table 3: Results of the statistical analysis of the effect of the three tested variables on the accuracy of a random forest trained to detect diarrhoea in slaughter pigs at section level.

Variable	Value	Estimated effect	Std.	*p*-value
(Intercept)	N/A	0.60	0.030	0.000002
Day/Night pattern	No	0.00		
	Yes	0.03	0.014	0.04
t-days[a]	1	0.00		
	2	0.02	0.019	0.40
	3	0.04	0.019	0.06
	4	0.05	0.019	0.01
Balancing Method	Over-sampling	0		
	Under-sampling	-0.01	0.014	0.71

[a] The number of days (24 hour periods) back in time, relative to a given observation, was used in the summary statistics transformation of the forecast error data.

In our study, the best performances are all significantly better than random chance, i.e. the 95 % CIs from Table 2 does not overlap of 0.5 for the best performances per farm. In fact, of the 64 performances achieved with various permutations of variables used in this study, only 7 had CI is which overlapped with 0.5, as seen in Table 2. However, when running the best performance models (Figure 1) for the given farms on the test data, we find that 2 of the 4 performances overlap 0.5. That being said, our best per-farm performances accuracies are in the range between 50 % and 56 %, which seem not to be good enough for practical purposes (Dominiak and Kristensen, 2017).

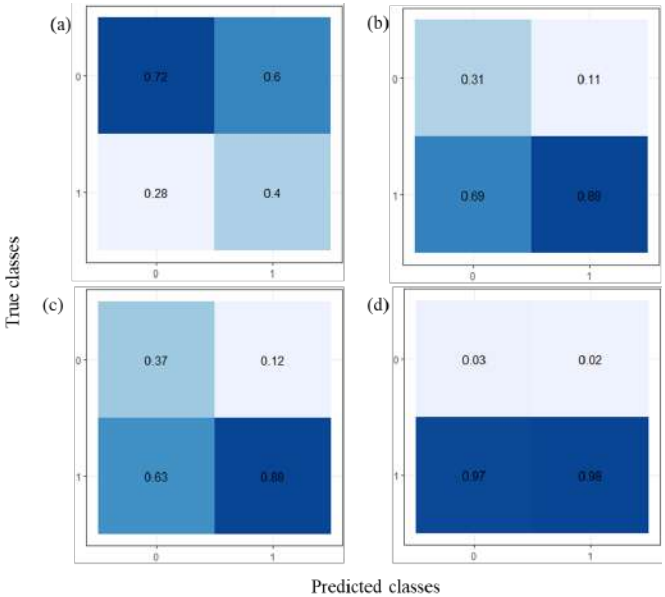

Figure 1: Confusion matrix of the Random Forest on test data sets test of the best performance model per farm (a) farm 1 liquid feed, (b) farm 2 liquid feed, (c) farm 3 liquid feed, (d) farm 3 dry feed.

Further research aims towards improving these performance further. For this purpose, it would be of interest to also have data on the number of pigs that are present in a given section at a given observation time; even though the farmer may insert a set number of pigs per batch, pig are occasionally removed due to illness, and towards the end of the batch the largest pigs will systematically be removed and sent to slaughter. Both of these causes for removals will change the water intake pattern, which could to more false positive results, negatively effecting the accuracy. Furthermore, having information about the temperature in a given section at a given observation time would likely provide valuable context for the drinking patterns of the pigs. Without this context, variations in temperature, and the corresponding changes in the pigs' drinking behaviour, may be lead to false alarms. Lastly, in this study we only considered registrations of diarrhoea. However, other undesired events such as pen fouling, tail biting, and respiratory disorders are known to occur at the farms included in our study. Since our study was focused specifically on detecting diarrhoea, based on the patterns in the water usage, these other undesired events may give rise to "false" alarms, as was the case for Larsen et al. (2019).

Conclusions

In this study we found that water usage data recorded at the section level contains information, which is useful for detection of diarrhoea. The best per-farm accuracies range between 50 % and 63 %. Further studies will aim to improve these performances by including additional information such as temperature, the number of pigs in the section, and the potential effect of other undesired events being the course for the alarms raised by our model.

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Development and evaluation of air recirculated ventilation system for piglet house to block livestock diseases, increase energy efficiency, and improve internal environment

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Abstract

Since the growth environment inside the piglet house is mainly controlled by ventilation, sufficient ventilation rate is required. However, it is difficult to overcome the excessive accumulation of odors and harmful gases because of low ventilation rate in winter. In addition, it is difficult to ventilate due to concerns about airborne disease transmission. The heat energy is high inside the facility due to the heat generation of the pigs, so it is necessary to recycle this thermal energy and reduce the exchange of outdoor air as much as possible to prevent diseases. Therefore, in this study, the air recirculated ventilation system was developed for pig house. The air recirculated ventilation system consists of 1) air scrubber module, 2) external air mixing module, 3) UV cleaning module, 4) solar heat module, and 5) air distribution module. First, the internal environment of target piglet house was evaluated. Based on this, the numerical model was developed in Python, and configuration the modules were selected. The performance evaluation of each module was conducted in test bed of AcSEC-A3EL (without piglets), and the optimal ventilation rates and external air mixing ratio were determined based on the data of each module. In order to control the selected ventilation rates and external air mixing ratio, the semi-closed duct system considering the pressure loss was designed. Finally, the control algorithm was developed to install and operate the air recirculated ventilation system in the demonstration piglet house, and the operation evaluation of this system will be conducted.

Keywords: Air scrubber, Air recirculated ventilation system, Energy efficiency, Internal environment, Piglet house

Introduction

Domestic livestock production has steadily increased every year, accounting for 39.4% of the total agricultural production, and the pig industry accounts for the highest proportion (MAFRA, 2020). In order to increase the production of pig farms, the scale of the facility is increasing, and dense breeding is increased. However, as the scale of the facility increases and the number of animals increases, the internal environment can be improper. Since the behavior and distribution of the internal environment can be shown by the airflow, most pig facilities control the internal environment through ventilation. However, there are many complex considerations such as environmental control inside the pig house, external exhaust gas, and odor. In addition, there are many difficulties in ventilation due to the occurrence and spread of diseases inside and outside the pig house.

There is an air recirculated ventilation system as a method designed to maximize the use of thermal energy inside the pig house and to block diseases inside and outside the pig house. The air recirculated ventilation system was conceived of cleaning and sterilizing the air exhausted from the inside to reuse the energy. If the air recirculation technology is applied to pig houses, the spread and inflow of livestock infectious diseases can be minimized. In addition, it is possible to improve the breeding environment by increasing the amount of ventilation rate inside the pig house in winter, and it is possible to minimize the emission of odor from pig house. Wenke et al. (2018) analyzed that when a filtration was installed in the air recirculation system, the dust concentration was the lowest and the pig's lung health was excellent. Anthony et al. (2017) analyzed the concentration of dust and carbon dioxide inside the pig house when the air recirculation system was applied to the farrowing house, and reported that the air recirculation system is an alternative to prevent the deterioration of workers' health. Mostafa et al. (2017) applied a wet scrubber to the air recirculation system, and reported that the wet scrubbing technique can reduce both ammonia gas and dust concentrations and has no negative effect on pigs.

A precise design is essential for such an air recirculated ventilation system. Since the air inlet and the outlet are connected rather than a general ventilation method, if the amount of inflow and outflow air is not accurately controlled, a ventilation problem can occur. If the air balance is not correct, negative pressure is applied inside the pig house. Then, the infiltration occurs through an unnecessary inlet, it may be difficult to control the environment in the pig house smoothly. Therefore, for the proper ventilation operation of the air recirculated ventilation system, an accurate evaluation of the recirculation air flow and a design considering the pressure load should be conducted.

Therefore, in this study, the pressure loss and actual air volume of the semi-closed duct system of the air recirculated ventilation system were evaluated. To this end, a semi-closed duct system simulating an air recirculation system was installed in the test bed of the piglet house test bed, and the air volume and pressure loss according to the ventilation rate were measured. Based on the measurement results, it was attempted to present standards such as the type, number, and location of ventilation fans required when applying the ventilation rate and external air mixing ratio when operating the air recirculated ventilation system.

Material and methods

Target facility

As shown in [Figure 2], the air exhausted from fan #1 passes through the wet scrubber, is cleaned, and re-introduced into the pig house through the duct. The wet scrubber has a role in making the air quality at an appropriate level so that the air reintroduced to the pig house can properly maintain the environment inside the pig house. In case of applying the recirculated ventilation system, even if the ventilation rate is increased by reusing thermal energy inside the pig house, it is advantageous to maintain the temperature in winter, and it passes through the wet scrubber to reduce harmful gases, dust, and odors to create an appropriate breeding environment inside the pig house. On the other hand, in the case of carbon dioxide generated by the respiration of pigs, since it is difficult to reduce it using the wet scrubber, it is necessary to keep it at an appropriate level by mixing some of the outside air. Therefore, the air that has passed through the air cleaner passes through some outside air mixing zone and is discharged to the outside, and the air flowing through the fan mixes with the outside air that has passed through the duct in the mid-ceiling and is designed so that it is re-introduced into the pig house.

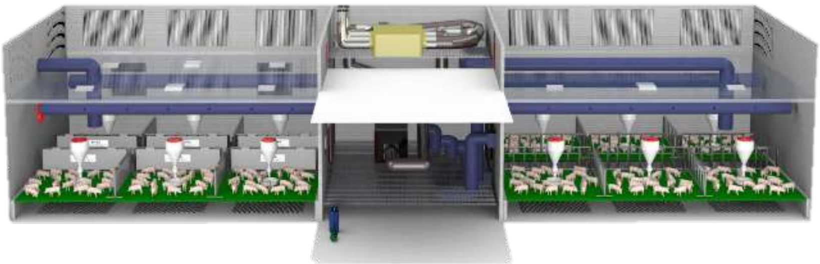

Figure 1: Test bed piglet room for air recirculated ventilation system experiment (the Artificially-controlled Smartfarm Engineering Center of Aero-Environmental & Energy Engineering Laboratory (ASEC-A3EL) of Seoul National University in South Korea)

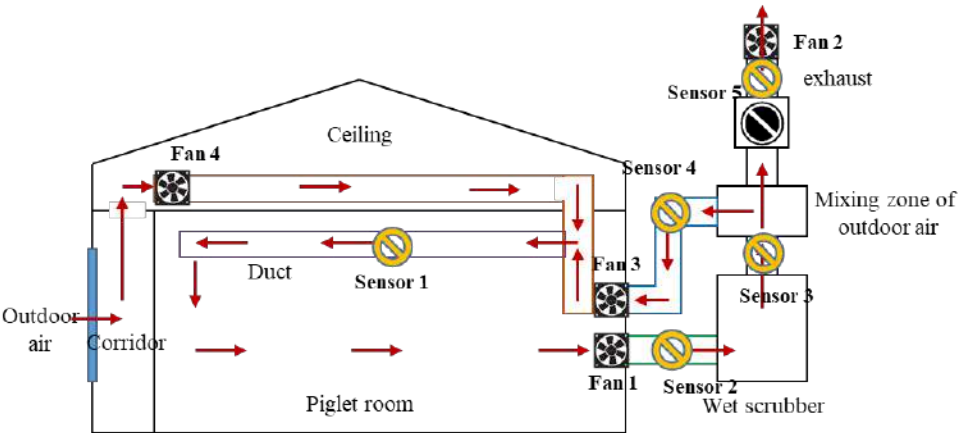

Figure 2: Schematic diagram of air recirculated ventilation system

<u>Calculation of pressure loss in ducts</u>

In general, the pressure loss in the pipe of the duct is the loss caused by friction between the air, the pipe wall, and the air. The pressure loss is proportional to the velocity pressure, which is the square of the velocity. The pressure loss is calculated from the equation below.

$$\Delta\mathbf{P} = \boldsymbol{\zeta} \cdot \frac{\boldsymbol{l}}{\boldsymbol{D}} \cdot \frac{\boldsymbol{\gamma V^2}}{\boldsymbol{2g}} \tag{1}$$

Where, ΔP is pressure loss (mmAq), ζ is pressure loss coefficient, is the length of duct (m), D is the diameter of duct (m), γ is the density of air (kg *m*-3), and g is gravitational acceleration (m*s*-2).

<u>Procedure of the experiment</u>

The object of analysis through the air recirculation experiment is to determine the location and combination of ventilation fans required to control the required ventilation amount and external air mixing ratio inside the pig house, and to find the control conditions for generating the required air volume from each ventilation fan. Therefore, the experiment was performed according to the fan combination, ventilation amount, and mixing ratio. In addition, in order to understand the position of the pressure load and the amount of loss, it was attempted to calculate the pressure loss for each flow measurement location. The experimental conditions for the combination of ventilation fan operation, ventilation amount operation conditions, and outdoor air mixing ratio are shown in the table below.

Table 1: Experimental condition of air recirculated ventilation system

Combination of fan	Ventilation rate	Mixing ratio of outdoor air
Fan #1 + Fan #2		100
		80
Fan #1 + Fan #3 Fan #1 + Fan #2 + Fan #3 Fan #1 + Fan #2 + Fan #3 + Fan #4	100 CMM 0.4 min^{-1}	60
		40
		20
		0

Results and Discussion

The following figure shows the results according to the operating conditions of fan #3, and by operating fan #3, the amount of inflow air was increased to compensate for the flow rate decrease due to friction loss in the duct. While the operating conditions of fan #3 were increased to 50%, compensation for pressure loss occurred insignificantly. It is thought that this did not significantly affect the operation of the fan compared to the amount of air recirculated. However, when the operating conditions are increased by 60% or more, it can be confirmed that the actual pressure drop is reduced compared to the friction loss of the duct. This means that the friction loss due to the increase in flow rate increased due to the increase in ventilation volume due to the serial arrangement of the two fans, and at the same time, the air volume was secured enough to compensate for the pressure loss of fan #3. When the maximum operation rate was reached, the pressure loss could be reduced to about 12% of the exhaust dynamic pressure. Therefore, when designing the air recirculation system, it is determined that the flow rate should be supplemented at the fan #3 position in order to reduce the difference in the inflow and outflow flow due to frictional loss.

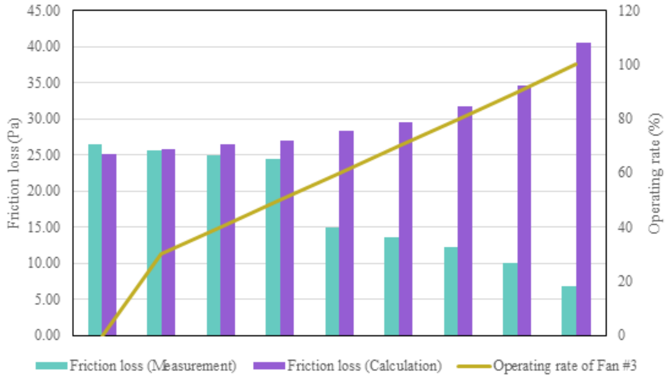

Figure 3: Friction loss measurement and calculation results according to the operating conditions of fan #3

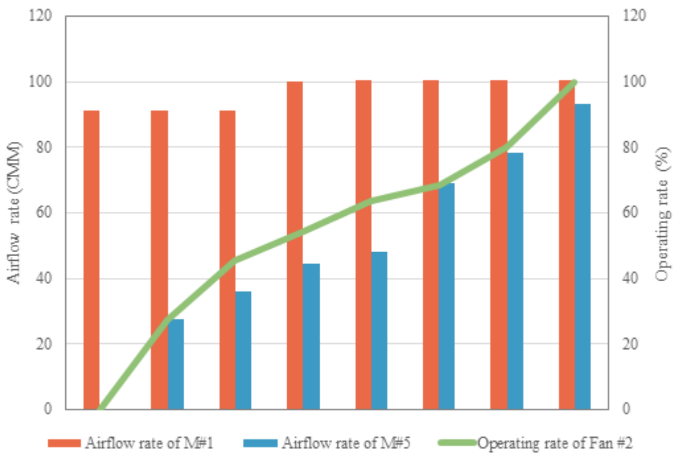

Figure 4: Outdoor air mixing ratio according to fan #2 control condition

After fixing the set ventilation rate of fan #3 to compensate for the pressure loss of the air recirculated ventilation system at 100% operating condition, the flow rate at each air flow measurement location was measured according to the control value of fan #2. The figure below shows the mixing ratio control results according to fan #2 operation. When the mixing ratio was controlled by using fan #2, the actual flow rate measured in M #5 responded well to the control value, showing excellent results. Meanwhile, the actual flow rate was measured to be about 20% lower than the control value in the 40 to 60% mixing ratio range of fan #2. It is not recommended to control a fan of a general single-phase motor power by adjusting the power value linearly. The input power of the ventilation fan should be constant at 220V, and the performance of the output motor may not be constant depending on the power value. Therefore, when the control is applied to an actual farm, it is preferable to control the inverter using a three-phase motor. In this experiment, since the purpose of this experiment is to adjust the external air mixing ratio according to the air volume of the ventilation fan, the evaluation was performed with power control. It is judged that it is appropriate to follow the installation environment and conditions for calibration of equipment and controller for precise ventilation fan control. While fan #3 was maintained at 100% operating condition to control the mixed air, the flow rate was kept constant at measurement position #4, the flow rate flowing into the pig room. Also, even if the mixing ratio was changed by adjusting the control value of fan #2, the average pressure loss in the duct was maintained at 8.35 Pa. Therefore, it is considered that the combination of #1, #2, and #3 of the ventilation fan is sufficient to control the ventilation amount and external air mixing of the air recirculation system.

Conclusions

In this study, an experiment to measure the flow rate of a semi-closed duct for the application of an air recirculation ventilation system was performed. For precise control of the actual ventilation fan, the air volume according to the control standard of the duct system was measured and analyzed. In order to compensate for the pressure loss in the duct, it is necessary to balance the exhaust fan and inlet fan of the facility. The air recirculation ventilation system should properly control the mixing ratio of the outside air. To this end, it was found that the external air exhaust fan must be operated quantitatively. For ventilation operation with the actual air recirculated ventilation system applied, it is necessary to correct the actual control value by calculating the duct loss and measuring the airflow rate as in this study.

Acknowledgements

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A study on the estimation of ammonia emissions considering factors influencing ammonia volatilization

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Abstract

Due to the adverse effects of ammonia emissions on the environment, the government is making efforts to adjust ammonia emissions through policies. Among ammonia emissions by industry in 2017, ammonia emissions from agriculture were the highest. Ammonia emissions from agriculture consist of emissions from fertilized agricultural land and emissions from livestock industries. In particular, ammonia emissions from the domestic livestock industry have increased by 24 % over the past decade due to the increase in the number of breeding heads. Literatures showed that the ammonia emissions from livestock industry are mainly from ammonia generated by manure. Therefore, the domestic pig industry, which accounts for the largest proportion of livestock manure generation, is an industry of high importance in ammonia emissions. In recent years, many studies were conducted to estimate and measure ammonia emission from pig house, but there were significant differences depending on measurement facilities and environment. These differences occur because the internal environment of pig house and the characteristics of manure are different. In order to consider these differences, it is necessary to calculate emissions in consideration of factors influencing ammonia volatilization. Therefore, in this study, factors influencing ammonia volatilization were identified through analysis of previous studies, and field monitoring was performed on factors influencing ammonia volatilization and ammonia concentrations. Based on monitoring results and equation of calculating ammonia volatilization in pig manure, the estimation model of ammonia concentration in pig house was presented and calibrated. Based on calibrated model, ammonia emission factors of pig house considering factors were presented.

Keywords: Factors influencing ammonia volatilization, Ammonia concentration, Ammonia emission factor, Pig house,

Introduction

About 73.5% of the total ammonia emissions in Korea were emitted by the livestock industry. Ammonia produced by the livestock industry is mainly from livestock manure. Therefore, the domestic pig industry, which accounts for the largest proportion of livestock manure generation, is an industry of largest proportion in ammonia emissions. Presently, the government included ammonia in the list of harmful atmospheric substances in its counterplans for fine dust management. Ammonia generates fine dust through chemical reactions with sulfur oxides and nitrogen oxides in the atmosphere (Jang, 2013). Furthermore, ammonia causes various environmental loads.

Many previous studies were conducted to estimate and measure ammonia emission of pig house, but there were significant differences depending on measurement facilities and environment. These differences occur because the internal environment of pig houses and the characteristics of slurry are different. Ammonia emitted from pig houses is mainly generated from slurry under pits, with the amount of volatilization varying according to slurry characteristics and internal environment factors (Aarnink et al., 1993; Meisinger et al., 2000; Ye et al., 2008). As these factors vary depending on the characteristics of each facility, including feed characteristics, breeding density, weather, environment, acid treatment of manure, and microbial treatment, it is important to identify factors influencing ammonia volatilization. As a result of the analysis of previous studies, the factors influencing ammonia volatilization were total ammonia nitrogen (TAN) in slurry, slurry pH and temperature, air temperature, ventilation rate, wind speed on slurry surface, emitting area and pig number. Nonetheless, studies on ammonia emissions linked to emission characteristics based on factors influencing ammonia volatilization are insufficient. Moreover, studies analyzing ammonia emissions according to pig ages using data measured throughout the breeding period are insufficient. Therefore, in this study, these factors were directly measured in pig houses and a model was developed to calculate the ammonia concentration and emission inside pig houses linked to these factors.

Material and methods

<u>Target facility</u>

Figure 1: Internal environment of piglet house located at Imcheon-myeon, Buyeo-gun, Chungcheongnam-do (126° 53’ 47.5” E, 36° 12’ 30.7” N)

The target facility is a mechanically ventilated piglet house located in Imcheon-myeon, Buyeo-gun, Chungcheongnam-do (latitude: 36°12’ 30.7” N, longitude: 126°53’ 47.5” E) (Figure 1). The floor area is divided into a pig breeding area and a corridor. The breeding area is composed of slat made of PE material, while the corridor is made of concrete. A total of 129 piglets enter at 28 days old and are moved to the finishing pig house at 82 days old. The ventilation system supplies air into the room through nine ceiling slots (0.6 m × 0.3 m) and two windows (0.4 m × 0.95 m) connected to the corridor, which is exhausted outside through three sidewall exhaust fans (2 fans with a φ of 350 mm, 1 fan with a φ of 500 mm).

Monitoring of factors influencing ammonia volatilization and ammonia concentration in pig houses

Factors influencing ammonia volatilization (TAN in slurry, slurry pH and temperature, air temperature, ventilation rate, wind speed on slurry surface, emitting area and pig number) and ammonia concentration inside pig house were measured. Since TAN is difficult to measure in real time, a manure sample was collected (a total of 7 times) during visit and measured through ion chromatography. The wind speed on slurry surface is difficult to measure through field experiments due to disturbance by pigs. Therefore, the wind speed on slurry surface was predicted through proportional relationship with the ventilation rate. Other factors were measured at 1-minute intervals. Measurement were conducted from 1st of April until 21th of May 2021 when the piglets were first entered the pig building until it was moved to the finishing pig house.

Development of model for estimating ammonia concentration inside pig houses

Ammonia in pig houses is mainly produced by the decomposition of urea in manure (Aarnink et al., 1993; Meisinger et al., 2000; Ye et al., 2008). In mass flow of ammonia in the pig house, ammonia volatilized on the slurry surface, accumulates under the pit, moves into the pig house, and is exhausted outside through fans. To predict the change of ammonia volatilization on slurry surface, the amount of ammonia volatilized was calculated based on the equation of Aarnink & Elzing (1997) by measuring factors influencing ammonia volatilization. Since this equation was developed in a different breeding environment from Korea, each coefficient was calibrated through the optimization technique based on the measured factors.

Eq. 1 was used to simulate the ammonia moving due to diffusion and advection from under the pit to the pig house.

Fick’s law was used to simulate the ammonia moving due to diffusion and advection from under the pit to the pig house (Equation (1)). The diffusion coefficient appears as Equation (2), and the change due to air temperature was applied (Gilliland, 1933).

$$\mathrm{J} = D_{AB} * {(C_A - C_B)}/{d_z} + C_A * v_c \tag{1}$$

$$\mathrm{D}_{AB} = 435.7 * \frac{{T_a}^{3/2}}{\rho\left({V_A}^{1/3} + {V_B}^{1/3}\right)} * \sqrt{\frac{1}{M_A} + \frac{1}{M_B}} \tag{2}$$

where J is flux caused by diffusion and convection (g s^{-1}), D_{AB} is diffusion coefficient (m^2 s^{-1}), C_A is ammonia concentration under the pit (g m^{-3}), C_B is ammonia concentration in pig house (g m^{-3}), v_c is convection rate (m s^{-1}), d_z is the amount of change in the z-coordinate, T_a is air temperature inside pig house, is total pressure, V_A and V_B are molal volumes at the normal boiling point, M_A and M_B are ordinary mol weight of the two gases.

The ventilation rate changes the ammonia concentration inside the pig house and emission. The amount of ammonia discharged outside and the amount of fresh air introduced were calculated through the measured ventilation rate. The estimation model was designed at 1-minute intervals in accordance with the law of mass conservation in consideration of the amount of ammonia generated under the pit, the amount of fresh inflow air by diffusion and debris, and ammonia emissions by exhaust (Equation (3), (4)).

$$C_{pit,t} = (C_{pit,t-1} * Volume_{pit} - J_{t-1} + E_{NH_3,t-1})/Volume_{pit} \tag{3}$$

$$C_{in,t} = (C_{in,t-1} * (Volume_{in} - V_{t-1}) + J_{t-1})/Volume_{in} \tag{4}$$

Where, $C_{pit,t}$ is ammonia concentration under pit at time t (mg m^{-3}), $Volume_{pit}$ is volume of pit (m^3), J is flux caused by diffusion and convection (mg min^{-1}), E_{NH_3} is the amount of ammonia volatilized (mg min^{-1}), $C_{in,t}$ is ammonia concentration inside pig house (mg m^{-3}), $Volume_{in}$ is volume of pig house (m^3) and V is ventilation rate (m^3 min^{-1}).

The ammonia concentration inside pig house and emission were calculated by substituting the measurement results of the factors affecting the volatilization of ammonia in the designed estimation model. The model was calibrated by applying the optimization technique to improve the accuracy of the estimated model by comparing the measured internal ammonia concentration with the estimated ammonia concentration.

Results and Discussion

<u>The results of predicting ammonia concentration through calibrated estimating ammonia concentration model</u>

First, the predicted amount of ammonia volatilization was compared with the amount of ammonia emission as in the study of Aarnink&Elzing (1997). The predicted results were qualitatively different from the actual ammonia emission trend (Figure 2). R^2 was also found to be low at 0.470, indicating that the prediction result did not show the trend of change in actual emissions. Accordingly, estimating ammonia concentration model attempted to increase prediction accuracy by simulating the diffusion and advection of ammonia generated in excrement and developing a model considering the mass flow of ammonia.

In the estimating ammonia concentration model, the accuracy for entire period of measurement for ammonia concentration before calibration has a R^2 is 0.871, root mean square error (RMSE) is 1.712 ppm, and mean absolute percentage error (MAPE) is 23.49 %. The statistical indices in some periods were lower than those in the entire period (Table 1). In addition, qualitatively, errors in the maximum and minimum values were largely confirmed in the daily change trend of the ammonia concentration.

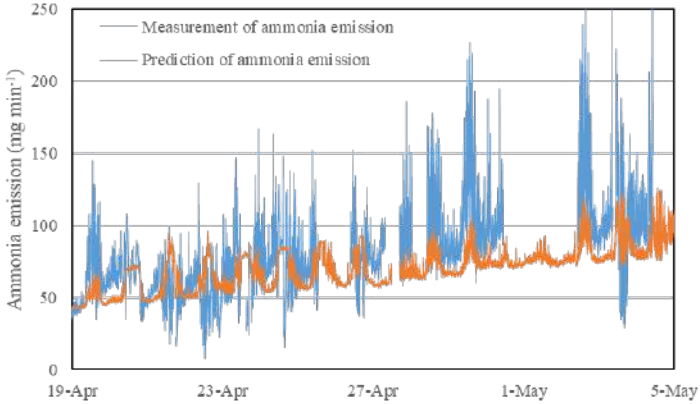


Figure 2: Prediction of ammonia emission of piglet house using Aarnink&Elzing's equation (1997)

The estimating ammonia concentration model was calibrated through the measured factors (Figure 3). The calibrated ammonia volatilization equation is as shown in Equations 5 to 9. As a result of predicting the ammonia concentration through the calibrated model, the R^2 values slightly increased from 0.871 to 0.906 whereas the RMSE values decreased by 34.6 % from 1.712 ppm to 1.119 ppm, and MAPE values decreased by 13.7 %, improving the overall accuracy (Table 1). However, the predicted concentration during day time when the ventilation rate was maintained high was higher than the measured concentration. These errors can be caused by the entry of farm manager and workers.

$$H = 1401 * 1.1^{(295.5 - T_s)} \quad (5)$$

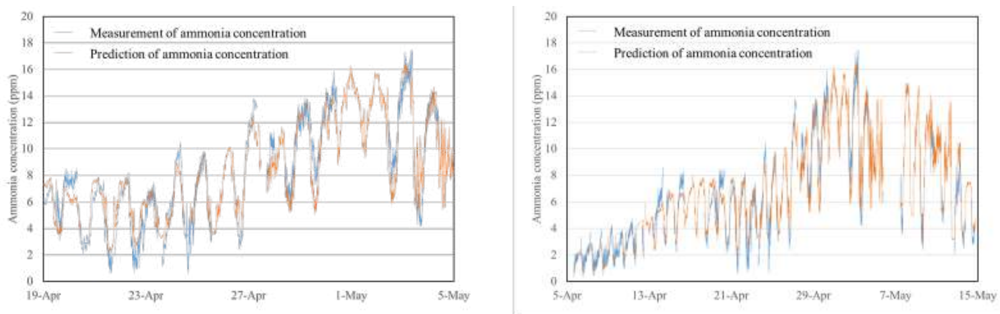
$$k = 55.5 * v^{0.554} * T_a{}^{-1.203} \quad (6)$$

$$v = 4.37 * V + 0.012 \quad (7)$$

$$f = \frac{10^{pH_e}}{10^{pH_e} + 4.78 * 10^{\left(0.0885 + \frac{3000}{T_s}\right)}} \quad (8)$$

$$pH_e = pH_s + 1.22 \quad (9)$$

Where, H is the Henry constant, T_a is the internal air temperature (K), k is the mass transfer coefficient (m s^{-1}), v is the wind speed on slurry surface (m s^{-1}), T_s is the slurry temperature (K), is the ventilation rate (m^3 s^{-1} m^{-2}), f is fraction of un-ionized ammonia in the liquid boundary layers of slurry, pH_s is the slurry pH measurement results.



(a) Result of estimating ammonia concentration of second stage of calibration in weaning pig house (19 April – 05 May 2021)

(b) Result of estimating ammonia concentration of second stage of calibration in weaning pig house (entire measurement period)

Figure 3: Prediction of ammonia concentration in piglet house using calibrated model

Table 1: Changes in statistical indices of calibration for piglet

Measurement period		R^2	RMSE	MAPE
19 April ~ 05 May 2021	Before calibrated	0.820	2.231	25.78
	After calibrated	0.886	1.287	19.20
Entire measurement period	Before calibrated	0.871	1.712	23.49
	After calibrated	0.906	1.119	20.27

Estimation of ammonia emission rate through calibrated estimating ammonia concentration model

To calculate the ammonia emission rate, the ventilation rate and the ammonia concentration at the inlet and outlet are required. The ammonia concentration at the inlet used the measurement results. The average ammonia concentration measured at the inlet was 0.08 ppm. As the concentration at the inlet was very low compared to the concentration at the outlet, it was determined that ammonia concentration at the inlet did not affect the calculation of the emission rate and was assumed to be 0 ppm. The factors influencing ammonia volatilization measured in the mechanically ventilated piglet house were put into the calibrated model for estimating ammonia concentration. The internal concentration was calculated through the model, and ammonia emission rate was calculated by multiplying the ventilation rate. The ammonia emission rate at the piglet house was 0.13 g day^{-1} head^{-1} to 1.97 g day^{-1} head^{-1}, tending to steadily increase as the age increased. The average ammonia emission rate was 0.86 g day^{-1} head^{-1} (0.32 kg year^{-1} head^{-1}).

Conclusions

In this study, a model to predict the internal concentration in connection with factors influencing ammonia volatilization inside a pig house was developed. The slurry characteristic factors, internal environmental factors, and ammonia concentration were measured in the target pig house, and the model was calibrated based on the measured data. As a result of the calibration, it is determined that the model can predict the ammonia concentration inside the pig house (R^2>0.9). Through the calibrated model, the ammonia emission rate of a mechanically ventilated piglet house was calculated for each age; the average emission rate of piglet was 0.32 kg year^{-1} head^{-1}. Through the results of this study, it is possible to quantitatively analyze facilities that do not satisfy emission regulations and to suggest measures to reduce emission for each facility.

Acknowledgements

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Computational fluid dynamics simulation for odour dispersion prediction for Korean pighouse

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Abstract

The odour dispersion modelling has been popular due to its capability to quantitatively analyze the amount of odour pollutants emitted in the environment. However, most odour dispersion models currently available are typically used for industrial odour transport and oftentimes neglected the topographical condition of the target experimental areas due to the difficulties of integrating the terrain into the computational domain. To supplement these limitations, this study aimed to develop a computational fluid dynamics (CFD) model to predict odour dispersion emitted from a pig farm. Specifically, a pig farm with complex terrain was designed and used to predict odour dispersion. In this study, the developed three-dimensional CFD model was validated through a comparison of the field-measured data and the CFD-computed results in terms of wind environment and dispersed odour. By comparing CFD-computed results with field-measured data, an appropriate grid size, time step, and turbulence model of the CFD model were determined. Considering various factors, case studies were also performed using the validated CFD model. The numerical analysis showed that low wind speeds and stable atmospheric conditions enhanced the transport of odour.

Keywords: complex terrain, computational fluid dynamics, odour dispersion, pig house

Introduction

Computational Fluid Dynamics (CFD) is a powerful tool involving fluid flow, heat and mass transfer and provides complete information related to the distribution of flow speed, pressure, temperature and even the target species concentration. The application of CFD has gained momentum in the field of aircraft, oceanography, medicine, biology, and architecture during the late 20th century. Other prime industries where CFD or fluid flow simulation is frequently used including aeronautics, automotive, HVAC system, power generation, oil industry and so on.

In recent years, CFD modelling has been applied in agriculture-related industries such as food processing, agricultural machinery and agricultural facility design. The use of CFD in these fields reduced the risk of actual design modification, provide accurate quantification of aerodynamic environment parameter analysis and limits the actual experimentation. However, many previously published CFD simulations researches are computationally expensive. For instance, Tseng et al. (2006) simulated the external airflow in 0.6 km × 0.6 km × 0.4 km urban region for almost 130 hours. The paper of Yeo, et al (2020) on the other hand predicted the odour dispersion of a pig farm in a 5 km diameter domain with complex topography required 8 million elements of unstructured grids. Li and Guo (2006) on the other hand compared the prediction of odour dispersion of a 3000-sow farrowing farm using CFD and CALPUFF models taking into account the various atmospheric conditions such as temperature, wind, vertical temperature and so on. Although the above examples were case-specific, this gives general information about the computing time using CFD. As implied, both the number of grid elements and the size of the domain used in the simulation model affects the simulation time. Moreover, the need for modelling bigger test domain with smaller grid sizes for more accurate results have also accelerated with the increase of computing resources. As a result, reducing the computing cost with acceptable accuracy has always been an ongoing focus of CFD research. Thus, in this study, a three-dimensional model containing various pig farms were designed to simulate the dispersion of odour outside each pig farm boundaries. This is the first step for an attempt to develop and integrate a odour forecasting systems to allow the residents prepare for the odour nuisance that may occur at an specific weather condition.

Material and methods

Selection of Experimental Farms

Since the study area covers several number of pig farms, it is important to properly design the selection of the target experimental area where the field experiment will be conducted. The selection of the target is a crucial stage in the field experiment as it will lessen the cost for the conduct of the field experiment but will also reduce the calculation cost for the validation of the CFD model. Shown in Figure 1 is the criteria for the selection of the target experimental farm where field experiment and CFD model validation will be conducted.

Field experiment devices and techniques

Several experimental devices were used to collect the needed data for the development of the three dimensional model of the experimental pig farm. This includes portable weather station (2900ET model of Spectrum Technologies' WatchDog Weather Station 2000 series) used to collect data on various climatical data such as wind speed, temperature, humidity, wind direction and so on. A Hobo data logger (UX100-003, Onset computer corporation, USA) was also used to identify the atmospheric stability of wind environment during the field experiment. Whereas, a TESTO manufactured sensor were used to measure the flowrate of ventilation exhaust fan of each pig buildings. Gas Tiger and MultiRAE was also used to record the emission of various gases such as ammonia, hydrogen sulfide and VOC. On the other hand, an odour chamber was used to collect odour samples at the specified sampling location. The evaluation of odorous air followed the standard dynamic olfactometry method established by the European Union (EN 13725 2003) to measure the concentration of odour using the human sense of smell.

(a) (b)

Figure 1: A) Satellite image of a selected farm; d) Sampling location outside the experimental pig farm

<u>Softwares for designing the CFD three-dimensional model</u>

In this study, the complex terrain was developed using commercial software such as ArcGIS, AutoCAD, SketchUp, Rhino3D and Fluent Design Modeller. The developed model was designed to have an 11 km diameter (including the 1 km buffer zone) and height of 1 m. Presented in Figure 2 is the sample design of the three-dimensional domain.

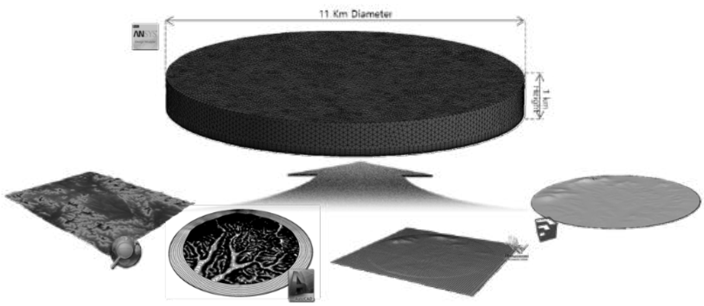

Figure 2:) a) Detailed procedure of developing the three-dimensional model of the experimental farm.

<u>Setting the CFD boundary condition</u>

Since the main goal of the research is to predict odour dispersion emitted from pig farm, it is important to properly address the wind environment which greatly influences the dispersion of odorous substances at the boundary of pig farm. In this case, the ABL of the experimental domain was expressed using the equation 1, 2 and 3 which represents the turbulent kinetic energy, dissipation rate and logarithmic wind profile, respectively. Whereas, equation 4, described the temperature profile at the inlet to induce buoyancy effects within the domain.

$$k(z)=\frac{{u_*}^2}{\sqrt{C_\mu}} \quad \text{Eq. 1} \qquad (1)$$

$$\varepsilon(z)=\frac{C_{\mu}^{0.75}\times k(z)^{1.5}}{L_x(z)} \tag{2}$$

$$U(z)=\frac{u_*}{k}\left[\ln\left(\frac{z}{z_0}\right)+b\frac{z}{L}\right] \tag{3}$$

where z0 is aerodynamic roughness length, u∗ is friction velocity, Cµ is k – model constant, z is the height, L is the Monin-Obukhov-length, u∗ is the friction velocity,and k is the von Karman's constant which is equal to k=0.4

$$L = -\frac{\rho_{cp} T_{ref}\, u^3}{\kappa g Q s} \tag{4}$$

where ρ is the density of air, g is the acceleration due to gravity, cp is the specific heat of air at constant pressure, and Qs is the sensible heat flux.

Results and Discussion

Field Experiment Result

Wind analysis of the nearest weather station from the target experimental farm was first done to identify the dominant wind occurring during daytime and nighttime. Accordingly, the most dominant wind direction in the target experimental farm with a wind speed ranging from <05 ~ 19.1 m/s (Table 1). The wind environment of the selected experimental pig farm has a high mainly due to its location which is relatively flat and away from mountains or hills.

Table 1: Wind analysis result of experimental pig farm

Direction	N	NNE	NE	ENE	E	ESE	SE	SSE	S	SSW	SW	WSW	W	WNW	NW	NNW
Frequency (%)	5.1	6.6	6.7	6.8	3.3	10.4	6.3	6.8	7.0	6.8	5.3	5.5	5.6	5.3	5.1	7.3

In this study first set of field experiments was obtained to determine the adjusted odour emission rate from each pig building considering the European standard and actual ventilation rates in the target experimental farm. Whereas, the next set of experiments were more focused on the evaluation of the odour dispersed outside the pig farm. In the set of experiments, a total of 9 samples were done from the month of June to October 2021. Specifically, three sets of samples (samples 1, 2 and 3) were collected from June 6, 2021, and two samples each from August 11, 2021 (samples 3 and 5), September 6, 2021 (samples 6 and 7), and October 5, 2021(samples 8,9) as shown in Table 2. Due to the effect of fluctuating wind environment on the odour dispersion during the field experiment, careful observation of wind direction was done before collecting odour samples outside the pig farm. For instance, in samples 1 and 2, a constant dominant wind direction must be observed for several minutes before collecting air samples. This is to ensure that the odorous air was dispersed along the downwind direction of the pig farms where sampling devices were installed. In addition to wind direction, the wind speed at the selected experimental farm was also observed and the recorded wind speed data was used for validating the accuracy of the three-dimensional model. However, the wind speed was <0.5 m/s for June and August field experiments which make it very difficult to use as experimental data for model validation. Thus, additional field experiments were conducted (samples 6 ~ 9) on the days with higher wind speed for a more accurate utilization of data for model validation.

Table 2: Measured odour concentration measured inside the pig building

Date	Odour Concentration (OU/m3)		
	P1	F1	F2
6-Jun	448.1	448.1	173.2
11-Aug	144.2	448.1	81.8
6-Sep	310	448.1	1442.0
5-Oct	66.9	669.0	2080.0
Average	242.3	503.3	944.3

*P1=piglet; F1=Fattening 1; F2=Fattening 2

In addition to the analysis of field measured data, it was found that both the ammonia and odour concentration inside the pig houses varies depending on the age of theanimals and exhaust ventilation flowrate (Figure 3). It appears that providing a sufficient ventilation rate during a specific period is required to reduce the concentration inside the rearing building.

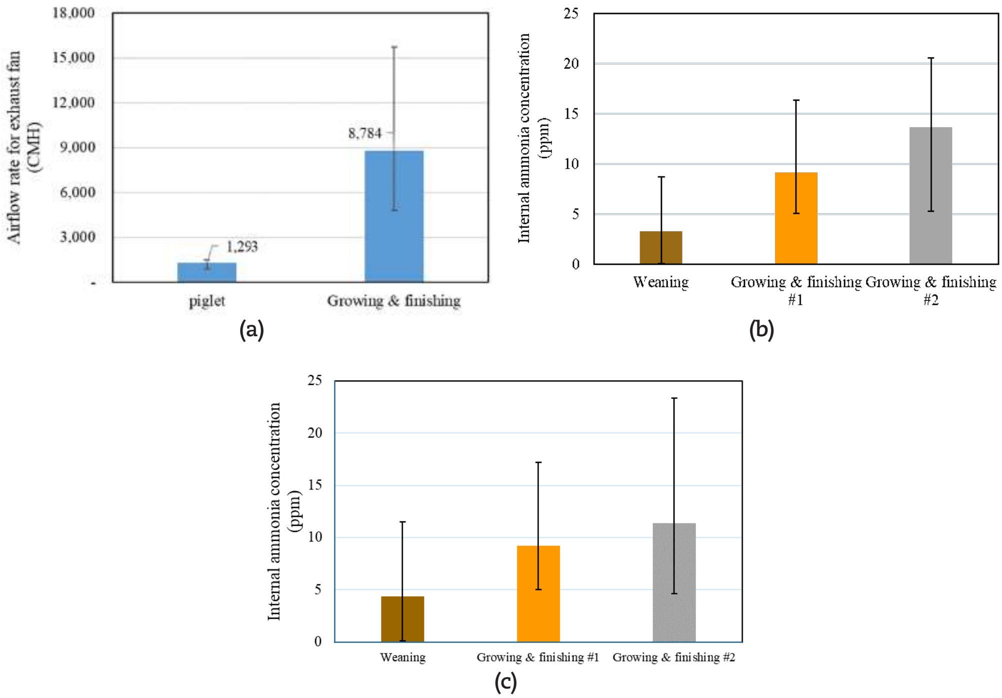

Figure 3: Measured odour concentration measured inside the pig building

Validation of three-dimensional model and simulation result

The wind and turbulence profiles were also checked to whether the simulation results have the same trend as the theoretical wind and turbulence profile. The result showed that in terms of the wind environment using the CFD model is in agreement with the theoretical wind profile which states that wind speed increases with the height from the surface to the upper troposphere due to the following reasons: 1) pressure gradient increases with height; 2) reduced the impact of ground surface friction caused by surface objects such as trees, mountains, buildings and so on which slows down the wind speed when collided, 3) air density is higher near the ground surface and decreases with the increase of the height. This implies that the wind profile in open terrain will recover its original shape at a specific distance when expose to some obstruction. The second step of the validation is through comparison of CFD simulated result and field experiment data. Shown in Figure 4 is a comparison of model using the field experiment data collected on Septer 6, 2021 with wind speed of 3.0 m/s from East direction. In validating the CFD model, various parameters are modified so that the predicted values will provide a reasonable result. Especially, the grid size close to domain was modified and the surface roughness was adjusted to reflect the actual terrain scenario as close as possible. The comparison of the result showed that the model has a r2 value of 0.983 and RSME valuse of 3.89. This means that the result of the validation is close enough to the field measured data.

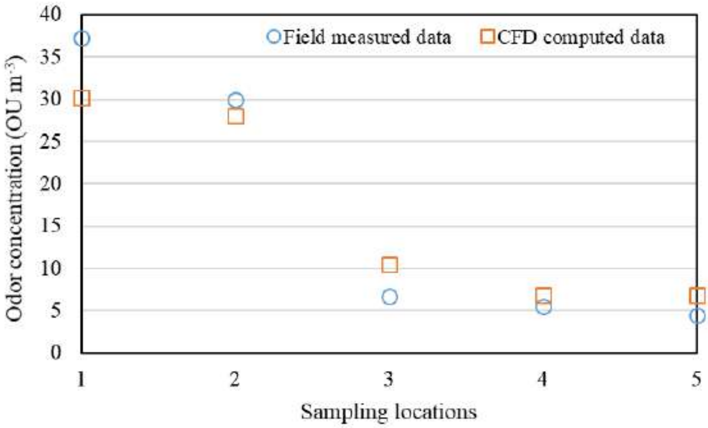

Figure 4: Sample comparison of field measure odour dispersion and cfd computed results.

Scenario cases

Various cases were also simulated to determine the effect of wind environment to the dispersion of odour outside the pig farm (Table 4). Result showed that not only the external environment affected the odour dispersion but it also showed that the amount of odour emission plays a vital role. Specifically, those farms (Farm C and D) with higher breeding head showed the highest dispersion distance. Similar to the result of Yeo et al (2020), the model also showed that a lower dispersion distance is expected at a higher wind speed due to the presence of turbulence caused by high wind environment which resulted to the mixing of fresh air and odourous air making it diluted. In the case of wind direction, a significant change was observed when the odour is transported at a higher terrain compared to those with almost flat terrain. This implies that that elevation also greatly affect the transport of odorous air to the nearby community. In summary, the impact of the terrain affect the easy transport of odorous air.

Table 4: Sample result of the experimental data.

Wind Speed	Wind Direction	Dispersion Distance (m)							
		Farm A	Farm B	Farm C	Farm D	Farm E,F	Farm G	Farm H	Farm I
1.5 m/s	NE	806.2	606.2	891.3	868.3	643	502.3	407.5	813.7
	SE	990.3	552.3	1208.2	1191.4	664.1	689.1	519.8	1002.5
2.0 m/s	NE	708.3	370.1	982.1	956.7	500.6	467.9	385.4	762.2
	SE	870.6	455.3	1187.1	1097.1	563.1	576.3	471	987.8

Conclusion

A three dimensional CFD model was developed to predict the dispersion of odour emitted from various pig farms. The model was validated by improving the grid size and choosing the appropriate turbulence model.Specifically, in this study, an appropriate turbulence model of k-epsilon model was found to show the highest accuracy among the different turbulence model available in CFD. Moreover, the surface roughness of the terrain to reflect the actual surface of the chosen domain. A scenario cases was also made to determine the dispersion distance of odours in accordance to the variation of the wind speed. The result of the analysis showed that the effect of the wind environment (such as wind speed and wind direction) plays an important role on the transport of odorous air to the outside environment. Moreover, the inclusion of complex terrain also affected the simulation results as it determine ability of odour to be transported. In the continuation of this study, the simulated odour dispersion was exported into a readable data and was attached to a odour forecasting system.

Acknowledgements

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Use of a Proximity Index to evaluate the influence of environmental conditions in the growing-finishing pigs' resting behaviour

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Abstract

This study was realized in the frame of the BIOma Project. The main goal was to create and develop an innovative precision livestock farming tool to support and reinforce the pig value chain. The environmental conditions have a great impact in animals' welfare. Animal welfare can be measured through some behavioural, physiological, productive and health indicators. In order to evaluate the impact of the environmental conditions in the growing-finishing pigs' resting behaviour, three experiments, each with 8 females Piétrain x TN60, were carried out in an environmental controlled room where the air temperature (T) and relative humidity (RH) were permanently monitored. A Proximity Index (P.I) to evaluate the level of the animal's dispersion in the pen, was developed based on artificial vision algorithm. This was possible thanks to the analysis of the images recorded by video cameras strategically placed in the room. The P.I was represented on a scale of 0 to 1, where "0" corresponds to the maximum dispersion between the animals and "1" corresponds to the maximum proximity. The P.I presented differences between all experiments, being higher in cold conditions and lower in hot conditions. These results highlighted the influence of the environmental conditions on the resting behaviour of pigs. This work is funded by National Funds through FCT - Foundation for Science and Technology under the Project UIDB/05183/2020

Keywords: pig welfare, monitoring, environmental conditions, resting behaviour

Introduction

The majority of pig production in the world is realized in intensive systems (90%), characterized by high animal density, using genetically improved breeds and developed and industrialized livestock facilities (Rodríguez *et al*., 2013). In these systems, animals are often subject to environmental conditions that can have great impact on performance, health and welfare (Cruz, 1997; Gebreyes *et al*., 2014).

Animal welfare is an expression that tends to resist a strict definition and that can have different meanings and interpretations for different people (Madzingira, 2018). Within scientific community, there is a clear lack of consensus on welfare definition. In 1996, Broom suggested the animal welfare is defined in function of attempts to deal with the environment (Broom, 1996; Hewson, 2003; Vieira *et al*., 2011) and that approach still is the most accepted.

In general, animal welfare is related to physical and emotional state produced in animals due to human attitudes and practices, quantity and quality of available resources and environmental conditions in the facilities (Madzingira, 2018).

Animal welfare can be measured through some behavioural, physiological, productive and health indicators (Candiani *et al.*, 2008). Most of these indicators provide information that allows to characterize the animal's status (Broom and Molento, 2004; Martins, 2020).

Behavioural indicators are based on variations in pig behaviour that can be manifested by the difficulty in expressing certain movements or in adapting to environmental stimuli (Costa *et al.*, 2009).

To deal with environmental conditions, animals adopt some behaviours that contribute to the thermoregulatory mechanisms. Regarding resting behaviour: when animals are in the thermoneutrality zone they adopt a lateral recumbent posture with about 40-50% of pigs touching each other (Ekkel *et al.*, 2003); when the temperature is below the animals' comfort zone, pigs crowding to prevent heat loss and adopt a sternal recumbent posture to reduce the surface area of the skin exposed to the environment, decreasing heat loss. In this situation, it is common for animals to tremble (Costa, 2015); when temperatures are above the comfort zone, they adopt a lateral posture, stretching as much as possible and avoiding contact with other animals, in order to expose a greater body surface to a colder surface (floor), in an attempt to lose heat by conduction. In hot conditions animals decrease activity (Jones and Manteca, 2009), increase respiratory rate (Linden, 2014) and use available water in contact with the body to evaporate, increasing latent heat losses (Cruz *et al.*, 2021).

The main goal of this work was to develop a Proximity Index (P.I) to understand the influence of environmental conditions in the growing-finishing pigs' resting behaviour.

Material and methods

Experimental design

Experiments were carried out in the environmental control room at the University of Évora. Three different conditions were defined: Winter (W) – cold stress (trial 1), Thermoneutrality (TN) – thermal neutrality (trial 2) and Summer (S) – hot stress (trial 3), shown in Table 1.

Table 1: Experimental environmental setpoints

Environmental Conditions	Winter (W)	Thermoneutrality (TN)	Summer (S)
Temperature (ºC)	10 ± 2	18 ± 2	30 ± 2
Relative Humidity (%)	80	70	60

In each experiment 8 female pigs of *Piétrain* x *Topigs Norsvin* (TN60) genotype were used with an initial body weight around 48 ± 3kg. Each animal had 1.5 m^2 of area in the pen. The animals were identified with an RFID ear tags system and each experiment started after 15 days of the habituation period in TN conditions (T_{mean} = 18 ± 2°C and RH_{mean} = 60%) and ended when the animals reached a commercial slaughter weight of around 95-105 kg live weight.

Structures and equipment

The animals were housed in a pen with an area of approximately 12 m^2 inside the environmental control room. The floor was partially concrete covered with anti-slip tactile. The pen had a manure pit and was equipped with an automatic feed station and two nipple drinking bowl.

Environmental control was carried out through ventilation, heating and cooling systems. Ventilation system was compound by two vertical extractors fans. The air came into the facility through a false ceiling to protect the animals and left through the extractors (negative pressure). The heating system consisted of a conventional gas heater. The cooling was by a nebulization system.

The environmental control room was equipped with different equipment and technologies that allowed to record experimental data, which are described in Table 2:

Table 2: Characteristics of the equipment used to record experimental data

Materials	Unit.	Measurement ranges	Accuracy
Video camera (Foscam FI9961EP)	6	continuous	–
Temperature probe (COPILOT)	4	-10 to 50 ºC	± 0.2 ªC (resolution 12 bits)
Temperature probe (CapTemp TH3-Temp OW)	7	-10 to 55 ºC	± 0.5 ªC (resolution 12 bits)
Relative humidity probe (EE06)	1	0 to 100% RH	± 3% (10 to 90% RH); ± 5% (<10% RH e >90% RH) (resolution 0.1% HR)

Data collection

Air temperature (T) and relative humidity (RH) was measured and recorded through an environmental control system (*Webisense*) and a data collector (*Nidus*) which allowed to record a high quantity of data simultaneously. These data were collected continuously and in real time throughout the experimental period.

Figure 1: Capture of the animals' pen through video cameras

The behavioural data was recorded through video cameras strategically placed in the room (Figure 1). Video cameras were integrated into the data storage system, which made it possible to continuously record and save video images in the cloud for further processing.

Proximity Index development

The disposition of the animals in the pen (removal/crowding) was studied through the development of a Proximity Index, using video images captured (24h/24h) and an artificial vision algorithm specifically developed for this purpose.

This algorithm receives video images and process it frame by frame. The analysis process occurred in two phases:

1. **Recognition of animals and/or groups:** This phase was developed based on the work of Nasirahmadi *et al.* (2015). Using a Delaunay triangulation method (applied in the software MATLAB), the algorithm searches for shapes that match the outline of an animal (elliptical shape) (Figure 2) and records the position of each one in the pen. If several animals are in contact, forming a group of animals, the algorithm also identifies this situation.

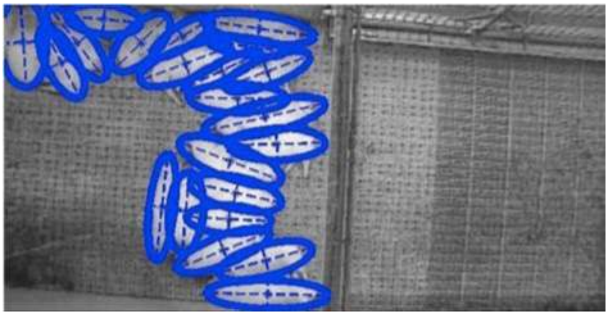

Figure 2: Example of pig shape adjustment (Nasirahmadi *et al.*, 2015)

2. **Proximity Index calculation:** Through the perimeter of each triangle, formed by the centre of the identified ellipses, the proximity of the animals was calculated. Taking as input the pen area, the total number of animals and the position of each one, the algorithm calculates the animals' proximity index, with the result changing between 0 and 1 (Figure 3). A value close to 1 means that the animals are all together in a group (1 = crowding) and zero means that the animals are as dispersed as possible throughout the entire pen area (0 = removal).

In other words, the calculation of the P.I. results of an analysis that considers the pen area in pixels. With this information, the algorithm competitively assigns values tending to 0 if the points (pigs) are further apart or values tending to 1 if they are closer.

Figure 3: Animals' proximity calculation

Results and Discussion

The air temperature, relative humidity and PI data collected during the entire experimental periods were analysed through a descriptive statistical analysis.

Table 3: Air temperature and Relativity humidity recorded during in the experiments

	Winter (W)		Thermoneutrality (TN)		Summer (S)	
	T (°C)	RH (%)	T (°C)	RH (%)	T (°C)	RH (%)
Average	12.5	74.5	20.7	74.0	28.9	63.1
Standard derivation (SD)	2.1	6.2	1.5	12.0	1.6	6.9
Maximum (max)	19.4	95.4	24.9	97.3	33.3	90.1
Minimum (min)	8.3	54.5	15.9	43.8	23.2	25.3

*(59 days in winter condition; 65 days in thermoneutrality; 58 days in summer condition)

Through the analysis of Table 3, it is possible to verify that the average temperatures and relative humidity recorded inside the environmental control room were in accordance with the work goals (Table 1) and represented real winter, thermoneutrality and summer conditions.

The values of the P.I achieved during the experiments are presented in Table 4.

Table 4: Proximity Index achieved during the experiments

	Winter (w)	Thermoneutrality (TN)	Summer (S)
Average	0.8821	0.7920	0.6502
Standard derivation (SD)	0.1360	0.1449	0.1656
Maximum (max)	1	1	0.9823
Minimum (min)	0.3622	0.3581	0.2828

Legend: 0 = removal; 1 = crowding

According to the Table 4, it is possible to say that the animals were closer in the winter condition. This behaviour was expected since the animals tend to be crowding when subjected to low temperatures. This behaviour occurs to avoid the loss of body heat to the environment that surrounds them (Cruz *et al.*, 2021). The opposite is verified for the summer condition, where the lowest P.I values were obtained.

The P.I presented less variation in the winter condition in relation to the thermoneutrality and summer conditions (Figure 4), as shown by the lowest SD found in the winter condition (Table 4).

Figure 5 presents the P.I for an average day. This average day was obtained for each experimental condition, by calculating the mean at 0:00 am; 01:00 am; 02:00; etc.

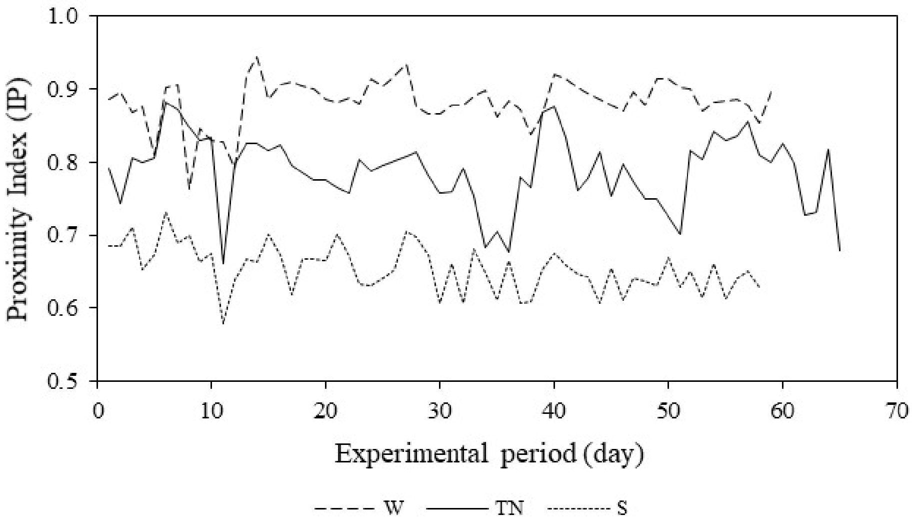

Figure 4: Average daily Proximity Index in the experimental period

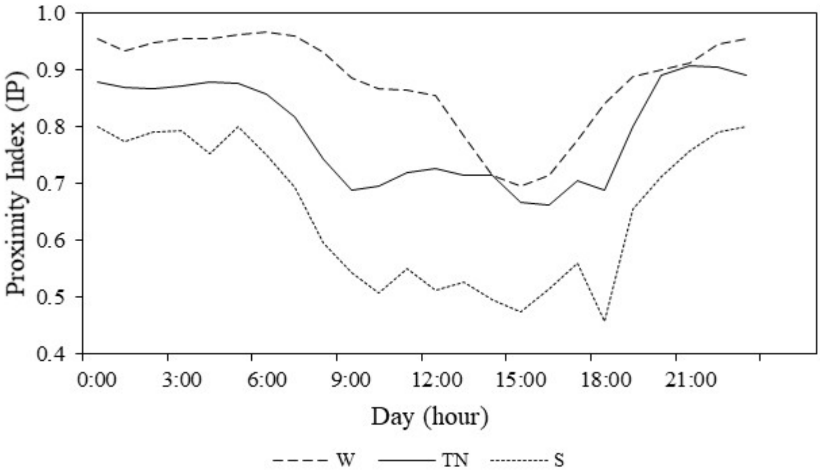

Figure 5: Proximity Index for an average day

Through the analysis of Figure 5, it is possible to verify similar behaviour for the P.I curves for the three simulated environmental conditions. The highest P.I values were recorded during the night period (7:00 pm to 6:00 am). During the daytime (7:00 am to 6:00 pm), a decrease in P.I. was observed. This behaviour can be explained by the fact that the animals tend to remain at rest for a longer time during the night, which leads to be closer to each other.

Conclusions

This paper proposed a real-time Proximity Index to evaluate the influence of air temperature and relative humidity in the growing-finishing pigs' resting behaviour, contributing to the scientific and technological advance of the pig sector.

Through the analysis of the P.I results, it was possible to verify that air temperature and relative humidity affect the pigs' resting behaviour: in hot stress conditions the animals tend to removal and in cold stress conditions they tend to crowd. This type of analysis makes it possible to understand the thermal comfort level of animals through their behavioural mechanisms.

The P.I developed and based on animal and environment real data proved to be a good precision livestock farming tool to evaluate animal welfare, being a non-invasive method that allows to monitor information continuously and remotely.

Acknowledgements

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SESSION 19

General:
Decision and Economics

Mapping information flow in the livestock supply chain for beef in Sweden

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Abstract

Transparency along the livestock supply chain (LSC) can generate numerous traceability benefits for stakeholders. Sharing data between actors and processing data into meaningful insights can promote data-based decisions, providing the potential to boost productivity, improve animal welfare and decrease administrative costs.

Today, few data are shared between different actors along the LSC and existing data are often not in sharing-friendly digital format. It is also difficult to define, contractually and otherwise, value extraction from data assets, especially as the competitive impact of data sharing is poorly understood. A significant challenge related to data sharing is lack of a single entity, trusted by all, that can drive digital transformation efforts.

Novel information system architectures, specifically decentralised computing frameworks (i.e. blockchains, distributed ledger technologies), provide new ways to share data and manage contractual agreements around data sharing and data usage. However, as with any information system, the design of decentralised and/or distributed computing frameworks involves several important trade-offs. This study was part of a larger project aiming to clarify such trade-offs in the LSC context.

In this study, information flow in the LSC for beef in Sweden from farm to slaughter was mapped. Details of the existing LSC system and associated data needs were obtained in interviews. Visualision of existing data and information flows was used to identify changes to improve future information flow.

Keywords: agriculture, agri-food, data sharing, traceability, digitalisation, decentralised computing frameworks

Introduction

Transitioning towards more sustainable and resilient food systems is key for the agri-food industry, and digitalisation is an important driver in transition (Amentae & Gebresenbet, 2021; Lezoche *et al.*, 2020). Digitalisation enables collection of large quantities of data throughout the supply chain, which can be used to optimise and increase efficiency of production and processing in a sustainable way (Eriksson, 2020). An important element in improving supply chain operation is integration of information flows. According to Buhr (2000), information flows are crucial for successful supply chain relationships and good flows are an important incentive for establishing supply chain integration. Information sharing creates closer collaboration between actors in the supply chain (Vickery *et al.*, 2003; Williamson *et al.*, 2004), improves customer satisfaction

(Singh, 1996) and increases competitiveness and innovation in the supply chain (Van Hoek, 2001). Changes in consumer preferences for information on product origin and food safety requirements place demands on businesses to improve their traceability systems (Amuno *et al.*, 2018) and integrate information flows across organisations in the supply chain so as to significantly reduce disruptions in data flow.

Sector-specific frameworks may be beneficial in developing effective traceability systems for the supply chain (Leteane *et al.*, 2021). This study focused on digitalisation of the Swedish beef supply chain. The business environment and production characteristics of Swedish beef production place specific requirements on supply chain information flows. For example, there is strong emphasis on downstream information flow and traceability, whereas conventional manufacturing industries require upstream information flow (Schroeder & Hope, 2004). The value chain is also complex and heterogeneous, including many small and medium-sized enterprises. A significant challenge related to data sharing is the lack of a single entity, trusted by all, that can drive digital transformation efforts (Leteane *et al.,* 2021).

Technologies for tagging, event detection, machine-to-machine communication and environmental data collection have increased data availability throughout the entire livestock supply chain (LSC). Consequently, data sharing and data-driven decisions are now possible at previously unprecedented levels. However, as data assets become valuable, conflicts around data sharing and data usage are likely to emerge (Altmann & Linder, 2019). There are also unresolved issues around privacy, data protection, relationships of trust and power, storage, usability, and security (Copa *et al.*, 2018; Zhao *et al.*, 2019). Another possible barrier to digitalisation of the beef supply chain is profitability, as actors in the supply chain may struggle to maintain profitability when implementing digital solutions.

This study mapped the information flow in the LSC for beef in Sweden from farm to slaughter. Through interviews with actors in the supply chain, the existing supply chain and associated data needs were identified. The existing data and information flows were then visualised and used to suggest changes to improve information flow.

Material and methods

An exploratory approach was used. First, stakeholders in the Swedish beef supply chain, including production businesses, authorities, and organisations with support roles, such as breeding companies, veterinarians, consultants, and tech businesses, were identified. Representatives from organisations across the supply chain were then selected for interviews by purposive sampling, aiming to cover all categories of organisations through the whole information supply chain from farm to slaughter.

A total of 18 interviews were conducted and additional informants were consulted to clarify information pathways. Interviewees included representatives of businesses directly involved in the supply chain (e.g. beef and dairy farmers, animal transporters, slaughterhouses), service organisations (e.g. agricultural advisors, veterinarians) and organisations with an oversight role (e.g. Swedish Board of Agriculture, Swedish Food Agency, certification bodies). Semi-structured interviews were conducted using an interview guide containing questions regarding information the stakeholder sought and supplied, type of data collected and stored, and how data were shared between stakeholders. The interviews also covered any deficiencies in data sharing, and barriers and motivators for sharing data between stakeholders.

Structured qualitative content analysis was used to analyse the interview data. Based on the qualitative data, the information flow in the Swedish beef supply chain from farm to slaughter was mapped. An alternative information flow, enabled by e.g. decentralised computing frameworks or distributed ledger technologies, was then described, as a possible solution to the identified deficiencies while also addressing challenges regarding data protection, traceability and transparency. The benefits of such an alternative information flow system were assessed.

Results and Discussion

Meat production from cattle has two pathways, via dairy and beef. Both were considered in this study, but the focus was on meat production and not on data relating to dairy production. Many different private and public authorities handle the data generated in the meat value chain. Figure 1 visualises the complexity of the information flow in the beef value chain, with its many actors involved, and how data are fragmented between various data formats and databases.

Most of the data generated in the meat value chain are entered manually when they first enter the information flow, either through a website or in an on-line decision support system (DSS). Large volumes of data are generated automatically by dairy production systems, some of which may be of use in the meat supply chain. However, in general dairy data were not considered in this study. Data requested from authorities are entered either directly on an official website or via an on-line DSS passing on requested information to the authorities, depending on the farmer's/producer's choice. Not all farmers use a DSS, and dairy farmers do so more commonly than pure beef producers. Such manually entered data may result in a data trust issue, as there is a possibility of loading inaccurate data or false data into the system, creating a risk of a mismatch between physical product condition and data in the digital information system (Letane *et al.*, 2021).

All producers and veterinarians need to be registered in different databases in order to enter data requested from the authorities. In Sweden, two national authorities (the Board of Agriculture and the Swedish Food Agency) request information from the value chain. On regional scale, the 21 County Administrative Boards conduct local checks on compliance with legal requirements. The National Veterinary Institute, the Swedish eHealth Agency, municipal monitoring bodies and several other authorities check compliance with legal requirements or use the information in an expert or service body role to provide information to other authorities or the public. All data generated by veterinarians are strictly regulated by EU legislation, with strong confidentiality regarding data sharing. Veterinary data are only shared with farmers and some required data with authorities.

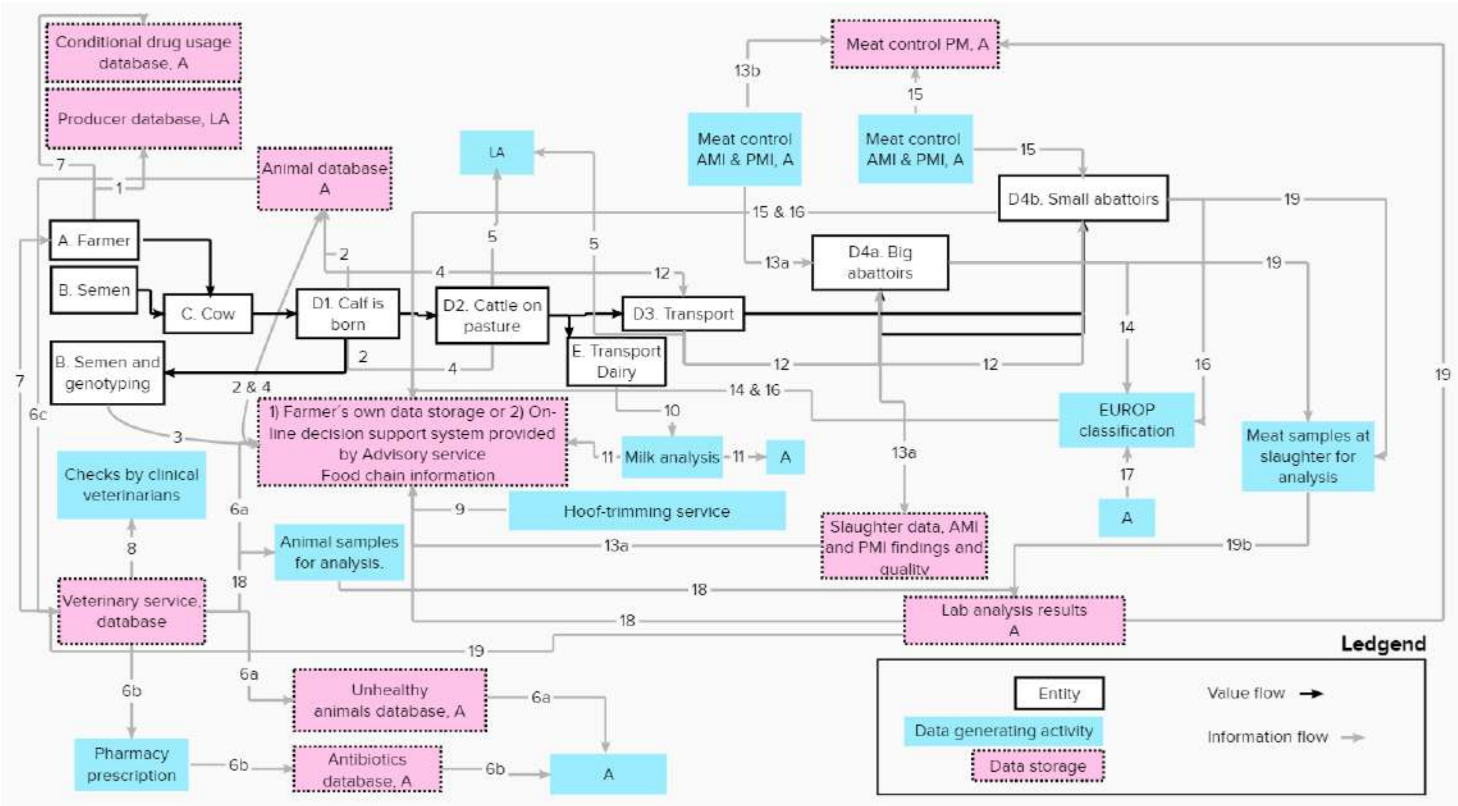

Figure 1: Information flow in the Swedish beef value chain from farm to slaughter, shown as the entity related to the value flow (white box), activities generating data (blue/no box) and actors storing the data (pink/dotted box). Black arrows describe the physical flow of entities such as animals, semen, samples for animal health and food safety, and meat; grey arrows describe the information flow related to the physical entities. Numbered information steps between the various actors are explained in Appendix 1. A=national authority. LA=local authority. PMI=post-mortem inspection. AMI=ante-mortem inspection.

Today, information is often shared between fewer actors than needed for efficient information flow and a competitive value chain. The quality of the information may differ if it is entered on a form in pdf-format or on a web-portal checking compliance with requested information. In particular, information generated by veterinarians, including essential information on medical treatments, may vary in quality.

When asked about the sensitivity of the information they generate, farmers mentioned information on unhealthy animals and treatments given to these animals and expressed unwillingness to share production expert knowledge. Information on treatments can be difficult to communicate to consumers and farmers did not consider it relevant for sharing with consumers, due to the risk of misinterpretation. Regulations on the use of antibiotics differ between countries and are very restrictive in the EU and especially in Sweden, where treatment at group level and preventive treatment are prohibited. Marketing meat as ‘antibiotic-free’ may have negative effects, such as failure to treat sick animals or implying to consumers that there may be residues of antibiotics in meat from treated animals. Regarding specific information on production, farmers stated that they had worked hard for their knowledge and saw no benefits in sharing information on their best practices with other farmers, as this might reduce their own competitiveness. If they were to share this information with anyone, it would be by visualising their production in figures directly to customers.

Figure 2 shows current and desired information flows between actors in the beef value chain, as identified in interviews. In the current situation there are deficiencies in the upstream information flow of the supply chain, as the focus has been on hygiene and product safety. However, both upstream and downstream information flows are crucial for efficient supply chain management (Schroeder & Hope, 2004). Much of the information handled by one authority is not available for other authorities. It can sometimes be made available on request, but not on a regular basis. This is especially true of information between the Swedish Board of Agriculture and Swedish Food Agency, an issue that the authorities are working to resolve. Many actors in the beginning of the value chain wanted more knowledge on consumer demands and preferences. These actors included farmers, breeding companies, calf producers who sell their animals (Farmer 1 in Figure 2) and farmers raising the animals to slaughter weight (Farmer 2). Farmer 1 producers also wanted access to information on quality and food safety findings generated in abattoirs. In order to improve or specialise their production, some farmers wanted information from meat processers and restaurants on the quality they require and their views on the quality of meat they receive from the farmer.

In the next part of the project, we will develop a technical solution using decentralised computing frameworks to resolve data sharing issues, including security, privacy, and control of data. The road map to utilise blockchain in the defined flows will comprise various components that are coordinated with each other, to serve traceability, security and privacy features. Solutions will be implemented in the form of a generic data-sharing platform where a wallet will hold core credentials, and a generic digital gateway will act as a single point of data exchange on every stakeholder premises. In addtion, the platform will be integrated with blockchain infrastructure to develop trust between all stakeholders in the supply chain, such as farm owners, veterinarians, authorities, transporters and slaughterhouses. Blockchain can increase the integrity of transaction information and privacy of enterprise information and improve the efficiency of the whole value chain system (Zhao *et al*., 2019).

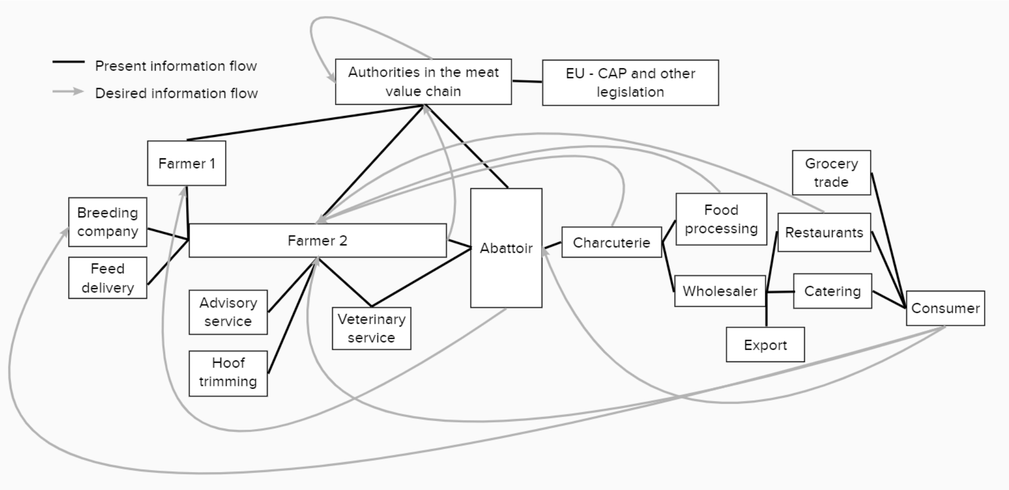

Figure 2. Present and desired information flow between actors in the beef value chain.

Conclusions

This study mapped information flow in the Swedish beef supply chain from farm to slaughter and devised an alternative map built on trusted information pathways. Information flow in the beef supply chain is very fragmented, with private and public actors of different sizes providing data in various formats stored in separate databases. The focus so far has been on sending more information downstream in the value chain. There are strong arguments for sending information back along the chain, but currently limited possibilities to actually do so, hindering the development of business models based on upstream information. Interview responses revealed lack of trust between stakeholders, with no single trusted entity for handling a common database. However, there is potential for new information flows to be facilitated through trusted and secure information sharing enabled by blockchain and distributed ledger technologies.

Acknowledgements

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APPENDIX 1: Key to data points, type of actors, type of information, and storage in the information flow depicted in Figure 1

Item	Actor	Information recorded	Format
1	Local authority (LA)	Producers' production number, address, type of production.	Database
2	Authority (A)	New cow ID, entered from DSS or directly on web page.	DSS/Animal database
3	Laboratory	Genome result from ear sample of cow, sent to farmer.	DSS
4	Authority (A)	Records of animal movement, from farm to grazing or from farm to abattoir. Animal ID, sex, time to transport, production site, reason for transport.	DSS/Animal database
5	LA	LA reports animal welfare inspections to a Control Register. Information saved in database at A. Animal Health Law (AHL)	Database
6a	Vet. service	Information generated from farm visits on unhealthy animals and treatments.	Database
6b	Pharmacy	Antibiotics sold to type of animal	Database
6c	A	Validates treated animal ID against Animal Database.	cloud service/ e-service
7	Vet. service	Conditional drug usage delegated to farmer.	Database
8	LA	Check by clinical veterinarian	Database
9	Hoof-trim. service	Farmer enters information about hoof-trimming activities.	DSS
10	Dairy transport	Information related to milk logistics and quality	Database
11	Laboratory	Analysis of bacteria, cell count and presence of antibiotics (or spores). Antibiotics reported to LA.	DSS
12	Animal transporter	Animal ID, time of transport	Abattoir DSS/ cloud service
13a	A	Postmortem (PM) findings and decisions in meat inspection (PMI), decisions in antemortem inspection (AMI).	Abattoir DSS
13b	A	AM and PM findings on animals and meat from official reports.	Database
14	Large abbatoir	Meat classification according to EUROP	Abattoir DSS
15	A	AM and PM findings on animals (AMI) and meat (PMI) inspections.	Database
16	Small abbatoir	Meat classification according to EUROP scale	Database
17	A	Calibration of EUROP classification	Html to A
18	Vet. service	Sampling animals	Database
19	A	Sampling meat	Database

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Pilot study on developing a sensor technology network to aid decision-making on-farm

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Abstract
Expectation of increasing productivity, profitability and sustainability on dairy farms on behalf of farmers and consumers meets many challenges. Sensor technologies have the capability to address this by provision of real-time information for more astute decision-making on-farm. This Pilot Study aims to create a template for installation, management and use of these sensors and the data generated from them in farm management decision-making. Six 'Ambassador Farms' were initially selected within the peninsular catchment area of Dingle (Ireland).The sensors were installed using LoRaWAN communication. The sensors were chosen based on the importance of their respective and combined data for decision-making on Irish dairy farms and cost effectiveness. They included technologies that continuously recorded milk/slurry volumes, weather conditions (e.g. rainfall, air temperature), soil moisture as well as the Decision Support Tool 'Pasturebase' for grassland management, and a nutrient management plan. Validation of the sensors was conducted. The framework for capturing and monitoring the data, analysis and interpretation is on-going. The ultimate aim is to use the information generated by the data, e.g. grass growth rates, milk production, soil characteristics, rainfall, volume of slurry usage, etc. to increase precision in decision-making, thereby improving production efficiency while reducing environmental impact in farming. The pilot study demonstration platform is currently being rolled out to 30 farms.

Introduction
Dairy farms in Ireland are currently challenged with finding implementable solutions to improve sustainability, in terms of environmental issues, labour demand and availability, herd management and welfare, while also improving profitability (Kelly et al., 2020). Precision livestock farming (PLF) incorporating digital technology presents a strategy with potential to address these challenges. Berckmans (2017) defined PLF as the integration of deployed hardware such as sensors and software systems on farms in order to extract information that help in subsequently generating insights which inform business decisions. The validity and viability of PLF as a framework that could support sustainable food production in terms of farm and supply chain performance improvement, along with task automation and compliance has been substantiated by Eastwood et al. (2021). However, Eastwood and Renwick (2020) have also addressed the limited understanding of how the use of smart farming technologies can be translated into effective use in the farming sector. While sensors may be considered as the foundational pillars

of a PLF framework and collect significant volumes of data, Bahlo et al. (2019) have highlighted that current PLF systems often utilize these datasets in a siloed manner for singular use-cases. The additional benefit is when different datasets can be integrated, e.g. allowing a farmer to predict grass growth as well as have current measured data, thus ensuring improved management of grass and performance of the system.

The motivation behind this project was informed by the need to equip dairy farmers, in the Republic of Ireland, with data and insights that inform holistic business decisions. The Farm Ambassador Programme was an initiative involving the local farming community located on the Dingle Penninsula in the southern part of Ireland. This programme aimed to investigate the feasibility, application and impact of digital technology in the farming business. The overall vision was to integrate smart technologies into pasture based farming systems, be they dairy, beef or sheep production with the objective of improving farm management, and ultimately have a positive impact on environment, profitability and lifestyle for the farmer. This was based on the premise that better and more precise management decisions can be made with the availability of 'real time' data from these smart technologies. But this data has to be captured, managed and used appropriately.

Material and methods

Six dairy farmers signed up to this Farm Ambassador Pilot Programme within the peninsular catchment area of Dingle, and a network of sensor technologies was put in place on the farms. This allowed 'real-time' automated monitoring of various aspects of the farm, e.g. grass and milk production, weather and soil. The sensors were installed using LoRaWAN communication technology. The sensors were chosen based on the importance of their respective and combined data for decision-making on farms, and cost effectiveness.

Figure 1: A range of deployed sensors

The six Ambassador Farms in the pilot study each had 11 different sensors deployed. These sensors measured the height of milk and slurry in their respective tanks, grass parameters, soil temperature and soil moisture. The remaining 6 sensors measured weather parameters such as: wind speed, wind direction, rain fall, air temperature, atmospheric pressure and relative humidity. The sensors measuring weather variables were attached to a sensor array on the Libelium Waspmote as shown in Figure 1, a sensor device for Internet of Things (IoT) applications. The sensors sent Unix timestamped values every 15±3 minutes to a cloud server managed by a local Information Technology (IT) partner. All the sensors used in this project were provided by Smart Agri with the exception of soil moisture sensors from Sensoterra. Other data sources integrated into the architecture included grazing data from PastureBase (https://pasturebase.teagasc.ie). Figure 2 shows the real time data architecture implemented in the study.

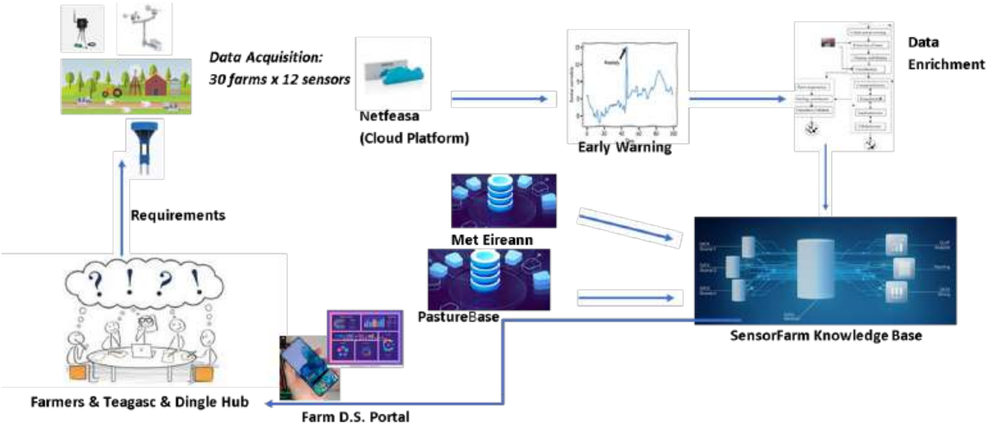

Figure 2: Data architecture of the study

Results and Discussion

In order to add value to the data and increase its utility, the captured data from each sensor should be examined individually and also in association with linked data. Data captured included milk volume on an hourly basis together with tanker collection times. The milk volume readings were validated on e.g. 3 occasions/week by matching the farm bulk tank readings with the collection tanker reading (Figure 3). Thus, morning, evening, daily and weekly milk production was available for the farm.

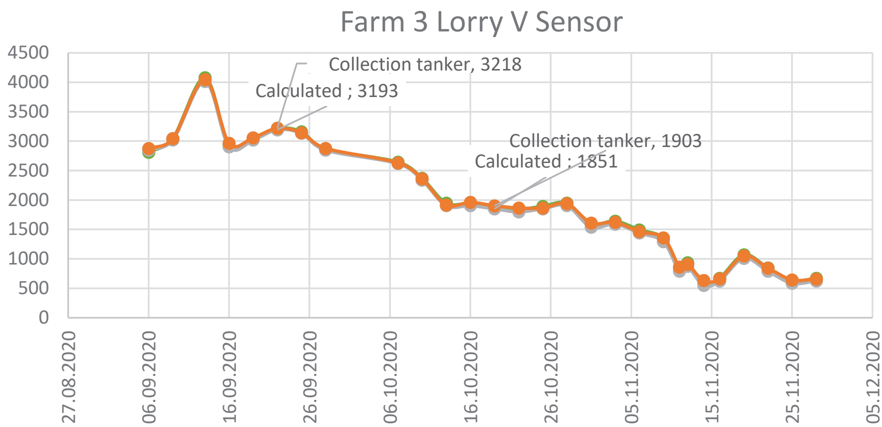

Figure 3: Milk volumes compared for farm bulk tank and collection tanker

Thus the individual farm milk production level could be examined on a weekly, daily or morning/ evening basis at a specific time point or on a continuous basis over a defined timeframe. It could also be used to benchmark the farm against other farm groups of similar size and management criteria or in comparison with appropriate targets. This milk sensor represents an inexpensive milk meter, whose output data may be associated with paddock data, e.g. herbage mass (HM) and grass growth rate (Figure 4), and with weather data, with a view to observing association between these parameters, and subsequently using those associations to predict what options should be taken in terms of management, e.g. allocation of grass to livestock. This is important as grazed pasture can make a contribution to dairy cow feeding systems but it's management can be challenging in parts of Europe (Hennessy et al., 2020).

LU = Livestock unit; MS = Milk solids

	Farm Cover kg DM/ha		Cover/LU DM/ha/LU		Stocking Rate LU/ha		Growth rate kg DM/ha/day		Group Growth rate Kg DM/ha/day		MS (kg) /cow/day		MS (kg) /ha/day	
Wk Start	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021
22-03	990	792	460	360	2.15	2.2	11	14	8		1.73	1.91	3.72	4.20
29-03	854	657	373	276	2.29	2.38	10	21		20	1.91	1.89	4.37	4.50
05-04	746	484	313	150	2.38	3.23	30	25	53	51	1.90	1.37	4.52	4.43
12-04	588	415	213	125	2.76	3.32	25	29	29	29	1.79	1.32	4.94	4.38
19-04	576	377	206	112	2.8	3.37	37	25	59	86	1.88	2.06	5.26	6.94
26-04	662	332	185	96	3.58	3.46	58	31	46	59	2.07	1.99	7.41	6.89
03-05	650	412	169	114	3.86	3.6	47	51	56	38	2.00	1.79	7.72	6.44
10-05	655	470	169	126	3.88	3.74	34	35	63	38	2.00	1.88	7.76	7.03

Figure 4: Grassland management parameters

Farmers were asked to do a farm walk weekly, record grass cover and upload this data to the 'PastureBase' decision support tool (https://pasturebase.teagasc.ie). The interaction of these data can be used to optimise and ensure more precise decision-making regarding grass allocation (Figure 5).

Furthermore, the grass data may be considered in conjunction with the weather data (Ruelle et al., 2018). Herbage mass/ha is a valuable parameter that may be used to advise on recommended time for fertilizer/ slurry application and to match grass growth rates to weather. Soil moisture can also be related to weather. Slurry tank volume data can indicate slurry production rate and days of storage remaining in the tank. This data, together with weather data and soil moisture may be used to advise on application/ spreading dates. Finally, the nutrient management plan developed for each farm details the fertility index of the soil and indicates the varying requirements for lime, N, P, K in the different paddocks, which in turn, facilitates nutrient management planning in terms of targeted application rates, thus minimizing wastage and potential environmental issues.

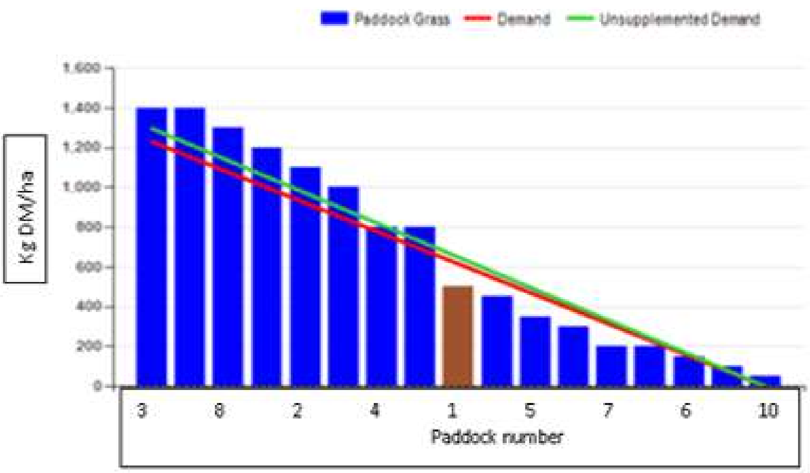

Figure 5: A 'wedge' developed within the PastureBase decision support tool

This work is continuing with respect to data analysis and obtaining maximum benefit from the data captured. Plans are now in place for progressing this work further and scaling up to 30 additional farms. This is made possible through partnership in a recently funded EU project (PLOUTOS). Decision making criteria will be developed through a co-creation process with farmers, technology providers and data analysts. These will be embedded in an online dashboard tool giving the farmer real-time access to information to support decision making. A further key aspect of this phase will involve looking to commercial models in terms of how the solution be packaged, delivered and implemented at scale.

Conclusions

This project is basically about getting maximum value from real time data on relevant parameters, captured using appropriate measurement systems, and modelled to generate decision support systems to ensure improved decision-making and precision management. This approach using smart farming technology can also provide evidence-based attributes for the farming system, such as traceability, sustainability and low environmental impact, and that, in turn, would support a high market value for the farmers produce and facilitate a brand for farm products from the Dingle Peninsula.

Lessons learned from the work so far include: (a) the technologies must be relevant, appropriate and cost effective, and operate as required; (b) data management is a significant part of the work incorporating building of databases, storage, data flows, automated checking and appropriate data combining for analysis; and (c) a necessity for support and training of farmers in the interpretation and use of the decision support tool output.

Acknowledgements

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The potential of Explainable Artificial Intelligence in Precision Livestock Farming

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Abstract

In the discussion on the increasing demand for food, which is to be met by efficient and sustainable increases in productivity, animal welfare is becoming increasingly important. Animal health issues must be identified to prevent epidemics that significantly impact the economic performance of farms or even cause societal harm.

The use of cutting-edge technologies (IoT, sensors, Big Data processing, etc.) is increasingly enabling early intervention in livestock farming to curb productivity losses through real-time monitoring, alerts, and decision support. The ubiquity of these technological solutions has enabled stakeholders to create more robust agricultural supply chains, that deliver sustainable nutrition for a growing population. However, the increasing use of Artificial Intelligence (AI), which is responsible for many of the current breakthroughs in Precision Livestock Farming (PLF) and agriculture in general, has meant that modern decision-support solutions have increasingly transitioned toward black box systems. It has become apparent that a gap exists between efforts to develop more advanced machine learning models, and the growing demands for ethical assessment and transparency in agriculture decision-making.

Explainable Artificial Intelligence (XAI) is one such solution that could prove effective in overcoming the current limitations of black-box models, by allowing the decision-making process of such models to be explored. Through a literature review, we evaluate the potential of XAI in various agricultural use cases and demonstrate the potential benefits of its application to precision livestock management.

Keywords: Artificial Intelligence (AI), explainability, animal welfare, farm management, monitoring.

Introduction

In agriculture, Artificial Intelligence (AI) has attracted great interest in both research and industry. AI is commonly defined as "simulated human intelligent behavior such as learning, judgment, and decision-making" (Caiming Zhang, 2021). In line with this definition, AI has enabled breakthroughs that until recently could only be achieved by humans.

Its ability to provide high accuracy classification and decision support has enabled breakthroughs in Precision Livestock Farming (PLF), Smart Farming, and many optimization and monitoring tasks. The addition of cheap Internet-of-Things (IoT) technology has further enhanced the abilities of AI, enabling large volumes of unstructured data to be collected with relatively little effort.

In this context, ML has helped distinguish AI from other traditional methods, such as the use of threshold and rule-based modelling. In contrast to these, ML offers the ability to make predictions as well as aiding in important decisions for livestock farms based primarily on learning models from real-world data, enabling actionable information and knowledge to be extracted from the ever-increasing and diverse pool of available data sources (e.g., image, video, sound, text, etc.) (Unal, 2020). The ability of ML algorithms to learn directly from firsthand observation has translated into reduced costs, labor optimization, and better-improved decision-support for the farming community.

These benefits have been exemplified by the application of AI in the form of ML and now Deep-learning (DL) in PLF, which has provided timely and comprehensive knowledge to farmers through animal monitoring, behavior classification, disease prediction, and personalized management-support (J. Pomar *et al.*, 2011; Mathieu Marsot *et al.*, 2020). Although the adaptation of AI in agriculture has provided considerable breakthroughs, it is not without challenge or opposition. From being considered unreliable and impractical in critical applications, to even delivering irreversible wrong results, due to the black box nature of the involved algorithms, assessing such characteristics is often impractical.

As AI research focuses increasingly on improving the accuracy models at the expense of increased complexity (Gunning, 2016), it is sometimes difficult to find application of the technology in socially sensitive domains, due to the ethical concerns of unexplainable decision processes. To address some of these issues and encourage the use of AI technologies, we have proposed the use of Explainable Artificial Intelligence (XAI), which attempts to explain and interpret highly complex machine learning models. Although commercialization of XAI in agriculture is still a challenge, there have been several attempts to create working XAI solutions (i.e., SHAP, LIME, CXplain) that can explain a wide range of AI models. XAI-techniques such as LIME, taking a human-centric focus, seeks to justify machine decisions by describing the model within a few critical use cases (Gunning, 2016). Therefore, this paper explores the main issues that arise in the application of AI in the livestock supply chain.

To this end, we use a literature review to create an initial set of exemplary use cases that highlight the trust requirements in AI-based PLF. The resulting use cases will then be used to explore the inclusion of explainability, to demonstrate how the use of XAI in PLF-AI is a prerequisite for building trust with the agricultural community.

Material and methods

This paper follows the PRISMA framework to conduct a thorough review of the available literature to identify the aspects of livestock farming in which AI has made an improvement and what AI technologies are currently being used, as well as discover if there are already any cases where explainability is being used to solve problems (i.e., ethical assessment, fidelity, reliability in technology) in agriculture. In this context, the following issues will be analyzed: i) How does XAI affect the interaction between the human factor in the farming communities and the technologies they use; ii) How can we improve AI-models and overcome their failures when using them in critical decision processes; iii) To what extent does the use of machine learning affect animal welfare and challenges. The assessment of these questions will be made through exploring the different directions of AI in agriculture, which are currently being researched. Furthermore, a guideline of possible use-cases of how AI can be supplemented by XAI can be implemented in livestock farming to overcome the limitations imposed by complex AI models and the difficulties that their application in the industry faces. The most popular topics in agricultural-AI will be discussed and through them an analysis of impact will be derived.

Results and Discussion

Overview

A review of current AI research in precision livestock farming identified the following terms, which give an overview of Agri-AI applications and key research directions. The phrase "Smart Farming" is used in a broad sense to refer to the application of information technology or AI in agriculture. A sub-area of smart farming is the application of these technologies in livestock farms, which is referred to as precision livestock farming. For the use of AI in precision livestock farming, we have identified three main areas: animal monitoring, sustainability, and farm management. In animal monitoring, the monitoring of behavior, feeding, and constant body measurements are included. These dependencies are as shown in Figure 1.

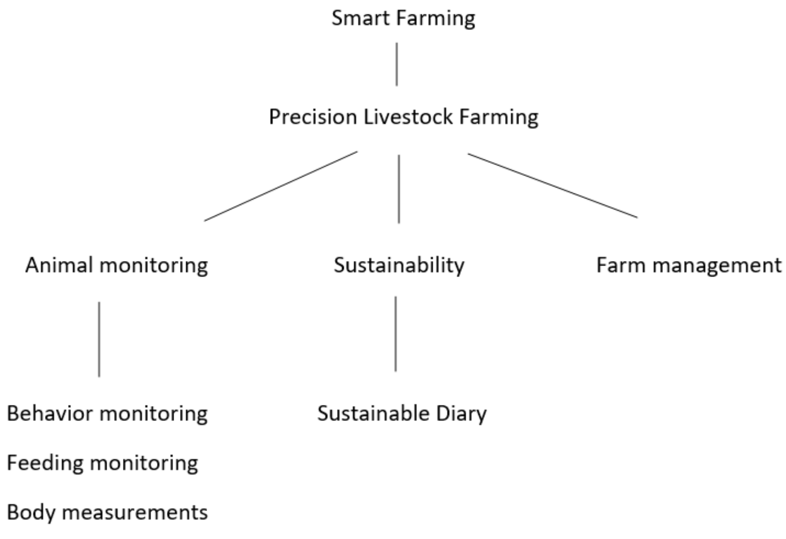

Figure 1: Core application areas of Agri-AI in precision livestock farming

Classification of behavior in livestock can be used to conduct performance classification which results in optimal management of resources (Reza Arablouei *et al.*, 2021). Since extensive monitoring via human labor can be considered almost impossible, the use of AI methods and IoT technologies to collect, process, and interoperate animal behavior is an extremely efficient and attractive substitute in livestock enterprises. Another key issue that AI adoption can address is deep learning-based face recognition and tracking, enabling remote identification that can replace chip implants, which can be costly and labor intensive to attach (Mathieu Marsot *et al*., 2020). Animal identification is an important procedure used for the personalized management of individual animals, especially in areas such as behavior assessment, disease detection, performance monitoring, and certification (e.g., Farm-to-Fork, etc.) (Mathieu Marsot *et al*., 2020).

Example use cases we have identified in machine learning applications for health assessment. One use-case that demonstrates how ML can be used for the classification of feeding behavior and, by extension, the health assessment of pigs utilizing pattern recognition and signal processing (José O. Chelotti et al., 2018; Berckmans et al., 2017). Research on such topics has clearly shown that physiological variables, if assessed correctly can provide valuable indicators for welfare issues (B. B. Odevci, 2021). By leveraging AI and its sub-domains ML and DL, models can be created that not only allow monitoring and classification of these variables, but also predict their future value. However, using these predictions to aid in farm management comes with several challenges, which will be discussed in the following section.

Challenges

Complex systems where processes and entities are not well understood need inter-disciplinary knowledge. Many of the methods used in agricultural applications of AI are "black-box" models which offer a high accuracy rate but with the trade-off of being non-transparent regarding their internal logic and decision-making process. Explainable Artificial Intelligence can tackle this problem by offering solutions which bridge such an interdisciplinary gap. XAI is a technology that creates a good cross-domain environment where domain experts can be incorporated directly into the model evaluation and validation processes. Precision Livestock Farming is a good example of a field that includes many researchers and professionals from differing backgrounds and thus could benefit greatly from a technology that initiates better understanding and transparency of models for all parties involved.

If the potential of AI is to be fully realized in the PLF community, there should be a certain level of trust built between the stakeholders and the technology that they are using. According to Steeneveld W. et al. (2017), farmers are hesitant to incorporate new technologies into their practices unless they are in more mature stages of development and fully reliable. AI has difficulty being applied in farming communities unless it fully addresses user concerns. Developing XAI systems that give full transparency in their decision-making processes offers more certainty and justified reliability (Marco Tulio Ribeiro *et al*., 2016) to the people who are using them. Since model trust, reliability, and fidelity are the main obstacles to the adoption of more Machine Learning technologies in agriculture, use-cases from other domains that successfully utilize XAI to achieve AI-integration could serve as a template for agriculture (Tjoa *et al*., 2021).

Therefore, a literature review on the implementation of XAI in non-agricultural domains was conducted. This review found that in human medicine and manufacturing the three most common applications of explainable artificial intelligence are used, namely environmental sustainability, diagnosis of disease, and classification. XAI is used for assessing environmental parameters and explaining the effect of phenomena on environmental sustainability. The next main utilization of XAI is in the field of health, more precisely in explaining the results of a diagnosis. XAI is commonly used for the classification of different events or objects, but the most relevant application to livestock can be found in research on behavior classification. Table 1. shows the three main topics where XAI has been successful in solving issues when adopting AI in decision critical systems.

Table 1: Explainable Artificial Intelligence applications

Application	Domain
Environmental Sustainability	Manufacturing
Diagnosis of Disease	Medical
Classification	Manufacturing, Medical

In nearly all the reviewed agricultural literature, the problems outlined, and solutions presented clearly lack the involvement of XAI.

The need to improve decision-making in the healthcare field can be exemplified in (Lamya *et al.*, 2019), where XAI is used to assist in making a diagnosis and prescribing medicine for breast cancer. They argue that this approach enables the user to understand the decision-making process of the AI model and how it diagnoses cancer, with it being suggested that the user could verify the model's decision by comparing output against their own personal knowledge. In a study by Sappagh et al. (El-Sappagh *et al.*, 2021), an explainable AI model is proposed that promises to overcome the difficulty of adopting machine learning systems for Alzheimer's disease detection in clinical practices. Looking at other critical domains, XAI is used to bridge the gap between the research efforts toward improving AI models and their implementation in practice. AI models face many issues and although accurate, are not seen as the most reliable tool, this is illustrated by examples identified in the aviation sector, where the introduction of composite components has led to a considerable increase in the amount of time needed to classify defects in the production line, here Neural Networks are suggested to help increasing efficiency. However, understanding the features which contribute to model decision itself can provide valuable knowledge, therefore more interpretable models are proposed (Meister *et al.*, 2021) as a method to increase Neural Networks utilization in practice, providing both a method to evaluate and investigate learned patterns.

While in many other sectors, due to the importance of explainability, XAI has been the answer to several issues, in farming enterprises AI-models that have been implemented or proposed are accompanied with almost no explanation about their predictions or how they work. The relevance of model explainability in livestock farming can be seen in several concrete use-cases that deal with crucial farming management decisions, methods like deep learning and artificial neural networks alone cannot be used in these cases because they are difficult to evaluate.

To illustrate the potential benefits of XAI, two PLF use-cases were derived based on XAI examples found in the medical and environmental domains.

1. **Explanation in culling decisions:** there are many examples (Anna Markella Antoniadi *et al.*, 2021; Tjeerd A.J. Schoonderwoerd *et al.*, 2021) in the medical domain where XAI-driven solutions have been proposed for critical decision-making processes. Model validation is a requirement that is currently lacking in the adaptation of machine learning systems in farming decisions. In PLF this could be meaningful when utilizing AI for high-cost decisions such as culling, which are complex and ambiguous in nature, requiring a model with high reliability and logical coherence (Saleh Shahinfar *et al.*, 2014).
2. **Feed intake monitoring:** animal nutrition is a key factor in environmental sustainability (A. Cerisuelo *et al.*, 2020). Feeding ingredients determine the environmental impact, performance, and health of animals, but precise results on how ingredients impact such KPIs can only be measured by collecting continuous data on farms using sensors as well as software that predicts outcomes based on this information. By using explainable AI based personalized feeding systems, the negative impact on the environment can be reduced by increasing the digestibility of feedstuffs or controlling gut health. XAI offers the opportunity to see which features have been the most influential in decision-making and explain for example the tradeoff of cost and environmental impact of selection and management of feedstuffs.

Another challenge that hinders the wide-spread adoption of AI in agriculture is that it is not perfect, if the model is fed with bad data it could lead to wrong correlations and invalid decisions. Mistakes in this aspect can be very costly and make the systems unreliable. Bias detection is something that can be achieved using XAI (Iam Palatnik De Sousa *et al.*, 2021), by identifying bias in a model XAI has the potential to allow the domain expert to assert any failure mode and minimize any potential damage that might arise from applying incorrect findings. In this approach, the user has an oversight over the decision-making process of these AI systems.

Conclusions

XAI can be a viable solution for precision livestock farming, as it has the potential to solve many of the limitations proposed by AI and even encourage the application of AI in agriculture by building trust among stakeholders. In this paper, we provide an overview of major issues of Agri-AI today, the challenges and limitations that AI poses due to its complexity and non-transparency, and how XAI can be used to solve many of these problems. XAI improves the interaction between users in the agricultural community and artificially intelligent machines by building trust and reliability. Offering reliability through explanations of "black-box models", exploiting the capacity of explainability to aid the creation of more complete models that do not lead to unexpected or undesirable results in, while enabling model validation, which is currently missing in the agricultural domain, create some of the foundational reasons why XAI can hold great potential to improve aspects of PLF.

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Systemic design requirements for sustainable Digital Twins in precision livestock farming

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Abstract

Facing the manifold sustainability challenges (GHG emissions, eutrophication, social welfare, etc.) in livestock farming, Digital Twins can help farmers to use available feed and nutrients efficiently, monitor livestock health, and control emissions to air, soil, and water. Combined with current precision livestock farming (PLF) technologies, Digital Twins (DT) enable real-time monitoring, simulation, and automation capabilities through real-world models and a two-way flow of information. As current applications are mostly focused on closed and highly regulated systems, this paper investigates the systemic challenges and associated design implications of DTs in complex PLF settings. By integrating a STES (social-technical-ecological system) design approach, the authors argue to foster design strategies that serve sustainable livestock governance and enable a sound and flexible basis for balancing associated engineering requirements such as privacy, security, ethics, and inclusion. We will use a qualitative assessment approach, discuss multi-disciplinary requirements for Digital Twins, and consolidate them in a high-level road-map.

Keywords: Digital Twins, Sustainability, Precision Livestock Farming, Technology Assessment, Systemic Challenges

Introduction

A Digital Twin (DT) is a virtual representation of a product, process, or environment with a bilateral exchange of information. By incorporating novel advances in Artificial Intelligence, IoT (Internet of Things), big data analytics, cloud, and edge computing, Digital Twins use the enhanced capacities of data storage, processing, and visualization to track, predict, and optimize the behavioural traits of its subject. Current successful applications of Digital Twins can be found particularly in closed and controlled environments such as industrial and engineering fields (Erol et al., 2020; Ibrion et al., 2019; Uhlenkamp et al., 2019). As the processes in these settings are easier to monitor and the external variables are limited, the reduced complexity allows faster development of robust DT models and therefore, a higher return of investment (Neethierajan and Kemp, 2021).

Recent reviews have been conducted to summarize the potential benefits of DTs for precision livestock farming (PLF) such as risk reduction, enhanced flexibility, and efficiency gains (Neethierajan and Kemp, 2021; Pylianidis et al., 2021). The same research also highlights the novelty of DTs and the so far limited number of prototypes in precision livestock farming, but also in other dynamic biological and ecological systems. Although first promising results have been achieved in more open environments

(Pylianidis et al., 2021; Ford et al., 2020), swift progress is hindered by the many design challenges that arise by working with different stakeholder needs and complex multi-variate systems causing a high degree of uncertainty, as well as through different and sometimes conflicting objectives (e.g., cost-reduction vs. animal well-being, animal health vs. ecological footprint, model fairness vs. model accuracy).

By connecting the biophysical realm with the virtual domain (models) under the prerequisite of stakeholder needs, the design of a Digital Twin is inherently co-dependent on ecological, social, and technological parameters. Therefore, sound development must refer to the individual requirements and standards of each perspective, but also include the complex feedback mechanisms that result from the practical application of DTs. To achieve this, the authors introduce a socio-technical-ecological systems (STES) approach (Ahlborg et al., 2019) for DTs that guides the incorporation of the manifold human-environment relationships in the design and development phase. By highlighting the systemic requirements that come with such an integrated approach, we aim to display some of many needed aspects for fair, inclusive, reliable, and sustainable technology development. As a complete overview of all possible challenges would go beyond the scope of this paper, we will highlight and exemplify design aspects that specifically address prominent effects of complex STES systems such as cascading error propagation, single points of failures, or unwanted emergent behaviour of DTs, but also foster multi-value effects for achieving sustainability from various perspectives.

Material and methods

This paper is following a *Requirement Engineering* approach, with its primary focus to generate a set of multi-disciplinary and inter-systemic requirement specifications that represent stakeholder needs (Braun et al., 2015). As defined by the IEEE (2010), *requirement* will be interpreted as the condition or capability of a system or a person to solve a certain problem or to reach an objective. In the scope of this paper, the objectives are defined in the results section and represent exemplified systemic interdependencies that arise through STES dynamics. Therefore, the requirement analysis follows a STES framework introduced by Ahlborg (et al., 2019) to analyze i) how technologies shape specific human–nature relations and with what consequences, for whom, and where; ii) how emergent pressures in complex socio-technical-ecological systems are interlinked and; iii) how intentional and unintentional technical mediation may result in ambiguous outcomes and feedbacks. The preliminary and potential systemic implications of different Digital Twin designs will be assessed by literature review. This will be complemented by incorporating known systemic risks of the fundamental technologies Digital Twins are based on. Thus, the qualitative assessment is practice-inspired, focusses on generalizing Digital Twin design requirements based on the various systemic threats and opportunities in PLF settings, and formulates the next steps for generating sustainable DT designs as a roadmap.

Results and Discussion

<u>Challenges</u>

Digital Twins incorporate a wide range of novel technologies to achieve high-fidelity virtual replication and optimization through the consolidation of large volumes of real-time data from distributed sources, simulation-driven insights, and feedback mechanisms which enables the user to replicate and manage entities with complex life cycles (Jones et al., 2020). As the DT is optimizing the biophysical realm set by the user's goals, the level of precision and success to achieve these goals is directly and indirectly linked to ecological and social feedbacks (see figure 1 and table 1) as well as to the capability of the DT design to process and display such (e.g., its visualization of information, automated management strategies). Therefore, the DT is in the very center of various dependencies, with the goal to mediate individual feedbacks and requirements (legal, technical, social, ethical, etc.). Because of its virtual and physical entanglement, it is extremely difficult to define external and internal boundaries of a Digital Twin. Defining challenges, requirements, and goals of DTs without acknowledging the intertwined feedback mechanisms will ultimately lead to designs that lack the flexibility, adaptability, and processing capacities to handle uncertainty and to manage complex real-world systems sustainably.

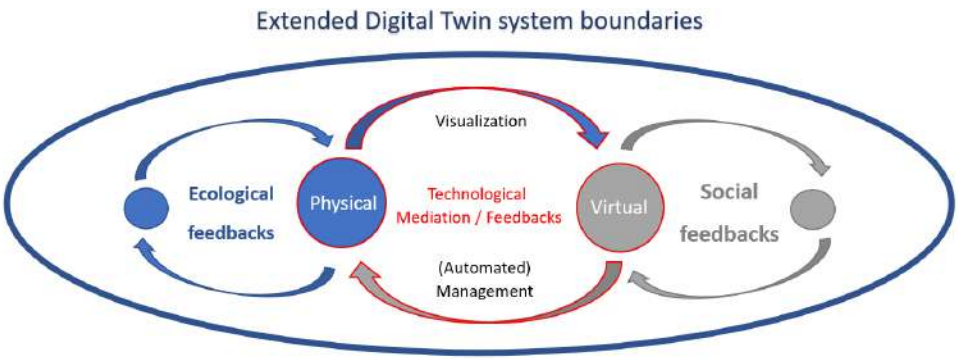

Figure 1: This representation shows the extended system boundary of a Digital Twin to capture the physical and virtual entanglement as well as the direct and indirect coupled dynamics that govern it.

As DTs build on the capacities and flaws of existing technologies, its hyper-connected design not only inherits those systemic connections (Fuller et al., 2020), but further intensifies existing dependencies. If not addressed properly in the early design phase, Digital Twins may accelerate current attitudes and barriers of PLF technology adoption such as the lack of trust and usability, the fear of a low return on investment, issues of interoperability, privacy, and security, as well as concerns about complexity and external dependencies (Boothby and White, 2021, Makinde et al., 2020; Drewry et al., 2019).

Following a STES approach, we distinguished the systemic dependencies of Digital Twins in the form of social, technological, and ecological perspectives and associated challenges (see table 1). As Digital Twins are at the intersection of all three areas (and many more), some dependencies can be assigned to several perspectives at once (such as data vendor lock-in). To avoid duplication, we chose to display certain dependencies only once and exemplify categories in more detail below.

Table 1: An exemplified overview of categorical dependencies that need to be examined to create sustainable Digital Twins and design strategies to manage systemic effects.

Social	Vendors, users, designer, third-party entities, farming community
	• **Drivers:** multi-user vs. single user design, lack of technological knowledge, technological blindness, cash-crop specialization, unclear data ownership, need of data sovereignty, economic scalability, etc. • **Effects:** monopolisation and low diversity, large-scale fragility, single-points of failure, increased external dependencies, loss of technological know how and economic autonomy
Technological	Data, algorithmic, visualization, physical infrastructure
	• **Drivers:** internal and external data dependencies, algorithmic layering, lack of transparency, diversity of adjacent PLF infrastructure, low understandability of output, high complexity of multidirectional data streams, etc. • **Effects:** single-points of failure, cascading error propagation, unwanted emergence, difficulties of achieving independent modules, unmanageable connections (technological debt and low maintainability)
Ecological	Livestock, biophysical farming environment
	• **Drivers:** unexpected behaviour of animal, environmental redeployment, integration of indirect environmental effects, unknown & hidden biophysical feedbacks, etc. • **Effects:** cascading error propagation, unwanted emergent effects, unknown ecological dependencies

In order to balance qualitative attributes like usability, maintainability, and legal adherence, **social** dependencies and interactions based on stakeholder incentives must be carefully explored. As many design aspects are driven by individual economic incentives, the deployment of DTs has the potential to accelerate prominent issues of data ownership, maintenance responsibilities, and the balance between scalability and use-case specific design (Fuller et al., 2020). Centralized data storage at the vendor site (Vendor-Lock in), infrastructure and technological know-how monopolization, and the primary focus on multi-user design and cash-crops, can lead to unwanted systemic effects that ultimately hinder sustainable farming (see table 1). Without carefully balancing the needs, incentives, and dependencies of the stakeholders, profit-driven DT design could increase single-points of failures, loss of crop diversity, lack of trust in technologies, and societal imbalances. The technological design must therefore acknowledge social feedback mechanisms and enable a careful balance of values without further deepening existing dependencies.

On the **technical** side, a critical aspect of Digital Twin designs is the automated information flow, data processing, or even decision making (Mallinger et al., 2021), which is often based on machine learning models. An unfit design might incorporate unknown biases (by insufficient modelling of use-case domains such as lack of health metric incorporation to enhance productivity) that can reinforce unwanted effects of animal production (animal mismanagement and lower yields) by algorithmic feedback loops. This situation is being aggravated by the combination of multiple and co-depended machine learning models that focus on individual but interconnected aspects of the animal and its environment. As the explainability and transparency of a single model is already very limited (Birhane et al., 2021), building a Digital Twin that exchanges data between multiple models and then uses model outputs further as input for other models, correlations, and calculations, creates an incredibly complex information flow. These direct and hidden machine learning dependencies lower the transparency of the system and in turn effect maintainability, error tracking, and may lead to unwanted emergent effects and feedback processes (Sculley et al., 2015).

Within its **ecological** environment, the DT is inherently linked with its physical entity/subject by monitoring and adjusting the state based on predefined goals. Therefore, any changes on either side (virtual or physical) create feedback mechanisms that alter the state of both. This is further complicated, as the DT farming environment is not a closed system. Any changes on the subject may lead to unforeseen systemic or even cascading effects of its environment. Designing algorithms and data streams without carefully assessing the individual DT environments, can therefore lead to direct or hidden feedbacks and unwanted emergent effects (Ibrion et al., 2019). Creating algorithms and architectures that are flexible enough to cope with such uncertainties and enable robust but also cost-efficient redeployment is therefore one of the biggest systemic challenges for sustainable DT development.

High-level roadmap

Balancing these interdependent social, technical, and ecological requirements is vital to truly realise multi-stakeholder Digital Twins in agriculture and Precision Livestock Farming. As such, the following high-level roadmap in the form of core milestones is outlined:

Milestone One: The alignment of Precision Livestock Farming use-cases and technologies. The arrival of low-cost sensors, cloud computing, and Artificial Intelligence has enabled considerable automation in animal monitoring, and other time-consuming tasks (e.g., automatic feeding, calving detection, etc). Although, many of these systems sit in isolation and data is often used for bespoke applications or singular decision-making tasks (Jayaraman et al., 2016; Neethirajan & Kemp. 2021) we can say with certainty that Digital Twins for Precision Livestock Farming are feasible (Jo et al., 2018). Limited examples in the area demonstrate that research has not fully matured, as the applications which do exist often mirror the technological use-case on which they are built (Neethirajan & Kemp. 2021; Verdouw et al., 2021). To fully leverage the benefits of Agricultural and PLF Digital Twins, data from multiple use-case dependant sources should be collected, combined, and modelled. Although these benefits are easily justified, a more complex task is the reconciliation of intermediate dependencies that must first be overcome to enable these benefits. These include questions pertaining to data privacy and processing. AI models are by their very nature data dependent, and farms are privately owned complex non-uniform environments. Therefore, data privacy and data processing should be considered a prerequisite for large scale data collection, owning to the sensitivity of the domain. For example, stakeholders may want to keep ownership or at least control over sensitive data, avoiding vendor-lock-in or undesirable data use. An initial step might be to research data management approaches which satisfy these privacy concerns, while allowing models to be leveraged for other purposes, or even by other stakeholders. Federated Machine Learning could be one such solution, allowing models to be shared while maintaining data sovereignty and privacy (Ramu et al., 2022). However, these consideration and requirements must be investigated in full and appropriate solution found for true use-case alignment and data consolidation to take place.

Milestone Two: Model modularity, fidelity & validation. Current examples of Digital Twins for PLF are tightly coupled in terms of design, technology, and use-case. An effect of this is that validation, and by extension assessment of model fidelity, is often complex and non-trivial, or overlooked entirely. Expert validation, although adequate for proof of concept and other simpler applications, can lead to significant problems as applications grow in scale and complexity. As current methods do not adhere to concrete methodologies or metrics by which an analytical comparison can be effectively and efficiently made, it will become increasingly difficult to identify models which accurately ensure fidelity, both in unknown and adverse conditions. To overcome these issues, methodological protocols and key performance metrics must be developed to ensure comparability through a set of concise design requirements, enabling standardised approaches for in-depth assessment and understanding of model behaviour and limitation. Such requirements and approaches could enable both decision-safety and ethical concerns to be assessed, and undesirable model behaviour to be mitigated.

The widespread availability of pre-validated modularised and standalone (i.e., single use-case) models would further facilitate such goals. These models would provide users with measured and known failure modes and expected behaviour, allowing Digital Twins to be developed safely and quickly for new applications without needing to undertake cumbersome validation processes (Mahmud et al., 2021; García et al., 2020).

Milestone Three: A FAIR Digital Twin Framework, the FAIR (Findability, Accessibility, Interoperability, and Reuse) principles are ubiquitous in the world of data, forming the conceptual underpinning of current state-of-the-art data management and open system design methodologies (Research Data Alliance, 2020). The Digital Twin as a concept is uniquely positioned to gain significant value from the FAIR methodology. If modular, validated, and use-case aligned Digital Twins are to be fully leveraged, their accessibility to industrial practitioners and the wider research community is a prerequisite. A methodological design framework which adheres to the FAIR principles would be a logical next step in this process. Although the value of such a framework is immediately evident, developing and implementing the required standardised methodological approaches may prove a formidable and complex challenge, requiring the integration and assessment of not only technological criteria, but social, privacy and ethical requirements. The involvement of these distinct and intersecting groups must be ensured, if coherent and applicable guidelines are to be developed and widely adopted.

Conclusions

Digital Twins in agricultural settings are specifically prone to various risks (e.g., single points of failure, cascading errors, unwanted emergence) due to their manifold technological, ecological, and social dependencies. Without proper management, the systemic implications of those risks negatively impact various design requirements simultaneously (e.g., reusability, scalability, maintainability, privacy, security, ethical, etc.) and ultimately, hinder technology adoption. Therefore, defining key design characteristics and management techniques that acknowledge these complex feedback mechanisms and enable flexible and robust DT development are key for sustainable farming, specifically in PLF settings. The authors acknowledge that these interdisciplinary challenges cannot be met by design decisions alone and are a matter of extensive regulatory efforts. Nevertheless, early identification of STES requirements can serve as a multiplier effect for technological and ecological sustainability and foster an environment for balancing economic and ecologic incentives. To achieve this, we identified three milestones that are necessary to manage systemic dependencies and lay the foundations for sustainable DT development. Firstly, the alignment of Digital Twin use-cases, requirements, technology and definitions with those of Precision Livestock Farming (PLF). Secondly, standardised criteria for the development and validation of subsequent models. Finally, the creation of a FAIR principle driven design framework which promotes Digital Twin accessibility.

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SESSION 20

Cows: Performance

An empirical analysis of economic herd performance in relation to herd lactation curve characteristics

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Abstract
Lactation persistency gets increasing attention, and previous studies stated persistent cows are more profitable. These studies were however at cow level, and associations might differ from herd level as other herd factors are interfering with herd economic performance. Additionally, for other lactation curve characteristics (magnitude, time to peak yield) no economic evaluation is performed yet. Our objectives were to 1) present a procedure to aggregate cow lactation curves into herd lactation curves (herd magnitude, herd time to peak yield and herd persistency); 2) investigate the association between herd lactation curve characteristics and herd economic performance. Longitudinal Dutch data (8 years) on milk production and accounting of 1,673 herds were evaluated. Cow lactation curve characteristics were summarized to weighted median herd lactation curve characteristics on a calendar year basis, for primiparous and multiparous cows (P1 and P2+). Data was analyzed using linear mixed modelling, with income over feed cost (IOFC) per cow as dependent variable, herd lactation curve characteristics and other herd variables as independent variables. Results indicated all herd lactation curve characteristics were associated with IOFC, except for time to peak yield for P1. All were positively associated with IOFC, except for the negative association with time to peak yield for P2+. In conclusion, we defined herd production patterns by aggregating the cow lactation curves into annual herd lactation curves for P1 and P2+. Associations between IOFC and the various herd lactation curve characteristics were deemed logical and interpretable, suggesting that the herd level aggregation was valid. More research is required to determine when herd economic analysis can be based on simple peak production or M305, or in which circumstances the more computationally challenging herd lactation curve characteristics are better suited.

Keywords: lactation curve, dairy cow, herd economics

Introduction
A lactation curve model can quantify the lactation curve shape for a single lactation of a dairy cow and consists of various lactation curve characteristics which describe the curve in different ways. The classic Wood model (Wood, 1967) is the most common lactation curve model, inspiring certain improvements and innovations (e.g., Wilmink, 1987). The Wood model consists of the scale (representing the level of production), the ramp (representing the rising rate of milk production up to the peak level) and the declining slope (Wood, 1967). The MilkBot model adjusts the Wood model with extended lactations (Ehrlich, 2011). In MilkBot, scale and ramp are similar to the Wood model but include other characteristics - the estimated time between the start of milk synthesis

and calving (offset) and the rate of late lactation decline (decay) - which can be transformed into a measure of persistency (Ehrlich, 2011).

Persistency is an important lactation curve characteristic describing the cow's ability to maintain a slow rate of decline in production after the peak (Wood, 1967). Persistent cows have increased milk yields, improved conception rates, extended productive lifetimes and decreased culling rates (Dekkers *et al.*, 1998; Hadley *et al.*, 2006; Togashi *et al.*, 2016). The economic consequences of persistency have mainly been evaluated with bio-economic simulation models (Dekkers *et al.*, 1996, 1998). Empirically, economic analyses have only included feed costs (Sölkner & Fuchs, 1987). Both normative and empirical studies have shown that cows with higher persistency are more profitable (e.g., Dekkers *et al.*, 1998; Němečková *et al.*, 2015).

To our knowledge, only Němečková *et al.* (2015) have presented empirical economic evaluations of other lactation curve characteristics (ramp, scale) besides persistency. Their study evaluated only 80 dairy cows from one herd. As lactation curve characteristics are only available at the cow level, economic evaluations (both empirically and normatively) were all performed at the cow level (Dekkers *et al.*, 1998; Němečková *et al.*, 2015; Sölkner & Fuchs, 1987). However, associations found at the cow level might differ at the herd level as other herd factors (e.g., management, herd size) can interfere with the herd's economic performance. Economic evaluations of lactation curve characteristics at the herd level need a valid aggregation of cow lactation curve characteristics. Such a herd lactation curve needs however to be summarized on a calendar year basis as only then it is possible to combine it with economic data, which is often expressed at a calendar year. This will, however, be challenging as individual cow lactation curves often belong to multiple calendar years. Aggregating methods from cow to herd level lactation curves, on a calendar year basis, have not previously been described.

This study aimed to 1) present a procedure to aggregate cow lactation curves into herd lactation curves (herd magnitude, herd time to peak yield and herd persistency); 2) investigate the association between the herd lactation curve characteristics and the economic performance of dairy herds.

Material and methods

Available data

Milk production data at the test-day level and herd level performance data for the years 2007 to 2016 were obtained from the Dutch Cattle Improvement Cooperative (CRV, Arnhem, The Netherlands). Originally, the cow test-day data included 159,173,868 test-day records from 6,710,117 cows in 20,760 herds. All test-day records included general cow information (e.g., birth date, calving date, parity, health status), milk yield (kg) and milk component (protein and fat percentage). At the cow level, days in milk (DIM), age in days and calving intervals were calculated for every lactation. Herd level performance data contained annual averages of somatic cell counts (SCC), calving intervals, age in days and the 305-day milk production level (M305).

Herd accounting data from a Dutch accounting agency (Flynth, Arnhem, The Netherlands) was obtained. The data represented 2,058 herds with 18,108 yearly records from

2008 to 2015. The herd accounting data included annual information on all revenues (e.g., milk, livestock), fixed costs (e.g., depreciation, maintenance costs) and variable costs (e.g., feed costs, breeding costs, health costs), as well as on general herd characteristics (e.g., soil type, herd size, milking system).

Development of herd lactation curve characteristics

We used the cow test-day data to calculate herd lactation curve characteristics. First, we fitted a lactation curve for each lactation with the MilkBot model using a proprietary maximum likelihood fitting algorithm by the DairySight fitting engine (Ehrlich, 2011). The MilkBot equation is shown as:

$$Y(t) = a\left(1 - \frac{e^{\frac{-t}{b}}}{2}\right)e^{-dt} \tag{1}$$

in which Y(t) is the estimated milk production when DIM is t, and a (scale), b (ramp), and d (decay) are lactation curve characteristics describing the lactation curve. As c (offset) is practically undetectable without daily milk production records at the beginning of lactation we decided not to use offset. In the current study, a (scale) was renamed magnitude of milk production (in kg day^{-1}), b (ramp) was renamed time to peak yield (in days), and d (decay) was transformed into a measure of persistency using the equation (Ehrlich, 2011):

$$Persistency = \frac{0.693}{\mathrm{d}} \tag{2}$$

Persistency (in days) is the time needed for milk production to drop by half after the peak.

After fitting, every lactation had a set of three lactation curve characteristics (magnitude, time to peak yield and persistency). Two parity groups were defined: primiparous and multiparous cows. To summarise herd lactation curve characteristics on a calendar year basis, we used a weighted method as the partitioning method to deal with lactations in multiple calendar years (Figure 1). Lactations belong to every calendar year with a specific weight relative to the number of test-day records. Using the number of test-days as weight, the contribution of the lactation for different calendar years was calculated. For example, cow A started a lactation in 2008 and finished in 2009. This lactation had 5 test-day records in 2008 and 3 in 2009. Suppose there were n and m test-day records in total from all lactations in 2008 and 2009 in the herd, in which cow A belonged. Then cow A's lactation curve characteristics would contribute 5 / n to the herd lactation curve characteristics in 2008 and 3 / m in 2009. Using the number of test-days as weight, weighted medians were calculated per parity group per herd for each calendar year.

To include only complete lactations for aggregation to herd level, we excluded herd level calculations for the first record year (2007) and last record year (2016), resulting in 273,322 records from 20,000 herds.

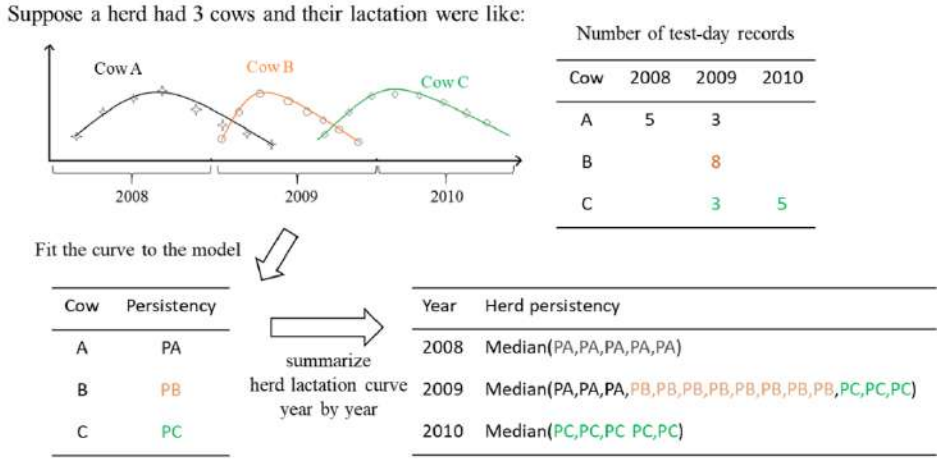

Figure 1: Example of how to aggregate herd lactation curve characteristics from individual cow lactation curve characteristics illustrated for persistency.

Data management

We defined several additional variables based on the accounting dataset. First, income over feed cost (IOFC) was calculated as total milk revenue minus total feed costs (Wolf, 2010), and was expressed per cow. Secondly, the relative yearly herd milk price was calculated as the difference between herd milk price and the Dutch raw milk price for the corresponding year. Finally, the equity ratio was calculated as the total equity divided by the total assets. The expansion rate was calculated as:

$$\text{Expansion rate} = \left[\frac{(\text{herd size in m year} - \text{ herd size in n year})}{\text{herd size in n year}}\right] / (m - n) \quad (3)$$

The yearly herd accounting data of 2,058 herds were merged with herd lactation curve characteristics (n = 20,000 herds) and herd performance data (n = 20,760 herds) for the corresponding years. This merging was possible for 1,887 herds and resulted in a dataset of 12,849 yearly records from 2008-2015. We first excluded 184 yearly records as they were not consecutive (< 2 years consecutive). Secondly, we excluded herds selling milk products on farm (direct sellers) and organic herds (153 yearly records). We also excluded extremely small herds (herd size < 1% percentiles; 126 yearly records). Finally, extreme outliers and records with missing values were excluded (1,578 yearly records). The final dataset included 1,673 herds with 10,808 yearly records.

Statistical analysis

Using IOFC per cow as the dependent variable, we developed a linear mixed model to analyse the association between herd economic performance and herd lactation curve characteristics. Apart from the lactation curve characteristics, other variables (e.g., soil type, equity ratio, milking system) were selected as independent variables based on an expected association with IOFC per cow. Multicollinearity between several variables was checked using variance inflation factors. A year variable was forced into the model as a fixed effect to account for potential year effects (e.g., absolute milk price differences). A herd variable was entered into the model as a random effect to account for unobserved herd-related heterogeneity (e.g., environment, feed management). In order to compare the strength of the effect of each individual independent variable to the dependent variable, we standardised continuous independent variables. Akaike information criterion (AIC) and backward selection were used to find the best model. The conditional R^2, the marginal R^2 and the part R^2 were calculated to describe the variance explained by the entire model, the fixed effects and a single variable, respectively. Data editing and analysis were performed using the Python API for the Spark platform (PySpark) and R version 3.6.3 (R Core Team, 2020), respectively.

Results and Discussion

This study presented a procedure to summarize individual cow lactation curves into herd level lactation curve characteristics per calendar year. Aggregating lactation curves fitted from data aggregated by DIM or pooled milk production data from all cows within groups has been applied previously (Dematawewa *et al.*, 2007; Vargas *et al.*, 2000). This method was, however, not applied in our present study, since a lactation curve from aggregated milk recording data would neglect individual cow variation (Ehrlich, 2013). Therefore, we fitted every lactation curve first and subsequently summarized the cow lactation curve characteristics to create annual herd level lactation curve characteristics. In this case, all information of cow lactation curves is available, which allows analysis of both inter-lactation and intra-lactation variability. It makes a better understanding of the variance of cow level lactation curve characteristics possible, opening possibilities to explore differences within and between herds.

Table 1: Distribution of annual herd lactation curve characteristics from weighted median method for primiparous cows (P1) and multiparous cows (P2+).

Lactation curve characteristics	P1			P2+		
	Mean (SD)	Q1[1]	Q3	Mean (SD)	Q1	Q3
Herd magnitude (kg day^{-1})	34.3 (4.08)	31.8	37.1	45.9 (5.85)	42.5	49.8
Herd time to peak yield (day)	29.6 (0.44)	29.4	29.9	22.0 (1.25)	21.9	22.5
Herd persistency (day)	373 (82.3)	316	417	255 (38.8)	229	277

[1]Q1 and Q3: The first and the third quartile

Average herd lactation curve characteristics are presented in Table 1. Herd persistency was on average 373 and 255 days for primiparous and multiparous cows, respectively. As in previous studies, primiparous cows tend to have higher persistency than multiparous cows (Gengler, 1996) and we found the variance of herd persistency was higher in primiparous cows as well (Table 1). Mean milk weights calculated for each DIM were often used when making aggregate lactation curves (VanRaden *et al.*, 2006). Previously, median and mean milk weights were aggregated for each DIM to describe aggregated curves for different dairy breeds and parities. These median and means were however based on normally distributed data, and therefore mean and median curves were similar in all cases (Ehrlich, 2011). We demonstrated that for a skewed distributed variable, like persistency, using median was an appropriate way to aggregate to herd level lactation curve characteristics as the variance was smaller.

Table 2: Results of the final reduced linear mixed model on the association between herd lactation curve characteristics and income over feed cost per cow (€).

Variable		β	S.E.	P value
Intercept		2,436.7	5.93	< 0.001
Primiparous cows	Magnitude	48.0	3.13	< 0.001
	Time to peak yield	1.1	1.85	0.600
	Persistency	14.1	2.44	< 0.001
Multiparous cows	Magnitude	152.9	3.77	< 0.001
	Time to peak yield	-5.2	1.98	0.010
	Persistency	66.4	2.87	< 0.001
Year	2008	Ref[1]		
	2009	-593.1	5.41	< 0.001
	2010	-225.0	6.45	< 0.001
	2011	80.7	5.86	< 0.001
	2012	-248.4	6.46	< 0.001
	2013	119.6	7.06	< 0.001
	2014	188.1	6.45	< 0.001
	2015	-492.6	7.20	< 0.001
Milking system	Conventional	Ref[c]		
	Automatic	14.2		0.030
Herd size		-16.1	3.44	< 0.001
SCC		-23.1	2.10	< 0.001
Equity ratio		6.4	2.55	< 0.001
Herd intensity		-13.9	2.82	< 0.001
Calving interval		-22.1	2.14	< 0.001
Relative herd milk price		149.0	2.32	< 0.001

[1]Ref: This category is used as a reference category in the regression analysis.

The results of the final reduced linear mixed model to estimate the associations between IOFC per cow and herd lactation curve characteristics are presented in Table 2. All herd lactation curve characteristics were associated (P < 0.01) with IOFC per cow, except for the time to peak yield for primiparous cows. Apart from the negative association with time to peak yield for multiparous cows, all estimated coefficients were positive, indicating that an increased lactation curve characteristic was associated with an increased IOFC per cow. The standardised coefficients indicated that for multiparous cows, herd magnitude had a larger effect on IOFC per cow than it did for primiparous cows. Increasing one unit of magnitude for multiparous and primiparous cows corresponded to a €152.9 and €48.0 increase in IOFC per cow, respectively. Of this model, the conditional R^2 and the marginal R^2 were 88.9% and 76.6%, respectively. Herd lactation curve characteristics explained 14.0% variance of IOFC per cow, 88.9% of which was explained by multiparous cows.

Magnitude was most strongly associated with IOFC per cow among the herd lactation curve characteristics of both parity groups. This was expected, as, of all lactation curve characteristics, herd magnitude has the highest correlation with M305 (Ehrlich, 2013) and M305 explains most milk revenues (Demeter *et al.*, 2011). Herd persistency of both parity groups was positively associated with IOFC per cow. These results correspond with earlier findings (Dekkers *et al.*, 1998; Němečková *et al.*, 2015; Sölkner & Fuchs, 1987), with previous studies also mentioning persistency as an important economic parameter (De Vries, 2006; Togashi & Lin, 2009). Time to peak yield was least associated with IOFC per cow in our study. This was expected because of the weak phenotypic correlation between the rising rate of milk to the peak yield and M305 (Atashi *et al.*, 2020; Elahi Torshizi, 2016).

Lactation curve characteristics for multiparous cows were more strongly associated with herd economics than those for primiparous cows. The herd magnitude of multiparous cows was positively associated with IOFC per cow. Multiparous cows have a higher milk production compared to primiparous cows (Cole *et al.*, 2012); they generally make up 60-70% of the dairy herd and are thus the main milk suppliers of the herd.

Conclusions

In this study, we defined herd production patterns by aggregating the individual cow level lactation curve characteristics to a yearly herd level for primiparous and multiparous cows separately. The associations between IOFC per cow and the various herd lactation curve characteristics were deemed logical and interpretable, suggesting that the herd level aggregation was valid. More research is required to determine when herd level economic analysis can be based on simple peak production or M305, or in which circumstances the more computationally challenging herd lactation curve characteristics are better suited.

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Decision parameters for individual lactation length of dairy cows

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Abstract

This study evaluates the ability of using cow and herd parameters from the early stage of lactation to predict milk yield and culling in an extended lactation as well as to predict yield and metabolic disorders in the early part of the subsequent lactation. This study is part of an ongoing project with the overall aim of developing a method to identify the most and least suitable cows for extended lactation within a given herd at an early stage. The study is based on routinely recorded data. A total of 680,000 calvings from 2016 and 2017 from cows in herds with milk recordings in the Danish Cattle Database were included. A two-step Lasso regression procedure was used. The predictions were done separately for primiparous and multiparous cows and for different breeds. Here results from Danish Holstein are reported. Calving interval, calving age, calving month, calving ease, previous lactation yield and persistency, dry period length combined with early lactation data on disease, milk yield and treatments are tested as cow level predictors. Mean herd yield, mean culling rate of cows in the same lactation are included as herd level predictors. Using only data until day 40 in lactation allows prediction of mean yield per day of lactation (kg energy-corrected milk (ECM)) with a root mean square error of prediction of 2.4 kg for primiparous cows and 2.8 kg for multiparous cows and R^2=0.68 and 0.72, respectively. The most important predictors are cow yield in early lactation and herd yield level. Area Under the receiver operating curve (AUC) for predicting cows leaving the herd after first insemination and before a new calving were 0.63 and 0.67 for primiparous and multiparous cows, respectively.

Keywords: Extended lactation, yield, reproductive management strategy

Introduction

Extending the voluntary waiting period is a dairy herd management strategy, which may benefit farmer economy and greenhouse gas emission (Kok *et al.,* 2019)the number of calves and the related labour for farmers. This study aimed to assess the impact of 2 and 4 months extended lactations on milk yield and net partial cash flow (NPCF. Many cows are capable of maintaining a high milk yield throughout lactation *(*Arbel *et al., 2001;* Lehmann *et al*., 2016)it is vital for the success of extended lactation practices that cows are able to maintain milk yield per feeding day when the length of the calving interval (CInt. Delaying pregnancy improves both persistency (Niozas, Tsousis, Malesios, *et al*., 2019) and reproductive performance (Niozas, Tsousis, Steinhöfel, *et al*., 2019). Studies suggest that the optimal calving interval might be different for individual cows (Lehmann *et al*., 2017; Burgers *et al*., 2019). Lehmann and colleagues (2017) suggested to combine information from early lactation production with information of previous and current reproduction, disease and animal welfare to predict which cows are suitable for extended lactation.

However, an actual method for selecting individual cows suitable for extended lactation is lacking. This study is a part of a project aiming to design a method for selecting cows that are suitable for extended lactation. The project consists of both a randomised field study of extended lactation in 48 Danish dairy herds and an analysis of routinely recorded data from the Danish Cattle Database. This study focuses on method development using data from the Danish Cattle Database. Our focus is predicting: milk yield per day of calving interval (Clint) in the extended lactation, culling risk before next calving, yield at the beginning of the next lactation, and health problems at the beginning of the next lactation, in all cases using information from the previous lactation and the first 40 days of this lactation. Predicting yield per day of Clint considers the longer lactation period and fewer days dry for cows with extended lactation length (Burgers *et al.*, 2021). Another part of the project focuses on predicting reproductive performance and the lactation curve, especially yield at the end of an extended lactation.

Materials and methods

All data included in this study were obtained from the Danish Cattle database (SEGES Innovation, Skejby, Denmark). Data selection criteria were as follows: Every cow that calved in 2016 and 2017, where the cow was alive minimum 40 days after calving and where at least 30 cows within the herd had a subsequent calving in the herd. Herds were required to be active (December 2020) and participate in milk recording with a minimum of 11 milk recordings/year, use artificial insemination (AI) for at least multiparous cows, defined as at least 90 % of the calves having an AI-bull as father. Herds with more than 50 days between 1^{st} and 2^{nd} AI or less than 35 % pregnant at first AI or more than 70 % pregnant at first AI where excluded.

Cows that were moved to another herd before next calving and cows that aborted in this or next lactation were excluded. A total of 681,301 calvings met the above requirements. Finally, calvings with abnormal production result were excluded, e.g. cows younger than 18 months or older than 42 months at 1^{st} calving or an ECM yield below 2 kg in the first 40 days of lactation. The final data included 679,493 calvings across 1,609 herds.

Features

The following features were considered in all prediction models; cow factors incl. breeding values, gestation length, season of calving expressed in months, calving difficulties, milk yield, somatic cell count and content of milk at the last milk recording before day forty, milk yield and content relative to standard/expected milk yield at the last milk recording before 40 days of lactation, treatments grouped by illness, and herd factors, e.g. relative production of the herd.

For multiparous cows (parities>1) the prediction models also considered; yield, somatic cell count and content of milk in lactation before, length of dry period and yield and somatic cell count at the last two milk recordings before drying off.

Except for the models for culling, all models included an effect of length of calving interval. The models for culling instead included an effect of days from calving to first insemination.

As a starting point the models for yield included 60 features for primiparous cows and 86 features for multiparous cows.

Model building

Model building was done separately for primiparous cows and multiparous cows and separately for the breeds Danish Holstein (DH) and Jersey. Results are reported on DH.

Calvings from 01/01/2016 to 30/06/2017 were used as training data, and the models were tested on calvings from 01/07/2017 to 31/12/2017. This matches the way the predictions will be used in the future, where we would have information until a certain timepoint (in lactation) and want to predict the near future.

Predictions were both made using Random Forest as an example of a Tree ensemble method and Lasso Regression as an example of a linear regression shrinkage method. Results were compared using the coefficient of determination (R^2) and the root mean squared error of prediction (RMSEP) on test data for numeric responses and using AUC for binomial responses. Models were implemented in R (version 4.1.2; R Foundation for Statistical Computing, Vienna, Austria). For all models except one, Lasso Regression gave the lowest RMSEP and AUC, therefore only Lasso Regression results are reported. In general, there were only small differences in prediction errors between the different models.

The Lasso regression was implemented using the R package glmnet. Lambda was chosen with a 10-fold cross validation to the largest value such that the error was within 1 standard error of the minimum (lambda.1se). The most important variable from a model was found comparing the standardized coefficient. Predictions were made with a two-step procedure. First, a full model without interactions was run, then a model with the 10 and 15 most important variables including interactions was run. Missing observations were imputed as mean value.

Results and Discussion

A two-step Lasso Regression with interactions in nearly all cases produced the lowest RMSEP, and the results from that model are reported. However, the difference in RMSEP between different models were very small, therefore, for an implementation meant to be used by farmers, the method is quite robust in case one or more features are not available. One may also consider a more simple and transparent model.

Generally, the variables that were included in the final models were the ones we would expect from biological and agricultural knowledge. As an example, Figure 1 shows the 15 variables with the highest standardized coefficient (most importance) from the Lasso model without interaction for the model for yield in ECM per day of Clint for multiparous cows. The variables can be grouped in ones describing; yield in the beginning of this lactation; average production in the herd; yield in the lactation before (average and at dry off); Clint both now and in the lactation before; and breeding value for yield and persistency. Many of these properties are the same as found in other studies (Lehmann *et al.*, 2017; Burgers *et al.*, 2019).

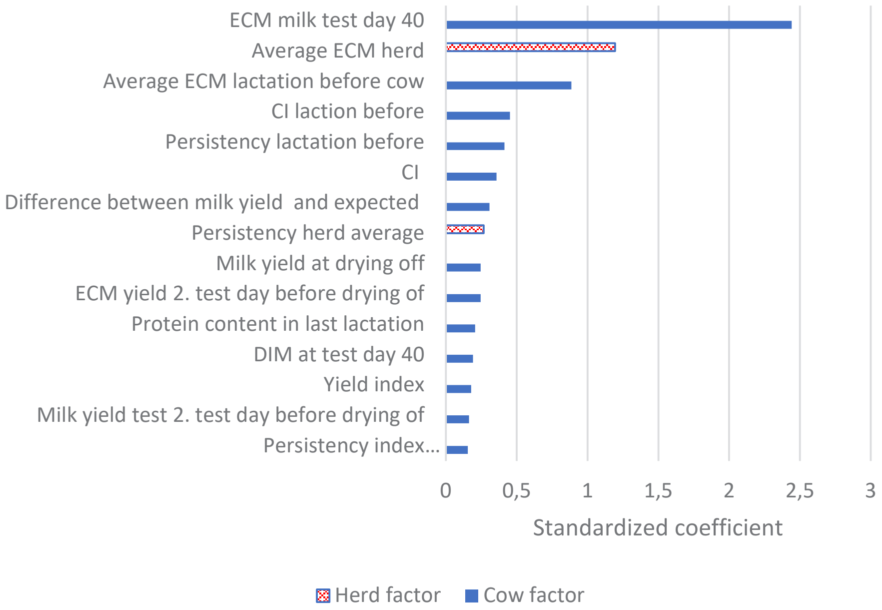

Figure 1: Variable importance for the prediction of yield in ECM per day of calving interval for multiparous DH cows. From Lasso-model without interactions.

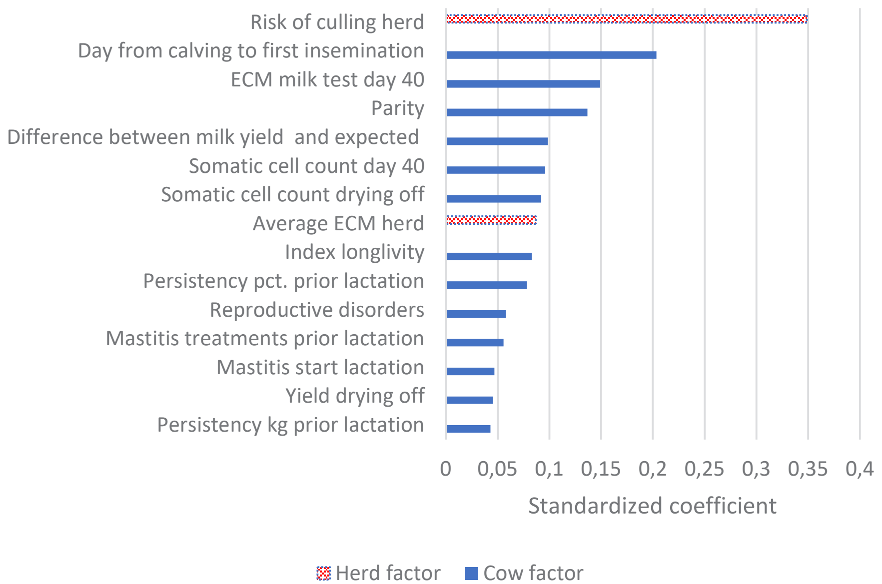

Figure 2: Variable importance for the prediction of risk of culling multiparous DH cows. From the Lasso model without interactions.

Figure 2 presents the 15 variables with the highest standardized coefficient (most importance) from the Lasso model without interaction for predicting the risk of culling multiparous cows. The yield of the cow also was important here, but as expected, average risk of culling in the herd, parity of the cow, somatic cell count, treatments for different diseases and breeding index for longevity also had an influence.

Altogether, the Lasso model was capable of predicting 68 % of the variation in ECM per day of Clint for primiparous cows and 70 % of the variation in ECM per day of Clint for multiparous cows (Table 1). The RMSEP was higher for long lactation than for short lactation, 8 % and 6 % for primiparous and multiparous cows, respectively. The models for yield in the early part of the next lactation where capable of predicting 41 % of the variation both for multiparous and for primiparous cows. Expectedly, the prediction error was relatively higher in the early part of the next lactation than in this current lactation, because there is a calving in between.

Table 1: Number of observations in training (N train) and test data (N test), RMSEP and coefficient of determination for prediction of yield in ECM per day of calving interval and yield in ECM in the first 150 days in the next lactation.

Response	N train	N test	RMSEP	R^2	RMSEP long Clint (>400)	RMSEP short Clint (≤400)
ECM per day of Clint, primiparous cows	90,400	32,309	2.36	0.68	2.48	2.29
ECM per day of Clint, multiparous cows	132,724	51,610	2.76	0.72	2.88	2.71
ECM first 150 days next lactation, primiparous cows	90,709	32,425	5.18	0.41	5.53	5.03
ECM first 150 days next lactation, multiparous cows	121,347	47,228	5.60	0.41	5.80	5.51

The AUC for predicting culling after first insemination and before a new calving with a Lasso model were 0.63 and 0.67 for primiparous and multiparous cows, respectively, see Table 2. The AUC for predicting metabolic diseases were a little higher. Only inseminated cows were included in the calculation of AUC. This may explain the relatively low AUC, because a cow is usually not inseminated, once the farmer has decided that it will leave the herd before next calving.

To improve the predictions, one option is to try to match cows from herds with short and long Clint to obtain a more balanced data set. However, the best option to improve the predictions is probably to include features with new information. An obvious decision would be to add daily milk measurement from robot milking systems or from milking parlours to the milk recording data.

In the future, when farmers are going to make decision based on these predictions, as few features as possible to relate to will be preferable. Therefore, we may decide to weigh the different properties in a combined index. The weights of the different properties should be determined by how important the different properties are from an economic point of view, how important they are for the farmers faith in the index, and how certain we are on the predictions made. The results of this study may serve as a basis for this.

Table 2: Number of observations in training (N train) and test data (N test) and AUC for prediction of cows leaving the herd after first insemination and before a new calving and for metabolic diseases in the early part of the next lactation.

Response	N train	N test	Mean risk (%)	AUC
Culling risk before new calving, primiparous cows	113,843	40,661	13.9	0.63
Culling risk before new calving, multiparous cows	193,578	76,262	26.8	0.67
Risk of metabolic diseases in first 150 days next lactation, primiparous cows	98,093	35,137	4.8	0.65
Risk of metabolic diseases in first 150 days next lactation, multiparous cows	142,274	55,567	17.7	0.69

Conclusions

This study is a part of a project that aims to develop a method for selecting cows suitable for extended lactation as decision support for farmers. A two-step procedure using Lasso regression was used to make predictions models for yield per day of Clint, yield in early part of next lactation, culling risk, and risk of metabolic disorder in early part of the next lactation. Only routinely recorded data available by day 40 in lactation were used in the predictions. The models for yield in the whole lactation had the highest accuracy. The most important predictors of ECM per day of calving interval were cow yield in early lactation and average herd yield. Adding data from daily milk recordings is likely the best way of improving predictive performance.

Acknowledgment

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SESSION 21

Cows: Reproduction

Evaluation of oestrus detection methods across three housing systems in Holstein dairy heifers

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Abstract

We evaluated the performance of three oestrus detection methods (visual detection, oestrus detection patch ("Oestrus-patch"), and behaviour monitoring ear tag ("Electronic ear-tag") in dairy heifers across three housing systems (bedded-pack, free-stall, and pasture). Thirty-six Holstein heifers were enrolled. Heifers were fitted with an eletronic ear-tag and randomly assigned to a housing system in a 3x3 Latin Square. Blocks were 29d and included two weeks of housing habituation followed by oestrous synchronization using a 7-day protocol (D0 CIDR insertion and GnRH [100 mcg]; D+7 CIDR removed and PGF2α [25mg]). Heifers received an oestrus-patch on D+7. Visual oestrus observations were conducted twice daily for 60 minutes, 12h apart. Uterine ultrasonography was performed on days -7, +2, and +7. True oestrus was defined if ovulation was confirmed via ultrasound following the oestrous synchronization protocol. The ovulation rate was 82%. Sensitivity (proportion of heifers in true oestrus detected), specificity (proportion of heifers not in true oestrus undetected), and accuracy (proportion of heifers that were correctly identified in oestrus or not) were calculated for each method. A logistic model determined the effects of housing and method on true oestrus detection. Oestrus detection was affected by detection method ($P<0.01$) but not by housing ($P=0.41$). Sensitivity, specificity, accuracy, and AUC were: 52.4%, 100%, 61.0%, and 0.53 for visual; 87.7%, 91.7%, 87.0%, and 0.55 for the oestrus detection patch; 90.8%, 91.7%, 90.7%, and 0.60 for the eletronic ear tag. In summary, oestrus detection method affected oestrus detection in dairy heifers, but no effects of housing were observed.

Keywords: reproduction, precision, validation

Introduction

In dairy cows, oestrus is associated with changes in the animal's normal behaviour that can last between 3 and 16 hours (Dransfield et al., 1998). A variety of methods such as visual observation, tail paint, oestrus detection patches, and precision dairy technologies can be utilized to detect oestrus (Dolecheck et al., 2016). Visual detection is the most common method utilized in the United States (USDA, 2007). Precision dairy technologies are an available and economically viable alternative that can supplement or replace visual oestrus detection methods (Dolecheck et al., 2015, Dolecheck et al., 2016). These technologies can detect changes in the animal's behaviour and generate automated oestrus alerts (Dolecheck et al., 2015). However, it is known that the type of housing system influences the ability of an animal to perform behaviours and is especially important for oestrus detection. Some authors have shown how housing environmental conditions impact cow oestrous expression due to factors such as floor type (Vailes and Britt, 1990, Platz et al., 2008) and area available for animal movements (Palmer et al., 2012, Roelofs et al., 2017). Thus, the objective of the current study was to evaluate the efficacy of three common oestrus detection methods (visual observation, oestrus detection patch, and behaviour monitoring ear tag) across three common housing systems (pasture, bedded pack, and freestall) in Holstein heifers.

Materials and Methods

Animals and housing

The experiment was conducted at the University of Kentucky Coldstream Dairy Research Farm in Lexington, KY, under the Institutional Animal Care and Use Committee protocol number 2018-3138. The experiment was conducted from March to June 2019. Thirty-six nulliparous Holstein dairy heifers (14.7 ± 2.2 months old) averaging 297.7 ± 65.2 kg of body weight were enrolled in this study from March to June 2019. Heifers were selected from the herd if in good health for the 6 months preceding the study, deemed not lame (gait score < 3; Flower and Weary, 2006), and were sexually mature (i.e. defined as the animal presenting at least one corpus luteum and an ovulation confirmed via ultrasound). Throughout the study, animals were housed in three different housing systems: pasture, bedded pack, and freestall. The pasture had an area of 1.47 hectares of mixed grasses with an adjacent concrete feeding area. The free stall barn consisted of six rows of stalls with nine dual-chamber cow waterbeds each (Advanced Comfort Technology, Reedsburg, USA). A detailed description of the free stall barn is provided in Wadsworth et al. (2015). The bedded-pack barn was 9.15 m in width and 21.34 m long, providing animals with a total of 195.26 m^2 of bedding. The bedded pack consisted of dry saw dust and was checked daily by farm staff. New bedding was added to the barn between each group of animals in this research project. The bedded pack and freestall barns provided animals with close to unlimited access to shade. However, animals housed in the pasture were provided with shade cloth structures and a covered feed bunk. Regardless of housing system, heifers had *ad libitum* access to feed and water throughout the study. All animals received the same diet formulated for growing heifers according to National Research (2001). Diets were composed of corn silage, alfalfa silage, alfalfa hay, whole cottonseed, and concentrate mix and were delivered once daily around 0900 h.

Experimental design

This study was conducted as a 3x3 Latin Square design, in which each animal had one oestrus synchronized in each one of the three housing systems. Each experimental period was 29 days long. During the first 13 days of the experimental period, animals were habituated to the randomly assigned housing system. Then, animals had their oestrus synchronized utilizing a seven-day protocol. Following the synchronization protocol, heifers had their oestrous behaviours recorded for eight days before being assigned to a new housing system.

Oestrous synchronization and monitoring

In this study, we utilized a seven-day oestrous synchronization protocol starting immediately after the end of the housing habituation period. At the beginning of the protocol (day 0), animals received a CIDR (Eazi Breed, Pfizer Animal Health, New York, USA.

1.38 g of progesterone) plus 100 mcg of GnRH (Factrel, Zoetis, NJ, USA). Then, seven days later (day +7) animals received one 25 mg injection of PGF2α (Lutalyse, Pfizer Animal Health, New York, USA) and had the CIDR device removed. Upon CIDR removal, heifers were fitted with an oestrus detection patch (Estrotect, Rockway Inc., Spring Valley, USA) placed on the anterior portion of the tail head.

All heifers were fitted with a behaviour monitoring ear tag (CowManager SensOor, Agis, Harmelen, the Netherlands). This behaviour monitoring tag constantly measures feeding and rumination behaviours and has been previously validated by Borchers et al. (2016). In addition, the behaviour monitoring ear tag can detect oestrus-related events based on changes in the behaviour variables recorded and generate automated oestrus alerts (Dolecheck et al., 2015). If an automated oestrus alert was generated, researchers recorded the oestrus as detected by the behaviour monitoring ear tag.

Visual observations were performed for one-hour periods twice a day at 0600 h and 1800 h. Visual oestrus observations were performed by three trained observers. During the visual observation period, observers used an oestrus scoring system developed by van Eerdenburg et al. (1996). Briefly, the system allocates scores for multiple common oestrus symptoms ranging from 3 points for observing vaginal discharges to 100 points for observed standing heat. A visual oestrus was was considered detected if the sum of points exceeded 50 during the observation period (van Eerdenburg et al., 1996). Following the visual observation period, researchers evaluated the oestrus detection patch. If the oestrus detection patch had more than 50% of its area activated, researchers recorded the oestrus as detected by the patch.

The ovarian follicles and corpora lutea ultrasound images were obtained by a transrectal linear probe (5 MHz. Ibex Pro, E.I. Medical, Loveland, CO, USA) performed on days -7, +2, and +7. . During the ultrasound, the operator recorded if the animal had ovulated or not. A heifer was in true oestrus only if the ovulation was confirmed by the presence of a correlated corpus luteum, detected via ultrasound.

A true positive (TP) oestrus detection event was considered if the animal was confirmed to be in true oestrus by the ultrasound and was considered to be in oestrus by the oestrus detection method. A false positive (FP) oestrus event was recorded if a heifer was not considered to be in true oestrus but was detected by either oestrous detection method. A true negative (TN) oestrus detection event was considered if the heifer was not in true oestrus and was not considered to be in oestrus by the oestrus detection method. A false negative (FN) oestrus detection event was considered if the heifer was in true oestrus but was not considered to be in oestrus by the oestrus detection method.

Statistical analysis

All statistical analyses were performed using SAS (version 9.4; SAS Institute Inc., Cary, NC, USA). Sensitivity, specificity, and accuracy were calculated for each of the three oestrus detection methods in each of the housing systems.

Sensitivity, the proportion of heifers in true oestrus detected was calculated as follows:

$$Sensitivity = \frac{True\ Positives}{(True\ Positives + False\ Negatives)} \times 100$$

Specificity, the proportion of heifers not in true oestrus undetected was calculated as follows:

$$Specificity = \frac{True\ Negatives}{(True\ Negatives + False\ Positives)} \times 100$$

Accuracy, the proportion of heifers that were correctly identified in oestrus or not was calculated as follows:

$$Specificity = \frac{True\ Negatives}{(True\ Negatives + False\ Positives)} \times 100$$

A logistic regression model (Proc Logistic) and a general linear model (GLM) parameterization were utilized to determine the effects of housing and method on true oestrus detection. The model considered both housing system and oestrus detection method as fixed effects. Further, the logistic model was used to generate a receiver operating characteristic curve (ROC curve) and calculate an area under the curve (AUC) for each oestrus detection method. Significance was declared at $P \leq 0.05$, and trends were defined as $0.05 < P \leq 0.10$.

Results and Discussion

In this study, we evaluated the performance of three oestrus detection methods (visual observation, oestrus detection patch, and behaviour monitoring ear tag) across three heifer housing systems (pasture, bedded pack, and freestall).

The overall true oestrus rate observed in this study was 82.4%. Although five-day oestrous/ovulation synchronization protocols are more common for dairy heifers, as they yield greater pregnancy rates. However, we opted we opted for a seven-day protocol where the heifers would have a longer exposure to progesterone (Islam, 2011; Lopes Jr. et al., 2013). Mean ± SD sensitivity, specificity, and accuracy for each of the oestrus detection methods is displayed on Table 1. Overall, housing did not affect how oestrus was detected ($P = 0.41$). However, true oestrus detection was affected by detection method ($P = 0.01$). The AUC for visual observations, oestrus detection patch, and the behaviour monitoring ear tag were 0.53, 0.55, and 0.60, respectively (Figure 1).

To our knowledge, our study was the first to investigate the performance of different oestrus detection methods across multiple dairy heifer housing systems. Yet, our study yielded similar results to the current literature, mainly regarding the automated behaviour monitoring ear tag. Mayo et al. (2019) also reported high sensitivity, specificity, and accuracy for the behaviour monitoring ear tag in freestall housed Holstein dairy cows. Further, Pereira et al. (2020) evaluated the oestrus detection performance of a behaviour monitoring collar in cows housed in a pasture during the summer and in a bedded pack during the winter. Like our study, Pereira et al. (2020) did not observe differences in the performance of the automated behaviour monitoring system across housing systems. Although we found that housing system did not affect oestrus detection, further research is needed to understand if there are any effects of housing system on the intensity of the oestrous behaviour and the reproductive physiology of dairy heifers.

It is known that relying on visual detection of oestrus can result in low oestrus detection rates (Roelofs et al., 2010). Additionally, Dolecheck et al. (2016) reported that the adoption of precision dairy technologies for oestrus detection is economically viable in various scenarios. Yet, the adoption of precision dairy technologies for oestrus detection remains fairly low among dairy producers (Denis-Robichaud et al., 2016). Thus, further research should investigate the reasons and possible strategies to remediate the low technology adoption by farmers.

Table 1: Mean ± SD Sensitivity, specificity, and accuracy for three heifer oestrus detection methods (visual observation, oestrus detection patch, and behaviour monitoring ear tag) across three housing systems (pasture, bedded pack, and freestall; n=36)

	Oestrus detection Method		
Variable	**Visual Observation**	**Oestrus detection Patch**	**Behaviour Monitoring Ear Tag**
Overall			
Sensitivity, %	52.43 ± 18.69	87.73 ± 9.36	90.84 ± 10.72
Specificity, %	100.00 ± 0.00	91.67 ± 25.00	91.67 ± 17.68
Accuracy, %	61.11 ± 13.82	87.04 ± 11.11	90.74 ± 9.72
Pasture			
Sensitivity, %	51.14 ± 13.40	92.80 ± 6.46	100.00 ± 0.00
Specificity, %	100.00 ± 0.00	100.00 ± 0.00	100.00 ± 0.00
Accuracy, %	58.33 ± 16.67	94.44 ± 4.81	100.00 ± 0.00
Bedded Pack			
Sensitivity, %	54.85 ± 5.01	80.61 ± 10.05	87.58 ±13.80
Specificity, %	100.00 ± 0.00	100.00 ± 0.00	83.33 ± 28.87
Accuracy, %	61.11 ± 4.81	83.33 ± 8.33	86.11 ± 9.62
Freestall			
Sensitivity, %	51.30 ± 34.34	89.77 ± 9.30	84.93 ± 8.66
Specificity, %	100.00 ± 0.00	75.00 ± 43.30	91.67 ± 14.43
Accuracy, %	63.89 ± 20.97	83.33 ± 16.67	86.11 ± 9.62

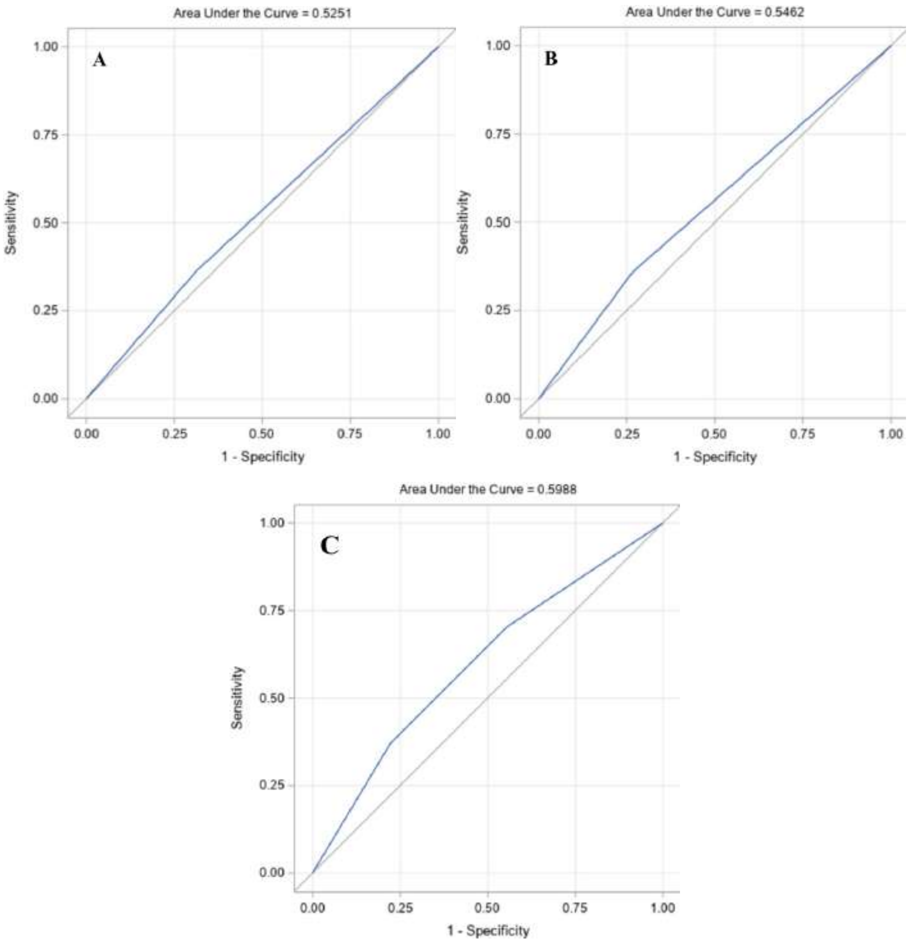

Figure 1: Receiver operating characteristic curve (ROC curve) for three heifer oestrus detection methods (A - visual observation, B- oestrus detection patch, and C- behaviour monitoring ear tag) across three housing systems (pasture, bedded pack, and freestall).

Conclusions

Overall, housing system did not seem to affect oestrus detection in Holstein dairy heifers. However, we did observe a significant impact of oestrus detection method on detection of oestrus. To our knowledge, our study was the first one to investigate the performance of different oestrus detection methods across multiple dairy heifer housing systems. Future research should investigate the effects of housing system on the intensity of the oestrous behaviour and the reproductive physiology of dairy heifers.

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Preliminary outcomes of a low-power cow oestrus detection system in dairy farms

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Abstract

In livestock management, accurate and timely detection of oestrus is a priority aspect to improve production systems. In a previous study, a moving mean-based algorithm for dairy cow's oestrus detection from uniaxial-accelerometer data acquired in a free-stall barn was developed. In this study, the algorithm was implemented in a stand-alone smart pedometer (SASP) which is a customised electronic device designed to be connected to Low-power wide-area networks (LPWAN). In detail, the SASP was specifically developed to provide farmers with a real-time tool able to detect the 'standing to be mounted' behaviour by computing a specifically oestrus index. The SASP was equipped with both a triaxial accelerometer, which acquired data at 4 Hz, and a microcontroller which calculated the moving-means. Then the computed means were sent to a cloud server at 15-min intervals. A WebApp was specifically developed to monitor the oestrus status by producing a graph of the oestrus index. The SASP was tested in a free-stall barn for dairy cows during summer. The farmer selected six cows among those at thirty days distance on average from calving and six SAPSs were attached to the cow forelegs. All cow oestrus onsets were detected through the WebApp and then validated by farmer. Moreover, the graphs of the moving mean highlighted the occurrence of other atypical conditions related to cow locomotion activity. This study makes a new step forward to development of cow's oestrus monitoring systems based on low-power wide-area networks (LPWAN).

Keywords: sensor-based systems, MEMS, cow welfare, automated monitoring systems, oestrus detection

Introduction

Since the second half of the last century, it was understood that the accurate detection of oestrus in dairy cows is an essential step for the improvement of production systems and, therefore, of livestock management. The first automatic systems for the electronic recording of milk production were implemented in the 70s, while for the first attempts to automatically detect oestrus it was necessary to wait until the 80s (Mottram, 2015).

During oestrus, many biological parameters of dairy cows (e.g., skin temperature, milk yield, milk conductivity, and motor activity) (Hurnik *et al*., 1985; Blanchard *et al*., 1987; and Schofield *et al*., 1991) can undergo more or less evident alterations and, therefore, the early detection of such modifications allows the timely recognition of oestrus. The increase in motor activity during the oestrous phase (Wendl *et al*., 1995) suggested the use of electronic devices to monitor restlessness embedded in collars or pedometers.

Nowadays most attention has been paid to the determination of behavioural models based on data acquired from triaxial accelerometers and wireless telemetry systems.

In a previous study (Arcidiacono *et al*., 2020), a moving mean-based algorithm for dairy cow's oestrus detection from uniaxial-accelerometer data acquired in a free-stall barn was developed. The algorithm was specifically designed to provide farmers with a real-time tool able to detect the 'standing to be mounted' behaviour by a specifically oestrus index. In this study that algorithm was implemented in the firmware of a stand-alone smart pedometer (SASP) which is a customised electronic device designed to use Low-power wide-area networks (LPWAN). After a testing period carried out during the year 2020, six SASPs were installed in a free-stall barn during the summer 2021. The farmer selected six cows among those at thirty days distance on average from calving and six SAPSs were attached to the cow forelegs. Data coming from the SASPs were used to develop a model based on pre-oestrus window, technically called *proestrus*. The novelty consisted in the possibility of identifying changes in motor activity preceding this physiological event, characterised by the development of follicles and the production of estrogen, which will reach its maximum in the true oestrus phase. Moreover, this study makes a new step forward to develop livestock monitoring systems based on LPWAN (e.g., Sigfox, and LoRa).

Material and methods

Stand-alone smart pedometer

The designed SASP was equipped with an accelerometer, which acquired data at 4 Hz, a Sigfox communication module, a microcontroller which calculated the moving-means by using equation 1, and a power supply system. The electronic device was sheltered into a customised case and then attached to the cow's leg (Figure 1a). To build the moving mean from uniaxial-accelerometer data (eq. 1), an algorithm implemented in the firmware computed the variables reported in Table 1. Since there are 96 intervals of 15 minutes in a day, the moving mean over 24 hours (mov_mean_h) was computed by using the following relation:

$$mov\_mean_h = \frac{\sum_{j=h-95}^{h} sum\_15min_j}{96} \quad (1)$$

The SASP sent the moving means computed by equation 1 to a cloud server at 15 min-intervals. A WebApp was specifically developed to monitor the oestrus status by producing a graph of the oestrus index (Figure 1b).

The proestrus - window based model

To develop a model based on pre-oestrus window, technically called *proestrus*, during the summer 2021 (period between 17 July – 31 August), the breeder selected six cows among those at thirty days distance on average from calving and one SASP for each cow was attached to cow's foreleg. All cow oestrus onsets were detected through a WebApp specifically developed and then validated by the breeder, through the visual and direct identification of all the typical signs of the oestrus phase (i.e., frequent bellowing, reflex at the mount, and presence of mucous discharge), and by the veterinarian, through the milk analyses. During the trial, six oestrus events occurred. The analysis of the accelerometer curve during oestrus (Figure 2) allowed the identification of recurring alternation of ‘standing’ behavior (corresponding to an increase in the accelerometer values) and ‘walking’ behavior (corresponding to a plateau of the accelerometer curve). During the standing phase, the cow exhibits the willingness to be mounted, as it is ready for insemination. Failure to mount favours the walking phase, since the restless cow tends to move more in search of the bull. The two behaviours alternate until the oestrus occurs, and the maximum value (peak) in the accelerometer curve is reached. When the oestrus event ends, there is a continuous decrease in the acceleration values detected by the SASP, corresponding to the rest of the animal in the lying posture.

Figure 1: a) SAPS attached to cow’s leg. b) Typical trend of the accelerometer curve including the peak due to oestrus (testing phase during summer 2020)

Table 1: Variables involved in the computation of the moving mean over 24 hours of the x-axis accelerations

Variable	Definition
acc_x	Acceleration along x axis, acquired at a 4Hz frequency.
$sma_x = \lvert acc_x \rvert$	Signal Magnitude Area (*sma*) along x axis computed at 4Hz frequency.
$\overline{sma_x}$	Mean value of *sma_x* in one second (1Hz).
$sum\_15min_j = \sum_{i=1}^{900} \overline{sma_x}_i$	Sum_15min_j is the sum of $\overline{sma_x}$ in each j-th 15-min time interval (900 s)

Data coming from the SASPs were used to develop a model based on a moving window whose duration is equal to *proestrus* time interval. As suggested in the literature (Allrich, 1994), the width of the *proestrus* time interval considered in this study was 3 days before oestrus event.

The analysis of the acceleration curve (Figure 2) was performed by identifying the following parameters:

- mean value of the acceleration in the three days of the moving window ($MV_{3\text{-}days}$);
- value of the local minimum (*MIN*) and value of the maximum (*MAX*) found during oestrus event;
- mean value of the slope of each single standing phase (*SMS*)

From the computation of these parameters, it was possible to define the following oestrus indicators:

- width of the oestrus window (*W*) expressed in hours (duration of oestrus event)
- mean value of the oestrus slope (*MS*) expressed in mg/h
- increase of the peak compared to the local minimum ($I_{\%}$) expressed in percentage as follows:

$$I\% = \frac{MAX - MIN}{MIN} \cdot 100 \tag{2}$$

It has to be noted that the fluctuations in the curve with respect to the average trend in the short term were considered, freeing the analysis from changes in behaviour due to seasonality that have nothing to do with oestrus event ($MV_{3\text{-}days}$ could also differ significantly from the average value in the long term).

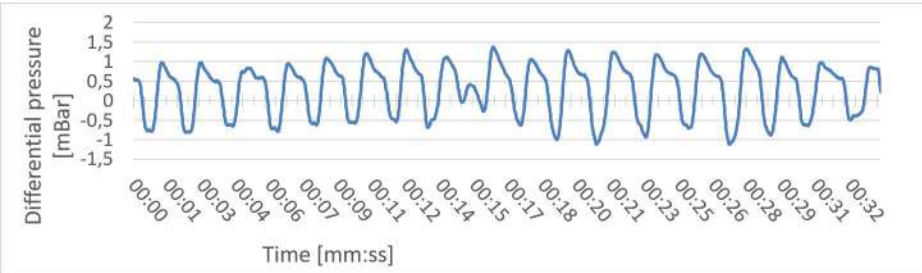

Figure 2: Main parameters in the acceleration curve related to an oestrus event detected for one of the six cows

Based on the previous observations, the proposed model for identifying oestrus can establish whether a given increase in the acceleration curve represents an oestrus event and, if so, what is the probability related to it. This model included an algorithm developed starting from the mean values and standard deviations calculated for the indicators chosen within the set of the six oestruses taken as sample. In detail, for each *i*-th indicator (*W*, *MS*, *I%*), the error range (*Ei*), expressing the measure of the uncertainty associated with the quantity, was defined as the difference between the highest and lowest error values computed as follows:

$$E_i = \overline{x_\imath} \pm \sigma_i \tag{3}$$

where $\bar{x}_\imath$ is the mean value of the *i-th* indicator and σ_i is the related standard deviation.

An increase in the acceleration curve is associated with oestrus if, from the analysis of the main parameters of Figure 2, at least two of the three indicators fall within the corresponding error ranges. In this case, the algorithm of the proestrus detection model generates the following alert: 'Oestrus detected'. Conversely, when no indicator falls within the error range, the algorithm does not generate any alert.

When only one indicator falls within the error range, the procedure must be repeated by widening the error range by an additional half standard deviation (extended error range Eext):

$$E_{ext,i} = \bar{x}_l \pm 1.5\sigma_i \tag{4}$$

In this case, if at least two of the three indicators fall within the extended error range, the algorithm generates the 'Probable Oestrus' alert. The algorithm can scan and update the computation about the oestrus indicators until the conditions of oestrus detection are achieved.

Results and Discussion

To assess the reliability of the proposed method, a statistical analysis of the data from acceleration curves of the sample (Figure 3) was carried out. As can be seen, in the observation time interval (from 17th July to 31st August), one oestrus event per cow was identified in cows n. 1, 2, 3, 5; in cow n. 4 two oestruses occurred; and no oestrus was detected in cow n. 6. The acceleration mean values and the maximum values over that period were the following, respectively: 535.8 mg and 745.1 mg (cow n. 1), 534.6 mg and 690.2 mg (cow n. 2), 421.2 mg and 628.9 mg (cow n. 3), 523.4 mg and 615.0 mg (cow n. 4), 521.2 mg and 712.3 mg (cow n. 5).

Table 2 shows the values of the indicators (W, *MS*, $I_{\%}$) computed for each oestrus event detected by the SASP and successively validated by both the breeder and veterinary.

Mean values and standard deviations of the indicators computed for the six oestrus events were found to be:

— width of the oestrus window: W = 16.8 h; σ_w = 2.5 h
— mean value of the oestrus slope: $\overline{MS}$ = 9.2 mg/h; σMS = 2.7 mg/h
— increase of the maximum: $\overline{I_{\%}}$ = 29.3 %; $\sigma_{I\%}$ = 6.8 %

In accordance with the proposed *proestrus* detection model, four oestruses could be considered as 'detected' (oestruses 1, 3, 4 and 6). Among the remaining two oestruses, one could be classified as 'probable' (oestrus 2). The event 5 was not recognised as oestrus. From this statistical analysis, it can be inferred that the proposed *proestrus* detection model is 67% reliable in recognising an oestrus event (4 events over 6) and 83% reliable in recognising a probable oestrus (5 events over 6). By adding new data input such as milk production and milk conductibility, the model could improve the detection accuracy.

The proposed *proestrus* detection model represents an advancement of knowledge compared to the previous studies (Arcidiacono *et al.*, 2017; 2018; 2020), as it overcomes the limitation due to the analysis of the absolute values of the moving mean over 24 hours.

Indeed, these absolute values could be influenced by practices performed by the breeder altering the natural behaviour of livestock. As already highlighted in Arcidiacono *et al.*, 2020, the breeder, once the first signs of oestrus were identified, moves the cow from the barn to a special separate box in order to practice artificial insemination, which can be carried out several hours after such movement. Since the animal is moved from the resting area, once the oestrous phase is over, it cannot express the physiological lying behavior, resulting in an increase in the acceleration curve. The proestrus detection model, based on the computation of the indicators, ensures the determination of oestrus event as independent from the effects of the aforementioned artificial insemination practice.

Table 2: Values of the indicators in the oestrus event defined as 'detected'

Oestrus indicator			Oestrus event					
			1	2	3	4	5	6
Duration of the oestrus window	(W)	[h]	17.8	18.8	19.0	16.8	12.3	16.0
Mean value of the oestrous slope	(MS)	[mg/h]	8.2	6.4	6.7	10.2	13.6	10.1
Increase percentage	(I%)	[%]	24.2	21.1	26.0	31.4	38.9	34.4

The mean value found for the indicator W fits well with the typical duration of oestrus event in dairy cows, that ranges from 3 to 28 h with a higher probability around 16 h (Allrich, 1994; Gilbert 2018). With regard to the assessment of the remaining two indicators, since they were introduced for the first time and constitute the main novelty of this study, a greater number of oestrus events (that can be determined using the acceleration curve provided by the SASP) should be analysed. It could be performed by applying a higher number of devices to monitor the whole herd. This further task will be useful in refining the error ranges and, thus, experimentally validating the model proposed in this work. However, despite the small number of samples tested, a good repeatability of the proposed model was achieved, and it was proved by the low values of the standard deviation compared to the mean values for all the indicators. In addition, in the oestrus windows related to each validated oestrus event, the indicators (Tab. 2) tend to settle on values close to the mean values calculated in the six oestruses. This evidence encourages future experimental validation.

All the three indicators (W, MS, $I_{\%}$) can be implemented in the customised WebApp of the SASPs, i.e., in devices not requiring any installation in the barn (as Personal Computers or wired communication and/or power supply networks). Indeed, such devices make use of wireless communication network infrastructures of the LPWAN type to allow long-range communications with a low bit rate between the various connected pedometers. The latter feature is important in rural areas where coverage of GSM/GPRS networks or wired networks (ADSL) is often missing. In this way, besides displaying the acceleration curve, the WebApp will provide the breeder with the early recognition of oestrus events and the relative probability of occurrence.

Conclusions

In the present paper, a new *proestrus* detection model for dairy cows was proposed. This model is based on the study of the acceleration curve provided by the SASP, which is a device not requiring any installation in the barn. A specifically developed algorithm can scan this curve and update the computation of appropriate oestrus indicators until the conditions of oestrus detection are met. When analysing relative fluctuations in the characteristic parameters of the curve, the algorithm does not consider unwanted influences of factors unrelated to oestrus event.

By considering only motor activity, the model was found to be 67% reliable in detecting an oestrus event and 83% reliable in detecting a probable oestrus. By adding new data input such as milk production and milk conductibility, the model could improve the detection accuracy.

Figure 3: Acceleration curves of tested cows with oestrus events. The dates indicate when the oestrus was detected. SASP malfunctioning intervals are highlighted in grey

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Association of estrous expression detected by an automated activity monitoring system within 50 DIM and reproductive performance of lactating Holstein cows

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Abstract

The objective of this observational study was to evaluate the association of estrous expression within 50 days in milk (DIM) using a neck-mounted automated activity monitor (AAM; Heatime Pro; SCR Engineers Ltd., Netanya, Israel) and reproductive performance in lactating Holstein cows. A total of 3,334 lactating cows (1,017 primiparous cows and 2,317 multiparous cows) from 7 commercial dairy farms were included in the statistical analyses. Cows were classified according to the number of estrus events from d 7 until d 50 into 4 categories: 1) no estrus event (ANESTRUS); 2) one estrus event (ESTRUS1); 3) at least two estrus events (ESTRUS2+). Generalized linear mixed models were used to analyze continuous or categorical data. Shared frailty models were used for time to event data. Overall, 41.9% (1,396/3,334) of cows had no estrus event detected by an AAM system from d 7 until d 50. Estrous expression within 50 d affected estrous duration (P = 0.001), estrous intensity (P = 0.001) and P/AI (P = 0.001) at first AI. Estrous expression within 50 d affected time to first AI (P = 0.001) and time to pregnancy (P = 0.001). Median DIM to pregnancy were 136, 118, and 103 for ANESTRUS cows, ESTRUS1 and ESTRUS2+, respectively. In conclusion, cows with no estrous expression from 7 to 50 DIM had reduced estrous expression at first AI and inferior reproductive performance compared with cows that displayed estrus activity. Future studies should address risk factors for ANESTRUS and evaluate intervention strategies in these cows to improve their reproductive performance.

Keywords: estrous expression, automated activity monitor, dairy cow

Introduction

Reproductive performance has a major impact on profitability in dairy farms (Overton and Cabrera, 2017). Resumption of ovarian cyclicity within the voluntary waiting period (VWP) is associated with improved reproductive performance (Dubuc et al., 2012; Santos et al., 2009). A delayed resumption of cyclicity reduced reproductive efficiency in both synchronized and non-synchronized cows (Walsh et al., 2007; Gümen et al., 2003) and was associated with an increased risk for pregnancy loss (Gümen et al., 2003; Sterry et al., 2006). Overall, the prevalence of anovulation was 23.3% (ranging from 7.3 to 41.7%) within 8 US herds including 5,818 cows (Bamber et al., 2009). In a Canadian survey including 1,341 cows from 18 herds the overall prevalence of anovulation was 19.5% ranging from 5 to 45% within herds (Walsh et al., 2007). Risk factors for anovulation included parity, calving problems (e.g., dystocia, stillbirth, twins), excessive body weight loss, negative energy balance (i.e., high NEFA and/or BHB), uterine inflammation, and extended dry period length (Walsh et al., 2007; Dubuc et al., 2012; Vercouteren et al., 2015). Anovular cows are not diagnosed on a routine basis, although it has been shown that an anovulatory condition until the end of the VWP has a strong negative impact on reproductive performance and consequently on the overall farm profitability (Walsh et al., 2007; Galvão et al., 2010; Dubuc et al., 2012). Assessment of anovulation prior to the end of the VWP is labor intensive requiring multiple examinations either by analyzing circulating progesterone (P4) concentrations or by visualization of a corpus luteum using transrectal ultrasound. In-line milk P4 analysis or automated activity monitoring (AAM) systems have the potential to identify anovular cows without additional labor. In-line milk P4 analysis has been utilized to demonstrate that cows with early postpartum luteal activity have improved reproductive performance (Bruinjé et al., 2017). Using a pedometer system, it has been shown that cows with more than 3 estrus events within 50 DIM were more likely to become pregnant within 90 DIM (Yániz et al., 2006). Automated activity monitoring systems based on 3-dimensional accelerometers have become popular in the last years (Fricke et al., 2014). Up to now these systems have been used rarely to assess the effect of estrous expression in early lactation on reproductive performance (Chebel and Veronese, 2020).

Therefore, the objective of this study was to evaluate the association of estrous expression detected by an AAM within 50 DIM and reproductive performance of lactating Holstein cows. We hypothesized that cows with a detected estrus event by 50 DIM using an AAM system would have 1) improved estrus expression at first AI, 2) greater odds of conceiving at first AI, 3) greater hazard of receiving first postpartum AI by 100 DIM, and 4) greater hazard of getting pregnant by 200 DIM.

Materials and methods

Animals, Housing, and Nutrition

This study was an observational cohort study including 7,687 cows (2,914 primiparous cows and 4,773 multiparous cows) from 7 commercial dairy farms in northeast Germany calving from May 2018 until September 2019. Inclusion criteria for farms were a herd size above 400 cows and the use of a neck-mounted AAM (Heatime Pro, SCR Engineers Ltd., Netanya, Israel). Herd size ranged from approximately 400 to 1,200 cows per farm. All cows were housed in free-stall barns and milked twice or three times daily. Milk yield ranged from 9,105 to 11,900 kg per 305 d. Exclusion criteria for cows were: “do-not-breed” status within the VWP, culling before first postpartum AI or before pregnancy diagnosis, and less than 95% usable activity data from 7 to 50 DIM. All experimental procedures were approved by the Institutional Animal Care and Use Committee of the Freie Universität Berlin.

Automated Activity Monitoring System

All cows were fitted with a neck-mounted AAM 14 d before their first calving (farm 5), or on the day of their first calving (farms 1 - 4, 6, 7). The AAM was attached to the cows until culling. Individual activity and rumination data of each cow were recorded in real time for 2 h periods by a wireless receiver box and transmitted to the on-farm computer, where the accelerometer software (DataFlow II, SCR Engineers Ltd., Netanya, Israel) was installed. The raw activity data from each cow was converted into an activity change index value using a proprietary algorithm. Index values for activity change ranged from 0 to 100 (0 = lowest, 100 = highest). The period of the cow's activity that exceeded an activity index value of 35 was considered an estrus event. For each estrus event, peak activity (PA) and duration (DU) were determined. The intensity of an estrus event was represented by the maximum peak value of the activity index during an estrus event. Onset of estrus was defined as the time a cow reaching an activity index value of 35 or higher. End of estrus was defined by the first instance at which the index value fell below 35 during the event. Estrus duration was defined as the interval from onset to end of an estrus event.

An estrus event within 50 DIM was defined as activity index ≥ 35 for more than 2 hours. Cows were classified according to the number of estrus events from d 7 until d 50 into three categories: 1) no estrus event (ANESTRUS); 2) one estrus event (ESTRUS1); 3) two or more estrus events (ESTRUS2+). Estrus intensity at first service was categorized arbitrarily based on peak activity of estrus into low (0 to 80) or high (80 to 100) intensity.

Reproductive Management

Lactating Holstein cows were inseminated based on the alert of the AAM, after visual estrus detection or receiving AI after hormonal intervention. A list of cows eligible for breeding with an activity alert was generated on a daily basis by the AAM on each farm. Based on these lists, cows were inseminated predominantly based on an AAM alert. Cows were inseminated once (farms 1, 3, 7) or twice daily (farms 2, 4-6) following the am-pm rule with each cow receiving a single AI based on the AAM alert. Cows that were not bred until a farm specific threshold were either examined by the local veterinarian and treated accordingly (i.e., cows with a corpus luteum received prostaglandin) or they received a timed AI using a simple Ovsynch protocol (GnRH – 7d – PGF – 56h – GnRH – 16h - AI).

Cows remained in the study until a confirmed pregnancy diagnosis, which was performed on a weekly basis by transrectal palpation 38 ± 3 d after AI (farms 1, 3-5), by transrectal ultrasound beginning at 28 d after AI (farm 2) or at 32 d after AI (farms 6 and 7). For simplicity, the time at which pregnancy diagnosis was conducted will be referred to as 38 d after AI throughout the manuscript. In case of transrectal palpation, pregnancy was based on a verified pregnancy diagnosis defined by the presence of uterine fluid, asymmetry, and a positive fetal membrane slip. Non-pregnancy was based on absence of pregnancy at the day of examination or a rebreeding to an estrus before pregnancy diagnosis. Positive pregnancy diagnosis performed by ultrasound was based on visualization of an embryo with a heartbeat. Cows diagnosed not pregnant were reassigned to breeding after spontaneous estrus or following a non-pregnancy diagnosis and a hormonal intervention. Open cows with a CL received prostaglandin and were bred upon estrus detection. Open cows without a CL received timed AI using a simple Ovsynch protocol as described above.

Data Collection and Statistical Analyses

Cow ID, parity, calving date, and breeding information (i.e., DIM, breeding code [estrus vs. hormonal intervention], outcome) were obtained through the on-farm computer software (herdeW and herdeplus respectively; dsp agrosoft GmbH, Ketzin/Havel, Germany).

All statistical analyses were performed using SPSS for Windows (version 22.0, SPSS Inc., IBM, Ehningen, Germany) or Stata (Stata/IC 13.1 for Windows; StataCorp LP, Station, TX). To evaluate the association of estrus expression detected by an automated activity monitoring system within 50 DIM and reproductive performance of lactating Holstein cows, a linear regression model (estrus duration at first AI) and 2 logistic regression models (pregnancy per AI at first AI and probability of high intensity estrus event at first AI) were built using the GENLINMIXED procedure of SPSS. Herd was considered a random effect. Cow was nested within farm. Parity was considered as a repeated measure because some cows had more than one calving within the observation period. Model building was conducted as recommended by Dohoo et al. (2009), where each parameter was first analyzed separately in an univariable model using the GENLINMIXED procedures as described above. Only parameters resulting in univariable models with $P \leq 0.10$ were included in the final mixed models. Selection of the model that best fit the data was performed using a backward stepwise elimination procedure by removing all variables with $P > 0.10$ from the model. The initial models included the following explanatory variables as fixed effects: parity (primiparous vs. multiparous), year of AI, season of AI (winter from 1st of December to 28th of February, spring from 1st of March to 31^{rst} of May, summer from 1st of June to 31^{rst} of August, and autumn from 1st of September to 30th of November), DIM at first AI, estrus activity within 50 DIM (ANESTRUS vs. ESTRUS1 vs. ESTRUS2+), breeding code at first AI (estrus vs. hormonal intervention).

Cox proportional hazards were used to model the time to event outcomes (i.e., time to first AI, time to pregnancy) while accounting for herd as a random effect(shared frailty term; cows within farm) and a random effect for cow for repeated observations of the same cow in different lactations. Cows were censored if they were culled before first insemination or pregnancy diagnosis or at the end of the observation period. The variables parity, year of calving, season of calving (winter from 1st of December to 28th of February, spring from 1st of March to 31^{rst} of May, summer from 1st of June to 31^{rst} of August, and autumn from 1st of September to 30th of November), and estrus activity within 50 DIM were tested as risk factors. The proportional hazard assumption was checked using Schoenfeld residuals. Frailty models were fitted in R version 4.0.2 (R Foundation Vienna, Austria) using the R package coxme (version 2.2-16). Survival Curves were plotted using the package survminer (version 0.4.8). Variables were declared to be significant when $P < 0.05$. A statistical tendency was declared when $P \geq 0.05$ and $P \leq 0.10$.

Results and Discussion

Overall, 7,687 cows (2,914 primiparous cows and 4,773 multiparous cows) were enrolled in this experiment. After exclusion of 1,208 cows (403 primiparous cows and 795 multiparous cows) due to “do not breed” status or culling before first postpartum AI, 3,065 (1,464 primiparous cows and 1,601 multiparous cows) due to incomplete activity data from d 7 until d 50, and 80 cows (20 primiparous cows and 60 multiparous cows) due to culling after first postpartum AI but before pregnancy diagnosis, 3,334 cows (1,017 primiparous cows and 2,317 multiparous cows) were included in the final statistical analyses. Overall, 41.9% (1,396/3,334) of cows had no estrus event detected by the AAM system from d 7 until d 50. Parity had no effect ($P = 0.711$) on the frequency of estrus events from d 7 until d 50. Farm ($P = 0.001$) affected the frequency of estrus events from d 7 until d 50. Herd level prevalence of ANESTRUS ranged from 30.4% to 47.4%. For cows having at least one estrus event from d 7 until d 50, median DIM for the first estrus event was 27 d. There was no difference between primiparous (28 DIM) and multiparous cows (27 DIM). Of these cows, 35% (269/780) had an inter-estrus interval between 18 to 24 d. Overall, 81.6% (2,719/3,334) of cows received first postpartum AI upon heat detection. Among cows without an estrus event from d 7 until d 50, 71.3% (996/1,396) received first postpartum AI upon heat detection. Among cows in ESTRUS1 and ESTRUS2, 87.0% (1,008/1,158) and 91.7% (715/780) received first postpartum AI upon heat detection, respectively. Activity data on estrus duration at first postpartum AI were available from 2,870 cows. The mean (± standard error of the mean) duration was 14.1 ± 0.10 h at first AI. Duration of estrus activity at first AI was affected by season of AI (P = 0.001), year of AI (P = 0.079), breeding code at first AI (P = 0.021), and estrus expression from d 7 until d 50 (P = 0.001). While parity had no effect (P = 0.488), there was a significant interaction between parity and estrus expression (P = 0.049). Overall, ANESTRUS cows had the shortest duration (13.2 ± 0.28 h). Cows in ESTRUS1 and ESTRUS2+ had a DU of 13.5 h (± 0.28) and 14.5 h (± 0.31), respectively. Estrus duration was reduced in the summer (12.7 ± 0.32 h) compared to spring (13.9 ± 0.31 h), autumn (14.4 ± 0.28 h), and winter (14.0 ± 0.30 h). Cows with spontaneous estrus (14.1 ± 0.25) at first AI had longer duration compared to cows after hormonal intervention (13.5 ± 0.34). A total of 75% (2518/ 3,334) had high PA at the first postpartum AI. Estrus intensity at first postpartum AI was affected by season of AI (P = 0.001), year of AI (P = 0.007), parity (P = 0.031), and estrus expression from d 7 until d 50 (P = 0.004). Among ANESTRUS cows, 85.7% had high PA at first postpartum AI. Among cows in ESTRUS1 and ESTRUS2+, 86.8% and 91.1% had high PA at first postpartum AI, respectively. There was a significant difference between ESTRUS2+ and ANESTRUS (P = 0.001) and ESTRUS2+ and ESTRUS1 (P = 0.009). There was no difference between ANESTRUS and ESTRUS1 (P = 0.459).

At d 38 after AI, overall P/AI was 34.6% (1,115/3,334). Pregnancy per AI at first postpartum AI was affected by parity (P = 0.001), season of AI (P = 0.001), and estrous expression from d 7 until d 50 (P = 0.001). Primiparous cows (44.6%) had greater P/AI compared to multiparous cows (34.7%: P = 0.001). Pregnancy per AI was reduced in the summer (32.7%) compared to spring (42.9%), autumn (38.1%), and winter (45.0%). For ANESTRUS cows, ESTRUS1, and ESTRUS2+ pregnancy per AI was 39.0%, 35.2%, and 44.8%, respectively. There was a significant difference between ANESTRUS and ESTRUS2+ (P = 0.019) and ESTRUS1 and ESTRUS2+ (P = 0.050). A tendency was observed between ANESTRUS and ESTRUS1 (P = 0.074).

Estrous expression from d 7 until d 50 affected time to first AI (P = 0.001). Compared to ANESTRUS cows, cows in ESTRUS1 (Hazard risk (HR) = 2.06; P = 0.001) and ESTRUS2+ (HR = 3.35; P = 0.001) had an increased hazard of being inseminated within 100 DIM. Median DIM to first AI were 83, 69 and 63 for cows in ANESTRUS, ESTRUS1, and ESTRUS2+, respectively. Parity (P = 0.003), year of calving (P = 0.001), and season of calving (P = 0.001) affected time to first AI.

Estrus expression from d 7 until d 50 affected time to pregnancy (P = 0.001). Compared to ANESTRUS cows, cows in ESTRUS1 (HR = 1.26; P = 0.001) and ESTRUS2+ (HR = 1.58; P = 0.001) had an increased hazard of becoming pregnant within 200 DIM. Median DIM to pregnancy were 136, 118, and 103 for ANESTRUS cows, ESTRUS1 and ESTRUS2+, respectively. Parity (P = 0.001), year of calving (P = 0.001), and season of calving (P = 0.001) affected time to pregnancy.

The overall herd level prevalence of ANESTRUS was 41.9% ranging from 30.4% to 47.4% based on estrus detection using a commercially available AAM system. This seems high compared to a US survey including 8 herds (23.3%; 7.3 to 41.7%) and a Canadian survey including 17 herds (19.5%; 5.0 to 45.0%), respectively (Walsh et al., 2007; Bamber et al., 2009). While parity had no effect on the frequency of estrus expression from d 7 until d 50 in our study it has been shown that primiparous cows have a higher risk for being anovular at the end of the VWP (Bamber et al., 2009). In a recent study, the prevalence of anestrus was 42.1% using activity data from a neck-mounted activity collar (Heat Rumination Long Distance, SCR Inc., Netanya, Israel) from calving until 62 DIM (Chebel and Veronese, 2020). Four hundred sixty-seven cows had at least one estrus recorded ≤62 DIM (1 estrus event = 271; 2 estrus events = 168; 3 estrus events = 27; 4 estrus events = 1). Although the prevalence of anestrus was similar as in our study, results can hardly be compared due to a different observation period and because only primiparous cows were used from a single herd.

The discrepancy might be due to the definition of anovular cows using serial measurements of circulating blood P4 concentrations in the US and Canadian studies compared with an anovulatory condition identified by behavioral changes using a commercially available AAM system in our study. Measuring P4 in milk or blood is considered the gold standard for defining patterns of estrus cyclicity (Lucy, 2019). A previous study showed only moderate agreement between the timing of the first estrus episode using either serial measurements of milk P4 concentrations or increased activity (Løvendahl and Chagunda, 2010). Although measurement of milk or blood P4 concentrations seems more accurate for phenotyping cyclicity patterns compared to AAM technology, there are a greater number of AAM systems in place on farm compared with commercially available systems that measure in-line milk P4. Using neck collars measuring activity patterns, the genetic correlation (0.96) between calving to first insemination and calving to first high activity was high (Ismael et al., 2015). The estimated heritability of calving to first high activity was 0.16 in that particular study indicating its potential use for selection of fertility traits based on AAM data. Therefore, calving to first high activity might be a more robust estimate in herds using TAI protocols compared to the calving to first insemination trait (Lucy, 2019).

Median time to the first estrus event was 27 d. This is an agreement with previous studies using either a neck-mounted activity monitor (33.1 d: Løvendahl and Chagunda, 2010) or milk P4 profiles (27.9 d: Nyman et al., 2014). There was a tremendous variation in the occurrence of the first estrus event using an AAM in our study.

It has been described that the first postpartum estrus cycle may be shorter, which is considered normal (Lucy, 2019). The following cycle length was observed to be 21 d with some variation (Crowe, 2008; Remnant et al., 2015). Using milk P4 profiles, one-quarter of postpartum estrus cycles were found to be irregular (Nyman et al., 2014; Petersson et al., 2006) because of 1) delayed cyclicity, 2) a prolonged luteal phase, or 3) cessation of cyclicity. Based on the interval between the first 2 estrus cycles from d 7 until d 50 in our study, only 34.5% had an interval between 18 to 22 d. The majority of cows (43.6%; 340/780) had a short inter-estrus interval (i.e., below 18 d). The first ovulation is not accompanied with estrus behavior and followed by a short estrus interval (Crowe et al., 2014). The underlying physiological mechanisms have not yet been fully resolved. It is assumed, however, that high levels of estradiol during late gestation and parturition induce a refractory state to the estrogens present at the first postpartum ovulation. However, P4 from the corpus luteum secreted after the silent ovulation seems to favor estrous expression during the next ovulatory cycle (Allrich, 1994). Also priming of the hypothalamus with P4 by an increased number of estrus cycles before the first insemination might be associated with a better responsiveness of estradiol receptors leading to improved estrus behavior (Thatcher and Wilcox, 1973). In our study we observed ANESTRUS cows displaying shorter DU and being less likely to have high PA supporting these early findings. Especially in multiparous cows we observed a linear increase of DU at the first postpartum AI with increasing numbers of estrus events from d 7 until 50. To the best of our knowledge, this is the first study showing an association between early resumption of estrus cyclicity and estrus expression patterns at the first postpartum AI.

Cows with two or more estrus events from d 7 until d 50 had higher odds of conceiving at the first postpartum AI compared to cows in ANESTRUS (+ 5.8%; $P = 0.019$) and ESTRUS1 (+ 9.6%; $P = 0.050$). This is in agreement with other studies using either milk (Walsh et al., 2007) or blood P4 concentration (Galvão et al., 2010) to determine estrus cyclicity in the early postpartum period, during which anovular cows had lower odds of conceiving at the first postpartum AI. Another study, however, did not observe any difference in first service conception risk for cows that were cyclic by 21 d or 63 d compared to anovular cows (Dubuc et al., 2012).

Postpartum estrus activity influenced time to first AI in our study. Anestrus cows had reduced hazard of being inseminated until 100 DIM. Median time to first insemination were 80.5 d, 71.4 d, and 66.3 d for cows in ANESTRUS, ESTRUS1, and ESTRUS2+, respectively. This corresponds with two studies in which anovular cows had a reduced likelihood of being inseminated early (Walsh et al., 2007; Galvão et al., 2010). In the first study (Walsh et al., 2007), median days to first insemination were 72 and 80 for ovular and anovular cows, respectively, using milk P4 profiles in herds with minimum hormonal interventions. In the study from Galvao et al. (2010), a Presynch-Ovsynch protocol with insemination after estrus detection was used to facilitate first postpartum TAI. Median days to first insemination were 71, 76, and 96 for cows cycling at 21 d, 49 d, and anovular cows, respectively, using blood P4 profiles. When comparing different studies regarding the effect of anovulation on insemination risk one has to be careful as interventions with TAI protocols might confound the effects.

Using time to pregnancy as the ultimate measure of reproductive performance (Lean et al., 2016), cows displaying estrus activity from d 7 until d 50 had increased hazard of conceiving until 200 DIM compared to ANESTRUS cows. Median time to pregnancy was 139.8 d, 128.6 d, and 118.1 d for cows in ANESTRUS, ESTRUS1, and ESTRUS2+, respectively. This is in agreement with three other studies using either milk (Walsh et al., 2007) or blood P4 profiles to identify anovular cows (Dubuc et al., 2012; Galvão et al., 2010). Median time to pregnancy was 126 d and 156 d for ovular and anovular cows, respectively, in herds with minimum hormonal interventions (Walsh et al., 2007). Median time to pregnancy was 103 d, 147 d, and 173 d for cows cycling at 21 d, 49 d, and anovular cows, respectively (Galvão et al., 2010). Interestingly, Dubuc et al. (2012) only observed a detrimental effect of anovulation in third parity or greater cows (cyclic by 21 d: 129 d; cyclic by 63 d: 151 d; anovular by 63 d: 180 d). Overall, this observational study provides evidence that displaying estrus activity in the early postpartum period is beneficial for subsequent reproductive performance. Therefore, activity data in early lactation might be useful in 2 different ways in herd management. They can be used 1) as a descriptive measure (i.e., how many cows are anestrous? Is there a change in the proportion of anestrous cows?), and 2) in a prescriptive way, such that there are different reproductive management strategies for anestrous cows (e.g., enrolment in a TAI protocol such as a Double-Ovsynch protocol) and cows that showed estrous expression in early lactation (i.e., rely on estrus detection after VWP).

Conclusions

Results from the present study provide strong evidence that early postpartum estrous expression influences fertility in dairy cattle. Cows with no estrus expression from d 7 until d 50 detected by a commercially available AAM system had inferior reproductive performance compared with cows that displayed estrus activity. Missing or incomplete activity data clearly limits the practical use of this system. Future studies should address risk factors for ANESTRUS and evaluate intervention strategies in these cows to improve their reproductive performance.

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Timing of artificial insemination and using sexed or conventional semen after automated activity monitoring of estrus in nulliparous Holstein heifers

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Abstract

The objective of this observational, retrospective study was to determine the association between the timing of artificial insemination (AI) and pregnancy per AI (P/AI) in nulliparous Holstein heifers inseminated either with sexed or conventional semen considering different characteristics of an estrus event (i.e., onset, peak, and end) using an automated activity monitoring system. A total of 4,265 AI services from 2,919 heifers based on the alert of Heatime (SCR Engineers Ltd., Netanya, Israel) were evaluated from 6 commercial dairy farms in Germany. The mean (± standard deviation) duration of an estrus event was 16.0 ± 4.8 h. Overall P/AI was 49.1%. Heifers inseminated with conventional semen (51.4%; 933/1,644) had similar P/AI compared to heifers inseminated with sexed semen (46.9%; 1,277/2,621; P = 0.14). Heifers at a younger age at AI were more likely to get pregnant (P = 0.01). The interval from onset of estrus to AI was associated (P = 0.01) with P/AI, with the greatest P/AI for heifers inseminated within 9 to 32 h after the onset of the activity alert. Whereas the interval from peak activity to AI was not associated (P = 0.58) with P/AI, there tended (P = 0.08) to be an association between the interval from end of estrus to AI and P/AI. There were no interactions between the intervals from onset, peak or end of estrus to AI and type of semen on P/AI. In conclusion, inseminating heifers within 9 to 32 h after onset of estrus increased P/AI irrespective of type of semen.

Keywords: insemination time, activity monitor, pregnancy, heifer

Introduction

Timing of artificial insemination (AI) is of major importance to achieve high conception risk. One of the major challenges, however, is to identify the time of ovulation (e.g. Saacke *et al.*, 2008). Using automated activity monitoring (AAM) systems, the mean interval from onset of estrus to ovulation was approximately 29 h in nulliparous heifers (e.g. Guner *et al.*, 2020). Therefore, implementation of AAM systems into reproductive management of dairy heifers may improve estrus detection rates and subsequent fertility by precisely timing AI.

Using a modern AAM system (Heatime), in a recent study we found greatest pregnancy per AI (P/AI) for lactating dairy cows inseminated within 7 to 24 h after the onset of estrus irrespective of type of semen (i.e., fresh vs. conventional semen; Tippenhauer *et al.*, 2021). There are only a few studies available, investigating the association between certain characteristics of an estrus event determined by AAM systems and timing of AI in nulliparous heifers. There are few studies available, however, that suggested delayed AI using sexed semen would improve P/AI (e.g. Sales *et al.*, 2011; Nebel, 2018).

Therefore, the objective of this observational study was to determine the association between the timing of AI and P/AI in nulliparous Holstein heifers inseminated either with sexed or conventional semen considering different characteristics of an estrus event (i.e., onset, peak, and end) using an AAM system. We expected delaying insemination after onset of estrus would improve P/AI in heifers inseminated with sexed semen compared to conventional semen.

Material and methods

Study Design

This study was an observational, retrospective cohort study including 4,265 AI services from 2,919 nulliparous Holstein heifers from 6 commercial dairy farms in Northeast Germany. The study was conducted from July 2018 until October 2021. All heifers were housed in freestall barns.

Automated Activity Monitoring System

All heifers were fitted with a neck-mounted AAM system (Heatime; SCR Engineers Ltd., Netanya, Israel) at the age of approximately 13 months. Raw activity data of each heifer was converted into an activity change index (ranging from 0 to 100) by calculating the difference of today's last 2 h of raw activity from the mean of last week's activity in the same period of the day weighted by the standard deviation of this specific heifer. The period where the heifer's activity change index exceeded 35 was considered a sensor based estrus event. Onset of estrus was defined as the first time an activity change index of 35 was exceeded. End of estrus was defined by the first instance at which the index fell below 35 again. The activity change peak index within a sensor based estrus event represented the estrous intensity, which was categorized into low (35–89 index) and high (90–100 index) based on previous work (Tippenhauer *et al.*, 2021). All parameters were determined for each estrus event and plausible intervals at 8 hour intervals from onset of estrus to AI (0 to > 32 h), peak of estrus to AI (-8 to > 32 h) and end of estrus to AI (-16 to > 24 h) were calculated for each heifer.

Reproductive Management of Heifers

A list of heifers eligible for breeding based on the activity alert was generated by the AAM system, whereas all farms had their threshold for an activity alert set at an index of 35. In addition, the responsible AI technician verified heifers with an activity alert to be in estrus via transrectal palpation. Based on farm-individual strategies, heifers were inseminated with either conventional or sexed semen at different intervals related to the alert (i.e., depending on performance of once or twice daily AI). Heifers remained in the study until a confirmed pregnancy diagnosis, which was performed by transrectal palpation 38 ± 3 d (farms 1, 3) after AI or by transrectal ultrasonography 28 ± 3 d (farms 2, 4-6) after AI.

Statistical Analyses

All statistical analyses were performed using SPSS for Windows (version 22.0, SPSS Inc., IBM, Ehningen, Germany). Heifer and insemination data, such as breeding date and time, was obtained through the on-farm computer software or it was documented on a list that was obtained on a monthly basis. To determine optimum timing of AI considering

3 intervals (i.e., onset, peak, and end of estrus to AI), 3 different logistic regression models using the GENLINMIXED procedure of SPSS were built. Farm was considered a random effect, whereas heifer was the experimental unit. Number of AI was considered as a repeated measure because some heifers had more than one AI from consecutive estrus cycles within the observational period. Only parameters resulting in univariable models with $P \leq 0.10$ were included in the final mixed model. Regardless of the significance level, type of semen, interval (onset, peak, and end) to AI, and the interaction between the interval to AI and type of semen were forced to remain in the final model. The final model therefore contained the following fixed effects: heifer's age at AI (month, continuous), month of AI (1 - 12), interval (onset, peak, or end) to AI, type of semen and the interaction between the type of semen and the 3 intervals to AI. Variables were declared to be significant when $P < 0.05$. A statistical tendency was declared when $P \geq 0.05$ and $P \leq 0.10$.

Results and Discussion

The mean (± SD) duration of sensor based estrus activity was 16.0 ± 4.7 h. The mean interval from onset of estrus to AI was 16.9 ± 7.6 h, from peak activity of estrus to AI 10.9 ± 7.6 h, and from end of estrus to AI 0.8 ± 8.7 h and did not differ between type of semen.

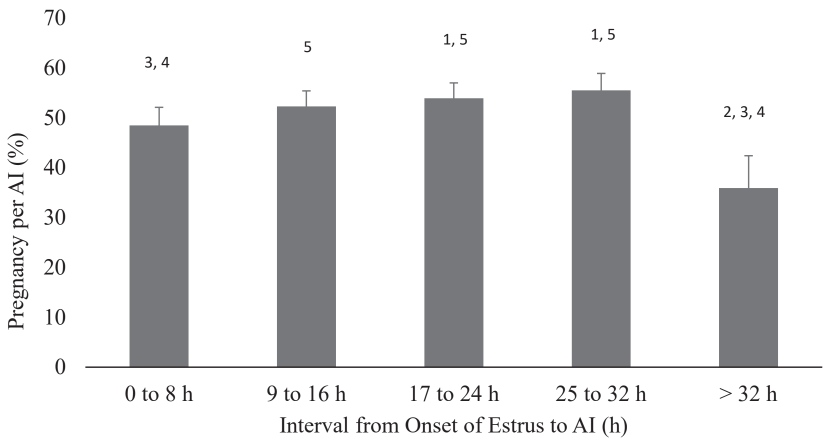

Figure 1: Pregnancy per artificial insemination (P/AI) (± SEM) for heifers (n = 4,265 AI services) inseminated considering different intervals from onset of estrus to AI using a neck-mounted activity monitoring system for estrus detection (Heatime; SCR Engineers Ltd., Netanya, Israel). Onset of estrus was defined as a heifer exceeding an activity change index of 35. A Bonferroni adjustment was used to account for multiple comparisons. Bars with different numbers indicate a significant difference ($P < 0.05$) among time. Therefore, time intervals were classified into numbers (1 to 5) with number 1 beginning at the first time interval in ascending order.

Overall P/AI was 49.1%. Heifers inseminated with conventional semen (51.4%; 933/1,644) had similar P/AI compared to heifers inseminated with sexed semen (46.9%; 1,277/2,621; $P = 0.14$). Heifers at younger age at AI were more likely to get pregnant ($P = 0.01$). Pregnancy per AI was not associated with estrous intensity ($P = 0.52$). Heifers inseminated in the late summer months (i.e., August and September) tended to have decreased P/AI ($P = 0.08$).

There was a quadratic effect of the interval from onset of estrus to AI on P/AI. The interval from onset of estrus to AI was associated (P = 0.01) with P/AI, with the greatest P/AI for heifers inseminated within 9 to 32 h after the activity alert (0 to 8 h: 48.5%; 9 to 16 h: 52.3%; 17 to 24 h: 53.9%; 25 to 32 h: 55.5%; > 32 h: 35.9%; Figure 1). Whereas the interval from peak of activity to AI was not associated (P = 0.58) with P/AI, there tended (P = 0.08) to be an association between the interval from end of estrus to AI and P/AI. Surprisingly, there were no interactions between the intervals from onset, peak, or end of estrus to AI and type of semen on P/AI.

There are only a few studies available, investigating the optimum timing of AI considering different estrus event characteristics detected by AAM systems in heifers.

Some studies suggested that delaying AI with sexed semen, thus, closer in time relative to ovulation, would optimize reproductive performance. They found increased P/AI for heifers inseminated within 16 to 24 h after onset of estrus when using sexed semen (e.g. Guner *et al.*, 2020). In another study, however, delaying AI by approximately 12 h did neither improve nor reduce P/AI in heifers (Chebel & Cunha, 2020).

Surprisingly, estrous intensity was not associated with P/AI in nulliparous heifers. In lactating cows, there is a strong association between estrous intensity and fertility (Tippenhauer et al., 2021). The reason for this discrepancy remains speculative but warrants further research.

Conclusions

Using an AAM system, inseminating heifers within 9 to 32 h after onset of estrus yielded greatest P/AI irrespective of type of semen (conventional vs. sexed).

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Validation of BovHEAT — an open-source analysis tool to process data from automated activity monitoring systems in dairy cattle for estrus detection

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Abstract

This study introduces the software called Bovine Heat Detection and Analysis Tool (**BovHEAT**), a validated and open-source analysis tool to process automated activity monitoring (**AAM**) data for estrus detection. We used activity data collected from a neck-attached accelerometer (Heatime, SCR Engineers Ltd., Netanya, Israel) that is widely adopted in the dairy industry. Developed with the Python programming language, BovHEAT offers fully automatic and scalable processing for estrus detection with additional functionality for handling missing values and a plausibility check for timing of events. Processed output is provided in an Excel file with result tables in the long and wide format. Additionally, a PDF file containing activity change line graphs is generated. For validation, we compared the accuracy and time of three different methods to process AAM data: 1) manual data evaluation (**MAN**), 2) Excel tool (**EXCEL**), and 3) BovHEAT. Two different datasets from 8 farms (1 farm in Canada; 7 farms in Germany) were used. Validation was performed independently by three investigators. In total, activity data from 60 cows representing a maximum number of 600 observations (50 days with 12 observations per day) per cow were used. Manual data evaluation was less accurate due to transcription errors, with 13 of 60 cows having at least one error. More specifically, 16 out of 110 estrus events were recorded incorrectly. The time to process AAM data and transfer the results into a standardized results table for 10 cows was 41.0 (range 28 – 53) minutes, 30.7 (18 – 48) minutes, and 11.7 (4 – 16) minutes for MAN, EXCEL and BovHEAT, respectively. Without the standardized results table, a fully automated run with BovHEAT processing the complete dataset of 5,477 cows, which consisted of 361 XLS and XLSX files, took 172 seconds. The results from this study indicate that BovHEAT speeds up processing, requires less user interaction and provides additional features. Our aim is to accelerate future research with AAM data and facilitate reproducibility via our validated analysis tool. Since BovHEAT is open-source and MIT-licensed, it allows customization to support different sensors and manufacturers. The BovHEAT tool can be evaluated, downloaded and contributed to on GitHub (https://github.com/bovheat/bovheat, https://doi.org/10.5281/zenodo.3890126).

Key Words: automated activity monitor, dairy cow, data processing, automation, heat analysis

Introduction

The dairy industry has undergone profound changes over recent decades. The number of farms has decreased considerably, whereas herd size has increased. The adoption of new technologies by dairy farmers is accelerating to improve efficiency and profitability (Barkema *et al.*, 2015). Precision technology (e.g., automated cow activity monitors and automated milking systems) helps to collect individual animal data and to provide farmers with real-time information that can be implemented in herd management (Rutten *et al.*, 2013). These new technologies have been evolving rapidly, and it has become difficult for animal scientists to fully utilize the increasing number of massive and permanent data streams (Cabrera *et al.*, 2020). Useful information needs to be extracted from the data to assist in the decision-making process (White *et al.*, 2018). Automated activity monitoring (**AAM**) tools were one of the first adopted technologies of so-called precision livestock farming (**PLF**; Rutten *et al.*, 2013).

Estrus detection for dairy cows in confined housing systems has become a greater challenge as milk production increases (López-Gatius *et al.*, 2005), and cows are less likely to express estrous behavior on dry grooved concrete surfaces (Britt *et al.*, 1986). The estrus detection rate in a recent survey of Canadian dairy herds (Denis-Robichaud *et al.*, 2016) was below 50%. The proportion of cows truly bred upon estrus detection, however, is unclear, as these data were confounded by the use of timed artificial insemination (**AI**) protocols. The failure to submit cows for AI not only has a major impact on reproductive performance but also indicates an opportunity to improve profitability (Overton & Cabrera, 2017). Automated activity monitoring systems have been reported as a useful tool for accurate detection of estrus, which has the potential to increase reproductive performance in dairy farms with both cows and heifers (Michaelis *et al.*, 2014). Furthermore, it has been shown that distinct characteristics of an estrus event such as estrus intensity provide useful predicting information on fertility in lactating dairy cows (Madureira *et al.*, 2015).

Managing and processing data from AAM systems for research and practice purposes have become complex and challenging tasks due to the increased volume, variety and sampling frequency of the data. One prevailing processing solution is a spreadsheet tool called HeatCalc, which has been used in recent publications (Madureira *et al.*, 2015). HeatCalc is built in Excel (Office 2019, Microsoft Corporation, Redmond, WA, US) and utilizes a sequence of functions, filters, user copy and paste tasks and pivot tables. However, the HeatCalc Excel tool lacks: 1) ease of use, as a multitude of manual steps have to be performed, 2) flexibility, as the solution is limited by Excel's functionality, and therefore 3) scalability. The use of such Excel-based solutions leads to time-consuming and error-prone analysis of AAM data, especially when analyzing large datasets. Furthermore, the mentioned processing sequence of the HeatCalc Excel tool has not been validated nor has the tool been published in a scientific journal. Therefore, the objective of this study was to develop and validate an open-source analysis tool for the automated processing of dairy cow activity data from AAM systems.

Development of BovHEAT

We developed an analysis tool, called the Bovine Heat Detection and Analysis Tool (**BovHEAT**), with the open-source Python programming language (van Rossum & Drake Jr, 1995) to batch-process multiple AAM files with minimal user interaction and provide additional features, including missing data interpolation and PDF visualization of activity data.

Internals and delivery

The analysis tool utilizes the following Python packages: 1) *xlrd* (https://github.com/python-excel/xlrd) and *xlsxwriter* (https://pypi.org/project/XlsxWriter/) to read and write both XLS and XLSX files, 2) *pandas — data analysis and statistics library* (McKinney, 2011) for data manipulation including filtering, merging and split-apply combine operations (Wickham, 2011) and 3) *matplotlib* (https://github.com/matplotlib/matplotlib) for visualization and PDF creation.

During the development of BovHEAT, we implemented fully automated unit and integration tests, which are performed on every code revision. These tests ensure correct results for all current and future BovHEAT versions by testing them against the validated dataset. Installation is not required, as the entire BovHEAT tool is packaged and delivered as one single standalone executable file for three commonly used operating systems (Windows, macOS and Linux). The executables are built and tested through GitHub Actions (https://github.com/features/actions).

Automated activity monitoring (AAM) data

To develop and validate a software tool to process AAM data, we used data from a neck-attached accelerometer (Heatime, SCR Engineers Ltd., Netanya, Israel), referred to as the AAM system in this paper, to conduct a proof-of-concept study. The AAM system was chosen because it is popular in the dairy industry (Michaelis *et al*., 2013) and has been used extensively in different research settings, including reproductive performance (Fricke *et al*., 2014) and health disorders (Stangaferro *et al*., 2016). Activity and rumination characteristics were monitored by the AAM system using tags that record the cow's movement and intensity, as well as rumination. The on-farm computer was equipped with the accelerometer software DataFlow II (SCR Engineers Ltd., Netanya, Israel), which stored the activity data as aggregated average activity blocks of 2-h time periods (12 blocks of 2 hours per day) per cow. The raw activity data from each cow were converted by accelerometer software into an activity change index using a proprietary algorithm. The algorithm uses the difference between the cow's momentary mean activity and its mean activity of the past seven days, weighted by its standard deviation (Bar, 2010). LeRoy *et al.* (2018) were previously able to explain the algorithm's calculation steps in detail. Index values for activity change range from -100 to 100 index points (decreased activity -100 to 0; increased activity 0 to 100).

Two datasets were used, which represented two possible data export schemes. Files from the AAM system were exported with the corresponding herd accelerometer software DataFlow II. The first dataset contained activity data of 260 Holstein cows from May 2018 until April 2019 from the University of British Columbia's Dairy Education and Research Centre in Agassiz, Canada. Activity data for all cows were exported on a weekly basis, which resulted in multiple files, each containing activity data from 7 days. Therefore, in this export scheme, the observations of a single cow are spread across multiple XLSX files. The second dataset contained activity data from 7 commercial dairy farms in Northeast Germany representing 5,217 Holstein cows from July 2018 until April 2020. The activity data were exported for all cows that calved within the last 7 d on each farm. The files contained the complete activity data from calving until 50 days in milk (DIM). In this export scheme, all observations of a single cow were stored in one XLSX file.

Sample activity data files with both export schemes from both datasets can be inspected in the BovHEAT GitHub and Zenodo repositories.

Estrus parameter definition

Each estrus event can be defined by three different behavioral events in the time sequence: onset of estrus (**ONSET**), peak of estrus activity (**PEAK**), and the end of estrus (**END**). The onset of estrus is defined as a cow passing a certain level for the activity change index. This level is a farm-specific threshold that is defined by the herd manager. An animal eligible for breeding is considered to be in heat as soon as it passes this threshold. The end of estrus is defined by the first instance at which the index value falls below this threshold again. The intensity of an estrus event can be defined by the peak of the activity change index during an estrus event. The duration (**DUR**) of an estrus event can be defined as the interval from ONSET to END.

Source data

The BovHEAT tool automatically detects and imports all folders containing XLS and XLSX files exported in the English or German language via DataFlow II. Additional languages can be added to the analysis tool by creating a translation table for the required column headings. Damaged files or files with incorrect column headings will be skipped. The user can define the desired threshold for estrus detection and specify an observation period by selecting DIM values for start and end. To include days before calving, the start value can be negative. The calving date is determined by DIM = 0. In the case that no observation with DIM = 0 is available (i.e., missing or corrupted), the earliest DIM value is used to retroactively calculate the calving date. If multiple lactations of one cow are detected in the read data, each lactation will be analyzed individually. Overlapping and duplicate observations are detected, and invalid observations are discarded. This scenario occurred in our first dataset, when several consecutive files, each containing 7 days of AAM data, had to be merged. The BovHEAT tool additionally supports unsupervised execution through command-line options (e.g., folder path, start and stop DIM value, threshold, language, core count, output file and interpolation limit).

Missing values and short interestrus intervals

The BovHEAT tool addresses missing values through a two-step method. First, missing values are interpolated if the number of missing consecutive observations is less than 3 (i.e., < 6 h). The imputation of missing data, however, should be used with caution, as it may lead to incorrect conclusions (White *et al*., 2018). The interpolation can be disabled, and the limit of missing consecutive observations can be changed. As a second step, information regarding the percentage of usable activity data in the selected observation period is reported in the XLSX results, granting the ability to filter for the desired amount of minimum usable data. Future studies need to address whether the introduction of cows with missing data leads to a bias when evaluating AAM profiles of cows and their association with biological outcomes. A plausibility check for short estrus intervals was added. A flag is set if two estrus events occur within less than 10 hours. Short interestrus intervals have been associated with reduced pregnancy per AI (Tippenhauer *et al.*, 2021), although the physiological reason is unclear.

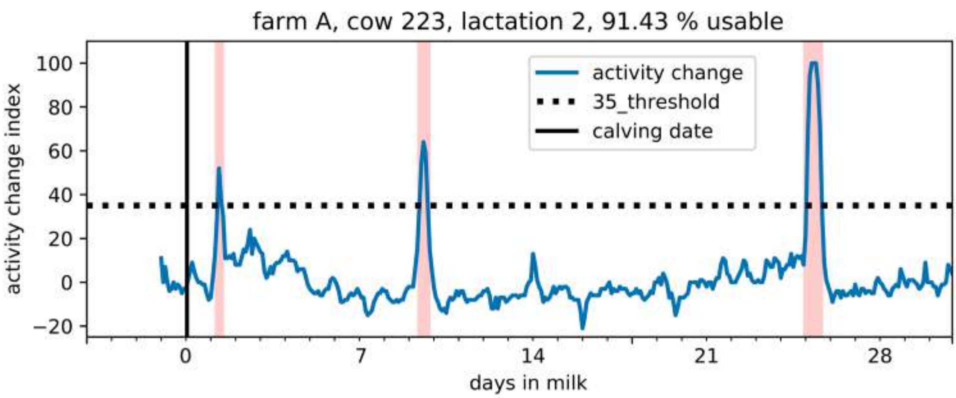
Output and visualization

After processing, the results are saved in a single XLSX file that contains two result table formats. In the wide-formatted table, each cow is contained in a single row. For each estrus event the cow had, several columns of estrus parameters were added. In the long-formatted table, each cow can occupy multiple rows, one for each estrus event. This format reduces the number of estrus parameters columns. All processed cows are listed and subdivided by their ID and lactation number. The tables contain the following information: folder name (i.e., farm name), cow ID, lactation number, calving date, warning flag for estrus events with an abnormal pattern (i.e., 2 estrus events within 8 h), usable activity data within the selected observation period (%), maximum activity change index value, and number of estrus events within the observation period. For each estrus event, the following values are calculated: the date and time for ONSET and END, activity change index value at PEAK, DIM value at PEAK, date and time for PEAK and DUR of the estrus event.

Additionally, a PDF file is generated containing line graphs showing the activity change index for the selected observation period for each lactation of each cow. Estrus events are highlighted, and the calving dates are marked within the graph. The searchable PDF file contains farm name, cow ID, lactation number, and the percentage of usable data for each cow and lactation.

Sample files for the PDF line graphs and the XLSX results with both wide- and long-formatted can be inspected in the BovHEAT GitHub and Zenodo repositories.

Figure 1: A sample activity change index line graph with highlighted estrus events and descriptive



title generated by BovHEAT. The calving date and the user-selected threshold for heat detection are marked. These graphs are generated for each lactation of each cow in the processed dataset and are saved in a PDF file, allowing the user to check and visualize the activity patterns and calculations performed by BovHEAT.

Validation and processing method

To evaluate the accuracy and functionality of the BovHEAT tool, we compared three different methods to process AAM data: 1) manual data evaluation (**MAN**), 2) the aforementioned HeatCalc Excel tool (**EXCEL**), and 3) the developed analysis tool BovHEAT. An estrus event was reported accurately if all five characteristics were identified correctly: timing of ONSET, END and PEAK, PEAK activity change index value and DUR. The validation was performed independently by three investigators (JL Plenio, A Bartel, S Borchardt). For this independent validation, activity data from a total of 60 cows were used. Sixty cows were selected by randomly choosing 30 cows from each of the two datasets. They were subsequently subdivided into six groups containing 10 cows each. The maximum number of observations regarding activity change data was 600 (50 days with 12 observations per day) per cow. Twenty out of 60 cows had complete datasets. Among the 40 cows with incomplete datasets, on average, 101 observations regarding activity change data were missing, ranging from 6 to 360 observations per cow

To compare the time to process the data and the accuracy of the results among the three methods, each 10-cow group was analyzed by the three investigators, each using one of the three methods. Each investigator performed the methods in a different order. Organizing and reporting the results into a standardized table was included in the time for analyses. The column order and format of the standardized results table was designed not to favor any of the three methods. If there was a disagreement among the three methods, the truth was determined by revisiting the raw data and reaching a consensus between the three investigators.

Statistical analyses to compare the time to process the data of the three methods were performed using R version 4.0.0 (R Foundation, Vienna). The time was log transformed to achieve a normal distribution. Statistical testing was performed using a repeated-measures ANOVA accounting for the triple analysis of the six datasets by each of the three investigators, followed by a post hoc multiple comparison *t*-test with Tukey correction (R packages emmeans version 1.4.6).

Results

Overall, the three investigators agreed that 110 valid estrus events were to be identified. The mean (± standard deviation) duration of an estrus event was 11.4 ± 4.8 h. The minimum and maximum estrus event duration was 2 hours and 22 hours, respectively. The number of estrus events per cow ranged from zero to six events. Four cows had an estrus event with a short estrus interval within the observation period and were flagged by BovHEAT. Three cows had no estrus events within the observation period. For each estrus event a cow reported, we evaluated the date and time for ONSET, PEAK and END, activity change index value at PEAK, and DUR of an estrus event. Both EXCEL and BovHEAT correctly identified all estrus events and their parameters. Manual data extraction was less accurate due to various human errors, including calculation, transfer and reporting mistakes, with 13 out of 60 cows having at least one error (3, 4 and 6 errors per investigator). More specifically, 16 out of 110 estrus events were recorded incorrectly. The time to process AAM data and copying the results into a standardized results table from 10 cows was 41.0 (range 28 – 53) minutes, 30.7

(18 – 48) minutes, and 11.7 (4 – 16) minutes for MAN, EXCEL, and BovHEAT, respectively, showing that BovHEAT considerably shortens the analysis time of the 10-cow group, being 3.51 times faster than MAN ($P < 0.001$) and 2.63 times faster than EXCEL ($P < 0.001$). A minor improvement by a factor of 1.34 was present for EXCEL when compared to MAN ($P = 0.196$). A greater advantage can be expected for larger datasets due to scalability using BovHEAT.

Discussion and outlook

The objective of this study was to develop and validate an open-source analysis tool for the automated processing of dairy cow activity data collected from an AAM system. Our results indicate that the BovHEAT tool has several advantages compared to manual data processing and data processing using the HeatCalc Excel tool that was previously used by several research groups. We were able to show that processing AAM data using BovHEAT required less time, provided more accurate results than manual data processing and eliminated potential human errors. We expect that the actual time-saving benefits for larger datasets will increase as our analysis also included the time consumed to copy the output of BovHEAT into a standardized table. However, since BovHEAT generates an Excel file with result tables in the long and wide format, this step may be skipped, as the data are usable directly after analysis without the need for further data transformation. For example, a complete run of the second dataset of 5,477 cows, which consisted of 361 XLS and XLSX files, took 172 seconds utilizing a computer equipped with an 8-core CPU. While incorporating the capabilities of the aforementioned HeatCalc Excel approach, our analysis tool offers additional features such as batch-processing of large amounts of AAM data, handling of missing values and short interestrus detection. As shown in our validation of the two datasets, missing values seem to be a common issue when processing AAM data. Only 20 out of 60 cows had complete activity data from an entire observation period of 50 d per cow. The reasons for missing activity data remain speculative. Possible causes are sensor malfunctions, data transmission errors or insufficient calibration time after a cow was fitted with an AMM system sensor. Contrary to the HeatCalc Excel approach, BovHEAT does not require an additional calving date column, as it utilizes the DIM column for calving date calculation. As a positive side effect, this allows for the inclusion of cows that received a neck collar after calving (i.e., without a calving date or an observation for DIM = 0). The additional PDF output, which contains activity change line graphs, helps to visualize and understand the activity patterns of the dairy cows. With the provided sample dataset and executables for Windows, Linux and macOS, our BovHEAT tool can be tested and evaluated immediately.

The presented advantages of our analysis tool could benefit future research using AAM data of thousands of animals while facilitating reproducibility. These advantages, in turn, support dairy scientists to gain a better understanding of the physiology and behavior of dairy cows and to develop new decision support tools to optimize reproductive management. The BovHEAT tool is released under the permissive and open-source MIT license and can be evaluated, downloaded and contributed to on GitHub (https://github.com/bovheat/bovheat, https://doi.org/10.5281/zenodo.3890126).

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SESSION 22

Calves:
Health and Welfare I

Automatic thermal monitoring of calves using low-cost infrared thermography

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Abstract
Infrared thermography offers a non-contact method to record the emitted heat signatures of animals, however its usage is constrained by high costs and requirement for trained staff. To tackle these limitations, we introduce a novel prototype system based on small single board computers and low-cost thermal camera units supported by an automated data management pipeline that allow continuous and automatic monitoring of livestock. We demonstrate the system using calves reared in single-animal pens. The system is composed of sensory platforms and an on-site server, connected wirelessly. The sensory platforms are equipped with a passive infrared motion sensor that triggers the thermal camera when the calf begins to feed or moves to locations relevant for thermal monitoring, i.e. where heat emitting areas such as eyes, ears and muzzle are visible. Thermal images are then collected by the server and stored locally or transmitted over the Internet. However, low-cost thermal cameras are inaccurate, up to ±7 Celsius in farm conditions, according to manufacturer's data. We explore two methods for performing calibration, validated on the eye temperature of calves. We show that an accuracy of 0.5°C is attainable using on-site calibration. Field tests of the proposed prototype system on a commercial dairy farm showed that it is robust and capable of continuous monitoring without interfering with farm operations.

Keywords: infrared thermography, automatic monitoring, thermal calibration, Raspberry Pi, FLIR Lepton

Introduction
Infrared thermography records heat emitted by objects and allows temperature monitoring of bodies, including animals. All objects with temperature above absolute zero emit heat, which thermal cameras can passively record from a distance. Passive monitoring is particularly desirable in veterinary settings, where disturbance to animals caused during inspection can influence their physiological state and behaviour (Waiblinger *et al.* 2004). Several diseases manifest in changes to local (e.g. inflammation) or body (e.g. fever) temperature and these changes can be picked up by thermal cameras. Abnormal temperatures can appear before more severe clinical symptoms become visible and early detection can therefore enable timely and milder intervention.

Thermal cameras have been successfully applied to detect and monitor a range of pathologies in domestic animals. Examples include early detection of bovine respiratory disease in calves (Schaefer *et al.* 2012), identifying mastitis in sheep (Martins *et al.* 2013) and cows (Machado *et al.* 2021), and detecting lameness by contralateral temperature differences in feet (Alsaaod *et al.* 2015). The utility of infrared thermography has also been demonstrated in equine sports medicine identifying muscle injury, bone fractures and incorrect saddle fit (Talas & Talas, 2017). Thermography can also be used to monitor animal welfare; for example, stress in dogs was found to be correlated with increased eye temperature (Travain *et al.* 2015). Additionally, thermography offers a safe and non-invasive method to monitor wild animals, both in zoos and nature (Hilsberg-Merz, 2008).

However, thermal imaging comes with limitations that affect its utility in veterinary medicine. Thermal cameras of high resolution (at least 320x240 pixels) and accuracy (not worse than ±2°C) are expensive, ranging between circa €5,000 to €20,000. These are typically hand-held cameras that require experienced personnel to operate. While they do not require physical contact with the animal, operators need to be present and animals, e.g. horses, often have to be taken out from their enclosures for inspection. This requirement heavily restricts the assessment of large groups of animals. Due to the associated cost and time constraints, infrared thermography in veterinary practice tends to be limited to high value animals (e.g. horses and zoo animals). As thermal images are heavily influenced by environmental factors (e.g. ambient temperature, relative humidity) and the physiological state of the animal (e.g. their Circadian rhythm), precise calibration and rigorous image analysis are required if only a few images taken at a single point in time are available due to assessment limitations.

Recent availability of low-cost computers and associated sensors could offer a solution to the challenges outlined above. Small single-board computers (e.g. Raspberry Pi, Arduino) can be equipped with tiny cameras and housed in robust enclosures that tolerate farm environments. These computers are powered with 5V USB cables and can transfer data through Wi-Fi therefore they pose no danger to animals or handlers and do not require significant infrastructure to be installed. They can be programmed to record data automatically and left operational for weeks. This enables continuous data collection over extended periods of time without any disturbance to animals. However, small thermal cameras available for these sensory platforms come with worse resolution and accuracy than more powerful hand-held models, therefore careful calibration is critical.

In this paper, we demonstrate the utility of sensory platforms designed around the Raspberry Pi single-board computer and Teledyne FLIR Lepton thermal camera for continuous and automatic thermal monitoring of calves on a dairy farm. We tested two methods for calibrating the cameras, validated on the surface temperature of calf eyes, and show that accuracy of 0.5°C is achievable using on-site calibration.

Material and methods

Equipment

The sensory platform was based on a Raspberry Pi 4 Model B single-board computer (Raspberry Pi Foundation, Cambridge, UK). The platform was equipped with a Teledyne FLIR Lepton 3.5 thermal camera unit (Teledyne FLIR, Wilsonville, OR, USA) using a Lepton Breakout Board V2 and connected to the Pi via its general-purpose input/output (GPIO) interface. A passive infrared motion detector was also added to trigger the thermal camera when a calf moved into view and a real-time clock ensured correct timekeeping as the Pi does not include one by default. The Pi and associated sensors were fitted into a custom-designed acrylic box for protection (see Figure 1). While the Lepton thermal camera comes with a shutter, it is used for internal calibration and does not protect the lens. We also found that it is very susceptible to dust, which can break down the moving parts. Germanium glass is typically used to protect thermal cameras as it is transparent to infrared radiation, however its high price was prohibitive for our purposes. We tested several materials to tackle this challenge and found that IKEA's ISTAD resealable bags (IKEA, Delft, Netherlands), made out of polyethylene plastic, let infrared waves through without any significant decrease in the resolution of the thermal sensor. We cut out 1x1 cm squares from the bag and attached them in front of the thermal cameras. The other major adversary to the platforms were insects that were attracted to the emitted heat and prospects of shelter. They were deterred using balsa wood sheets soaked in lavender oil and attached to the plastic lunch box that acted as the outer protective shell for the platform. The sensory units were mounted on a custom-made aluminium stand fixed to the calf pen and provided the thermal camera a field of view looking at the calves' feeding buckets from approximately 1 m away at a 45-degrees downwards angle (see Figure 1).

Data collection

Thermal images of seven calves feeding from buckets in single-calf pens were collected on a dairy farm in Devon in the UK during May 2021. The calves were fed twice a day, morning and afternoon. In this study, we present data collected during the afternoon feeding, between 4 and 5 o'clock. Once a calf approached the bucket, the motion detector triggered the thermal camera to take images approximately 1 frame a second for 8 seconds (the cooldown period of the motion detector). The image collection loop was repeated as long as the calf remained in the field of view of the motion sensor. Images were first stored locally on a SD card and sent off to an on-site server, a Raspberry Pi 4 connected to 2 TB external storage, once a day over Wi-Fi. Thermal images were visualised and manually assessed in MATLAB 2021a (MathWorks, Natick, MA, USA). Images where the calf was present perpendicular to the camera with the left eye clearly visible were selected for processing. The position of the eye was manually selected using a mouse click and the pixel with the maximum temperature was then located within an 8 pixel radius. This pixel was treated as the centre of the eye and the average temperature was calculated under a 5x5 pixel window around this point, which approximated the size of the eye on the image (see Figure 1). For each day and sensor, we took the median value of 8 randomly picked averaged eye temperatures. Medians were selected as they are robust against outliers. Reference eye temperatures of calves, used later as calibration and validation data, were also collected during afternoon feeding using a Tecnimed VisioFocus VET 06610 non-contact infrared thermometer (Tecnimed, Vedano Olona, Italy). We chose this thermometer as it allows non-invasive data collection and is similarly accurate to rectal thermal measurements. Measurements were taken by the farmhand who the calves were familiar with in order to minimise disturbance. Ambient temperature and relative humidity of the calf shed was also recorded at 5-minute intervals using an EasyLog EL-SIE-2+ data logger (Lascar Electronics, Whiteparish, United Kingdom).

Calibration

According to the manufacturer, Lepton thermal cameras can produce an error of ±7°C if the temperature of the assessed object and ambient temperature ranges between 0 to 30°C (FLIR, 2014). The potential for this magnitude of error makes the Lepton unreliable to detect clinically meaningful changes in temperature. For example, the body temperature of healthy calves is typically 38.6 to 39.4°C and considered pyrexic above this range (Burfeind *et al.* 2012). We tested two methods of calibrating the thermal cameras in order to reduce the error. The first method, similar to the calibration described by Hedge and colleagues (2020), uses an open container of cooling water and a submerged temperature sensor. The Lepton thermal camera recorded the average surface temperature of the water between 28 and 40°C from a distance of 1 m. The average was calculated using a circle with a radius of 5 pixels centred at the middle of the container, while temperature recordings are matched to measurements taken by the submerged thermometer. A linear model is then used to calculate the intercept and slope of the difference between the Lepton and the reference temperature sensor. Water temperatures were recorded indoors with ambient temperature of 20°C and relative humidity of 60%. The second method uses the eye temperatures collected on-site using the non-contact infrared thermometer and leave-one-out cross-validation. To adjust eye temperatures measured by the Lepton for a given day, we fitted linear models to a set number of randomly chosen measurements (5, 10, 15 and 20 days) from other days by the same sensor to the associated reference eye temperatures. We then applied the resulting linear model to the uncalibrated value and repeated the same process for every day.

Statistical analyses

First, we tested whether ambient temperature and relative humidity had a significant effect on the model that fitted thermal camera measurements to reference eye temperatures. We used linear mixed effects models with different sensory platforms as random variables. This determined whether we included ambient temperature and relative humidity in further analyses. We measured the effectiveness of calibrations by calculating the mean absolute error of fitted data and running permutation tests, using 10,000 resamples, to compare whether the means were significantly different to the mean of the uncalibrated data. All statistical analyses were carried out in R (R Foundation for Statistical Computing, Vienna, Austria) and linear mixed effects models were fitted using the lme4 package (Bates *et al.* 2015).

Results and Discussion

A linear mixed effects model with variable intercepts and slopes for the random variable of sensors was a significantly better fit when ambient temperature and relative humidity were included as fixed variables (Δdeviance = 4481.2, df = 4, $p < .0001$). Both temperature (Δdeviance = 3484.1, df = 3, $p < .0001$) and relative humidity (Δdeviance = 1767.1, df = 1, $p < .0001$) had significant effects on their own. This meant that while the Lepton is regularly recalibrating itself using its shutter, the thermal images are considerably influenced by varying environmental conditions on the farm. Therefore, both ambient temperature and relative humidity were included in linear models fitted when calibrating with the eye temperature data. During the studied period, ambient temperature ranged between 9.2 and 18.9°C while relative humidity fluctuated between 50 and 88%. Ambient variables were not included for calibrations done with cooling water as those recordings were carried out in a stable uniform environment.

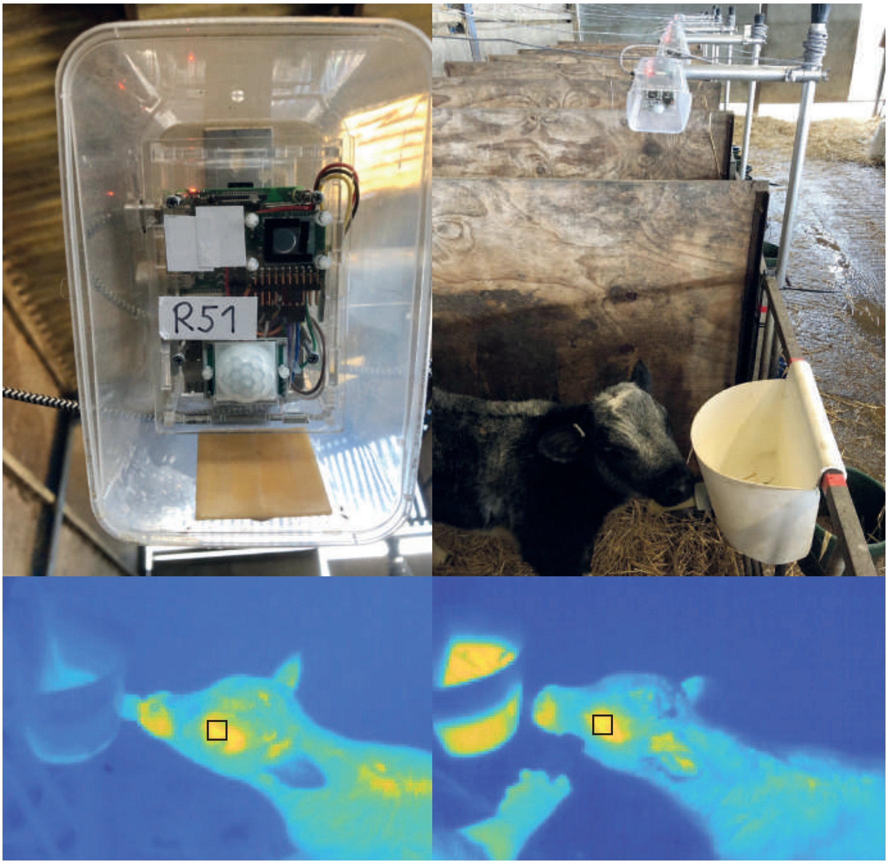

Figure 1: (Top left) Images of the sensory platform and (top right) their placement in relation to calves. (Bottom) Example thermal images of calves used in the study with black squares marking the sampled areas to calculate eye temperatures. The bottom right image also shows how eye temperature was recorded for reference

The means and standard deviations of differences of uncalibrated and calibrated eye temperatures to references readings per sensor are shown in Table 1. The results of the permutation tests showed that the 'water calibration' was ineffective in this setting (see Figure 2); the mean of absolute error between temperatures calibrated using cooling water and the reference eye temperatures was significantly higher than the mean of absolute differences between uncalibrated and reference readings (ΔT = 0.37°C, p = .0003). On the other hand, calibrating with values taken at different days yielded a better result over uncalibrated values if 10 days' worth of samples were taken (ΔT = 0.81°C, p < .0001). Overall, using 15 days was even more effective and produced a significantly lower mean of absolute error than 10 days (ΔT = 0.12°C, p = .0308), however this difference is clinically less significant. Calibrating with 20 days did not have a significantly lower mean in comparison to 15 days (ΔT = 0.02°C, p = .6880). A density plot for each type of calibration is shown in Figure 2.

Table 1: Means (and standard deviations) of error between thermal camera readings and reference eye temperatures for each sensor. Values are in °C

			Calibrated on			
Sensor	**Uncalibrated**	**Water**	**5 days**	**10 days**	**15 days**	**20 days**
1	1.05 (0.80)	1.47 (0.97)	1.37 (1.22)	0.85 (0.88)	0.64 (0.61)	0.57 (0.60)
2	1.27 (0.83)	1.51 (1.06)	1.34 (1.88)	0.51 (0.34)	0.45 (0.38)	0.46 (0.38)
3	1.10 (0.86)	1.39 (0.99)	1.14 (0.81)	0.68 (0.52)	0.59 (0.49)	0.57 (0.51)
4	1.13 (0.70)	1.94 (1.12)	0.92 (0.83)	0.88 (0.66)	0.57 (0.49)	0.53 (0.49)
5	1.40 (1.06)	1.49 (1.05)	1.27 (1.42)	0.57 (0.49)	0.49 (0.31)	0.46 (0.32)
6	0.52 (0.37)	1.22 (0.84)	0.84 (1.16)	0.44 (0.31)	0.44 (0.33)	0.44 (0.29)
7	1.07 (0.71)	1.10 (0.67)	0.89 (0.97)	0.51 (0.27)	0.46 (0.31)	0.47 (0.27)

Interestingly, the error of uncalibrated readings is still relatively low; less than 2°C which is typically the factory quoted error rate for high-end thermal cameras. However, we consider that the low error may be a coincidence. The thermal cameras were fitted with polyethylene sheets for protection which had an effect of reducing the recorded temperatures. Despite the apparent error of <2°C on average, given the unreliable conditions, we argue that calibration is necessary in all circumstances.

While minimising the error is obviously desirable in all settings, the effect of the type and magnitude of error is determined by the application. Because our proposed equipment allows rapid collection of large amounts of data over extended periods of time, if for example, the error is linear and only the intercept is affected (i.e. the thermal camera consistently over/underestimates the correct temperature by the same amount), even an uncalibrated sensor is adequate to track temperature changes within a single animal. Temperature readings would be inaccurate, but in a consistent manner and abnormal temperatures, caused for instance by fever, could be determined by changes within the subjective time-series rather than by an external threshold (e.g. 39.5°C). However, we found that both the intercept and slopes of linear models are affected in the case of Lepton cameras, therefore calibration is unavoidable (see Figure 2).

Using on-site calibration, we were able to reduce the mean error to approximately 0.5°C, which is comparable to a standard thermometer. In veterinary settings, a temperature difference of 1°C could be clinically significant (Turner *et al.* 1986). Our method yields an average error that is lower than this threshold, however errors over 1°C can occur occasionally. Therefore, we do not advocate that method could lead to clinical decisions *per se*, but rather consider our application as a prototype for an automatic, non-invasive early warning system that could flag potentially ill animals for further inspection.

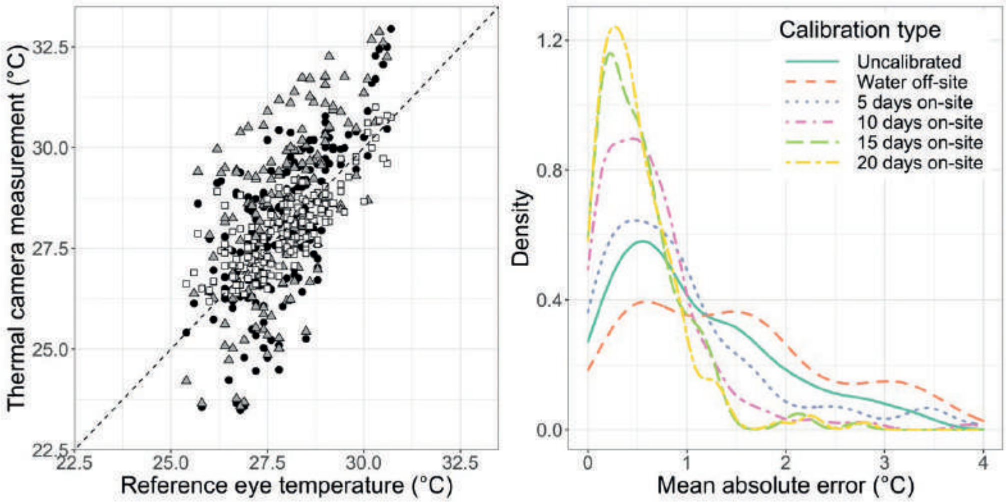

Figure 2: (Left side) Reference eye temperatures plotted against measurements without calibration (black circle), calibrated with cooling water (grey triangle), and calibrated with randomly selected eye temperatures from 15 days (white square). The dashed diagonal line shows a hypothetical perfect calibration. (Right side) density plot of mean absolute error for each type of calibration performed in the study

Conclusions

Single-board computers fitted with small thermal cameras promise a versatile and economic solution for an automatic and non-invasive early detection system for pathologies related to temperature changes. Our proposed system, based on Raspberry Pi computers and Teledyne FLIR Lepton 3.5 cameras, costs less than €300. This is not only an order of magnitude less than hand-held thermal cameras generally available in the marketplace, but the system is fully programmable for custom operations. In our example, single-calf pens were used to tackle the issue for identifying animals. A sensory platform per animal is not economical in a commercial setting and therefore identification is crucial. A Raspberry Pi-based system is advantageous as it can be extended with further sensors, such as low-cost visible light cameras or RFID, which could enable identification and allow more animals to be monitored by the same sensor (Andrew *et al*. 2020).

Low-cost thermal cameras are less accurate than expensive ones ‘out of the box’ and require calibration to attain more reliable temperature readings. We found that ambient temperature and relative humidity have a considerable effect on measurements, which need to be taken into consideration during calibration. This means that calibration performed in stable environments (e.g. indoors) is not effective and reference temperature readings have to be taken on-site over a period of time, enabling posterior calibration of thermal images. We found that taking reference eye temperatures of calves for 10-15 days is sufficient to reduce the mean error of thermal cameras to 0.5°C and thus enables a system to flag cases that could be clinically relevant and provide early warning for farmers and veterinarians.

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Early detection of respiratory diseases in calves by use of an ear-attached accelerometer

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Abstract

Identification of calves affected by Bovine respiratory disease (BRD), one of the most important disease in calves, is challenging. Therefore, tools for an automated monitoring and fast and easy identification of diseased calves would be a breakthrough in health management. The aim of this study was to examine the association between BRD and behavioral changes detected by an ear-tag based accelerometer system (SMARTBOW, Smartbow GmbH / Zoetis LLC) in weaned calves. Accelerometer data were analyzed retrospectively from 7 d before to 1 d after clinical diagnosis of BRD. Classified activity measures determined by the accelerometer system (active, inactive, high active), lying, and rumination times (min/h) were evaluated. As a reference, all calves in the study (n=508) were checked by daily observation by use of the respiratory score by McGuirk and Peek (2014). Calves with a total score ≥ 4 and rectal temperature ≥ 39.5°C for at least two consecutive days were categorized as diseased. Overall, 48 calves were classified as diseased. For each diseased calf, at least one clinically healthy control calf was enrolled. The data analysis showed a significant difference in high active times between groups, with diseased showing less high active times on every day, except d -3. Diseased calves showed significantly more inactive times on d -4, -2, and 0, as well as longer lying times on d -5, -2, and +1. The results showed the potential of the system to detect disease early, but further studies with higher numbers of diseased animals are necessary.

Key words: bovine respiratory disease, calf behavior, accelerometer.

Introduction

Bovine respiratory disease (BRD) is one of the most important diseases in calves in dairy as well as in beef production. The disease leads to impaired animal welfare, increased use of drugs (especially antimicrobials), and economic losses. Economic losses are due to costs for diagnosis, treatment, increased labor, increased risk for other diseases, impaired development of the calf, loss of the animal, and long term consequences on, e.g. weight gain, reproduction, and milk production (Adams and McGuirk, 2016; Cramer and Ollivett, 2019; Buczinski *et al.* 2021). One important point is an early detection of disease on farm. This can lead to fast intervention and consequently minimize suffering of animals, use of drugs, and economic losses.

Detection of BRD is mainly based on physical examination of individual animals. This is time consuming and often not feasible in larger groups of animals. Hence, clinical signs-based scoring systems in groups of animals were introduced, e.g by McGuirk and

Peek (2014). New technologies for an automated identification of calves suffering from diseases like BRD could improve animal health and welfare monitoring.

In the last few years, accelerometer-based technologies became more and more important for the automated monitoring of feeding, health and detection of behavioral changes (Chapa *et al.*, 2020). These technologies are able to measure and record activity, lying, and rumination times to detect changes in behavior that might be indicative of diseases and other conditions, e.g. estrus (Schweinzer *et al.*, 2019, Gusterer *et al.*, 2020). Recent studies showed the high potential of accelerometers to monitor rumination, activity, and lying behavior in calves (Bonk *et al.*, 2013, Krieger *et al.*, 2019, Swartz *et al.*, 2020). It has been reported that these behavioral changes can be detected in diseased (diarrheic) calves before clinical signs were evident (Goharshahi *et al.*, 2021). The objective of this study was to determine differences in behavior of calves diagnosed with BRD and clinically healthy controls kept in groups by use of an ear-attached accelerometer. In practice, this should help to identify affected calves prior to the clinical detection of the disease.

Material and methods

Animals and examinations

All calves were equipped with an accelerometer (details see below) approximately two weeks before entering the study barn. All animals under study were scored daily by observation using a calf scoring system for group-housed calves adapted from McGuirk and Peek (2014). The daily scoring included evaluation of cough, nasal and ocular discharge, as well as head and ear position. Each parameter was classified using a four-point scale where 0 was considered normal and 3 as severely abnormal (Table 1). All examined parameters were summarized to one score. Calves with a total score of ≥ 4 or at least two parameters with a score ≥ 2 were considered for further clinical examination.

Table1: Scoring system and definitions for daily observations in group housed calves adapted from McGuirk and Peek (2014).

Score	Observed parameter			
	Cough	Nasal discharge	Ocular discharge	Head and ear position
0	none	serous	none	normal
1	single (≤3), induced	unilateral, cloudy	small	ear flick or head shake
2	single, spontaneous	bilateral, mucus	moderate	slight unilateral ear drop
3	repeated (>3), spontaneous	bilateral, mucopurulent	severe	severe head tilt or bilateral ear drop

The clinical examination included lung auscultation for respiratory sounds, examination for dyspnea, and measurement of the rectal temperature. Calves were only defined as diseased if the rectal temperature ≥ 39.5°C and at least one parameter score ≥ 2 were present for two consecutive days. Day 0 was defined as the day when BRD was first diagnosed, whereas d +1 was the day of confirmation. For each diseased calf, a control calf was chosen. Control calves had to be of the same age, with a total score ≤ 1 and no abnormalities during clinical examination. In this study, the classified measures of the accelerometer, i.e. activity, lying, and rumination time were compared between diseased and control calves starting 7 d before BRD diagnosis.

Accelerometer data collection

A 10Hz accelerometer-equipped ear tag (SMARTBOW, Smartbow GmbH / Zoetis LLC) with a size of 52 x 36 x 17 mm and a weight of 34 g was attached to the left ear of the study animals. The ear tag collected data every second. Data were wirelessly transmitted from the ear tag vi receivers (Smartbow wallpoints) to a server every 4 sec if a calf was active and every 16 sec if a calf was inactive. The continuously recorded acceleration data (raw data) were further processed by algorithms developed by the manufacturer. Data classification was based on algorithms originally developed for adult cows. Classified data based on these algorithms for lying, standing, active, inactive, high active, and rumination were presented visually on a local computer or on a mobile device and recorded in the SMARTBOW software. All parameters were presented as minutes per hour (min/h) that the animal spent with this activity. Consequently, if the min/h of these three parameters were summarized it revealed 60 min.

Statistical analysis

Accelerometer data were summarized per calf and day starting with d -7 to d +1 relative to first diagnosis of BRD (d 0). Variables were tested for normality using the Shapiro-Wilk test. Averages were reported as mean ± SD. To test for an association between the duration of activity level, lying, and rumination of the two groups of calves (diseased and control), the Mann-Whitney U test was performed. P-value < 0.05 was considered as significant.

To evaluate the adequacy of the accelerometer data to predict the calves' health status for each day, Lasso regularized multivariate logistic regression models (L1 RMLM) were used. No other disease then BRD or special pathogen was taken into account in these models.

Results and Discussion

In total, we enrolled 508 calves, of which 48 calves were categorized as diseased by observation and scoring. Seven of these calves had to be excluded due to partial data losses by the accelerometer system.

Activity (i.e. active, inactive, high active) for the last 7 d before, up to one day after clinical diagnosis are presented for both groups (diseased and control) in Figure 1. Diseased calves showed more inactive times compared to their controls. The differences were significant on d -4 (17.1 ± 16.0 *vs* 15.8 ± 15.3 min/h, $P = 0.03$), day -2 (18.4 ± 16.6 *vs* 16.7 ± 16.4 min/h, $P = 0.03$), and day 0 (17.4 ± 17.1 *vs* 15.4 ± 15.9 min/h, $P = 0.03$).

Consequently, high active times were shorter in these calves. High active values ranged between 0 and 23.0 min/h in diseased and 4.1 to 31.1 min/h in control calves. Differences between groups were significant on all days, except on d -3.

Lying times were higher in diseased than in control calves. Differences were significant only on d -5, d -2, and d+1. Active and rumination times did not differ significantly between groups.

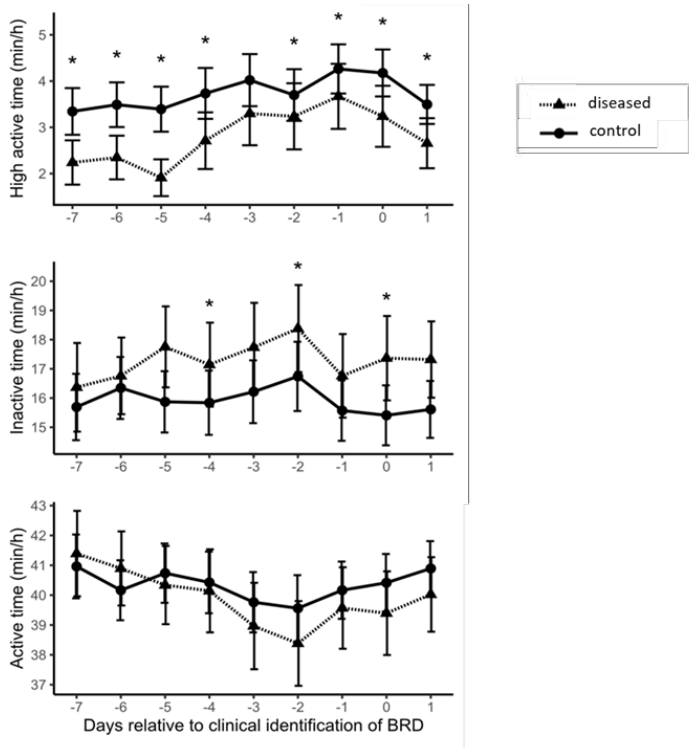

Figure 1. High active, inactive, and active times for diseased and clinically healthy control calves from d -7 to d +1 relative to clinical diagnosis of bovine respiratory disease (BRD) (d 0); *changes between groups with a $P < 0.05$.

The aim of the present study was to test the accelerometer system as a device to detect behavioral changes indicative for BRD prior to manual observation. Previous studies showed that the used accelerometer system is a reliable device to monitor lying and feeding behavior (Borchers *et al.*, 2016), rumination (Reiter *et al.*, 2018), estrus detection (Schweinzer *et al.*, 2019), onset of calving (Krieger *et al.*, 2019), and drinking behavior in calves (Roland *et al.*, 2018).

Depression, decreased activity, decreased feeding and rumination times, increased lying times, and number of lying bouts have been associated with BRD (Borderas *et al.*, 2009, Belaid *et al.*, 2020). These changes can be used to detect disease or at least calves at risk for diseases by use of accelerometers. In our study, differences in activity and lying could be detected in accelerometer data between diseased and control animals up to seven days before the onset of disease. However, the number of diseased animals in the study was low. Further studies including a greater number of diseased calves are necessary to confirm or disprove our results and to develop an alert system for early detection of BRD in calves. In this context, the development of specific algorithms for calves to detect age-specific behaviors (e.g. playing behavior) should be considered.

Conclusions

Sensor technology can be a reliable method for early detection of disease, especially in group-housed calves where the monitoring of individuals is difficult. The results of this study indicate that ear-tag based accelerometers for monitoring lying and activity parameters have the potential to discover animals at risk for BRD before the onset of clinical signs. Nevertheless, further research is needed with a larger sample size.

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Early BRD detection in young cattle

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Abstract
This paper proposes an algorithm to detect bovine respiratory disease (BRD) 24 hours before the onset of clinical signs. The algorithm uses signals from a collar, a pedometer and an intraruminal bolus. The algorithm using only the collar and pedometer signals resulted in Se=75% and Sp=74%; this performance increased to Se=75% and Sp=76% when the ruminal temperature signal was added.

Keywords: BRD early detection, Collar and pedometer, model selection, signal processing.

Introduction
Bovine respiratory disease (BRD) is the most important health problem in cattle feedlots. Therapeutic solutions include the use of antibiotics to reduce the spread of the bacterial infection. Indeed, the aetiology of BRD leads to a rapid development of the disease in the feedlot if nothing is done to treat an infected young bull, with a decrease in performance and even mortality (3% on average related to BRD (Engler *et al*., 2014)). Thus, BRD is the main cause of antibiotic use in cattle feedlots: on average, 20% of fattening animals receive antibiotic treatment (Assié *et al*., 2009). The causes of BRD are known to be multifactorial. The onset of BRD requires one or more non-infectious factors depending on the animals themselves (breed, immunity, etc.) or on the farming conditions (transport, housing conditions, feed, etc.). Furthermore, the severity of BRD cases varies greatly, ranging from moderate to severe cases combining local clinical signs (nasal discharge, ocular discharge, coughing, dyspnoea, etc.) and general signs (hyperthermia, weakness, anorexia). Again, animal and farm factors play a role in modulating the severity of clinical signs (Cusack & Lean, 2003; Duff & Galyean, 2007)2003; Duff and Galyean, 2007. Secondly, the detection of BRD cases by the farmer is complicated, often delayed, leading to the spread of the disease in the feedlot, and sometimes over-diagnosed. Traditionally, BRD cases are detected on the basis of cattle behaviour and appearance, which have limited sensitivity (62% (White & Renter, 2009)) and do not allow for early detection (Weary *et al*., 2009). This is because cattle often adopt predatory/prey behaviour and mask early symptoms (Griffin, 2010). Early intervention is the key to effective treatment of BRD to reduce relapse rates and mortality (Ferran *et al*., 2011)it should be stressed that in early curative antimicrobial treatment as in metaphylaxis, the bacterial burden at the infection site is often very low, and so the rapid eradication of the bacterial population could result. We investigated the impact of early versus later curative administrations of 1 or 40mg/kg of marbofloxacin on the survival of mice, the eradication of the targeted pathogen and the selection of resistant bacteria in a mouse lung infection with Pasteurella multocida. In this model, for a given marbofloxacin dose, the clinical and bacteriological outcomes were better, and

the selection of resistance less frequent, for the early rather than for the late treatment. Moreover, the early administration of 1mg/kg led to better clinical and similar bacteriological (eradication and selection of resistance. Diagnosis based on clinical signs alone may not be specific to BRD (Griffin, 2010). Therefore, a large proportion of treated cattle are not actually affected by BRD (specificity of clinical diagnosis: 63% (White & Renter, 2009)). An increase in the specificity of BRD diagnosis would allow for more prudent use of antimicrobials and lower costs of BRD control (Theurer *et al.*, 2015).

The recent development of Precision Livestock Farming (PLF) (Allain *et al.*, 2014), offers the possibility of a real-time monitoring and management system for the farmer, with the aim of providing a real-time alert when problems occur (Berckmans, 2014). Multiple sensor technologies are now available on the market (accelerometer, thermometer, microphone, video, etc.). They provide measured responses on animals, called bio-signals, which can be temperature measurement, GPS position, accelerometer data, real-time image analysis, sound analysis or water or food consumption activity. While these technologies are mainly oriented towards assisting herd management, they also offer interesting prospects in terms of research and development, particularly for better assessing health problems. Biosensors aimed at measuring indicators related to the condition and health of animals (behaviour, temperature, and coughing) are already the subject of numerous studies (reviewed in (Guatteo *et al.*, 2015)). Regarding body temperature, (Timsit *et al.*, 2011)clinical examination was performed by a veterinarian and then repeated every 12–24h until the end of RH episode. Fifty-two RH episodes were detected in 22 animals. High rectal temperatures (40.1±0.6°C used reticulo-rumic temperature boluses in young bulls following their entry into a fattening unit. The study showed that 73% of hyperthermia episodes could be linked to BRD. Furthermore, the onset of BRD signs mainly occurred after the onset of reticulo-rumic hyperthermia episodes, with a time lag of 12-36 h. (Schaefer *et al.*, 2007) detected an increase in the orbital temperature of juveniles 4-6 days before the onset of the first clinical signs of BRD. Despite these encouraging results, all the above studies have two major drawbacks. Firstly, the results cannot be used as a predictive model: they have not been validated and consist mainly of the presence of significant correlations between the indicators and the appearance of clinical signs. Indeed, individual conditions influence the onset and expression of BRD, so it is easy to imagine that the model built and tested on the same individuals would be less efficient if tested on new individuals. The use of cross-validation is an appropriate solution to this problem of over-fitting and will be used in this paper. Secondly, the previous studies only consider univariate signals and, due to the complexity of BRD, when considered separately, these health indicators may not be specific. For example, the social behaviour of young bulls, particularly agonistic interactions (e.g. fighting, pawing and threatening) and mounts, can lead to an increase in core body temperature for several hours. Episodes of fever due to vaccination or diseases other than BRD (e.g. internal abscesses) can also lead to an increase in core body temperature (Timsit *et al.*, 2011).

In this paper, we propose a detection algorithm that uses biosensor data as a predictor of the onset of clinical signs of BRD. A binary health state based on clinical signs was constructed and defined as the gold standard of a sick animal. Then, many variables were derived from the initial sensor signal, called "behavioural data" and used as explanatory variables. A logistic regression model was fitted to explain the probability of disease occurrence as a function of these behavioural data. To avoid overestimation, the performance of the model was evaluated by cross-validation. As there was a large amount of behavioural data, the best subset of explanatory variables (giving the best cross-validated performance) was sought using a statistical optimisation method known as simulated annealing.

Material and methods

Experimental data

Two herds of 52 Charolais young cattle were observed during 30 days in an experimental fattening feedlots (Etablières farm, Vendée, France). The first herd was observed from November 7th to December 6th 2019; the second herd was observed from November 5th to December 4th 2020. The cattles were homogeneous in weight and age when arriving at the farm: 313 ± 34 kg and 235 ± 25 days for the first herd and 341 ± 42 kg and 248 ± 21 days for the second herd. The 52 calves were spread over four pens in the same building. When necessary, treatments (of BRD or others pathologies) were administrered, under the control of the farm veterinarian.

Two types of data were collected: clinical data from veterinary examination and behavior data measured by automatic sensors.

The clinical data consisted in regular rectal temperature measurement and daily clinical examinations (by veterinarian or authorized veterinary students). The daily clinical examinations were performed by visual inspection. There were based on a grid designed by veterinarians. This grid included general criteria (appetite, rumen fill score and depression) and respiratory criteria (respiratory rhythm (mpm), cough, dyspnea, nasal and ocular discharge).

Table 1: Notation grid for the visual clinical inspection. Each criterion was rated according to a scale from the healthiest level to the sickest (left to right). The cough strength was an indicator of the severity of the respiratory system damage. Generally, a strong cough is painless and corresponds to an upper respiratory tract damage when a weak cough is painful and corresponds to a low respiratory tract damage (lungs).

Clinical visual criteria	Notation scale
Rumen fill score	Bounced=0, Flat=1, Hollow=2
Appetite	Normal=0, Decreased=1, Absent=2
Depression	Absent=0, Light=1, Severe=2
Ocular discharge	Absent=0, Serous weak=1, Serous moderate=2, Serous high=3
Nasal discharge (quantity)	Absent=0, Weak=1, Moderate=2, High=3
Nasal discharge (quality)	Absent=0, Serous=1, Mucous=2, Purulent=3
Respiratory amplitude (RA)	Normal=0, Increased=1
Respiratory frequency (RF)	≤40 npm=0, 41-50=1, 51-60=2, 61-70=3, 71-80=4
Cough frequency	number of events per 5 min observation sequence
Cough strength	Strong=1, Weak=2

The rectal temperature was measured regularly (herd one: measure on days 7, 14 and 30; herd two: measure on days 1, 8, 15, 22 and 29). When the animal's health required it, additional rectal temperature measured were performed by the farm staff and those data were included in the data set. A clinical score was defined using this clinical examination as described below.

The behaviour data consisted in measurement of the calves' activity by automatic sensors. They were equipped with three different sensors: a pedometer (IceQube), an accelerometer collar (HeatTime) and a ruminal thermometer bolus (Médria). The activities monitored were the activity, the feeding, the rumination and the rest. Precisely, the pedometer counted the number of steps in 15 minutes intervals and recorded the time and duration of the lying bouts. The accelerometer collar measured the time allotted to feeding, rumination and resting for every hour. The ruminal thermometer bolus recorded the reticulo-rumen temperature every 5 minutes. The ruminal temperature allowed computing the moments of drinks.

The clinical data were used to create a clinical score. To do so, a general health score (GS) was computed as:

GS = Rumen fill score + Appetite + Abatement + Rectal temperature$\geq$ 39.7).

As the rectal temperature was not measured daily, for a given day, say *j*, the rectal temperature considered was the maximal rectal temperature measured between days *j*-6 and *j*+6 (included).

In the same way, the general health score, a respiratory score (RS) was computed by adding the scores of the respiratory criteria, i.e.:

RS =Ocular disch. + Nasal disch.(quantity) + Nasal disch.(quality) +Increased RA + RF + (Cough frequency > 0) + Cough strength.

Then, the clinical score was the multiplication of the two previous scores. An animal with a positive clinical score necessarily had general and respiratory symptoms. Even if it should be interpreted with great care, one can consider that this clinical score increased with the severity of the respiratory illness.

Finally, a binary health variable was defined by setting a threshold on this clinical score. For the animal *i* on day *j*, the health variable was denoted Y_{ij} with $Y_{ij} = 1$ if the clinical score was greater than or equal to 4, and 0 otherwise.

Note that others thresholds than 4 could be tested. An animal with a $Y= 0$ was considered as healthy and was it was considered as sick when $Y= 1$.

Since the health variable was daily, the behaviour data were pre-processed to also correspond to daily information. First of all, daily variables were computed.

Second, daily variations with respect to previous "averages" were computed as follows. Each variable was gathered on 6 intervals by day: 0h-6h / 6h-9h / 9h-12h / 12h-15h / 15h-18h / 18h-24h (sum, average or maximum, accordingly to the list above). Then, for each variable the magnitude of the daily intra-individual variation was computed.

Third, all the previous variables (daily totals or variations) were divided by the maximum value they reached during all the previous days. Hence, departing from the 8 daily measures, 32 explanatory variables were computed.

Finally, for a given day (say *j*) the values of the 32 variables for days *j* to *j*-4 were considered as explanatory variables. To summarize, an observation of explanatory variables, for day *j* and individual *i*, consisted in a vector of length .

<u>Prediction model</u>

Let $s = (s_1,\ldots,s_p) \in \{0,1\}^p$ a p-uple containing only 0 and 1.

Because at a given point in time an individual's past information is stored in the covariates, we renumber the health variable Y_{ij}(i=1,…,N, j=1,…,p) without distinguishing the individual and the point in time at which the individual was observed. In other words, Yij becomes Y_k (k=1,…,Np). We denote x_k^j the kth value of the jth explanatory variable. For a given $s \in \{0,1\}^p$, the following model was used to predict the health variables

$$Y_k = 1 \text{ if } \sum_{j=1}^{p} s_j \theta_j x_k^j > c \text{ and } Y_i = 0 \text{ otherwise.} \tag{1}$$

The vector *s* serves as a switch allowing to select variables. In order to avoid overfitting a random selection Γ of K values of Y_i and of the corresponding covariates were used to estimate the parameters (θ_j). The sensitivity $Se(s, \Gamma, c)$ and the specificity $Sp(s, \Gamma, c)$ were then computed for each value of *c* in (1) from the values $k \notin \Gamma$. Next, the average (over the different randomly chosen Γ's) Sp and Se were computed ; they are respectively denoted $Se(s, c)$ and $Sp(s, c)$.

At, the end, for a given choice of explanatory variables (*s*), the following criterion was computed:

$$U(s) = \min_c \left(1 - Se(s, c)\right)^2 + \left(1 - Sp(s, c)\right)^2 \tag{2}$$

Choosing the best set of explanatory variables means minimising $U(s)$. Because *s* can take a large number of values (2^p), it is not possible to minimise *U* by exploring all possible values of *s*. Instead, the different sets of exploratory variables were evaluated by exploring randomly the values of *s* according to the following simulated annealing algorithm: if at iteration *k*, $s = s^{(k)}$, the algorithm moves to $s^{(k+1)}$ with a probability

$$q_{\beta_k}\left(s^{(k)}, s^{(k+1)}\right) = exp\left(-\beta_k[U(s^{(k+1)}) - U(s^{(k)})]^+\right) q_0(s^{(k)}, s^{(k+1)}) \tag{3}$$

where $[a]^+ = \max(a, 0)$, (β_k) is a sequence going to +infinity with *k*, and q_0 $(s^{(k)}, s^{(k+1)})$ is a transition probability function on $\{0,1\}^p$ corresponding to the probability of proposing the neighbour $s^{(k+1)}$ of $s^{(k)}$. A general property of this algorithm is that if β_k increases slowly enough, it converges toward the values of *s* where *U* reaches its absolute minimum.

Two sets of exploratory variables have been investigated. The first set includes all the variables constructed from the collar, pedometer and intra-ruminal bolus recordings. The second set contains only the variables from the collar and the pedometer.

Results and Discussion

To save space, we chose to show only the results obtained using the exploratory variables computed using the signals obtained from day j-3 to j-1. The best performances obtained with the models described by equation (1) were respectively Se=0.75, Sp=0.76 when the ruminal bolus information were included in the model and Se=0.75, Sp=0.74 without the bolus information. The best model was found after two weeks of parallel computation on a PC with a 12-core processor. Table 1. shows that the best models need mainly the information recorded the day before the prediction is to be performed. Surprisingly, when the ruminal bolus variables are not taken into account for the prediction, less exploratory variables are required.

Table 1: Number of variables included in the best model

	J-3	J-2	J-1
With bolus variables	13	11	17
Without bolus variables	6	6	11

The Figure 1. Represents the ROC curves obtained with the best model with and without the bolus data. They were obtained by varying *c* in the best model. Because a model is optimal only for a single value of *c*, the curves presented in this Figure are not point by point optimal. Only the closest point to Se=1 and 1-Sp=0 is optimal.

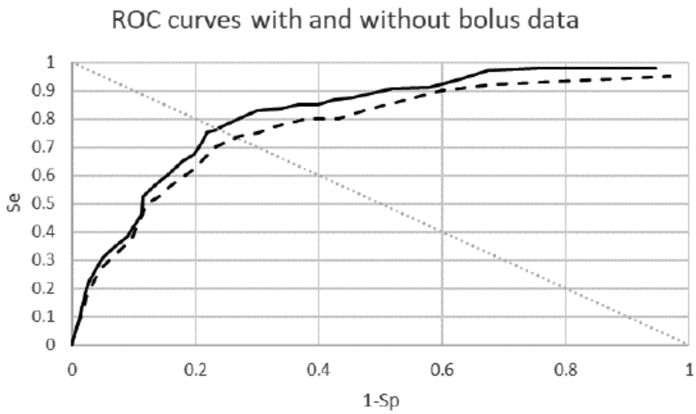

Figure 1: The solid (resp. dotted) line curve represents the roc curve obtained using (resp. without) the intra-ruminal bolus data with the best model. These curves were obtained by varying *c* in eq. (1)

Overall, although the results of this study are better than those obtained by other authors, at least to our knowledge, the decision rules are not good enough to be used as they are. A sensitivity and specificity of about 75% is not sufficient to build a reliable livestock management system. However, it is probably not always necessary to have decision rules that have high sensitivity and specificity at the same time. For example, in the early stages of a farm infection, it is probably better to have high sensitivity even if specificity is lower. On the other hand, if BRD is established on the farm, high specificity would probably be useful.

This raises questions about the choice of the *U* function described in equation (2) that we have optimised. In this function, sensitivity and specificity have the same weight. In this context, it seems to us that a U-function of the form (4) would be much more useful

$$U(s) = \min_{c} \alpha(Pr)\big(1 - Se(s, c)\big)^2 + \beta(Pr)\big(1 - Sp(s, c)\big)^2 \quad (4)$$

where *Pr* is the expected prevalence in the herd, $\alpha(Pr)$ and $\beta(Pr)$ are the weights favouring Se or Sp.

Conclusions

This paper shows that it is possible to detect BRD contamination of an animal at least one day before clinical symptoms based solely on information from a collar and pedometer. The results obtained in this study are extremely encouraging even though they are mainly based on a human assessment of the clinic (labelling of the animals). Perhaps better results could be obtained if the vocabulary and clinical assessment of the disease were standardised and/or if the emergence of symptoms could be obtained in an automatic, reproducible and continuous manner.

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Using machine learning and precision livestock farming technology for early indication of health status in preweaned dairy calves

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Abstract
The objective of this study was to determine which algorithm, using machine learning techniques, accurately identifies calves destined to be positive for Bovine Respiratory Disease (BRD) status. We followed the health of 106 calves for 53±2 days using manual health scoring. Calves wore an accelerometer on the rear leg which recorded daily lying time, lying bouts, step counts, and an activity index. Calves were offered up to 10 L/d milk replacer by an automated milk feeder which recorded daily milk intake, drinking speed, and feeder visits. Of these calves, 54/106 were diagnosed with BRD based on two abnormal scores from the Wisconsin Health Scoring, and 3 cm2 of lung consolidation (day 0). First, we evaluated the potential of Ridge Classifier, linear SVM with Stochastic Gradient Descent learning (SGD), Gaussian Naïve Bayes, Decision trees, Adaboost classifier, and a K-Nearest Neighbor's algorithm (KNN) for accuracy to classify data as positive or negative for BRD status using different window sizes (3 to 14d). The KNN and Decision Tree algorithms were the most accurate and had high precision and recall for BRD labelling correctly using 14d window size. For experiment II, two accurate algorithms were tested to identify calves destined to be positive to BRD in 7d prior to diagnosis using PLF variables. We found that KNN was highly accurate (80%) at classifying data as pre-sick up to -3d prior to BRD diagnosis. In summary, automatically collected behaviours and the use of KNN were found to have the potential to identify BRD in calves.

Keywords: precision livestock farming, bovine respiratory disease, automated feeder, accelerometer

Introduction

Bovine Respiratory Disease (BRD), an infection of the respiratory tract in cattle, is the second leading cause of morbidity in dairy calves in the USA (USDA, 2018), and over 90% of all infections were reported by producers to be treated with antimicrobials (Urie et al., 2018). In addition, it can take several days before outward clinical signs of BRD status are evident in calves when compared to the positive presence of lung consolidation on ultrasound (Rhodes et al., 2021). Since judicious use of antimicrobials is imperative for the dairy industry and affects public perception of the industry (Wemette et al., 2021), there is a need to find calves who are potentially at risk for BRD status in a timely manner.

Sickness behaviour, such as depressed feed intake and reduced activity in mammals is a motivational state initiated by a cascade of immune responses (Hart and Hart, 2019) and this behavioural repertoire precedes clinical signs of BRD in calves (Cantor and Costa, 2022). Indeed, we can use automated precision technology devices to record sickness behaviours using an automated robotic feeder, and accelerometer, respectively. For example, using these technologies for the 5 days prior to BRD diagnosis, we found that on average, dairy calves destined for BRD declined their feed intakes (e.g., milk and starter intakes), and reduced all behavioural activity levels (e.g., increased lying times, and reduced step counts and reduced activity indices) when compared to healthy calves. However, we know that differences on average between healthy and sick groups of cattle cannot be used to find an individual sick calf which is the goal behind precision livestock farming data. Thus, we set each calf's baseline behaviour at 5 days before BRD diagnosis, and we found that there were relative changes in a calf's unrewarded visits to the feeder, and relative changes in calf starter intake prior to BRD diagnosis (Cantor and Costa, 2022). Since we observed significant relative changes in behaviour prior to BRD diagnosis, we knew there was the potential to use feeding behaviour and activity levels collectively using machine learning techniques.

Machine learning algorithms are advantageous over linear regression as we can predict BRD outcomes over multiple iterations to find the most accurate, and precise algorithm over repeated iterations (Buitinck et al., 2013). Furthermore, we can use machine learning techniques to explore the potential of different window sizes to determine the most accurate labelling of calves as BRD positive or negative. To our knowledge, only one study has explored the potential of machine learning algorithms (e.g., decision tree) to indicate calves as BRD positive or negative, but a moderate sensitivity was observed (Bowen et al., 2021). Thus, we aimed to explore the potential of Ridge Classifier, linear SVM with Stochastic Gradient Descent learning (SGD), Gaussian Naïve Bayes, Decision trees, Adaboost classifier, and a K-Nearest Neighbour's algorithm (KNN) for accuracy to classify data as positive or negative for BRD status using different window sizes (3 to 14). For experiment II, we evaluated the potential of two accurate algorithms from experiment I to indicate calves destined for BRD status in the 7 days leading up to BRD diagnosis using automatically collected features.

Material and methods

Experimental data

We followed a cohort of 106 calves born at the University of Kentucky Research Dairy daily from birth until 2 weeks post-weaning (90 d) for disease outcomes including navel infection, diarrhea, and Bovine Respiratory Disease (BRD) status. For this study, we only included calves for the preweaning period which occurred from training to drink milk from an automated feeder (Forster-Technik, Engen, Germany) at 3 ± 2 days of age until 50 days later. Calves could consume up to 10 L/d milk replacer (Cows Match, Purina, MN, USA) from the feeder, and calves also had free access to grain (starter) from a separate automated feeder (Forster-Technik, Engen, Germany). The feeders recorded total daily intake, and the milk feeder also recorded drinking speed and visits. All calves also wore an accelerometer (IceQube, IceRobotics, Edinburgh, Scotland) on the rear left leg which tracked activity levels such as lying time, lying bouts, step counts, and an activity index based on acceleration and total movement.

We scored calves for signs of BRD daily (McGuirk and Peek, 2014). Twice weekly, we also weighed the calves and scanned both sides of the calf's lungs to assess for lung consolidation (Dunn et al., 2018). A calf was diagnosed with BRD status when the calf was positive on the manual system (McGuirk and Peek, 2014) and had lung consolidation ≥ 3 cm^2 (Dunn et al., 2018). All calves on the first day of BRD diagnosis were labeled as day 0 in the dataset. All BRD positive calf days were labelled sequentially (day 1, day 2, day 3 etc.,) until cured when lung consolidation resolved, and the calf was negative for signs of BRD status. The 7 days prior to BRD diagnosis was labelled as pre-sick data as day -7 until day -1 prior to BRD diagnosis.

Statistical analysis

We had previously observed that BRD status was associated with feeding behaviour and activity levels for the 5 days before BRD diagnosis in preweaned calves, and that calves had relative changes in individual behaviours (Cantor and Costa, 2022) when controlling for season, weight, and sex. Specifically, we observed that there were associations of BRD status with decreased milk intake, starter intake, unrewarded visits, step counts, and the activity index and increased lying times when compared to healthy calves (Cantor and Costa, 2022). Since these automated features might serve as indicators of BRD status in the calves, we included milk intake, starter intake, unrewarded visits, step counts, the activity index, and lying times as automated feature inputs into the algorithm. We also included sex, season, and weights as manual features into the machine learning algorithms since we knew these variables were associated with BRD status in the calves. We labelled the data by day, where BRD positive days were when a calf had positive BRD status (day 0 onwards) and BRD negative days were when the calf was negative for BRD status. We labelled the 7 days prior to BRD diagnosis for all BRD positive calves as pre-sick data and excluded this data from the first experiment.

For all experiments, cross-validation was performed for 10 iterations and the average accuracy and standard deviations of these 10 iterations are reported. For experiment I, we were interested to determine which window size (size 3 to 14) of feeding behaviour and activity level data (mean and SD) was required to classify these calves most accurately as BRD positive or BRD negative using the automated feature data, and the manual features. We ran 10 iterations of the following algorithms Ridge Classifier, linear SVM with Stochastic Gradient Descent learning (SGD), Gaussian Naïve Bayes, Decision trees, Adaboost classifier, and a K-Nearest Neighbour's algorithm (KNN) for accuracy, precision, and recall classifying data as positive or negative for BRD status using different window sizes.

For both experiments, we left out the pre-sick data to train the algorithms to classify BRD status using 70% of the dataset. For experiment I where the algorithms classified data as BRD positive or BRD negative, testing was performed with the remaining 30% of the dataset, excluding the pre-sick data. For experiment II, the pre-sick data was used to test algorithm performance.

For experiment II, we took the two best performing algorithms from experiment I to assess for algorithm accuracy to label pre-sick BRD data for the 7 days prior to BRD diagnosis. We ran 10 iterations for both algorithms (mean ± SD) using the best performing window size from experiment I to standardize each feature.

Results and Discussion

Each window size represented indicated that the KNN was the superior algorithm accuracy, precision, and recall performance for classifying the data as positive or negative for BRD status, and a window of 14 yielded the best results for all algorithms **Table 1**. **Figure 1** presents the algorithm performance (mean ± SD) for Ridge Classifier, linear SVM with Stochastic Gradient Descent learning (SGD), Gaussian Naïve Bayes, Decision tree, Adaboost classifier, and a K-Nearest Neighbour's algorithm (KNN) for accuracy to classify data as positive or negative for BRD status using different window sizes (3 to 14) across 10 iterations. In brief, KNN and decision tree were the most accurate in Figure 1.

Table 1: Identification results of the machine learning algorithms for classifying data as positive for Bovine Respiratory Disease (54/106 preweaned calves) or negative using a window size of 14. Automated input features were feed intake, visits, lying time, step counts, and activity index, and manual features were weight, season, and sex.

Algorithm (mean ± SD)	Accuracy	Sensitivity	Specificity
K-Nearest Neighbour	0.99 ± 0.00	0.99 ± 0.00	1.00 ± 0.00
Ridge Classifier	0.80 ± 0.01	0.82 ± 0.02	0.77 ± 0.02
Stochastic Gradient Descent Learning	0.74 ± 0.03	0.73 ± 0.03	0.75 ± 0.07
Gaussian Naïve Bayes	0.78 ± 0.02	0.80 ± 0.02	0.75 ± 0.02
Decision Tree	0.93 ± 0.01	0.93 ± 0.01	0.93 ± 0.01
Adaboost Classifier	0.84 ± 0.02	0.85 ± 0.02	0.85 ± 0.02

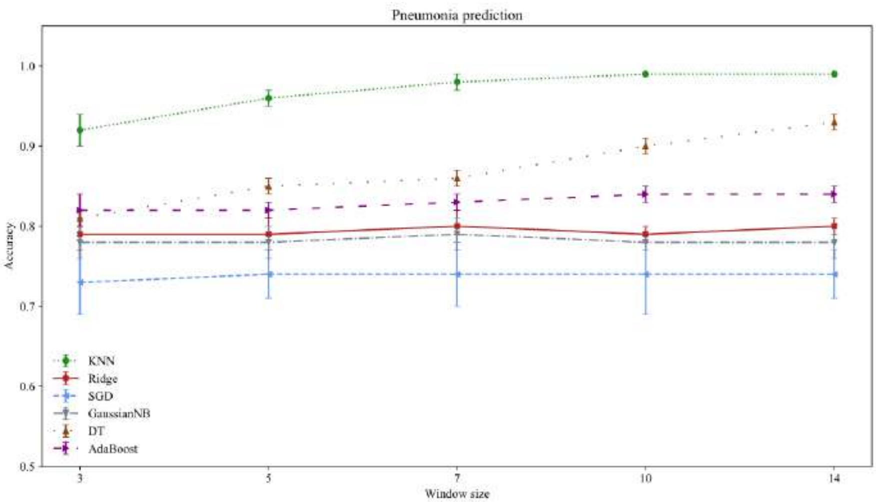

Figure 1: The algorithm performance (mean ± SD) for Ridge Classifier, linear SVM with Stochastic Gradient Descent learning (SGD), Gaussian Naïve Bayes, Decision tree, Adaboost classifier, and a K-Nearest Neighbour's algorithm (KNN) for accuracy to classify data as positive for BRD status (54/106 calves) or negative for BRD using different window sizes (3 to 14) across 10 iterations.

Our findings indicate that a KNN algorithm at a window size of 14 was nearly perfectly accurate at classifying data as BRD positive or negative of the dairy calves followed in this experiment. Diagnosing BRD in a timely manner is important as BRD compromises calf productivity during disease advancement, suggesting it compromises calf welfare (Rhodes et al., 2021). The findings in this study contrast with Bowen et al., (2021), who selected a decision tree algorithm, and a smaller window of data to classify BRD status in calves using similar input features to our study. We hypothesize that our results differ from Bowen et al., (2021) because while we also used automated feeding behaviour and activity level data, we had additional feature information such as grain intake, and an activity index to input into our models. For example, we previously observed that calf starter intake and relative changes in calf starter intake was a robust feature for indicating BRD status (Cantor and Costa, 2022), and BRD relapsed status in calves (Cantor et al., 2022). Similarly, we also included seasonal information and weights as manual feature inputs for these experiments. Thus, it is possible that our results differed from Bowen et al., (2021) because we had additional information to feed into our algorithms which improved the ability of the algorithm to classify BRD status with a near perfect accuracy, precision and recall when compared to the other algorithms tested in this experiment. This agrees with a review by Cockburn (2020), and a systematic review by Slob et al., (2020), they suggested that the addition of information which partially explains variation in the dataset improves model accuracy and data output for managing cattle using machine learning techniques on farm.

For experiment II, we selected the KNN and decision tree algorithms for their ability to label pre-sick data accurately for the 7 days prior to BRD diagnosis using a window size of 14. As depicted in **Figure 2**, the KNN had high accuracy 80% as early as 3 days prior to BRD diagnosis, compared to the negligible accuracy of the decision tree algorithm.

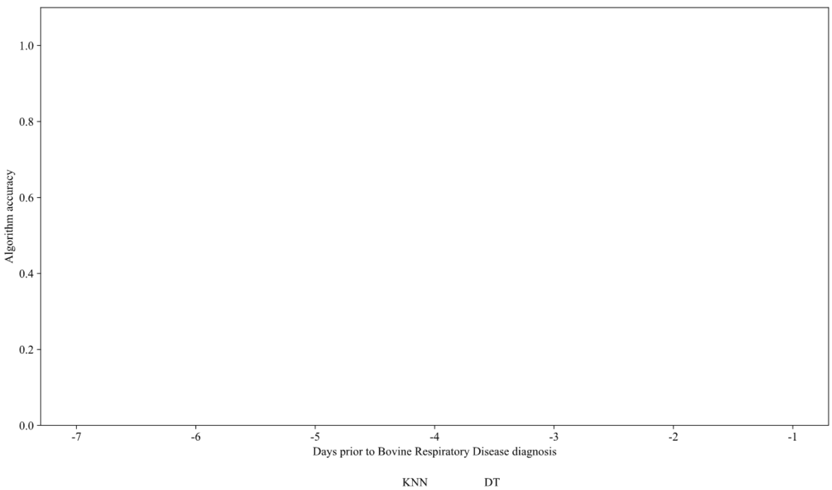

Figure 2: The ability (mean ± SD 10 iterations) of a K-nearest Neighbour's algorithm (KNN) and a decision tree algorithm (DT) to accurately classify pre-sick calves (54/106) for the 14 days before diagnosis of Bovine Respiratory Disease on day 0.

To our knowledge, this was the first study to quantify those calves destined for BRD status could be identified with moderate accuracy up to 3 days prior to diagnosis. Our findings with our decision tree algorithm were very similar to Bowen et al., (2021), who used decision tree and observed only moderate accuracy 60% of calves at one day prior to BRD diagnosis. Thus, it is possible that a KNN better predicts BRD status in calves. We believe the KNN was the most accurate algorithm for indicating calves destined for BRD in this study because the KNN is useful for time series data since it uses a consistent number of neighbours to make predictions, thus handling correlated data in proximity accurately. For example, days that were farther away from BRD diagnosis such as days -14 to days -10 were no better than chance since this information was more closely related to healthy calf data than that of a calf destined to be sick, and a KNN can accommodate this relationship using the closest neighbours to place weight on correlated relationships. In contrast, our decision tree algorithm labelled data without consideration of neighbours, potentially subjecting this algorithm to higher error (Charbuty and Abdulazeez, 2021). However, the novelty in these findings is that behavioural data surrounding the 3 days prior to BRD diagnosis is closely related to BRD status. Thus, a KNN may be useful for algorithm development to capture calves destined for disease in real time to generate alerts. We suggest there is the potential to improve calf welfare if the KNN is further developed for incorporation of real-time use on farm. This will add to the value of the automated feeder data and accelerometer technology, potentially encouraging producer adoption (Drewy et al., 2019). Furthermore, for this study, we only incorporated automated features which were associated with BRD status from our mixed linear models (Cantor and Costa, 2022). Our future research aims to incorporate all automated features collected by the precision technology devices into the KNN, to use feature extraction techniques to determine which features should remain in the KNN, and to also weigh these features by cost in future experiments to further explore the utility of this data for indicating a calf destined for BRD status.

Conclusions

We found that a K-Nearest Neighbour's algorithm had the highest accuracy, precision, and recall using a window size of 14 to classify data as BRD positive or negative. Furthermore, when compared to a decision tree algorithm, the KNN had the most superior accuracy performance for classifying calves as predestined for BRD status, with moderate accuracy up to 3 days before disease diagnosis. We suggest that the KNN should be further explored as a potential alert for indicating calves with BRD in commercial settings. This is particularly useful as adding value to precision technology data may encourage the adoption of such technologies on farm, and farms using automated milk feeders have been observed to offer more milk to calves.

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SESSION 23

General:
Product Development

Evaluation of the Vienna Surface Tester for the application on bedding materials used in livestock farming

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Abstract
The Vienna Surface Tester (VST, patented by Schramel and Peham, University of Veterinary Medicine, Vienna) was developed for measuring the mechanical properties of sport surfaces such as turf or riding arenas. It uses a bowling ball (6.15 kg) equipped with two accelerometers and calculates impact acceleration, stiffness, and energy return. Impact velocity ranges from 1.0 ms^{-1} to 4.5 ms^{-1}. Current methods for estimating the hardness of lying surfaces for cows are quite subjective. Hence, the main objective of this study was to evaluate whether the VST is suitable for measuring the properties of different kinds of bedding materials as used in cattle farming. Further aims were to determine the inter-observer-reliability and the inter-device-reliability. The different materials for this evaluation were sand, horse manure, bark mulch and rubber mats. A wooden frame with the standard dimensions of a cubicle was filled with those materials one after another. Six measurements per floor type were carried out by two examiners with two devices in a crossover design. Results showed significant differences ($p < 0.001$) between stiffness values of different surfaces. The mean stiffness values for distinct materials were 21.4 kNm^{-1} (sand), 55.1 kNm^{-1} (horse manure), 99.1 kNm^{-1} (bark mulch), 475.0 kNm^{-1} (soft rubber mat) and 1394.2 kNm^{-1} (hard rubber mat). The overall inter-device-variability was 2.52 %, correlation coefficients were CCC > 0.99 and $r_s = 0.99$ for comparative measurements with both devices. These findings indicate that the VST is suitable for measuring the stiffness of different lying surfaces.

Keywords: bedding materials, dairy cows, evaluation, floor properties, surface testing

Introduction
Quality and management of cubicles are essential aspects in dairy farming. Dairy cows spend approximately 8 to 16 h/d lying down (e.g., Jensen *et al.*, 2005; Charlton *et al.*, 2015) and 35 to 175 min/d standing in cubicles (Stefanowska *et al.*, 2001). Recognized benefits of longer lying times include increased feeding and rumination activity. During lying, the claws can dry and are relieved. Increased standing times, e.g., in the alleys bear the risk of developing claw disorders and injuries (Vokey *et al.*, 2001). In addition, the blood supply of the udder is ameliorated in lying position, which increases the metabolic rate and milk production (e.g., Munksgaard & Løvendahl, 1993; Delamaire *et al.*, 2006). As already described in previous research, the type of lying surface has a major influence on cubicle quality and lying times (Tucker *et al.*, 2009). Cows prefer, and spend more time lying in well bedded, soft and dry cubicles (e.g., Tucker & Weary, 2004; Reich *et al.*, 2010; Wolfe *et al.*, 2018). The focus of this study was on the sensor-based, objective

assessment of the softness/hardness of different bedding materials. For a long time, only subjective methods were available to assess the hardness of lying surfaces, such as the 'knee drop test' (Nordlund & Cook, 2003) and observation of the cows' standing up and lying down behaviour (Wechsler *et al.*, 2000). In recent years, various sensor systems have been developed in order to assess the quality of lying surfaces. One possibility is to measure the lying times of cows to draw indirect conclusions on the comfort around resting (e.g., Henriksen & Munksgaard, 2019; Leach *et al.*, 2022). The other option is the direct measurement of floor properties with devices such as the Clegg hammer (Fulwider & Palmer, 2004; Villettaz Robichaud *et al.*, 2020). The Vienna Surface Tester (VST) is another sensor system that provides objective measurements of surfaces and floors. It was developed by Schramel and Peham at the University of Veterinary Medicine in Vienna and has been primarily used for measuring the mechanical properties of sport surfaces such as turf or riding arenas. It is an adopted bowling ball equipped with two accelerometers. As it is operated in free fall, the measurements are not influenced by friction losses. The main objective of this study was to evaluate whether the VST is suitable for measuring the hardness of different types of bedding materials as used in cattle farming.

Material and methods

Experimental sites

The study was carried out in two steps. The first part took place in July 2021 on a large commercial dairy farm in northern Germany, using the following bedding materials: horse manure, bark mulch and a soft rubber mat. The second part of the study took place at the Teaching and Research Farm (VetFarm) of the University of Veterinary Medicine Vienna in Austria in February 2022, where sand and a soft rubber mat were tested.

Vienna Surface Tester

The Vienna Surface Tester (VST) is a sphere with a weight of 6.15 kg that is equipped with two accelerometers. It calculates impact velocity, impact acceleration (G_{max}), stiffness (spring rate) and several other parameters. For this study, only the impact velocity and stiffness values were considered. According to the standard operating procedure (SOP), the sphere has to be dropped repeatedly from random heights. At least 14 drops are necessary to complete one measurement. This is required to determine the surface parameters under different loads and to take the variability of natural surfaces into account. The sphere has to be dropped at different spots of one measurement plot (e.g., area of one square meter), because every drop can already alter the floor compaction. A color LED bar indicates the status of measured data. It displays whether two valid drops were measured and stored at all required heights. Data are stored on a micro-SD card in csv format.

Study design

For the whole experiment, five different types of floors, two devices and two examiners were available. For the standardisation of the experiment, a wooden frame with the dimensions of a standard cubicle (20 x 200 x 120 cm) was used to surround the different materials to ensure a standardised thickness of each material. A wooden slat with a measurement tape was used as a measuring aid to facilitate dropping the device from seven distinct heights. Six measurements were carried out per bedding material with each device, this were three per person. For one measurement carried out by one examiner, both devices were dropped alternatingly across the test cubicle. As the surface of most of the materials changed visibly after each drop, this approach was chosen to enable direct comparability of the devices. The preparation of the floors prior to the start of a measurement was dependent on the properties of the material and the way each individual bedding material is used in cubicles under practical conditions (loose filling or filling and compaction). The rubber mats did not need specific preparations before and between measurements. The 25 x 25 cm soft rubber mat was placed on an even concrete floor, surrounded by padding material (for protecting the VST). The 'hard rubber mat' used for the evaluation is laid out in the barn alleys of the VetFarm.

Data pre-processing

Data of both VST devices were merged in Microsoft Excel (MS Excel 2016, Microsoft Cooperation, Redmond, USA), according to the chronology of the experimental procedure. Coding variables were added to identify the device, the examiner, the floor type, the drops belonging to one measurement (continuous number), and the measurements from each device for direct comparison (measurement number). Comments regarding issues while dropping the ball or technical difficulties were documented in the spreadsheet. After a validity check, drops were arranged in pairs, sorted by 'measurement-number', 'LED-number' and time in order to compare the two devices directly.

Statistical analysis

Statistical analysis was carried out with SPSS (version 27, IBM Corporation, Armonk, NY) and with R (version 4.0.4, Copyright 2021, The R Foundation for Statistical Computing). The stiffness measures of both devices were tested for normal distribution using Shapiro-Wilk test. Lin´s concordance correlation coefficient (CCC) as well as Spearman´s rank correlation coefficient (r_S) were calculated for the paired drops of the VST, i.e. device_01 and device_02 across, the entire dataset. Descriptive statistics were calculated for each floor type separately. Wilcoxon-test was performed to test for significant differences of the stiffness between the five floor types. Linear regression analysis was conducted on floor-level and on measurement-level for the comparison of the two devices as well as for the comparison between the two examiners. The regression coefficients were used to calculate the stiffness (k) values at given impact velocities (v_0 = 2 ms^{-1} and v_0 = 4 ms^{-1}) with the formula of linear equation,

$$k = a * v + b \tag{1}$$

where k is the stiffness, v is the impact velocity, a is the slope and b is the intercept of the linear equation. Percentage differences of both devices at the same impact velocity were calculated in Excel using the formula,

$$\text{Percentage difference} = \left(\frac{kd2 - kd1}{\frac{kd1 + kd2}{2}}\right) * 100 \tag{2}$$

with kd1 as the stiffness value (calculated as described above) for device_01 and kd2 for device_02. Percentage differences of both examiners at the same impact velocity were calculated in Excel using the formula,

$$\text{Percentage difference} = \left(\frac{\text{ke2} - \text{ke1}}{\frac{\text{ke1} + \text{ke2}}{2}}\right) * 100 \tag{3}$$

with ke1 as the stiffness value (calculated as described above) for examiner_01 and ke2 for examiner_02. For the comparison of the two examiners, only measurements on rubber mats (soft rubber mat and hard rubber mat) were included for analysis, as these surface types are not likely to change significantly due to the drops. The setting for the comparison of the two devices on other materials did not allow the direct comparison between the examiners, as the surface had to be restored and prepared between the measurements of the different examiners. A Bland-Altman plot was created for the comparison of the two devices on measurement-level for the stiffness measures calculated at $v_0 = 2\ ms^{-1}$ and $v_0 = 4\ ms^{-1}$.

Results and Discussion

After data pre-processing, 408 data points from each device were available for analysis. For each of the five floor types there were six valid measurements per device. The stiffness values were not normally distributed across the dataset. There was high agreement of stiffness values between the two devices (CCC > 0.99; $r_S = 0.99$). The means ± SD for each floor type were 21.4 ± 7.9 kNm^{-1} (sand), 55.1 ± 14.9 kNm^{-1} (horse manure), 99.1 ± 31.9 kNm^{-1} (bark mulch), 475.0 ± 90.9 kNm^{-1} (soft rubber mat) and 1394.2 ± 584.9 kNm^{-1} (hard rubber mat). Although the mean values can only offer a rough overview of the data, it is useful to show the major differences between the different floor types. Table 1 provides more details of the absolute stiffness values calculated by using linear regression for two different impact velocity values.

Table 1: Absolute stiffness values in kNm-1 at given impact velocities (v0) and R2-values in direct comparison between the two devices (D_01 and D_02) stratified by floor type.

Floor type	$v_0 = 2\ ms^{-1}$ D_01, D_02	$v_0 = 4\ ms^{-1}$ D_01, D_02	R^2 D_01, D_02
Sand	19.6, 18.8	24.0, 24.0	0.1, 0.1
Horse manure	49.6, 47.2	67.2, 66.2	0.3, 0.4
Bark mulch	78.0, 78.0	138.4, 131.1	0.7, 0.7
Soft rubber mat	400.9, 409.3	594.7, 596.7	0.9, 0.9
Hard rubber mat	929.3, 881.6	2160.3, 2128.5	> 0.9, > 0.9

The stiffness values of the five floor types differed significantly (Wilcoxon-test: $p < 0.01$). With softer bedding materials (sand, horse manure), the stiffness values did not increase significantly at higher impact velocity. This indicates that the properties of these surfaces are closer to the characteristics of an ideal spring than other materials with higher R^2-values. An R^2-value of zero would describe a horizontal line and therefore show the properties of a spring constant. Thus, it can be concluded that sand and horse manure are more favourable lying surfaces for cows in terms of stiffness.

Percentage differences

The difference of stiffness measures (calculated by regression analysis) between the two devices was on average 3.24 % at an impact velocity of 2 ms^{-1} and 1.80 % at an impact velocity of 4 ms^{-1} across the five floors. We aimed to standardise as many factors as possible for the direct comparison between the devices, e.g. by performing alternating measurements with both devices at the same condition of the test cubicle as described above. Although we worked through the materials after each measurement as standardised as possible, it cannot be excluded that there were minor differences across the bedding materials, which lead to randomly different measurements. One of the main reasons for using the measuring aid was the aim to minimise possible confounding factors.

Despite the above-mentioned issues, no difference greater than 6 % (range: 0.01 – 5.48 %) between the devices across the floors were observed. Hence, the agreement of the devices is considered as suitable for practical use as well as research purposes.

For the calculation of the difference between the two observers, 36 paired stiffness values calculated by regression analysis were used. Examiner_01 had on average 1.73 % greater values compared with examiner_02. This small difference indicates that results of different examiners are comparable.

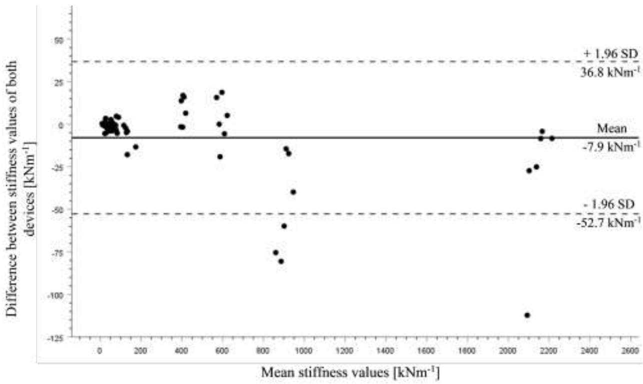

Figure 1: Bland-Altman plot for stiffness values calculated at $v_0 = 2\ ms^{-1}$ and $v_0 = 4\ ms^{-1}$

According to the Bland-Altman plot in figure 1, a high agreement between the two devices across all measurements was observed.

Conclusion

The results of this study show that different bedding materials used in cubicles on commercial cattle farms can be objectively evaluated using the Vienna Surface Tester. Furthermore, high agreement was observed between two different devices. Considering the high inter-observer agreement, it can be concluded that the results obtained by different trained examiners using different devices are comparable and can be considered as valid. Further research should focus on the practical application of the VST in dairy cow barns in relation to animal health and welfare topics, as this study only examined different types of bedding materials under standardised conditions outside of the barn. Cow preferences of certain bedding materials and the change of mechanical properties over time under practical conditions are research questions that could be addressed in future using this device.

Acknowledgements

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Cow locomotion energy harvester for powering IoT wearables

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Abstract
This paper presents a novel idea of converting farm animal locomotion into electrical power for enabling precision livestock farming applications with autonomous power. A brief description of the problem is presented followed by a review of the state-of-the-art. Further on numerical modelling and experimental methodologies are presented which are used to analyse the proposed concept and produce a proof-of-concept. Finally a wearable prototype is built and tested in-lab and on-field with free grazing Finn cattle.

Keywords: electromagnetic induction, energy harvesting, kinetic energy, precision livestock farming, wearables, wireless sensor networks

Introduction
In this paper, research progress and results emerging from the first two-year period of work on project ENTRAP - 'Energy harvesting for precision agriculture applications'- will be disseminated. This is a pioneering project, aimed at developing a kinetic energy harvesting (KEH) device for converting livestock locomotion into electrical power thus enabling a wide range of precision agriculture (PA) and precision livestock farming (PLF) applications with autonomous power.

Precision livestock farming
PLF is a key staple of the PA concept and relies on extensive utilization of wireless communication and wireless sensor network (WSN) technologies (Jawad, H. M. *et al.* 2017). The usual generic WSN architecture consists of miniature battery powered nodes or motes embedded with sensing, communication and/or processing modules for edge computing (Figure 1, Left). Nodes can transmit data to the gateways which are connected to a mainframe data processing unit and/or communicate with each other. For enabling the PLF concept, the nodes are then placed on individual animals and used to record numerous animal attributes (health, metabolism etc., Neethirajan, S. 2017), as well as to monitor and control animal behavior with virtual fencing (Campbell, D. L. M. *et al.* 2017). Some of the commercially available devices are being marketed under these brands: Nofence, Digitanimal, Moomonitor+, Cattlewatch, Silent Herdsman, Afi-Act, SMARTBOW etc.

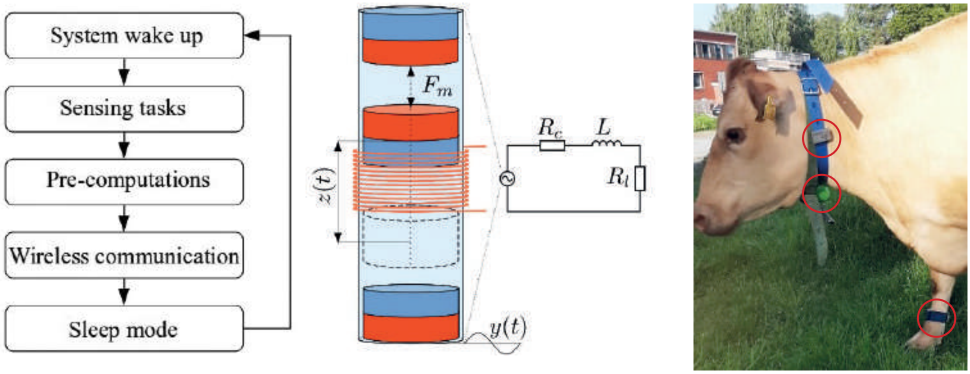

Figure 1: Left: a generic WSN cycle, Centre: a magnetic levitation electromagnetic induction energy harvester, Right: locations of instruments for locomotion logging trials

WSN: power and ecology

Most of these PLF sensors are to be driven worldwide by billions of batteries with limited lifetime, which once depleted, need to be replaced and recycled. The EU is home to more than 343 million of ungulates (E. Heidorn *et al*. 2017) and if half of these were utilized in a PLF concept requiring a finite lifetime battery - 170 million batteries would have to be produced and replaced in application defined intervals. This practice produces a hindering impact on the agricultural sustainability due to low recycling rates and high environmental burdens caused by battery production (E. Olivetti *et al*. 2011). A long-lasting alternative to finite lifetime batteries is energy harvesting. WSN nodes, depending on the application requirements, usually require power ranging from tens of µW to 100 mW in application specific intervals. An energy harvester coupled with a power management integrated circuit (PMIC) has been proven to provide as much.

Harvesting kinetic energy from the animal body

Energy harvesting is the process of converting ambient energy, like sunlight, water flow, heat or vibrations into electrical energy for powering low power. The most elegant and mature form of energy harvesting is photovoltaics, but extensive research has also been performed on thermoelectric, RF, triboelectric and kinetic energy harvesting (Shaikh, F. K. and Zeadally, S. 2016). Mechanical systems have been thoroughly studied as a power source in the last two decades, but much less attention has been directed to the energy of bio-mechanical systems such as animal bodies. Most inertial KEH devices require to be operated at a specific excitation frequency, while animal locomotion occurs stochastically in the range of 0-10 Hz so a low frequency KEH design must be considered. Based on the current state-of-the-art and recent findings, the most promising KEH solutions in this frame are inertial electromagnetic (EM) devices (Joon Kim, K. *et al*. 2010), with novel triboelectric generators also showing promise. The simplest device design to be considered is in fact the 1-D inertial EM harvester consisting of a cylindrical tube, in which a permanent magnet can travel axially, where the springs can be mechanical or magnetic (Figure 1, Centre). When excited by an outside source of vibration, the tube establishes motion marked with $y(t)$. In response to inertial forces, the central magnet then travels back and forth inside the tube with relative motion z(t). The springs are defined by end stops in the shape of permanent magnets arranged so that they act with a repulsive force F_m on the moving magnet. As the magnet is traversing the tube, voltage is induced in the coil wrapped around the tube. The accompanying electric circuit shows the EM KEH as an AC generator connected in series with coil resistance R_c, coil inductance L and electric load represented by an equivalent load resistance R_l (usually a WSN sensing node and a PMIC). In this frame, the possibilities of converting human locomotion to electrical power for powering assistive wearable technologies have been thoroughly studied (Gljušćić, P. *et al.* 2019). As far as non-human animals are concerned, KEH research has been limited. The premise of project ENTRAP is that the existing human KEH technologies can be easily transferred and used on other animals with an increase in inertial masses and device dimensions while still maintaining a small and light footprint (below 200 g).

Material and methods

This section includes a short description of animal locomotion measurements, the simulation tool developed to estimate available powers and materials and methods used for the design of the prototype and measurement devices used for field trials.

Animal locomotion measurements and analysis

To define a precise design of a KEH device best suited for a specific species of animal, field measurements were performed the details of which are presented in a separate work presented at this conference ('Kinetic energy harvesting potential of grazing livestock'). Here we offer a brief description of the methodology used at the Ahlman dairy Farm (Tampere, Finland). Locomotion of two Finncattle cows was measured in 5 consecutive trials via three Axivity wireless acceleration loggers attached to the cow's neck, marking weight and front leg strap (Figure 1, Right). The underlaying idea was to obtain locomotion profiles, analyse them and calculate Fast Fourier Transforms (FFT) to extract frequency information associated with animal movement. These frequencies would then be a starting point for designing cattle KEH devices akin to methods of eigenfrequency matching in mechanical systems. Based on the envisioned harvester concept and measurement results, the front leg strap location was chosen as suitable. This was decided due to strong accelerations of vertical leg locomotion which also coincides with the longitudinal axis of the EM KEH device. A cow's step (Figure 2, Left) can vary greatly but through all the measured steps several frequencies were identified as interesting, first the ~1 Hz walking frequency and second the interesting higher order harmonic identified in a cow step around ~8 Hz (Figure 2, Right). The latter was chosen to test the hypothesis of a frequency matched KEH device which are generally more easily designed for higher than lower resonant frequencies.

KEH device design and simulation

In the last two decades, many KEH devices have been investigated (Wei, C. and Jing, X. 2017). The EM harvester has proven to be well suited for random meso-scale operation such as harvesting animal locomotion. Numerous EM KEH designs have been investigated due to simplicity, device lifetime and low resonant frequencies (Khan, F. U. 2016).

These devices have been mostly analytically modelled as single degree of freedom spring- mass-damper systems coupled with analytical solutions of magnetic fields and experimentally obtained magnetic force values. For the purpose of this work, a 2D ax-isymmetric finite element model simulation has been developed and tested. The flux linkage of the coil and the electromagnetic force acting on the moving magnet are calculated for fixed values of the magnet position and the coil current using a series of magnetostatic solutions. These coupled together with equations of motion and electric circuit equations allow for simulation of any type of excitation as previously reported in T. Kivimäki *et al*. 2021 where this methodology was put to test in designing a car tire EM KEH. For the purpose of this research a sensitivity analysis was performed over a set of parameters from which it was found that the number of turns *N*, coil dimensions d_C and load resistance R_l have optimal values. The gap between the coil and the magnet, *t*, also influences power generation and should be as small as possible. Final dimensions of the laboratory prototype are presented in Figure 3, Left & Table 1.

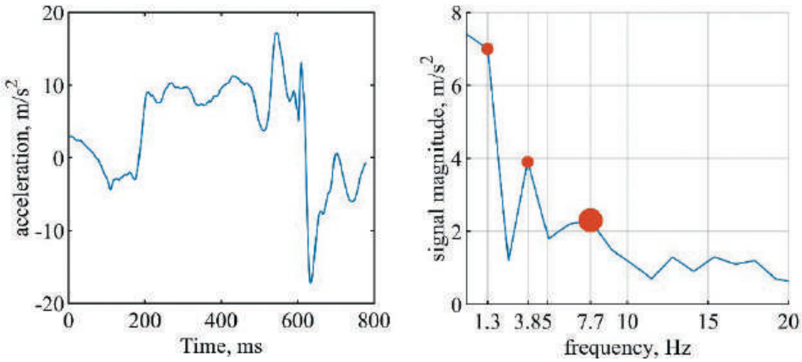

Figure 2: Left: Cow step profile, Right: Frequency information of a single cow step

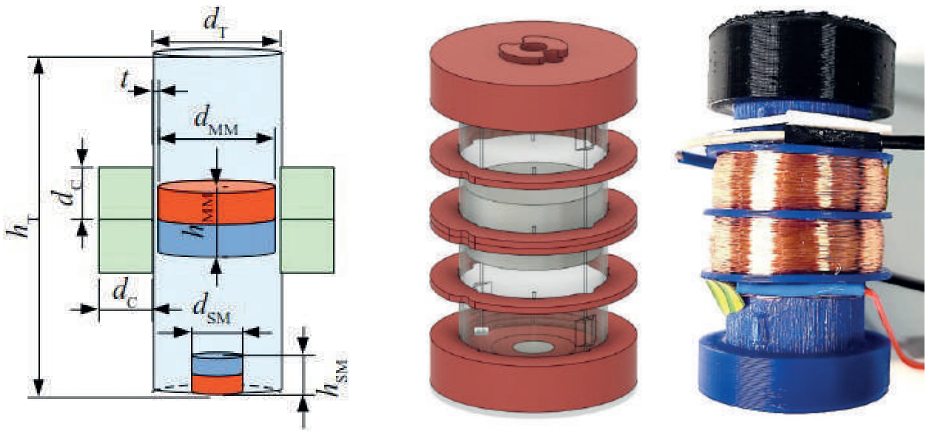

Figure 3: Left: Harvester schematic, Centre: 3D model, Right: 3D printed prototype

KEH Device prototype

The harvester structure and cow leg attachments were designed with Fusion360 3D modelling software (Figure 3, Centre). The Prusa I3 MK3 3D fused deposition modelling (FDM) printers were used in the FabLab facility of Tampere University to manufacture the parts with PLA (for the tube, coil and spring magnet attachments) and PETG filament (for the leg strap casing) totalling in 7 separate parts. The tube was printed in two separate parts for the purpose of achieving a suitable orientation of deposited print material (for lowest possible friction between the magnet and the tube) as well as the possibility of reworking the inside of the tube with fine wet sanding paper and smoothing out surface roughness resulting from the FDM process. Once assembled, the inside of the tube was also coated with Teflon spray before the magnet was inserted. Printed coil former elements were slid across the harvester tube and placed at specific points where the magnetic flux density of the PM is strongest. Two coils in series, each with 1500 turns, were wound by using a modified coil winding machine QIPANG FZ-180 using enamelled magnet copper wire with a diameter of 0.1 mm resulting with total coil resistance of 515 Ω. The magnets used were commercially available N42 grade strong NdFeB magnets with dimensions specified in Table 1.

Table 1: KEH device dimensions as seen in the left of Figure 3

Parameter	Value	Unit	Description
h_T	40	mm	Tube length
d_T	22.6	mm	Tube diameter
N	3000	–	Number of turns
d_C	10	mm	Coil height and width
c	5	mm	Coil distance equilibrium
d	0.1	mm	Coil wire diameter
t	0.8	mm	Wall thickness
d	20	mm	Distance between magnets
h_{SM}	2	mm	Spring magnet height
d_{SM}	6	mm	Spring magnet diameter
R_l	1000	Ω	Load resistance
h_{MM}	10	mm	Moving magnet height
d_{MM}	20	mm	Moving magnet diameter
m	0.024	kg	Moving magnet mass

Power management and communications module

KEH devices produce alternating currents which require rectifying and conditioning if they are to be used for powering electronic devices requiring specific DC voltage levels. For this project we selected a miniature PMIC - SparkFun Energy Harvester Breakout board based on the Linear technologies LTC3588-1 (Figure 4, Left). This PMIC rectifies AC sources with an integrated full wave bridge rectifier and has an over voltage protective shunt. It is intended to be used with an output capacitor for buffering charges from intermittent energy sources. Output voltage is selected by solder pins on the board, and for this purpose a, 3.3 V output voltage was selected. For capacitor dimensioning purposes, 10 mW of maximum required energy was assumed. Based on the formula for energy calculation available on page 13 of the datasheet (Linear Technology, 2015) and assumed capacity of the output capacitor of 2200 μF, a power of 13.24 mW was calculated. An nRF52840 Bluetooth USB dongle was chosen (Figure 4, Left) as a communication module due to in-built capability of using external power and ease of configuration via USB connection and the NRF Connect software. The beacon transmission setting was set at minimal frequency of 10 Hz.

Portable data acquisition and data logging

To determine the dynamics of the prototyped KEH device and its coupling to cattle leg locomotion, a portable and lightweight data acquisition and data logging device was required. A suitable commercial device which could simultaneously log induced voltage and acceleration is still not available, so a custom device was built. The custom device is based on the Adafruit Feather M0 Adalogger development board (Figure 4, Left), with in-built microSD card logging and battery powered operation (a 3.7 V, 550 mAh, LiPo battery was used). An additional Adafruit MMA8451, 3D accelerometer breakout board was chosen for measuring acceleration of the cow's leg. Harvester voltage output (V_{KEH}) was set to be measured with the onboard analog to digital converter (V_{ADC}) with 0 - 3.3V input levels. To achieve this, the harvester's output voltage was reduced with a voltage divider and offset into positive with onboard reference voltage set to 1.65 V (V_{ref}) (Figure 4, Centre). The system was then simulated with the LTspice software with a damped sine wave used as the input signal (Figure 4, Right).

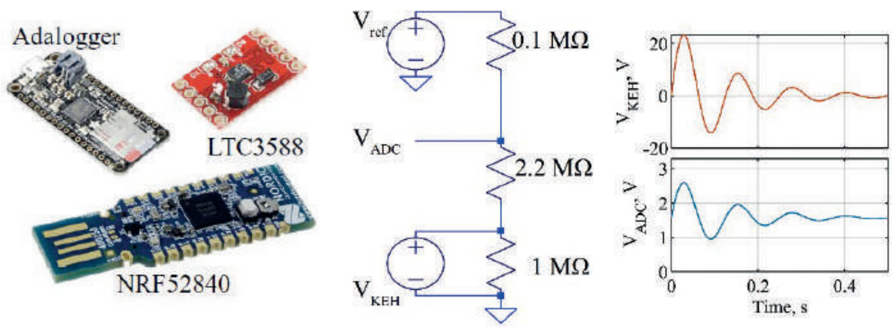

Figure 4: Left: Used components, Centre: Voltage divider, Right: LTspice simulation

Results and Discussion

Laboratory experiments: Shaker and human excitation

The shaker experiments shown in Figure 5, Left, were designed according to the schematic in Figure 5, Centre (detailed in T. Kivimäki *et al.* 2021). Frequency sweeps were performed to investigate resonant frequencies. Figure 5, Right displays the results: 'v1' harvester version has two full size spring magnets and resonance at 10.5 Hz; 'v2' has the top magnet lifted 5 mm from the moving magnet equilibrium resonating at 9 Hz; 'v3' uses a smaller top spring magnet (diameter 1 mm, height 2 mm) and resonates at 7.25 Hz while 'v4' had the top magnet removed without a further significant frequency shift. Configuration 'v4' without the top magnet was used in further tests.

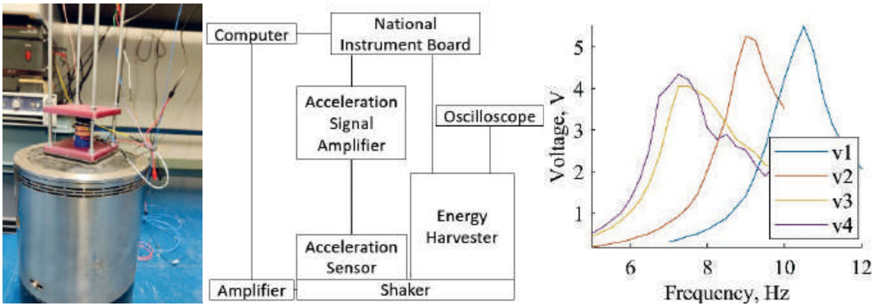

Figure 5: Left: Harvester mounted on a shaker, Centre: Experiment schematic, Right: Measurement results displaying 4 different harvester variants

The nRF dongle energy dissipation was measured with the harvester connected to the PMIC and manually shaken to charge the capacitor. The energy required for the dongle cold start-up was 6.9 mW while a single beacon transmission consumed 49 μW (Figure 6, Left). The dongle transmission distance was determined experimentally at a diameter range of ~35 m. Shaker tests were also performed at 7 Hz, 2 V sine excitation level, during which the time required to charge the capacitor was measured. In average it took 28.05 mW during 188 s to charge the capacitor from a completely discharged state. Then the PMIC releases a portion of the energy, and the next charge requires less energy – 13.24 mW during 40 s. Finally, the harvester was strapped to a student's leg for a stepping test. Here the charging from a discharged state took ~39 steps with each following charge taking ~15 steps (Figure 6, Centre).

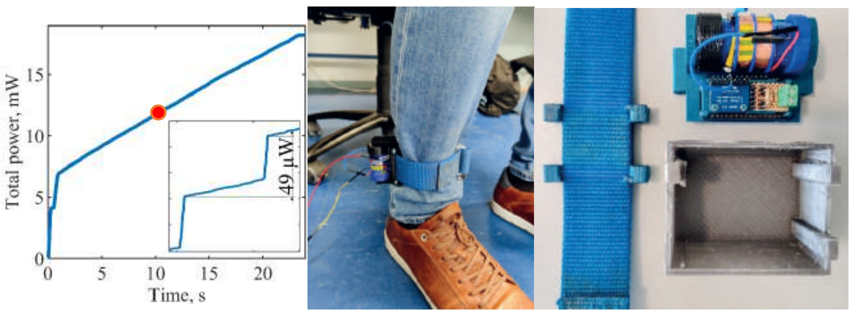

Figure 6: Left: nRF dongle power consumption, total consumption and detail of single transmission, Centre: Lab walking test, Right: Open cow leg strap assembly

Field experiments: Ahlman dairy farm (Tampere, Finland)

Two field experiments were performed at Ahlman dairy farm (Ahlmanin koulun saatio, Tampere, Finland). In the summer season the herd is allowed to freely graze in a rotational grazing scheme. A three-year-old eastern Finncattle cow Pinja was chosen as a test subject. In the first experiment the harvester was tested for leg locomotion coupling. The casing was 3D printed with PETG filament (Figure 6, Right). The whole device mounted on the front leg (Figure 7, Left), including the harvester, PMIC, logger and the rugged outer casing weighed ~0.2 kg. The subject seemed undisturbed by the wearable and moved unhindered. The device proved to withstand harsh conditions and clear collisions with farm infrastructure and the experiment resulted with 1 hour of logged data. From the analysis it was observed that the accelerometer's Z axis (gravity) often reaches its ±6g limit while in such cases the harvester induces over 20 V. Total log of the experiment displays beautiful coupling of the harvester to leg locomotion (Figure 7, Centre). Single step analysis reveals that when the cow steps on the ground, a high deceleration impact occurs. The harvester trails behind with a positive and negative peak and rings down brought into a free vibration state. A second field trial took place with the same test subject. This time the nRF dongle was used as well powered solely by the PMIC. Bluetooth traffic was monitored via laptop with Wireshark software and a nRF52840 dk transceiver. nRF Bluetooth LE packet sniffer app was also installed on two mobile phones. It proved impractical to follow the subject with a laptop and thenceforth mobile phones were used for continuous scanning of Bluetooth traffic. With this we were able to recurrently capture the 'Test beacon' signal (Figure 7, Right) which would occur when the cow would change position (5-15 steps). Based on the intensity of motion the 'Test beacon' would stay visible from 10 seconds up to a full minute.

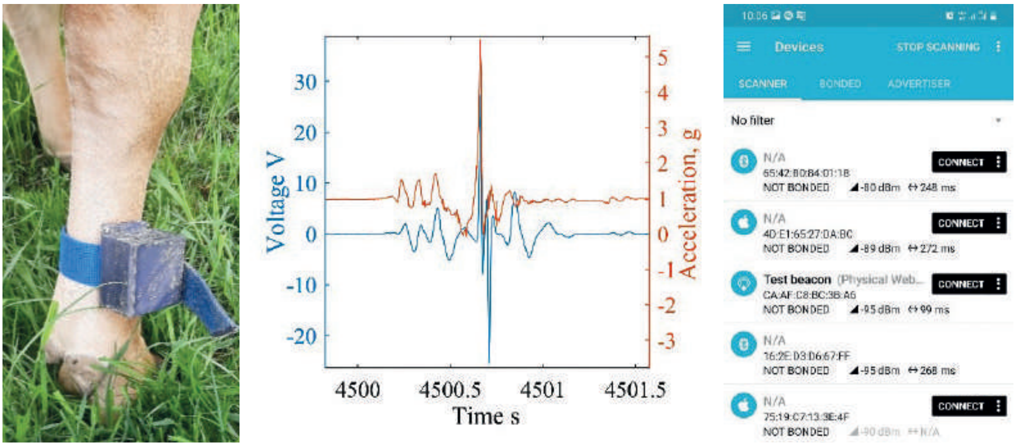

Figure 7: Left: Trial device, Centre: Voltage (b) and leg motion (o), Right: Sniffer log

Conclusions

This paper details the development of a KEH device for converting locomotion of a cow's front leg into electrical energy for powering or recharging of IoT PLF devices. A device was built and tested in laboratory and field trials in which it was proven that it can successfully power wireless transmissions of a Bluetooth beacon and output ~13 mW of accumulated electrical power after 5-15 cow steps. The device is based on a moving magnet mechanism which comes into motion with each step taken by a cow. Animal KEH has its drawbacks - the device produces energy only during movement. This makes it suitable for free grazing scenarios where the animals change position frequently to forage. At this point the tested KEH generator can be used for recharging PLF devices and increase battery lifetimes. Some low power - low transmission frequency devices could even be made autonomous. Power generation is influenced not only by the amount and intensity of movement but also by the mounting position. In the laboratory stepping experiments, changing the position from the side to the back of the calf resulted with an increase in harvested powers. Further research is required to identify which position on the leg is the most suitable for harvesting maximum locomotion energy while still retaining comfort and wearability. Novel EM KEH architectures will be tested as well on other locations besides the cow's leg (collar, ear).

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Development of a wearable RFID reader to monitor animal information through smart glasses for augmented reality in livestock farms

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Abstract

In recent years, scientific research and development activities have focused on the application of Precision Agriculture techniques. This approach determines an increase in the sustainability of productions together with a quantitative and qualitative increase in agricultural products. In this context, smart glasses for augmented reality (ARSG) represent a useful tool to provide on-farm information in real-time, that facilitates and assist agricultural operators during on-field activities.

The aim of this work was to bridge the technological gap between the identification of animal RFID (ear tag; rumen bolus) and the real-time access to individual animal information. Specifically, the research team developed a prototype called 'SmartGlove' (SG) that combines the functionalities of an RFID reader with ARSG.

This tool was designed as an operator's wearable device equipped with a function for reading the animal's RFID identification code and for communicating with the ARSG, via Bluetooth connection. The identification code retrieves the information related to the individual animal through a custom application specifically developed for the ARSG.

SmartGlove has enabled the farmer to enhance the RFID identification system to access and monitor (hand-free) the animal information (milk production, health status, etc.) displayed in augmented reality on ARSG devices. This innovative system allowed to make timely decisions in the management of farms, reducing the required workforce while improving productive performances, in line with animal welfare and precision livestock farming principles.

Keywords: Animal identification, AR headset, PLF tool, Electronic identification, Ear tag, Rumen bolus.

Introduction

Since the first patent of radio-frequency identification (RFID), in 1975, the technology has spread in a large variety of contexts. Over the years, multiple reviews and surveys have been published exploring the use of RFID from various perspectives, such as the use for the Internet of Things (IoT; Khoo, 2010), the aviation industry (Mishra, 2010), the healthcare-related context (Yao *et al.*, 2011). In the European Union, electronic identification of sheep and goats has been mandatory since January 2010 (Reg. CE n. 21/2004), while it is voluntary for cattle. Nowadays, three types of RFID tags are adopted for animal identification: ear tags, rumen bolus applied by oral ingestion, and subcutaneous glass or plastic tags. For cattle, sheep and goats, the code structure and the operating frequencies must be compliant with the International Organization for Standardization (ISO 11784:1996 and 11785:1996), which were firstly defined and adopted in the early 1970s (Kampers *et al.*, 1999) and then approved by the International Committee for Animal Recording (ICAR, 2005). At present, there are no defined standards for pigs. Most of the tags work in a frequency between 124.2-135 kHz and can store from 112 to 128 bits. The low frequency used corresponds to a low distance of reading, around 0.5-9 m. (Floyds, 2015). The process of reading RFID tags (transponders) can be carried out through a handheld device with an extended antenna of about 30~50 cm or with a fixed device located in a strategic point of the farm (e.g., the entrance of the milking room) representing the transceiver. The communication protocols accepted by the ISO are two: Full-duplex (FD), and Half-duplex (HD). The two protocols differ in the frequency used, and in the method of information exchange. The FD method communicates the information while the transceiver activates the transponder. Whereas the HD method communicates information after that the transceiver stopped transmitting the activation field to the transponder (ISO 11785).

The farmer, thanks to Precision livestock Farming (PLF) technologies, store multiple information about every single animal like biometrics and historical productive and reproductive data that can be used in the decision-making processes (Halachmi *et al.*, 2019). In particular, the planning of an adequate system of data collection and consultation, about individual animal performances, might support business investments towards the most productive animals and might allow identifying the subjects that limit the average efficiency of the farm and need to be managed separately. Access to such information can be particularly laborious and time-consuming, involving a considerable number of human resources (Caria *et al.*, 2020). To successfully meet this objective, operators must be highly prepared and equipped with efficient technology for supporting the decisional-making process. In the last years Augmented Reality Smart Glasses (ARSG) showed high potential in supporting operators during various tasks such as assembly, maintenance, quality control, and material handling (De Pace *et al.*, 2018; Caria *et al.*, 2020; Chandan *et al.*, 2021). Augmented Reality (AR) represents a high-interest topic for many kinds of industries since its capability to increase the amount of information available to operators, overlaying digital contents to the real world, in form of text, images, icons and video. The use of AR and ARSG has shown successful results concerning both work productivity and quality (Paelke, 2014; Syberfeldt *et al.*, 2016).

The aim of this study was to develop a wearable mobile system to read RFID tags and associate the animal identification code to a database that can be displayed in AR, bridging the technological gap related to animal identification and real-time information visualization and consultation.

The SmartGlove system

The developed system framework is composed of four main components: tags or transponder, SmartGlove (SG) or transceiver, Augmented Reality Smart Glasses (ARSG), and management Software (ST) both for ARSG and SG.

The SG is a prototype hardware composed of an Arduino Control Unit with integrated Bluetooth, an RFID reader chip, a Lithium-polymer 3.7 V battery, and a 134.2 kHz antenna. All the components are enclosed in a 3D printed case that can be used as a bracelet, with the antenna extended in the back of the hand (Figure 1). This SG hardware represents a TRL3 (Technology Readiness Level; proof-of-concept demonstrated) prototype that will be improved in future stages.

Figure 1: SmartGlove prototype. Hardware case (left) and RFID antenna (right).

Table 1: Epson Moverio BT-300 smart glasses' main features and components.

Item	BT300
Processor	4 Core 1.44 GHz Intel Atom
Flash memory	16 Gbytes
Operating System	Android 5.1.1
Display	Binocular Si-OLED 24 bit color, 1.280x720
Field of View	23°
Sensors	Gyroscope-accelerometer-magnetometer (3 axis), lux sensor
Connectivity	GPS, WiFi, Bluetooth, microUSB
Camera	5 Megapixel
Battery	Lithium polymer
Battery Duration	4 h
Controller input	Joypad (touch pad)
Weight	69 g

The ARSG used to visualize the information related to the tags are EPSON Moverio BT-300 (BT300). The BT300 features are listed in Table 1. To connect the AR headset to the SG a dedicated mobile application was developed, which connects the identification code received from the SG to a database containing individual information about the identified animal (productive, reproductive, and health data).

Material and methods

Laboratory tests were carried out to evaluate the SG operating performances. The transponder activation distance and the time interval required to visualize the data on the BT300 display were measured. Moreover, two types of transponders were used i.e., ear tag and rumen bolus (Figure 2). The rumen bolus used was made in ceramic with a cylindric shape (67.4 x 17.3 mm) and a weight of 52 g. Inside the bolus, there is the encapsulated HDX transponder. The ear tags adopted have an HDX transponder. The BT300 is provided by a binocular optical see-through display where the augmented information related to the transponder code is projected.

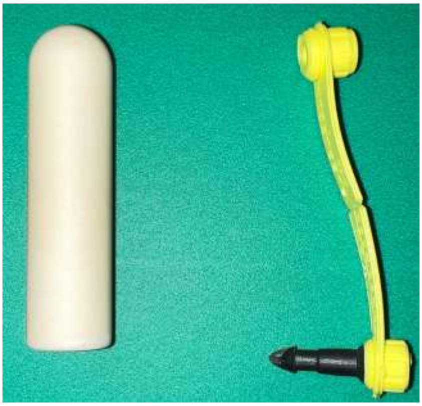

Figure 2: Rumen bolus (left) and ear tag (right) transponders used for the trials.

Activation distance

The transponder activation distance by the SG was measured by performing laboratory tests. During the measurement process, the transponder was gradually brought closer to the SG antenna and left for 3 seconds at determined distances (50 cm, 20 cm, 10 cm, 5 cm, 4 cm, 3 cm, 2 cm, and 1 cm). For each distance were carried out 20 reading processes and the positive/failed responses were recorded. A correct reading consists of the transponder activation and the transceiver response. The test was performed using both the ear tag and the rumen bolus transponders.

Reading time

The time interval required to visualize the animal's information, associated with the transponder code, on the ARSG was evaluated. The reading time was measured starting from the transponder activation until the information appeared on the BT300 display.

This interval was measured 20 times both for the ear tag and rumen bolus transponder. The maximum distance between the transponder and the reader for each reading was 2 cm.

Software and user interface development

In this section, we discuss the implementation of the mobile and augmented reality interface for interacting with the SmartGlove data. The solution consists of different modules: a Kotlin application for the BT300 AR headset, and MicroPython module reading the SG data. The software solution consists of three parts: the SG, the database, and the AR headset interface. We control the glove through an Adafruit board connected to an RFID antenna. It reads the rumen bolus tags or the ear tags for recognizing the animal and sends the identifier to the AR headset through a Bluetooth connection. In turn, when the interface receives a new identifier, it displays the complete information about the animal in the database. The database structure is quite simple. It consists of a shared Google Sheets spreadsheet that farmers can freely modify in all its fields, for adapting to their needs. The only assumption in the structure is having the RFID identifier as the first column in the spreadsheet, which acts as the primary key. We can upload a copy of the shared spreadsheet in the interface application as a Comma Separated Values (CSV) for offline working and synchronize the changes back when the network is available.

Figure 3: The interface of the application. From top left to center bottom: a) the connection status of the glove; b) the “Connect” button; c) the “Update Database” button; d) the resulting data table from a scan; e) the “Parameters” button, used to show or hide columns from the result table.

Through the AR headset interface, farmers can access the database on the field, and it can be displayed as an overlay on their field of view in the real world through the headset’s screen. At startup, the application shows the interface in Figure 3, enabling the glove scanning features through the “Connect” button. By pushing it, the headset will search for the SG, automatically establishing a connection, and exchanging the information required by the GATT protocol for the Bluetooth Low Energy devices, which saves the SG battery. Once connected, the farmer can use the SG for scanning the bolus or the animals’ ear tags. When it reads an RFID, the application checks the code against all saved entries in the database. If it finds a match, the application retrieves all the related data and present it to the farmer in a tabular fashion, as depicted in Figure 2. If the farmer scans for a tag that is not in the database, or any error occurs during the scan the application shows a proper error message. It is possible to configure the number of columns in the database the farmer needs to display. By pressing the "Parameters" button, the application shows the list of all the columns in the spreadsheet, together with buttons for showing or hiding the related information. Indeed, we expect that the database structure may change over time and that different farmers may require particular pieces of information. Finally, since we foresee that a stable connection may be lacking in the field (e.g., rural areas, poor reception, etc.), the internal database in the application is a copy of the Google Sheets spreadsheet, converted as a standard SQLite database. This allows querying data without a connection, at the cost of an explicit request for synchronization by pressing the "Update Database" button. The application notifies the farmer when any problem occurs during the update of the database, or when the application has no locally saved data.

Results and Discussion

Table 2 reports the results of the activation distance test performed in the laboratory. It was observed that the maximum useful distance from the SG to ear tags and to rumen bolus was 5 cm but with a low success rate (5 % and 25 % respectively). A higher reading rate was observed at 3 cm (success ≥ 60 %), up to a reading rate of 100 % at 1 cm.

Table 2: Success rate of transponder activation (ear tag, bolus) in relation to the distance between transponder and transceiver (SmartGlove). N = 320

	Success Rate (%)	
Distance (cm)	**Ear Tag**	**Rumen bolus**
50	0.0	0.0
20	0.0	0.0
10	0.0	0.0
5	5.0	25.0
4	10.0	15.0
3	70.0	60.0
2	100.0	75.0
1	100.0	100.0

The results reported in Table 2 underline how the distance between the SG's antenna and the RFID tags should be small in order to identify the specific animal tag. Although 1-3 cm activation distance might be acceptable for the ear tag, this distance range might not be suitable for the bolus tag as this is located in the animals' rumen (sheep, goat, cow).

Table 3 reports the results of the reading time test, where the time required to visualize the augmented information on the BT300 display, after the transponder activation, was evaluated. It was observed for both types of transponders used that the reading time was in the range of 2 seconds. In addition, the maximum time required to visualize the animal-specific information in augmented reality was 3 seconds using the ear tags and 2.86 seconds using the rumen bolus.

Table 3: Average times of transponders code (ear tag, bolus) reading by the SmartGlove and visualization of the information in augmented reality on smart glasses. SD = standard deviation. N = 100.

	Reading time (s)	
	Ear Tag	**Rumen bolus**
Mean	2.16	2.22
SD	0.37	0.27
min	1.59	1.23
max	3.00	2.86

The time range recorded could be considered acceptable as the waiting time to activate the transponders through the SG antenna and then visualize the desired information overlayed to the specific animal. The responding times measured in the tests are in line with what has been observed in other experiments related to the identification and selection of animals with physical markers and visualization of information in augmented reality (Caria *et al.*, 2019). Moreover, the maximum time (3 s) needed for the visualization of the animal data is a reasonable timeframe to accomplish farmers' operations, in line with their routinary activities. The developed system could be implemented in different farming contexts, both by farmers and technicians. The farmer may identify animals during the selection process, reading tags with the SG and visualizing the information through the ARSG. This would enable the detection of the most productive subjects or isolate animals with sub-clinical health problems directly in the field. In the same way, technicians could have the updated status of the animals e.g., during the pregnancy checking process updating their status during work.

Conclusions

In this paper, the development of a prototype RFID wearable reader was described. The aim of this device was to bridge the technological gap between the electronic identification of livestock animals and real-time access to individual productive, reproductive, and health information. Specifically, the SmartGlove was developed by combining the functionalities of an RFID reader with augmented reality smart glasses. In this way, the animal information was available in any part of the farm and superimposed, in real-time, to the specific animal. The laboratory tests underlined promising operating performances of the SmartGlove. Anyway, further, improvement will be focused on upgrading the rumen bolus reading performances. This device represents a preliminary step in the development of a more comprehensive and automated system for precise animal and livestock farm management. SG will enable farmers to enhance the RFID identification system to access and monitor (hand-free) the animal information displayed in augmented reality on ARSG devices. This innovative system allowed to make timely decisions in the management of farms, reducing the required workforce while improving productive performances, in line with animal welfare and precision livestock farming principles.

Acknowledgements

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SESSION 24

Sheep and Goats

Calibration of a novel Bluetooth Low Energy (BLE) monitoring device in a sheep grazing environment

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Abstract

Interest in Bluetooth Low Energy (BLE) as a proximity sensor has increased in recent years, but few studies have investigated its potential in an outdoor environment or as a means of localisation. A purpose-built device was designed for the study, which aimed to conduct a calibration to assess the relationship between the Received Signal Strength Indictor of a BLE beacon and BLE reader to develop a distance prediction model. This was then utilized in a series of static beacon and on-sheep studies, using a multilateration approach to determine a beacon's location within a field environment.

Keywords: bluetooth, BLE, proximity, localisation, sheep

Introduction

Animal location and proximity can provide valuable information regarding landscape and resource use, animal performance, behaviour, and social contacts (Maroto-Molina *et al.*, 2019)animal tracking solutions based on global positioning systems (GPS. However, many of the technologies currently used to collect these characteristics can be costly and impractical to implement in an extensive sheep system due to the low value of individual animals, and typically large flock sizes (Umstätter *et al.*, 2008). Still, enhanced connectivity options through the introduction of the Internet of Things (IoT) and low power wide area (LPWA) networks, along with development in technologies such Bluetooth Low Energy (BLE) present opportunities for development of real-time monitoring within extensive systems.

Studies in recent years have begun to explore the potential of BLE within animal monitoring (Makario & Maina, 2021; Maroto-Molina *et al.*, 2019; Nyholm, 2020), and as a means of examining the ewe-lamb relationship, such as to determine maternal pedigree (Sohi *et al.*, 2017; Waterhouse *et al.*, 2019). Commercial options utilizing Bluetooth as an alternative to traditional mothering up and genomic testing are also available (e.g., Smart Shepherd). In comparison with options such as GNSS, BLE could offer a cheaper and less power-intensive alternative. However, the use of BLE as a means of animal monitoring and localisation, particularly within extensive systems is still in the early stages of development.

The purpose of this study was therefore to firstly assess the relationship between the Received Signal Strength Indicator (RSSI) of BLE beacons and their distance from a BLE reader. Then utilising this calibration, to explore whether a field location could be obtained through a series of static and on-sheep beacon tests to explore the potential of BLE as a means of localisation.

Sensor and BLE device design

A purpose built Wearable Integrated Sensor Platform (WISP) was developed for the study, commissioned from Scotland's Innovation Centre for Sensor and Imaging Systems (CENSIS). The WISP consisted of multiple sensors including GNSS receiver, accelerometer, and BLE reader. Each WISP was programmed to record and report data on a 5-minute duty cycle, both in real-time via LoRa (where gateway coverage was available) and to an 8 MB Flash Drive. The multi-sensor kit was contained within an IP65 enclosure, weighing an average total of 333 g, and was designed for use as both a static BLE reader, or as a wearable on-animal device.

BLE can operate most simply as beacons which transmit (called advertising) their unique ID, and readers which collect these IDs and the beacon's RSSI, reported at minus values (in units of dBm, decibels per milliwatt).

The BLE reader (BLE 4.2) within the WISP was designed to report the identity and RSSI of the 16 'closest' beacons seen within a duty cycle. The receiver would scan for 30 seconds, then idle for 30 seconds. During each scanning window the RSSI of any beacon seen was added to that of any previous adverts. At the end of the duty cycle the beacons were sorted based on their average RSSI (e.g., Total Power (sum of beacon RSSI) / No. of Adverts (No. of time beacons seen by WISP)). The 16 beacons with the highest average RSSI were the ones then reported by the WISP for that duty cycle.

Alongside the WISP, BLE 5.0 beacons were used throughout the series of studies, which had a reported advertising distance of up to 130 m (Bluetooth 5.0 Low Energy proximity Mini beacon, Shenzhen Feasycom Technology Co., Ltd). These were pre-programmed with a beacon identity and set to an advertising interval of 1285 ms.

BLE distance calibration

<u>Materials and methods</u>

The calibration study was conducted in field conditions at Auchtertyre Farm, SRUC's Hill and Mountain Research Centre, near Crianlarich, Scotland. Six WISPs were attached to an electrical fence post located at a central point in the field, with 8 beacons attached to posts located at log intervals ranging from 1-128 m from the WISPs. Beacons were left in position to obtain a total possible 5 RSSI readings per distance for each WISP-beacon pairing, before being rotated to the next post. This was repeated for 4 different device height combinations, with WISPs and beacons tested at heights of 0.7 m (representing ~ewe standing height) and 0.3 m (~ewe lying / lamb height). Hence a total of 240 possible RSSI readings per distance could be obtained for each group.

<u>Results and discussion</u>

The device height was found to have an impact, with a decline in the number of beacons reported occurring at a shorter distance in WISPs at the lower height of 0.3 m, which appeared to reach its distance limit at ~32 m. At WISP heights of 0.7 m the limit was between 32-64 m, declining at a slightly shorter distance when beacons were located at a height of 0.3 m. Only 11 out of 240 beacons were reported at 64 m across the study, and only when both devices were at heights of 0.7 m. Further analysis to obtain a distance prediction based on RSSI therefore included observations from 1-32 m only.

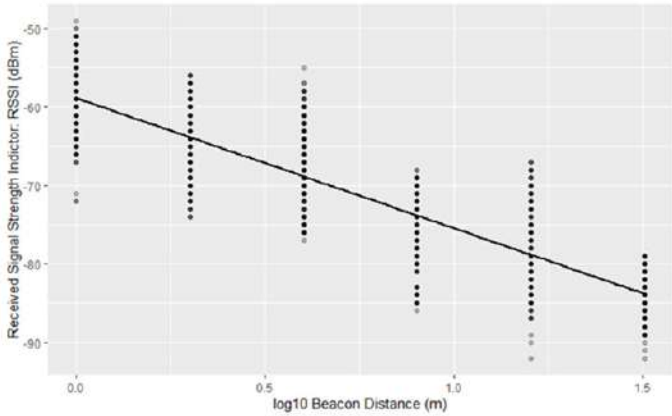

Figure 1: Change in RSSI over distance (WISP height 0.7m / Beacon height 0.7m)

An example of the relationship between RSSI and log distance for 1-32 m (based on both devices being located at 0.7 m) is shown in Figure 1. Whilst demonstrating the decline in RSSI with increasing distance from the BLE reader, it also highlights the fluctuation in RSSI reported per distance. This was similarly observed across all device height groups, but particularly when both devices were at a height of 0.3 m. RSSI can vary significantly depending upon a variety of factors, including transmission power, enclosure and device orientation, as well as the operating environment (Townsend *et al.*, 2014). The reported RSSI is also influenced by path loss; the natural decrease in signal strength of a wave over a given distance, and shadowing; whereby obstacles between the receiver and transmitter cause absorption, reflection, scattering, and diffraction (Nyholm, 2020). Hence in a field environment the RSSI is likely to fluctuate depending upon the surroundings, and beacon position on the sheep relative to the BLE reader.

Distance prediction model

A distance prediction model was developed based on the regression:

$$\log 10\,(Beacon\ Distance\ from\ WISP) = \ -2.494050 + (RSSI * -0.045394) \tag{1}$$

($R^2_{Adjusted} = 0.7529$, $F(1,1375) = 4193$, $P < .0001$), when both devices were at a height of 0.7m. This was used to create a distance prediction equation of:

$$Predicted\ Distance = 10^{-2.494050+(-0.045394*RSSI)} \tag{2}$$

For the calibration data the predicted distances were then calculated, and the mean predicted distance plotted against the actual beacon distance. As distance increased, it was found that the model underestimated the actual distance:

$$Mean\ Predicted\ Distance = 2.18817 + (0.63999\ \times Actual\ Distance) \tag{3}$$

($R^2_{Adjusted} = 0.9587$, $F(1,4) = 117.1$, $P < .001$), hence an adjusted prediction model was also generated, whereby:

$$Adjusted\ Predicted\ Distance = \frac{Predicted\ Distance - 2.18817}{0.63999} \tag{4}$$

Localization of static BLE beacons

Materials and methods

To determine whether RSSI could be used as a means of localisation in a field setting, a further static test was conducted at Firth Mains Farm, Roslin, Scotland (Moredun Research Institute). The aim was to examine whether a beacon's location could be established through a multilateration approach, using the predicted distance, or adjusted predicted distance from multiple WISPs. In this instance 6 WISPs were attached to fence posts along 2 adjoining paddocks at a height of 0.7 m; 2 WISPs along the width of the paddocks, and 4 along the length of the outer fence line. Sixteen beacons were then attached to posts (also at a height of 0.7 m) laid out in a grid-like array approximately 60 x 90 m.

A 2-hour window of data was selected and reviewed to determine which WISPs had reported which beacons and compare variation in the reported RSSI. There was very little fluctuation in RSSI for each WISP-beacon pairing, with a maximum difference of 6 dBm, and average of 2.21 dBm. The mean RSSI was therefore used to calculate the predicted and adjusted predicted distance from each WISP to compare models. Field boundaries were established based on coordinates of corner and mid-paddock fence posts, and the location of WISPs plotted based on their mean GNSS coordinates.

To illustrate the methods used to estimate beacon location this section will go through an example for one of the beacons (Beacon E). A visual assessment was first conducted by plotting circles around each WISP (whereby the predicted / adjusted predicted distance was the radius). The circle for each WISP is therefore given by:

$$(x - WISP\ Longitude)^2 + (y - WISP\ Latitude)^2 = \\ Predicted\ or\ Adjusted\ Predicted\ Distance^2 \tag{5}$$

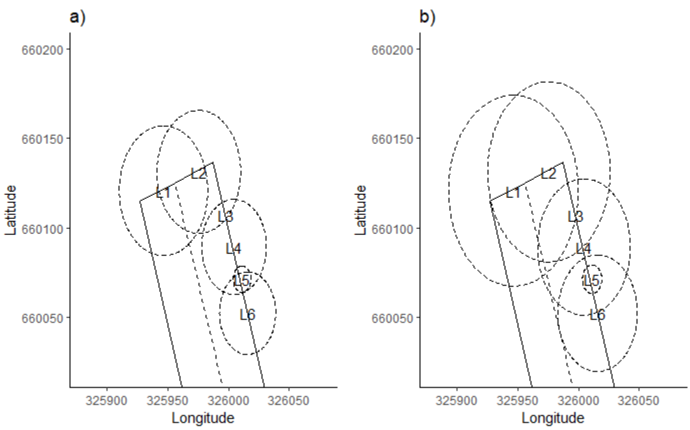

Figure 2: Comparison of resulting intersection of circles using the a) predicted distance and b) adjusted predicted distance. Straight lines represent field boundary.

Figure 2. shows how the intersecting circles of both distance predictions compared for Beacon E, which was reported by 5 of the 6 WISPs (L1-6).

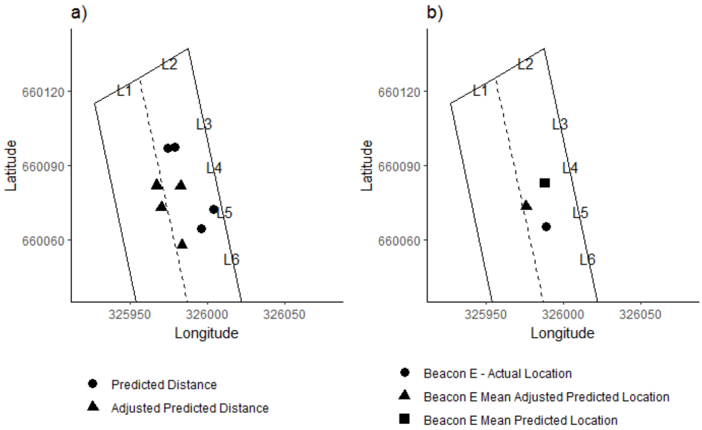

Figure 3: Estimated beacon locations based on a) any points where circles intersected and fell within the field boundary b) the mean location of potential points (those in 3.a) in comparison with the actual beacon location.

Where pairs of WISPs resulted in overlapping circles, the intersection of these circles was solved to generate potential beacon locations using:

$$Beacon\ x\ coordinate_{1,2} = \frac{a+c}{2} + \frac{(c-a)(r_0{}^2 - r_1{}^2)}{2D^2} \pm 2\frac{\mathrm{b-d}}{\mathrm{D}^2}\partial$$

$$Beacon\ y\ coordinate_{1,2} = \frac{b+d}{2} + \frac{(d-b)(r_0{}^2 - r_1{}^2)}{2D^2} \mp 2\frac{\mathrm{a-c}}{\mathrm{D}^2}\partial$$

$$\partial = \frac{1}{4}\sqrt{(D+r_0+r_1)(D+r_0-r_1)(D-r_0+r_1)(-D+r_0+r_1)} \tag{5}$$

where: a = 1st WISP Longitude / b = 1st WISP Latitude / c = 2nd WISP Longitude / d = 2nd WISP Latitude / D = distance between 1st and 2nd WISP / r_0 *= 1st WISP predicted or adjusted predicted distance /* r_1 *= 2nd WISP predicted or adjusted predicted distance.*

In this case, the intersecting pairs of WISPs resulted in 8 potential locations for Beacon E, but only 4 fell within the field boundary for both prediction models (Figure 3.a). The mean estimated beacon location was then calculated based on the mean of locations within the field boundary. Figure 3.b shows the mean predicted location in relation to the actual beacon position for Beacon E. The predicted distance resulted in an estimated location 17.33 m from the actual location, and the adjusted predicted model 15.21 m.

Results and discussion

In the same way, this was conducted for each of the 16 beacons, using both models where possible. Based on the distance prediction and adjusted distance prediction, beacon locations were able to be estimated for 11 and 12 beacons respectively. The other beacons were unable to be solved either due to being reported by too few WISPs or the resulting circles not intersecting. The initial distance prediction resulted in beacon locations ranging from 2.38-44.63 m from the actual beacon location, with a mean distance of 32.55 m. Whilst the adjusted distance prediction did not produce any results as close to the actual location; adjusted predicted distances ranged from 6.53-32.38 m, the mean predicted distance from the actual beacon was slightly closer at 28.5 m.

One issue highlighted during the analysis was that some beacons may have been on the edge of the BLE distance limit, reporting a very low RSSI and underestimating the distance, whilst another WISP could predict the same beacon within very close range (i.e., within a few meters). However, where the radius is such that these circles do not intersect, a more typical proximity based measurement of locating the beacon to within a defined range may still be possible based on the WISP with the highest RSSI.

On-sheep localisation

Materials and methods

The final stage in the study was to test the localisation method on-sheep. Data from a larger project being conducted at Moredun Research Institute was provided for analysis. This study was conducted within the same 2 paddocks (~1.4 Ha) utilised for the static beacon localisation. In this case, 9 WISPs were attached to fence posts; 4 fitted along the length of both outer fence lines, and an additional WISP located at the gate between paddocks. Twenty-four weaned lambs (Texel x mule) were fitted with a BLE beacon, with 12 lambs additionally fitted with GNSS (i-gotU 200 / i-gotU 600).

A sample of data from the same day was selected for 3 lambs, where at least 3 WISPs had reported that lamb's beacon within a 5-minute timeframe, and where the lamb appeared to be stationary. A lamb was determined to be stationary on the basis that the GNSS location was consistent for at least 6 minutes prior to the timestamp of the first WISP reporting, through to the timestamp of the last WISP. Potential lamb locations were then generated using the multilateration approach described, based on the adjusted distance prediction. This was chosen as the adjusted model provided more promising results at longer distances in the static tests and provided better overlap of intersecting circles in initial analysis of the lamb data.

Results and discussion

A predicted lamb location was generated in all 3 instances. The beacon for Lamb 1 was reported by 3 WISPs, with all 3 pairs producing intersecting circles, resulting in a total of 6 potential lamb locations, 4 of which fell within the field boundary. Both Lamb 2 and 3 were also reported by 3 WISPs, however, only 2 pairs produced intersecting circles. This resulted in 4 potential lamb locations for both lambs: 2 within the field boundary for Lamb 2, and 3 for Lamb 3. Figure 4. shows the final mean predicted location for each lamb, compared with the actual location from the GNSS. The distance between the predicted and actual lamb location was 18.38 m, 35.12 m, and 3.91 m for Lambs 1, 2, and 3 respectively.

To further examine the difference between the predicted and actual lamb location, the distance between each reporting WISP and the actual lamb location was calculated. On average the difference between the adjusted predicted distance and actual distance resulted in an overestimation of 5.46 m. The largest difference occurred for Lamb 2, with a particularly large overestimation of almost 35 m by WISP 22, and the largest underestimation of 11 m by WISP 23. When the RSSI of the preceding timestamp of WISP 22 was checked (lamb stationary for 4 minutes) there was a difference of 18 dBm between the reported RSSI. This could be a result of individual device variation or a shadowing effect due to the field environment. Underestimation by WISP 23 is possibly a result of reaching the edges of the BLE readers capacity and operating in distances beyond that of the calibration data used to generate the initial distance prediction.

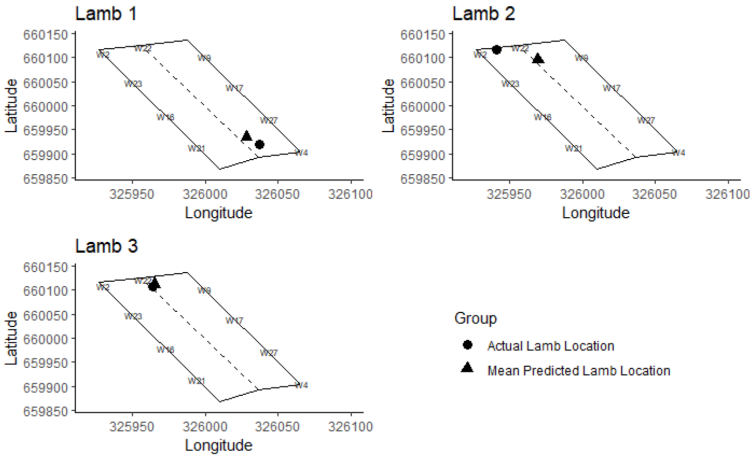

Figure 4: Mean adjusted predicted lamb location vs actual location within paddocks.

Conclusions

The results of the study indicate that BLE could be utilised as a means of sheep localisation in outdoor environments. Whilst the multilateration approach is reliant on obtaining RSSI readings from multiple readers at a similar timepoint, it could provide more information regarding localisation and movement than simple proximity ranges or presence/absence. Due to device variation and environmental factors within the field there is likely to be variability within the distance estimates produced. However, being able to locate a sheep to within ~30 m within a field environment is a step in the right direction. The level of accuracy required in localisation is likely to vary depending upon the system and intended application. However, as BLE technology continues to develop, and ranges increase, this could provide greater scope for BLE to be applied as a means of animal localisation within more extensive systems.

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Nematode parasitism affects lying time and overall activity patterns in lambs following pasture exposure around weaning

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Abstract

We investigated the effects of gastrointestinal nematode (GIN) challenge on activity in first season grazing lambs exposed to two levels of infection. Ewes and their twin-born lambs were turned-out to graze in two permanent pasture enclosures naturally contaminated with GIN. Animals in the dewormed group (DW) were drenched monthly with ivermectin, whereas the other group (NT) was left untreated. At weaning, lambs were allocated to one out of four groups based on weight and sex (NT-E, n = 15; NT-R, n = 15; DW-E, n = 14; DW-R, n = 14), in four ley enclosures. Activity patterns were monitored with IceQube-sensors from 7 days pre-weaning until 49 days post-weaning. Body weight was monitored weekly, whereas faecal egg counts (EPG) were investigated every four weeks. Statistical analyses were performed in RStudio, using mixed models with repeated measures. Weekly recordings was treated as a period. Average lying time had an interaction between parasite exposure and period ($P = 0.0013$), with NT having a 101 ± 31 min shorter daily lying time compared with DW. Motion Index had an interaction between parasite exposure and period ($P = 0.0001$) with NT having a lower daily MI compared with DW. Both weight gain and EPG levels differed ($P < 0.0001$) between groups. In conclusion, this study shows that lying time and MI of lambs around weaning was affected by nematode infections. This indicates a potential use of automated behaviour recordings as a diagnostic tool for detection of nematode parasites in lambs.

Keywords: Accelerometers, Activity, Behaviour, Gastrointestinal nematodes, Health monitoring, Sheep

Introduction

Infections with gastro-intestinal nematode (GIN) parasites is a global problem in pasture-based sheep herds and it is associated with reduced animal health and welfare which affect farm productivity and profitability (Charlier *et al.*, 2020). Current control practices of GIN infections depend largely on use of anthelmintic drugs, often in conjunction with grazing management strategies (Sutherland & Scott, 2010). However, misuse of these drugs has led to a widespread development of drug-resistant worm populations (Rose Vineer *et al.*, 2020). This underlines the need for sustainable management approaches that minimize overuse of anthelmintic drugs and thereby the selection for anthelmintic resistance (AR) (Velde *et al.*, 2018). Targeted selective treatment (TST), where only individual animals within a group are treated, has been proposed as a sustainable long-term strategy to yield individual benefits to animal health and at the same time decrease the risk for AR (Charlier *et al.*, 2014). Several indicators have been proposed, i.e. faecal egg counts (FEC), weight gains and other production traits, as well as pathophysiological indicators such as the FAMACHA© system. However, the implementation of TST approaches is today limited on commercial farms and the future integration is dependent of user-friendly, reliable and affordable indicators. Sickness behaviour has been suggested as an applicable indicator for monitoring various diseases in animals. Furthermore, deviating feeding behaviour and general activity can provide specific information about an animals health and welfare (Weary *et al.*, 2009). The advancement of Precision Livestock Farming (PLF) enable real-time monitoring of such behaviours (Berckmans, 2017) and could potentially be utilized to monitor GIN challenge. However, the knowledge of responses in host activity in relation to GIN infections in ruminants is today limited and needs to be developed before it can be integrated in parasite management (Vercruysse *et al.*, 2018). To date there are only a handful of studies assessing activity patterns with a sensor approach as an indicator of GIN infections in sheep on pasture. Burgunder *et al.* (2018) observed with 3D-accelerometers that GIN infected sheep exhibited a smaller behavioural complexity compared with dewormed animals, suggesting that organizational patterns of their behaviour changes with GIN infections. Ikurior *et al.* (2020) showed that sheep naturally infected with strongyles had a lower activity level compared with dewormed animals after 42 – 46 days on pasture. Moreover, first season grazing (FSG) steers infected with GIN showed a lower activity level compared with dewormed animals as well as a higher number of conducted lying bouts 74 – 86 days after turn-out (Högberg *et al.*, 2019). In addition, FSG steers inoculated with *Ostertagia* and *Cooperia* at turn-out showed a longer lying time the 40 first days on pasture as well as a higher number of steps day 62 – 69, compared with dewormed animals (Högberg *et al.*, 2021).

Material and methods

Animals and Experimental design

The study took place at Götala Beef and Lamb Research Centre, Sweden (58° 42′N, 13° 21′E; elevation 150 m MSL) from April 25th until August 13th 2019. A total of 34 multiparous ewes with two lambs of each sex from the same commercial herd were included. The ewes consisted of 23 pure Dorset breed and 11 Dorset and Swedish Finewool cross-breeds. The study consisted of two periods, one pre-experimental period of five weeks from turn-out until three weeks pre-weaning followed by an experimental period with data collection lasting to seven weeks post-weaning. At turn-out, ewes with their twin-born lambs were allocated to one out of two pre-experimental groups (NT, not treated, and DW, dewormed). The ewe groups were balanced for breed, body weight (NT: 68.9 ± 9.5 kg; DW: 72.9 ± 13.2 kg), body condition score (NT: 2.8 ± 0.5; DW: 3.0 ± 0.4) and age (NT: 3.8 years; DW: 3.5 years). Ewes in group DW were dewormed prior to turn-out with 0.2 mg ivermectin (Ivomec® vet, oral suspension) per kg body weight and thereafter at four-week intervals, whereas their lambs were dewormed four weeks after turn-out and thereafter at four-week intervals until the end of the experiment. Two ewes from NT and three ewes from DW were treated for mastitis six to seven weeks prior to weaning and were excluded from the study. One ram lamb in group NT was treated with benzylpenicillin (Penovet® vet) and meloxicam (Metacam® 20 mg / ml) for lameness, six weeks post weaning. Altogether 58 lambs were used in the experiment. Each group was released into one of two similar permanent pasture enclosures, naturally contaminated by sheep with strongyle nematode larvae the previous year. At weaning, lambs were allocated to one out of four groups based on sex (E = ewe; R = ram) and experimental group (NT-E, n = 15; NT-R, n = 15; DW-E, n = 14; DW-R, n = 14). Each experimental group was allowed to graze in one of four non-contaminated 1.0 ha ley enclosures, whereas ewes were removed.

<u>Activity measurements, sampling and parasitological examination</u>

One week prior to weaning all lambs were fitted with IceQube® 3D-accelerometers (IceRobotics Ltd, Edinburgh, UK; Validated for use in lambs by: Högberg *et al.*, 2020) on the left hind leg above the fetlock. Sensor dimensions were 55 x 55 x 27 mm and 75 g. The tri-axial accelerometer operates using a sample rate of 4 Hz with a time resolution of 15 min, with a 9-day internal memory. The accelerometers continuously recorded Standing (indicates whether the animal is upright or not), Lying (indicates whether the animal is lying down or not), Lying bouts (indicates the start of a lying bout) and Motion Index (the measured net acceleration, indicates total activity). Recordings from IceQubes, expressed as minutes per 24 h and lying bouts per 24 h, were downloaded at weekly intervals from one week before weaning and then for the seven consecutive weeks, using the download station IceReader, when the animals were handled. In the data analyses, recordings from the same lambs (i.e. 7 days of data) was treated as a period, generating a total of eight periods. Recordings from the first day of period 1 and last day of period 8 was not included so that each analysed day contained 24 h of data. Body weights of lambs were registered on a digital scale three weeks from prior to weaning and thereafter every week for ten weeks. In connection with weighing, rectal faecal samples were collected i) three weeks prior to weaning, and ii) one week iii) five weeks, and iv) seven weeks post weaning. Faecal egg counts (FEC) was determined using a modified McMaster method based on 3 g faeces dispersed in 42 mL saturated NaCl, providing a minimum diagnostic sensitivity of 50 strongyle eggs per gram (EPG) faeces. In addition, remaining faecal slurry was transferred into 15 ml sterile tubes (Sarstedt, Nümbrecht, Germany) and stored at -18°C. Total DNA was then extracted using the NucleoSpin DNA Stool kit®, following the guidelines issued by the manufacturer (Macherey Nagel, Germany). The proportions of *Haemonchus* spp. and *Teladorsagia* spp. DNA copies situated in the internal transcribed spacer region 2 (ITS2) of the ribosomal RNA gene array were then determined in relation to the universal strongyle egg DNA copies in duplex reactions using a droplet digital (dd)PCR assay (BioRad), as described earlier by Elmahalawy *et al.* (2018).

<u>Statistical analysis</u>

The statistical analyses were performed using RStudio. Assumptions of variance homogeneity and normal distribution of residuals of the data were checked by inspection of residual plots. Differences in activity were analysed using mixed models, with repeated measures using the LME function in the NLME package. For IceQube data GIN exposure level (NT, DW), and experimental period (1-8) were treated as fixed factors with the experimental group and individual as nested random effects. Start weights were treated as a covariate in the model. Data from one animal in group NT-R, treated for lameness, was excluded from period 6 until the end of the study. To account for time autocorrelation, a continuous autoregressive structure for a continuous time covariate (CorAr1) was fitted for the model. Pairwise differences were compared with ANOVA in the NLME package. Differences between experimental groups during the different periods were compared using Tukey's pairwise comparisons with the emmeans package. BWG and EPG were analysed in a repeated measure mixed model with GIN exposure level (NT, DW) and day as fixed factors and the experimental group and individual as nested random effects. A continuous time covariate (corAr1) was also fitted to account for autocorrelation.

Results and Discussion

Average daily lying time had an interaction between GIN exposure and period ($P = 0.0013$), that was most pronounced from day -7 until day 7, with mean lying times being 667 ± 244 in NT and 760 ± 257 in DW, during these days, respectively (Fig.1a). The pairwise comparisons for each period did not show any differences. Motion Index had an interaction between GIN exposure and period ($P = 0.0001$), that was most pronounced from day 0 until day 14, with mean Motion Index being 11836 ± 250 in NT and 13156 ± 278 in DW, during these days, respectively (Fig.1b). The number of lying bouts recorded was not affected by GIN exposure ($P = 0.51$) or exposure by period interaction ($P = 0.82$) (Fig.1c). The mean body weight (Fig.2a) seven days prior to weaning did not differ between exposure groups ($P = 0.58$) and was 28.1 ± 4.68 kg in NT and 28.7 ± 3.7 kg in DW, respectively. The average body weight gain (BWG) was on average 19.1 % higher ($P < 0.0001$) in DW (362 ± 5 g) compared with NT (304 ± 6 g). Strongyle eggs were present in both experimental groups at day – 21 from weaning. The FEC (Fig.2b) was higher ($P < 0.0001$) in NT than in DW throughout the study, decreasing from day – 21 to day 7. The highest FEC in DW was observed at day – 21. *Haemonchus* spp. was found in both experimental groups, with 7 % of animals in DW and 100 % of animals in NT being positive at least on one occasion. *Teladorsagia* spp. was found in all animals on at least one occasion.

In this study strongyle nematode eggs were observed in both groups three weeks prior to weaning, but FEC was higher in NT compared with DW throughout the study. *T. circumcincta* and *H. contortus* were identified as the two most abundant pathogenic species. The relatively low EPG levels in combination with predominantly low proportions of *H. contortus*, indicates moderate infections with this parasite also in NT animals. Still, we observed a difference in BWG throughout the study period with the daily weight gain in DW being 75 ± 18 g higher than in NT. Furthermore, no clinical signs of parasitism, such as diarrhoea and anaemia, were observed. Together, this implies a moderate subclinical course of disease also in NT. Despite all of this, our results indicate that the differences in GIN infections generated herein had effects on the activity patterns in lambs and that could be registered with commercially available on-animal sensors. Animals in NT had a lowered MI compared with DW throughout the study. This finding is in agreement with those of Ikurior *et al.* (2020) that also detected a reduced activity in sheep challenged with subclinical levels of GIN. Similarly, FSG steers inoculated with *O. ostertagi* and *C. oncophora* at turn-out and further exposed to larvae on pasture, had a reduced activity compared with dewormed animals (Högberg *et al.*, 2019). Previously, a reduction in activity in grazing steers have been suggested to be linked with a dose dependent mucosal damage mainly associated with *O. ostertagi* infection (Högberg *et al.*, 2019). The lambs in the present study were primarily exposed to *Teladorsagia* spp. that inhabit the same niche in sheep as *O. ostertagi* in cattle, with similar pathological effects on the host (Sutherland & Scott, 2010). This further underlines the possibility of a connection between nematode induced mucosal damage in the abomasum and deviation in host activity patterns. There was also an exposure by period interaction on lying time with NT animals having a shorter daily lying time compared with DW throughout the study. This is in direct contrast with the findings of Högberg *et al.* (2021), where FSG steers challenged with a subclinical infection of GIN had a longer daily lying time during the 40 first days after infection, compared with dewormed animals. Again, this emphasises the need for species-specific interpretation of associated sickness behaviour for different host-parasite relationships. In addition, the differences in lying time patterns observed in the lambs studied herein was present already at the start of recording. This indicates that the influence of GIN infection on the activity patterns in sheep may arise early and could be explained by the difference in FEC levels observed three weeks prior to weaning, reflecting a manifest GIN infection. This underlines the potential use of behavioural variation as an early indicator of GIN infection, as suggested by Szyszka *et al.* (2013). In contrast, long term differences in activity may have a more limited value for the implementation of a TST-system. However, more studies are clearly needed to determine the relationship between infection levels and individual behavioural responses, under varying exposure conditions. Nevertheless, in our study the variation of FEC within NT was moderate reflecting minor variations in GIN infection levels between the animals in this group. This underlines that individual variation needs to be taken into account when developing PLF-systems evaluating treatment thresholds that can be used in parasite control programs.

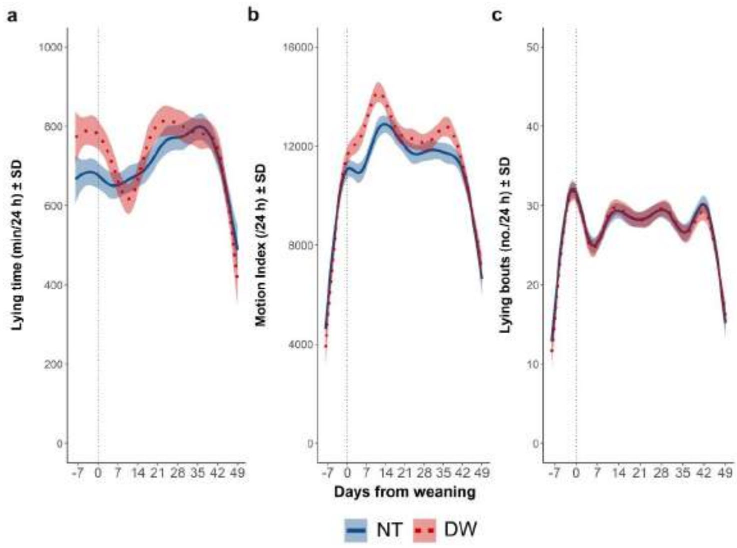

Figure 1: a) Duration of mean lying time ± SD (min / 24 h), b) mean Motion Index (/ 24 h), and c) mean number of lying bouts (no. / 24 h) in four groups, based on sex (E = ewe; R = ram) and experimental group (NT = not treated; DW = dewormed), of first season grazing lambs exposed to overwintering strongyle larvae at pasture. One experimental group (DW) (red) was dewormed with Ivomec® (0.2 mg kg^{-1}) monthly (DW-E, n = 14; DW-R, n = 14), exposing them to a lower parasite challenge compared with DW (blue) (DW-E, n = 15; DW-R, n = 15).

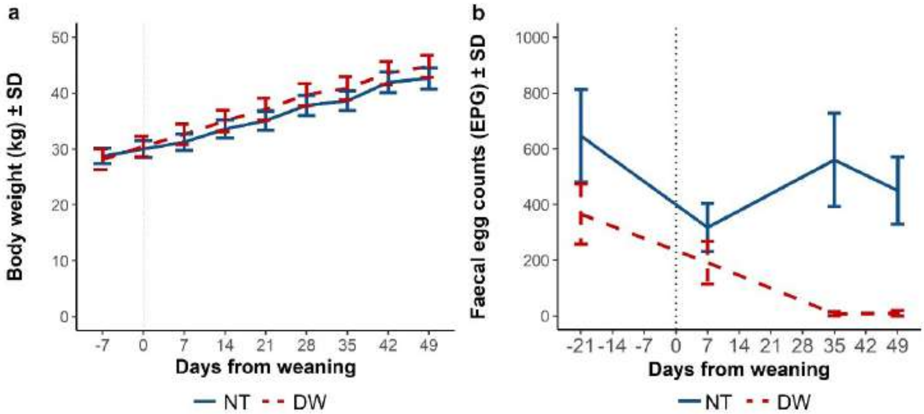

Figure 2: a) Mean body weight ± SD, b) Mean gastrointestinal nematode faecal egg counts (EPG) ± SD in four groups, based on sex (E = ewe; R = ram) and experimental group (NT = not treated; DW = dewormed), of first season grazing lambs exposed to overwintering strongyle larvae at pasture. One experimental group (DW) (red) was dewormed with Ivomec® (0.2 mg kg–1) monthly (DW-E, n = 14; DW-R, n = 14), exposing them to a lower parasite challenge compared with DW (blue) (DW-E, n = 15; DW-R, n = 15).

Conclusions

This study constitutes an attempt to evaluate the effects of multispecies nematode parasitism on the activity level in grazing lambs in connection to weaning, using commercially available on-animal sensors. The results show that the activity measurements lying time and Motion Index differed between NT and DW, despite that infection levels were considered to be low also in NT. Although additional research regarding individual variation in connection to GIN infections is needed, we have demonstrated the potential use of automated behaviour recordings as a diagnostic tool for detection of major nematode infections of sheep to be integrated into future parasite control programs.

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Assessing goats fecal avoidance using image analysis based monitoring

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Abstract

Recent advances in sensor technologies and data analysis helped monitoring animal behavior over long time periods. This is particularly interesting to study the link between behavior and animal health. In this work, we studied the capacity of Creole goats to avoid feces on pasture. We developed an experimental framework, composed of a small pasture of 12x12=144m2 with two zones of 6x2=12m2 infested with feces, and a monitoring system, based on a time lapse camera, taking pictures every 20s from 6:30 to 18:00. A set of 3,800 images were manually labeled to (i) train a Yolo based neural network, ables to detect goats on the images and (ii) train a resNet50 neural network, ables to identify the goats present on pasture. We used the framework to monitor the location of four Creole goats, selected for their various colors, to make automatic animal identification easier. We were able to determine when the animals were on the infested areas or not. Goats were allowed to graze for two weeks, separated from more than 2 months. Goats were worm free when grazing started and the level of infection was evaluated after grazing, using fecal egg count. Goats were detected in 88% of the cases and the precision for animal identification was estimated to 95%. Although goats exhibited various level of avoidance, it increased for all goats during the second grazing week, and the level of increase was proportional to the level of infection resulting from the first grazing week.

Keywords: Image Analysis, goats, fecal avoidance.

Introduction

Goats are an important resource mainly for meat and milk production, with approximately 94% of the animals located in Asia and Africa. Infection with gastro-intestinal nematodes (GIN) parasites is one of the main health constraints, responsible for reduced performances production and increased mortality, especially in young animals and adult females, during the periparturient period. In the past, GIN management successfully relied on systematic anthelmintic (AH) treatment. Unfortunately, resistant GIN populations to AH were gradually selected (Kaplan and Vidyashankar 2012). Thus, it is now widely admitted that relying only on AH is not a sustainable strategy. To design alternative strategies adapted to farmers constraints, modeling could be an interesting tool, in order to simulate infestation dynamic, compare, and optimize management strategies. One of the main challenge to model GIN infection dynamic is to model ingestion, i.e. the timing and quantity of ingested larvae. Larval ingestion is related to animal behavior and recent developments in precision livestock farming tools offer new opportunities, especially to characterize behavior, and to study the relationship with GIN infection.

In this article, we proposed an experimental framework to study a particular aspect of animal behavior concerning feces avoidance, based on automatic monitoring of the animals using image analysis (Li *et al.* 2021). Convolutional neural networks (CNN) are generally the most adapted image analysis tool and has been used successfully, mostly for pigs (Marsot *et al.* 2020; Zheng *et al.* 2020; Gan *et al.* 2021), but also for goats (Bonneau *et al.* 2020; Jiang *et al.* 2020; Su *et al.* 2021). Several methods for cattle monitoring also successfully identified animals using deep-learning technics (Qiao *et al.* 2019; Achour *et al.* 2020). The main advantage of using CNN is that powerful models, trained on millions of images and designed by research teams with relevant engineering skills, are available free of charge. Then, new users can almost directly use these CNN, just by retraining some parameters in order to be able to detect and classify their objects of interest. In this article, we proposed to use YOLO (*You Only Look Once* - Redmon and Farhadi 2017) associated with resNet-50 (He *et al.* 2016) to detect and identify the animals.

Material and methods

All animal care handling techniques and procedures were approved by the French Ethics Committee n°069 (Comité d'Ethique en Matière d'Expérimentation Animale des Antilles et de la Guyane, CEMEAAG) authorized by the French Ministry of Higher Education, Research and Innovation. The experiment was performed at the INRA Experimental Facilities PTEA (Plateforme Tropicale d'Expérimentation sur l'Animal) according to the certificate number A 971-18-02 of authorization to experiment on living animals issued by the French Ministry of Agriculture.

Experimental setup

The objective of the study was to monitor goats while grazing an experimental pasture, where the location of feces infested with GIN was known, in order to study their ability to avoid feces. The experiment was first conducted during *Week 1*, from April 12th 2021 to 19th, and repeated during *Week 2*, from June 28th 2021 to July 5th. The same pasture and animals were used for the two weeks.

We designed an experimental pasture of $12m \times 12m=144m^2$, with two infested areas A and B, of $2m\times6m=12m^2$ each (see Figure 1). A total of 900g of infested feces with GIN were dropped homogeneously within each infested area. Feces were dropped manually 13 days before grazing on Week 1 and 10 days before grazing on Week 2, to maximize the number of infective larvae on pasture during grazing. The feces level of infection was measured using fecal egg count (FEC), in eggs per gram of feces (EPG, Aumont, Pouillot, and Mandonnet 1997). FEC was estimated from 10 different feces samples, for Week 1 mean FEC was 567 *eggs/g* and was 4431 *eggs/g* for Week 2.

To ensure that animals were not infested with GIN before grazing on Week 1 and 2, they were drenched using anthelmintic. Treatment efficacy was controlled by measuring the FEC one week before grazing. After grazing animals were maintained together in a stall and were fed with dry hay to avoid parasite ingestion outside of the grazing week. After grazing, the animals level of infection was finally assessed using FEC, at least every week, starting 8 days after grazing.

Animals

Four male Creole goats were selected to maximize color differences between individuals. The first goat, referred as *white*, had a black coat with white color patches on the belly, weighted 34.13kg and was 16 months old at the beginning of the experiment. The second goat, referred as *brown*, has a brown coat with a black strip on the back, weighted 33.93kg and was 12 months and 17 days old. The third goat, referred as *black*, had a homogeneous black coat, weighted 31.62kg and was 12 months and 17 days old. The last goat, referred as *red*, had a reddish brown coat with a black strip on the back, weighted 39.92kg and was 12 months and 11 days old. The animals from different sire origins, were raised at pasture and exposed to natural GIN infection, until the first stage of the experiment.

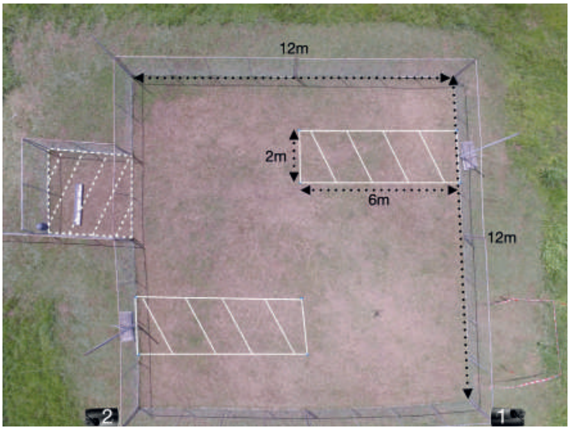

Figure 1: Pasture setup. The white dashed zones with solid lines are infested areas A and B. The white dashed square with dashed lines is the resting area. During experiment, we placed water and a sheet of metal inside this area to produce shade. On Week 1, we used the camera located on the bottom right corner of the pasture and on the bottom left on Week 2

Recording behavior with time-lapse cameras

We used a construction time-lapse camera (Brinno TLC2000 pro 2018), setup to take one picture every 20s from 6:30 to 18:00. The analysis of the images acquired during Week 1, showed that the camera was facing the sun during sunrise, decreasing the quality of the images. The location of the camera was adapted accordingly for Week 2. Animals were grazing the paddock continuously but we were only able to record during daylight.

Animal detection

To detect animals, a common approach was used, based on the CNN YOLO v2 (Redmon and Farhadi 2017), known to run fast, with high accuracy and high learning capacities. For image feature extraction, we trained YOLO based on resNet-50 (He *et al.* 2016). In very few cases, YOLO returned more than 4 detections, mostly when multiple bounding boxes was associated to the same animal. When more than four bounding boxes was found, a non-max suppression method was used to remove the overlapping bounding boxes (i.e. rectangles around the detected objects).

Animal identification

The results of the YOLO detection stage was a set of bounding boxes, $(x_a, y_a, w_a, h_a)_{a=1\ldots n}$, around the detected animals, where x_a and y_a were the column and row numbers of the top left corner of the bounding box number a. w_a and h_a were the width and height of the bounding box, and n was the number of bounding boxes/detected animals. We then moved to the next step: identify the animals inside each bounding box.

This second step is an image classification problem, with 4 different classes, *white goat*, *brown goat*, *black goat* and *red goat*. There is several CNN that are available free of charge, and trained on more than one million of images to perform image classification with common objects such as dogs, stop signs or humans. However the network architecture and most of the layers can be directly used to recognize new classes, which is known as transfer learning. We also used resNet-50 with only the parameters of the last 10 layers being re-trained. When labelling the training images for YOLO, the color of the animals was also labeled. Thus the 3,820 training images labeled for YOLO were used, to extract 12,236 images with color labels. In total, approximately 3,400 images were available for the white goat and 2,900 images for the other goats.

Compared to other image classification problem, an extra information was available: two detections cannot be in the same class. Instead of using the prediction of the CNN directly, we used it to compute the probability of each bounding box being from an animal of the four different colors. For each bounding box number a, (x_a, y_a, w_a, h_a), the CNN associated a set of probabilities $(p^a_{white}, p^a_{brown}, p^a_{red}, p^a_{red})$. A score was then calculated for each possible color configuration of the bounding boxes. If c^a is the color of the bounding box number a, the score of a configuration $(c^1, \ldots, c^n)$ is simply the sum of the probabilities of the bounding boxes to be in that colors:

$$V(c^1, \ldots, c^n) = \sum_{a=1}^{n} p^a_{c^a}.$$

Finally the color configuration with the highest score was chosen, to ensure that each color class was associated to a maximum of one detection.

Evaluate detection

To evaluate the capacity of the method to detect and identify animals, a MATLAB application was designed to select randomly an image on the data bank and displayed the detected animals with their estimated color. For each color (i.e. white, brown, black and red), the user first selected if the animal was detected, non-detected or absent (i.e. inside the resting area). When the animal was detected, the user also had to record its true and estimated color. A second script was designed to manually record the location of the missed detection.

We ran the application to control more than 600 images for each Week. In order to assess the capacity of the method to detect the animals, we computed the percentage of detected animals. In order to assess the capacity of the method to identify the animals, we compared the estimated and true color of each detection. Then we evaluated the sensitivity and precision for each color class.

Fecal avoidance capacity

To characterize the capacity of the animals to avoid infested areas, the number of times each animal was detected on the infested and non infested areas was computed. In order to compare the two quantities, the number of detections was normalized by the surface area of each zone, which provided a number of detections per m^{2}. Finally, the avoidance index was defined as the ratio of the number of detections per m inside the non-infested and the infested areas:

$$Avoidance\ Index = \frac{d^{nia}/120}{d^{ia}/24}.$$

Whered d^{nia} is the number of detection inside the Non-Infested Area and d^{ia} is the number of detection inside the two Infested Areas A and B.

An avoidance index >1 means that the number of detections per m^{2} was strictly higher for the non-infested area. The greater was the avoidance index, the greater was the feces avoidance. Note that avoidance of freshly dropped feces is not accounted for.

Statistical analysis

In order to quantify the animals level of infection after grazing, FEC was determined on a regular basis. To summarize this information, we used the logarithm of the are under the FEC curve (LAF). The LAF allowed the characterization of the infection dynamic over the entire measurement period. The LAF increased with the animal level of infection.

The correlation between the individual LAF obtained on Week 1, denoted LAF_i for animal i = 1,…,4, and the increase in the weekly avoidance on Week 2, denoted AV_i, was studied using the Pearson's correlation coefficient. It is equal to:

$$\frac{1}{3}\sum_{i=1}^{4}\left(\frac{LAF_i - \mu_{LAF}}{\sigma_{LAF}}\right)\left(\frac{AV_i - \mu_{AV}}{\sigma_{AV}}\right)$$

Where μ and σ are the mean and standard deviation.

Results and Discussion

Animal detection and identification

The white goat had the highest detection rate (95% - See Table 1). The white coat patches on the belly of this goat was highly discriminant and certainly helped the detection and identification by the algorithms. The red and black goats had similar detection rates (89.45% and 87.9% respectively), whereas the brown goat was the one with the lowest detection rate (79.4%). Most of the missed detections were located on the part of the pasture farthest from the camera. It has also been noted that missed detection was highest between 6:00 to 8:00 during Week 1, due to sunrise.

The sensitivity and precision of the animal identification method are available Table 1. The average sensitivity was close to 95% for each week. We observed confusion between the brown and red goats, which had similar shade. There was also some confusion between black and white goats, which had most of the coat of black color. When the white coat patches on the belly was not visible, the identification method recognized the white goat as the black one. As for the detection method, a better sensitivity and precision during Week 2 was observed, due to camera position.

Tableau 1: Percentage of detected animals using Yolo, as well as sensitivity and precision of the animal identification method

	Animal detection		**Animal Identification**			
			Week 1		**Week 2**	
	Week 1	**Week 2**	Sensitivity	Precision	Sensitivity	Precision
White	95%	95%	98.9%	95.7%	99%	97.6%
Brown	78%	80.8%	95.9%	85.9%	94.4%	94.1%
Black	84.3%	91.5%	89.4%	95.7%	94.2%	96.7%
Red	86.8%	92.1%	92%	97.6%	95.7%	95.1%
Average	**86%**	**89.9%**	**94%**	**93.7%**	**95.8%**	**95.9%**

Post-grazing level of infection

The FEC remained relatively low (< 4,000 EPG) after Week 1 (see Figure 2. a and b). The brown goat had the highest FEC value (mean FEC = *2653 eggs/g*). On the last FEC measurement, the black and white goats had relatively similar FEC values, close to 2,000, although the white goat had lower FEC at the beginning (mean FEC = *934 eggs/g* for the white and *1,467 eggs/g* for the black). The FEC of the red goat did not exceed *700 eggs/g*, which could be considered as a low level of infection.

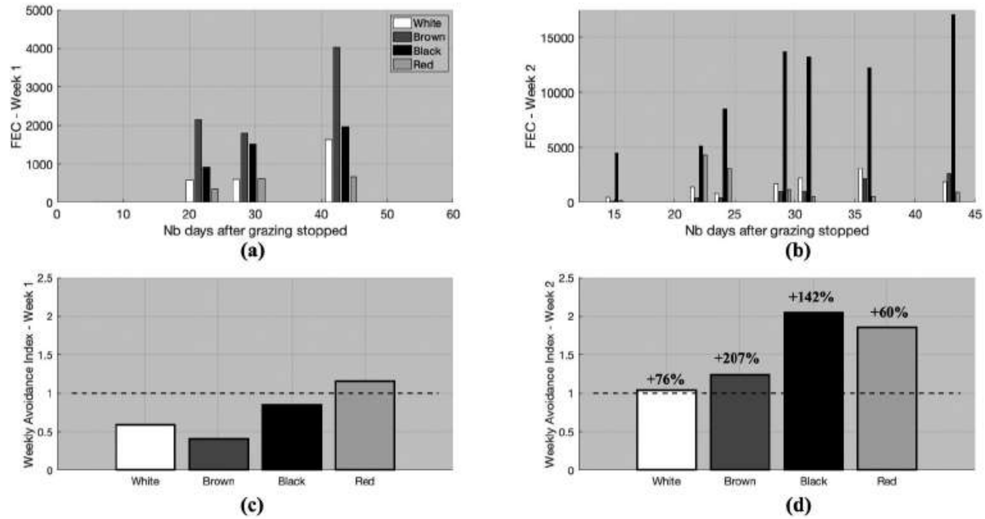

Figure 2: Individual fecal egg count (FEC), in eggs/g of feces, for Week 1 (a) and Week 2 (b), as a function of the number (Nb) of days after grazing stopped. Individual avoidance index during Week 1 (c) and Week 2 (d)

After Week 2, the level of infection of the black goat was high with FEC value close to 17,000 eggs/g (mean FEC = 11,415 eggs/g). The FEC of white and brown goats were similar, with a maximal value close to 3,000 eggs/g (mean FEC = *1,679 eggs/g* for white and *1,342 eggs/g* for brown). A peak of FEC (*4,290 eggs/g*) for the red goat was observed 21 days after the grazing period. Thereafter, the FEC decreased to reach levels similar to the white and brown goats (mean FEC = *1,473 eggs/g*).

<u>Avoidance capacity</u>

The weekly avoidance index increased between Week 1 and 2 for all the animals (see Figure 2. b and c). The weekly avoidance index increased by 76%, 207%, 142% and 60% for the white, the brown, black and red goat respectively. Interestingly, the greater LAF value was observed during Week 1 and the greater weekly avoidance index was observed during Week 2. The Pearson's correlation coefficient between the LAF on Week 1 and the increase in the weekly avoidance index on Week 2 was 0.93. In line with this result, for sheep, it has been shown that the avoidance capacity increased with the level of infection (Hutchings *et al.* 1999; Cooper, Gordon, and Pike 2000).

Conclusions

In this study, we provided a conceptual framework to study goats behavior at pasture and tested it to study the interaction with parasitism. This framework is based on automatic animal monitoring using image analysis, to detect and identify the animals on the images, allowing to record the spatial coordinates of the animals over time and derive interesting indicator, such as the avoidance index. Overall, image analysis could be a useful tool to monitor animal behavior on pasture. The main advantages being the low cost of the cameras and no handling of the animals. With more developments, it could be expected that a variety of variables, such as locations, activities or animal interactions, could be computed from only one sensor, the camera. However, using image analysis remains technical, as it needs to train specific deep neural network, which could be complicated for non-specialist. In this work, we showed that animal identification was possible, thanks to the various colors of the individuals. This might not be possible for generic studies and automatic identification remains a major constraint for grazing goats. By now, GPS combined with accelerometers probably remains the easiest solution to get continuous individual data. However, ou study demonstrated that image analysis is a potential alternative, and future improvements could open new perspectives for monitoring animal behavior.

Acknowledgements

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Validation of a 3D imaging device to measure new morphological phenotype on ewes

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Abstract

Monitoring of body condition and/or morphological changes is essential for optimal management of ewe health and welfare, but also production and reproduction performance. However, due to implementation difficulties (handling, workload, skills and training), body condition scoring is rarely implemented on sheep commercial farms. New technologies based on three-dimensional (3D) shape analysis combined with electronic identification could solve this issue. The purpose of the present study was to develop, test and validate a device that can record and analyse 3D body shapes of shorn ewes. Manual measurements on 12 Vendéen breed ewes (gold standard) were compared to measurements from the 3D images. Height at withers (HW), chest circumference (CC), chest depth (CD) and chest width (CW) were registered. Correlations between 3D device and manual measurements were 0.37 for HW, 0.80 for CC, 0.80 for CD and 0.82 for CW. For the 3D system, the repeatability standard deviation ranged from 1,53E-03 to 1.65 (coefficient of variation (CV) from 1,54% to 3,77%) and the reproducibility standard deviation ranged from 2,36E-04 to 0,77 (CV from 0.3% to 1.17%). Repeatability values are very close between the two methods, and 3D device measurements are more reproducible than manual measurements. In the future, automatic determination of ewes body condition score thanks to this technology will be tested, as well as the possibility of measuring new phenotypes such as the volume or the surface, which are of many interest in ewe selection and production.

Keywords: 3D imaging, precision livestock farming, body measurement, sheep, sensors

Introduction

Ewe weight, body condition score (BCS) and morphology are important indicators for monitoring animal health, reproduction, feed and production (Yakubu, 2009). They allow changes in the condition of the animals identification which make possible the detection of health or feeding problems, for example. However, due to the large size of sheep flocks, the measurement of BSC or weight can be time-consuming, which severely limits their use by farmers. Automatic solutions exist in sheep for weight measurement (e.g. weighing crate) but their cost remains high and not yet very accessible on farms. Besides weight measurement, which can be automated, the methods for measuring morphological traits and body condition score are still manual.

In the case of small ruminants, imaging methods seem to be interesting and inexpensive solutions for monitoring the morphology and condition of animals (Menesatti *et al.*, 2014). 3D imaging, a recent technology in animal husbandry, has shown interesting results on the implementation and accuracy of morphology traits measurements and body condition score estimation of dairy cows (Le Cozler *et al.*, 2019). 3D imaging could be a solution to meet the time and cost constraints of sheep farmers.

The aim of this study is to develop and validate a prototype for automatic acquisition of 3D images of ewes.

Material and methods

Device and 3D images

The OtoP 3D prototype was developed in partnership with the 3DOuest company in their laboratory in Lannion and then installed on the Digiferme® of Le Mourier in Saint-Priest-Ligoure, France. The prototype is based on a fixed arch which five cameras embedded (Figure 1). A sixth camera is present at the rear to improve image accuracy of the lower back and rear of the animal, which are the areas of interest for BCS. The cameras work with active stereo, i.e. by projecting an infrared test pattern that facilitates the matching of the left and right images for distance map inception. The cameras have a horizontal of 85° and a vertical viewing angle of 58°. The 6 cameras are synchronised with each other to capture a complete image of the animal. The 3D image capture time is less than one second. It can be activated by an operator on a computer or directly through the identification of the animal by the RFID (Radio-frequency identification) antenna placed at the front of the prototype. The ewes are contained between two wide-mesh nets to limit the impact of restraint on image quality. Two doors, one at the front and one at the back, allow the management of animal flow.

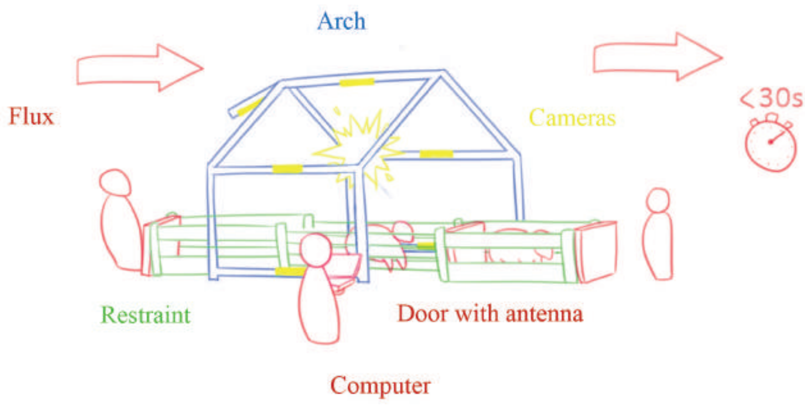

Figure 1: OtoP 3D prototype and installation

The images captured from each camera are sent as a distance map to the computer. A Poisson reconstruction algorithm is used to reconstruct 3D images of the ewes from the distance maps. The quality of the images is then improved by removing environmental artefacts, filling in uncaptured holes and homogenising the 3D surface. Manual verification and correction was applied to some images to remove environmental features. A sorting of the images was carried out to remove the images that could not be used because of the movement of the sheep.

Animals and measurements

The measurements were done in June and July 2020, on 12 ewes of the Mouton Vendéen breed from Le Mourier experimental farm (87, France). For each ewe, the measurements were done manually on live animals and on 3D images from the OtoP 3D prototype. The measurements taken were Wither Height (WH), Chest Width (CW), Chest Depth (CD) and Chest Circumference (CC). Two additional measurements, Volume (V) and Surface (S) area, were measured on the 3D images.

Five 3D images of each animal were acquired for repeatability and reproducibility. For the manual method, three repetitions of measurements by one operator were performed as well as three repetitions by three operators for the reproducibility of the manual method. For the measurements from the 3D images, repeatability was carried out on 5 redundant measurements by the same operator and reproducibility on five different operators. The 3D images were processed with the Metrux2α® software developed by 3D Ouest.

Data analysis

Repeatability and reproducibility of the two methods (manual and from OtoP 3D prototype) were evaluated. The aim of repeatability is to evaluate the error generated when estimating an indicator several times on the same sample with the same methodology, in the same environment, over a short period of time. It was estimated by making measurements five times the same day, from the OtoP 3D prototype with the same ewe. Reproducibility aims to assess the same error but under varying environmental conditions. It was estimated with twelve ewes scanned or with four different operators, with only one measurement per 3D image. The 3D variations were corrected to account for the effect of animals in extracting ANOVA model residues. The coefficients of variation for repeatability (CVr) and reproducibility (CVR) were evaluated as $CVr = (\sigma r / \mu r) * 100$ and $CVR = (\sigma R / \mu R) * 100$, where σr and σR are respectively the standard deviations of the corrected 3D measurement for the repeatability and reproducibility datasets and μr and μR are respectively the average 3D measure of the repeatability and reproducibility data. With the same idea, repeatability of the manual method was estimated by making measurements three times the same day, by the same operator with the same ewe. Reproducibility was estimated by making measurement by three operators with twelve ewes, with only one measurement per ewe. All the data analysis were performed using the statistical software R.

Results and Discussion

Validation: Comparison between 3D images and manual measures

The measurements obtained from the 3D image of an animal were compared with those collected manually on ewes. Each average measurement on 3D images was per animal subtracted from the manual measure average. A confidence interval was calculated for each measurement: if it is not centred on 0, this means that a bias exists between the two methods. The amplitude of this interval provides information on the average deviation in centimetres. A coefficient of variation was also calculated to estimate this deviation in percent.

Table 1: Comparison between 3D images and manual measures

3D average – Manual average	WH	CW	CD	CC
Confidence interval 95%	[-1.16 ; 3.06]	[1.48 ; 3.1]	[1.39 ; 2.72]	[5.34 ; 8.57]
Amplitude (cm)	4.23	1.62	1.33	3.23
Standard deviation (cm)	3.15	1.20	0.99	2.41
Coefficient of variation (%)	5.09	4.49	2.98	2.47

The confidence intervals are positive, except the wither height: 3D imaging generally overestimates the measurements compared to the manual method. This bias can be explained by the wool that is captured on the 3D images for the measurements but is crushed with the tools for manual measurements (Table 1).

However, the deviation remains small, maximum 4.23 cm for wither height. The coefficient of variation shows a low variation, less than 5%. The 3D imaging seems to be a precise way to get measurements from ewes (Table 1).

<u>Repeatability</u>

Table 2: Repeatability of the two methods

Measurement Average		Repeatability		
		Standard deviation	Coefficient of variation	
Wither Height (WH)	Manual	61.86	1.71	2.76
	OtoP 3D	63.04	1.65	2.62
Chest width (CW)	Manual	26.04	0.89	3.43
	OtoP 3D	28.38	1.07	3.77
Chest depth (CD)	Manual	32.54	0.32	0.99
	OtoP 3D	34.73	0.8	2.3
Chest Circumference (CC)	Manual	94.58	1.29	1.36
	OtoP 3D	101.9	1.56	1.54
Surface (S)	Manual	–	–	–
	OtoP 3D	1.41	0.05	3.22
Volume (V)	Manual	–	–	–
	OtoP 3D	0.08	1.53E-03	1.97

The automatic volume and surface measurements show the variability resulting from the 3D images cleaning. The others show the variability of the manual steps (cleaning and measurements on 3D images). In both cases this variation is small, less than 2% (Table 2). The 3D imaging method with the OtoP 3D prototype appear to be repeatable. The coefficients of variation of manual method and OtoP 3D method are similar for the repeatability except for the chest circumference. This can be explained by the different positions of the animals on the 3D images and the difficulty of finding a reliable reference point to make the measurement on the 3D images.

For Otop 3D method, the values of reproducibility are quite comparable to those for repeatability. Changing operators seems to have no impact on the measurements on 3D images. The variations observed for the manual method are higher than repeatability variations. The manual measurement of an animal seems to be hardly reproducible, and a real difference exists from one operator to another depending on his experience and habit (Table 3).

<u>Reproducibility</u>

Table 3: Reproducibility of the two methods

Measurement Average		**Reproducibility**		
		Standard deviation	**Coefficient of variation**	
Wither Height (WH)	Manual	60.63	6.14	10.13
	OtoP 3D	66.12	0.77	1.17
Chest width (CW)	Manual	25.40	3.75	14.78
	OtoP 3D	29.01	0.17	0.57
Chest depth (CD)	Manual	31.78	4.40	13.86
	OtoP 3D	32.93	0.51	1.56
Chest Circumference (CC)	Manual	93.22	7.31	7.84
	OtoP 3D	97.74	0.26	0.27
Surface (S)	Manual	–	–	–
	OtoP 3D	1.51	0.02	1.6
Volume (V)	Manual	–	–	–
	OtoP 3D	0.08	2.36E-04	0.3

Conclusions

The 3D images taken by the OtoP 3D prototype allowed the acquisition of the animal's measurements with almost the same measurments than manual method. These 3D measurements are not totally identical to the manual measurements, but they are comparable. They are generally overestimated because they are less adaptable to the animal's morphology and wool. These measurements, like manual measurements, are very repeatable for an operator. OtoP 3D measurements are not subject to operator bias and are much more reproducible than manual measurements. 3D imaging makes it possible to immortalise the animal at a given moment, and this allowed to keep safe operators and get more repetable and reproducible measurements. This new technology is very promising and it possible to consider many valuations as automatic BCS, automatic and low cost estimation of body weight, measurement of the surface and / or the volume of the animal…

Acknowledgements

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POSTER SESSION

Cows

Application of a simulation model to test milking management strategies in an Automatic Milking System

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Abstract
We used a published simulation model to create a herd of cows, simulate several milkings for those cows and create quarter milk flowrates for each milking to derive quarter and cow milking durations and box duration in an automatic milking system (**AMS**). Then, we applied several teatcup removal settings to the simulated quarter milkings to predict their impact on quarter and cow milking duration and box duration in an AMS. The settings were teatcup removal at 0.2 kg/min, 0.4 kg/min and 0.6 kg/min; or 20%, 30% and 50% of the quarter's 30 s rolling average milk flowrate.

Quarter milking duration was reduced by 9% for teatcup removal at 0.4 kg/min and 19% for teatcup removal at 0.6 kg/min compared to 0.2 kg/min. Box duration was reduced by 4.4% for teatcup removal at 0.4 kg/min and 6.5% for teatcup removal at 0.6 kg/min compared to 0.2 kg/min. Quarter milking duration was reduced by 7% for teatcup removal at 30% of the average milk flowrate and 16% for teatcup removal at 50% of the average milk flowrate compared to 20%. Box duration was reduced by 3% at teatcup removal of 30% of the quarter average milk flowrate and 8% at teatcup removal of 50%, compared to 20%. These results show that the quarter milk flowrate simulation model is a useful tool to examine the effect of milking management practices on milking efficiency of AMS.

Keywords: teatcup removal, quarter milk flowrate, simulation, automatic milking system, milking efficiency

Introduction
Milking represents one the most important tasks on dairy farms, accounting for roughly a third of the farm's total labor demand (Deming *et al.*, 2018). Farms using Automatic Milking Systems (AMS, robots) usually require a large initial capital investment which results in the need to achieve high levels of milking efficiency to justify the technology used. In AMS, an important driver of profitability of the system is related to the milk harvested by the robot each day. This, in turn depends on the number of cows milked and the number of milkings per cow per day (Castro *et al.*, 2012). Since the box-style AMS can milk one cow at a time, each individual milking is important and therefore milking management strategies that can optimize cows milked per day and milk harvested per AMS/day have an impact on system profitability. Strategies such as increasing the teatcup removal setting (i.e., testing different milk flowrate switch-points for teatcup removal; Krawczel *et al.*, 2017; Silva Boloña *et al.* 2019) can reduce individual milking duration and optimize the capacity of the AMS. Additionally, quarter milking

information has become available with the use of AMS which creates the opportunity of exploring milking management practices at the quarter level to improve milking efficiency.

Some of the challenges around testing different teatcup removal settings in cows milked with AMS are related to the lack of repeatability of experiments, difficulty to control for certain parameters (for example milking interval) or the requirement of long periods of observation (Halachmi *et al.*, 2009). Therefore, sometimes it is preferable to resort to modeling techniques or simulation.

The objectives of this research were to use the model developed by Silva Boloña et al. (2022) that simulates a herd of cows with several milkings and each with their quarter milk flowrates in 1 s intervals, to apply different teatcup removal settings and predict its impact on quarter and cow milking duration and box duration in an AMS.

Material and methods

The model developed and published by Silva Boloña et al. (2022) simulates a herd of cows, each with an assigned parity, days in milk (DIM) and cow milk production rate (kg/hr). Additionally, we simulated several milkings for those cows by randomly assigning a milking interval to each milking. Multiplying milking interval by the cow's milk production rate, allowed for estimation of accumulated milk yield available for harvesting at each milking. Each quarter of the cows was assigned an accumulated quarter milk yield considering the proportion contribution of front and rear quarters to total milk yield. With the data of milk available for harvesting at each milking at the quarter level, we were able to simulate quarter milk flowrates in 1 s intervals (kg/min) for each milking.

Quarter milk flowrates were used to estimate quarter milking duration. By adding an attachment time for each quarter, we estimated cow milking duration as the time from the first quarter attached to the last quarter detached. Finally, we modelled box duration by adding a random preparation time to each cow milking (see Figures 1 and 2).

We used the simulation to evaluate the effect of teatcup removal settings on quarter and cow milking duration and box duration. By applying this model we can test the impact of several milking management strategies on milking efficiency and therefore expand its usefulness. We modeled a set of quarter level absolute milk flowrate-based settings on the simulated milkings. These consisted of removing teatcups at 0.2 kg/min, 0.4 kg/min and 0.6 kg/min. We also modeled a set of quarter level percentage-based settings that consisted of removing the teatcups at 20% of the quarter's 30 s rolling average milk flowrate, 30% of the quarter's 30 s rolling average milk flowrate and at 50% of the quarter's 30 s rolling average milk flowrate. Results were analyzed with a mixed model to assess the effect of treatment on quarter and cow milking duration and box duration. The mixed model accounted for the fixed effects of treatment, DIM, parity, milking interval and the random effect of cow.

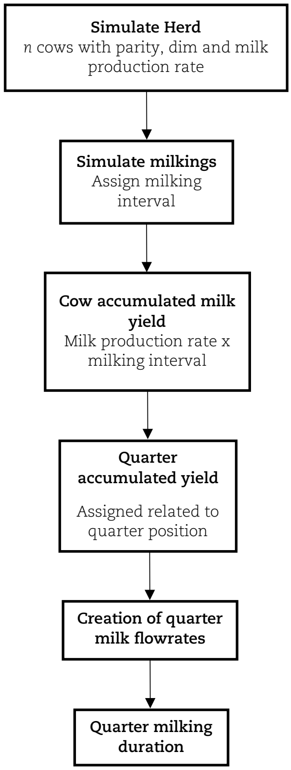

Figure 1: Workflow of the simulation model. The model created a herd of *n* cows with their corresponding parity, days in milk and cow milk production rate. Several milkings of each cow were simulated by assigning a milking interval to each cow milking. Milking interval multiplied by cow milk production rate resulted in cow accumulated milk yield. Each quarter was assigned a fraction of cow accumulated milk depending on position to obtain quarter accumulated yield. This value helped construct quarter milk flowrates for each cow milking. With the milk flowrates, quarter milking duration was calculated.

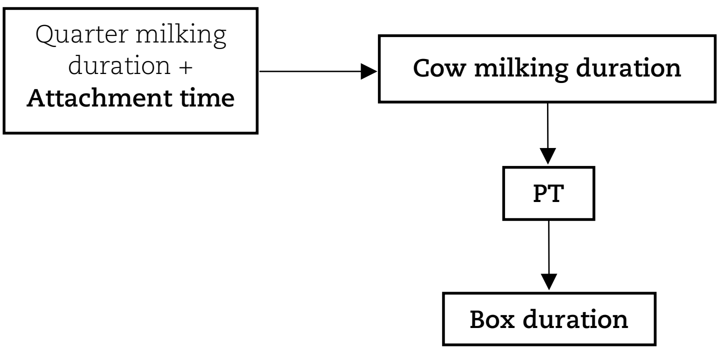

Figure 2: Calculation of cow milking and box durations in the simulation model

Results and Discussion

We found statistical difference between all the teatcup removal treatments on quarter milking duration, cow milking duration and box duration. For quarter milking duration we found a 9% difference between using a 0.4 kg/min switch-point compared to 0.2 kg/min. Milkings under the 30% teatcup removal treatment had 4% shorter cow milking duration than in the 20% teatcup removal treatment. Additionally, we found a 3% difference in box duration between teatcup removal at 20% of the rolling average milk flowrate and 30% of the rolling average milk flowrate. The treatment where teatcups were removed at 50% of the average milk flowrate had a 6% and 10% lower cow milking duration compared to the 20% and 30% treatments respectively. Results of this application of the simulation model are summarized in Table 1.

Table 1: Effect of quarter teatcup removal settings on quarter milking duration, cow milking duration and box duration

Treatment	20%	30%	50%	0.2 kg/min	0.4 kg/min	0.6 kg/min	P-value
Quarter milking duration (s)	259^{a}	241^{b}	218^{c}	209^{a}	190^{b}	170^{c}	< 0.001
Cow milking duration (s)	498^{a}	480^{b}	450^{c}	419^{a}	403^{b}	387^{c}	< 0.001
Box duration (s)	590^{a}	573^{a}	543^{b}	512^{a}	495^{b}	479^{c}	< 0.001

0.2 kg/min = teatcup removal at 0.2 kg/min; 0.4 kg/min = teatcup removal at 0.4 kg/min; 0.6 kg/min = teatcup removal at 0.6 kg/min; 20% = teatcup removal at 20% of the average flow rate; 30% = teatcup removal at 30% of the average flow rate; 50% = teatcup removal at 50% of the average flow rate.
Different letters represent differences at the α=0.05 level

Application of the teatcup removal settings to the simulated milkings showed similar results to other trials in the literature for cow milking duration and box duration (Krawczel et al., 2017; Silva Boloña et al. 2020). The absolute magnitude of some of these effects (as opposed to the percentage magnitude) was different between our simulation results and the ones obtained by Silva Boloña et al. (2020) trial, most likely due to different experimental conditions leading to basal differences in milking duration and milk yield. However, these results show that the model can be applied to predict the impact of certain milking management strategies on milking efficiency.

Conclusions

We used a previously developed simulation model that simulated several milkings of a herd of cows. These milkings were simulated based on quarter milk flowrates which helped estimate quarter and cow milking duration and box duration. We applied several quarter teatcup removal settings to this simulation. Model application showed that quarter milking duration could be reduced by 9% when increasing the flowrate for teatcup removal from 0.2 kg/min to 0.4 kg/min. By using a teatcup removal setting of 20% of the quarter's rolling average milk flowrate, quarter milking duration was 4% longer than by using 30% of the rolling average flowrate.

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Calibration and quality assurance of accelerometer data for monitoring dairy cow behaviour: procedures and challenges

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Abstract

The use of accelerometers is an integrated part of available commercial systems for monitoring dairy cows. Because ear-tagging of cows is required by law, and braces and belts constitute additional materials and costs, the Intelligent Ear Tags project intends to investigate the utility of acceleration data collected by ear tags for monitoring purposes. Ear tags were placed on 14 lactating cows between October 31, 2020 and January 6, 2021, for a total of 558 cow-days. Acceleration data in three dimensions were recorded at a rate of 10 hertz and sent by RFID to a server, resulting in 864000 rows of data/day. Cameras were placed in the barn, so selected behaviours could be associated with the data. To ascertain the synchronization between timestamps from the data and video-servers, all ear tags were shaken in front of a camera for 10 seconds. The start and end-time of each shaking bound in the videos and of the corresponding disturbance in the data were compared. In this paper, we aim to describe the procedures and challenges related to ensuring the quality of the collected data. A total of 320 (57.4%) cow-days of data passed the quality test, 208 (37.3%) datasets were not generated, and 30 (5.4%) did not meet data quality standards. Main challenges included inconsistent timestamps, battery life, temporary interruption in transmission, missing values, and unnatural linarites in the data.

Keywords: accelerometer, dairy cattle, data quality, ear tags, monitoring

Introduction

The daily behaviours and activity patterns of cows are closely connected to their health status and productivity (Bikker *et al.,* 2014), and changes in those patterns have been used as an indication of oestrus or the onset of diseases (Yeikser *et al*., 2012; Hendricks *et al.,* 2020). The previous two decades have seen an increase in research and commercial products in the field of wearable electronic monitoring technologies (Hendricks *et al.,* 2020), which can be used in farming environments, allowing cattle to be monitored without interfering with their natural behaviour (Borchers *et al*., 2016). Accelerometers are the most common type of device used for this purpose, with several commercially available options of leg braces, nosebands, collars, or ear tags (Caja *et al*., 2016; Chapa *et al*., 2020; Hendricks *et al*., 2020). Since, by EU regulation (2019), all cows need to be ear-tagged, a system based on ear tags makes for an option that does not require the extra equipment necessary for the other devices. For precision monitoring to be efficient, the measurements collected by the accelerometers must be accurate, and the data generated by them must be reliable. Past studies have mainly focused on validating the algorithms and the predictive ability of ear tag-based monitoring systems (Pereira *et al*., 2018; Bikker *et al.,* 2014; Borchers *et al*., 2016; Chapa *et al*., 2020), but an evaluation of the quality of the acceleration data produced by the ear tags is not yet readily available or published. The Intelligent Ear Tags project (GUDP, J.nr. 34009-17-1249) includes the objective of investigating the utility of acceleration data collected by ear tags for monitoring purposes.

Material and methods

The data analysed here corresponds to the latest iteration of the ear tags produced. Previous prototype batches were evaluated in the same manner described here, but failed at earlier stages.

Acceleration data

The data were collected at a Danish dairy herd located in northern Funen, Denmark. The herd was composed by 340 dairy cows, 380 heifers and 10 bulls, all pure- or crossbred Danish Holstein. ADXL363 accelerometers (Analog Devices Inc., 2013) were placed inside plastic ear tags and encased in epoxy resin, to reduce the exposure to shock, water and other substances.

The tags registered acceleration in G-force units (multiples of 9.82 m/s^2) in three dimensions (X, Y, Z), and transferred the data by radio frequency (RFID) to a server located in the barn. The data were recorded at a rate of 10 hertz, meaning one row every 0.1 second, and corresponding to 864000 rows of data over a period of 24 hours. The data files were automatically uploaded to a Dropbox account once a day.

A set of seven tags (from here on referred to as 71-75, 77 and 79, or Group 1) were initially mounted on dairy cows between the 31st of October and 13th of November, 2020. Tags 72, 75, 77 and 79 did not function from the start, so they were discarded from further descriptions and analyses. A second set of six tags (70, 76, 78, 80, 81 and 82, Group 2) were placed on November 17th, and the last five tags (83-87, Group 3) were placed between November 26 and January 6. In total, 14 tags attempted to collect data during 65 days (not all tags running simultaneously), resulting in 558 cow-days.

Data quality assessment

Each ear tag produced one dataset every 24 hours. Four main types of data issues were evaluated, before a dataset was considered useful: dataset creation, number of rows, missing data and presence of non-intended linear blocks.

Dataset creation

For every cow-day, a data file in a proprietary *.dat* format should be present in the Dropbox folder. Before the data could be used, the *.dat* files were converted to *.csv* format using the program TagLogConverter version 3.5, a proprietary software developed by the company producing the ear tags. Instances where a dataset was not available, or when a *.csv* file could not be produced due to corrupted *.dat* files, were considered under this category.

Number of data rows

Failure in the number of rows comprises instances when the converted *.csv* file contained less than 864000 rows. The ear tags should be able to store at least 24 hours of data before transmitting, in order to avoid data loss in cases where transmission fails, or when the cow is temporarily located too far from the RFID receiver. The batches of data contained in this buffer should be automatically transmitted when the tag is in range again. However, the dataset is created by initially reading the timestamps of the first and last observations for the day, and building an array to fit the data collected between those two. Missing observations in the beginning or at the end of the day may result in datasets which are shorter than expected. A dataset was considered complete enough to be used when more than 90% of its rows were present.

Missing data

The accelerometers were calibrated to a measurement range of ±2 G, so expected values should be in that range. After the initial dataset array was built, all fields were filled with the value 20, and then overwritten with actual observations. Whenever a pulse was transmitted, but no values were received, the fields remained filled with the number 20, indicating a missing value. Datasets were considered usable if they contained less than 10% missing values.

Linear blocks

Instances occurred (and the reason is still unclear) in which rows contained linear interpolations of values generated by the ear tag between two real values. Those blocks were identified by running linear regressions over a moving window of 10 seconds (100 rows). The data was considered as fitting a linear model when an R^2 value of 0.8 or higher was estimated. As those were not considered true values, a dataset was considered usable if it contained less than 10 % of rows belonging to linear blocks.

Video data

Five cameras were placed under the roof covering the whole length of the barn section where the tagged cows were housed. Those cameras recorded 24 hours per day, and the video files were stored online in a server belonging to the company responsible for the video monitoring. The videos could be playback or downloaded using XProtect Smart Client (Milestone, 2019).

Calibration of video and acceleration timestamps

The client software used to play recorded video displays the time directly, while the data sets sampled from the ear tags contain timestamps for each recorded sample. Both systems provide timestamps with a resolution down to one millisecond. Since the two systems are provided by different suppliers, it was important to ensure that they were time-synchronized in a manner befitting this project. In order to investigate and determine potential time discrepancies, which needs to be accounted for in post-processing, a synchronization experiment was performed before tagging the cows.

A *shaking session* was defined as the process of shaking all the tags available on that day, following the procedures described next. For each session, all tags were aligned on the floor, and made to stand still for at least 10 seconds. Each tag was then picked up and, after standing still for 10 seconds, shaken with the arm standing up, so the start and finish of the shaking bound was detectable on the camera image by the arm shooting up, and then down again. The tags were identified by a sign with the tag's number being held up at the same time as it was shaken. The signs were held by a person standing next to the person shaking the tag. Each tag was shaken for 10 seconds, stopped for five seconds, and shaken for another 10 seconds. Five seconds standing still were then awaited, before setting the tag down again. The next tag was picked up, and the process was repeated until every tag had been shaken. Depending on the time availability on the day, between one and three shaking sessions were performed, with intervals between sessions varying between 30 minutes and 1 hour.

Analysis of the calibration tests

The datasets from the ear tags provide acceleration in three dimensions. For the purpose of this experiment, those were unified as their Root-Mean-Square (RMS) value, to depict a dimensionless curve of the accelerations over time.

The video client was used to determine the exact video-time for when each shaking session started (arm shooting up) and ended (arm coming down again). Those time points were used to colour plots of the acceleration RMS curves, where a perfectly calibrated match would have the colour changing precisely when the RMS oscillations denoting the shaking started and ended. This approach made it possible to calculate the lag between the systems, and to test whether the mismatches were constant or would drift over time between sessions. Differences of up to one second were considered acceptable. Figure 1 illustrates how mismatches between the timestamp of the ear tags and the videos were determined.

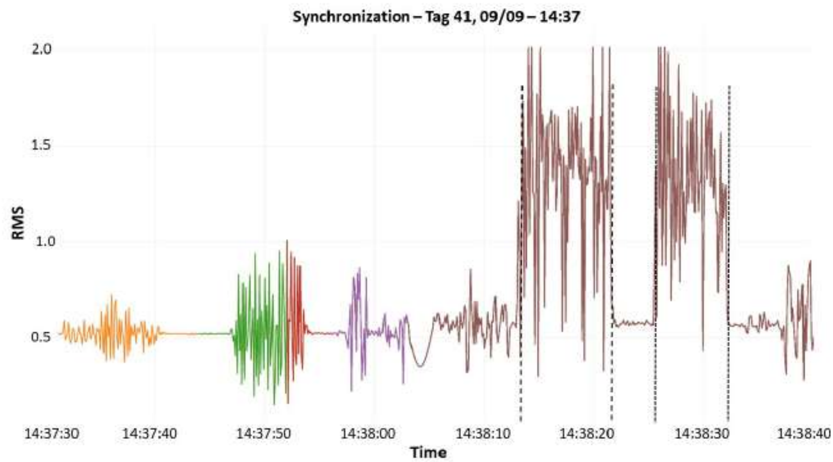

Figure 1: RMS values during a calibration experiment for one ear tag from a previous iteration. The two sets of vertical dashed lines indicate the start and stop of two shaking bouts. The colours indicate the events taking place on the video at each time, according to the time stamps from the videos.

Orange: Before experiment starts. Green: 1st shaking bout. Red: holding the tag still. Purple: 2nd shaking bout. Brown: the tags sitting in the box after the experiment. A mismatch of 29 seconds is seen.

Results and Discussion

Data quality assessment

The summary of when tags were placed and a qualitative evaluation of their performance is shown in Figure 2. Of the expected 558 cow-days, 320 (57.35%) contained data of acceptable quality. The largest observed issue was when datasets were not produced, because the ear tags stopped working due to a short battery life. This was responsible for the loss of 208 of the expected cow-days. The tags were running for an average of 25.50 days (median 25, range 5-51), and produced, on average, 22.86 days (median 22.5, range 5-48) of useful data during that time (Table 1).

Date / Tags	71	73	74	70	76	78	80	81	82	83	84	85	86	87
31/Oct - 4/Nov	x	x	x											
5-7/Nov	x	x												
8/Nov	x	R												
9-13/Nov	x													
17/Nov				x	x	x	x	x	x					
18/Nov				x	x	x	x	L	x					
19-25/Nov				x	x	x	x	x	x					
26/Nov - 11/Dez				x	x	x	x	x	x	x	x	x	x	x
12/Dez				x	x	M	x	x	x	x	x	M	x	R
13/Dez				x	M	M		x	M		M	M	x	
14/Dez				x	x	x		x	x		x	x	x	
15/Dez				x	x			x	x		L	M	x	R/M
16/Dez				x	x	R/M		x	x		x		x	
17/Dez				x	x	R		x	x		x		x	
18/Dez				x	x			x	x		x		x	
19/Dez				M	x			x	x		x		M	
20/Dez					x			x			M			
21/Dez								x	x					
22/Dez								x						
23/Dez					M	M		L	M		R/M			
24/Dez								x			R/M			
25/Dez								x			R/M			
26-28/Dec								x						
29-30/Dez								x			R/M			
31/Dez								x			M			
1-5/Jan								x						
6/Jan								L						

Figure 2: Overview of the experiment. Blocks with the letter "x" indicate days with acceptable data. Grey blocks indicate days when datasets where not produced. The letter "M" indicates more than 10% of missing data, "R" indicates more than 10% of missing rows, and "L" indicates more than 10% of unnatural linearities. Empty blocks indicate the tags were not mounted.

A total of 10 (1.79%) datasets contained less than 90 % of the expected number of rows. The overall mean percentage of rows observed was 97.92 %, and among datasets which failed the test, this number was 38.55 %. A total of 23 (4.12%) datasets contained more than 10 %, missing values. The average percentage of missing values per dataset was 3.25%, and among those with more than 10 % missing, it was 44.65 %. Also, four tags (0.72 %) had more than 10 % of linear blocks in at least one of the three dimensions. Two of the linear block issues occurred for dimension Y (13.93 % and 10.74 % of linear blocks) and two for vector Z (10.61 % and 13.23 %). Several instances were present, in which missing rows and missing values were observed concurrently.

Group 1 tags worked during a relatively short time. Tag 71 functioned normally until November 13 (in a total of 14 days), when it was removed for diagnostics, before more tags could be mounted. Based on what was observed in tag 71, the other tags underwent a re-working of the battery soldering method, to try and prevent early failure, before Groups 2 and 3 were mounted on the cows.

Table 1: Number of days running and producing acceptable data for each ear tag

Group	Tag	Days running	Days with useful data	
			n	%
1	71	14	14	100.0
1	73	9	8	88.9
1	74	5	5	100.0
2	70	33	32	97.0
2	76	37	33	89.2
2	78	37	26	70.3
2	80	26	26	100.0
2	81	51	48	94.1
2	82	35	33	94.3
3	83	17	17	100.0
3	84	31	22	71.0
3	85	20	17	85.0
3	86	24	23	95.8
3	87	18	16	88.9

The second and third groups of tags had longer lives, albeit still shorter than the intended six to eight weeks. Tag 81 was the only one that continued to produce mostly acceptable datasets until the 6th of January, but it was a special case; during the whole period while it was mounted on the cow, it only transmitted seven datasets on sporadic days. When it was dismounted, the data was downloaded directly from its memory, and that is why there are so many useful data days for this tag. Also, its battery most likely lasted longer than the other tags because it did not regularly transmit data. So, although the performance for acceleration measurement and data collection functions was good, the tag did not work from the point of view of automatic monitoring.

Calibration of video and acceleration timestamps

As with the data quality, Group 1 needs to be described separately from Groups 2 and 3. On the 27th of October, tags 71, 73 and 74 were tested, showing an average delay of 2.7 seconds, which was considered substandard, but consistent over all tags. On the 29th of October, the tags were tested again, and had an average of 5.4 seconds delay, again consistent over all tags. These results pointed to a clock-drift, which happens when the local server clock goes out of sync with official time. Depending on how frequently the server time is synchronized with a public time-server, the delay tends to systematically increase until the next synchronization event. Before Groups 2 and 3 were tested and mounted, the issue was fixed by increasing the frequency of time-checks between the two servers. Groups 2 and 3 were tested on November 11th and 17th, and Group 3 again on November 26th. There was no indication of clock-drift between the three days, with average daily delays of 0.9, 0.8, and 0.8 seconds, respectively. The overall average delay for these groups was 0.8 seconds, and the variation around that value for each tag can be seen in Figure 3. Tag 84 tended to show higher delay values than the other tags, but the difference was not significant ($p = 0.2$). It should also be kept in mind that, although the value range seems to fluctuate in the figure, these are decimals of seconds, and therefore, the delay for all tags in those groups was considered acceptable and consistent both within and between tags.

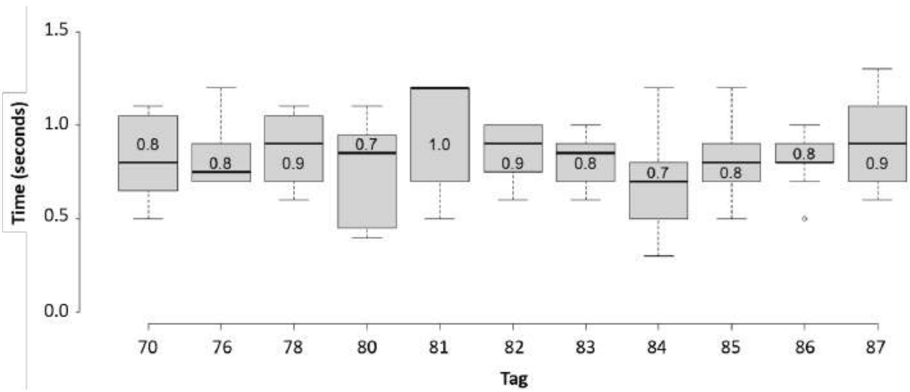

Figure 3: Delay in seconds for ear tags from Groups 2 (70, 76-82) and 3 (83-87). Values in each box show the mean for that tag. Dark horizontal lines show the median, and whiskers show 1.5x the interquartile range.

Conclusions

Considering the number of days actually running, most tags performed quite well, when it comes to producing acceptable data, and nearly all instances of quality loss started happening when the battery started failing. Some tags still produced datasets after "blanking" for some days, but they were mostly useless. Studies focused on a relationship between quantitative measurements of battery life left and the quality of data produced could be useful, so commercial products based on this system would interrupt data transfer when the tag starts failing. This makes battery life the most challenging aspect of this process, particularly if it is expected that data pre-processing or prediction algorithms run inside the tag in the next steps of this project, as that would increase battery consumption and shorten the tag's life even further. It should, naturally, be noted that these were prototypes, and challenges, as well as further improvements, are an expected part of the process. However, the authors recommend that, whenever other studies intend to use raw acceleration data, particularly with associated video or audio features from different systems, a similar process of data quality and between-system time-synchronicity checking is followed.

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Deep neural network applications on pose estimation and action recognition for precision dairy farming

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Abstract

Recent advances in Computer Vision (CV) have yielded great improvements in tasks such as Pose Estimation (PE) and Activity Recognition (AR) and their application to the field of Precision Livestock Farming (PLF) have the potential to enable truly non-intrusive animal monitoring. These systems can help detect health issues by providing detailed behaviour analysis and automatically detect problematic conditions like lameness. Past solutions rely on RFID chips and inertial measurement unit (IMU) to identify and classify cattle behaviour, while existing research of CV solutions for animal PE or AR often focus on scenes with single animals and in very clear conditions. Our work aims to study the capabilities and limitations of Computer Vision systems applied under industrial conditions. We train a Deep Neural Network (DNN) system that can predict the pose of each animal in the image, and to also predict the activity they are performing. Furthermore, we explore the deployment capabilities of these systems in industrial settings by studying the effect of neural network pruning in the inference accuracy and cost of the system in an effort to help future solutions be light-weight and with affordable hardware requirements.

Keywords: activity recognition, pose estimation, computer vision, deep learning

Introduction

The recent advances in the task of activity recognition applied to humans have the potential, if translated to cattle, to enable truly non-intrusive animal monitoring in the field of Precision Livestock Farming.

Pose estimation is the process of predicting the location and orientation of an individual's different body parts (head, body and limb locations and attitude) from a single image. Pose estimation is interesting to us because the information about a cow's pose can support other tasks like tracking or activity recognition. PE is also often considered a segmentation task, as the goal is to accurately identify every pixel that correspond to each of the body parts shown in the image: Body Part Segmentation is the task of, given an input image, partition it into multiple labelled *segments* (sets of pixels or *masks*) that correspond to each body part of the subject in it.

Activity Recognition consists of identifying the action that a certain subject is performing given one or a series of images. It can be performed using multiple types of sensors, but our interest lays only on image-based activity recognition. Past solutions for animal AR often relied on (RFID) chips, accelerometers, magnetometers or inertial measurement units (IMUs) to identify and classify cattle behaviour, which are most commonly attached by using collar systems (Chapa *et al.* 2020). However, the processes of attaching and maintaining these devices can cause the animal certain amount of stress and are labour intensive, they are prone to damage and loss and can actually perturb the normal behaviour of the animal.

In this paper we explore the possibilities of computer vision methods applied to the field PLF, the way of transferring and translating the knowledge of existing architectures and pre-trained models that focus on humans to work on cattle. We also study the limitations of the methods that the quality of the data imposes, that is determined mainly by settings and the environments where the data is acquired.

Related Work

For both tasks at hand, AR and PE, the field is mostly dominated by solutions that focus on human data-sets. Here we discuss some of the methods that are used in the general field of PE and AR and that have also been used with animal subjects.

For PE, using the same approach as for instance segmentation, Mask R-CNN (He *et al.*, 2017) obtained a state of the art result in key-point detection. In their approach, for each of the keypoints of an instance, the training target is a one-hot binary mask where only a single pixel is labelled as foreground.

Li *et al.* (2019) study different methods of CV based cattle PE, and obtain the best result using the stacked hourglass model (Newell *et al.*,2016) when comparing its performance against convolutional pose machine model and the convolutional heat-map regression model.

Past solutions for animal AR often relied on attaching different devices to the animals. For example, authors in Peng *et al.* (2019) attach collar IMU sensors to collect acceleration data. They develop a method using Long Short Term Memory (LSTM) units, a type of recurrent neural network (RNN) algorithm designed to process time series information, and their results show how the LSTM architecture outperforms a Convolutional Neural Network (CNN).

Existing research of CV solutions for animal AR often use handcrafted features that are fed into algorithms like Support Vector Machine (SVM) or different neural networks. Additionally, usually their data is composed by images taken under very good conditions, in which the scene does not contain a big number of animals, the lighting conditions are optimal, and there are no obstacles that occlude or hide the animals.

An example of handcrafted features used for video classification is the proposed method in Guan *et al. (*2020), that are used to classify their position and actions.

Recent research of behaviour analysis focuses on the time series aspect of the task by extracting the spatio-temporal features present in videos. This mainly involves the use of 3D convolutions that try to capture spatial information from several frames at the same time, or incorporate motion information by using Optical Flow (OF) methods.

In this fashion, the authors in Fuentes *et al.* (2020), inspired by the approach of Carreira *et al.* (2017), build a 2-stream 3D convolutional network in order to recognise the behaviour of cattle and classify it in 15 different categories.

In Quiao et al.(2022), authors use a 3D CNN to extract spatio-temporal features directly from video, that are then fed to a ConvLSTM module, an extension of LSTM units that involve convolutional operators, to further exploit these features.

Material and methods

Data acquisition and annotation

The data-sets for both tasks consist of images of a research dairy farm taken by surveillance cameras. The area recorded is a roofed pen of around 570 m^2 that presents real life conditions that could be found in any other farm, with natural and artificial lighting, a variable number of cows varying in size, age, stage of pregnancy, etc. The cows and calves present in this area belong to two different races: most of them are of the Simmental breed, while some of the cows belong to the Holstein-Friesian breed.

For the development of this project, 7 cameras where placed on the structure of the pen to record the behaviour of the cattle present. The cameras record video at 25FPS with a 1920 x 1080 resolution. For the creation of the data-sets, the images where resized to a lower resolution in order to lower computational costs, and, following the usual methodology, extracted 1 frame every second, according to the reasoning that the slow movement of the cows makes this 1FPS sampling strategy miss little detail.

For activity recognition, we chose 8 of activities in which to categorize the cattle behaviour, in a similar fashion as Fuentes *et al.* (2020), Peng et al. (2019) or Quiao *et al.* (2022). With these we aim to capture the most relevant and common activities of the cattle so the system returns an accurate classification and we do not miss any important behaviour. Those categories are: walking, stand, resting eating, standing up, lying down, self-grooming and social. The last is a placeholder for social behaviours when the animal interacts with another, e.g. social licking or headbutting.

Figure 1: a example image extracted from the dataset. The bounding boxes around each animal and the keypoints locating each of their body parts are shown.

For the task of pose estimation, we decide to describe the "skeleton" of each cow using 16 different keypoints: muzzle, forehead, pin, withers, left and right shoulder, left and right knee, left and right front hoof, left and right stifle, left and right hock, left and right rear hoof. Following the COCO (Lin *et al.*, 2014) annotation format, each image has an entry that locates every cow via its bounding box and the location of every keypoint, with an additional flag that tells the learning algorithm if it is visible or not.

Figure 1 shows an image illustrating the information contained in the data-sets annotation process with each animal. For every cow present in the image, the bounding box is defined, the body part key-points localized, and (although not pictured) the activity they are performing annotated

Object Detection Algorithm

For both tasks discussed in this paper, an object detection model is necessary to build a baseline to compare with and use as a starting point to evolve a new architecture.

For that purpose, we choose Faster R-CNN due its popularity, ease of implementation and existing supporting tools. To describe how it works, we have to describe how it evolved from the first iteration: Region-based CNN (R-CNN) (Girshick *et al.*, 2014). It was one of the earliest object detectors based on neural networks. It falls into the 2-stage detector category: it first extracts a fixed number of region proposal or Regions of Interest (ROIs), which are then fed to a neural network (by then AlexNet or VGG16) to extract features that are the input of a final SVM classifier.

The next iteration, Fast R-CNN (Girshick, 2015), replaced the SVM with Fully Connected (FC) layers that made localization and classification much more efficient by sharing CNN computations.

The third iteration of this architecture, Faster R-CNN (Ren *et al.*, 2015), extended this approach by replacing the slow region proposal module with a convolutional region proposal network (RPN) that uses the same layers as the detection network. The architecture then splits into two different heads that locate each object and find the right classification for each one. The unification of the networks makes training much faster and, thanks to concept of separating the main body of the architecture from the heads, the framework can be customized in many different ways, making it one of the most popular in the computer vision field.

Cattle Pose Estimation

In this paper, we try to solve the problem of PE for cattle with multiple individuals in the image. For this, we make use of two popular architectures: Mask R-CNN and Stacked Hourglass.

Mask R-CNN is an extension of Faster R-CNN incorporates an additional head to the architecture to perform image segmentation in order to detect the body parts present in the image. Its output is a series of image masks that encode if each of the image pixel belongs to a certain body part.

Inspired by Li *et al.* (2019), we compare the performance of stacked hourglass architecture against Mask R-CNN and study how it behaves against the challenges of different image scales, occlusions and crowded scenarios found in real farm scenarios.

In order to evaluate the performance of these algorithms, we follow common methodology in PE and use the Percentage of Correct Keypoints (PCK) measure. It is defined by the proportion of detentions made by the model that fall within a normalized distance to the annotated ground truth, which is often a fraction of the size of the bounding box or distance between two relevant keypoints such as, in this case, the muzzle and the forehead.

Cattle Activity Recognition

Our goal is to develop a method that performs cattle behaviour recognition in video containing several individuals. In order to evaluate its performance we propose different architectures that perform 1) single-frame level activity recognition using R-CNN, 2) multi-frame level AR based on 3DCNN, 3) 2-stream multi-frame level AR using 3DCNN.

Frame level AR. The goal of this first method is to serve as a baseline to compare the other methods. Taking an existing object detection architecture, our aim is to train a it to recognize the activity the animals are performing by looking at a single video frame. For this purpose. we used Faster R-CNN with a ResNet backbone and a FPN for region proposal network.

Multi-frame level AR. We extend this approach to incorporate spatio-temporal information across different consecutive video frames. The objective is for the algorithm to extract spatial features of each frame and aggregate them in order to obtain a representation of the scene that incorporates both image and time information. For that, we take the Faster R-CNN and attach a 3D ROI pooling head to merge the features of the different frames, locate each animal in the picture and classify its behaviour.

2-Stream Multi-frame level AR. Another common way of incorporating temporal information is to implement a second branch in the architecture that is fed motion information. Following the most common methodology, for each frame of the video sequence, we compute the Optical Flow (OF) using the previous frame, and extract features using a CNN, that are merged with those features from the 3D R-CNN branch.

Results

[This result section is pending the conclusion of the experiment regarding the training and evaluation of the different architectures and their corresponding models]

Conclusions

In this paper, we studied the application of recent computer vision advances to the field of precision livestock farming. We studied the state-of-the-art methods regarding the tasks of keypoint detection for pose estimation and activity recognition, and researched.

Regarding pose estimation, the comparison among the different architectures concludes that using [Faster R-CNN/ Hourglass] architecture obtains a relevant advantage.

Our results show that the incorporation of temporal information and motion information to detect the activity of cattle has a [positive / negligible / negative] impact on the accuracy of the models.

Regarding training time and dataset size, we obtain best results when using a X number of training iterations with X number of training samples. Data augmentation techniques [do / do not] a significant improvement on model accuracy. The models perform [well / badly] in crowded scenes with many cows present and occlusions.

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Development and validation of a new method to attach HOBO-loggers to the cows' legs

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Abstract

HOBO-loggers (HOBO Pendant G logger, Onset Computer Corporation, Bourne, MA) are accelerometers with gyroscope function. They were originally designed for industry use, but there is evidence that they are suitable for estimating, e.g., the lying time of cows using an instantaneous sampling technique (once per minute). The standard operating procedure for mounting HOBO-loggers to the legs of animals is time-consuming and includes applying bandage material, which cannot be reused after one measurement period. This study aimed to develop and validate a new, reusable method to attach the data logger to a cow´s leg. It consists of a small textile bag with hook-and-loop closure that is fixed to a common ankle strap for cows. The study was conducted at the Teaching and Research Farm of our University in 2020 and 2021. In the first step, a prototype was developed and tested on ten lactating cows for fourteen days in order to assess the bags robustness, stability and tolerability. Adaptions were necessary to ensure a stable position of the logger. For the validation part, ten lactating cows were equipped with two HOBO-loggers at the same time (conventional bandage method on the right, new method on the left hind leg) for seven consecutive days.

Preliminary results showed almost perfect correlation (CCC > 0.99, r_s > 0.99) of summed hourly lying times (900 pairs) between both methods. The bag was robust and well tolerated by the cows. These findings indicate that the new mounting method can be useful for research purposes.

Keywords: cows, behaviour, standing and lying, sensor, accelerometer, fixation

Introduction

Monitoring the herd health in dairy farming is key for a high production level. Several approaches have been suggested for using lying behaviour of dairy cows as a measure for animal health and welfare. Prior work has shown that at least three consecutive days are needed to assess the lying behaviour of a dairy cow herd (Ito *et al*., 2009). For continuous monitoring of cow behaviour many Precision Livestock Farming (PLF) tools are available (Stygar *et al*., 2021). Especially for research purposes, high accuracy of the behavioural classification is required. Furthermore, flexibility in monitoring frequency and raw data handling are advantageous. Ito *et al.* (2009) evaluated the HOBO-logger (HBL, HOBO Pendant G logger, Onset Computer Corporation, Bourne, MA) to detect standing and lying position in dairy cows. This device is an accelerometer with gyroscope function and was originally designed for industry applications. Several other researchers evaluated or employed this accelerometer in their studies under different conditions (Ledgerwood *et al.*, 2010; Bonk *et al.*, 2013; Sepúlveda-Varas *et al.*, 2014; Borchers *et al.*, 2016; Sepúlveda-Varas *et al.*, 2018). The most frequently reported method for attaching HBL to the cows´ legs requires bandage material, which allows accurate positioning and keeps the logger firmly in place. However, this method has also some shortcomings. Firstly, it is time-consuming and can be challenging in nervous cows. Secondly, the bandage material is not reusable. Especially in long term studies, where the bandage has to be changed regularly, e.g. to manually download the data (Sepúlveda-Varas *et al.*, 2014; Sepúlveda-Varas *et al.*, 2018), this can lead to high costs and a large amount of waste. Finally, a bandage can cause swellings and bruises, if fastened too tight, and it has to be removed completely whenever issues occur. Therefore, we aimed for an attachment method that is reusable, easy to handle and cheap in production. Furthermore, it should be robust and well tolerated by the cows. In terms of data collection, the most important function is to ensure a stable position of the logger. The objective of this study was to develop and validate a new method to attach the HOBO-logger to the hind legs of cows that meets the above mentioned requirements.

Material and methods

All procedures that involved animals were approved by the Austrian Federal Ministry of Education, Science and Research (BMBWF, GZ: 2021-0.236.444).

Experimental farm

The study was carried out in two parts, during the summer of 2020 and spring of 2021. Both parts took place at the dairy cow barn of the Teaching and Research Farm (VetFarm) of the University of Veterinary Medicine Vienna, Austria. Approximately 80 dairy cows are housed in a free-stall barn with cubicles. Cows are milked twice a day in a tandem milking parlour for eight cows.

Sensors and mounting methods

HOBO-loggers are accelerometers that measure tilt values in the x-, y- and z-axes. Data are written to an internal memory. HOBO-loggers are managed and read out via cable connection using the HOBOware (HOBOware, Onset Computer Corporation, Bourne, MA). The logging frequency can be chosen individually prior to the start of a measurement series, e.g. according to the research topic. In this study, the logging frequency was set to once per minute for all three axes (x, y and z). It is possible to collect about fifteen days of continuous data from cows with this setting, limited by the memory capacity of the logger. However, it is recommended to remove the loggers after seven consecutive days to prevent swelling and bruises of the leg. According to the raw data classification procedure as described by Ito *et al.* (2009), it is necessary to place the logger in the correct orientation (x-axis parallel to the ground, facing to the front).

Conventional mounting method

The conventional mounting method (CM) used in this study was similar to the method previously described by Ito *et al.* (2009). The data logger is placed in a foam cover, which is then attached to the cow´s leg using flexible bandage material. The sensor is attached either on the medial side of the left metatarsus or on the lateral side of the right metatarsus.

New mounting method

For the new mounting method (NM), a small bag (11.5 x 7.5 x 0.5 cm) with hook-and-loop closure was designed in collaboration with a local tailor. The bag was made of robust textile and two loops were sewed at both ends in order to be attached to commercially available ankle straps for cows. Different stages of the prototype are shown in Figure 1.

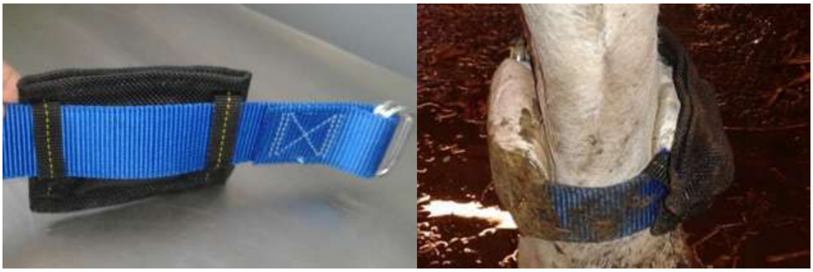

Figure 1: Original version of the prototype (left), final version of the prototype (right)

Due to the small size of the bag, the logger could not turn around inside. In the final version of the prototype, pieces of foam were attached to the ankle strap with adhesive tape on the medial and lateral side of the leg. This had a cushioning effect for the cows and kept the ankle strap and the bag in place.

Study design

The first part of the study was the development of the prototype. After designing and producing the first version of the bag, ten lactating cows, which were already habituated to wearing sensor technologies and handling, were enrolled. Cows were equipped with the data loggers using the NM for fourteen days in total. The trial days were divided into three testing periods. In between, issues with the prototype were discussed and adjustments were implemented.

For the validation experiment, another group of ten cows was selected from the herd, according to their stage of lactation. Cows were equipped with two loggers at the same time for seven consecutive days. One HOBO-logger was fixed according to the CM with bandage material on the right metatarsus. The second logger was mounted with the NM to the left hind leg.

Cows were checked at least twice a day for bruises and sensor position during each study period. These observations were documented for later analysis.

Data preparation

Data from the checks were entered in Microsoft Excel (MS Excel 2016, Microsoft Cooperation, Redmond, USA). Sensor data were read out using HOBOware. Raw data were classified into 'standing' and 'lying' in 1-min time resolution, using a Python script (Python 3.7.9) based on an algorithm described by Ito *et al.* (2009). The script also applied the correction to eliminate erroneous values caused by leg movements during lying or standing bouts adapted from Ledgerwood *et al.* (2010). Classified data in 1-min time resolution were then summed to hourly values [min h^{-1}].

Statistical analyses

Statistical analyses were conducted with the software SPSS (version 27, IBM Corporation, Armonk, NY) and R (version 4.0.4, Copyright 2021, The R Foundation for Statistical Computing). Data were checked for normal distribution using Shapiro-Wilk test and histograms. A confusion matrix was computed for the 1-min dataset. For the visual analysis of agreement, a Bland-Altman plot was created with hourly lying data. Concordance Correlation Coefficient (CCC) and Spearman´s rank correlation coefficient (r_S) were calculated for both datasets.

Results and Discussion

In total, no severe skin lesions, swellings or bruises were observed. Only one cow was observed licking the bandage of the CM on the last day of the validation experiment, but no clinical signs of lesions could be found when removing the bandage. Bags and ankle straps were well tolerated by all cows. In some cases, slight abrasions of the coat underneath the cushion material were detected for NM, probably due to small rubbing movements. None of the bags were damaged during the study. Overall, the NM is considered as robust, well tolerated and suitable for the use in dairy cows.

Development period

Sensor data of the development period were not analysed, because further adjustments were necessary to ensure a stable position of the logger. During this first period, different levels of cushioning were applied. In the next period, the prototype was improved in order to keep the HOBO-logger in place. The development part was completed after six consecutive testing days with no major issues regarding the stability of the NM. Minor adjustments were implemented prior to the validation part.

Validation period

For preliminary analysis, paired sensor data of five cows were available. The dataset in 1-min time resolution consisted of 54,005 data points. Therefore, the 1-hour time resolution dataset included 900 data points. The results of the confusion matrix for sensitivity, specificity, positive predictive value and accuracy were SE = 99.3 %, SP = 99.7 %, PPV = 99.8 % and ACC = 99.5 %, respectively. Table 1 presents the CCC and r_S for the comparison between both methods in 1-min and 1-hour time resolution.

Table 1: Correlation coefficients between the two logger mounting methods based on 1-min and 1-hour resolution. CCC = Concordance correlation coefficient, rS = Spearman´s rank correlation coefficient.

Time resolution	CCC	r_S	N (min)
1-hour	0.997	0.995	900
1-min	0.990	0.990	54005

Figure 2 shows the Bland-Altman plot of hourly lying times, comparing data of two loggers mounted with the two different methods on each cow.

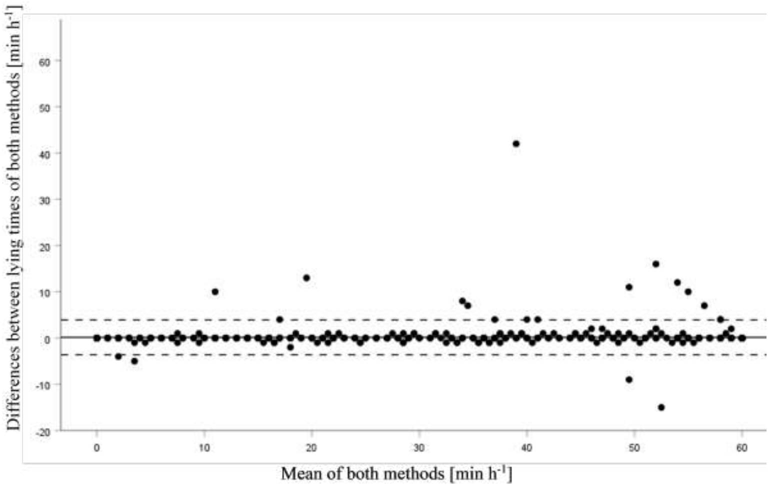

Figure 2: Bland-Altman plot for hourly lying times from both mounting methods

Preliminary results of the validation period show almost perfect agreement of the two loggers mounted on the same cow, as indicated by the correlation coefficients and confusion matrix results. According to the Bland-Altman plot, there is also an almost perfect agreement of sensors attached with the different methods. Ledgerwood *et al.* (2010) validated the HOBO-logger by visual observation as gold standard and reported sensitivity and specificity in a range of 97.4 – 99.3 % and 99.4 – 99.8 %, respectively, using different filter macros to exclude erroneous events.

Preliminary analysis of examination results at regular checks during the validation period revealed the following: Minimal shift of the bag to the back during the whole week was noticed in five cows. In another cow, the bag had completely turned to the lateral side of the leg on the second day. This was probably due to poor initial fixation of the ankle strap, as it did not occur again after tightening. In one cow, the bag was slightly shifted to the back every day and had to be readjusted at almost every check. Nevertheless, even without excluding data from periods when the loggers were slightly out of ideal position for preliminary analysis, the agreement with the CM was almost perfect. This indicates that these minimal changes of position had no influence on the classification of lying and standing behaviour.

As indicated by the observations in this study, NM continues to require regular visual checks of cows and loggers. We recommend checking the correct position of the logger and performing a brief examination of the skin twice a day during measurement periods, e.g. during milking times. Tightening of the ankle strap may be necessary during a study to prevent loosening. One shortcoming of this NM is the required adaption of the cushion material to individual cows prior to a measurement series. This is necessary for the correct position and stability of the bag. However, in cows with similar leg diameter the same ankle strap cushioning can be used without changes. Therefore, the

NM seems to be most beneficial in longitudinal studies, as the ankle strap has to be adjusted only once at the start of an experiment.

One of the practical advantage of the described new method is the easy handling. Once the ankle strap is cushioned and the bag is attached to the strap, the correct position of the logger (x-axis parallel to the ground) is predetermined by the position of the ankle strap. Nevertheless, the user has to take care of the correct position of the logger inside the bag (facing to the front). Further improvements might include the refinement of the cushioning technique in order to facilitate adjusting the ankle strap to individual cows.

Conclusion

Based on preliminary findings and compared to the literature, the NM is considered a comparable to the CM for detection of lying and standing positions in dairy cows. In general, we conclude that the NM is suitable for research purposes. It can be especially advantageous for longitudinal studies, where loggers have to be removed and reattached repeatedly to the same cows. The deployment of this reusable attachment method can help to avoid waste and could therefore be seen as a small contribution to more sustainability in research.

Acknowledgements

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Direct measurements of ventilation rates and emissions on a naturally ventilated dairy barn

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Abstract

In the FACCE ERA-GAS project MilKey, a low cow-cost sensor system for monitoring barn climate and emissions (OTICE) from naturally ventilated barns (NVDB) is developed. In order to validate and assess OTICE, a reference measurement method is needed. This study investigates the feasibility of a direct estimation method for ventilation rates and emissions to serve as a reference measurement method.

Measurements were done in a 1:100 scaled model of a NVDB in an atmospheric-boundary-layer wind tunnel. Tracer gas was released inside the model and measured at the outlet area, using a fast flame ionization detector. Additionally, the normal velocity on the area was measured using laser Doppler anemometry. Overall, for a matrix of 65 x 4 sensor positions, the normal velocities and the concentrations were measured and used to estimate ventilation rates and emissions. This baseline-dataset (BDS) was used to assess the accuracy while systematically reducing the number and varying the positions of sensors.

Compared to the BDS, the results showed systematic errors in the emission estimation up to +97 %, when measurements of concentration and velocity were done at one constant height. This error could be lowered under 5 %, when the concentrations were measured as vertical composite samples.

Based on the results, the method of direct measurements could be indicated as a feasible reference method and will further be used to assess the performance of OTICE in the MilKey project. After validation, OTICE will be a useful tool for a wide application in barn climate and emission monitoring.

Keywords: reference method, wind tunnel, sensor positions, sampling optimization

Introduction

In the FACCE ERA-GAS project MilKey, a low cow-cost sensor system for monitoring barn climate and emissions (OTICE) from naturally ventilated barns (NVDB) is developed for the widest possible application. In order to validate and assess OTICE, a reference measurement method is needed. This study investigates the feasibility of a direct estimation method for ventilation rates and emissions to serve as a reference measurement method.

In dairy farming, accurate measurement of gaseous emissions from naturally ventilated barns (NVB) is an unsolved problem. Emissions from NVBs are usually determined using indirect tracer gas methods, which are subject to high uncertainties (Calvet *et al.*, 2013). An alternative to indirect measurement methods is the direct measurement method (De Vogeleer *et al.*, 2017). Here, the volume flow Q through the barn is measured directly by measuring the incoming or outgoing velocities v at the openings of the barn and then multiplying them by the area A associated with the measurement location per sensor: $Q=v*A$. If the concentration c of the respective pollutant gas is also measured at the respective measurement location, the emission E can be calculated accordingly: $E=Q*c$.

The challenge when using this method is the correct selection of the number and positioning of measuring points. Due to the interaction of weather-related turbulent flow and large opening areas of the NVBs, both velocities and gas concentrations at the opening areas are highly variable. Consequently, a large number of sensors or measuring positions should be aimed at for a representative recording of these measured variables. Economic and practical considerations, however, aim for the smallest possible number of sensors.

The aim of this study is therefore to determine the influence of the number and positioning of the velocity and gas sensors on the achievable accuracy of the direct measurement of emissions. From this, practical recommendations for action for the economical use of the sensors while maintaining a high level of accuracy are to be derived. The derived results will then be used as the desired reference method for the OTICE system.

Material and methods

The measurements were carried out in an atmospheric boundary layer wind tunnel (ABL-WT). With the help of roughness elements, a turbulent velocity profile was generated that meets the requirements of a moderately rough boundary layer according to VDI 3783/12 (VDI, 2000).

A scaled model of an NVB at a scale of 1:100, which is shown in figure 1, was examined. In the model, the tracer gas ethane was let out at constant source strength through two porous stones in the area of the feeding alley. The model was aligned at perpendicular to the flow, so that there was a pure cross-flow.

The measurements were carried out on the outlet area (green area in fig. 1). Measurements were taken on four horizontal measurement lines (y1-y4 in fig. 1). The width of the four measuring lines was divided into 65 measuring points (MP), resulting in a matrix of 4*65=260 MP. In the following, this set of MPs is referred to as the baseline (BL).

The normal part of the velocity v and the ethane concentration c were measured at each MP until the measurement results statistically converged in each case. The mean values for v and c were then formed for each MP from the measurement data and Q and E were calculated. The total emissions E_{BL} of the baseline were formed as the sum of the emissions from all 260 MP. E_{BL} serves as a reference data set to calculate the relative error ΔE [%] that occurs when the number and position of sensor positions are varied: $\Delta E = (E_{var}-E_{BL}) / E_{BL} *100$, with E_{var} as the measured emission value with the varied configuration.

The variations of two strategies were examined: (I): E_{var} is determined only with sensors at one measuring height (either y1, y2, y3 or y4). The width W of the outlet plane is divided into n sections of equal width. n is increased incrementally from n=1 to 65, for each n, an emission value $E_{var,n}$ is calculated. (II): Proceed as in (I), but the concentration c is not only measured at one height, but as a vertical collective sample of the four sensor positions one above the other.

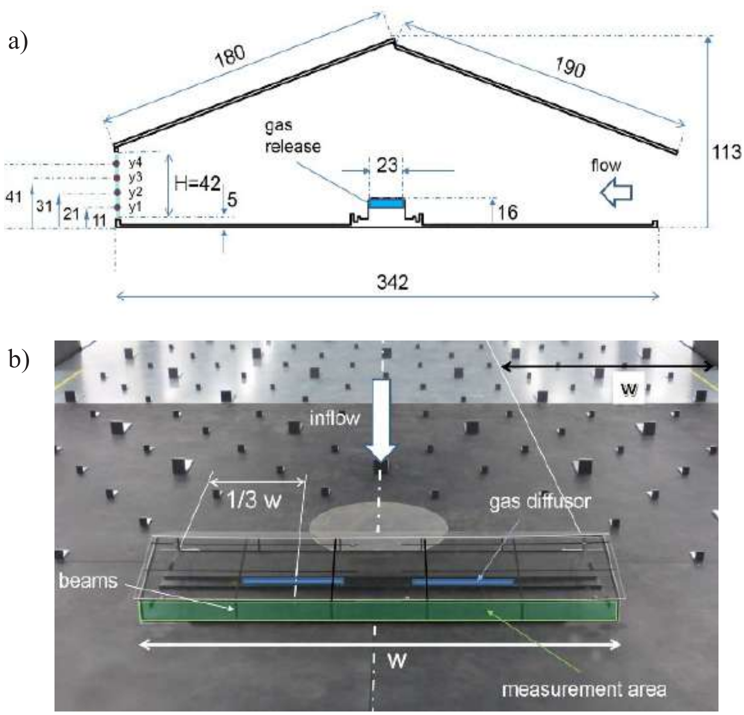

Figure 1: Model of the barn. a) Sectional view, all dimensions in mm. y1, y2, y3 and y4 indicate the heights of the horizontal measurement lines. Blue areas mark the gas inlet. b) Positioning of the model in the wind tunnel. (Janke et al., 2020).

Results and Discussion

The distributions of v, c and E for the BL configuration are shown in Figure 2. The velocity v shows a gradient in the vertical direction, with higher velocities towards the edge of the roof. In addition, at positions 14, 27, 39 and 52 on all four vertical SPs there was a slowdown in speed. This is due to the influence of the pillars of the model ('beams' in fig. 1).

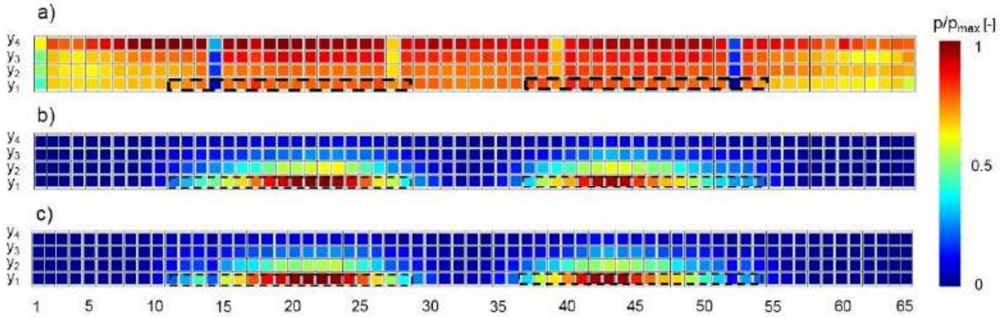

Figure 2: Measured properties at the outlet area. a) Mean velocity u in normal direction. b) Mean concentration c. c) Computed emissions E=Q * c. Results are normalized with the respective maximum values of u, c and E. "p" is a placeholder for the property shown. Numbers on the x-axis index the lateral sampling position (Janke et al., 2020).

The gas concentrations show high vertical and horizontal gradients. Higher concentration levels can be clearly identified in the area behind the two porous gas wells. In this area, the gas concentrations on the lower measuring line y1 are about 14 times higher than on the uppermost y4.

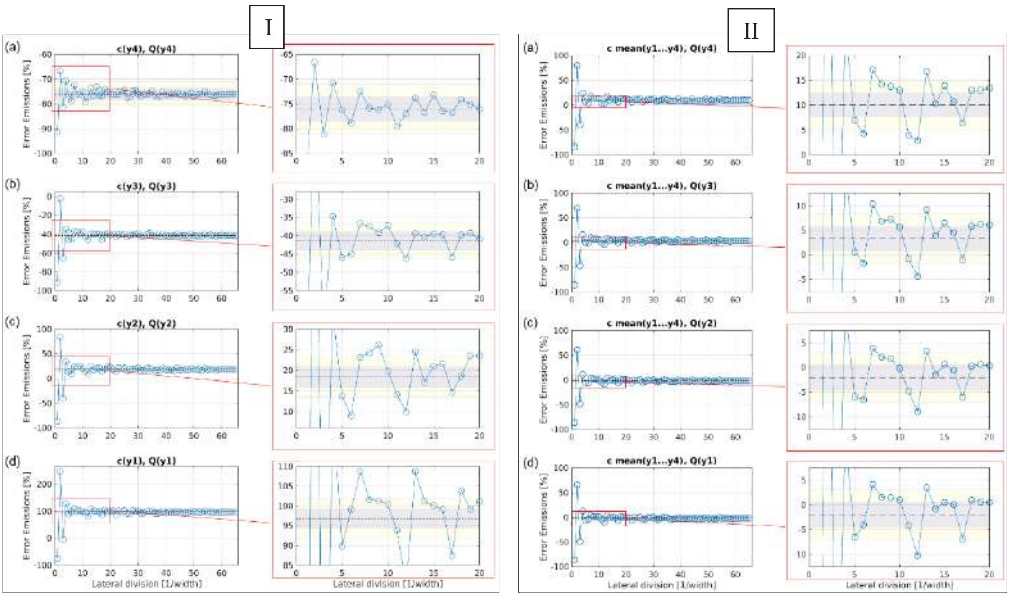

Figure 3: Error development in the emission measurement depending on the number of sensors and their position (lateral division) for sampling variant I and II. Figures a), b), c) and d) each show the relative errors in the horizontal measurement series y1, y2, y3 and y4 (Janke et al., 2020).

The development of the error for the emission measurement as a function of the number and positioning of the sensors is shown in Figure 3. If velocity and gas concentrations are only measured at one measurement height, as in variant I, there is a systematic measurement error of +97% (y1), +18% (y2), -41% (y3) and -76% (y4), depending on the measurement height, if the maximum number of sections or sensors n=65 is used. These relatively large errors mainly result from the high vertical gradients of the gas concentrations. If gas concentrations are measured as a mixed sample as in variant II, there are significantly lower systematic errors for the maximum number of sensors n=65 of -2% (y1), -2% (y2), +3% (y3), or +10% (y4), depending on the measurement height. For variant II, it is possible to reduce the number of sensors while maintaining these accuracies: If, for example, only n=5 sensors were used instead of n=65 sensors, relative errors of -6.5 % (y1), -6 % (y2), +0.5% (y3) or +7% (y4) would result depending on the measuring height.

Conclusion

Due to the heterogeneous distribution of velocity and gas concentrations at the opening surfaces, the gas concentrations in particular should be measured with the highest possible spatial resolution. This can be done economically by using, for example, gas manifolds with critical nozzles that sample a large area of gas mixture around each velocity sensor. If this succeeds, a relatively accurate result can be achieved with manageable effort: in the case shown here, for a barn 100 m long on the natural scale, the emissions with 5 velocity sensors with corresponding gas sampling could be determined with an error of 7%. Based on the results, the method of direct measurements could be indicated as a feasible reference method and will further be used to assess the performance of OTICE in the MilKey project. In case of sufficient performance, OTICE will be a useful tool for a wide application in barn climate and emission monitoring.

Acknowledgments

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Effect of claw block application on locomotion characteristics and weight distribution in cattle

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Abstract

The application of a claw block is a common tool for pain relief and treatment of various foot pathologies in cattle. The aim of this study was to evaluate the effect of the wooden block on locomotion characteristics and weight distribution of healthy (group C; n = 17) and lame (group L; n = 17) cattle. Subjective locomotion scoring and automatic measurements with two acceleromenters (400 Hz; kinematic outcome = stance phase duration; kinetic outcome = foot load and toe-off) and a 4-scale weighing platform (weight distribution and SD of the weight) were performed before and after application of a wooden block on a randomly assigned claw in group C or on the healthy claw of the affected limb in group L. The wooden block significantly reduced lameness score and the differences across limbs in lame cattle during walking, but showed no significant effect on weight distribution while standing.

Keywords: cattle, lameness, claw block, locomotion, accelerometer, weight bearing,

Introduction

Lameness in cattle is often associated with pain in the lower limb and is therefore regarded as a major welfare issue. The application of a wooden block on the healthy claw of the affected limb is a widely known and commonly used method in treatment of cattle with some foot pathologies (Cutler et al. 2015). This study aimed to measure the effect of the wooden block on locomotion characteristics and weight distribution in healthy and lame cattle.

Material and methods

Experimental data

Data were collected of two independent groups of cows. The control group (group C) consisted of 17 dairy cows with a lameness score < 3, using a 1 to 5 numerical rating system (NRS; where 1 = non-lame and 5 = severely lame) according to Flower and Weary (2006). The lame group (group L) included 17 cattle with a unilateral pathology in a front- or hindlimb with only one digit affected. Foot pathologies were described according to the guidelines of the ICAR Claw Health Atlas (http://www.icar.org/Documents/ICAR_Claw_Health_Atlas.pdf).

Measurements of locomotion characteristics

In a claw trimming chute, a wooden block was applied on a randomly assigned lateral or medial claw of the fore- or hindlimb using an adhesive tape in group C and on the claw of the healthy partner digit in group L. Measurements of locomotion characteristics and weight distribution were performed before and after block application. Gait cycle variables of the cow pedogram were measured using two stand-alone 3D accelerometers (400 Hz; USB-Accelerometer X16-4; Gulf Coast Data Concept, Waveland, USA). They were fitted at the level of both metatarsi or both metacarpi, either depending on the location of the pathology in group L or on the location of the randomly assigned wooden block in group C. The gait cycle variables were extracted using the Cow-Gait-Analyzer as described by Alsaaod et al. (2017) and comprised of temporal events of kinematic outcomes (relative stance phase duration) and peaks of kinetic outcomes (foot load, toe-off). Weight distribution across contralateral limbs was measured as described by Nechanitzky et al. (2016), using a 4-scale weighing platform (1.94 × 1.06 m; ITIN & HOCH GmbH, Fütterungstechnik, Liestal, Switzerland).

<u>Statistical analyses</u>

The variables were expressed as the differences across the limbs. A paired-sample t-Test was performed to compare the variables before and after wooden block application within group C and group L, and a one-way ANOVA was used to determine the differences between group C and group L using the statistics package NCSS (NCSS, LLC, Kaysville, UT; http://www.ncss.com/).

Results and Discussion

Table 1: Mean ± SD of NRS, differences in gait cycle variables and Δ_{weight} of lame cattle (group L) versus non-lame cattle (group C) before wooden block application, and within each group before and after wooden block application. Gait cycle variables were calculated as the absolute difference across the contralateral limbs, and weight distribution was calculated as the percentage absolute difference of the mean weight across the contralateral limbs.

	Group comparison before wooden block application		Effect of wooden block within each group			
			Group C		Group L	
	Group C	Group L	before block	after block	before block	after block
NRS	1.87 ± 0.28^a	3.40 ± 0.62^b	1.87 ± 0.28	1.93 ± 0.36	3.40 ± 0.62^a	2.88 ± 0.49^b
Stance phase (%)	2.13 ± 1.94^a	16.34 ± 10.78^b	2.13 ± 1.94	2.87 ± 1.94	16.34 ± 10.78^a	7.66 ± 9.96^b
Foot load (g)	3.26 ± 3.69^a	9.68 ± 8.06^b	3.26 ± 3.69	4.23 ± 3.13	9.68 ± 8.06^a	4.26 ± 4.14^b
Toe-off (g)	0.78 ± 0.66^a	3.91 ± 3.14^b	0.78 ± 0.66	0.99 ± 1.07	3.91 ± 3.14	2.28 ± 1.27
Δ_{weight} (%)	8.52 ± 6.19^a	53.62 ± 28.85^b	8.52 ± 6.19^a	20.69 ± 17.01^b	53.62 ± 28.85	53.11 ± 25.89

^{a,b}Means within a row with different superscripts differ significantly ($P \leq 0.05$); separate analyses for comparison before wooden block application between groups and comparison within each group before and after wooden block application.

Group L had a higher locomotion score and showed significantly higher differences across the limbs in gait characteristics and in weight distribution compared to group C (Table 1). After application of the wooden block, cattle in group L showed a significant improvement in relative stance phase duration and in foot load, but no significant difference was observed in weight distribution variables (Table 1). This means that we observed improvements in parameters measured in lame cattle while walking, but no improvements were found in parameters measured while standing. Therefore, wooden block application should not be used as the only tool for pain relief and support of healing in cattle with unilateral pathologies of the digits. A combination with other methods for pain relief, e.g. analgesic medication, is needed.

Conclusions

This study underlines the usefulness of the application of wooden blocks in treatment of lame cattle and emphasizes the potential and the importance of additional treatment modalities such as administration of analgesics, as lameness is an important issue in animal welfare.

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Estimating pasture dry matter intake of grazing dairy cows from their chewing behaviour as measured by an automatic sensor system

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Abstract

Quantifying pasture dry matter intake (PDMI) of grazing dairy cows is crucial to evaluate their nutritional status and to facilitate precise supplemental feeding. Sensor data on cows' chewing behaviour can be used to estimate PDMI. The aim was to evaluate the adequacy of existing models to predict PDMI on commercial dairy farms in Southwest Germany using semi-natural grassland for grazing. The prediction accuracy of three behaviour-based models (CH, AU, DK) were evaluated using the mean bias (MB) relative prediction error (RPE), partitioning of mean square error of prediction (MSEP), and concordance correlation coefficient (CCC). The reference dataset contained 220 individual animal observations with a mean daily DMI (± standard deviation), PDMI, and milk yield of 21.1 (± 3.2) kg, 12.0 (± 4.9) kg, and 23.9 (± 5.6) kg, respectively. The model AU had the lowest RPE (41.9 %) and greatest CCC (0.57) among the evaluated models, i.e. the greatest modelling adequacy among the three models. Its MB, however, demonstrated a mean underestimation of the observed PDMI by 22 %. Its RPE value > 20 % further served as indicator for unacceptable predictions of PDMI for the reference dataset. The partitioning of the MSEP showed that 59 % of the prediction bias was attributable to random variation in the reference data. This indicated that the remaining bias was likely owing to the model's structural deficiencies, which could be a result of the systematic differences between the grazing conditions of the reference dataset, and the data underlying the models' empirical regression equation.

Keywords: feed intake, grazing management, semi-natural grassland, chewing behaviour, intake models

Introduction

Reliable measurements of the pasture dry matter intake (PDMI) of grazing dairy cows is the key to regulate pasture utilisation. The PDMI constitutes the basis for matching indoor supplementation, and grazing management to biomass availability on pasture, and the animals' nutritional status. Sensor-based recordings of the cows' behaviour can be used as tool to estimate the real-time PDMI of individual, grazing cows. Several studies have attempted to estimate PDMI from chewing behaviour data using empirical regression models. The objective of this study was to test whether such existing behaviour-based models were applicable for dairy cows grazing on semi-natural grasslands. This type of grassland can constitute the predominant feed source for low input dairy farms in semi-mountainous regions, such as found in Southwest Germany. The generally lower biomass yield of semi-natural grassland, and its spatial and temporal variability make supplementation in barn indispensable. Real-time quantification of

PDMI could help preventing an overly substitution of pasture herbage through supplementation in barn. Thus, to evaluate existing behaviour-based PDMI models using data from automatic sensor systems, a reference dataset was gathered on 9 commercial, organic dairy farms in 2019 and 2020. A double-marker technique, using titanium dioxide (TiO_2) as external marker and faecal crude protein (CP) concentration as internal marker, was used as reference method to determine dry matter intake (DMI) and PDMI of the grazing animals.

Material and methods

Model selection

Three behaviour-based PDMI prediction models were found through literature research. The model CH (Rombach *et al.*, 2019) uses behavioural observations from Swiss dairy farms, as well as milk performance, animal characteristics, feed quality, and supplementation parameters to predict PDMI, whereas the Australian model AU (Greenwood *et al.*, 2017) and Danish model DK (Oudshoorn *et al.*, 2013) solely relied on behavioural parameters.

Reference data

In 2019 and 2020, 9 commercial, organic dairy farms were visited during 1 to 2 examination periods per year. Every period lasted 11 days. The TiO_2 marker was fed twice daily throughout the 11 days, whereas sampling of faeces, feed, and milk and behaviour recordings took place on days 6 to 11. Eight to 28 cows per farm and examination period were chosen among the herd for sampling. Jaw and head movements were recorded in up to 10 cows per farm and sampling period by noseband-pressure-sensors with integrated 3-axial accelerometers (ITIN+HOCH GmbH, Liestal, Switzerland, validated for grazing animals by Werner et al., (2018)). The recordings were converted to total number of eat chews per day (i.e. mastication and prehension bites), bite rate (i.e. eat chews per minute of eating time), daily eating time on pasture, and daily number of prehension bites (i.e. only eat bites excluding mastication) in a 1-h resolution, and then averaged across the 6-d period per animal. During days 6 to 11, milk yield was measured and sampled daily, faecal grab samples taken twice daily, offered and refused feed weighed and sampled daily, and bodyweight measured and pasture herbage sampled once per examination period. In the laboratory, faeces samples were analysed for TiO_2 (Boghun *et al.*, 2009) and CP (VDLUFA, 2007; method 4.1.1), and feed samples for CP (VDLUFA, 2007; method 4.1.2). Total DMI was determined from daily faecal output measured using TiO_2 as marker (Glindemann *et al.*, 2009), and the apparent total tract digestibility of ingested organic matter derived from faecal CP concentration (Lukas *et al.*, 2005). Additionally, DMI of supplemental feed in the barn was measured daily, and subtracted from total DMI to estimate PDMI. The measurements of supplemental feed intake in barn were made on herd level. The cows' individual intake of supplemental feed was estimated proportionately to the cows' recorded eating time in barn.

Statistical analysis

The mean bias (MB), mean square error of prediction (MSEP), and relative prediction error (RPE) were calculated to evaluate the accuracy of the models' predictions. The MSEP was calculated as the sum of three error terms, representing the prediction bias, line bias, and random variation, respectively (Fuentes-Pila *et al.*, 1996). The RPE was classified according to Fuentes-Pila *et al.* (1996), who assumed that the prediction accuracy is satisfactory with an RPE < 10 %, acceptable between 10 % and 20 %, and not acceptable with an RPE > 20 %. Additionally, the Concordance Correlation Coefficient (CCC) was calculated to assess the models' adequacy on a scale from 0 to 1, where 1 signifies perfect concordance between observed and predicted values. The CCC was calculated as the product of the Pearson correlation coefficient (r) and bias correction factor (C_b), which evaluate precision and accuracy, respectively (Tedeschi, 2006).

Results and Discussion

Data of a total of 296 individual animals were collected. The final evaluation dataset comprised 220 observations, because of missing records of chewing behaviour, due to technical issues with the sensors, or exclusions if animals refused to ingest daily TiO_2 dosages. For the model DK, 12 more observations were excluded from evaluation, because these were lacking the records of the prehension bites. Mean daily measured DMI (± standard deviation), PDMI, and milk yield were 21.13 (± 3.21) kg, 12.05 (± 5.10) kg, and 23.90 (± 5.55) kg, respectively.

Table 1: Statistical evaluation of behaviour-based models to predict pasture dry matter intake (PDMI) of lactating dairy cows grazing on semi-natural, permanent grassland.

Models	MB[1], kg DM d^{-1}	MSEP[2]	Partitioning of MSEP, % Prediction bias	Line bias	Random error	RPE, %[3]	CCC[4]	R[5]	C_b[6]
CH	3.3	27.1	40.9	7.2	51.9	43.2	0.55	0.68	0.82
AU	2.6	25.5	27.4	13.5	59.1	41.9	0.57	0.65	0.88
DK	-3.1	26.6	36.0	1.2	62.9	42.6	0.39	0.62	0.63

[1]MB: Mean bias. [2]MSEP: Mean squared error of prediction. [3]RPE: relative prediction error, % of observed mean PDMI and DMI. [4]CCC: Concordance correlation coefficient. [5]r: Pearson correlation coefficient. [6]C_b: bias correction factor.

The MB demonstrated that the PDMI was on average underestimated by the models CH and AU by 3.3 and 2.6 kg d^{-1}, respectively (Table 1). The model DK overestimated the PDMI on average by 3.1 kg d^{-1}. The RPE values of the three models ranged between 41.9 and 43.2 %. According to the thresholds established by Fuentes-Pila *et al.* (1996), this indicates a lack of accuracy, i.e. unacceptable prediction values. The r values declared a moderate precision (r = 0.62 to 0.68) for all three models, and the CCC values ranging between 0.4 and 0.6, attested an overall moderate concordance between observed and predicted PDMI (Landis & Koch, 1977). The model AU had the lowest RPE (41.9 %) and greatest CCC (0.57) among the evaluated models, i.e. the greatest modelling adequacy. Based on the RPE of AU and its MB demonstrating a mean underestimation by 22 % of the observed PDMI, it can be concluded that none of the evaluated behaviour-based models achieved adequate PDMI predictions.

The partitioning of the MSEP into the prediction and line bias, and the random error illustrates 51.9 to 62.9 % of the MSEP was attributable to random variation in the data. This substantial share of bias coincides with the possibility that the reference dataset contained measurements errors. These were likely related to the method chosen for estimating the individual PDMI measurements. Due to the on-farm conditions of the current study, the DMI of supplementation indoor was measured on herd level, and the individual DMI of supplemental feed estimated using the individual eating time in barn. Leiber *et al.* (2016), for instance, pointed out the significant variation in eating behaviour between individual animals. They concluded that the eating time was, thus, unsuitable as direct proxy for feed intake. In view of the on-farm approach of this study, however, this method was the most reliable alternative to approximate the variation in individual feed intake in barn. The evaluation of the prediction accuracy of CH, AU, and DK using the mean PDMI across animals per examination period and farm (n = 28), rendered RPE values of 36, 35 and 36 %, respectively. This illustrates that the measurement bias for individual cow observations is not the sole source for the observed lack of prediction accuracy. Further, it is a truth universally acknowledged that it is inherently challenging to measure the actual intake of cows on pasture. The double-marker technique used to determine the PDMI for the current study is therefore an inevitable source of error in the observed PDMI due to its limitations regarding total faecal marker recovery, and faecal sampling (e.g. Hellwing *et al.,* 2015).

Likewise, it can be concluded that at least part of the structural bias, i.e. the MSEP minus the random variation, is attributable to the measurement errors underlying the empirical regressions of CH, AU, and DK: for CH, the n-alkane method was utilised, the measured pasture biomass removal for AU, and for DK, the difference between calculated energy requirements and energy intake from supplemental feed to estimate the PDMI. Another technical issue explaining discrepancies between observed and predicted PDMI depict the used sensors and underlying algorithms applied to converse sensor-based records into chewing behaviour observations. The same sensor than in the current study was used for the CH model, whereas chewing behaviour data for DK, and AU were recorded via accelerometers.

An overfitting of the models' regression equations to the underlying grazing conditions of the modelling dataset is likely another source for prediction bias. The average observed pre-grazing herbage mass used in the model for CH (1206 kg DM ha^{-1}), for instance, exceeded the herbage mass available to the animals of the reference dataset substantially (348 kg DM ha^{-1}). This likely had an effect on the selection and foraging behaviour of animals on pasture, which might explain differences in the chewing behaviour between animals grazing on highly productive or lower yielding pastures. The low biomass availability was also a result of the low sward height observed in the current study (average compressed sward height = 42.4 mm; Grasshopper, True North Technologies, Shannon, Ireland). A decrease in sward height was related to a decrease in bite-mass (Bargo *et al.*, 2003). Differences in sward height can, thus, add a substantial bias to intake predictions if they are based on number of chews or bite rate such as the models DK, or CH.

Despite the low prediction accuracy of the evaluated models for the grazing conditions of the reference dataset, there is clearly a high potential in the use of behaviour-based models to estimate the intake of grazing animals on semi-natural, or improved grassland. A more recent study, for instance, created a model exclusively using a combination of chewing behaviour parameters (Schori *et al.,* 2021). Their model, had an RPE of 15 % for their own dataset. This and the fit of the evaluated models to their respective datasets demonstrate that the use of chewing behaviour sensors can provide reliable PDMI records of individual animals. Due to herd- and management-specific differences in the learned and socially driven behaviours of lactating dairy cows (Illius *et al.*, 2000), it seems that a sensor-based approach is most suitable when the model is adapted on a farm-individual basis. The practical application of such farm-specific, sensor-based models, however, calls for farm-specific records of chewing and intake behaviour. This in turn, might be solved by integrative approaches such as the use of machine learning approaches and applying milk production records as feedback loop to adapt PDMI equations to individual herds.

Conclusions

This paper tested the prediction adequacy of existing behaviour-based models to estimate the PDMI of individual animals grazing on semi-natural grassland. Based on the RPE values (> 20 %), and the MB values for the models CH, AU, and DK indicating a mean under- or overestimation of 28, 22 and 26 % of the observed PDMI, respectively, it can be concluded that none of the three evaluated models were able to predict the PDMI of the reference dataset adequately. Part of the prediction bias was clearly attributable to bias related to measurement errors. But it was shown that systematic differences between the reference dataset, and the models' underlying datasets are also accountable for deviations between observed and predicted PDMI.

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Evaluation of an Arduino based individual water intake measurement system while using InfluxDB and Grafana for integration, storage and visualization of data

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Abstract

Integration, storage and visualization of sensor data is essential for Precision Livestock Farming (PLF) applications. Affordable and easy to integrate sensors and microcontroller (MCU) boards are predestined for cost effective experimental designs. In this research, low budget radio frequency identification (RFID) readers and self-designed antennas were used to identify cattle at a water trough. Additionally, a water flow sensor was utilized to measure the water intake. The RFID readers and the water flow sensor were connected to an MCU development board (Arduino MKR Zero), which was sending the data via local area network (LAN) to the on-site InfluxDB OSS 2.0 time series database (InfluxData Inc., San Francisco, US). Grafana (Grafana Labs, New York, US) was used for data visualization and for alarm notification. Our technical setup allowed monitoring sensor data and providing it to the researchers in real-time. The RFID system was tested for reliability in a pen with 7 animals over a period of 8 days. Out of 7 animals in the pen 2 had RFID ear tags. Throughout the experiment, the water trough area was video recorded continuously. The recorded video was analyzed for drinking events and these results were compared with the RFID data. The maximum reading distance of 35cm of the RFID system was not enough to reliably identify the animals, because the percentage of detected visits to observed visits was 64.3% and 37.5% for the 2 different animals. The use of an RFID reader with an enhanced reading distance is planned for future studies.

Keywords: LF-RFID, water intake, time series database, Arduino, InfluxDB, Grafana

Introduction

PLF companies offering monitoring systems tend to provide recorded data via an Application Programming Interface (API) to a cloud service, e.g. classified acceleration and position data for animals equipped with Smartbow ear tags (Smartbow GmbH, Weibern, Austria) or records of meteorological data from a weather station (HOBO RX3004, Onset, Bourne, United States). Furthermore, proprietary farm management software, e.g. DairyComp 305, usually does not provide a free API for accessing data easily. Exporting the data into CSV files, to make records accessible, would be the workaround in such cases for scientists that aim to analyze datasets recorded by commercial PLF systems. Therefore, setting up a centralized database, e.g. InfluxDB v2, into which all measured time series data from various data sources is automatically stored, would be beneficial for scientists since there would be no need to manually retrieve data from multiple sources. InfluxDB is currently the most popular time series database (TSDB) (DB-engines, 2022) and, in combination with Grafana as visualization tool, is widely used within scientific applications (Beermann *et al.*, 2020; Cicioğlu *et al.*, 2021). InfluxDB v2 is a NoSQL database, developed to store vast amounts of sensor data efficiently with high read-write performance (Nasar *et al.*, 2019).

Utilizing MCU development boards one can set up a sensor network, which is flexible and scalable. Using Arduino (Somerville, United States) compatible boards makes code development fast, due to the availability of many libraries for peripheral devices and sensors. (Kondaveeti *et al.*, 2021).

The individual water intake of an animal has been investigated with RFID and water flow sensors before and can be used as an indicator of an animal's health status (Maselyne *et al.*, 2016).

The first goal of this research was to build a measurement system, which writes RFID and water flow data into an InfluxDB OSS 2.0 time series database, and to provide a Grafana dashboard as a user interface for scientists. The second goal was to evaluate the reliability of the system for identification of individual animal drinking patterns.

Material and methods

Location and general setup

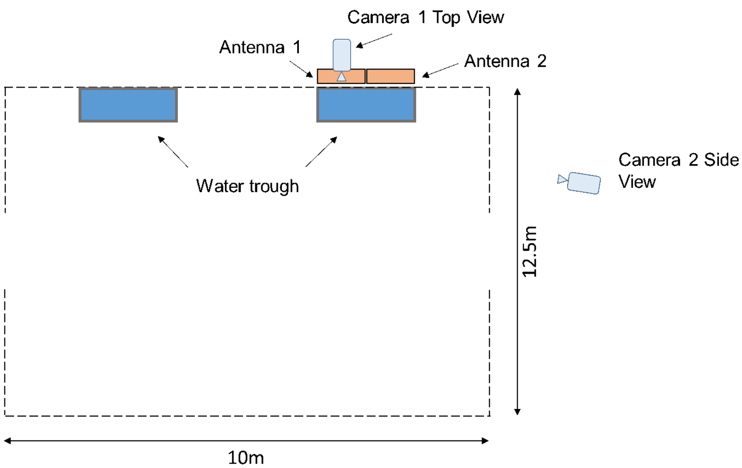

Figure 1: Location of water troughs, RFID system, cameras and pen size

The system for measurement of individual water intake was located in a pen in a cattle barn at the experimental farm of the University of Veterinary Medicine Vienna. An RFID system and a water flow sensor were installed at only one of the two water troughs in the pen (Figure 1). A camera (DS-2CD2642FWD-IZS, Hikvision, Hangzhou, China) was mounted above the water trough to provide a top view and an additional camera (DS-2CD2642FWD-IS, Hikvision) provided a side view of the entire pen (Fig. 1). Both cameras recorded continuously in the experimental period. Drinking events were labeled on the recorded video and compared with visits to the trough recorded with the RFID system. It was possible for two animals to visit the water trough (Kompakt-Trogtränke 100cm, Suevia, Kirchheim, Deutschland) simultaneously, due to its horizontal length of 100cm. There were 7 cows in the pen during the experimental period, which lasted for one week from 11.02.2022 until 18.02.2022, but only 2 of them were equipped with RFID ear tags.

Water flow measurement system

FCH-midi-POM, (B.I.O-TECH e.K., Vilshofen, Germany) was used to record the water flow. The trough was refilled with water when the water level dropped below a threshold. The output of FCH-midi-POM was a square wave signal with a frequency matching the flow rate. Every rising edge of the signal triggered an interrupt at an interrupt pin of an Arduino MKR Zero microcontroller, which was then executing an interrupt service routine (ISR) for counting the impulses. The MKR Zero was also equipped with an Arduino MKR Ethernet shield connecting it to the LAN. It was necessary to use Power over Ethernet (PoE) splitters, since the MKR Ethernet shield did not provide PoE capability. Every 15s the cumulated water throughput in mL and the average of the flow rate in L/min were written into InfluxDB.

Temperature sensors

Two TH3 (Papouch, Prague, Czech Republic) temperature sensors were installed next to the top view camera to monitor the temperature and humidity in the pen. The TH3 sensors were connected to a Papago Meteo ETH (Papouch, Prague, Czech Republic) weather station module. Telegraf, InfluxData’s open source server agent for collecting and sending metrics, was used to retrieve every minute the temperature-humidity data from the Papago Meteo ETH via Simple Network Management Protocol (SNMP).

RFID measurement system

Table 1: Specification of the used RFID antennas

Name	Windings N	Inductance L (mH)	Resistance R (Ω)	Physical dimension (cm)
Antenna 1	20	0.66	9.4	47x47
Antenna 2	28	1.3	13.7	48x48

The low frequency (LF) RFID measurement system consisted of 2 antennas, 2 low budget RFID readers (RFIDRW-E-TTL, Priority 1 design, Melbourne, Australia) and an MKR Zero combined with an MKR Ethernet shield. Every antenna was connected to an RFID reader and they were positioned next to each other, as shown in Fig. 2. Due to the parallel alignment of the antennas and the trough, the animals could freely access the drinker. As shown in Fig. 2, the antennas were mounted at an angle to cover the trough area. Table 1 lists the specifications of the RFID antennas.

Figure 2: Installation of the RFID system at the water trough

Identifying animals with LF RFID applications is regulated with ISO 11784/11785. Within these standards there are two transmission protocols defined, the full duplex (FDX-B) and the half duplex (HDX) protocol (Finkenzeller, 2003). The FDX-B protocol uses a 134.2kHz carrier frequency where the information of the transponder is transmitted by Amplitude-shift keying (ASK) modulation. In Austria, newborn cattle has to be equipped with FDX-B ear tags since 2019 (AMA, 2019). Therefore, in our study we used RFID readers with FDX-B reading capability. A major advantage of LF RFID systems is better performance in the vicinity of metal and water compared to HF and UHF RFID systems (Brown-Brandl *et al.*, 2017; Fennani *et al.*, 2011).

Since the carrier signal is amplitude-modulated by the transponder, the sensitivity is greatly impacted by the noise level of the power supply. Thus, a low pass filter was designed to damp the power supply noise in the frequency range of the modulated signal. The LC circuit, consisting of the antenna inductance and the capacitance of the RFIDRW-E-TTL, was tuned according to following equation

$$C_{ges} = \frac{1}{(2\pi f_{res})^2 L_{ant}} \tag{1}$$

in order to achieve the needed resonant frequency of 134.2kHz, where f_{res} is the resonant frequency, L_{ant} the antenna inductance and C_{ges} is the sum of the capacitance value soldered onto the RFIDRW-E-TTL and external added capacitors.

Using two RFID readers, one for every antenna, instead of just one RFID reader for both antennas greatly reduced the electric circuit complexity. Especially because we were using antennas with different winding numbers, otherwise a multiplexing circuit must have been designed.

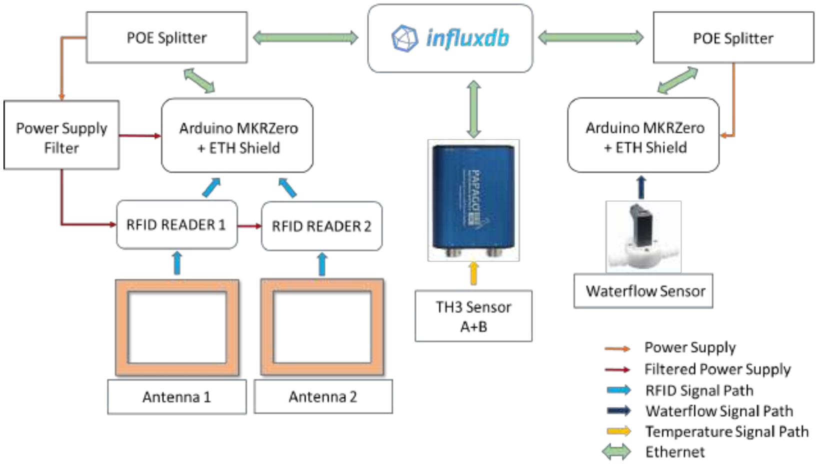

Figure 3: Individual water intake and temperature measurement system

The RFIDRW-E-TTL reader was wired to an UART interface of the MKR Zero. On a successful read, the reader transmitted a string, which included a 3 digit country code and the 12 digit national identity code e.g. 040_000000299116. Furthermore, the Arduino can issue a serial command to the reader for measuring the current resonant frequency of the LC-circuit.

The Arduino activated the two RFID readers alternately, thus only one reader at a time recorded data from the corresponding antenna. In order to investigate the influence of the inductance on the reading distance two antennas with different winding numbers were produced. The reading distance was defined as the distance from the antenna to the transponder, when the transponder was first recognized. The duration of the activation for both antennas was 1s. The resonant frequency of each antenna circuit was sampled once every 4 minutes. Metrics for the resonant frequency and RFID data (animal ID) was sent to the InfluxDB v2.

<u>InfluxDB v2 TSDB</u>

Data was directly written to InfluxDB v2 by issuing a HTTP POST request to the /write endpoint of the REST-API. The InfluxDB v2 was installed on a server within the LAN. The data-string had to have the InfluxDB line protocol structure (Influxdata, 2022). Due to the lack of a dedicated InfluxDB v2 client library for an MKR Zero with Ethernet shield, the easiest way to write metrics into the InfluxDB was to set up a dedicated HTTP POST request. A token, which had writing access to a bucket, had to be passed in the header of the HTTP request.

<u>Grafana dashboard</u>

User segregation or restricting access to dashboards for users within the same InfluxDB organization is not possible in InfluxDB v2 OSS. However, this fine-grained access control was implemented into the InfluxDB Enterprise version. Using Grafana, an analytics and visualization tool, as an UI is also an option to refine user access. In Grafana it is possible to restrict access to dashboards to certain users or teams. Grafana also provides a large set of overriding and tweaking options, for instance changing labels, color schemes and unit definitions. Access to the InfluxDB was established by configuring an InfluxDB datasource in Grafana.

Data analysis

The video recorded in the experimental period was analyzed, by counting the visits at every water trough. Furthermore, the animals with RFID ear tags were manually identified when they visited the trough with the RFID system. The visiting times were also registered to compare them to the RFID data by calculating a detection rate. Detection rate was defined as the percentage rate of RFID detected visits to total visits.

Results and discussion

Visits to the water trough

The detection rate of the first out of 2 animals that had RFID transponder was 64.3%, and of the second animal 37.5%. The second animal had been wrongly equipped with RFID transponders on both ears, which was the reason for the worse performance. ISO 11784/11785 does not specify any anti-collision protocol, thus the reading distance was greatly reduced when two or more tags were read by the same antenna. The measured maximum reading distances for FDX-B ear tags of antenna 1 and antenna 2 were 32.5cm and 35cm, respectively. Reliable identification of animals would require an increase of the reading distance. For the same antenna configuration and reading area, an RFID reader with increased reading range has to be utilized for a more reliable identification, e.g. WL-134 (ZocoRFID, China) or ASR550 (Agrident GmbH, Barsingshausen, Germany) During the experimental period, there were 6 visits out of 129 where 2 animals were drinking simultaneously at the water trough with the RFID system.

Table 2: Drinking events at water troughs

Visits at RFID water trough	Visits at non RFID water trough	Detected visits animal 1	Not detected visits animal 1	Detected visits animal 2	Not detected visits animal 2
129	86	18	10	9	15

The RFID detection rate could be useful for computer vision applications, where a re-identification of cows might not be necessary with each visit. Furthermore, with a computer vision approach it could potentially be possible to evaluate the water intake of each animal more precisely than with our current approach, when multiple animals visit the same water trough simultaneously (Kashisha *et al.*, 2013).

Figure 4: Grafana dashboard

<u>RFID Grafana dashboard</u>

An alarm was configured within the panel showing the resonant frequency (Fig. 4). It was triggered when the value was out of bounds, indicated by the red and orange horizontal lines, which were set to 135.7kHz and 132.7kHz respectively. Slack (Slack Technologies, San Francisco, United States) webhook was used as notification endpoint and alarm messages were posted in a Slack channel. We had to re-match the capacitance value at the reader, if an alarm was triggered. As expected, the resonant frequency declined with higher temperatures because of the change of the antenna's dimensions. The right panel in Fig. 4 shows the combination of the water flow measurement with the RFID detections. For the experimental period, the water intake was associated with an animal ID by RFID system.

Conclusion

This work presented the setup of a small sensor network with different measurement sources. With Arduino development boards, it was possible to set up a flexible and scalable real time monitoring system with low budgetary effort. Metrics were written to the InfluxDB v2 by using either the REST-API or the Telegraf collection agent. Grafana is a comprehensive tool for visualizing data from different sources and combining them into one dashboard. It also allowed us to set up an alarm-messaging pipeline. The combination of InfluxDB v2 and Grafana allowed researchers to view, analyze and extract data without using proprietary software.

A more reliable RFID system with higher reading distance would need to utilize a different RFID reader with better performance.

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Mastitis early warning system based on MIR spectrometric tools in D4Dairy MIR Project

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Abstract

Use of Milk Mid Infrared (MIR) analysis is well established in milk recording organisations due to the wide range of characteristics that can be measured in milk. Not only milk components are determined using MIR spectrometry, also warning systems are being developed to help farmers to better address their production objectives and to improve animal health. The aim of the current study was to evaluate two different spectrometric tools for predicting mastitis risk and udder health status of dairy cows. The objectives were to develop discriminant models to predict mastitis events and to evaluate their accuracy by using clinical diagnosis as a reference. Results of prediction models are planned to be used as an early warning system for mastitis within the routine milk recording system. Large amounts of milk recording (including MIR spectra) and clinical mastitis diagnosis data from Austria, Baden Württemberg (Germany) and Alsace (France) were jointly analysed. The spectral data was first standardised, then pre-processed by first derivative and the Legendre polynomial model was applied for days in milk correction. In one of the two approaches somatic cell count (SCC) was used as an additional predictor variable, improving prediction accuracy. Farmer reports were developed combining MIR predictions with milk components related to mastitis in order to detect subclinical mastitis and to prevent clinical or chronical mastitis. MIR predictions of mastitis risk are regarded as a useful and valuable precision livestock farming tool when used with standardised spectral data.

Keywords: mid-infrared spectrometry, MIR spectra, health monitoring, mastitis, dairy cattle

Introduction

Mastitis is an inflammation of the mammary glands and can be caused by more than 50 different organisms. Usually, mastitis is diagnosed somatic count and laboratory diagnostic methods, also it can be detected by visual by observation or palpation of the udder, or changes in milk secretion and application of the California Mastitis Test. At farm level, occurrence of mastitis prevalence decreases milk production, produces veterinary costs, welfare issues, and increases culling rate or causes lower milk payment.

Mastitis is associated with a wide range of characteristics that can be measured in milk with recent advances in the estimation of milk components using mid-infrared (MIR) spectrometry. Also, if a cow has mastitis, the composition of milk will be affected and with it the MIR-milk-spectrum. The important message from the project OptiMIR was that not only the main components can be analysed with the MIR spectrometer, but also fatty acids (Grelet et al., 2014), minerals, lactoferrin (Soyeurt et al., 2011), BHB, acetate and citrates (Grelet et al., 2015). Complex features). Complex traits could also be assessed, and, models for ketosis (Grelet et al., 2016), energy deficiency (McParland et al., 2011, Smith et al., 2018) and methane emissions (Dehareng et al., 2012) were developed. Nowadays, work on pregnancy (Laine et al., 2017) and mastitis tools could help farmers for the herd management and better production. The objective of this study was to build a spectrometric tool, such as MastiMIR for Austrian datasets, for the determination of the animal health status from the milk quality with the aim to evaluate the usability of mastitis diagnosis in combination with MIR indicators in order to improve early mastitis risk prediction at the milk recording organisation LKV Austria.

Material and methods

Experimental data

Due to the health monitoring in Austria, which started in 2006, diagnoses of approx. 10.000 validated farms were used for research and the MastiMIR model. The diagnoses were documented by veterinarians using a 86-part diagnostic key. The reference data to create the MastiMIR model were cinical mastitis (acute and chronic) diagnoses, the spectral data were predictor variables. The model is based purely on standardized spectral data, since all spectra registered at LKV- Austria have been standardised starting from Janurary 2015, due to the OptiMIR project participation. All data editing, modelling and calculations were done using the R statistical language and environment.

Signal analysis

To identify variables that were positively or negatively associated with mastitis determination, the spectral data set was first pre-processed by Savitzky-Golay first derivative in order to remove the offset differences between samples for baseline correction before performing Legendre polynomial transformation based on days in milk (Gengler and Wiggans, 2001). Then the data was submitted to logistic regression in combination with LASSO variable selection and regularization and 10 fold cross validation using the "glmnet" R package. Parts of the test day data available were used to modeling. Test day data from 7 to 0 days prior to mastitis diagnosis were assigned to the mastitis class. For the healthy class, only spectra which had no diagnosis associated within ±60 days were used. For the "glmnet" model following variables were considered as, fixed effects: milk included sampling moment (with three variants: standard, mix sample between morning and evening, morning and evening), parity (1, 2, 3, 4, 5+) and breed (Holstein, Brown-Swiss and Simmental) and a 212 OptiMIR wavenumbers subset of the pre-processed spectral data.

The calibration data set contained around 4.140 spectral data from around 10.000 Austrian herds and if it was applied the SCC filter the data was around 34215 spectral data (Table 1). The first validation approach was based on a random split of data, 70% of data was used for the calibration model and 30% for the validation model. The second validation model was based on independent dataset with different farms as in the calibration model and an external validation in order to exclude animal and farm effects. These selected 11 farms were farms with high diagnosis registration rate and had to cover the most important breeds e.g. Holstein, Brown Swiss and Simmental. For these two validation models the same data cleaning approach as for the calibration model was used, , such as diference between fat detected in lab and fat predicted form the MIR spectral data had to be lower then 5, and the GH was aroung 5. In addition to the external validation with the extreme values diagnosis cases, a third validation model is proposed with test day data from a whole production year. Data from 1st October 2017 till end of September 2018 in combination with diagnosis data was used to verify if the proposed model could be implemented in routine, those dataset was not used in the calibration model.

Table 1: MastiMIR calibration and validation datasets

MastiMIR Model	Healthy	Not Healthy
1st Calibration	83.891	1.078
1st Calibration – SCC Filter	33.877	338
1st Validation – random split	30.525	3.715
2nd Calibration	86.029	994
2nd Calibration – SCC Filter	33.562	510
2nd Validation – external validation with 11 farms	25.863	457
Final Model	256.150	14.640
3rd Validation – external validation with production data	54.839	3.294

To interpret the prediction of the MastiMIR model, the survival analysis were performed with the help of survival package in R in order to build the classes of MastiMIR. The idea was to cover the group of data by means of a mastitis risk probability provided by a presumed logistic-linear relationship (S-curve) between MastiMIR probability and the mastitis danger. This model allowed by using different thresholds to distinguish 4 danger/risk classes. The class limits were determined by using statistical methods such as cumulative probability and Cox event time analysis. The class size was negatively correlated with the mastitis class such as not, moderately, significantly and severely endangered.

Results and Discussion

Mastitis can only be predicted to a limited extent via somatic cell count. Therefore, a new model MastiMIR based on spectral data, animal parameters such as parity, breed and milking moment, and the gold standard the mastitis diagnoses such as MastiMIR has been developed. Table 2 presents the MastiMIR calibration and validation statistics. After modelling with GLMNET in R, a sensitivity (the percentage of sick cows that were correctly identified as having the condition) of 60.3% in calibration and more than 73% for the73.6-75.5% in validation and external validation models could be obtained. The specificity (the percentage of healthy cows that were correctly identified as not having the condition) is 71.6% in 71.3-72.0% in the range of 71-72% for calibration and all validation sets.

Table 2: MastiMIR calibration and validation statistics

MastiMIR Model	Sensitivity	Specificity
1st Calibration	60.3%	71.6%
1st Calibration – SCC Filter	87.6%	87.8%
1st Validation – random split	75.5%	71.4%
2nd Calibration	61.1%	74.3%
2nd Calibration – SCC Filter	70.2%	80.3%
2nd Validation – external validation with 11 farms	73.6%	72.0%
Final Model	67.3%	78.1%
Final Model – SCC Filter	78.9%	84.1%
3rd Validation – external validation with production data	74.5%	71.3%

Regarding the 3rd validation model with production data, it can be seen that the sensitivity is 74.5% while the specificity is 71.3%. This can be explained by the probable presence of untreated mastitis cases, subclinical mastitis and missing registration of diagnosis events in the production data.

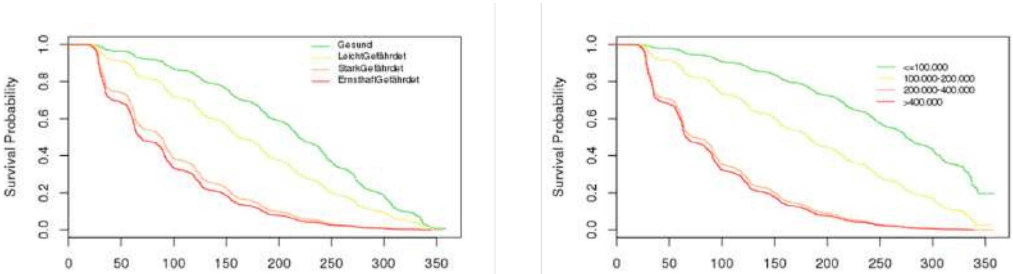

Figure 1: Survival Analysis SCC classes and MastiMIR classes

It can be seen in Figure 1, for example, the distributions of the MastiMIR and the SCC classes over the lactation week, that the mastitis class distribution has the shape of the lactation curve on both models. The MastiMIR class distribution on whole population from Austrian herds for the year 2017 is more pronounced than SCC class. Regarding the animals with MastiMIR danger or risk it can be pointed out that mastitis can occur also when the cows have a low SCC. Animals with higher SCC may still have other diseases. There is also a difference between the healthy classes and moderately endangered and also significantly endangered. The size of the group decreases as with the SCC classes with the danger. The Cox event time analysis improved the classification. If an animal has mastitis diagnoses, it can be detected earlier with the MastiMIR model than with the SCC class model. The transition from significantly endangered to severely endangered was better separated (differentiated). The transition from healthy to moderately endangered class was displayed earlier. If a cow has health problems due to mastitis, she not only has a lower amount of milk or a higher SCC, but also reacts with a change of the main milk components: the lactose content is negatively correlated with mastitis and the protein content and the fat-lactose ratio are positively correlated.

A positive correlation also applies to the milk fine components sodium, lactoferrin and BHB, as the literature has already confirmed.

Conclusions

The model provides four classes of mastitis warning such as not, moderately, significantly and severely endangered. MastiMIR can be a good risk indicatorsignal for mastitis. The moderately endangered class is a signal for the farmer. In that case the farmer would contact the veterinarian and a control would be made in order to prevent the occurrence of mastitis. Compared to the SCC model, which was defined such as not (less than 100.000 SCC), moderate (100.000-200.000), significantly (200.000-400.000) and severely (more than 400.000) endangered, the MastiMIR model shows an earlier occurrence of the 'slightly at risk' classification. The MastiMIR model is a complementary tool for the SCC model, MastiMIR can supplement the SCC classes.

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Monitoring milking parameters to improve milking operations through machine learning algorithms

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Abstract

The operation of milking is one of the most time-consuming in a dairy cattle farm. Because the management and duration of the whole milking session can be affected by some cows that need a longer milking time than others, it can be useful to shorten the milking time of these cows. In this study, a full dataset of milking data was collected and processed for three months from a dairy cattle farm located in Northern Italy. The aim was to understand how to reduce the daily milking time by evaluating the effect of a different pulsation ratio and detachment flow rate on the duration of milking and udder health. A prediction model for the duration of milking was developed, which was able to identify the proper pulsation ratio and detachment flow rate based on the first 2 minutes of data on milking. If implemented on machines, it can lead to an automatization in the change the pulsation ratio and detachment flow of every cow.

Keywords: data analysis, milk production, pulsation ratio, prediction model

Introduction

Milking routine is very intensive and time-consuming for the farm management activities (Celozzi et al., 2020). In some cases, to solve problems related with working time, availability of workers, and milking issues linked with the quality of milking operations, the introduction of Automated Milking Systems (AMS) has occurred. AMS spread first in Northern Europe (Jacobs & Siegford, 2012) and then in Western Europe and United States. Broucek & Tongel (2017) report that in 2012 more than 19 thousand robots were used, and this number has further increased.

AMS has the benefit to properly manage the milking daily operations of about 55-65 cows, which is the medium size of European herds (Broucek & Tongel, 2017). Respect to management, AMS has some advantages, among which an increased economic profit, improved animal health and welfare, milk quantity and quality (due to higher milking frequency and better detection of diseases), and farmer and workers' lifestyle. Brito et al. (2020) quantified in 18-46% labour cost savings the introduction of AMS respect to the conventional miking. However, also some drawbacks can be identified, among which the problems related to stress, fear or general attitude of cows, undesired behaviours due to the queue prior to the milking, lack of adequate udder conformation to the milking (Broucek & Tongel, 2017; Brito et al., 2020), lack of proper barn structures for the free or forced walking (Bewley et al., 2017) and the consequent possible delays in milking. In addition, early udder health deterioration was found by Hovinen & Pyöräläudder (2011) when AMS is used.

In Italy, despite the strong investments of the last years towards this direction, the presence of AMS is still small. Abeni et al. (2019) report that only around 3% of dairy cattle farms is equipped with AMS, which anyway is one of the most interesting technologies for Italian farmers. The reasons include costs, labour, and in some cases the PDOs' disciplinaries. In fact, Pezzuolo et al. (2017) monitored 15 farms in Italy finding a general underuse of AMS, which were active for about 70% of daily time. Therefore, it seems that not all farmers are yet attracted by automatization and improving the traditional milking operations still presents interest, especially by having efficient milking procedures and low-cost sensors supporting them (Celozzi et al., 2020).

In this study, by monitoring one dairy cattle farm of Northern Italy in which milking operations occur in a traditional herringbone milking system with cow identification and milk data collection, some considerations were made about how to shorten the duration of milking operations, especially focusing on those cows that have milking time higher than 8 minutes. This was achieved by varying the pulsation ratio, and artificial intelligence was applied to evaluate how to vary automatically the pulsation ratio based on the milk flow in the first two minutes of milking.

Material and methods

Experimental data

The monitoring took place in a dairy cattle farm located in the North of Italy equipped with pedometers and a milking monitoring system by a commercial firm, from which were collected data of each session of milking. The farm milks about 1000 milking cows per day, and the milking routine is quite long, requiring about 7 hours daily. For this reason, the farm manager asked for information about how to reduce the duration of milking operations, without the willingness to adopt AMS. The focus was paid, therefore, on those cows that are slow to eject milk and prolong the whole milking operation.

Data about the herd and milking variables were collected for each milking session (2 per day) for 3 months, from September to December 2021. In this period, on the whole herd, an expert observed the udder health through the Teat End Score (TES) test every 3 weeks to evaluate possible damages to teats. In particular, a score from 1 to 4 is given to each teat of the udder based on its hyperkeratosis level: 1 is attributed for normal, 2 for smooth, 3 for rough and 4 for very rough (Mein et al., 2001).

From the whole herd, dairy cows with the average milking time (AMT) >8 minutes were identified for further evaluations. In particular, to some of these cows the pulsation ratio was randomly modified, from 60:40 to 65:35. Instead, from the whole herd, some cows were also randomly selected for evaluating the effect of changing the detachment flow, from 600 g min^{-1} to 800 g min^{-1}. According to this distinction, two different tests were performed:

— Pulsation ratio 60:40 vs 65:35. This test was carried out with focus on the cows characterized by AMT>8 minutes;
— Detachment flow 600 vs 800 g min^{-1}. This test was carried out using a sample of cows from the whole herd.

All the selected cows for the trial had, on average, 93 DIM and parity equal to 1.6. Therefore, changes along the lactation period were not affected by differences in DIM. Before the start of the trial, the somatic cells count (SCC) were measured and were equal, on average, to 2.43 as linear score.

Data processing was performed with the SAS Software 9.4. A GLM Procedure (Proc GLM) was carried out to calculate corrected least square means (LS Means) and the statistical differences of the tested trials and variables. In particular, LS Means were calculated for trials puls60:40 vs puls65:35 and separately for detach600 vs detach800. As abovementioned, the reason for the analysis carried out separately was that the two combined trials occurred separately from each other.

Since the milking monitoring system makes available on a computer on farm all the data related to milking, some further considerations can be made. In particular, the availability of cow ID, average milk yield of the 10 previous days, and flow rates of 0-15, 15-30, 30-60, and 60-120 seconds allows to predict the individual cow milking time and removal flow within the first 2 minutes of milking. With an accurate prediction model, guidance for precise milking parameter customization for individual cows can be offered.

Model development

A modified Support vector machine, namely the Least Squares Support Vector Machines (LSSVM) algorithm proposed by Suykens and Vanderwalle (1999) was used. It uses a least-squares linear system as a loss function to change the inequality constraint of SVM into an equation constraint. In addition, a novel swarm intelligence optimization algorithm proposed by Xue and Shen (2020) was used, which is the Sparrow Search algorithm (SSA). It is a heuristic algorithm that mimics the cooperative behaviour of a group of sparrows during predation, improving the exploration and use of the optimal search space.

Since the parameters used in this study significantly influence the prediction performance of the LSSVM algorithm, the LSSVM algorithm parameters have been optimized based on the SSA algorithm to address the problem of blind selection of the parameters and the difficulty of jumping out of local extremes.

Results and Discussion

The average and standard deviation results of the main parameters of the studied trials are reported in Table 1. In Figure 1 is reported the milk yield and average milking time (AMT) of the 4 trials during the whole period.

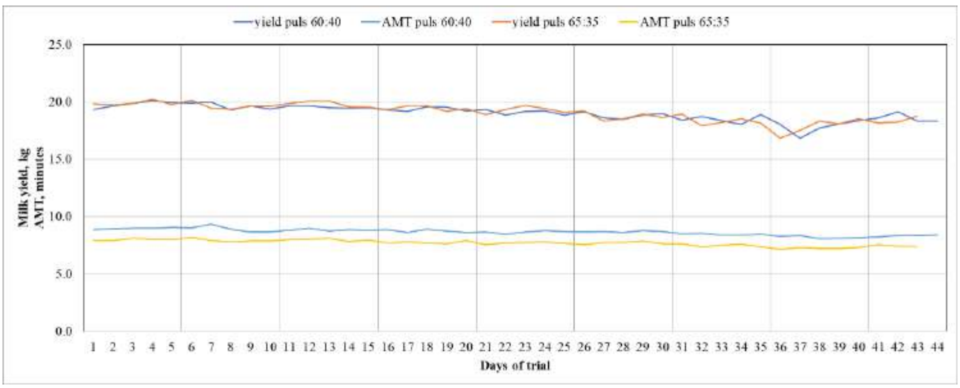

Figure 1: Average Milking Time (AMT – min) and Milk Yield (kg) of the 4 trials for the whole duration of the trial.

Table 1: Mean and standard deviation of the main parameters tested

trial	detach800	detach600	pul 60:40	pul 65:35
Milk yield (kg) (*)	18.1± 4.1	18.3± 4.2	19.04± 4.07	19.11± 3.98
AMT (min)	5.0± 1.1	5.0± 1.1	8.66± 1.77	7.71± 1.62
Flow rate0-15 (kg min^{-1})	1.12± 0.85	1.27± 0.84	0.20± 0.42	0.37± 0.57
Flow rate15-30 (kg min^{-1})	3.67± 1.48	3.90± 1.45	1.75± .943	2.18± 1.13
Flow rate30-60 (kg min^{-1})	3.95± 1.62	4.20± 1.71	2.16± 0.83	2.59± 1.14
Flow rate60-120 (kg min^{-1})	4.83± 1.54	5.05± 1.54	2.56± 0.87	3.11± 1.17
Peak flow (kg min^{-1})	6.40± 3.17	6.68± 2.93	3.41± 2.3	4.11± 2.74
Removal flow (kg min^{-1})	1.22± 0.50	1.08± 5.51	0.83± 0.46	0.91± 0.39
Total low flow (kg min^{-1})	0.6± 0.7	0.8± 0.7	1.32± 0.99	1.18± 0.96
SCC_1 (^)	2.6± 1.9	2.6± 1.8	1.92± 1.64	2.11± 1.88
SCC_2 (^)	2.5± 2.4	3.6± 2.9	1.53± 2.03	2.07± 2.56
SCC_3 (^)	2.9± 1.8	3.4± 2.3	2.09± 1.84	1.93± 1.66
TES_1_back (°)	2.1± 0.4	2.0± 0	2.03± 0.26	2.22± 0.5
TES_1_front (°)	2.1± 0.5	2.0± 0.2	2.1± 0.27	2.22± 0.5
TES_2_back (°)	2.1± 0.4	2.0± 0.3	2.11± 0.56	2.16± 0.51
TES_2_front (°)	2.1± 0.5	2.0± 0.3	2.09± 0.31	2.22± 0.5
TES_3_back (°)	2.1± 0.4	2.0± 0.3	2.1± 0.41	2.25± 0.55
TES_3_front (°)	2.2± 0.5	2.0± 0.4	2.21± 0.5	2.3± 0.58
TES_4_back (°)	2.1± 0.5	2.0± 0.3	2.26± 0.48	2.36± 0.65
TES_4_front (°)	2.2± 0.5	2.1± 0.4	2.35± 0.5	2.42± 0.65
TES_5_back (°)	2.1± 0.6	1.9± 0.5	2.39± 0.56	2.41± 0.65
TES_5_front (°)	2.2± 0.7	2.0± 0.5	2.57± 0.58	2.65± 0.64

Note: (*) milk yield is expressed per session (two sessions per day); (^) SCC= somatic cells count expressed as linear score (1-3 refers to the first, second and third measurement); (°) TES= teat end score (values from 1 to 4) for front teats and back teats (1-5 refers to the measurements, starting from the first at the beginning of the trial in September – 1- to the last at the end in December - 5).

From the figure it can be observed that while the milk yield is very close between the tests of pul60:40 and pul65:35, the AMT is always lower if the test is puls65:35. This means that the test in which the pulsation ratio is equal to 65:35 allows to reduce the milking time. However, to verify the statistical significance of this consideration, a GLM Procedure in SAS Software 9.4 was carried out to calculate LS Means, standard errors and significance of the tested variables. In Table 2 are reported the corrected LSMeans of the trials of puls60:40 and puls65:35 with the related significant differences. The same is shown in Table 3 for the trials of detach800 and detach600.

Table 2: LS Means and standard error (S.E.) of the trials of puls60:40 and puls65:35 with the related significant differences (p).

Variables	puls60:40		puls65:35		p
	LS Mean	S.E.	LS Mean	S.E.	
AMT (min)	8.11	0.04	7.80	0.03	***
Milk yield (kg)	19.30	0.11	19.70	0.10	***
TES_1_back	2.22	0.01	2.33	0.01	***
TES_1_front	2.04	0.01	1.95	0.01	***
TES_2_back	2.32	0.02	2.14	0.02	***
TES_2_front	2.14	0.01	2.27	0.01	***
TES_3_back	2.28	0.01	2.24	0.01	***
TES_3_front	2.25	0.01	2.29	0.01	***
TES_4_back	2.37	0.01	2.49	0.01	***
TES_4_front	2.37	0.01	2.34	0.01	***
TES_5_back	2.48	0.02	2.35	0.02	***
TES_5_front	2.49	0.02	2.59	0.02	***
Peak Flow (g min^{-1})	3367	100	3484	98	0.06
Peak Time (min)	4.60	0.06	4.27	0.06	***
Removal Flow (g min^{-1})	822.6	16.8	842.1	16.5	0.1
Total Low Flow (kg min^{-1})	1.28	0.03	1.44	0.03	***
SCC_1	2.14	0.06	1.53	0.06	***
SCC_2	2.64	0.07	3.05	0.06	***
SCC_3	2.56	0.06	2.40	0.06	***

Note: ***= significance of <0.0001.

From the results it can be observed that all variables show significant differences between puls60:40 and puls65:35 except for the peak flow and the removal flow. This is expected because no difference is present in the 2 trials respect to the removal flow (set at 800 g min^{-1}). Instead, it can be observed that with puls65:35 the AMT reduces below 8 minutes and also the peak time is lower (7% less in puls65:35). However, milk yield increases significantly (19.30 and 19.70 kg cow^{-1} $session^{-1}$, for puls60:40 and puls65:35, respectively). When analysing the SCC, statistical differences are present in all the tests, with values higher in the puls60:40 in 2 out of 3 cases. Respect to the TES, teats show in all cases an increase in the hyperkeratosis, with values always above 2. In general, TES of the back teats shows more damages than the front ones, even if slight differences – even though significant- are found. Instead, in the last monitoring, the TES is worse for the front teats (2.49 and 2.59 for puls60:40 and puls65:35, respectively) than for the back teats (2.48 and 2.35 for puls60:40 and puls65:35, respectively).

Table 3: LS Means and standard error (S.E.) of the trials of detach800 and detach600 with the related significant differences (p).

Variables	detach800		detach600		p
	LS Mean	S.E.	LS Mean	S.E.	
AMT (min)	5.15	0.02	5.22	0.02	***
Milk yield (kg)	17.77	0.07	17.94	0.07	*
TES_1_back	2.08	0.00	2.08	0.00	*
TES_1_front	1.96	0.00	2.00	0.01	***
TES_2_back	2.00	0.00	2.00	0.00	0.14
TES_2_front	2.03	0.00	2.00	0.00	***
TES_3_back	2.08	0.00	2.05	0.00	***
TES_3_front	2.02	0.00	2.04	0.00	***
TES_4_back	2.13	0.01	2.09	0.01	***
TES_4_front	2.11	0.01	2.13	0.01	***
TES_5_back	2.00	0.01	2.05	0.01	***
TES_5_front	2.16	0.01	2.09	0.01	***
Peak Flow (g min^{-1})	6469	80	6218	82	*
Peak Time (min)	2.26	0.02	2.26	0.02	0.96
Removal Flow (g min^{-1})	1270.4	17.1	1187.0	17.7	***
Total Low Flow (kg min^{-1})	0.60	0.01	0.62	0.01	0.11
SCC_1	2.45	0.03	2.08	0.03	***
SCC_2	2.77	0.05	3.59	0.05	***
SCC_3	3.99	0.04	4.28	0.04	***

Note: ***= significance <0.0001; * significance <0.05

When analysing the results of the second trial, it can be observed that peak time and total low flow do not show significant differences between the trials, similarly to the second measurement of TES for back teats. In general, AMT is much lower than in the previous case, because in this case long cows were not present. Furthermore, milk production is slightly lower, the peak flow and the removal flow are much higher than in the previous trial. While comparing these results, statistical differences are observed for SCC and TES. In particular, SCC result higher in 2 out of 3 cases in the detach600, highlighting problems probably due to overmilking. It must be highlighted also that in the last SCC measurement, the threshold of linear score of 4 was very close or even exceeded by the detach800 and detach600, respectively. Respect to TES, instead, statistical differences between the trials are observed, but the values of the whole test are in all cases close to 2 for the whole duration of the test, therefore only a smooth hyperkeratosis, probably related to the combination of different variables, was observed.

As reported in Atakan et al. (2021) it is important to monitor the teat end score because hyperkeratosis on the teat end is caused mainly by errors, high vacuum of the milking machine, increased milk yield, prolongation of milking, dirtiness of the animals and insufficient bedding. Therefore, reducing the milking time may help in reducing the TES of the first trial (puls60:40 vs puls65:35, where long cows were tested). However, the higher vacuum and other characteristics not monitored in this case (e.g., dirtiness and bedding) could affect this result. TES is important also because of its relationship with a higher risk for mastitis and high SCC.

Considering these results, it is important to have the possibility to modify the milking parameters during milking, based on cows' specificities. With the model developed in this study, it results that the SSA-LSSVM algorithm achieves 92% accuracy for AMT reduction and 78% accuracy for the differentiation of the removal flow, and F1 score is 0.95 and 0.88, respectively for the 2 cases.

Conclusions

This study aimed to monitor and evaluate different parameters of milking in order to improve the average milking time and the milking quality. Different pulsation ratio shortened the milking time while not negatively affecting TES and SCC. Having a higher detachment flow also reduced average milking time and improved SCC, while not affecting much the TES and milk yield. The possibility of introducing artificial intelligence algorithms that modify the milking machine parameters. Therefore, being able to modify the milking machine parameters while milking and based on the first 2 minutes milking can represent a big step forward to improve the quality of milking operations for dairy cows' health taking into account single cows' specificities.

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Soft-Sensing Approach for Predicting Bovine Respiratory Disease Severity

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Abstract

Bovine respiratory disease (BRD) is the most common cause of morbidity and mortality in cattle around the world causing important health problems (e.g., mortality, growth problems, and low productivity) in all cattle husbandry systems. BRD is a multifactorial syndrome, with various predisposing factors (stressors) being necessary to induce disease and affect disease severity. Predisposing factors include external stressors such as inadequate vaccination protocols, comingling with other cattle, dusty environment, sudden and extreme weather changes, and dehydration. Additionally, internal factors such acute metabolic disturbances and inadequate transfer of passive immunity are involved as well. BRD is one of the most extensively studied diseases since the beginning of 19th century until today. However, it is still a challenge to predict which specific groups of cattle are at the highest risk of BRD progression (i.e., severity and morbidity) and other BRD-related outcomes (e.g., mortality and disease severity). In the present paper, a conceptual framework for streaming adaptive machine-learning algorithm for farm-based prediction of the BRD progression outcomes (mortality and severity) is introduced. The introduced approach is based on combining farm (activity, animal-to-animal contact and feeding behaviour) and (sub)-clinical data (body temperature, nasal and ocular discharges and respiration rate) measurements together with a machine-learning-based prediction model. A hybrid machine learning approach based on localised least-squares support vector machines (LS-SVM) and k-nearest neighbours (kNN) is proposed. The developed adaptive model is suitable for online prediction of BRD-related mortality and severity for clinical decision support systems.

Keywords: bovine respiratory disease (BRD), morbidity, mortality, predictive model, machine learning, streaming algorithm

Introduction

Bovine respiratory disease (BRD) is the most common cause of morbidity and mortality in cattle around the world. BRD is a multifactorial syndrome, with various predisposing factors (stressors) being necessary to induce disease and disease severity. The predisposing factors include management and environmental (external) stressors such as transportation, comingling with other cattle, dust cold, sudden and extreme weather changes and dehydration that in addition to internal factors such acute metabolic disturbances (Kelly & Janzen, 1986; Lillie, 1974). BRD, depending on the pathogen involved, can cause death within 24 to 36 hours of symptoms appearing, or the infection can become chronic, not causing death but instead producing widespread, permanent lung damage, thus resulting major economic losses to the Dairy Industry (Brooks et al., 2011).

It is a big challenge to predict which specific groups of cattle are at the highest risk of BRD occurrence and other BRD-related outcomes (e.g., mortality, relapse treatment response and disease severity). One reason that the prediction of BRD-related outcomes is difficult is that the aetiology of BRD is multifactorial as explained earlier. Computational and mathematical modelling can be utilized to improve prediction of BRD-related outcomes.

Given rapid progression and potential long-term and lethal impact of the BRD, electronic health monitoring and sensing systems in combination with machine learning would play an essential role in preventing and containing the disease and diseases-related risks (Vuppalapati et al., 2018)an estimated 640 million dollars is lost annually due to BRD. Respiratory diseases are responsible for 21.3% of mortality in calves and 50.4% of deaths in weaned heifers. Additionally, there are many negative long-Term consequences for survivor calves including poor growth, reproductive performance, milk production, and longevity and can become sources of infection for other calves, and can cause outbreaks after weaning in-group pens. BRD poses huge challenges and economic losses to the dairy industry. This research paper addresses the challenge by developing and deploying Convolutional neural networks (CNN. Many farms, collect real-time animal clinical information and this information could be combined with historical cohort and farm data, processed through predictive classification algorithms, and then used these prediction to provide real-time guidance and warning to farm managers and veterinarians regarding probabilistic outcomes for individual animals (Amrine et al., 2014). Additionally, the ability to use real-time information to predict an individual animal's response at the time of respiratory disease treatment would provide great advantages and offer the ability to targeted treatment programs for individual animals.

In the present paper, we present a conceptual machine-learning framework to improve the prediction of BRD-related outcome. This paper introduces a framework for developing localised machine-learning suitable for online and streaming prediction of farm-based BRD-related outcome.

Potential predictive biomarkers (predictors)

The early stages of the host response to infectious agents include several physiological changes known as the *acute phase response*. The acute phase response is comprised of reactions localized at the site if infection, as well as the initiation of systemic responses, which include a rapid increase in the serum concentration of some proteins and other blood components, which can be used as physiological biomarkers for BRD outcomes (Table 1). In addition to the physiological biomarkers, which can be measured in the serum, other potential biomarkers based on the behavioural bio-responses of the infected animals can be used to predict the BRD outcome and severity as well. The behavioural predictive biomarkers are measured using precision livestock farming (PLF) technologies including wearable sensors cameras and microphones (Table 1). Both biomarkers can be used in combination or individually as predictors that can be utilized in predictive models for BRD-related outcomes and severity.

Table 1: Potential predictor for Bovine Respiratory Diseases (BRD) outcome using serum and behavioural biomarkers

	Potential predictor	Disease outcome	Accuracy
physiological biomarkers	Eosinophils, Neutrophils, Lymphocytes, Monocytes, Basophils, RBC*, WBC**(JT et al., 2013) and Neurophils/lymphocytes ratio (JT et al., 2013)	BRD development within (≤42 days)	0.51 – 0.67 AUC
	WBC and Neurophils/lymphocytes ratio (Schaefer et al., 2007)	BRD development within (4-6 days)	Sensitivity: 0.46 – 0.62 Specificity: 0.68 – 0.77
	Lactate (J et al., 2000), Haptoglobin (Humblet et al., 2004; Wright et al., 1995)	Case Severity and treatment response	Sensitivity: 0.57 – 0.95 Specificity: 0.50 – 0.96
behavioural & physical biomarkers	Feeding behaviour (Quimby et al., 2001; WC et al., 2019), animal-to-animal contact (DD et al., 2018), activity (G et al., 2018; MA et al., 2019) and infrared thermography (Schaefer et al., 2007)	BRD development 2-9 days prior to clinical observation	Accuracy: ~0.87 Sensitivity: 0.6 - 0.96
(sub-)clinical signs	Ocular and nasal discharge, hear drop/ head tilt, hyperthermia (temperature), respiration rate and coughing (Amrine et al., 2013; Lago et al., 2006; McGuirk, 2008).	BRD development and severity	Accuracy: 0.85 - 0.96

*RBC: red blood cells count, **WBC: white blood cells count

Streaming prediction algorithm

Predictive models, which aims to predict a current or future event, is an effective way to enhance the identification of cattle at-risk for new onset bovine respiratory disease (BRD) and other BRD-related outcomes, including mortality, treatment response, relapse, and disease severity.

As explained earlier, BRD is a multifactorial disease, and can be caused by a spectre of pathogens, often in combination. Which makes any sort of 'global model' not suitable for predicting the BRD-related outcome under different conditions and different data, specially, in case of continuous streaming data. Hence, in such cases a real-time model adaptation is needed to deal with the time-varying, individual-based, and multifactorial nature of the BRD. Furthermore, the stream of the generated farm and veterinarian data is continuously increasing in time, which requires streaming analytics to maintain the prediction performance. Most machine learning algorithms are basically global offline algorithms. In other words, they are trained by all available training data (global) and then applied to new unseen data (validation) without adapting to newly measured information (offline). Therefore, streaming new data points cannot be considered in the training process unless the model is retrained or adapted to the new data points. Both options are expensive and therefore enough new data points are required for an efficient update of the model. The other option is to continuously add new data points to the training set and to develop a model that is continuously updating (online) with a minimal computational cost. That requires to apply adequate and reliable machine learning algorithms. Unlike traditional machine learning models, adaptive machine learning models are capable to quickly adapt to new information and gain insight into how important that information is.

In this article, a 'localised learning' approaches of machine learning is proposed for adaptive streaming modelling.

Localised learning

Most of the well-known supervised machine learnings algorithms are based on inductive inference, which leads to 'global learning'. Global learning generates a generalised hypothesis (model) from specific examples (i.e., training data) to assign a value or a label to different data points. In this case, the local properties of the observed examples are prone to be compromised to obtain generalisation (A Y A Amer, 2016). In other words, if the feature space is not providing the possibility to find a solution considering both local and global properties of the observations, then the model may tolerate minority data points as an error. Local algorithms can provide the advantages of adapting the model to the local properties.

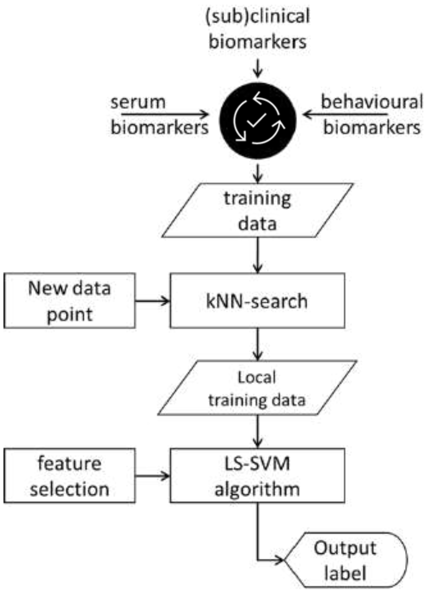

Figure 1: Flowchart showing the proposed localised learning algorithm (kNN-LS-SVM) to predict the BRD-related outcome.

The prediction of BRD-related outcome can be considered as a classification machine learning problem whose input is the set of extracted features based on the physiological, behavioural, and clinical data and the output is the BRD-related outcome. Several machine learning techniques can be used for such problem. However, support vector machines (SVM's) is one of the efficient classification techniques used in different similar studies in health care and human applications. In this study, least squares support vector machine (LS-SVM) is proposed to be used for general models as it is same powerful as standard SVM's, but, it has less computational cost. Most, if not all, relevant studies of diseases prediction rely on global general models (e.g., Amrine et al., 2014; Babcock et al., 2013). However, global models are not that efficient for online classification and streaming analytics applications in which a stream of new data is collected, from animals or farm via PLF technologies, especially when aiming at farm-based models. For example, Amrine et al., (2014), used different global classification models (e.g., Bayesian networks and decision trees) to predict the BRD-related outcomes. Amrine concluded that the accuracy of all the model varied by the dataset and ranged between 63% in one dataset up to 95% in another. Hence, for the purpose of this paper, a localised version of LS-SVM, namely k-Nearest Neighbours (kNN)-LS-SVM (A Y A Amer, 2016) is suggested to be compatible with streaming farm data for online and streaming analytics. The suggested algorithm, as depicted in Figure 1, is successfully used in an earlier work (Youssef et al., 2019) to predict the thermal sensation of building occupants.

Support vector machines (SVM)

SVMs are originally presented as binary classifiers, that assign each data instance $X \in \mathbb{R}^d$ to one of two classes described by a class label $y \in \{-1,1\}$ based on the decision boundary that maximises the margin $2/\|\mathbf{w}\|_2$ between the two classes. Generally, a feature map ϕ: $\mathbb{R}^d \Rightarrow \mathbb{R}^p$ is used to transform the geometric boundary between the two classes to a linear boundary L: $\mathbf{w}^T\varphi(x) + b = 0$ in feature space, for some weight vector $\mathbf{w} \in \mathbb{R}^{p\times 1}$ *and* $b \in \mathbb{R}$. The class of each instance can then be found by $y = sign(\mathbf{w}^T\varphi(x) + b)$, where *sign* refers to the sign function (Suykens et al., 2002).

The estimation of the boundary L is performed based on a set of training examples x_i $(1 \le i \le N)$with corresponding class labels $y_i \in \{-1,1\}$. An optimal boundary is found by maximizing the margin that is defined as the smallest distances between L and any of the training instances. In particular, one is interested in constants $\boldsymbol{w}$ and b that minimize a loss-function:

$$\min_{\mathrm{w,b;\,\xi}} \frac{1}{2}\,\mathbf{w}^{\mathrm{T}}\mathbf{w} + \mathrm{C}\sum_{\mathrm{i}=1}^{N}\xi_i\ ,$$

and are subject to:

$$y_i(\mathbf{w}^T\varphi(xi) + b) \geq 1 - \xi_i \; and \; \xi_i \geq 0, i = 1, 2, \dots, N.$$

The constant C denotes the penalty term that is used to penalize missclassification through the slack variables ξ_i in the optimization process.

The so-called kernel-trick avoids the explicit introduction of a feature map ϕ and implicitly allows to use feature spaces of infinite dimensionality. A commonly used kernel is given by the Gaussian kernel:

$$k(x_i\,, x_j\,) = \exp\left(\frac{||x_i - x_j\,||^2}{2\sigma^2}\right),$$

where σ denotes the kernel bandwidth. Both σ and C can be optimized as hyper-parameters in a cross-validation experiment.

LS-SVMs are obtained by using a least-squares error loss function (Suykens et al., 2002):

$$\min_{\mathrm{w,b};\, e} \frac{1}{2}\, \mathbf{w}^T\mathbf{w} + \gamma \sum_{\mathrm{i=1}}^{N} e_i^2\,, \tag{1}$$

such that

$$y_i(\mathbf{w}^T\varphi(x_i) + b) \geq 1 - e_i \; and \; e_i \geq 0, i = 1, 2, \dots, N.$$

This optimization procedure introduces errors e_i such that 1– e_i is proportional to the signed distance of x_i from the decision boundary and γ represents the regularization constant. In fact, the non-negative slack variable constraint is removed and the solution of the optimization problem can be obtained by a set of linear equations, reducing computational effort (Suykens et al., 2002).

The kNN-LS-SVM algorithm

While global SVMs consider the same weight for all training instances in the optimization process, local learning approaches allow that the training samples near a test point are more influential than others. Localised approaches of SVMs (A Y A Amer, 2016) are based on weighting functions $\lambda(x_s, x_i)$ that express the similarity between the features vectors of the i^{th} data point x_i and the test instance x_s. For an LS-SVM, this leads to the following cost function:

$$\min_{\mathrm{w,b};\, e} \frac{1}{2}\, \mathbf{w}^T\mathbf{w} + \gamma \sum_{\mathrm{i=1}}^{N} \lambda(x_s, x_i) e_i^2\,, \tag{2}$$

such that

$$y_i(\mathbf{w}^T\varphi(x_i) + b) \geq 1 - e_i \; and \; e_i \geq 0, i = 1, 2, \dots, N.$$

For kNN-LS-SVM a binary valued similarity criterion:

$$\lambda(x_s, x_i) = \begin{cases} 1 & \text{if} \quad ||\varphi(x_s) - \varphi(x_i)||^2 \leq r_s \\ 0 & \qquad\qquad \text{otherwise} \end{cases} \tag{3}$$

where r_s is the k^{th} smallest distance among $\{\|\varphi(x_s) - \varphi(x_i)\|; 1 \leq j \leq N\}$. This formulation leads to the hybrid kNN-LS-SVM method (A Y A Amer, 2016). In practice, implementing the hybrid classifier of kNN-LS-SVM, as shown in Figure 1, starts with receiving an unlabelled new test point x_s and finding the nearest k points from the training set in the feature space. Based on the nearest k points, an LS-SVM model is trained only with the new subset. Hence, for each test point a dedicated model is trained. The advantage of this localised approach is that it can enhance the classification performance in case of class imbalance, in addition to the computational and temporal efficiency especially for online modelling and streaming analytics. For more details about localized learning the reference (A Y A Amer, 2016) include a detailed explanation of the algorithms. The choice of LS-SVM to be localised instead of the SVM because of it computational advantage of solving a set of linear equations instead of solving a quadratic programming problem of standard SVM. As shown in Figure 1 (for more information see Amer, 2016), the kNN-LS-SVM algorithm for online prediction of BRD-related outcome is as follows:

1. Given a new data instance (from new animal), compute the distance to all training (old) data points and select the nearest k-neighbours,
2. If all k-neighbours would have the same label, assign the same lable to the new data point,
3. Else, train a new LS-SVM model using 'only' the k nearest neighbours (data points),
4. Use the new model to label the new data instance.

Conclusions

As mentioned earlier, the BRD is multifactorial disease, and the BRD-related progression outcome is farm-dependant if not individual-dependant as well. Hence, the localised kNN-LS-SVM algorithm is proposed to provide an adaptive framework to predict the BRD-related outcome based on streaming farm and clinical data. The hybrid mode of kNN-LS-SVM algorithm is providing several advantages. In the local learning part, represented by the kNN, the nearest neighbour's classifier suffers from the problem of high variance in the case of limited sampling. However, the use of a SVM classifier can overcome such problem as it often perform well compare to other classifiers in case of small number of data points (Vapnik, 1999). On the other hand, the complexity of global SVM grows with the size of the training data (e.g., in case of streaming farm data), which is computationally expensive due to the quadratic programming of the SVM algorithm. Hence, the local SVM is proposed to overcome the aforementioned problem by building small SVM models based on data in the neighbourhood around the test sample. This will provide a computational advantage in case of online learning and streaming analytics.

The proposed kNN-LS-SVM is successfully used for prediction problems related to healthcare and wellbeing applications (e.g., Ahmed Y.A. Amer et al., 2019; Ahmed Youssef Ali Amer et al., 2020; Youssef et al., 2019)it is attempted to improve ICU mortality prediction in field conditions with low frequently measured data (i.e., hourly to bi-hourly.

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What's the effect? - Presence of a sensor system and its effects on animal health and production in dairy herds

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Abstract

Despite their increasing usage in dairy herds, the actual effect of monitoring systems on the production and animal health is largely unknown. In a retrospective study, the influence of a monitoring system on the milk production and certain health parameters was investigated in four dairy herds.

Selected were four dairy farms (herd size 500 - 1500 animals), that had installed the Smartbow® System (Zoetis; Weibern, Österreich). Health and production data were available for the time before and after installation of the system. 24 parameters were used to compare the time periods. Next to the presence of the system, THI-indices and farm-specific factors were used for a multivariate analysis. Analysis was done for all data and specifically for the herds, respectively.

After sensor introduction there was a significant increase of milk production (+0,96 kg / cow/ d; p <0,001), this effect was in individual analysis only found in two farms. All parameters related to reproduction improved, partly significantly, after introduction of the system. Again, this effect was not maintained in all herds when analysed separately. After introduction, somatic cell count dropped significantly (SCC -37.000/ml; p=<0,001), again, this was not significant on all farms in separate analysis. There was no change in new udder infections.

The introduction of the Sensor system led to an improvement in milk production, reproduction and partly udder health. The significance of the positive effect was different between farms evaluated.

Introduction

Digital technology is increasingly used on dairy farms: In a 2020 survey by the German business-association Bitkom, 8 out of 10 dairy farmers stated they were using digital technology of some kind on their farms (BITKOM 2020). "Digitalization" describes various processes and products, e.g., sensor technology, electronic data management or automatic milking systems. Often, the term "precision livestock farming" is used to collectively name this complex (Berckmanns 2008). PLF generally comprises of technology collecting data (milking robots, sensors) and algorithms computing the data. The results of these algorithms are information, e.g., "alarms" serving as basis for decision making (Wathes et al. 2008).

It appears that estrus-detection technology is the most widespread type of sensor technology used on dairy farms (Knight 2020) and the effectivity of various sensors to recognize cows in heat is well documented (e.g., Kempf 2016).

Identifying animals that are diseased or require special attention is another field of PLF. It was shown that ear-based accelerometers can monitor the rumination of cattle (Reiter et al. 2018) and reliably predict disease in dairy cows (Iwersen et al. 2018).

It is, however, not certain whether the use of PLF technology has advantages for animal health and production on individual animal or herd level (Knight 2020). It was the aim of this study to gauge what effect the presence of a sensor system has on animal production and animal health on dairy farms.

Material and Methods

Farms enrolled

Four German dairy farms that had installed the Smartbow® sensor system ((Zoetis; Weibern, Österreich).; SB) where approached to collaborate in the study as a convenience sample. The farms had to have the system installed for at least four months and the herd management software HERDEPLUS (dsp Agrosoft GmbH, Ketzin) installed to provide production and health data.

The farms selected had an average herd size of approximately 1200 cows (500 – 1700) and an average milk production of 34,4 kg/d/cow at the time of the study. Health and production data were accessed from the farm herd management software and transferred to Microsoft Excel (Microsoft Corp., Redmond, USA) for further processing.

Data collected and analysed

Health and production were assessed by using the following indicators:

Milk production:
— Average milk per cow per day (Mkg) based on monthly milk recording
— Lactation peak yield (LP; kg) and day of lactation peak (LPD) as calculated by the herd management system
— Milk production on day 206 (L206) for assessment of lactation persistency

Reproduction:

The reproduction was assessed using the parameters computed by the herd management system, including:
— Insemination rate
— Insemination Index (Inseminations per pregnancy)
— Pregnancy Rate
— Days to first insemination
— Days open

Furthermore, the usage of semen portions was calculated by
— The Semen Portion Index, defined as (Number of portions used x 100 / Number of pregnancies) and

— Percentage of repeated inseminations defined as (Number of repeated insemination / total inseminations)

Udder Health

Udder health was assessed by using the following parameters:

— Average Somatic Cell Count (SCC) from monthly milk recording
— Monthly New Infection Rate, calculated for thresholds SCC/ml: 100,000; 200,000; 400,000

Metabolic Health

The records were assessed for the recorded events of Clinical Ketosis, Clinical Hypocalcaemia and unspecific events of metabolic disease.

Statistical analysis

For analysis, parameters were assessed for the months available on the herd management-software per farm with and without SB. All analyses were done per farm and for the sample as a whole. The procedure ProcMEANS in SAS (SAS Institute, Cary, USA) was used to compute means, deviation and extremes, ANOVA was used for describing interaction farm and presence of SB, taking farm, presence of SB, and level of Temperature-Humidity-Index (THI; blocked 1- 3: summer, autumn/spring; winter) as fixed effects:

$$Y_{ijk}=\mu + B_i + V_j + T_k + BV_{ij} + e_{ijk}$$

With Y=observation; μ = Population mean; B_i = fixed farm effect (i = farm 1 – 4); V_j = fixed effect of variant (j = 1 with SB and 2 = without SB), T_k= fixed effect of season-dependant THI; BV_{ijk} = interaction of B and V; e_{ijk} = random residual error.

Significance was computed using the Scheffé-test to account for skewed distribution of values. It was possible to include into the analysis (with / without presence of SB): Farm 1: 11 / 18 months; Farm 2: 8 / 13 months; Farm 3: 18 / 18 months and Farm 4: 23 / 32 months, respectively. A total of 60 months with SB and 81 without SB were analysed and compared as described.

Results

Milk production

Table 1: Overview of differences in milk production parameters between Variant 1 (with SB) and V2 (without SB). MKg: Average milk yield per cow and day in milk recording; LP: Lactation peak yield [kg/d]; LPD: Day of lactation peak; L206: Milk yield at day 206 of lactation [kg/d]

	Mkg [kg]		LP[kg]		LPD [d]		L206 [kg]	
Variant	LSM	SE	LSM	SE	LSM	SE	LSM	SE
1	35,51[a]	0,16	44,01[a]	0,33	52,40[a]	1,79	34,64[a]	0,31
2	34,55[b]	0,13	43,81[a]	0,27	56,23[a]	1,48	33,98[b]	0,22

Comparing the variants with or without SB, analysis of production parameters showed significant higher production in months with SB compared to months without: Production without with SB (1) LSM = 35,51; SB (2) LSM = 34,55; p <0,0001. Production at day 206 was in average 0.66 kg higher with SB present. Other results were not significant (Table 1).

Analysis within farms revealed a higher milk production with SB on 2 out of 4 farms (Farm 1: +1,75kg p=0,0391; Farm 3: +1,98kg, p=0,0016).

Reproduction

Insemination Rate. Calculated between variants, no significant difference was found in insemination rate. Calculated per farm, the results were inconclusive with only one farm (Farm 4) showing a significant higher insemination rate with the presence of SB.

Insemination Index. Between variants, the Insemination Index decreased from 3,15 to 2,8 using SB (p= <0,0001). Computed per farm, however, only one farm (Farm 3) showed a statistically significant decrease with other farms only showing a tendency towards less inseminations necessary.

Pregnancy Rate. Between variants, the PR increased significantly when SB was present (21,96% vs 18,64%; p= <0,0001). Again, only Farm 3 maintained a significant difference when calculation was done with farm as point of interest, with other farms showing a positive, however insignificant increase.

Days to first insemination and Days Open. Neither in variant nor farm calculation was there a statistically significant difference when SB was present. Days Open, however, decreased significantly over all farms with SB present (120,66 d vs. 111,86d; p= <0,0001). The tendency was shown on all farms analysed, however only statistically significant on Farm 3.

Semen Portion Index. The portions of semen used decreased with presence of SB in the herd (2,91 vs 3,39; p= <0,0001). Again, only on farm 3 the difference remained significant if calculated per farm.

Percentage of repeated inseminations. The proportion of repeated insemination decreased with 1,24% (5,81% vs. 4,57%, p= 0.0064), the difference per farm only being statistically significant on farm 3.

Udder Health

Somatic Cell Count. The SCC as found in milk recording decreased over all farms with the presence of SB (241.920 cells/ml vs. 204.820 cells / ml; p= <0,0001). Calculated per farm, only one farm (Farm 4) showed a statistically significant decrease (245.060 cell/ml vs. 196.960 cells/ml; p= 0,0211).

New Infection Rate. No statistically significant effect of the presence of SB was found on new infection rates, independent of SCC threshold for new infections.

Metabolic Health

Although a change of reported incidence of various metabolic conditions could be detected once SB was present on a dairy farm, the farm records could not point to an increase, decrease or any significant change at all.

Discussion

Very few studies report the changes a dairy herd experiences after introduction of a sensor system. The system Smartbow® is not only functioning as an oestrus detection system but also claims to be able to detect differences in animal health due to changes in the rumination pattern of individual animals. It has been shown to achieve that in dairy cows (e.g., Gusterer et al. 2020).

The main difficulty for studies on herd level is to have comparable data before and after the introduction of a sensor system. In this study, we were able to include herds with a significant herd size and months with and without the SB system, covered by the same herd management system, thus allowing for comparison of data in animal health and production. Although it has to be conceded that the number of farms involved was low and farm-specific effects partly not very clear, the introduction of the sensor system led to remarkable changes in health and production.

The overall increase of milk yield may partly be attributed to the genetic progress, the model used does however point to the presence of the sensor system as a main explanatory variable. Rutten et al. (2014) pointed to possible pathways in which a sensor system could contribute to increased milk yield: An improved reproductive performance could lead to shorter calving intervals, increasing milk production by a lower average lactation stage of the herd. Indeed, the presence of SB in this study improved reproductive performance and shortened the Days Open on the farms involved. Unlike reported by Rutten et al. (2014), however, the system apparently did not only increase the efficiency of oestrus detection, but also improved performance of artificial insemination. Clearly, less inseminations and semen portions were necessary to achieve one pregnancy. In other words, not only the likelihood for insemination increased, so did the likelihood to conceive. This points to an apparently very efficient recognition of the oestrus cycle and identification of the optimal insemination time.

The Somatic Cell Count obtained from monthly milk recording served as main proxy indicator for udder health. The decrease of SCC in the herds after introduction of SB is significant but should probably not overestimated. The change of approximately 30.000 cells / ml is easily achieved in large herds by very few individual animals with higher or lower cell count. Moreover, udder health is a multifactorial issue, depending on a lot of external factors. It could be speculated that the improved health monitoring leads to earlier recognition of udder health problems, decreasing the probability of a cow to become chronically ill. However, the unchanged new infection rate, computed for different thresholds, remained largely unchanged.

The inconclusive results of analysis of metabolic health point to largely subjective diagnosis and documentation in this disease complex. While farmers generally reported a good recognition of disease by SB, no significant change in documented disease incidence could be found. This points to the limitations of a retrospective study design like in this study, where objective criteria for diagnosis are not available. To test the effect, prospective studies on large farms are necessary, involving independent staff to make diagnoses.

Conclusions

The introduction of a sensor system monitoring activity and rumination was correlated with a marked increase of milk production in the four large dairy farms analysed. Reproduction did benefit not only in oestrus detection but apparently also from a more precise identification of the time of insemination. While udder health generally improved after introduction, this effect should be valued with care. A retrospective study design did not allow for analysis of incidence of metabolic disease in the farms involved.

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POSTER SESSION

Pigs

A two-step deep learning model for pen-level estimation of slaughter pig live weight distribution

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Abstract

Accurate and automatic estimates of slaughter pig live weights are valuable to farmers. We present a two-step deep learning model for estimating the distribution of pig live weights at pen level, based on images of the whole pen. We use a pre-trained convolutional neural network combined with a secondary model with regression outputs. The convolutional neural network extracts feature vectors from the input images. These, in combination with relevant metadata, are then used as inputs for the secondary network, which estimates the live weight distribution per image as its output. In this preliminary study, we systematically compare combinations of network architectures and training strategies to identify the optimal set of strategies. Application on a final test set yielded R^2 values ranging from 0.90 to 0.94.

Key words: Automatic weighing, deep learning, live weight, slaughter pigs

Introduction

When pigs are slaughtered, the price per kg depends on what weight range the carcass falls into. Pigs that are either too small or too heavy will yield a smaller profit for the farmer, compared to pigs in the optimal range. Thus, accurate monitoring of the pigs' live weights has the potential to be of significant economic importance for pig farmers. Manual weighing of pigs is one of the most time-consuming management tasks in the finisher unit (Kristensen et al., 2012), so being able to infer the live weight of the pigs indirectly via e.g. video images would be preferable. Some commercial systems for video-based weight monitoring already exist (e.g. SKOV, 2021). These systems are placed above the feeding station in selected pens with dry-fed pigs, and make a weight estimation whenever a single pig is eating at the trough. These single weight estimations are then aggregated to averages for the whole pen. This naive method of aggregating to pen-level mean weight is likely to be influenced by biased image samples, as larger and more dominant pigs will tend to feed more frequently at the expense of smaller pigs in the same pen (Schrøder-Petersen and Simonsen, 2001). We present a novel two-step method to estimate the pen-level live weight distribution based on images of the whole pen captured from above. The two steps combine the use of a convolutional neural network (CNN) and a fully connected artificial neural network (FC-ANN). Our aims are to (1) introduce this novel method, (2) identify optimal strategies for data pre-processing and model architecture for our data set, (3) assess whether the inclusion of the time stamps of the input images as an input for the secondary FC-ANN affects the accuracy of the predicted live weight distributions, and (4) determine if the model can be easily calibrated to work with data from a previously unseen pen.

Materials and Methods

All data pre-processing and model training was done in R version 3.5 (R Core Team, 2017).

Data

The data used in this study were collected from four grower/finisher pig pens in a commercial Danish pig farm with 20 pigs per pen at the time of insertion. More details about the farm can be found in a previous publication (Jensen et al., 2017). Video data were continously recorded from above each pen, and the video data from all cameras were stored together in a single MSH file per growth period. Still frames were extracted from the relevant cameras, using a specialized program called MSH Image Extractor. The settings to the program were chosen so that the extracted images would be at least 600 seconds apart in the video.

For three of the pens (Pens 1, 2, & 3), data for this study were only available for one growth period, due to technical issues. For Pen 4, data were available for two growth periods.

Individual pigs were weighed manually once per week from the day of insertion until the first pigs per pen were sold to slaughter after 8-10 weeks. From these individual weight measurements, the mean and standard deviation of the weights per pen per weighing day (henceforth “Mean” and “SD”, respectively) were calculated. For each growth period of each pen, two linear functions were then defined to describe the Mean and SD, respectively, given the number of days since insertion. These pen-specific linear functions were then used to interpolate the Mean and SD values for all days in the growth periods, where manual weighings were not performed. These interpolated values were used in the later training of the secondary FC-ANNs, as described further below.

The timestamps for the individual images were first transformed into a decimal value by keeping the hour as is and dividing the minutes by 60, e.g. the 12:15 would be transformed to 12.25. The decimal timestamp would then be sine-cosine-transformed as shown in eq. 1:

$$\sin(\omega \cdot Time) + \cos(\omega \cdot Time) \qquad (1)$$

, where *Time* is the decimal timestamp and $w = (2\pi)/24$.

Image data pre-processing

Each image in the extracted image data set was transformed into a latent feature representation with a length of 4096 via the pre-trained VGG-16 model (Simonyan and Zisserman, 2015)potent and selective peptidomimetic inhibitors have been developed; these compounds share with the peptide substrate a free thiol and a C-terminal carboxylate. We have used a synthetic tetrapeptide combinatorial library to screen for new leads devoid of these features: the peptides were C-terminally amidated, and no free thiol was included in the combinatorial building blocks. To compensate for this negative bias, an expanded set of 68 amino acids was used, including both L and D as well as many non-coded residues. Sixteen individual tetrapeptides derived from the consensus were synthesized and tested; all were active, showing IC50 values ranging from low micromolar to low nanomolar. The most active peptide, D-tryptophan-D-methionine-D-4-chlorophenylalanine-L-gamma- carboxyglutamic acid (Ki = 2 nM, which was truncated after the second-to-last fully connected layer before the final output layer of VGG-16. The actual or linearly interpolated target values (Mean and SD) and the sine-cosine-transformed timestamp for each image were subsequently added to its corresponding latent feature vector.

Optimizing the secondary FC-ANN

Three of the four pens (Pens 1, 2, & 3) were used to estimate the effect of different strategies for data pre-processing and FC-ANN architecture, and to identify the optimal combination of strategies. We used per-pen cross-validation, where each of the three pens were iteratively used as the validation set, while the remaining two were used as the training set.

In each iteration of the per-pen cross-validation, all latent features which had a variance of 0 in the training set were removed from both the training set and the validation set.

The compared strategies where as follows:

1. Adjustment of the extracted latent features. We compared *no adjustment* to adjustments using the *Sigmoid* and the *hyperbolic tangent* (tanh) functions.
2. The number of principle components of the latent features, N_{PC}, which were used as input for the FC-ANN. In each iteration of the cross-validation, principle component analysis (PCA) was performed on the training set, and the resulting PCA transformation model was applied to both the training and validation set. The first N_{PC} principle components were used as inputs for the FC-ANN, where $N_{PC} = 2^j$ and $j \in \{3, 4, 5, 6, 7, 8, 9, 10\ 11\}$. As a baseline, we included the case where PCA was not applied and all latent features (with a variance greater than 0) were used as inputs.
3. The inclusion the sine-cosine-transformed time stamp of the image in the input vector, compared to not including the time stamp in the input vector.
4. The number of hidden layers, $N_{hidden} \in \{1, 2, 3\}$, used in the FC-ANN.

The FC-ANN was trained using the *MxNet* library for R (Chen et al., 2015) with a batch size of 128. The number of hidden nodes was defined as the average of the number of inputs and the number of outputs. The hidden nodes were evenly distributed between all hidden layers. The evaluation metric was the root mean squared relative error (RMSRE). A dynamic learning rate was used with an initial learning rate of 0.001. The FC-ANN was trained on the training set for 10 epochs at a time, after which the trained FC-ANN would be applied to the validation set. If the RMSRE on the validation set was reduced compared to the previous lowest value, the training would continue for 10 epochs with the same learning rate. If the RMSE on the validation set was not reduced, the learning rate was reduced by a factor of 10, and the training would resume for another 10 epochs. When the RMSRE on the validation set had not been reduced after two consecutive sets of 10 epochs, the training was terminated. The best trained model was applied to the validation set, and the predicted values were aggregated to daily averages. The coefficient of determination (R^2) between the observed Mean & SD and the aggregated predicted Mean & SD were saved for subsequent analysis.

After the per-pen cross-validation, a linear mixed-effects model was defined to estimate the effect of the different strategies on the R^2 values between the observed and per-day aggregated predicted values. The pen-ID was included as a random effect. An ANOVA test was used to identify the variables which had a significant effect on the R^2 between the observed and predicted values for Mean and SD.

Final test

The best set of strategies, identified from the per-pen cross-validation, was used to train a final FC-ANN using the Pens 1, 2, & 3 as the training set. The number of training epochs was defined as the average number of epochs used to reach the best performance in each iteration of the cross-validation with these strategies. The trained FC-ANN was applied to data from the two growth periods of Pen 4. The first growth period was used to estimate the linear relationship between the observed and predicted values for Mean and SD in Pen 4. This linear relationship was used to adjust the predicted values for the second growth period.

Results and Discussion

Image data

Figure 1 shows the same group of pigs at two different times in the growth period, i.e. when the pigs' mean weight is 66 kg and 108 kg, respectively. As is seen, the effects of the live weight on the appearance of the pigs in the images are readily apparent, even to the untrained eye. It is thus sensible to assume that a neural network would be able to learn to infer information about the live weight from the pigs' apparent sizes in the images.

Figure 2 shows the same group of pigs at different times during one day. As is seen, the appearance of the pigs within the pen and the lighting conditions vary considerably over the course of a day. The appearance of the pigs within the image depends on their behaviour, i.e. sleeping, exploring, and eating, which in turn depends directly on the time of day. It thus seem reasonable to assume that including information of the time of day as input for the secondary FC-ANN would have the potential to improve the performance.

Figure 1: The same pen at two different times. A: mean weight = 66 kg, standard deviation = 3.5 kg. B: mean weight = 108 kg, standard deviation = 7.0 kg.

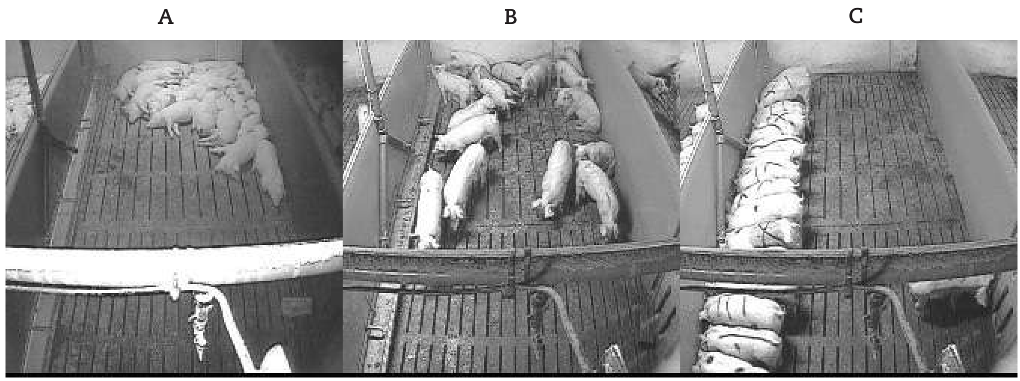

Figure 2: The same pen at three different times. Examples of the differing behaviors and lighting conditions given the time of the day. A: 06:00, B: 09:00. C: 10:47.

Optimization results

Table 1 shows the results of the ANOVA analysis on the effect of the various strategies on the R^2 values between the observed and predicted values of Mean and SD. The number of principle components and the number of hidden layers are statistically significant at the 95 % confidence level for predictions of both Mean and SD. The inclusion of time as an input variable is significant at the 90 % confidence level for the prediction of Mean, but not for the prediction of the SD. The method for adjusting the latent features was not significant in either case.

Table 1: Results of ANOVA analysis on the effect of the various components on the R^2 values between the observed and predicted values of Mean and SD.

Output	Variable	Sum of squares	Mean sum of squares	DF	*p*-value
Mean	Adjustment of features	0.04	0.022	2	0.59
	No. of hidden layers	0.46	0.231	2	0.004
	Inclusion of time	0.12	0.124	1	0.08
	No. of principle components	47.58	4.758	10	$< 2.2 \cdot 10^{-16}$
SD	Adjustment of features	0.05	0.023	2	0.59
	No. of hidden layers	0.49	0.242	2	0.005
	Inclusion of time	0.12	0.116	1	0.11
	No. of principle components	46.39	4.639	10	$< 2.2 \cdot 10^{-16}$

Figure 3 shows the effect of the number of principle components on the R^2 values, compared to using all latent features without PCA. For both Mean and SD, the best performance is achieved when using 64 principle components, resulting in R^2 values which are 18 and 17 percentage point better, respectively, compared to when PCA is not used. Using 32, 64, and 128 principle components is significantly better than not using PCA, while using 256+ is significantly worse. Using 8 and 16 is not significantly different from not using PCA.

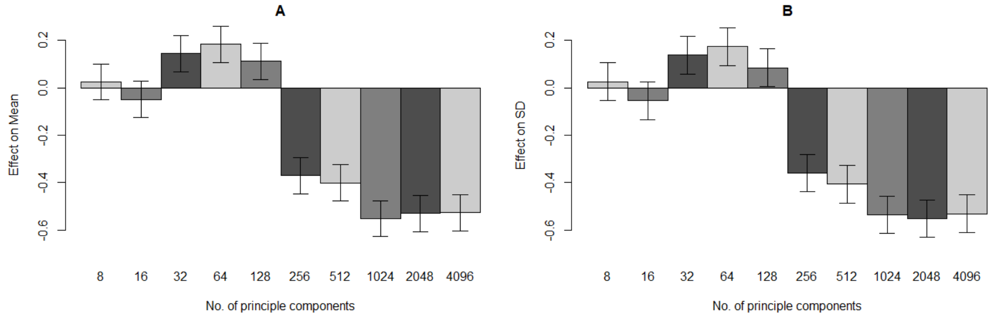

Figure 3: The estimated effect of the number of principle components on R^2 between predicted and observed values of Mean (A) and SD (B). Not using PCA was the baseline for all comparisons.

Table 2 shows the post-hoc analysis of the effects of the number of hidden layers on the R^2 values between the observed and predicted values for Mean and SD. All *p*-values are adjusted using the Holm-Bonferoni method. In both cases, the best estimated performance was seen when using a network with just one hidden layer. The difference between 1 and 2 hidden layers is not statistically significant, but the differences between 1 and 3 layers and 2 and 3 layers are statistically significant at the 95 % confidence limit in both cases.

Table 2: Post-hoc analysis of the effects of the number of hidden layers on the R^2 values between the observed and predicted values for Mean and SD of pen-level live weight.

Comparison	Mean			SD		
	Estimate	Std. Error	p-value	Estimate	Std. Error	*p*-value
2-1	-0.0002	0.02	0.99	-0.007	0.02	0.76
3-1	-0.059	0.02	0.01	-0.064	0.02	0.01
3-2	-0.059	0.02	0.01	-0.057	0.02	0.01

The overall best R^2 value for the per-pen cross-validation of the three training pens was achieved when using 1 hidden layer, Sigmoid adjustment of the latent feature vectors, the first 64 principle components of the adjusted features, and when including the sine-cosine-transformed time of day as an input variable. With these settings, the R^2 values ranged from 0.91 to 0.97 for Mean and from 0.90 to 0.93 for SD in the per-pen cross-validation for Pens 1, 2 and 3. With these settings, the average number of epochs used to optimize the three models of the per-pen-cross-validation models was 210.

Final test

Figure 4 shows the results of applying the final ANN to the final test pen, i.e. Pen 4. The equation describing the linear relationship between observed and predicted values from the first growth period is shown in the plots in the top row. As seen in the bottom row of Figure 4, this equation worked very well for adjusting the predicted values for the second batch. This shows that the pre-trained ANN can be directly applied

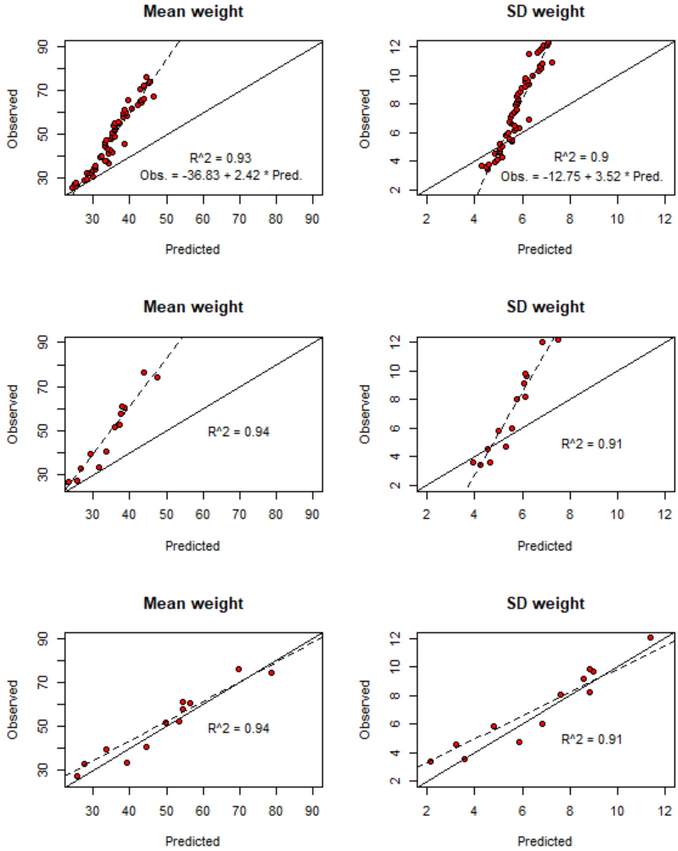

Figure 4: Top row: Observed and predicted values for live weight Mean and SD for the first growth period of the final test set, based on interpolated and actual weight measurements. Middle row: Observed and predicted values for the second growth period of the final test set, based only on actual weight measurements. Bottom row: Observed and predicted values for the second growth period, after adjusting the predictions with the linear equation found for the first batch. Solid diagonal lines represent the hypothetical perfect predictions. Dashed lines represent the linear relationship between predicted and observed values.

to a previously unseen pen without the need for fine-tuning the ANN itself, which is the approach often used in other studies, e.g. (Bourgin et al., 2019; Chebet et al., 2019; Jensen and Pedersen, 2021)which increases labour costs for the farmer, worsens the hygiene and welfare of the pigs, and has negative environmental consequences. Previous research suggests that monitoring the positioning behaviour of grower/finisher pigs within their pen has the potential to be used in early warning systems that can alert the farmer to an impending pen fouling event 1–3 days in advance. For such a warning system to be feasible, monitoring of the pigs' positioning behaviour must be automated. To this end, we present a novel yet relatively simple method, namely a convolutional neural network (CNN. This is a strong advantage for use in practice, as calibration by adjustment with a linear equation is relatively easy, whereas fine-tuning a pre-trained ANN to work in a new environment requires highly specialized skills within the field of machine learning. Notice that Pen 4 came from the same herd as Pens 1, 2, & 3. Further studies should determine if this method of easy calibration will also work when the pre-trained ANN is applied to pens from a different herd.

The linear equation defined from the first batch of Pen 4 was based on linearly interpolated values between weekly weight measurements of individual pigs. Weighing all pigs every week for a full growth period would require a massive investment of time and resources in practice. Therefore, further studies should determine the minimum number of manual weighings needed for the interpolated values to be useful for the type of calibration by linear equation shown in this study.

Conclusion

We demonstrate a novel method for estimating the distribution of slaughter pig live weights at pen level based on images from above the whole pen. A pre-trained convolutional neural network was used to extract latent features from the images. A fully connected neural network was then trained to take the latent feature vectors and relevant metadata as input, and estimate the mean and standard deviation of the weights at pen level as its output. The best performance of the secondary network was achieved when the feature vector was transformed with the Sigmoid function (non-significant), when the time stamp of the image was included as an input (borderline significant), when using one hidden layer (significant), and when only the first 64 principle components of the feature vectors were used as input (highly significant). Application on a final test set resulted in R^2 values ranging from 0.90 to 0.94. After training, the outputs of the secondary network can easily be calibrated for use on a pen which was not included in the training set. This is done by adjusting the predicted values with linear equations derived from one batch of data from the otherwise unseen pen.

Acknowledgements

This research was done with support from The Danish Council for Strategic Research (The PigIT Project, Grant number 11-116191) and the EU's Horizon 2020 programme (CYBELE, grant No. 825355 and Code Re-farm, grant no. 101000216)). We further wish to thank IT worker Mads Ravn Jensen at Aarhus University for developing and providing the software called MSH Image Extractor, used to extract the frames from the videos in the MSH files.

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Analysis of odour reduction efficiency of pig house by various odour reduction systems

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Abstract

Various odour reduction systems have been introduced to reduce the odour emitted from the pig house which include bio-curtain, bio-filter, scrubber, windbreak wall, and so on. Several quantitative analysis studies on the odour reduction efficiency were also conducted. However, studies that focused on evaluating only single odorous gases were mainly conducted and few experiments were done to measure complex odours. Since most complaints arise from complex odours that are felt by local residents, it is necessary to measure and manage complex odours. Therefore, the efficiency of bio-curtains and scrubber systems in reducing complex odours and single gases (NH_3, H_2S) were analysed through field experiments. When using bio-curtain, complex odours could be reduced by 58.1% on average. In the case of NH3, 76.0% was reduced, H_2S was reduced (79.9%). On the other hand, the scrubber system showed an average of 58.9% reduction in complex odour and showed a better effect than the bio-curtain. It showed a reduction effect of average 50.0% on the NH_3, while H_2S had an average reduction effect of 32.0%. In the case of the scrubber systems, the larger the empty bed residence time (EBRT), the better the effect, and it was determined that the circulation water condition (pH, water temperature) would be important. In the single gas reduction effect, the pH of circulating water made a big difference in the reduction efficiency of H_2S and NH_3.

Keywords: odour, pig house, reduction systems, reduction efficiency

Introduction

The total production of the domestic livestock industry was 1.064 billion US dollars, accounting for approximately 40% of the total agricultural sector. As meat consumption increases, the size of rearing is increasing to sustain the productivity and price competitiveness of livestock products, and livestock facilities are becoming larger. In particular, the pig industry (47.9%), which accounts for the highest proportion of production for the livestock industry, causes a lot of odour complaints. Of the total odour complaints, about 35% of the livestock industry-related odour complaints were reported (Korea Environment Corporation, 2015). Of these, 46 percent occurred in pig farming facilities. Korean government is actively responding to complaints about livestock odour by improving the ventilation method of conventional livestock facilities, modernizing aged facilities, and distributing odour reduction facilities. Various odour reduction systems have been introduced to reduce the odour emitted from the pig house which include bio-curtain, bio-filter, scrubber, windbreak wall, and so on. Several quantitative analysis studies on the odour reduction efficiency were also conducted. However, studies that focused on evaluating only single odorous gases were mainly conducted and few experiments were done to measure complex odours. Since most complaints arise from complex odours that are felt by local residents, it is necessary to measure and manage complex odours. Therefore, the efficiency of bio-curtains and scrubber systems in reducing complex odours and single gases (NH_3, H_2S) were analysed through field experiments. The correlation between complex odours and single gas was analysed using field-measured data.

Material and methods

Odour reduction systems

As for the experimental odour reduction systems (Figure 1), fogging, bio-curtain, and scrubber systems, which are widely used in domestic pig houses, were selected. Field experiments for the analysis of odour reduction effects were repeatedly conducted from June 29, 2021. The fogging system was installed and operated inside the pig house of Farm A for the purpose of reducing odour concentration. The bio-curtain system was installed and operated for the purpose of reducing odour exhausted from Farms B, C, and D. The size of the bio-curtain installed in each farm varies according to the size of the pig house to which the sidewall exhaust fan is applied. However, in all farms, washing water was sprayed inside the bio-curtain through the on/off control method. The odour reduction effect on the scrubber system was analysed for scrubber systems installed on farms D, E, and F. Packing materials were applied to improve the contact of washing water with odour compound, the water was continuously sprayed in the scrubber system to reduce odour.

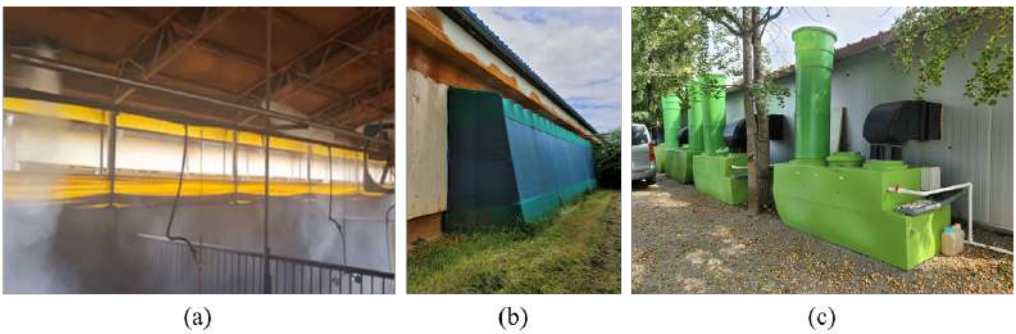

Figure 1: Odour reduction systems (a) fogging system, (b) bio-curtain, and (c) scrubber

Measurement of odour sources

The odour inside the pig house was measured at the outlet of the pig house, and the odour outside was measured after passing through the odour reduction system (Figure 2). The installation height of measurement devices was located at 1.5 m from the ground surface. A portable air collection device (Odotech, Korea) and Multi-Rae Lite (Honeywell, USA) were used to measure the inside and outside livestock odour of the experimental pig houses.

Figure 2: Measurement of livestock odor concentration for scrubber system (Preparation of experimental device)

Quantification of odour compound

Livestock odour samples collected from field experiments were evaluated according to the ES09301 (dynamic olfactometry) to quantify odour concentration. In order to make a diluted sample for the dynamic olfactometry of livestock odour, an odourless air sample was made using the odourless air generator shown in Figure 3(a). This device first removes moisture from the air using silica gel and removes odour components from the air using activated carbon. The odour samples were provided to five panels according to the dilution rates (10, 30, 100, and 300 times) (Figure 3 (b), (c)). Before the evaluation of the next step, all equipment such as glass syringes was washed using 99% nitrogen gas, and the laboratory was ventilated to maintain a clean state. In addition, after one evaluation experiment, the panels took sufficient rest prior to performing the succeeding evaluation. The livestock odour concentration was calculated by the average geometrical mean and excluding the maximum and minimum values from the experimental data measured from each panel.

Figure 3: Process of preparing odor samples for quantification evaluation of livestock odor (a) manufacturing odorless air, (b) preparing a sample bag, and (c) diluting the air in the sample bag

Results and Discussion

Fogging system

The complex odour concentration for the air sample collected just before water-fogging was 100 OU m^{-3}. The concentrations for NH_3, and H_2S were measured at 11.6 ppm, and 0.12 ppm, respectively. The odour concentration after spraying water should be no different from the first evaluation of 100 OU m^{-3}(Table 1). In addition, NH_3 was 10.1 ppm, and H_2S was 0.12 ppm. The reduction effect on complex odour was 0%, which did not show a reduction effect, and H_2S was the same. However, in NH_3, the odour reduction effects were 13.1%. In particular, since NH_3 concentration is a water-soluble gas, it was thought that NH_3 concentration was reduced due to water-fogging.

Table 1: Odour concentration and reduction rate inside the pig house before and after operating a fogging system

Fogging system	Complex odour (OU m^{-3})	NH_3 (ppm)	H_2S (ppm)
Before	100	11.6	0.12
After	100	10.1	0.12
Reduction rate (%)	0	13.1	0

Bio-curtain system

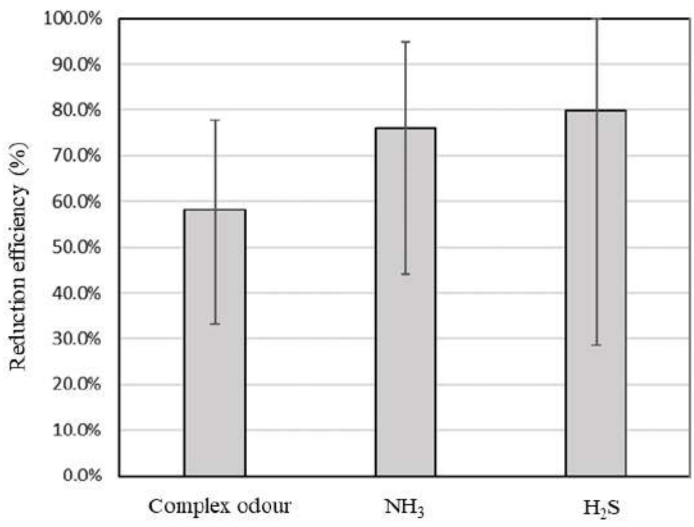

Figure 4: Analysis of odour reduction effect on bio-curtain system

Figure 4 shows the odour reduction effect of the bio-curtain system. The average reduction effect on complex odours was 58.1%, while NH_3, and H_2S were 76.0%, and 79.9%, respectively. In evaluating the odour reduction efficiency of bio-curtain, it was thought that the effect of bio-curtain could be sufficiently overestimated according to external wind environment conditions. Therefore, in order to solve this problem, it was necessary to design an experiment so as not to affect the external wind environment in measuring odour using an elbow-type duct. In general, the odour reduction effect on H_2S was greater than that of NH_3. The reason for this was that the pH of the washing water was about 7.8, which showed a positive effect on H_2S reduction. In the case of NH_3, when the washing water used has high PH (alkaline), the cleaning effect decreases. However, it was thought that the NH_3 gas was dissolved by the washing water sprayed in the bio-curtain, resulting in a reduction effect on NH_3.

Scrubber systems

The effects of scrubber systems were analysed (Figure 5). The average odour reduction effect of scrubbers on complex odours was 58.9%, NH_3 was 50.0%, and H_2S was 32.0%. However, in the case of odour compounds, there was a large variation in the field-measured value. It was thought that the effect on odour reduction was different depending on the type, design, and operation method of the scrubber (Melse & Mol, 2004). In addition, it was thought that there were differences depending on rearing facilities, EBRT of the scrubber, livestock size, feed, management of manure, storage, treatment, and climatic factors. The higher the nitrogen content, the more ammonia emission characteristics are (Canh et al., 1997, 1998a, 1998b, 1998c). Since the high temperature and humidity environment in summer promotes the decomposition of organic nitrogen in manure, it was thought that climate factors affect odour reduction efficiency. Therefore, NH_3 concentrations in summer were slightly higher than in spring and autumn. In addition, the reason for the difference in odour concentration is the designed air temperature of the pig house. According to a study by Cho et al. (2015), the concentration of odour was low at 5°C and high at 35°C ($p<0.05$).

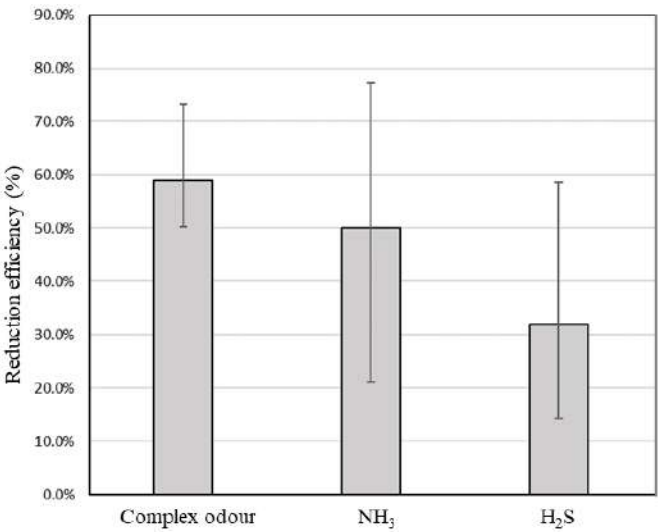

Figure 5: Analysis of odor reduction effect on the scrubber systems.

Conclusions

Odour reduction systems (fogging, bio-curtain, and scrubber systems), which are widely used in domestic pig houses, were analysed. The fogging system showed no significant reduction in odour concentration (complex odour and H_2S) before and after fogging, but NH_3 decreased by 13.1%. This reduction could possibly be the effect of sprayed washing water which reduced its concentration as the ammonia is known as a water-soluble gas. In the case of bio-curtain, it showed an average of 58.1% reduction in complex odour, and more than 76% reduction in single gas. The effect of the bio-curtain was overestimated because there were farms that opened the lower part of the bio-curtain which caused the fan load. The average odour reduction effect of scrubbers on complex odours was 58.9%, NH_3 was 50.0%, and H_2S was 32.0%. However, in the case of odour compounds, there was a large variation in the field-measured value. Odour reduction was different depending on the type, design, and operation method of the scrubber. Since the difference in the size of the scrubbers installed on each farm causes a difference in EBRT, the odour reduction effect varies greatly. In addition, there were differences depending on rearing facilities, livestock size, feed, management of manure, storage, treatment, and climatic factors.

Acknowledgements

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Case study: is growth curve monitoring a useful tool for identifying production efficiency problems on commercial livestock farms?

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Abstract

This paper reports on a case study that was undertaken by using/analysing data collected on farms, not strictly for scientific, but mainly for commercial purposes. Growth rates were measured over time in three pens on a commercial farms in Australia. In addition, a number of production related parameters, such as air temperature, relative humidity, the concentrations of carbon dioxide and ammonia, and ventilation rates were also measured in the same buildings. The information collected has been used to explain the significant differences observed in the growth performance of pigs housed on the same farm but in different pens. The growth rate and environmental variables associated with 'fast' and 'slow' growing groups were compared during the trials being reported. Improved thermal control, provision of optimal air quality, and maintenance of health status of animals are all important factors that can improve productivity. The differences observed in production efficiency could be used to alert farm managers of periods of inefficiencies that might go undetected under normal management conditions. In this way, they can action appropriate management interventions to rectify issues related to under performance. Thus, it was concluded that real time monitoring and better controlling production conditions in piggery buildings could result in improved profitability of commercial livestock farms.

Key words: Sensors, Precision Livestock Farming, continuous monitoring

Introduction

Managers of livestock farms are constantly searching for new ways of improving profitability via the utilisation of new technologies and management procedures (Banhazi and Harmes, 2018; Hartung *et al.*, 2017). The implementation of Precision Livestock Farming (PLF) technologies on farms is one such production enhancing method. The so-called PLF technologies are essentially enabling livestock managers to (1) collect information about key aspects of livestock production, (2) automatically analyse the collected information and (3) implement automated or semi-automated management responses based on the analysis of the collected information. PLF Agritech Pty Ltd., an Australian start-up company, has developed a number of technologies over the years that could potentially decrease the production related costs of pig farms by up to 30% (Black *et al.*, 2013). In this article, the performance of pigs monitored by the Weight-Detect™ and the Enviro-Detect™ devices will be discussed with special attention to the benefits they offered in relation to providing decision support tools to farm managers.

Materials and methods

This paper reports on a case study that was undertaken by using/analysing data collected on farms, not strictly for scientific, but mainly for commercial purposes. Because the commercial focus of the data collection, some information that would have been essential for scientific data analysis was not collected, such as information about medication, vaccination or other veterinary treatments. However, the main aim of the study was to demonstrate the value of more in-depth analysis of routinely collected information on commercial farms.

Long-term weight and environment monitoring were carried out in three different grower/finisher pens on a farm in Queensland, Australia. The pens monitored were located in traditional grower-finisher building with natural ventilation systems installed. All pigs in the trials were fed mash or pelleted feed and were kept on partially slatted floors. In each pen a Weight-Detect™ (PLF Agritech, Toowoomba, Australia) system was installed approximately in the middle of the pen at 2m height (Banhazi *et al.*, 2011; Banhazi and Dunn, 2016). In the same pens, Enviro-Detect™ (PLF Agritech, Toowoomba, Australia) devices were also installed (Clements *et al.*, 2011; Banhazi, 2021) on the walls of the piggery buildings. The positioning of the equipment was selected high enough to be out of reach of adult animals. Enviro-Detect™ acquired continuous measurements of air temperature, relative humidity, ventilation rates, carbon dioxide (CO_2), ammonia (NH_3) and airborne particle concentrations (Banhazi, 2009). In addition, attempts have been made to predict emission rates, based on previously published scientific methodology (Seedorf *et al.*, 1998a; Seedorf *et al.*, 1998b; Takai *et al.*, 1998). Automated reports and associated descriptive statistics were emailed to the producers in a PDF format reporting on growth rate and environmental conditions of individual pens. In addition, a more detailed statistical analysis was undertaken on the collected environmental data using correlation analysis and t-test principally to compare environmental parameters between different buildings.

Results and discussions

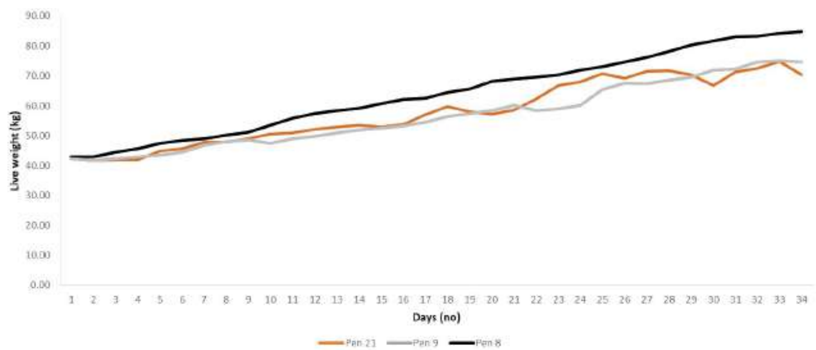

Figure 1: Live weights (kg) recorded on farm 'X' in different pens and different buildings during similar time period. Pigs started from identical starting weight. Pigs in pen 8 achieved an ADG of 1.20 kg over 34 days, while in pen 21 animals grew at a much lower rate achieving an ADG of 0.82 kg over the same 34-day period. Pigs in pen 9 grew at the rate of 0.95 kg (ADG) over 34 days.

Figure 1 shows results that were recorded on the farm, in different buildings and different pens. Pen 8 and 9 were in the same building, while pen 21 was located in an adjacent building. The nutritional and health status of the animals were the same, but potential differences in environmental quality and social conditions resulted in different growth rate patterns. Clearly the shapes of the growth curves were related to production performance.

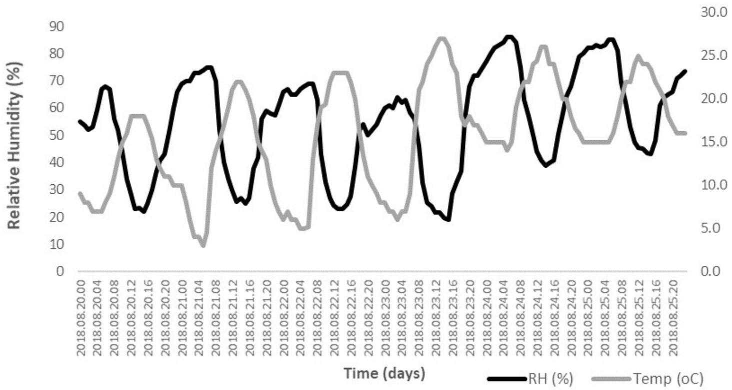

Figure 2: Air temperature (°C) and relative humidity (%) values measured continuously in one of the study buildings on the farm ‘over a 6-day period.

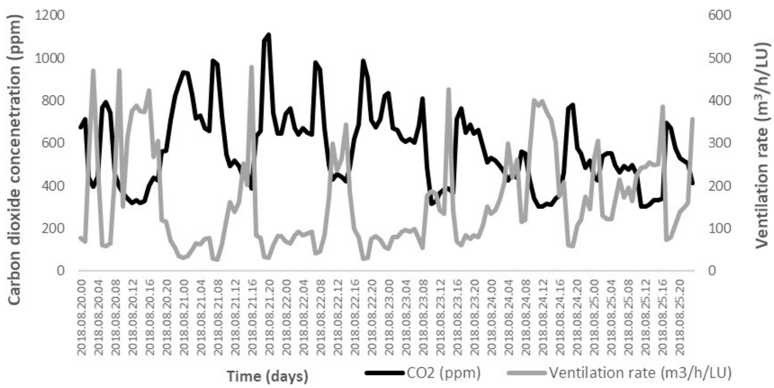

Figure 3: Ventilation rate (m^2/h/LU or Livestock Unit) and carbon dioxide concentrations (ppm) values measured continuously in one of the study buildings on the farm over a 6-day period.

The smoothest growth curve (pen 8) resulted in the best production performance out of the 3 different pens. A significant amount of environment related information was also captured in the buildings studied, as a data point was recorded every 6 minutes. The various environmental values captured are displayed in Figures 2-4. Only a short period of sample data is displayed to demonstrate the quality and volume of data captured continuously during the study period. In Table 1 the comparisons of the averages of various environmental parameters captured in the two study buildings over a 34 d period are shown.

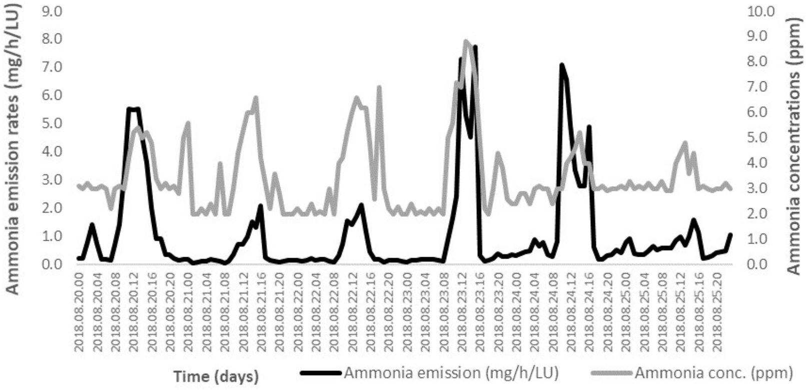

Figure 4: Ammonia concentrations (ppm) and ammonia emission rates (mg/h/LU or Livestock Unit) measured continuously in one of the study buildings on the farm over a 6-day period.

Table 1: Environmental parameters in the different pens/buildings averaged over 34 days

Parameters	Building A: pen 8 & 9	Building B: pen 21	P
Temperature (^{o}C)	19.8	17.4	<0.05
Humidity (%)	63	57	<0.05
Carbon dioxide concentration (ppm)	748	477	<0.05
Ventilation rates (m^2/h/LU)	108	198	<0.05
Ammonia concentration (ppm)	1.1	2.9	<0.05
Dust concentrations (mg/m^3)	0.098	0.192	<0.05

A number of issues can be highlighted based on the environmental data captured in the study buildings (Figures 2-4 and Table 1). Temperature and humidity information was considered to be reliable and the electrical cable connecting the temperature/humidity sensors to the enclosure enabled the research team to record data close to pig level. During this study a good set of reliable information was captured (Figure 2). Humidity values collected during this study in the two different buildings were very similar but there were 2.5 ^{o}C differences in air temperatures between the two buildings that might have been important and could partially explain the grow rate differences and resulting growth curve shape. During winter time, when temperatures were actually as low as 5^{o}C on same days, this extra temperature lift could have been contributing to the more even growth patterns observed in building A (housing pen 8 and 9). As expected, there was a good negative correlation observed between the temperature and humidity measurements in this study (r^2 = - 59%)

Ventilation rates and CO_2 concentrations were reliably captured. CO_2 concentrations inside and outside were used to calculate ventilation rates, based on published scientific methodology (Seedorf *et al.*, 1998a; Seedorf *et al.*, 1998b; Takai *et al.*, 1998). A clear circadian variation was observed in ventilation rates as well as in the concentration of CO_2 that peaked during night-time and negatively correlated with ventilation rates (Figure 3). The data indicated that the general ventilation levels were adequate, and suitable for the winter period when the data collection was undertaken. The generally accepted practical recommendation is to have around 100-200 m^2/h/LU ventilation rate during cold periods and around or above 300 m^2/h/LU during hot periods. In Australia, it is not unusual to encounter high ventilation rates during wintertime as well, due to the open nature of buildings that typically rely on natural ventilation systems with limited control. Therefore, it can be concluded that in this instance, building B was over ventilated (while still remaining within recommended ventilation rates), but not building A. This has resulted in higher temperatures, lower dust and NH_3 concentrations in building A. Counterintuitively, both high dust and NH_3 concentrations are often associated with high ventilation rates, due to the increased levels evaporation (in case of NH_3) and increased stirring of fine airborne particles by the increased air movements (in terms of dust levels). This has led to a statistically higher dust ($p<0.05$) and NH_3 ($p<0.05$) concentrations in building B. Ventilation rates and CO_2 concentrations were highly correlated (r^2 = - 84%), which was not surprising since CO_2 concentrations (inside and outside of the buildings) were used to calculate ventilation rates.

NH_3 concentrations recorded were in agreement with previously reported results (Banhazi *et al.*, 2008) (Figure 4) but in building B the concentrations were almost 3 times the levels of building A (Table 1). However, these concentrations were still below the maximum concentration level recommended by multiple authors (Donham, 1991; Donham and Thu, 1993; Donham *et al.*, 1977; Donham *et al.*, 1995). NH_3 concentrations are not always characterised by circadian variation (Banhazi, 2013b), but in this instance (at least during the 6-day period that is displayed as an example), a clear circadian variation was observed. NH_3 concentrations peaked a number of times during daytime (Figure 4). Positive correlations between air temperature and NH_3 concentrations have been reported before (Banhazi *et al.*, 2008; Banhazi, 2013b; Groot Koerkamp *et al.*, 1998). It is hypothesised that NH_3 concentrations might increase during daytime, because higher (daytime) temperatures tend to increase NH_3 evaporation rates from sources in livestock buildings, such as urine puddles or manure patches (Groenestein *et al.*, 2007; Aarnink *et al.*, 1997). Dust concentration was higher in building B when compared to building A (Table 1).

Ammonia emission rates were calculated based on published methodology using the concentration levels and ventilation rates (Seedorf *et al.*, 1998a; Seedorf *et al.*, 1998b; Takai *et al.*, 1998). The emission rates recorded were realistic and plausible (Figures 4), and corresponded well with previously published emission rates (Groot Koerkamp *et al.*, 1998; Takai *et al.*, 1998; Banhazi *et al.*, 2008). However, these measurements were at the very low end of values, when compared to the Australian and European published emission rates. A clear circadian variation was detectable, due to the influence of the circadian ventilation rates (Figure 4). NH_3 concentrations and emission rates moderately correlated, (r^2 = 62%).

In summary, significant differences ($p<0.05$) were detected in all environmental parameters recorded in the two livestock buildings on a commercial farm. While a casual effect could not be directly proven, there was definitely an association between environmental parameters and the performance of pigs in the particular building. However, other parameters such as health status, medication/vaccination, social parameters (such as stocking density) could have also impacted on the performance of animals. Many of these factors were not monitored during this study as the aim of the experiment was mainly to prove the reliability of the instrumentations deployed. However, even if health status differed, the likely influence of the prevailing conditions in the study buildings was obvious. It appeared that building B was over-ventilated that resulted in decreased thermal control and increased dust and NH_3 concentrations within the building. Building A was ventilated at a much-reduced rate, and therefore had higher CO2 concentrations and lower NH_3 and dust concentrations. In addition, building A had around 2.5 degrees extra temperature lift (compared to building B). Building A also had a slightly increased humidity ($p<0.05$) that was still within the acceptable rate but could have contributed to the reduced dust concentrations observed.

This monitoring study provided the farm managers with information about the fluctuating ADGs that can be observed on farms under commercial conditions. It was important to document the differences observed in the growth efficiency between seemingly identical pens on the same farm. This study highlighted the fact that short periods of growth efficacy reduction is often undetected on commercial farms, resulting in unexpected underperformance of batches of pigs at the end of growth periods. Anecdotal evidence provided by farm veterinarians in the past case studies indicated that growth rates on farms could fluctuate significantly without being noticed in a timely manner. What also became evident that the shape of the growth is important. Better performance was clearly associated with a 'smooth' growth curve that can be characterised by relatively straight growth line. On the other hand, pigs that underperformed had typically a crooked or irregular growth curve. This wavy growth pattern indicates that pigs were not kept under ideal conditions and their growth patterns were characterised by periodic stagnations peppered with periods of compensatory growth. Under such circumstances, pigs cannot perform to their maximum growth capacity. Thus, the shape of the growth line can give famers an indication if their animals are performing close to their genetic potential or if there are conditions holding them back. The environmental parameters recorded in the building also provided valuable insight for the managers of the piggery and a strong association between production environments and growth rates were demonstrated in this study. Similar results have been obtained in the past (Donham, 1991; Murphy *et al.*, 2012; Banhazi, 2013a). Therefore, this study provided farm managers with new information that was previously unavailable to them as they did not have the capacity to collect such information without the introduced new technologies.

Conclusions

The new technologies, Weight-Detect™ and Enviro-Detect™, provided practical information to livestock producers that empowered them to make management changes based on objective data to enhance the profitability of their operation. The weight monitoring tool pinpointed problem areas (such as uneven growth patterns) and potentially enhanced the effectiveness of management procedures of the participating livestock producers. The environmental monitoring kit gave a good indication of the suitability of growth environment. This case study was not a controlled experiment, but it has demonstrated the value of using data collected routinely on commercial farm for the purpose of exploratory data analysis.

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Evaluation of pressure loss factors considering various ventilation systems for optimal ventilation design in piglet house

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Abstract

The indoor environment conditions of mechanically ventilated piglet houses depend on the performance of exhaust fans. Owing to fan performance which has a great impact on the comfort of animals and pollutants emission, appropriate selection of fans should be properly considered. However, in-situ fan performance has reduced compared to design fan performance because of the various pressure loss factors. This study attempted to evaluate pressure loss factors by measuring airflow rate of fans and static pressure in piglet house. The experiments were conducted in a standard Korean pig house with a combined ceiling slot inlet, side window inlet, side exhaust fan, chimney exhaust fan among others. The pressure loss factors were evaluated using the fan law and orifice theory. Analysis of the result showed that in-situ fan performance was reduced by 7 ~ 35% compared to the design fan performance. Furthermore, the comparison of side and chimney exhaust fans showed that the side exhaust fans had a higher 20% airflow rate due to duct friction loss and aerodynamic difference. On the other hand, pressure losses due to inlet were different from inlet types and inlet opening size. Because the pressure losses depend on inlet and outlet type, location, size, and so on, those characteristics should be considered for the optimal ventilation design.

Keywords: Fan performance curve, Mechanically ventilated pig house, System effect factor

Introduction

In order to meet the increasing meat consumption, modern pig facilities are getting larger and adopting a system that concentrates and supplies feed by densely populating the pigs. However, since this environment adversely affects the control of contaminants, heat and moisture environment in the air inside the pig house, it is important to operate adequate ventilation in the pig house (Seo *et al.*, 2012, Kwon *et al.*, 2016).

On the other hand, in Korea, more than 70% of pig facilities were constructed with windowless pig houses that use exhaust fans to ventilate. There is a method using the CFD model to predict the amount of ventilation by the exhaust fan (Hong *et al.*, 2017; Li *et al.*, 2017; Seo *et al.*, 2008; Seo *et al.*, 2012), and it has the advantage of being able to analyze various ventilation system structures regardless of the actual building. However, when referring to the fan performance data provided by the manufacturer for this purpose, the fan performance appears differently depending on the ventilation structure of the pig house, the location of the exhaust installation, and the aging of the belt. In order to estimate the ventilation amount by predicting the exhaust fan performance degradation in the field, it is necessary to measure various factors in the field, but studies on the ventilation amount estimation for various ventilation structures of pig houses are insufficient (Chen *et al*., 2014).

Therefore, this study tried to estimate the actual ventilation volume for piglets by considering the fan performance degradation due to various ventilation systems. To this end, it was attempted to quantitatively calculate the factors necessary for predicting fan performance degradation through field experiments, and to develop a formula for estimating the actual ventilation volume through the calculated factors. In addition, the developed formula was evaluated by comparing it with the measured ventilation amount.

Material and methods

Target pig house

In this study, the fan performance degradation factor according to the structure of the ventilation system in the pig house was calculated through field experiments. When pigs are actually raised, it is impossible to conduct field experiments through the establishment of various ventilation systems under the experimental plan desired by the researcher because ventilation is performed according to the breeding environment of the pigs. Moreover, appropriate operation of ventilation system is needed to avoid serious livestock issues such as spreading of illnesses and diseases. To overcome this limitations, the field experiment was conducted in the standard piglet house test bed of the Smart Livestock Engineering Demonstration Center of the Seoul National University A3EL located in Pyeongchang, Gangwon-do (37°54’82”N, 128°43’45”E) (Fig. 1).

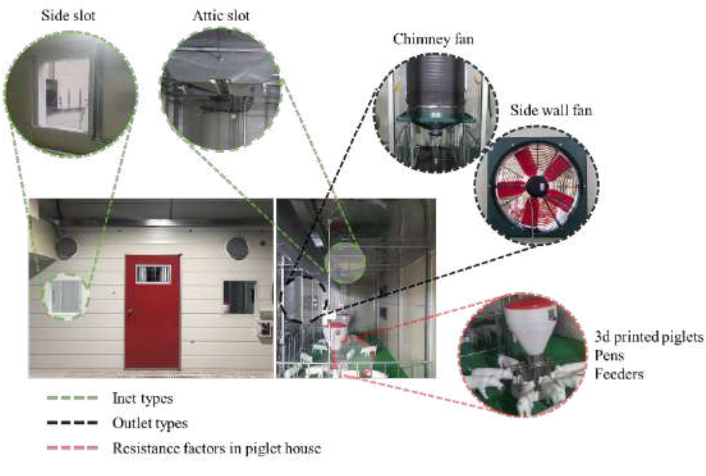

Figure 1: Experimental mechanically ventilated piglet house in Pyeongchang, Gangwon-do, Republic of Korea.

The standard piglet house of the Smart Livestock Engineering Demonstration Center is a facility designed based on the Korean piglet house standard design (MAFRA, 2016). This standard piglet house is in the form of a forced ventilation windowless facility and is equipped with a variety of typical intake and exhaust systems, which are typically used in actual pig farms. The ventilation structures used in this study were sidewall slots, mid-ceiling slots, sidewall fans, and exhaust fans, which are the typical intake and exhaust structures used in South Korea. The two side wall slot windows (0.6 m wide and 0.6 m long) act as an intake structure in which air flows in through the side wall of the pig room. The type of fan with exhaust structure is an axial fan, which is the most commonly used fan in agricultural facilities. Both the sidewall fan and the chimney fan use an exhaust fan(COCO-630A, Dongsung COCOFAN co. Ltd., Korea) with a diameter size of 630 mm, and variable speed inverters are installed in both fans to control the ventilation fan speed from 0 to 100% depending on the set voltage.

Fan performance curve

In this study, the fan performance curve that can express the characteristics of the exhaust fan and the system resistance curve that can be expressed according to the characteristics of the inlet were calculated for estimating the amount of on-site ventilation. The two curves were intended to be expressed through a curve (P-Q curve) expressing the relationship between static pressure and airflow rate. (Fig 2).

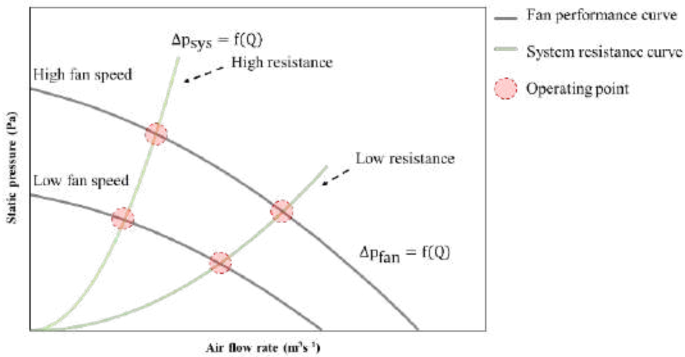

Figure 2: Typical fan performance curve and system resistance curve

Experimental procedure

This study tried to quantify the reduction in the exhaust fan performance of pig houses by applying fan performance and system effects, and to apply this to the ventilation design of pig houses. To this end, the fan performance was quantified by controlling various exhaust fan structures and speeds for a building designed on a real piglet scale. In addition, the system performance curve for estimating the operating point of the exhaust fan was estimating by calculating the coefficient of the system resistance curve according to the type and area of the inlet. After that, the calculated fan performance coefficient and system resistance curve were used to apply the formula for deriving the actual ventilation volume in the pig house. The performance degradation of the exhaust fan was considered in the formula, and this was used to design the pig house ventilation.

Results and Discussion

Comparison of field and actual fan performance curve

The design fan performance curve is generally performed under environmental conditions in which the fan can achieve maximum performance under the maximum operating rate condition (Cory, 2010). However, field fan performance generally deteriorates due to the installation conditions of the ventilation fan and the wear and tear due to the aging of the fan and equipment. The reduction in design performance and actual performance of the ventilation fan installed in the field conditions of the test bed is shown in Fig. 3.

Evaluation of system curve coefficients according to inlet characteristics

The ventilation amount derived from the actual fan is explained by the fan operating point, and in order to derive the actual ventilation amount based on the fan performance curve, it is necessary to calculate the static pressure difference. Accordingly, in this study, the coefficient of the system resistance curve was evaluated for the inlet, which is a factor that can greatly affect the system resistance in the ventilation structure of the pig house. Since the static pressure difference that can occur in ventilation management of a building is mainly caused by the inlet control, in this study, the orifice theory applicable to the inlet was applied to calculate the static pressure difference according to the inlet characteristics. In particular, in the case of corridor slots, the orifice formula can be directly applied depending on the area, but in the case of a mid-ceiling, the inlet area does not change as the opening rate increases. Accordingly, the effective opening area ratio was converted according to the angle of the mid-ceiling. As a result, the effective opening ratio of the mid-ceiling slot according to the angle showed a tendency to decrease as the effective area increased sharply when the ceiling slot was first opened. When the mid-ceiling slot was opened at an angle of 45 degrees or more, the effective area ratio was maintained at 85% or more (Fig. 4.).

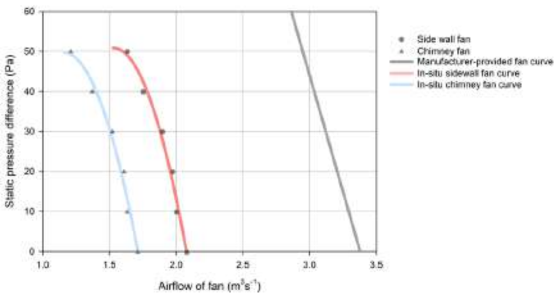

Figure 3: Comparison of In-situ fan performance curve and in-situ fan curve according to fan placement types.

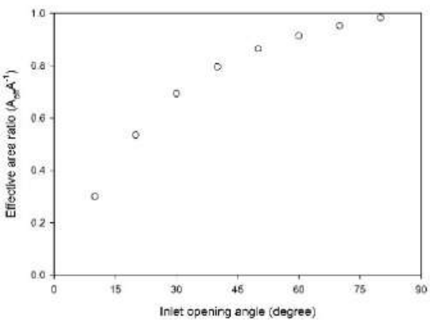

Figure 4: Effective flow area to inlet-area ratio of attic slot

Estimation of actual ventilation rate from actual fan performance curve

Previously, the system effect according to the facility structure and exhaust fan location and the system resistance curve coefficient according to the opening rate were calculated. The static pressure difference inside the facility was calculated according to the opening rate of each inlet, and the fan performance was applied using the system resistance coefficient calculated from the fan performance curve provided by the manufacturer.

Here, the fan curves of the sidewall fan and the chimney fan for estimating the actual ventilation rate are as shown in Equation (1-2) below. As a result of estimating the actual ventilation amount, it was found that the actual ventilation amount could be estimated well with an R^2=0.9947 for the side wall fan and 0.9935 for the chimney fan.

$$Q_{side} = \frac{\sqrt{169.2^2\varpi^2 - 4 * -344.8\varpi^2(326.5 - SEF_{slot})} - 517.4\varpi}{165.4 - 2SEF_{slot}} \tag{1}$$

$$Q_{chimney} = \frac{\sqrt{169.2^2\varpi^2 - 4 * -344.8\varpi^2(224.3 - SEF_{slot})} - 517.4\varpi}{127.2 - 2SEF_{slot}} \tag{2}$$

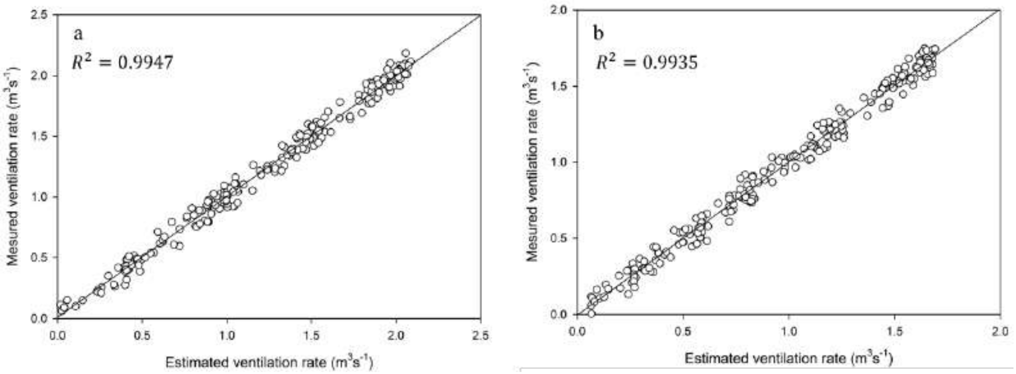

Figure 5: The relationships between estimated and measured ventilation rate (a: side wall fan, b: chimney fan).

Conclusions

In this study, the actual ventilation amount for piglets was measured in the A3EL test bed. The test bed was designed to have various ventilation designs that allowed to test various ventilation structures, and the fan performance curve. Moreover, the outflow coefficient that can indicate the characteristics of the inlet were evaluated and quantified. The field fan performance curve showed a tendency to decrease by about 35% compared to the actual fan performance provided by the designer, and it was analyzed that the ventilation performance of the chimney fan was reduced compared to the sidewall fan. The system resistance was predicted according to the inlet type and area adjustment, and the actual ventilation amount was predicted through the calculated fan performance curve and the coefficient of the system resistance curve, resulting in a high predicted value(Side wall fan R^2>0.9947, chimney fan R^2>0.9935). Through the results of this study, a coefficient for estimating the actual ventilation rate of the livestock house was provided, and it is thought that it can be used as basic data for designing ventilation operation plans and appropriate ventilation structures.

Acknowledgements

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Evaluation of Wet Scrubber for Mitigation of Ammonia Emission from Pig House

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Abstract

A wet scrubber could be the solution to ammonia emissions by directly removing ammonia gas from the pig house. However, most previous studies of wet scrubbers have focused on industrial facilities. To optimize the design and control of the wet scrubber, it is needed to evaluate the ammonia removal performance by various parameters considering pig house conditions. In this study, the wet scrubber performance was evaluated considering physical parameters, such as the concentration of inlet ammonia, exhaust airflow rate, and the gas-liquid flow direction. The ammonia removal performance was evaluated through a statistical method with removal efficiency and removal amount. Exhaust airflow rate and gas-liquid ratio were major influence factors on removal efficiency. The lower the exhaust airflow rate, the higher the removal efficiency. This was considered due to increasing the residence time of the ammonia gas. Gas-liquid flow direction and number of the nozzle were related to the removal amount caused by the pressure drop of the exhaust fan. The influence of pressure drop was high at low fan speed. Therefore, it was considered that parallel flow was advantageous over counterflow at low fan speeds. The results of this study demonstrate that optimal design and control of wet scrubber could effectively mitigate ammonia gas emissions.

Keywords: Ammonia, Gas-liquid ratio, Removal efficiency, Wet scrubber

Introduction

Ammonia gas emissions from pig houses account for 15% of global ammonia emissions. The ammonia emission not only contributes to surface water eutrophication and acidification of ecosystems but also affects the generation of particulate matter through atmospheric secondary synthesis (Sari et al, 2019, Philippe et al., 2011). Therefore, it is needed effective strategies for reducing ammonia emissions from pig houses. A wet scrubber is an effective ammonia mitigation technology that directly reduces the emitted ammonia gas (Melse et al., 2009). The wet scrubber is mainly using types of scrubber technology in pig houses. The wet scrubbers applied to pig houses could remove more than 65% to 95% of ammonia gas (Sheridan et al., 2002, Melse et al., 2009).

However, the removal efficiency was different depending on ammonia concentration at the inlet, aerodynamic residence time, liquid flow rate, temperature, and liquid pH (Chen et al., 2008). The performance of scrubber can change depending on the ventilation management and pig growth enviornments. Therefore, it is necessary to consider the variable foctors of the pig house. Moreover, scrubber systems to pig houses are an efficient system for mitigating ammonia emissions, but there are problems with energy and high installing costs and maintenance.

Therefore, the objectives of this research were to optimize design parameters of a wet scrubber for ammonia remove considering pig house environment. The labolatories experiments were conducted in a can control the environment like pig house. The experiments were conducted in a laboratory that can control environments like a pig house. An ammonia removal performance was analyzed according to the spraying method, ammonia concentration, exhaust flow rate, circulating water pH, and liquid to gas ratio through the lab-scale scrubber. A scrubebr performance model was developed to predict the ammonia removal efficiency through correlation analysis through the experimental results, and through this, the capacity of the scrubber capable of design optimization and efficient operation was evaluated.

Material and methods

Lab-scale scurbber system design

The scrubber consists of a scrubber bed, exhaust fan, nozzle, mist elemintor, and recirculation pump. The air flowrate of the fan can be operated in the range of 0.085-0.990 m3/min/aniaml, which is the ventilation rate range at pig house (Table 1).

Table 1: Design parameter of lab-scale scrubber

Parameter		Value
Liquid phase	Liquid flow rate	30 ~ 120 L/min
	Nozzle type, Spraying degree	Spiral type, 120
	Number of nozzles,	27
	Nozzle to packing distance	100mm
Gas phase	Liquid to gas ratio	Fan and water pump control
	Maximum fan flow rate	55 m^3/min
	Pressure loss	70 Pa
Packing meterials	Turn-dwon ratio	2 ~ 2.5
	Packing type	Structured type (Polyvinyl chloride)
	Pressure loss	Under 10 Pa
Eliminator	Eliminator type	Packed bed
	Pressure loss	9.81 ~ 19.61 Pa
Scrubbing type		Counter flow, Parallel flow

The wet scrubber is a rectangular shape with a size of 1300 mm 950 mm and a length of 950 mm. Spraying direction also can be adjusted to the type of counter and parallel flow (Figure 1). The liquid flow rate was adjusted by changing the operation of the pump and the number of nozzles. The mist elimator was installed to reduce liquid loss. The amount of pressure loss is 70pa in experimental wet scrubber.

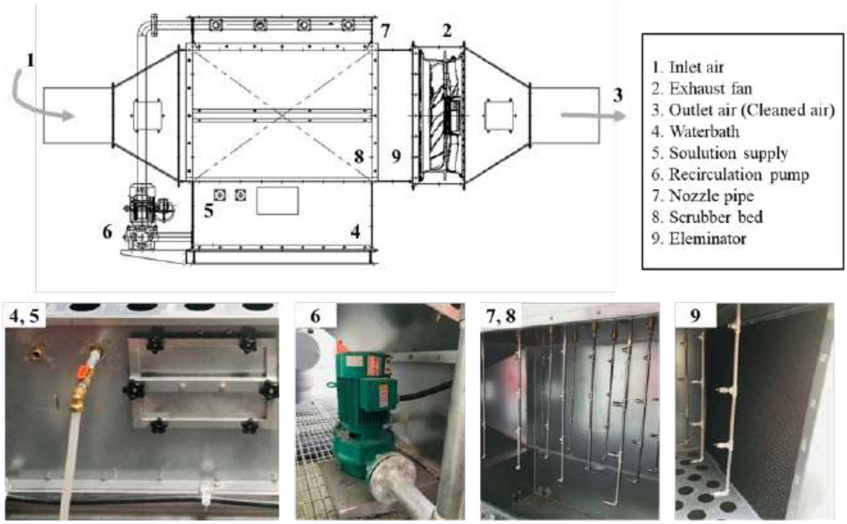

Figure 1: Schematic diagram of the scrubber for lab-scale experiment

Inlet air environment control

Wet scrubber systems are installed at the outlet of pig houses, and the temperature and humidity of the outlet are the same as the air environment according to pig rearing. In this study, an experiment was conducted in a pig house of ASEC-A3EL that can artificially control the environment to consider the air environment according to the heat generation, moisture generation, and rearing environment of pigs. The ammonia concentration flowed into the pig house through gas generation systems connected to the ammonia tank based on the amount of ammonia emission rate from the pig house.

The ammonia emission rate ranges depending on the pig growth stage, ventilation rate, and season. Thus, the ammonia concentration was adjusted using a needle valve, an MFC mass flow controller (MR-300-1CH), and a mass flow meter (3660-NH3-500sccm-1/4SW) in the gas generation systems.

Experimental procedure

This experiment was conducted by dividing each design factor of the scrubber through the one-factor test method. The ventilation rate was set to 174 head (3.5 m2/2/animal) according to the animal welfare standard to the general control factors of scrubbers. The ammonia concentration was determined in consideration of the emission coefficient range, and each concentration range was set to 20 to 80 ppm by generating ammonia gas of 132.4 to 529.7 mg/min.

In addition, the airflow rate range was set to 18.6 to 55.5 m3/min (0.11 to 0.35 times/ min) assuming that it was a scrubber installed in one exhaust fan of the experimental pig house. The airflow rate was controlled by a fan speed, the nozzle direction, and the ammonia concentration rate was adjusted according to each case (Table 2).

Table 2: Experimental cases according to optional variables

Experiment number	Ammonia concentration (ppm)	Liquid flow direction	Fan operating rate (%)	Packing meteiral step
1	20, 40, 60, 80	Counter	50	0
2	40	Counter	25, 50, 75, 100	0
3	20, 40, 60, 80	Parallel	25, 50, 75, 100	0
4	40	Parallel	25, 50, 75, 100	0
5	40	Counter	50	1
6	40	Counter	50	3

The scrubber performance was analyzed with ammonia removal efficiency and removal amount per minute through each data set measured through 3 times repeated experiments. The ammonia removal efficiency and removal amount of the cases was calculated by the following Equation (1) ~ (2), respectively.

$$\eta_{NH_3} = \frac{C_{in \cdot NH_3} - C_{\mathrm{out} \cdot NH_3}}{C_{in \cdot NH_3}} \tag{1}$$

$$Q_{NH_3} = \frac{\eta_{NH_3}}{100} \times C_{in \cdot NH_3} \times V \times \rho_{NH_3} \tag{2}$$

where, η_{NH_3} is the ammonia removal efficiency (%), $C_{in\,NH_3}$ is the ammonia concentration at scrubber inlet (ppm), $C_{out\,NH_3}$ is the ammonia concentration at scrubber outlet (ppm), Q_{NH_3} is the ammonia removal amount (kg/min), V is the ventilation rate (m^3/min), ρ_{NH_3} is the The density of ammonia (kg/m^3).

Statistical methods for error analysis, such as the absolute error (AE), relative error (RE), root-mean-square error (RMSE), and coefficient of determination (R^2), were used to validate the estimated ammonia removal efficiency. The mean absolute percentage error (MAPE) is a measure of the prediction accuracy of a forecasting method in statistics. The statistical values are expressed in Equotions. (21) ~ (22). Two statistics were selected to validate the measured and estimated ammonia removal efficiency.

$$RMSE = \sqrt{\frac{\sum_1^n (\mathrm{x_{meas}} - \mathrm{x}_{esti})^2}{\mathrm{n}}} \tag{3}$$

$$\mathrm{MAPE} = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{\mathrm{x_{meas}} - \mathrm{x}_{esti}}{\mathrm{x_{meas}}} \right| \tag{4}$$

where, *RMSE* is the root-mean-square error (%, %), *MAPE* is the mean absolute percentage error (%), x_{meas} is the measured ammonia removal efficiency (%), x_{esti} is the estimated ammonia removal efficiency (%), and n is the number of fitted points.

Results and Discussion

Wet scurbber performance of liquid flow dirrection

As a result of the experiment, the ammonia removal efficiency of counterflow was statistically significantly higher than that of parallel flow when the fan speed was operated by 50% or more depending on the liquid flow direction (Figure 2a). However, at 25% fan speed, the ammonia removal efficiency of parallel flow was 78.33%, which tended to be higher than 76.97% of the ammonia removal efficiency of counter flow (Figure 2b).

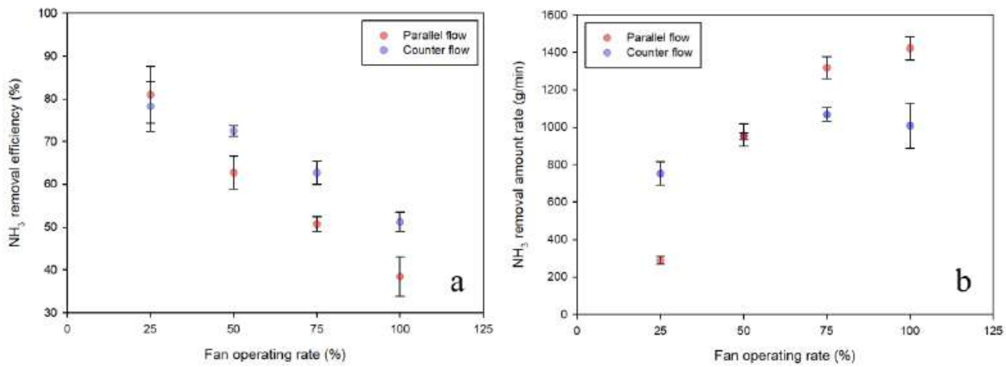

Figure 2: fan operation rate and ammonia removal efficiency depending on nozzle direction. (Ammonia concentration 40 ppm, water pH 7~8)

However, this difference was not shown statistically significant results. This result shows that the ammonia removal efficiency was high in low-pressure drop conditions (Table 3).

Table 3: Static pressure and airflow rate of the fan according to fan operating rate and scrubbing method

Fan operating rate (%)	Counter Flow		Parallel Flow	
	Static Pressure (pa)	airflow rate (m^3/min)	Sstatic Pressure (pa)	airflow rate (m^3/min)
25	12.7	7.4	4.3	18.6
50	39.2	26.2	25.9	30.5
75	79.1	42	77.4	42.1
100	137.9	55.5	131.2	54.2

The amount of removal ammonia could be reduced in counter flow when low fan operation rate. These results show that the pressure loss of the counter flow is higher than that of the parallel flow. Therefore, the pressure loss due to liquid flow should be considered because a low fan operating rate is required in winter. In addition, the nozzle direction should be designed to consider the characteristics of the pig rearing environment.

Effect of ammonia concentration and fan operating rate

When the ammonia concentration was 20, 40, 60, and 80 ppm, the ammonia removal efficiency of the scrubber ranged from 60 to 70% on average (Table 4). As for the change in cleaning efficiency according to ammonia concentration, the p-value (0.866) was above the significance level (0.05) range, and since all sub-group classifications by Duncan's post-test were classified as the same group, it was judged that there was no significant difference in cleaning efficiency according to the ammonia concentration.

Table 4: Effect of scrubber performance according to design factors

Fan operating rate (%)[a]	Removal Efficiency (%)	Ammonia concentration (ppm)[b]	Removal Efficiency (%)
25	78 ± 5.7 [c]	20	66 ± 4.7 [a]
50	52 ± 4.5 [bc]	40	64 ± 4.3 [a]
75	43 ± 1.6 [b]	60	67 ± 1.5 [a]
100	35 ± 4.2 [a]	80	67 ± 6.2 [a]
F-value	38.85	F-value	0.497
Significance	**	Significance	***

**: $p < 0.05$

***: $p < 0.001$

[a] Ammonia concentration 40ppm, counter flow type

[b] Fan operating rate 50%, counter flow type

The ventilation rate according to the fan operating rate was 18, 26, 42, and 55.5 m3/min (0.11, 0.16 and 0.26 and 0.35 times/min), respectively, at 25%, 50%, 75%, and 100%. There was a significant difference in ammonia removal efficiency between fan operating rates in the statistics of the ammonia removal efficiency according to the exhaust flow rate was lower than the significance level (0.009). In addition, Duncan's post-test showed that there was a difference in ammonia removal efficiency when the set ventilation amount was 25% and 75% and 100%. the ammonia removal efficiency tended to decrease with increasing the fan operating rate. In particular, the exhaust flow rate is used as an important factor in the capacity design and operation of the scrubber. Mesle (2004) reported that ammonia removal efficiency could increase as the exhaust flow rate of the scrubber decreases, but accordingly, the excessive pressure load and the initial investment cost of manufacturing the scrubber increase. Moerever, Haldcon and Zhao (2014) reported that the exhaust airflow rate of the scrubber was an important factor in determining the ammonia removal efficiency, and it was possible to predict the ammonia removal efficiency

Regression analysis of ammonia removal efficiency

The experiment results showed that ammonia concentration, air flow rate were major factors in scrubber design. The ammonia removal efficiency was predicted through the factors of change in scrubber performance. The ammonia removal efficiency estimated through ammonia concentration and airflow rate showed a high coefficient of determination (R^2=0.928) compared to the measured ammonia removal efficiency (Figure 3).

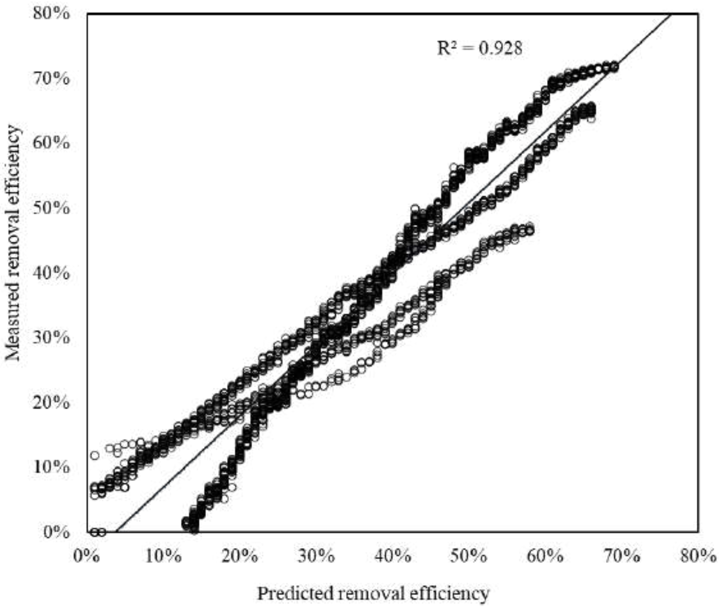

Figure 3: The relationships between predicted and measured ammonia removal efficiency

The model predicting ammonia removal efficiency was designed based on the solubility of ammonia, and it is believed that it can be used in the design by reflecting the complex gas of pig house.

Conclusions

The airflow flowing into the scrubber is determined according to the ventilation rate in the pig house. The ammonia removal efficiency according to liquid direction was evaluated due to this change in air flow rate. At low airflow rates, the parallel flow type with low-pressure loss executed better than the counter flow type. Therefore, scrubber design should consider the ventilation rate of the target pig house as a major factor. In addition, the ammonia concentration generated in pig houses changes depending on the pig growth stage. As mentioned, these two main factors should be considered in scrubber design due to controlled ventilation rates. In particular, the ammonia removal efficiency decreased as the airflow rate increased. this paper proposed a model to predict ammonia removal rates through major scrubber performance factors. This model can be used to design scrubbers to reduce ammonia in pig houses.

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POSTER SESSION

Poultry

Applications of precision livestock farming technologies in broiler production

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Abstract

Precision livestock farming (PLF) aims to improve farmers' decision-making via real-time monitoring of housing environment and animal-related outcomes. Although many PLF technologies were tested in the past two decades, few have been applied to assist farm stewardship in commercial broiler production. The objective of this light review is to summarize PLF technologies used for precision broiler management and discuss their practicality and challenges for applications in commercial production. It shows that top-view cameras and microphones are the most promising solutions for commercial production. Video analysis is commonly used for behavior and activity monitoring, and audio analysis shows the potential of detecting bird diseases and stress conditions. Challenges associated with these two technologies include accuracy in bird segmentation from image background under low light intensity and uneven light distribution, exclusion of birds and equipment (feeder line, drinker line, and heater etc.) in the images, and extraction of bird vocalization from background noises (ventilation system, heater, feed system etc.). Wearable sensors may be suitable tools for lab-scale research, but they are not economically feasible nor generally robust enough for applications in commercial poultry farms. Little research has demonstrated the economic benefits of using PLF systems at commercial farms, which may discourage farmers to adopt PLF technologies.

Keywords: precision livestock farming, broiler, image processing, sound analysis

Introduction

Global poultry meat production became the largest meat industry in 2020 (USDA, 2020). According to the recent data from U.N. Food and Agriculture Organization (OECD/FAO, 2021), global poultry meat consumption is expected to increase to 152 Mt by 2030, accounting for a 52% increase. The U.S. is leading broiler production in the world, producing 9.22 billion broilers for a total value of $21.7 billion in 2021 (NASS, 2012). Due to the ever-growing volume of the broiler industry and labor shortages, flock management is increasingly challenging for growers. In addition, public concern over animal health and welfare is another driving force for farmers to seek new farm management solutions (Cornish *et al*., 2016). As such, Precision Livestock Farming (PLF) attracts increasing attention as a promising solution in animal management.

Precision livestock farming (PLF) is a concept of monitoring animal-based measures and the housing environment in a continuous and real-time manner, thereby improving animal health, welfare and productivity (Berckmans, 2017). Generally, PLF systems can be categorized into: 1) animal-based technologies, 2) environment-based technologies, and 3) product-based technologies. Animal-based technologies aim at monitoring behaviors, activity and physiological conditions of live animals using PLF tools, including cameras, microphones, and wearable sensors (accelerometer, radio-frequency identification 'RFID') (Carpentier *et al.*, 2019; Li *et al.*, 2020b; Yang *et al.*, 2021b). Environment-based technologies strive to provide animals a comfortable environment, e.g. using internet of things (IoT) technology which integrates sensors (temperature, ventilation rate, ammonia, etc.) and shares the useful information via the internet. Product-based technologies are applied to animal products (e.g. chicken meat). Examples include using image analysis for meat grading and woody breast identification (Caldas-Cueva *et al.*, 2021; Park *et al.*, 2005). For the scope of this study, only animal-based technologies are reviewed.

Among PLF technologies that have been tested in the past two decades, over 96% were prototype systems (Rowe *et al.*, 2019). Even though a small portion of PLF systems have been commercialized, they haven't been widely applied to assist farm management in commercial broiler production, especially in the U.S. The eYeNamic camera system (Fancom, Panningen, Netherlands) is one of a few commercialized PLF systems. It can monitor bird activity and distribution at the flock level, which are critical indicators of broiler welfare. Another example is Chickenboy (renamed as 'Scout', AGCO, Duluth, GA), which is an integrated robot with the capability of measuring environment parameters, identifying dead birds, and detecting bird intestinal diseases. Understanding the advantages, challenges, and feasibilities of applying different PLF technologies in commercial broiler houses, may assist researchers in choosing directions of future research, thus, speed up the development and commercialization of PLF technologies in poultry.

The objective of this study was to briefly review different animal-based PLF technologies developed in our previous studies and by others. In addition, the practicality and challenges of applying these methods to commercial farms were discussed.

PLF technologies in broiler production

Image processing

Cameras have been widely used in broiler research due to their capability for monitoring birds continuously and non-invasively. The most used cameras include 2D cameras, 3D cameras and thermal cameras. Image processing based on 2D or 3D cameras mostly focused on monitoring broiler locomotion, including flock activity and distribution, lameness (Dawkins *et al.*, 2013), and behaviors. Thermal cameras have been used to monitor broiler surface temperature.

An activity index (AI) quantifies the activeness of broilers (Aydin *et al.*, 2010), and distribution index (DI) evaluates how evenly the broilers are distributed within a house (Kashiha *et al.*, 2013). Deviations of AI and DI determined by top-view camera systems can be used to detect hock burns and footpad lesions (Fernandez *et al.*, 2018). Features derived from AI before and after a human assessor walking through the flock were used to predict gait scores of broilers (Silvera *et al.*, 2017). Aydin (2017a) also developed a top-view camera system to assess broiler gait score by looking at different feature variables, including walking speed, step frequency, step length, lateral body oscillation and back area. Besides 2D cameras, a 3D camera with a depth sensor was used in the same experiment (Aydin, 2017b). The results showed strong correlations of gait score with number of lying events (R^2 = 0.934) and latency in lying (R^2 = -0.949).

Monitoring specific broiler behaviors is another major application of image analysis. Poultry behaviors, such as feeding, drinking, preening, stretching, wing flapping, etc., have been identified through image analysis (Li *et al*., 2020a; Li *et al*., 2020b; Nääs *et al*., 2012). Frequencies of performing these behaviors were considered as indicators of broiler health and welfare.

Additionally, broiler disease can be detected using image processing. Chickens infected with microorganisms within 7-10 days after hatching were detected using video analysis (Colles *et al*., 2016). Zhuang *et al*. (2019) used image processing to detect sick broilers, yielding 99.7% average precision.

Surface temperature is an important indicator of broiler's comfort and thermal stress. Thermal imaging technology has been employed to monitor broiler surface temperature non-invasively (Nascimento *et al*., 2011). Xiong *et al*. (2019) developed an algorithm to automatically detect the head temperature of broilers using top-view thermal cameras. Noh *et al*. (2021) reported that thermal imaging technology could detect the fever induced by highly pathogenic avian influenza 24 hours before the clinical signs.

Sound analysis

Animal vocalization contains massive biological information that may be relevant to animal stress, health, and welfare (Fontana *et al*., 2016). For broilers, sound analysis is commonly used for body weight prediction (Fontana *et al*., 2017), behavior monitoring (Aydin *et al*., 2016), and diseases/stress detection (Huang *et al*., 2019).

Yang *et al*. (2021a) conducted research to determine baseline sound data for future sound analysis in commercial farms. A microphone was installed in a commercial house to continuously record different sources of sound throughout the entire production cycle. Frequency ranges of different sounds (bird vocalization, ventilation system, feed system, heater, wing flapping and dustbathing) were determined at different bird ages. Peak frequency of bird vocalization was highly correlated with bird age ($p < 0.05$). Fontana *et al*. (2017) also reported a strong correlation (R^2 = 0.943) between peak frequency of bird vocalization with body weight. Additionally, it was observed in our study that spectrograms of sounds produced by broiler wing flapping and dustbathing behaviors had unique patterns, indicating the potential of using sound analysis to monitor behaviors. Aydin *et al*. (2015) developed a lab-scale system to monitor feeding behavior of a group of chickens in real-time by identifying the sound of pecking, yielding 86% of accuracy. Furthermore, sound analysis could be a useful tool of detecting animal diseases. Banakar *et al*. (2016) developed an intelligence device for avian diseases based on sound features. The total accuracy of diagnosing Newcastle, infectious bronchitis, and avian influenza in a lab-scale experiment was over 91%.

Sensor signal processing

Wearable sensors, including accelerometers and RFID systems, have been used to monitor movement and behavior of individual birds. Yang *et al*. (2021b) previously attached triaxial accelerometers to the back of broilers with chicken harnesses, and continuously recorded bird motions for three days. By developing a machine learning model based on three-dimensional accelerations, high accuracies of identifying resting (85%), walking (99%), feeding (88%) and drinking (75%) were achieved (Yang *et al.*, 2021b). In the same experiment, the accelerometers were also used to determine broiler activity (Yang *et al.*, 2020).

Radio-frequency identification (RFID) is mostly applied as a research tool for registering and tracking individual birds. Li *et al.* (2019) attached RFID tags to the neck of broilers to monitor feeding and drinking behaviors of individual birds by determining the time spent on each behavior. Taylor *et al.* (2017) fitted RFID tags to 1,200 randomly selected broilers using silicone leg band. Frequency and duration of range visits of individual bird were determined to monitor ranging behavior at a commercial free-range broiler farm.

Costs of PLF technologies

The average price of a decent 2D camera is about $100. Assuming that one ceiling-mounted camera (horizontal field of view: 100°; vertical field of view: 70°; height of installation: 3 m) can cover an area of 6 m × 4 m, it would need 60 cameras or $ 6,000 to fully cover a single commercial broiler house that measures 120 m × 12 m. Price of a thermal camera widely ranges from $200 (e.g. FLIR ONE) to over $25,000 (e.g. high-end FLIR T-series) depends on its temperature range, accuracy, spectral range, sensitivity, resolution, etc. The balance between performance and price should be considered when deploying thermal cameras to commercial farms. A sound sensor module can cost less than $10 if the audio system is developed independently. There are also some off-the-shelf audio recorders that already have the well-developed system of data collection and storage. For these recorders, the price may go up to $100 - $300. Based on a previous quote, an RFID system that can track 300 individual broilers' feeding and drinking behaviors may cost approximate $30,000. The total cost would be overwhelming for commercial production.

In addition to hardware, there are some essential steps of developing a complete PLF system, including algorithm development, system design, production preparation, maintenance service, etc. Each step will put additional cost to the final price. A commercially available top-view camera system (with 8 cameras) that can monitor flock activity and distribution costs about $25,000. The high costs of PLF systems are the one of the major reasons that farmers hesitate on investiment. Some potential benefits of using PLF systems, such as increase of production performance, improvement of bird welfare conditions, and reduction of labor needs, are all important factors for system evaluation. Return in investment (ROI) is commonly used to identify the profitability of an investment. However, few studies have been conducted to evaluate the ROI of PLF systems in broiler production.

Other considerations

Top-view camera is one of the most feasible tools of monitoring broilers at commercial farms. Camera systems are non-invasive. Operation of these systems will not interfere broiler natural behaviors nor cause additional stress. Side-view cameras can be a useful tool for lab research, however, it would be challenging to be used in commercial broiler farms. One of the reasons is that broilers would overlap when cameras record from the side. In addition, broilers would be blocked by feed lines, drinker lines, heaters, and other equipment, thus compromising the performance of the system. Top-view cameras, on the contrary, are capable of covering more birds without the concern of overlapping. Another advantage of top-view cameras is that they enable the determination of flock measurements, which have been reported as useful indicators of monitoring broilers in commercial farms. For instance, the eYeNamic camera system monitors bird welfare by determining the flock distribution and activity (Van Hertem *et al.*, 2018). The optical flow patterns made by the movements of broiler flocks were highly correlated with the mortality and occurrence of hock burn (Dawkins *et al.*, 2021). Although many image processing technologies have been developed, few of them were applied to commercial farms. Segmenting birds from background accurately has been a big challenge for image analysis. Low light intensity (5 lux) and uneven lighting distribution (e.g., feedline lighting) in commercial farms may reduce image quality, and thus, influence the performance of image processing algorithms. Poor accuracy of differentiating equipment and bird pixels is another challenge that needs to be addressed.

Audio analysis could be applied to commercial broiler farms. The advancement of electronics and signal processing technologies enables microphone systems to monitor broilers automatically and continuously. A commercialized sound monitoring system (SOMO, SoundTalks NV, Leuven, Belgium) was reported to be capable of detecting pig respiratory diseases up to 2 weeks earlier than farmers (Berckmans *et al.*, 2015) with an accuracy of 94% (Genzow *et al.*, 2014). However, to date, no real-time audio analysis system in broilers is available. Categorization of different sources of sounds is the first and important step of audio analysis in commercial farms. Removing sound noises is critical for further analysis. Moreover, how to strategically distribute microphones within the commercial house, and how to effectively capture key features/signs of specific behavior/disease within a large flock, haven't been fully understood.

Wearable sensors are more practical in lab research. Wearable sensors have been widely used in large livestock animals. In the study by Yang *et al.* (2021b), accelerometer was attached to the back of bird using chicken harness. As bird grew, the size of chicken harness needed to be adjusted frequently. In commercial houses, attaching sensors to each bird would be an impractical approach. In addition, power supply is a common limitation for wireless sensors targeting small animals. Large animals can carry a large battery, while broilers may only afford light batteries with short lifetime.

Few studies on economic analysis of using PLF technologies at commercial farms have been conducted due to the scarcity of commercialized PLF systems. As the first priority of farmers, the economic benefit of using a PLF technology may directly affect their decision on investment. Although simple estimations were mentioned above, systematic techno-economic analysis will be needed in the future.

Conclusions

In this review, three animal-based PLF technologies in broiler production, including image processing, audio analysis and sensor signal processing, were reviewed briefly.

We conclude that top-view cameras and microphones are the most promising PLF tools for applications at commercial farms. Wearable sensors are good candidate tools for lab research. Applications of image processing include behaviors and activity monitoring, and audio analysis could be potentially used for disease and stress detection. Barriers to applying image analysis in commercial farms include low accuracy of bird segmentation, poor image quality due to low light intensity or uneven light, and misclassification of bird pixels and equipment pixels. For audio analysis, differentiating bird vocalization and sound of other mechanical systems is crucial. Development of PLF in broiler production is still in the early stage. Systematic ROI analysis will be needed for the evaluation of the benefit of PLF systems in commercial settings. These findings provide insights into the development of PLF technologies in commercial broiler farms.

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Quantifying specific behaviours related to positive and negative broiler welfare: a preliminary study

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Abstract

Multiple behaviours are expressed when commercially-housed broilers are given the opportunity to make use of free space unexpectedly appearing inside the barn. In addition to general displacements or movements also play behaviours are observed after a person has walked through the flock creating an empty area behind. Therefore, we developed an algorithm that first automatically captures all bird movements into the free space and outputs a corresponding short video sequence of the detected event using computer vision methods. In a second step, different classification techniques are investigated to quantify specific behaviours related to positive or negative welfare. A top-view camera installed inside a commercial broiler house captured a video each time a person walked through the barn. Walkthroughs were performed when birds were 21, 28 and 33 days of age. To capture all displacements, Gaussian Mixture Models were applied to the videos and heatmaps were created. The latter were used to derive movement features for every detected event. In a first analysis of single videos, the developed algorithm was able to 1) create short video sequences of all bird movements and 2) assign movement features for every detected event.

Keywords: positive welfare, broiler welfare, multiple action recognition, Gaussian Mixture Modeling, behaviour classification

Introduction

Broiler chickens are among the most numerous farm animals in the world today (OECD/FAO, 2017). As such, they have been subjected to intensive genetic selection to ensure a high efficiency of productive traits (Weeks *et al.*, 2000). Simultaneously, there has been an increasing public concern over the standards of farm animal welfare, with the widespread perception that the drive for efficiency has been responsible for several animal welfare problems (Dawkins, 2017). Animal welfare has traditionally been evaluated based on the absence of negative subjective states (Edgar *et al.*, 2013). However, during the last decade, there has been an increased focus on positive welfare, such as pleasure, curiosity and playfulness (Lawrence *et al.*, 2019). Such positive states cannot be measured directly, rather they are monitored through several validated indicators, e.g. through behavioural monitoring (Dawkins, 2003; Mellor, 2012). The monitoring of behaviour can be performed automatically through the use of camera-based technology (Peña Fernández *et al.*, 2018). Previous studies have used camera-based techniques in broiler houses, linking the birds' behaviour to their welfare status (Dawkins *et al.*, 2012; Dawkins *et al.*, 2013; Kristensen & Cornou, 2011). For example, the study by Aydin *et al*. (2010) modelled the activity of broilers as a consequence of changes in walking ability, whereas Kristensen *et al*. (2006) used camera-based monitoring techniques to model the activity of broiler chickens to changes in light intensity. Such studies provide examples of how camera-based techniques can be used to non-invasively and non-intrusively monitor the behaviour, and in extension the welfare, of broiler chickens. After a person has walked through the barn, a free space becomes available to the animals unexpectedly. As such, behaviours linked to positive welfare, such as frolicking and sparring, are being expressed more frequently (Baxter *et al*., 2019). In addition, walking and running events can be monitored and used to assess walkability, a trait related to negative welfare.

Therefore, it was the aim of this preliminary study to quantify a multitude of expressed behaviours linked to either positive or negative welfare of broilers using 2D wide angle camera technology. To this end, a multi-stream Gaussian Mixture Modeling (GMM) (Zivkovic & Van der Heijden, 2006) approach was implemented to capture all bird movements after a walkthrough.

Materials and methods

Camera setup and region of interest (ROI)

A wide angle top view camera was mounted on the ceiling of the barn to record videos of broilers at fifteen frames per second with a width and height of 2688 and 1520 pixels, respectively. The ROI was manually defined between the feeder line on the right side of the field of view (FOV) and the drinker line on the left side of the FOV (Figure 1).

Walkthrough experiment

Figure 1: Raw video data (left) and manually selected ROI (right)

Figure 2: Example of a walkthrough leaving an empty area behind

A person walked through the flock between the feeder and drinker lines entering the FOV at the bottom and leaving the scene at the top when broilers were 21, 28 and 33 days old. A walkthrough caused the birds to scatter away, leaving an empty area behind the person (Figure 2). In turn, this created an opportunity for the birds to make use of the free space and express a multitude of behaviours.

Detection of events using the multi-stream GMM algorithm

The purpose of the developed algorithm is twofold: a) create short video sequences of every detected event and b) calculate movement features for every detected event

In a first step, the bird occupation density in the FOV is computed before a person enters the scene. When the bird occupation density reached 70% of the start value again, the algorithm stopped producing outputs as individual behaviour classification becomes irrelevant as there is not much free space left for the birds to move around. In a second step, the animals are segmented out of the images based on their color to calculate the mean area of the birds. The latter parameter was used for preprocessing in following steps to filter out movements smaller than the mean bird area. A third step consists of capturing movement in the video by applying two separately tuned Gaussian Mixture Models (GMM) to the video frames producing an 'all activity' (GMM_{all}) – and 'fast activity' (GMM_{fast}) video stream with the background subtracted. A 'slow activity' (GMM_{slow}) video stream was produced by subtracting the GMM_{fast} from the GMM_{all} video stream. In addition, the animals were tracked using the GMM_{all} stream. In a fourth step, all GMM-frames of each separate stream within 2 seconds are summed to create a corresponding Movement Map (MM_{all}, MM_{fast}, MM_{slow}). By combining the 2-second Movement Maps MM_{all} and MM_{fast}, we create Heatmap 1 (HM1). By combining MM_{fast} and MM_{slow} we create Heatmap 2 (HM2). By using both HMs, we can extract several unique features indicative for a specific behaviour (e.g. ratio of fast – and slow pixels in HM1 as compared to HM2). HMs contain several regions of movement where a displacement of any kind took place. When a region of movement is created by more than one bird, the animals within that region are tracked based on their movement and each event is segmented out of the scene resulting in short video sequences for every single bird. The left side of Figure 3 (see bottom left 'Events detection'), provides a general overview of the aforementioned approach.

Behaviour classification of detected events

In this section we explain the behaviour classification of the multi-stream GMM algorithm in more detail (see bottom right corner 'Behaviour classifier' in Figure 3). For every detected event, corresponding HM-features were calculated and a short video sequence was generated. Every short video sequence was labeled manually according to one of six observed behaviours being wing flapping, flying, running, walking, sparring or frolicking. Table 1 provides an overview of the labeled dataset of expressed behaviours. A first classification of detected behaviours, produced by the algorithm, is based on imposing hard thresholds on the calculated HM-features of a particular event.

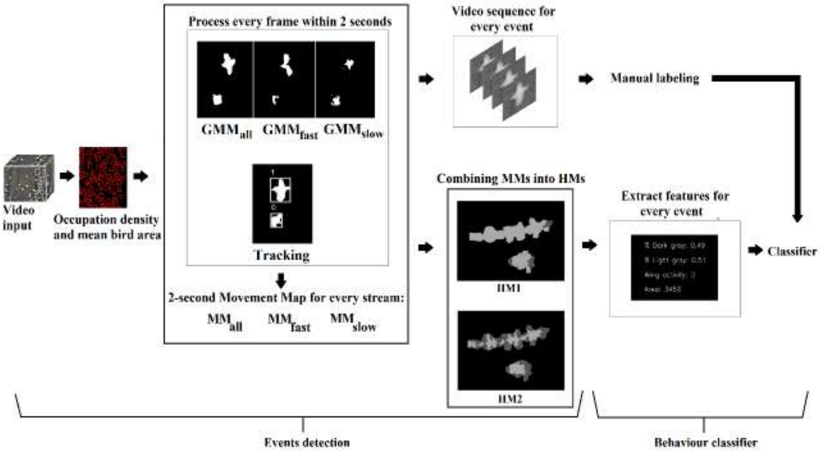

Figure 3: Overview of the multi-stream GMM algorithm. GMM: Gaussian Mixture Model, MM: Movement Map, HM: Heatmap.

Table 1: Overview of expressed behaviours for the walkthrough at age 21 days

	Wing flapping	Flying	Running	Walking	Sparring	Frolicking	Total
Labeled	23	12	49	73	13	6	176

Results and discussion

With the proposed events detector (multi-stream GMM), 176 events were detected in 190 seconds (all behavioral expressions larger than the mean bird area can be detected) for the walkthrough performed when birds were 21 days of age. With the proposed hard threshold classifier, the preliminary results show sixty-two out of seventy-three walking events can be successfully distinguished from all others, while twenty events were falsely classified as walking. This resulted in a precision and recall of 75.6 % and 84.9 %, respectively.

Conclusions

The proposed method can capture all expressed behaviours of broilers when a person has walked through the barn. By using a multi-stream GMM approach, unique movement features are assigned to every detected event which, in turn, can be used for behavioural classification. Preliminary results for the detection of walking events using hard thresholds showed a precision of 75.6% and a recall of 84.9%. Future work includes feature engineering in order to improve behavioural classification.

We anticipate that the proposed approach, together with the labeled dataset, can be used as a basis for multiple action recognition in videos of broilers expressing a multitude of behaviors when they enter an empty space after a walkthrough. Therefore, state-of-the-art classification algorithms that use short video sequences as an input to classify multiple actions in a scene are currently being explored. As such, a finalized method could be used to detect behaviors related to positive and negative broiler welfare.

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Where does it hurt? Injury identification in turkeys using keypoint detection

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Abstract

Injurious pecking against conspecifics is a serious problem in animal welfare in turkey husbandry. As bloody injuries act as trigger mechanism to induce further pecking, a timely detection and intervention could prevent massive animal welfare impairments and/or animal losses. Thus, the overarching aim is to develop a camera-based system to monitor the flock and detect injuries using neural networks. In a preliminary study, images of turkeys were manually annotated by labelling potential injuries and were used to train a network for injury detection. With the present study, we aimed to improve the injury identification by applying a keypoint detection model to provide more information on animal position. Therefore, seven keypoints on turkeys were defined and overall 244 images (showing 7,660 birds) were annotated. Two state-of-the-art approaches for pose estimation were adjusted and their results were compared. Subsequently, the better keypoint detection model (HRNet-W48) was combined with the segmentation model for injury detection. The classification of the individual injury was noted using “near tail” or “near head” labels for instance. To summarize, the keypoint detection showed good results and was clearly able to differentiate between individual animals even in crowded situations. In further research, specifying the injury location should improve the accuracy of an injury detection system.

Keywords: turkeys, injury localisation, pose estimation, crowded dataset, keypoint detection

Introduction

In turkey husbandry, injurious pecking against conspecifics is a widespread, serious problem in animal welfare (Dalton et al., 2013). The predestined body regions for such pecking injuries include the scalp, the neck, the snood as well as the back, the wings and the cloaca of the birds. As bloody injuries act as a trigger mechanism to induce further pecking behaviour (Huber-Eicher and Wechsler, 1997), an early detection of the occurrence of injurious pecking in the turkey flock and a subsequent intervention can avoid serious wounding and prevent an outbreak of this behavioural disorder (Krautwald-Junghanns et al., 2011). Over the last years, research on animal welfare and behaviour was improved with the continuous advancement of computer vision and deep learning technologies. In the best case scenario, such approaches can support, simplify and, above all, accelerate the continuous observation of animals. Furthermore, an implemented real-time monitoring of large animal flocks, such as in conventional poultry farming, using computer visions and machine learning algorithms can help to prevent large-scale outbreaks of diseases or behavioural disorders (Zhuang et al., 2018).

Analysing animal behaviour and health needs to be conducted with minimal human interference and involvement. Thus, computer vision is a proven non-invasive technology for video/image data collection (Leroy et al., 2006). Computer vision tasks are carried out, for instance, by pose estimation, which can provide important behavioural information. The method of pose estimation can be described as follows: Individual objects are abstracted into keypoints, which are spatial locations of interest, such as body parts or joints, and finally skeletons are estimated on them. To enhance the recognition precision, additional markers can be placed on the studied animals, however this method could have effects on them and be very expensive depending on the number of animals. Alternatively, modern approaches for pose estimation of animals are determined by non-invasive, vision-based solutions as keypoint detection (KPD). Thus, keypoints are marked manually on sample images or video frames in order to form a skeleton model and to purpose recording an individual animal as well as its pose estimation (Psota et al., 2020).

In a previous study, an image-based automated system using a neural network to detect pecking injuries in a turkey flock should be developed (Volkmann et al., 2021). Based on the manual annotations of such pecking injuries on images of turkey hens, a neural network was trained and various additional work steps were carried out to improve the detection assessment. The present study aimed to develop a KPD model on turkey hens to recognize the individual animals and their body regions (e.g. head, neck, back, tail and wings). In a second step, the detected injury should be localised. Therefore, information on pecking injuries (generated in the preliminary study) should be combined with their localisation (resulting from the KPD in the present study). Thus, the aim is to finally provide a method for injury localisation.

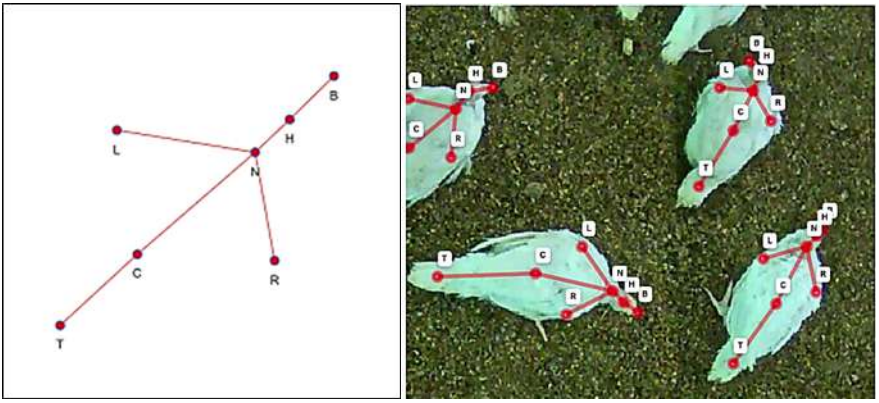
Material and methods

Preliminary research

The dataset of turkey images used in this study originate from a previously described study, which aimed to detect pecking injuries in the turkey flock using neural networks (Volkmann et al., 2021). Three top view video-cameras (AXIS M1125-E IP-camera, Axis Communications AB, Lund, Sweden) were installed at approximately 3.0 m above the ground to capture top-view videos. The recorded videos were cut into individual images for further processing. A software was developed for marking the injuries visible on the images by human observers. Afterwards, a neural network was trained with these annotations in order to learn to detect pecking injuries on other unknown images from the same domain.

Keypoint annotation

As the images of the observed animals were recorded by top view cameras, the turkey keypoints were defined by seven points also visible from the top and shown in Figure 1 (a) and (b).



(a) (b)

Figure 1: (a) Keypoint skeleton showing the beak (B), the head (H), the neck (N), the left wing (L), the right wing (R), the center of the body (C) and the tail (T). (b) Example image showing the keypoints on turkey hens.

The turkey data set was manually annotated using the annotation tool of Supervisely (San Jose, CA, US) which is a web platform for computer vision developed by Deep Systems (Moscow, Russia). Overall, 244 images showing different situations, compartments as well as age groups of the turkeys and thus stocking densities in the barn, were marked and the total number of annotated individual animals was 7,660 turkey hens.

Keypoint detection models

Two state-of–the-art deep learning algorithms for KPD were evaluated, namely the "Baseline for Human Pose Estimation" by Xiao et al. (2018) as well as the "High-Resolution Network" (HRNet) (Sun et al., 2019).

The first step of the evaluated keypoint estimation network by Xiao et al. (2018) was to apply a backbone network on the input image to generate the network activations, the so-called feature maps, marking a lower dimensional response of the network. The second step was to predict the keypoint location individually from this lower dimensional response. The ResNet (Residual Neural Network) (He et al., 2014) architecture was chosen for the backbone networks.

The HRNet combines low resolution features with intermediate high resolution features to achieve a high resolution and reduce loss of information. In this study, ResNet was used with different depths with 50, 101 and 152 layers, while the HRNet was evaluated using W48 (big size) and W32 (small size), where 32 and 48 represented the widths of the high-resolution subnetworks. All networks were initialised by pre-training on the ImageNet (Deng et al., 2009) classification dataset.

The implementation of both methods was based on the OpenMMLab Pose Estimation Toolbox (MMpose Contributors, 2020) and tested on benchmarks of the COCO keypoint detection dataset (Lin et al., 2014).

The metric of OKS (Object keypoint similarity) was used to quantify the closeness of the predicted keypoint location to ground truth keypoints on a scale between 0.0 and 1.0. An OKS-threshold was applied to classify if a keypoint location was correct or not. The keypoint evaluation was performed according to the COCO evaluation metric (see http://cocodataset.org/#keypoints-eval) with 0.50 (loose metric) and 0.75 (strict metric) as reported thresholds. We evaluate the average precision at these thresholds as AP_{50} and AP_{75} as well as the average recall (AR_{50}, AR_{75}). The average precision without a named threshold AP is a more abstract measure, which averages over different OKS-thresholds between 0.50 and 0.95 and allows a combined view. Average recall without a named threshold AR is the analogue measure for the recall.

Segmentation model

As described in Volkmann et al. (2021), human observers processed the images of turkey hens and annotated manually the visible injuries on them. With these annotations a network for semantic segmentation was trained: the U-Net based on an Efficient-Net backbone (Ronneberger et al., 2015; Tan and Le, 2019). Thus, pixelwise masks of injuries were generated building on this previous work.

Combination of models

The evaluated KPD models and the segmentation model were combined. First, the keypoints were detected and mapped to the original image to preserve the original scaling. Afterwards, the segmentation model for injuries was applied and rescaled accordingly. Before the injury segmentation was finally added to the keypoint output image, several post-processing steps were implemented. For each injury, the closest keypoint was noted and thereby any detection was identified as one of the following injuries: Beak (B), head (H), neck (N), left wing (L), right wing (R), center of the body (C) and tail (T). This classification followed the keypoint schema shown in Figure 1. If no closset keypoint was found, the 'related' injury was identified as a false positive segmentation.

Results and discussion

In this study, two state-of-the-art approaches for KPD on turkeys were adjusted and evaluated. On an evaluation set of images, which was withheld during the training of the KPD, the baseline method with 152 layers and the HRNet with 48 layers were tested.

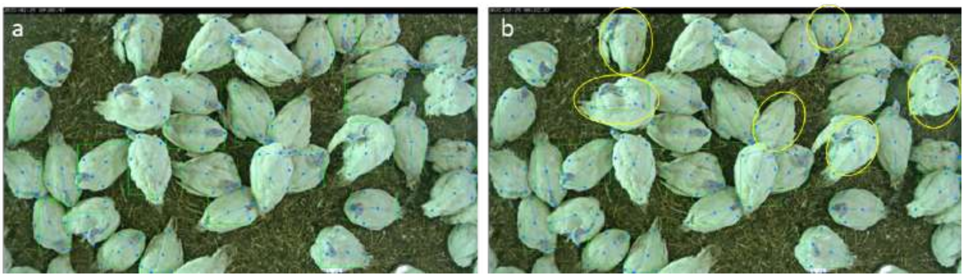


Figure 2: Comparison of KPD using (a) baseline method with 152 layers and (b) HRNet-W48. Turkey showing differences between the results of the baseline and HRNet are highlighted with yellow circles on the right image.

The qualitative results are shown in Figure 2 on two example images. They show that turkey KPD based on images of top view cameras was possible even for such images with situations of touching and moving turkeys, which were overlapping in the images. Overall, there were clear differences between the results of the baseline and HRNet-W48 (highlighted with yellow circles see Figure 2), the HRNet results were superior in most cases. The HRNet-W48 model required approximately 750 ms processing time on a 2017 Nvidia TITAN Xp GPU, which was sufficient for our application with low framerate footage.

For a more in-depth analysis we used a quantitative evaluation. The results of the metrics for the two performed KPD model evaluations are listed in Table 1. They showed that higher network complexity led to better results and the differences between baseline and HRNet were confirmed. In terms of quantitative results, the HRNet-W48 model showed the best performance values. High values for the loose metric AP_{50} of up to 0.75 were reached, similarly to results reported by other authors in challenging situations (compare AP_{50} = 0.85 for ankles in pose estimation by Sun et al., 2019). This confirmed the visual findings, which were able to reliably localise turkey keypoints even in top-down view in a crowded dataset. The values for the AP_{75} strict metric and also the AP, which includes even a stricter threshold, were lower, showing a less accurate result for some keypoints. As the exact location of some keypoints - such as left or right wing - were only roughly visible in top-down-view – especially when the animals had moved, were grooming themselves or were sleeping in a different posture - the detection accuracy of these keypoints was limited. Since such situations occurred frequently in the recordings of turkeys' natural behaviour in the flock, this could explain the reduced values of AP_{75} and the AP. Furthermore, it has to be considered that the annotation of keypoints on the all-white body of the turkeys was already difficult and therefore, it could not be guaranteed that, for instance, the 'center of the body'-keypoint always had the same position. A study of Doornweerd et al. (2021) on pose estimation in turkeys placed the keypoints on hocks and feet. Such keypoints are to define more precisely than ones on images from a top-view camera.

Table 1: Object keypoints similarity metrics resulting from the different keypoint detection models stating the average precision with the threshold values of 0.50 (AP_{50}) and 0.75 (AP_{75}) and averaged over thresholds from 0.5 to 0.95 (AP) as well as the average recall with the threshold values of 0.50 (AR_{50}) and 0.75 (AR_{75}) and averaged over thresholds from 0.50 to 0.95 (AR). Best performing values are printed in bold.

Architecture Type	AP_{50}	AP_{75}	AP	AR_{50}	AR_{75}	AR
Baseline - ResNet50	0.648	0.107	0.213	0.691	0.198	0.292
Baseline - ResNet101	0.640	0.107	0.228	0.687	0.200	0.288
Baseline - ResNet152	0.659	0.134	0.254	0.703	0.231	0.313
HRNet-W32	0.692	0.158	0.267	0.726	0.241	0.323
HRNet-W48	0.735	0.246	0.322	0.762	0.355	0.383

The network for injury detection from previous work (Volkmann et al., 2021) yielded an agreement with the human observers of F1-score = 0.14, a recall of 0.19, and precision of

0.11 (Figure 3). For the next step in this study, the combination of KPD with the injury detection, we used the previously identified, quantitatively best KPD method HRNet-W48.

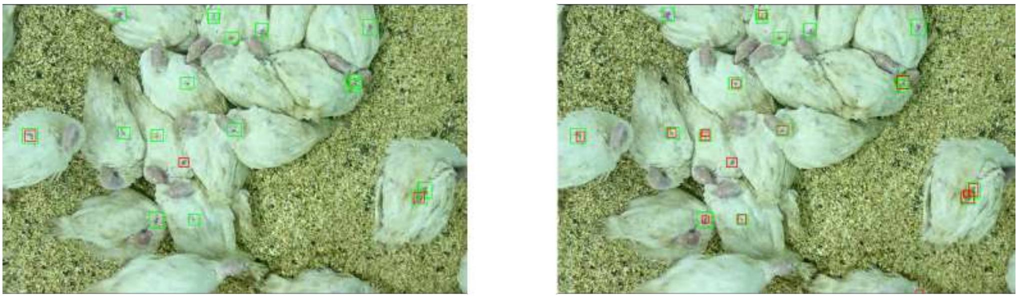


Figure 3: Example image which was annotated by the neural network for injury detection from previous work (Volkmann et al., 2021). The human annotations are framed with green bounding boxes and those of the network are framed with red bounding boxes.

An example image of the combination of the detection models is shown in Figure 3. Because the turkey hens presented on this image are very close to each other, the classification of the individual injury was challenging. However, the KPD was able to differentiate between individual animals, even in such crowded situation as found in conventional poultry housing where several thousand animals are kept together in a flock. In the evaluation, some only partially visible turkey hens on the image border were missed with KPD, but due to our striven use case, this was not detrimental. Finally, the injury locations were noted using labels as for instance “near neck”, “near beak” or “near tail” (Figure 4). Thus, the developed KPD combined with the injury detection could be used for injury localisation.

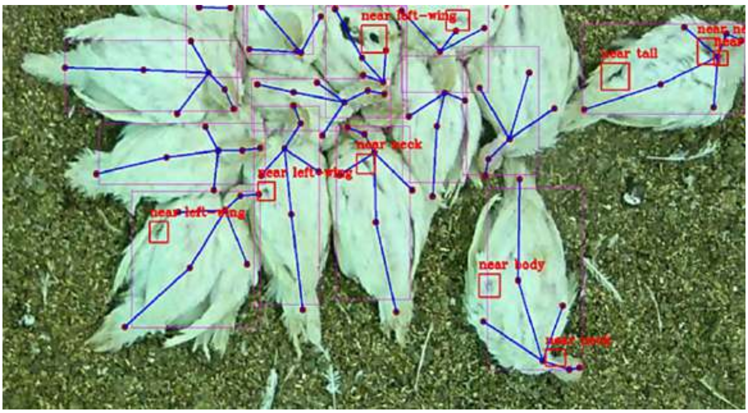


Figure 4: Combination of KPD generated in this study and injury detection from previous work on the evaluation dataset. The keypoints are shown in lilac connected by blue lines. The injuries detected previously are highlighted using red boxes, while the classification of the injuries is marked using labels such as for instance “near neck” or “near tail”.

Further research should be conducted to ensure that the use of KPD has the potential to improve the accuracy of an injury detection system. Obviously, the overarching aim remains, providing a system to monitor the turkey flock with regard to animal welfare in order to support the farmer in surveillance assistance. Nevertheless, such a system can only be used to draw attention to already existing pecking injuries in order to intervene and for instance separate the injured animal. Unfortunately, such a monitoring system cannot offer a method which prevents such injurious pecking behaviour from the very beginning.

Conclusions

This paper proposed and evaluated different keypoint detection models on images recorded in a turkey hen flock, where the partially crowded situation of the animals led to overlappings on the images. Overall, the pose estimation methods showed good results and the HRNet-W48 model finally provided the best performance. Therefore, the HRNet-W48 model was combined with an injury detection model to establish a system for injury localisation. The classification of the individual injuries such as "near tail" or "near left wing" has the potential to reduce false-positive injury detections. Therefore, it is assumed, that this injury localisation could finally improve the accuracy of the aimed automatically injury detection.

Acknowledgement

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POSTER SESSION

Various Topics

Are GPS sensors and density-based classification suitable to ensure traceability of dairy cows on pastures? Part II: on-farm deployment

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Abstract
Consumer's expectations are shifting towards natural and animal-friendly productions. Consequently, several dairies developed a 'pasture milk' label which requires dairy cows to spend a minimum time per day on pasture, and they are looking for tools to ensure this traceability. To achieve this, an algorithm to automatically estimate the time spent on pastures based on GPS collars data, was previously developed and validated in experimental farms. This trial in experimental conditions gave good results: the time spent outdoor (T_{out}) were estimated with RMSEs between 17 min/d to 53 min/d (Lebreton *et al.,* 2022). Our objective was then to test these devices and algorithm in real farm conditions with a variety of geographical territories (plain and mountain areas), and different grazing systems (opened or controlled access to pastures). The trial was performed on 22 commercial farms located in the French Normandy and Massif Central regions. In each farm, approximately 15% of the herd was equipped with a GPS collar. The farmers recorded the real access time to pasture, the GPS sensors recorded cows' locations and the algorithm calculated the outdoor access time. Unlike the good results obtained on experimental farms, the trial faced several issues. The bad GPS network or the poor GPS accuracy in the barns and the lack of 2G or SigFox networks in some areas caused a lot of gaps in the data. Moreover, the recording of reference data by the farmers was heterogeneous and only a few recordings were exploitable. This field trial was a good example of the issues to face when a precision livestock farming tool is deployed in real conditions.

Keywords: traceability, grazing time, dairy cattle, GPS, algorithm

Introduction
In France, several dairies decided to develop a 'pasture milk' label a few years ago to answer the consumers' expectations towards natural and animal welfare respectful products. Therefore, dairy farmers subscribing to this label, have to respect specifications that require the milk to be produced from cows that graze a minimum number of days per year and a minimum number of hours per day. In France, most of the dairies have set up thresholds at a minimum of 6h/day and 120 days/year (CNIEL, 2019). Currently, the compliance with this specification is ensured by an audit done directly by operators on the farms. They are controlling the grassland area, grazing evidences (fences, drinkers and dungs in the pastures), as well as interviewing the farmer and checking the grazing calendar manually filled by the farmer. To help both the farmers and the dairies, a service was developed to objectify these indicators thanks to cows geo-tracking and algorithms to automatize grazing time calculation. For the farmers, these new available data can also provide additional information for decision making on grazing

management. One algorithm and tools developed were previously validated in experimental farms and gave good results in these experimental conditions with an outdoor access time (T_{out}) estimated with RMSEs of 17min/d, 53 min/d and 50min/d (Lebreton *et al.*, 2022). Before to launch this service on the field, a new trial was performed in 22 commercial farms located in Normandy and Massif Central between March and October 2021 to check the performances of the algorithm in real life conditions.

Material and methods

Deployment design

A total of 22 farms from the Normandy and Massif Central regions were involved in this trial. These 22 farms represented a diversity of farm size (31 to 150 cows), farm systems (plain and mountain), milking systems (robot and milking parlour) and access to pasture (free access, restricted access, night paddocks). The farms were recruited with the support of 2 dairies ('Maîtres Laitiers du Cotentin' and 'Jeune Montagne'). On each farm, a proportion of the herd was equipped with GPS collars (DigitAnimal, Spain): between 10 and 15% depending on the milking system, the type of access to pastures and the herd composition. A total of 134 collars were deployed (77 in Normandy and 57 in Massif Central) to check the daily movement of the herd between the barns and pastures.

Network coverage and data quality

The GPS sensors recorded timestamped cows' locations data (latitude and longitude). The data quality received from the sensors can be affected by two issues: the quality of the GPS network coverage and the quality of the SigFox or 2G network coverage. In Normandy, GPS collars used the 'Sigfox' network. This network communicates over long distances with low energy supply. In Massif Central, the SigFox network coverage is poor, therefore the 2G network, also called GSM (Global System for Mobile Communications), was used. With optimal conditions (GPS and data networks), location data are sent every 11min in Normandy and every 15 min in Massif Central, leading to a maximum of respectively 130 and 96 data per day received per collar. However, if the network quality is poor, some gap in the data can occur. To check the quality of the networks, the data emission rate (DER) was used. The DER was calculated by the ratio between the total number of location data emitted by a collar per day and the maximum number of location data per collar and per day (130 and 96).

Calculation of the time spent outside

The algorithm described by Lebreton *et al.* (2022) was used to discriminate the positions of cows when they are into the barn from when they are on pasture. This algorithm, called algorithm A, was based on the hypothesis that when processing all the data of a sufficient time window, the density of cows' positions would be higher when they are in the barn than on pasture. Thus, the algorithm A needs enough position data from both the barn and the pastures. It makes it very sensitive to the missing data due to lack of connectivity because of the barn structure or of poor network coverage.

Therefore, a second algorithm, called algorithm B, was developed using as input the geolocation data of the animals provided by the GPS collars and the map data of the farm system (position of the barn and the paddocks). Unlike the algorithm A that automatically detects the barn, farmers must draw the map of their farm system on a map application. The algorithm B crosses the map data and the cows' positions data. Each cows' position is labelled as "barn", "paddock" or "NA". The "NAs" were affected to the closest polygon (representing the barn or the paddocks). Around the barn, a buffer area was then defined and the cows' position inside the buffer zone was affected to the barn or the closest paddock regarding cow's trajectory patterns. The algorithm estimates the time spent outside the barn (T_{out}) daily by multiplying the theoretical interval between 2 positions (11 min in Normandy, 15 min in Massif Central) by the number of positions labelled "paddock". Moreover, the reference T_{out} was recorded by the farmers. Indeed, all the farmers were asked to record, for a period of 15 days, the opening and closing times of the pasture access. Some of them maintained this recording more occasionally after this 15-d period. All these reference times were then compared with the T_{out} estimated by the algorithm. Finally, we decided to use the algorithm B for its reproducibility.

Results and Discussion

Evaluation of the DER

The Figure 1 represents data emission per collar during the day. This example for a Normandy farm with good average data emission illustrates the bad network coverage when the cows are indoor for milking, at 7am and 6pm.

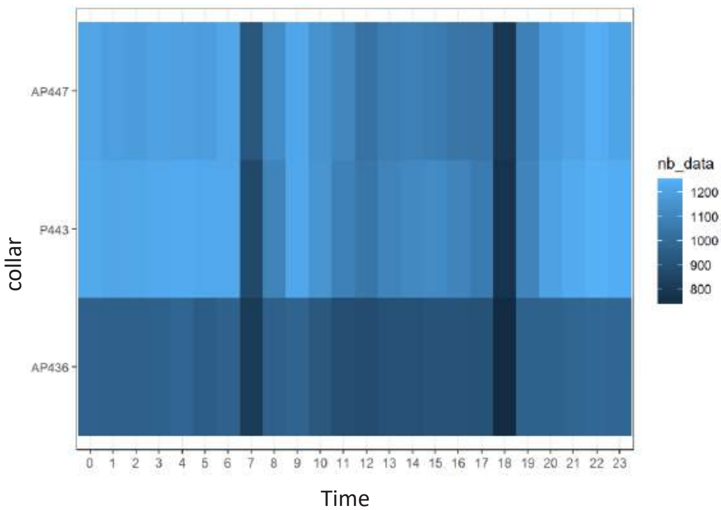


Figure 1: number of data emitted during the day per collar for one Normandy farm

In Normandy, the average DER was around 50% with a large diversity (from 10 to 85 %, figure 2). In Massif Central, the average was only around 35% (from 12 to 80%). None of the 22 farms had a DER of 100%. This low DER can mostly be explained by the poor GPS, SigFox or 2G network coverage in some areas but also because of the barn interferences.

Indeed, the average location accuracy is 5 meters on the pasture and 50 meters on the barn. This rather low DER affected the quality of the data and the quality of the estimation of T_{out}. To improve the DER and to avoid the loss of data due to a poor GPS signal inside the barns, several solutions exist and could be used. To improve 2G or Sigfox networks coverage, relay antennas could be installed in the areas with poor coverage.

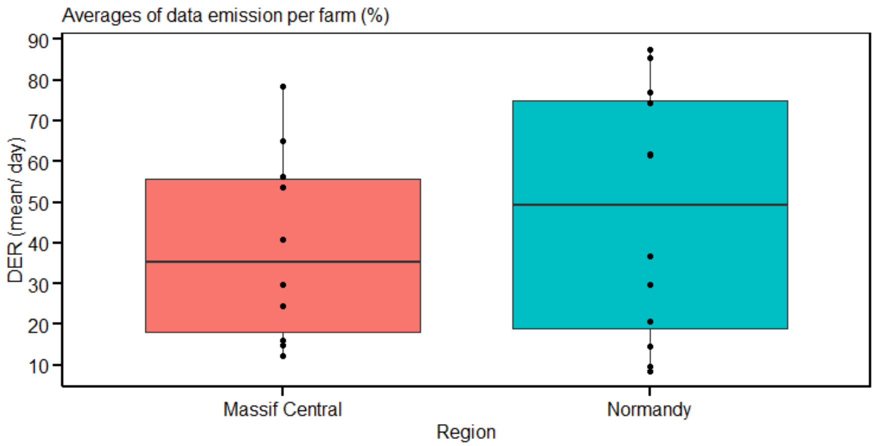


Figure 2: Average DER per farm and per region

Evaluation of the T_{out} calculation

The T_{out} was calculated on each farm based on the algorithm B. The figure 2 below shows the daily T_{out} calculated and the reference T_{out} recorded by a farmer from Normandy on one of the 22 farms involved in the trial. This figure 3 is a good example to show a change in the grazing system, here in June and October.

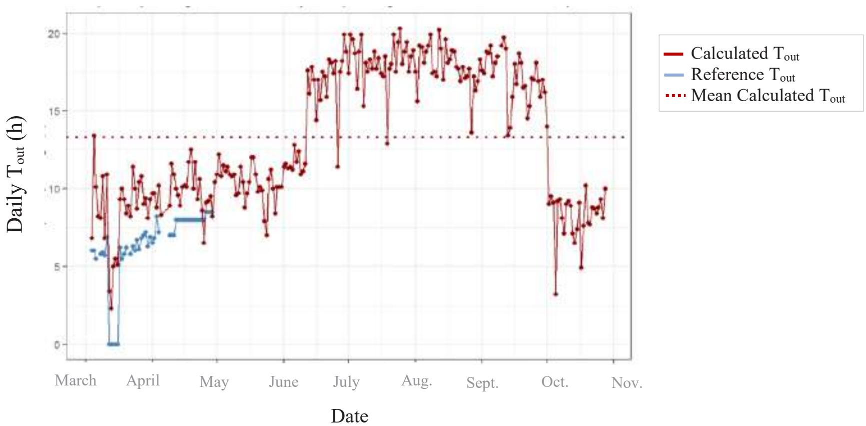
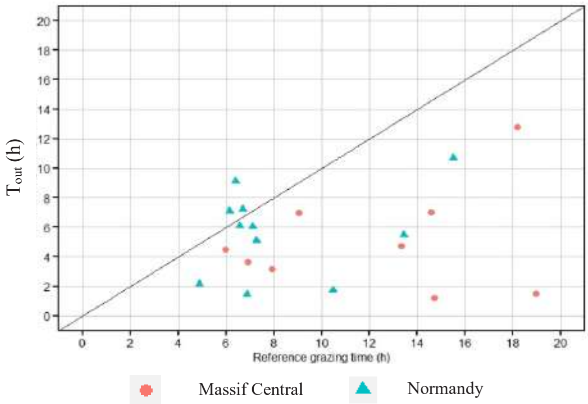


Figure 3: Daily T_{out} over the trial period for a given farm (in blue the reference T_{out} and in red the calculated T_{out})

The T_{out} calculation strongly depends on the data quality discussed previously. Indeed, gaps in the sensor data can generate an underestimation of the T_{out} and GPS inaccuracy when the cows are inside the barns can generate an overestimation of the T_{out}. When the GPS signal is poor, as it is often the case when the cows are inside the barns, the location accuracy is not better than 50 meters and the cows are often located as being outside.

The Figure 4 illustrates the effect of the bad data quality on the T_{out} accuracy. It presents the correlation between the T_{out} and the reference T_{out} for all the farms in Normandy and Massif Central. The correlation is positive, but weak, for Normandy and Massif Central. This can be explained by missing data and because most farmers lacked precision in recording reference data. Indeed, the recording of real access time to pastures by the farmers was heterogeneous and only a few recordings were really exploitable.



	Correlation	*P.value*
Normandy	0.32	0.34
Massif Central	0.21	0.58
Normandy + Massif Central	0.19	0.43

Figure 4: correlation between grazing time calculated and reference grazing time

GPS is a suitable solution for estimating days spent on pasture but it is affected by the network coverage. Therefore, additional devices could be used to improve data quality or give additional grazing evidences. To improve data gap issues, especially when the cows are indoor, a Bluetooth beacon or a RFID reader could identify if cows are entering or exiting the barns. An accelerometer could also be complementary used to analyze cows' movements and monitor the real grazing behavior and not only the outdoor access time (Allain *et al.*, 2015)

Tools developed to ensure traceability of dairy cows on pastures

Even with poor data quality, and thanks to the position of the barn and the pastures provided by the farmers, it was possible to develop additional tools to ensure traceability of cows in pasture.

The first of them is a grazing calendar (figure 5) displaying the paddocks visited by the herd and the time spent on each paddock. This can give evidence of rotational grazing and avoid the farmer to fill his grazing calendar manually. This calendar can also help him to better manage grazing strategies on his farm and to keep a history of the grazed paddocks.

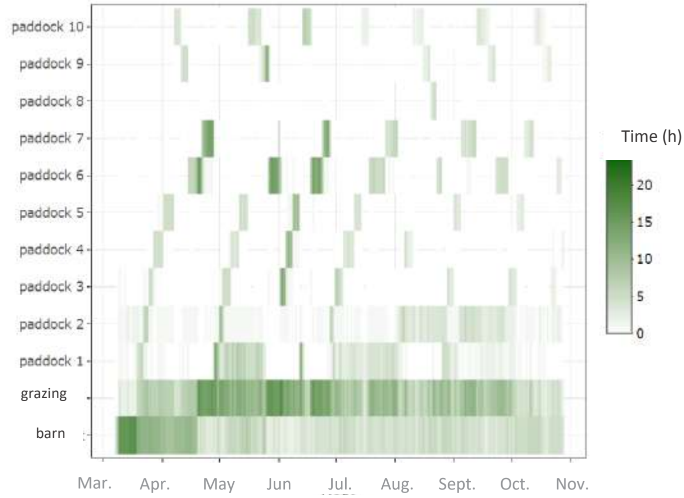


Figure 5: Automated grazing calendar

The second tool is an interactive map representing animals' positions in the paddocks (Figure 6). This map shows the daily position of the cows equipped in the paddocks, each day being represented by a distinct color point. This map has a visual interest and can show that cows were outside every day and that they were moving from one paddock to another and therefore give additional evidence of a rotational grazing on the farm. The last output is a heatmap (Figure 7) representing the location densities of cows in the paddock. This heatmap could be used by the farmers to identify overgrazed or undergrazed areas and help him to better design his paddocks.

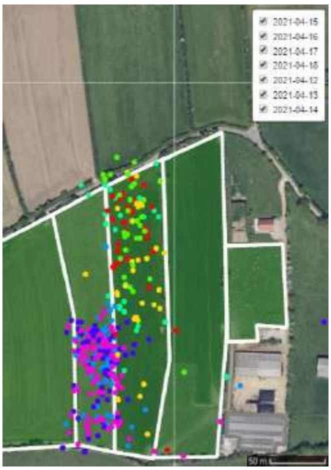


Figure 6: Example of the map representing animal location in the paddocks. Each colour stands for a different day.

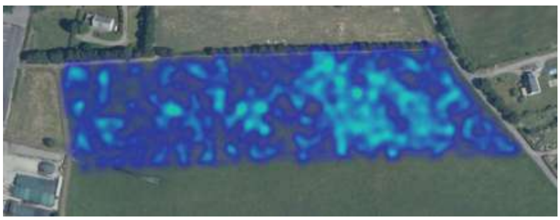


Figure 7: Heatmap of the cow's location on a given paddock. The lighter the colour, the more the cow was in this area.

Conclusions

We developed an algorithm in experimental farms which automatically estimates the time spend on pastures based on GPS collars. This experimental trial gave accurate grazing time results. However, deploying this algorithm on commercial farms with a diversity of situations is necessary to check its robustness before to use it more widely on the field. Unfortunately, this solution was not as accurate as what we observed in experimental conditions. This was mostly due to poor networks coverage in some areas. This trial is a perfect example of the gap between experimental and real-life conditions and the difficulties faced by manufacturers when they launch a new commercial product on the field. However, solutions exist. Indeed, it could be relevant to use complementary tools to GPS sensors, to compensate these network deficiencies, and strengthen the precision of this traceability tool. Even with poor data quality, we showed that additional data exploitation (grazing calendar, location map) provided sufficient evidence of grazing presence on farm. Therefore, GPS is a suitable solution to estimate the time spent on pasture, but it is not the most appropriate technology to accurately certify grazing time when the network coverage is poor. The main purpose of using GPS is to propose additional services such as grazing calendars, heatmaps, or cows' location per day on each paddock.

Acknowledgements

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Assessment of productive anomalies in dairy cows

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Abstract

In the panorama of precision livestock farming animal welfare, which the quality of products inevitably depends on, is increasingly important. Nowadays, automatic milking systems allow a more detailed monitoring of individual animals and the customized modelling of the productivity trend of each cow, as well as of the herd. It is already known that a warm, humid environment is the main cause of heat stress for dairy cows, and this is becoming even more serious due to climate change. Data from environmental sensors in the barns together with productivity and activity data enable the study and assessment of production loss due to heat stress. In this work, a new method for identifying production anomalies by modelling the lactation curve is presented. The model allows us, on the one hand, to study the residuals (difference between the observed data and the corresponding prediction) and, on the other hand, to examine the production deficit at the end of the lactation cycle. Furthermore, the use of a machine learning model applied to the data obtained from the first analysis shows it is possible to predict the milk yield loss due to heat stress. The training of the model on several animals in similar conditions (e.g. lactation, age) can be a valuable support for the farmer to predict the potential milk yield losses of the herd and to introduce the necessary preventive or mitigative measures.

Keywords: Precision livestock farming; Data analysis; Agricultural engineering; Animal welfare; Numerical model

Introduction

Heat stress is one of the most critical issues jeopardizing animal welfare and productivity in dairy farms, with consequences for both milk quantity and quality, and for the efficiency of the use of natural resources (Benni et al., 2020), as well as and for the energy required for milk production (Strpić et al., 2020). In this regard, the global trend of higher average temperatures coupled with more frequent temperature peaks reduces the lactation efficiency and thus indirectly increases the negative environmental impact of dairy cattle farming (Heinicke et al., 2019). Moreover, prolonged stresses may harm the cow's health, and the consequent treatment of animals is a burden for the overall economic balance of the farm and, whereas it includes the use of antibiotics, this entails the well-known drawbacks on the environment and on human health.

In the last decades, many devices have been introduced in livestock farms to monitor and control environmental conditions, animal behavior and production parameters (Bonora et al., 2018). Available data types usually include on-farm sensors, providing detailed milk composition (monthly on a cow level, bi-weekly on a herd level), other performance data (e.g., fertility), weather and environmental data (Mbuthia et al., 2022). Additionally, milk quality reports at dairies and labs are often logged for long-term analysis. Nevertheless, such data processing practices do not allow a daily monitoring of the trends so the farmer can take prompt action (Bovo et al., 2021). Moreover, the information from different sources are almost never crossed among different systems and different levels. A proper numerical modelling for early diagnosis and the identification of optimal prevention strategies requires good data management, in terms of acquisition, processing and harmonization, particularly in fields where very heterogeneous data may be collected (Bovo et al., 2020), and agreed protocols have not been yet standardized. Essentially, tools to effectively interpret the already available information are lacking.

In this study, a new method for identifying production anomalies by modelling the lactation cycle is presented. The model allows both to study the residuals and to examine the production deficit at the end of the cycle. In particular, the term "residual" stands for the difference between the observed data and the corresponding prediction. Furthermore, the use of a machine learning model applied to the data obtained from the first analysis has shown it is possible to predict the milk yield loss due to heat stress. The training of the model on several animals in similar conditions (e.g. lactation, age) can be a plausible support for the farmer in order to predict the potential milk yield losses of the heard and to introduce the necessary preventive or mitigative measures.

Material and methods

The numerical models

The study was conducted using data collected in an experimental farm in Groß Kreutz, Germany. The barn is equipped with a Lely™ "Astronaut" automatic milking system (AMS). More information about the farm is available in earlier publications, e.g. (Hempel et al., 2018)in situations where monitoring in the direct vicinity of the animals is not possible, we collected long-term data in two naturally ventilated dairy barns in Germany between March 2015 and April 2016 (horizontal and vertical profiles with 10 to 5 min temporal resolution.

The dataset covers the period 2015-2020 and entails:

— time series of milk yields of 189 cows, from the AMS;
— time series of temperature and relative humidity from multiple sensors inside the barn.

The packages "*matplotlib*" (Hunter, 2007) and "*seaborn*" (Waskom, 2021) were used to display results and intermediate plots, while other Python (Van Rossum & Drake, 2009) libraries like "*lmfit*", "*numpy*" and "*pandas*" proved to be useful for handling data. The Wood model (Wood, 1967) was used to obtain a curve representing the "expected" yield of each animal during the lactation cycle. As proved by the Random Sample Consensus (RANSAC) approach (Fischler & Bolles, 1981)Random Sample Consensus (RANSAC, the sampling operation followed by a multiple fit, can lead to a solid result and is capable of interpreting/ smoothing data containing a significant percentage of gross error.

Description of the pipeline

The datasets related to the AMS and to the microclimatic data were first read using the *pandas* library and subsequently joined in order to obtain a dataset containing all the information needed for the analysis.

$$THI = 0.8T + RH(T - 14.4) + 46.4$$

The Temperature-Humidity Index (THI) was calculated in the following way (National Research Council, 1971):

For each animal and for each lactation, it is possible to fit the Wood model to obtain the parameters *a, b, c*:

$$MY(DIM) = a\mathrm{DIM}^{b} e^{-c\mathrm{DIM}}$$

Where: MY is the daily milk yield [kg/d] and DIM is days in milk.

A filter was applied to select only the data where the daily THI did not exceed a threshold of 65, used as a predicator of potential heat stress.

A more robust statistics can be obtained by randomly sampling the original amount of data and producing a different Wood fit for each sample.

This way, a collection of Wood models is obtained:

$$\mathrm{MY}_k(DIM) = a_k \cdot \mathrm{DIM}^{b_k} \cdot e^{-c_k \cdot DIM}$$

where are the parameters of the k^{th} curve.

The sampling and fitting process can be repeated *N* times, selecting each time a fixed fraction *f* of the original data. Here, we used *N*=500 and *f*=1/10. The obtained family of curves and the corresponding parameters can then be used to define a representative median curve:

$$\mathrm{MY_{median}}(\mathrm{DIM}) = A \cdot \mathrm{DIM}^{B} \cdot e^{-C \cdot DIM}$$

where:

$$\begin{cases} A = median(a_k) \\ B = median(b_k) \\ C = median(c_k) \end{cases}$$

The median values of the parameters have been assumed instead of the mean values since they are not affected by outlier values. In some cases, unacceptable curves are obtained, e.g., entailing negative or infinite values or unrealistic trends. For this reason, it has become necessary to perform a selection of only the meaningful curves. Then, residuals were calculated as the difference between the actual milk yield data and values of the median curve. The beam of such curves is then filtered selecting only curves with an initial positive trend. The dispersion of the different values obtained in correspondence of the different curves can be used to define a criterion for the detection of anomaly values, for instance by selecting a proper multiple value of the standard deviation value of defining a confidence interval. This because the values more distant from the median curve would be considered in the method as anomaly points.

Production anomalies

The method proposed here allows the introduction of a lactation model that is robust with respect to statistical fluctuations and automatically creates an acceptability range linked to the dispersion of the curves belonging to the beam.

The standard deviation and its multiples can be used to find a threshold for the residuals in order to determine whether any given value is an anomaly. All points out of the beam were considered "anomalies", Note that positive residuals were also considered. While positive residuals cannot be attributed to heat stress or other adverse effects, they can be informative and could serve as indicators of change in the physiological condition of a cow.

Results and Discussion

The use of a multiple fit on different partial datasets obtained after the sampling operation, led to 500 Wood curves for each lactation. In Figure 1, the curves deemed physically acceptable are shown for a lactation cycle of one sample animal.

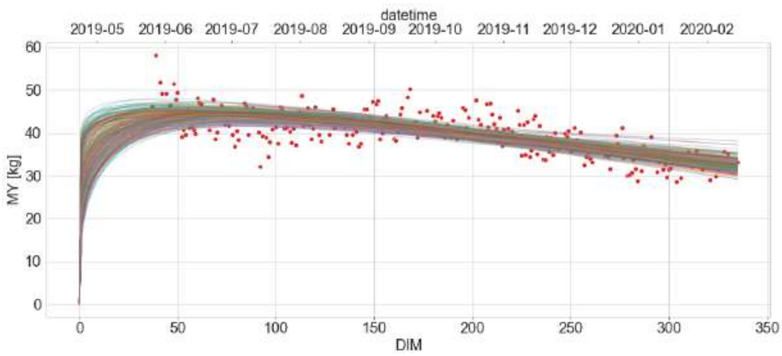

Figure 1: Wood curves with zootechnical significance for one lactation of a cow considered in the study.

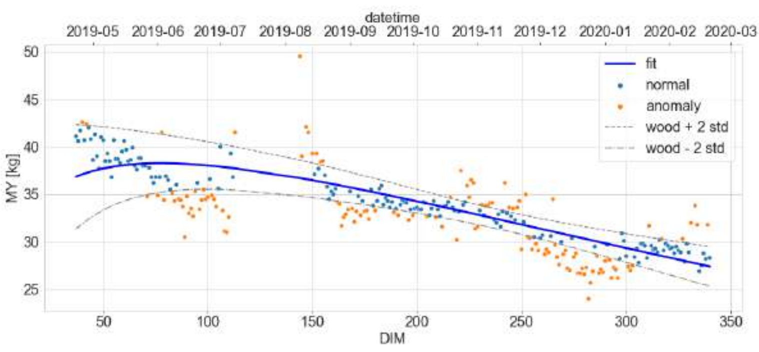

Figure 2: Anomaly detection in the plane DIM Vs MY.

Figure 2 shows, in solid blue, the median curve obtained by computing the median values of the parameters of the fit curves of Figure 1. Then it shows the 95% confidence interval expressed by two standard deviations from the median curve. Blue points are considered within normal range (could be attributed to the expected normal dispersion), while orange points, outside the 95% range have been considered as anomaly points.

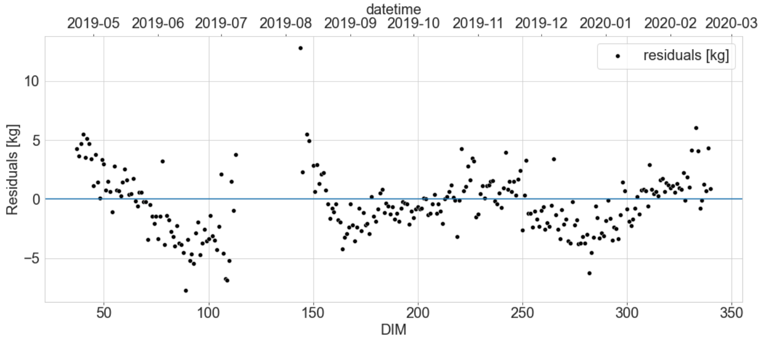

Figure 3: Scatterplot of the residuals of a fit curve.

As seen in Figure 3, residuals can be negative or positive, meaning in the latter case that milk yield can exceed the expected value. Therefore, in order to detect net production deficit in consecutive intervals, the daily residuals must be accumulated. In Figure 4 the cumulative curves of the expected and real milk yield trends are shown and overlapped to the trend line of their differences (the solid blue line). It is interesting to note that this differences (solid blue line in Figure 4) reach the value in correspondence with a DIM value equal to 90 days, about corresponding to the days with a production peak in the lactation curve. This is a recurrent condition with reference to the group of cows analysed, meaning the model was able to predict with high accuracy the cumulative milk yield in the first 90 days corresponding to the most productive stage of the lactation.

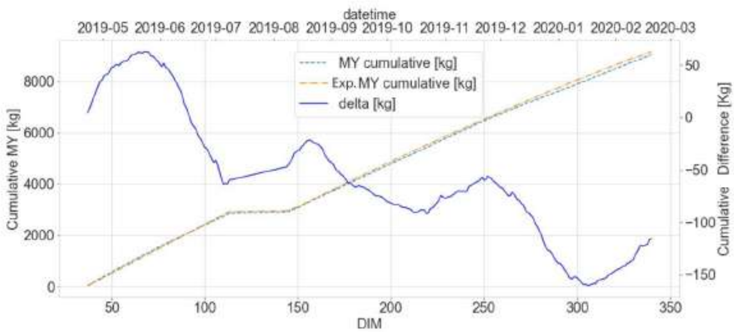

Figure 4: Cumulative curves of the expected and real Milk Yield (dashed and dash-dotted lines, respectively) and the corresponding differences (continuous blue line). In the legend delta represents the curve of the differences between the real and expected values.

Figure 5 shows the trend of the average difference between the expected and real cumulated milk yield for the entire group. As above anticipated the minimum values can be observed in correspondence to DIM ranges characterized by high values of the lactation curve (see also Fig. 2). This analysis has been performed on all the cows counting at least 100 consecutive days in milking and at least 8 valid fit curves.

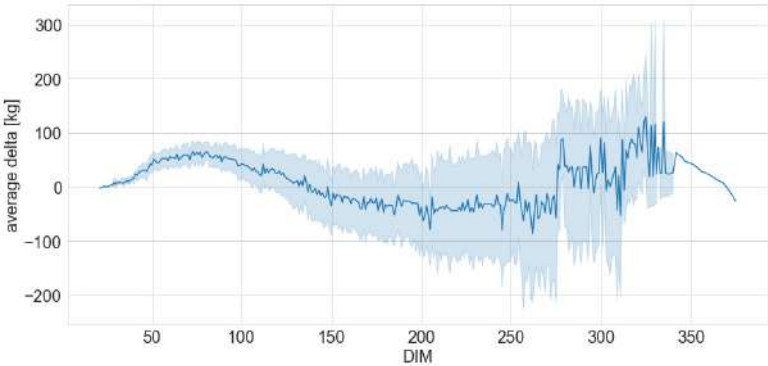

Figure 5: Average delta between expected and real cumulated milk yield. The light-blue coloured interval represents the 95% confidence interval.

Conclusions

Currently there is no systematic and statistically robust method for detecting production deviations from caused by various factors, such as environmental stress. The statistical method developed in this paper offers a robust way to identify production anomalies in the lactation period of individual cows on the basis of a multiple fit. Moreover, the use of a multiple of the standard deviation to define the acceptability range of the daily milk yield can leads to the introduction of a variable threshold, which could be used for production anomaly detection.

The anomalies identified with this method can be both positive and negative with respect to the range of acceptable values. This feature makes it clearly visible a further prospective of the use of this method: its application to an even greater number of cows and lactations will allow to collect an increasing number of anomalies. This can help a machine learning model, which is the subject of an ongoing study, in its training phase, making its forecasting performances more stable. This approach can be also used to classify daily production data as “normal” or “abnormal”.

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ATLAS livestock monitoring architecture and services

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Abstract

The continuous monitoring of livestock behaviour is an important task in precision livestock farming. An early recognition of critical events in a herd can lead to an improved animal welfare and thus for example in a reduced need of antibiotics. Furthermore, it has been found that even feeding intake and efficiency can be affected by animal behaviour. Due to the size of modern livestock farming operations, the usage of automated systems becomes necessary.

We present a scalable automated monitoring system composed of low-cost IP video surveillance cameras and affordable edge-computing hardware on-site, complemented by standardized web services that allow for long term video storage and analysis. For the automated analysis of eating- and resting time as well as activity levels in videos, we perform state-of-the-art object detection and tracking using a YOLOv3 DeepSORT Convolutional Neural Network.

Data management and the integration of the analysis system into the farmers' workflows are achieved using a distributed service interoperability network that allows the exchange of data between different services related to livestock management. The interoperability network is completely federated and based on established web technologies. Interoperability is achieved through standardized APIs and data formats.

This enables farmers for example to seamlessly integrate behaviour analysis results into feeding management systems, or to share the results with external consultancy services or other stakeholders in the production chain. Furthermore, the standardized data exchange removes the extra workload that is caused by entering the same data into different systems.

Keywords: behaviour analysis, Deep Learning, data integration

Introduction

There will be an increase in demand for animal products by 2050 (FAO. 2017). At the same time, the number of livestock is increasing, while the number of farmers is decreasing. This means there are bigger herds per farmer (Egger-Danner et al., 2020). For farmers, it's thus becoming more impossible to monitor or follow their animals in a reliable way (Berckmans, 2017). Several problems like monitoring health and welfare of the animals, reducing the environmental impact and assuring productivity per livestock needs to be addressed. This is where Precision Livestock Farming (PLF) comes in. PLF aims to provide a real-time monitoring and managing system for farmers (Schillings et al., 2021). It provides early warning and advice system while the animal is being reared. This is very different from the current manual monitoring of animal welfare by human experts (Berckmans, 2017, Schillings et al., 2021). Such methods do not help in the betterment of the life of the animal under investigation. For example, it is nice to detect a problem after an animal has arrived at the slaughterhouse, but it is much better to detect a problem while the animal is still being reared and to take immediate action. The idea of PLF is to provide a real-time warning so that when something doesn't go right, immediate action can be taken to solve the problem. For these purposes a camera network will be installed within the barn to analyse animal behaviour by means of image processing. The video streams onsite will be stored on a hard-disk and video data would be uploaded to cloud storage in a timely manner. The behavioural analysis service will then access the video data to the make the analysis results available via the ATLAS interoperability network to the visualization services providing the farmers a more real-time update on the welfare and health of the livestock. Thus, PLF will act as an early warning and advice system, thereby improving the overall monitoring and welfare of the livestock.

State of the art PLF

PLF is an approach in livestock management which starts to become more and more necessary over the years. PLF aims at managing individual animals using technology means such as sensors, cameras, microphones etc. That way an ongoing real-time monitoring process is performed to have a continuous overview of parameters such as animal's health, biological functions (productivity, reproductivity, waste) or even animal welfare and the impact of livestock on the environment (Berckmans, 2017). Up to now several technologies concerning PLF systems and approaches have been developed. A holistic PLF system usually combines several technologies to provide the total monitoring of all the parameters that are considered sufficient for livestock proper development. Many PLF systems has already been commercialized. The most basic parts of a PLF system are monitoring the environment parameters of the animals' housing building and feeding ratios. Environmental parameters such as temperature, relative humidity, light relates to animal welfare, health issues and productivity rates. Especially temperature and relative humidity relate to the thermoneutral zone of animals, therefore actions must be taken to control the microclimate when the values of these parameters are beyond the acceptable range (Lees et al., 2019, Ribeiro et al., 2020, Mayorga et al., 2019, National Research Council, 1981). Feeding ratios are than connected also with the environmental parameters or animals' weight and behavior. Measurement of gases concentration is also included in many monitoring systems and are connected with air quality regulation in the farm. In more sophisticated approaches, cameras, microphones, or more specialized sensors such can be used. Cameras based technologies are focus on tracking the behavior of animals. Eating, resting and other behavior factors can be tracked with camera systems and provide information concerning the welfare of animals (Herlin et al., 2021). Detecting heating anomalies in buildings with the assistance of cameras is also possible if the density of the animals' presence in this area is low (Berckmans, 2014). The use of cameras is opening many promising perspectives, which are still under development (Gómez et al., 2021). The issues of individual animal tracking, body weight estimation etc. are some of the challenges of this type of systems (Gómez et al., 2021). Microphones have already been used in commercial systems. The analysis of sound has been also investigated and applied in commercial systems. The analysis of the sound tracked in livestock buildings such as pigs can indicate diseases in a significant percentage (Berckmans, 2014). Currently the livestock sector which presents a significant implementation of PLF technologies is dairy cows' farming, while the market with the most PLF systems is Europe (Markets and Markets Research, 2022). Many of the industry leaders on PLF systems are in Europe. On the other hand, Asia and Oceania are mitigating the distance as the digitalization of livestock is proceeding and software companies start being involved in the sector (Markets and Markets Research, 2022).

Data Exchange and Service Interoperability

The dataflow from the barn to the end-user who accesses the analysed data for decision making is implemented using the functionalities of the ATLAS Interoperability Network[1], a decentralized network of standardized agricultural services providing defined interfaces to exchange data between services on behalf of a user. The technical implementation is based on REST interfaces and OAuth2 Authorization Code flows. Within the context of this work, two different services are involved: a *Video Storage Service* providing capabilities to store and access video data, and a *Livestock Analysis Service* which consumes data from a video storage service and delivers time-series data for several parameters related to livestock behaviour (c.f. section "Livestock Behaviour Analysis")

The ATLAS Video Storage Service acts hereby as the cloud endpoint for the Livestock Monitoring System (c.f. section "Livestock Monitoring System") which regularly uploads the video data. Metadata detailing time of record and camera identifier in the form of hardware MAC address are stored alongside each video, as well as a unique video identifier. The service provides REST endpoint to retrieve a list of available video IDs along with metadata, with the option to query for specific cameras and times of recording, while another REST endpoint allows to download the corresponding video file given the unique video ID. Furthermore, a subscription-based notification system is implemented in the form of additional REST endpoints, which allows registration of a callback URL, that will receive a notification message, whenever new videos are available. Optionally, a list of camera IDs can be specified to allow subscribing to a specific subset of cameras.

Livestock Monitoring System

Standard surveillance cameras (IP 66 protected RGB network cameras) are installed in the barn, one camera hereby monitors one group of animals. The cameras are connected to a storage and processing unit via Ethernet. This processing unit records the video streams coming from each camera in chunks of a defined length and encodes them with MPEG-4. In our installation, one camera is connected to one processing unit, therefore the processing and storage devices can be designed quite compact. Larger installations with multiple cameras would require a more complex processing infrastructure. The conceptual design however allows for scalability. Figure 1 shows an overview of the system.

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1 https://www.atlas-h2020.eu/

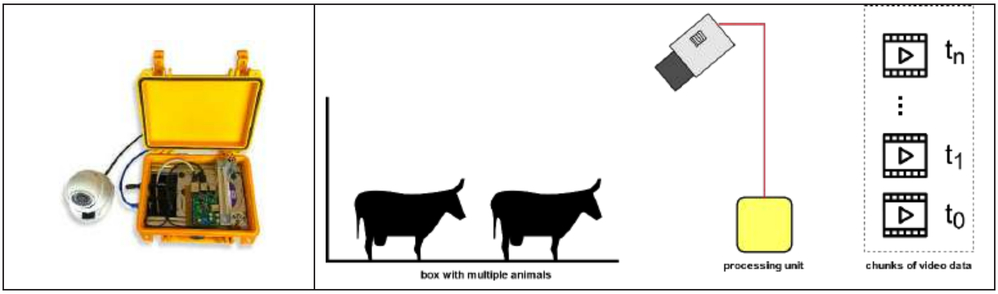

Figure 1: Surveillance camera and processing unit to be installed in a barn (left), schematic overview of the animals in a box monitored by one camera, chunks of video data are stored in a buffer space and transmitted to the cloud according a configurable schedule

The data is uploaded from the processing unit to a cloud-storage service following a configurable schedule. This allows for the management of the potentially limited bandwidth on the farm. From the cloud storage service, the data can be accessed by other processing services (see following section). Processing of data in the cloud has the advantage that no expensive high performance computing infrastructure needs to be installed on-site. However, such a setup requires a significant available bandwidth, depending on the number of cameras installed. The system design is however flexible enough to allow for a processing on-site, with an analysis service in the cloud connected. The cloud service would then receive the timeseries of the processed data for further usage. The processing unit does furthermore offer remote-maintenance functionality.

Livestock Behaviour Analysis

Livestock behaviour analysis, in the frame of ATLAS program, includes most of the tools and methods that is included in modern PLF systems. The case examined includes a beef barn in Germany. Beef barns are not a so common case of PLF systems implementation, so it is a challenge to examine the benefits for the farmer. The system includes a camera monitoring system which can track information concerning the welfare and health of the beef such as eating minutes, lying minutes and activity. On the same time the animals are weighed each day with a scaling system and information on feeding quantities and composition are measured by the producer. The combination of the above with the measuring of environmental conditions such as temperature, relative humidity etc is providing a spectrum of information that can be utilized in the frame of the program on behalf of the producer's benefits.

The scaling of animals in a daily basis can give information to the farmer concerning the body growth of the animals and how close to the ideal curve is standing. Body growth according to the standard rate ensures that heifers will not be overweight (increased fat percentage) or low weight which can be inefficient to the farmer. The rest of the parameters monitored can provide information of the reasons of a possible deviation of the ideal body growth of animals. So, inefficient feed intake or other behaviour which might connected with health issues can be tracked with the camera monitoring system and inform the farmer to change the farming method he is following or pay attention in some animals. Deviations on weight gain might also be due to environmental conditions which are also monitored by the installed systems. That way the farmer can have the information on whether an artificial cooling or ventilation system must operate if it is already installed or be installed in the future. The up mentioned information is important for the farmer to modify and adjust the feeding model followed in the barn. So, all the above information can work as an input to a feeding model which will be directed to the needs of the farmer.

Beyond feeding and weight gain, other issues concerning health issues can be tracked by the camera monitoring system according to the behaviour of the animals. If a health issue is referred to the whole herd it will be tracked as a total behaviour trend (change in eating minutes, resting minutes etc.).

To measure the eating minutes and resting minutes for a group of animals, object detection and tracking approaches based on CNNs are used. In the recent decade many deep learning models have been proposed by the researchers and are used in various fields, based on their accuracy and computing power. In this research paper, three Neural Network models are considered based on a prior literature survey: SSD MobileNet (Liu et al., 2016), Faster RCNN (Ren et al., 2015), YoloV3 Darknet (Redmon et al., 2018) .The performance of these models was evaluated by the number of bulls detected in relation to the ground truth over a defined range of image frames, as well as by the variance in detections. All models were trained for the classes “bull” (bull is standing or walking), “bull eating” (bull sticks his head into the feeding area) and “bull resting” (bull is laying down) on a manually labelled dataset using transfer learning.

Within Table 1 it can be seen that the YoloV3 Darknet model showed the best results with the highest number of detections and the smallest deviation of detected bulls compared to the ground truth with a training time of approx. one hour. Based on the bounding box information of the detections, an object detection based on Deep SORT (Wojke et al., 2017) is performed, a tracking-ID is assigned to each of the bulls in the video.

Table 1: results of the model evaluation of the three machine learning models

Model	Ground Truth	Average Detection	Accuracy
MobileNet SSD	42	33	79.5%
Faster RCNN	42	37	88.5%
YoloV3 Darknet	42	41	98.0%

The Deep Learning video analysis software is part of an Analysis Services which implements an ATLAS-conform interface to deliver livestock behaviour analysis results which can for example be used by decision support systems. The Analysis Service delivers time series data: a time interval with a given start and end time is divided in a set of sub-intervals with a given length, for each of these sub intervals the total activity minutes, resting minutes and eating minutes are delivered. Figure 2 shows a schematic overview of the complete system.

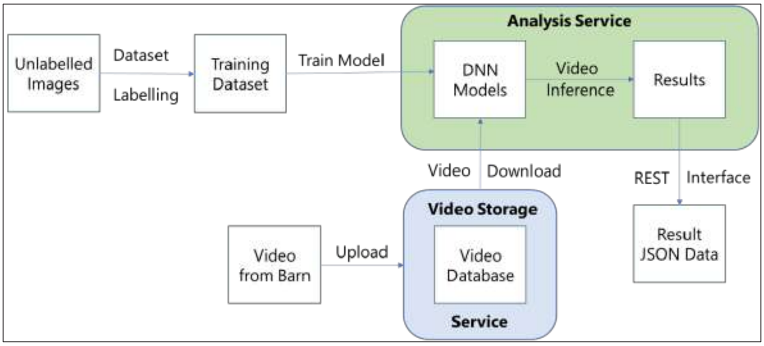

Figure 2: Overview of the complete behaviour analysis system. The training of the DNN models involves manual annotation of a sufficient amount of training data. The Video Storage Service and the Analysis Service are implemented as standardized ATLAS conformant services and deliver time series in JSON format.

Results

It is planned to bring the implemented system consisting of the camera surveillance installation in the barn and the backend services into full operation mode in spring 2022. Video data from the pilot farm has been recorded with a preliminary camera installation, delivering images from the same perspective than the intended setup. These datasets have been used to train and test the behaviour analysis system.

Figure 3: Image depicting one frame from the test-video stream with the detected animals annotated. For eating bulls, only the head is marked.

We have built three surveillance systems which are planned to be installed in barns with either bulls, pigs, or chicken. The system is configured process chucks of video data with a length of 20 minutes each. The cloud-based behaviour analysis service is implemented as a distributed application, with a web-server providing the REST endpoints to the service and responsible for the user-and data management. The Deep Learning application is running on a separate high-performance machine with a GPU, connected to the web-server via MQTT messages.

Discussion and Summary

In this work, a system to analyse the behaviour of livestock using video cameras was presented. Our work covers the whole processing chain from image acquisition to cloud processing and standardized data exchange of the analysis results using ATLAS services.

We have chosen standard RGB-cameras as sensors to measure activity and eating minutes. The advantage of such cameras is their cost effectiveness, which makes the whole approach scalable for larger farms. Furthermore, cameras are non-invasive so that no sensors need to be attached to animals, omitting all problems related to this approach. However, video surveillance produces large amount of video data which must be processed. If the processing happens within a cloud-based system, sufficient bandwidth needs to be available. Edge-computing systems can be a solution for this, on the other side they require a larger financial investment.

We have trained, tested and compared three state-of-the-art Deep Learning based object detection algorithms, where Yolo V3 Darknet architecture performed best. We have chosen a transfer-learning approach on pre-trained standard models. This technique enabled us to use a relatively small amount (approx. 1.000) of labelled training images with good detection accuracy. Using a transfer-learning based training allows to adapt the object detection to various barn setups with a reasonable effort.

All three implemented Deep Learning models may fail to reliably detect bulls when there is an overlapping of animals in the image. This happens frequently in the feeding area, where usually a large number of animals is staying. To get knowledge about the suitability of the approach More long-term tests are needed with a comparison to the real amount of food consumed by the animals.

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Coordinated innovation network for advancing Computer Vision in Precision Livestock Farming

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Abstract

Despite the promise of precision livestock farming (PLF) to enhance animal welfare and profitability, on-farm adoption of PLF has been slow due to technology costs, lack of commercially available equipment, and the limited knowledge-base currently focused on developing and implementing PLF. Sparking interest in PLF and connecting experts already working in the field are both critical to developing PLF that is usable on the farm. Additionally, many PLF studies are conducted using a limited number of animals or under very specific conditions, which generally result in tools that are not robust enough to generalize to other contexts. A low-cost technology that holds great promise for further advancing PLF is computer vision (CV). Our group is executing a five-year project funded by the National Institute of Food and Agriculture (NIFA) of the United States Department of Agriculture (USDA) to: 1) advance CV applications in PLF, 2) attract top talent from engineering, computer science, data science, and animal science to PLF, and 3) create a synergetic network of professionals working to solve pressing issues in PLF. Among the outputs of this project will be the delivery of recorded and archived webinars on current topics related to CV, the release of reference and benchmarking datasets to facilitate the development and validation of CV tools in PLF, and the creation of analytical challenges based on the published datasets. In this paper, we explain current and planned activities of our network. We also present opportunities for members of the global PLF community to be involved in those activities.

Keywords: Computer vision, Animal behaviour, Data sharing.

Introduction

While the potential of precision livestock farming (PLF) to increase profitability and productivity of livestock production systems, on-farm adoption of PLF remains limited. Two limiting factors that impede the adoption of PLF outside the dairy industry are 1) the cost of the technology relative to the value of commodity animals and their products and 2) the limited capacity of the current knowledge base (developers and engineers) in livestock agriculture to develop and implement PLF.

A low-cost, non-invasive technology that holds great promise for further advancing PLF is computer vision (CV). CV enables task automation by using computers to extract and interpret important features of a physical system from digital images or videos.

There are currently several interdisciplinary groups developing CV applications for specific PLF purposes. However, there are some acknowledged limitations to the described approach of in-house data generation and analysis for CV in PLF. One is the lack of appropriately trained human resources to develop CV algorithms. Second, research groups with ample experience in CV are not attracted to work in animal agriculture due to lack of awareness of the grand challenges for CV in PLF. Moreover, for existing collaborations, specific datasets are collected, used, and archived without being shared with other researchers and analysts. Thus, the level of solution validation is often limited because the generated CV algorithms are not benchmarked against common datasets. Thus, creating reference datasets and distributing datasets among a broader research community, can contribute to 1) advancing CV applications in PLF, 2) attracting top talent from engineering, computer science, data science, and animal science to PLF, and 3) creating a synergetic network of professionals working to solve pressing issues in PLF.

Our consortium received funding from the U.S. National Institute of Food and Agriculture to address the described needs through pursuing the following goals:

Objective 1: Generate reference datasets and benchmarking data for facilitating the development of computer vision applications that address key challenges in precision livestock farming.

Objective 2: Build a coordinated innovation network of stakeholders, researchers, and students to develop computer vision applications in precision livestock farming.

Material and methods

Coordinated Innovation Network (CIN)

Coordinated Innovation Networks are projects funded by the U.S. Institute for Food and Agriculture (NIFA 2021). A CIN fosters creation of communities that address bottlenecks in critical areas by bringing together experts from different disciplines to identify innovative and synergistic solutions. The CIN in this project promotes collaboration among researchers in computer vision and precision livestock farming.

Five institutions (see names and affiliation of coauthors) participate in this project represented by at least one co-principal investigator (co-PI). Each broad objective of the project has several sub-objectives led by members of the co-PI team (Figure 1).

Sub-objective 1a: Generate reference datasets for testing animal identification algorithms.

The general problem addressed in this sub-objective is the generation of reference datasets for animal detection, identification, and tracking from imagery data.

The overall challenges that we intend to address with these data are the following:

1. Detect individual animals within a picture of a group containing multiple animals;
2. Assign an identity to each detected animal;
3. Track individuals through sequences of images maintaining their identity despite contact and occlusions; and
4. Re-identify each animal over an extended period of time using different sensors if necessary.

The generated data will include multiple images from each animal. Images will be time-stamped and span at least one full production cycle (e.g., a full lactation for a dairy cow, or the full time that a pig spends in a nursery or in a finisher facility). The images of each animal will come from several contexts, including different positions and different surrounding animals. All images will have a positive ID from one or more of the following sources: RFID systems, visual markings (numbers painted in the back of the animal), visual ear tags, or from their natural coat color variation of the animals.

We will complete this sub-objective by using existing and newly recorded images and videos.

Sub-objective 1b: Generate and distribute reference data for quantifying behavior using CV

Under this sub-objective, we will focus on the generation of video to automatically detect specific behaviors in pigs and cattle. We chose this application because changes in the behavior of animals can provide insights into their physical and psychological health and welfare (Špinka, 2006) and because measuring behavior is useful for modeling performance phenotypes (Angarita-Barajas et. al 2019).

Examples of behaviors and activities include:

1. Post-mixing pig-pig aggression. These will include damaging aggression such as attacks and bites and non-damaging aggression, such as inverse parallel pressing.
2. Non-damaging behavioral interactions to displace animals from feeders, including those that imply physical contact, such as mounting, head knocking, pushing, mounting, and those that do not include physical contact as described below.
3. Feeding and drinking activity, including growing and nursing animals.
4. Play and other positive interactions between animals.
5. Interactions of animals with enrichment objects.

For dairy cattle, the generated dataset will include Holstein calves and cows. The labels will include the following animal postures: standing, drinking water, lying down, and eating. For grow-finish pigs, the datasets will include annotation for animal-animal interactions including aggression and competition for access to feeder space. For farrowing sows, sow postures will be annotated.

Sub-objective 1c: Provide a set of baseline performance results from applying existing analysis algorithms to the data generated in Sub-objectives 1a and 1b

The annotated datasets that will be released in Sub-objectives 1a and 1b are vital for measuring the performance of algorithms and promoting advancements in the field. In addition, for the purpose of facilitating the engagement of the CV community into the proposed CIN, it is also essential that researchers have an expectation regarding what constitutes good or bad performance. Furthermore, there may be researchers that do not seek state-of-the-art performance and instead want an easy-to-use application that they can adapt for their purposes.

For this reason, we will provide baseline algorithms for each of the tasks proposed in Sub-objectives 1a and 1b and the associated analytical challenges in Sub-objective 2a.

These algorithms will be described and released along with datasets and challenges in open access publications. Github pages will be used to manage and distribute each baseline algorithm.

The computer vision algorithms that apply to the tasks listed in Sub-objectives 1a and 1b can generally be broken up into: 1) Multiple Instance Detection and Pose Estimation, 2) Target Re-Identification and Long-Term Tracking, and 3) Action Recognition. Thus, baseline analyses and algorithms distributed under this objective will include these steps.

Sub-objective 2a. Organize a "Computer Vision-for-PLF challenge series".

The team will generate analytic challenges centered around the data generated under Objective 1. Each challenge will address important aspects of PLF for which computer vision and machine learning could leverage our datasets to provide solutions. Each analytical challenge will be organized by a committee initially composed of members of the PI team, but which will include other participants of the network over time. For each challenge multiple training datasets, consisting of annotated video and images, will be made publicly available. Each challenge will have two phases. Phase 1 starts after data are publicly released and culminates in a workshop or meeting with peer-reviewed publications, and during which official winners are announced using a leaderboard. Phase 2 is an indefinite open challenge during which data remains available, and the leaderboard is maintained and updated. Challenges will be designed to spur development of CV techniques that advance the field of PLF. Some examples of possible challenges are 1) Image-based re-identification of marked and unmarked pigs and cattle. Large datasets will be used in which animals are observed from multiple viewpoints and annotated with a unique ID and relevant metadata, such as social group/pen membership. 2) Video-based tracking of livestock including through occlusions and hand-off of tracks between sensors. RFID tags and other sensors will be used for ground truth annotation. 3) Automatic detection of aggression from video clips including behaviors such as reciprocal fights, single-sided attacks, and non-aggression. 4) Activity classification from video including drinking, feeding, standing, running and exploring.

Sub-objective 2b. Host a webinar series on translational topics in Computer Vision and PLF.

A webinar series covering a range of topics to promote understanding of and innovation in using CV for PLF applications is underway. These webinars combine presentation and 'unconference' discussion elements. The goal of these webinars is to showcase diverse perspectives and evolving knowledge related to CV and PLF, to stimulate and create opportunities for discussion that will inform current and future research, provide learning opportunities for students/postdocs in the project and beyond, and serve as the basis for future courses in PLF. Speaker presentations are 20 to 30 minutes in length, followed by moderated discussions. During discussions, the organizing team will gather data about topics of interest and identify future tentative speakers from among the participants and their suggestions for others.

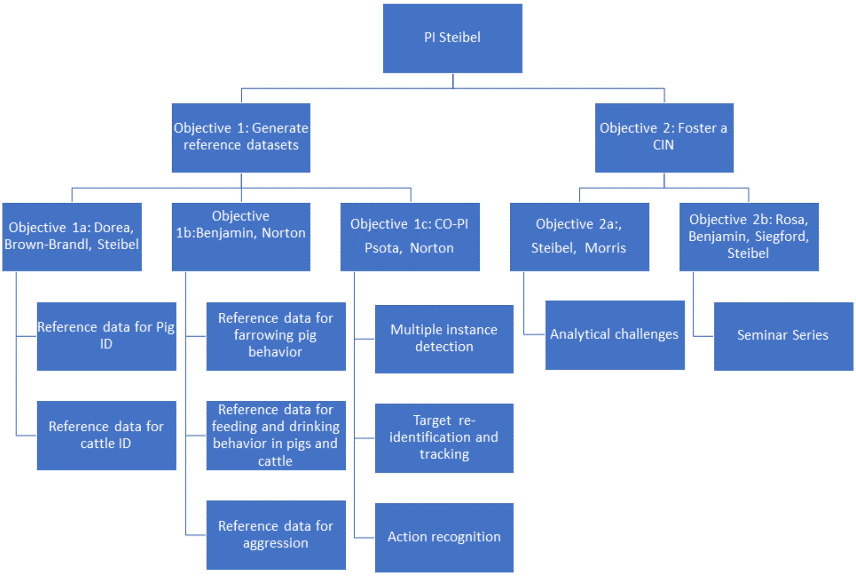

Figure 1: Management structure for the project sub-objectives. Each sub-objective has two leaders that represent different institutions and different disciplines.

Results and Discussion

The CIN on computer vision for precision livestock farming started in 2021, and in this section we report its ongoing activities.

Review of publicly available data

A review of publicly available data suitable for application of CV in livestock is underway. A total of 23 datasets have been identified, 12 correspond to cattle, 7 to pigs, and one each of horse, chicken, goat, and sheep. The datasets are being summarized in terms of animal features, environmental features, image features and annotation features.

Published data

Members of the CIN are generating and analyzing data in the context of objective 1. One dataset with short video episodes of pigs competing for feeder space has been shared (https://osf.io/wa732/). And a companion GitHub site with analysis code has been published (https://github.com/jun-jieh/AgonisticPigBehav/).

Webinar Series

The webinar series started in January 2022. The first edition included an introductory presentation and small group discussions (n= 6 to 8 persons per group assigned at random), where participants were asked what research and instructional topics in CV applied to precision livestock farming they would like to see featured in the series.

A total of 102 participants attended the webinar and 75 participants contributed to the discussion. For the question on research topics there were 30 suggestions from nine groups. As specific topics, long-term tracking and animal identification were the most requested topics (n=4 each). As general topics, data management and integration of hardware and software were mentioned the most times by group participants. Each group also requested seminars addressing a wide variety of applications of computer vision in livestock systems, including the use of drones in animal husbandry, feed use, and measuring climate-change relevant phenotypes.

The second webinar of the series focused on animal identification. It was attended by 75 participants. Two short seminars were delivered. Dr. Eric Psota presented: “How do we know who is who?” and Dr. Joao Dorea presented: “Challenges and opportunities of cattle identification through CV systems”.

An exit poll of this webinar was immediately responded to by 32 respondents, of which 23 identified themselves as interested in using computer vision for animal identification, seven respondents were already using computer vision and two were not considering using computer vision for animal identification. Also, important information about the intended use of CV for animal identification by webinar participants was collected, for instance: in which environment (production farm, research farm or laboratory) and for which species participants envisioned using CV for identification.

<u>Opportunities for the PLF community to participate.</u>

There are multiple ways in which the community of researchers interested in computer vision and precision livestock farming can participate in this coordinated innovation network.

For Objective 1, community members can participate by sharing their own data. The CIN team can provide storage and permanent links to the data to facilitate access and reuse interoperability of the data. The CIN can also collaborate on re-annotation of important data features.

For Objective 2a, community members are welcome to participate in challenges by submitting solutions or they can work with the CIN team to generate challenges around existing data. For Objective 2b, in addition to attending seminars and contributing to post-seminar discussions, researchers in the field of computer vision and precision livestock farming are encouraged to propose and co-organize webinars consisting of presentations and unconference activities.

Conclusions

Precision Livestock Farming holds the hope to enhance animal welfare and profitability; however, the development and the adoption of PLF systems has been slowed by many factors. This paper presents a coordinated innovation network that addresses critical challenges in computer vision applied PLF. The team provides opportunities to learn about the needs of the industry to develop a set of easily accessible webinars with presentations made by leaders in the PLF area, along with opportunities for interactions. These webinars have been well attended, with close to 100 participants at each event. In addition, the publicly available reference datasets are being developed for students and researchers to use to develop skills, knowledge, and abilities in image processing applications for PLF tool development.

Acknowledgements

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Development of educational Virtual Reality simulator for visualizing the Aerodynamic data in livestock houses

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Abstract

While the livestock industry has been greatly developed recently in Korea, many problems have occurred in terms of maintaining optimum micro-climate in the facility. Especially, many consultants as well as farmers have easily made misunderstanding and wrong judgement on ventilation efficiency and internal airflow distribution. The air flow is the main mechanism of internal environmental distribution such as gas, temperature, humidity, and dusts, but, as well known, the airflow is invisible and difficult to predict and measure. Therefore, it is essential to develop the training materials for the farmers to recognize micro-climate visually. In this study, aerodynamic approach was carried out using CFD (computational fluid dynamics) for combining with VR (virtual reality) technology. First, all research papers, reports, journals, and publications on livestock industry have been reviewed to find representative problems at swine houses during hot and cold seasons in Korea. Then, Open-source CFD, was used for computing the selected problems and their solutions. The livestock house models were designed based on 2009 Korean Standard of swine houses. These CFD computed results such as airflow, temperature, humidity, gas, etc were applied to VR simulator for educating swine farmers.

Keywords: Computational fluid dynamics, Livestock houses, Visualization, Virtual Reality

Introduction

Livestock facilities in South Korea have become larger and more automated to increase meat production. However, it is difficult to keep the micro-climate uniform and suitable in large facilities because most swine facilities are managed using limited resources. It is common for livestock facilities to occur many problems in terms of maintaining optimum micro-climate.

Recently, computational fluid dynamics (CFD) has been widely used for analysis of air flow, temperature, humidity, gas, and dust concentration under various environmental conditions. (Bartzanas, Kittas, Sapounas, & Nikita- Martzopoulou, 2007; Bjerg, Lee et al., 2002, 2004, 2009; Seo, Lee, Kwon, et al., 2009). However, livestock farmers and consultants are not easy to understand these computed results. Therefore, educational technology, which can effectively display the aerodynamic results, is necessary to help maintaining optimum micro-climate in livestock facility.

Virtual reality (VR) technology that can offer virtual experience of invisible things has been developed and used in various fields. It helps users to make clear decisions and visualization so that they can easily understand the environment in the facilities. In this study, aerodynamic approach was carried out using CFD (computational fluid dynamics) for combining with VR (virtual reality) technology and educational materials were made for general commercialization.

Material and methods

Experimental swine house

In South Korea, a lot of mechanically ventilated facilities are made based on 2009 Korean Standard of swine houses (Korea Pork Producers Association, 2009). In this study, one nursery swine room based on this standard design was chosen as the experimental room to make simulation model to analyse the inside micro-climate. The size of the experimental room was 5.5 m wide, 9.0 m long, and 2.4 m high, as shown in Figure 1.

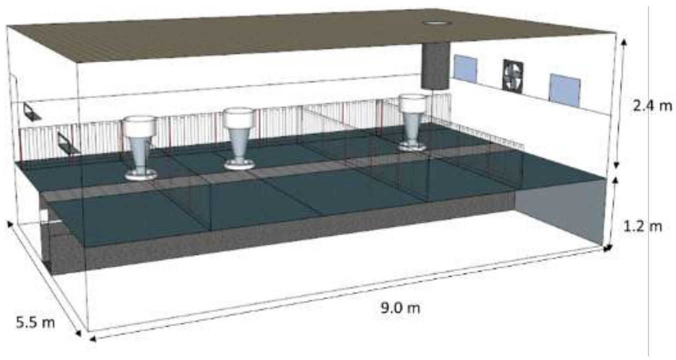

Figure 1: Schematic diagram of the experimental nursery swine house.

Computational fluid dynamics (CFD)

CFD is a numerical method for computing the behavior of fluids by solving a non-linear partial differential equation, such as the Navier-Stokes equation. CFD analysis is a technique that numerically solves equations based on the finite volume method (FVM), which consists of three design stages. In the pre-processing stage, the physical shape of the target area is designed, on which its grid mesh is generated. In the main processing stage, each governing equation for the physical phenomena is discretized and solved. A qualitative and quantitative analysis of computation results is conducted in the post-processing stage.

Virtual Reality (VR)

Virtual reality (VR) typically refers to computer technologies that use virtual reality headsets to generate the realistic images, sounds and other sensations. Recently, researches focused on practical application and industrialization based on ICT have been going on development. The invisible air and heat flow can be visualized through VR. Because of these advantages, in this study, VR technology was used to develop training materials.

Development of CFD simulation model

Design-modeler (Release 16.1, ANSYS Inc, U.S.A) was used to design the 3-D computational domain with meshes. The designed mesh domain, as shown in Figure 2, was exported to OpenFOAM (version 2.1.1). Based on previous study, validated model was used in this study (Seo et al., 2009; Kwon et al., 2016). Therefore, turbulence model was determined as RNG k-ε and grid size was determined as 0.1 m based on grid independence tests.

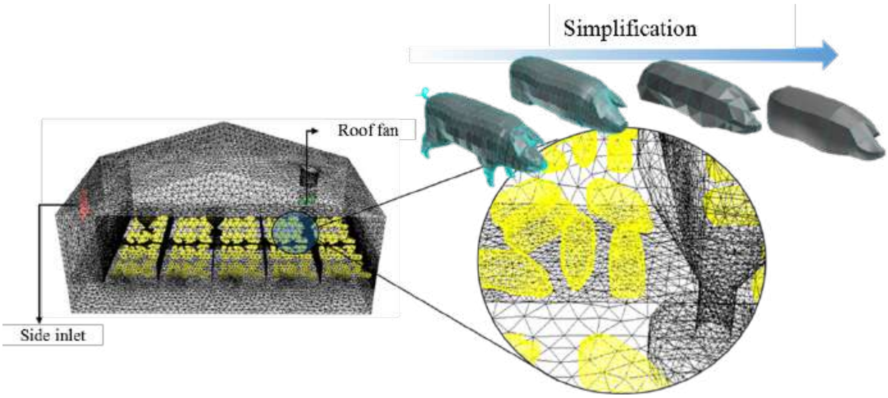

Figure 2: Computational domain and mesh design for the nursery swine house.

Table 1: Statistics data of mesh and environment condition.

Contents	Values
Model size	5.5 m width 9.0 m length 2.5 m height
Shapes of mesh	Tetra, Multi-zone
Number of meshes	6,107,109
Orthogonal Quality	Min 0.219 > 0.01
Skewness	Max 0.850 < 0.95
Outdoor temperature	264 K (cold season), 304 K (hot season)
Velocity outlet (total)	0.9 m/s (cold season), 15.5 m/s (hot season)
Pig surface temperature	313 K

Results and Discussion

CFD simulation results

In cold season, while ventilating through the side slots in the swine house, cold air might come in contact with swine directly. Figure 3-(a) shows the temperature and direction of inflow air through side slots. However, it is difficult to measure the temperature distribution exactly through several thermometers because of non-uniformity of indoor air temperature. The average temperature near the slots was about 274 K, while the average temperature of center was about 301 K. This temperature is far lower than appropriate temperature for nursery swine. Also, as shown in Figure 3-(a), ammonia gas was accumulated increasingly as the distance from the side slots. It means that the fresh air could not reach the end of the facility. In order to solve these problems, there is a method of making inlet angle. When the inlet angle is adjusted to 45 degrees at the side slot, the inflow air rises up to the top and falls down to the nursery swine, as shown Figure 3-(b). Since the risen air relatively mixes more with upper warm air, the difference between inflow air temperature and indoor temperature could be reduced about 2-3 K. In cold season, however, the ventilation rate is low, so the inflow air does not stay long on top. The air temperature has still unsuitable and non-uniformity for nursery swine. Also, this modified structure cannot remove ammonia gas sufficiently. For alternative way, making a hole on the ceiling is available to avoid inflowing cold air and to improve internal uniformity (Figure 3-(b)). The cold air stays in the ceiling to warm up and it slowly flows out through small holes. In hot season, the air temperature in the ceiling is lower than outside. It could help to prevent hot-air-inflow from outside directly

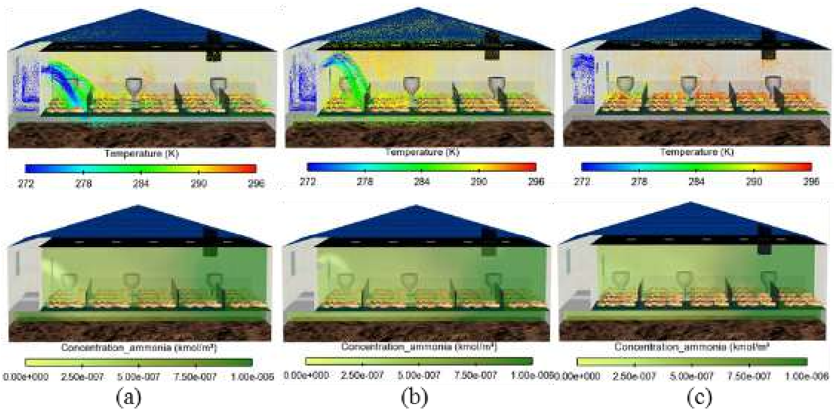

Figure 3: Temperature (top row) and concentration of ammonia (bottom row) by using side slots (left column), modified side slots (middle column) and ceiling holes (right column)

<u>Design of VR simulator model</u>

It is important to make realistic swine model in virtual reality simulation. In CFD simulation, structures and swine shapes were simplified for efficient computation. However, in virtual reality, they must be realistic models. As shown in Figure 4, to determine the optimal number of polygon, the proper quality was used for operating smoothly. Consequently, for VR simulator, middle poly model was chosen as a VR simulation model.

<u>Design of VR simulator</u>

To combine CFD simulation data and virtual reality simulator, it is necessary to determine same data point to display same contour or vector field in virtual reality simulation. The distance between points should be modified to reduce the total number of points. To find optimal distance, 0.05 m, 0.1 m, 0.15 m, and 0.2 m were used in the test.

The distance of points was determined 0.1 m based on the test. In virtual reality simulation, visualized air flow streamline, temperature, gas concentration with colors will be inserted with contour and vector field.

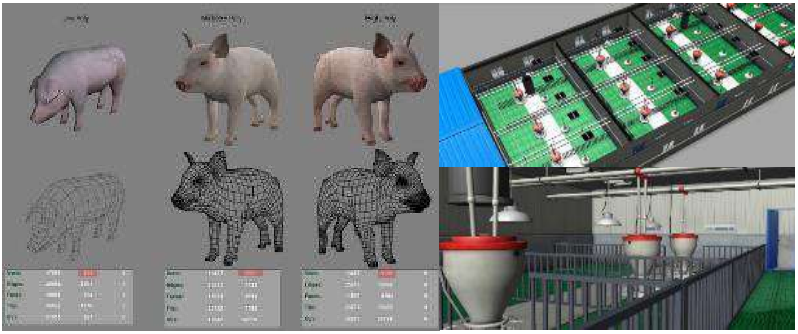

Figure 4: The comparative data of pig model quality (left) and the views of nursery house in virtual reality simulation (right)

In next step, virtual reality simulator, which provide micro-climate information for educating farmers, will be developed with various case. In order to obtain sufficient data, various case must be computed by CFD. Each case has different structure, environment condition, and ventilation system. Because each case takes considerable computation time, computation should proceed with the most typical problems.

Figure 5: Various example application of virtual reality technology on swine house.

Conclusions

In this study, aerodynamic approach was carried out using CFD (computational fluid dynamics) for combining with VR (virtual reality) technology and educational materials were made for general commercialization. This results show the problems of side slot in the swine house. Also, the method of inflow through ceiling holes was proposed. It was an appropriate way to solve cold stress and non-uniformity. To develop virtual reality simulator, the data points including computed results should be converted for high quality resolution. Also, to prevent overloading of VR simulation, the number of polygons should be reduced until keeping high quality sufficiently.

In a future study, to develop higher resolution simulator, the computed results must be optimized. The results have many data points including micro-climate information. The distance between the points must be modified for stable virtual reality simulation.

With improved computer resources, higher quality model and structural configurations including the detail resolution could be considered. Also, more cases should be computed by CFD for various training situation.

Acknowledgements

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Estimation of canopy parameters in wheat using radiative transfer modelling and artificial neural networks

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Abstract

Optimal crop management is necessary for sustainable food and feed production. Continuous monitoring of crop canopies is important in order to adapt management processes, e.g. fertilisation and plant protection, but also time-consuming. This task can be supported using remote sensing data. Many previous studies applied vegetation indices in order to retrieve information on crop canopies. They can be calculated easily and provide information on relative differences in crop canopies regarding e.g. plant health and biomass production. Vegetation indices, however, require continuous calibration as well as validation and often do not use the full spectral resolution of many sensor systems. An alternative to vegetation indices are radiative transfer models. These models describe the interaction of solar radiation and vegetation canopy. Radiative transfer models have low calibration as well as validation needs and allow the use of all available spectral information. In this study, a dataset was simulated based on the radiative transfer model PROSAIL. An artificial neural network was trained and tested with this dataset. For further evaluation, field experimental data of autumn and spring sown wheat with different nitrogen fertilisation levels at the experimental farm Groß-Enzersdorf of the University of Natural Resources and Life Sciences Vienna (BOKU) was used. Preliminary canopy parameter estimations on LAI and chlorophyll content were promising. In future, this work can help monitor crop canopies, optimise management processes and improve the sustainability of food as well as feed production.

Keywords: wheat, sowing date, nitrogen, remote sensing, radiative transfer modelling, artificial neural network

Introduction

Radiative Transfer Models (RTMs) were developed to better understand the complex interaction of solar radiation and vegetation canopy (Monteith, 1965). RTMs have low calibration and validation needs and therefore generalize well. Additionally, they allow the use of all available spectral information (Berger *et al.*, 2018).

The objective of this study was to estimate LAI and chlorophyll content of wheat (*Triticum aestivum* L.) by inversion of the RTM PROSAIL using an Artificial Neural Network (ANN).

Materials and Methods

The RTM PROSAIL estimates the spectral reflectance of plant canopies from 400 to 2500 nm in 1 nm increments based on 16 input parameters (Figure 1).

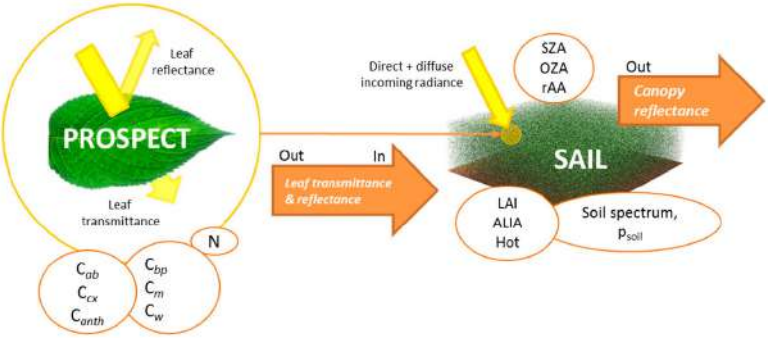

Figure 1: Spectral reflectance estimation of plant canopies using the PROSPECT + SAIL model (PROSAIL) (Berger ***et al.***, 2018). N (leaf structure parameter), C_{ab} (chlorophyll content a + b), C_{cx} (carotenoid content), C_{anth}, (anthocyanin content), C_{bp} (brown pigments), C_m (dry matter content), C_w (water content), LAI (leaf area index), ALIA (average leaf inclination angle), Hot (hot spot parameter), ρ_{soil} (soil reflectance), SZA (soil zenith angle), OZA (observer zenith angle) and rAA (relative azimuth angle).

A dataset of 10000 observations was simulated. Each observation consisted of a random set of PROSAIL input parameters, which were based on uniform distributions within lower and upper wheat specific boundary values by Danner *et al.* (2017). The spectral reflectance for each simulated observation was estimated using the RTM PROSAIL. The simulated dataset was divided into a train and test set in a ratio of 9:1. A preliminary ANN consisting of three dense layers (128 neurons each, ReLu activation function) was set up. Selected loss function was 'Mean Absolute Error' (*MAE*) and selected optimizer was the adaptive optimization algorithm 'Adam'. Training epochs were set to a maximum of 500. Early stopping was applied to prevent overfitting. An existing Keras implementation in Python was applied to set up the ANN. Model performance of the ANN was evaluated using the simulated test set and experimental data. Spectral reflectance (FieldSpec Handheld 2, ASD Inc.), LAI (AccuPAR LP-80, Meter Group Inc.) and nitrogen content of green leaves was measured in a field experiment with autumn and spring sown wheat and five nitrogen fertilization levels (0, 5, 10, 15 and 20 g m^{-2}) at the Experimental Farm Groß-Enzersdorf of the University of Natural Resources and Life Sciences, Vienna (BOKU). Since the spectral sensor provided data at a spectral resolution of 400 to 1075 nm in 1 nm increments, the same spectral resolution was applied in setting up the ANN.

Results and Discussion

Measured and estimated LAI based on the simulated test set showed high variation (Figure 2, left). The second order polynomial featured a high coefficient of determination (R^2 = 0.81). *MAE*, however, was high (1.05, mean LAI: 3.94). This can be explained by the reduction in spectral resolution due to the spectral sensor used in the field experiment (400 to 1075 nm), as previously mentioned. A comparable ANN using the extended spectral resolution from 400 to 2500 nm resulted in a higher coefficient of determination and lower *MAE* (not shown). Estimated chlorophyll content matched measured chlorophyll content in the simulated test set (Figure 2, right). Outliers occurred due to extreme input parameter values.

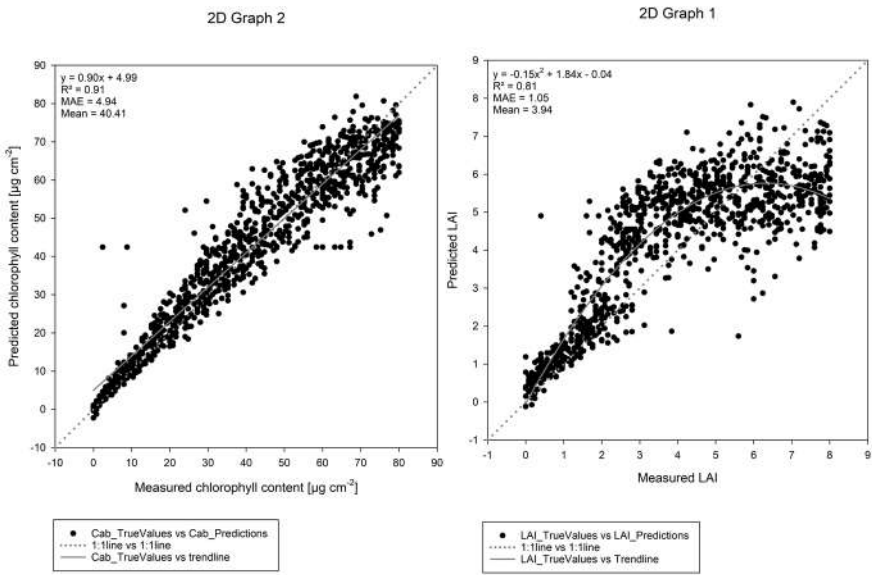

Figure 2: Measured and estimated LAI (left) and chlorophyll content [µg cm^{-2}] (right) based on the simulated test set.

Table 1: Analysis of LAI and nitrogen content of green leaves (N%) estimations based on field experimental data.

Date	Autumn sowing					Spring sowing				
	BBCH	LAI			N%	BBCH	LAI			N%
		Mean	MAE	R^2	R^2		Mean	MAE	R^2	R^2
09.03.2020	23				0.39					
23.03.2020	24				0.00					
06.04.2020	30	1.58	0.71	0.89	0.69					
20.04.2020	32	1.92	1.94	0.86	0.63					
04.05.2020	45	2.51	1.37	0.94	0.76	30	0.30	0.74	0.26	0.01
17.05.2020	59	2.88	0.22	0.97	0.85	37	0.77	0.48	0.22	0.14
01.06.2020	77	2.85	0.48	0.94	0.80	51	1.30	0.24	0.50	0.02
15.06.2020	85	2.27	0.35	0.96	0.80	71	1.80	0.21	0.92	0.70

The results of field experimental data in Table 1 show, that the coefficients of determination of LAI estimations in winter wheat are high (April until June). *MAE* values were high early in the season (April until start of May) and were low later in the season (mid-May until June). High *MAE* values early in the season indicate systematic deviations of LAI estimations. This can be explained by the low soil coverage early in the season. Soil reflectance was an important disturbing effect, when measuring spectral reflectance of plant canopy with low soil coverage. Nitrogen content estimations in winter wheat showed increasing coefficients of determination over the course of the season. LAI and nitrogen content estimations of spring wheat resulted in low coefficients of determination from May until start of June. In mid-June, coefficients of determination were high (Table 1).

Conclusion

The preliminary ANN resulted in promising LAI and chlorophyll content estimations for wheat. In future, the simulated dataset as well as the ANN structure will be optimized and the ANN will be tested with more extensive field experimental data.

Acknowledgements

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Heterogeneity of sheep grazing a cover crop as measured using remotely sensed vegetation indices

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Abstract

Integrated crop and livestock systems (ICLS) that rely on grazing of cover crops to control weed infestation and cover development depend on heterogeneous effects of grazing in space and time, as opposed to chemical or mechanical destruction. This heterogeneity affects grazing management, and a method is proposed to evaluate its evolution using remotely sensed vegetation indices. The study was performed on the ECOFOODSYSTEM platform of AgricultureIsLife in Gembloux (University of Liège, Belgium) on four experimental fields of 0.15 ha each, sown with multispecies cover crop composed of oat, phacelia and two clover varieties. The four fields were grazed consecutively by ewes over 7-day periods from February to March 2021. Unmanned Aerial Vehicles (UAV) equipped with a multispectral camera were flown before and after the passage of the sheep on each field. Normalized difference vegetation index (NDVI) and grey level co-occurrence matrices (GLCM) were used to calculate the Angular Second Moment (ASM) to measure the local homogeneity of the grazing intensity within 5x5m² windows, with values ranging between 0 and 1. Results show distinct patches of homogenous and heterogenous grazing on each field and strong differences in the heterogeneity in grazing between the fields. Further data processing will allow inference of these changes in heterogeneity to differences in time and space between the fields as well as animal grazing behaviour. In future works, the level of heterogeneity in grazing could be integrated with data from portable sensors to allow a better management of animals when they are used as an agroecological lever to control cover crops in ICLS.

Keywords: pasture heterogeneity, grazing, multispectral camera, ICLS

Introduction

Integrated Crop Livestock systems (ICLS) are farming systems in which animals are present on agricultural fields at a given moment within the crop rotation. If correctly managed, such systems experience advantages linked to the presence of animals such as diminished needs of fertilisers or complementary feed, profitability of cover crops that are generally not useful (Lemaire *et al.*, 2014), and improvement of nutrients cycles (Lemaire *et al.*, 2014). The grazing of cover crops by ruminants in ICLS implies that the biomass will be destroyed by repetitive defoliation and trampling of the animals.

Heterogeneity of the vegetation height and biomass after the grazing session is a factor of importance in grazing management and especially in ICLS. It has been observed in ICLS conditions that a homogenous vegetation after grazing can be a sign of intensive grazing and sometimes overgrazing (Nunes *et al*., 2019). The latter is something to avoid; the grazing target in ICLS is to effectively destroy the cover crop without having an animal experiencing excessive hunger or damaging the ability of the field to produce biomass. It has been also shown that heterogeneity can be managed by adapting the stocking method on the field and is a parameter that must be integrated in future grazing management planning (Pontes-Prates *et al*., 2020).

The use of unmanned aerial vehicles (UAV) for the assessment of pasture biomass and/or chemical composition is a verified practice in the field of Precision Livestock Farming (PLF) with a great potential to assess plant-animal interactions and spatial heterogeneity of pastoral systems (Michez *et al*., 2020). It has also the advantage of being non-destructive and less time-consuming than usual field measurement methods, with a better accuracy (Michez *et al*., 2019). One of the most common indexes used in remote sensing for vegetation monitoring is NDVI. It provides an indication of the standing biomass (Michez *et al*., 2019) and allows assessment of the evolution of crop phenology or yield (Wang *et al*., 2005; Zhao *et al*., 2009). Nonetheless, this index must be calibrated for each type of cover and geographical location, which implies that a lot of data must be collected beforehand, especially if the cover composition or the location has not been studied previously. The lack of pre-existing data, especially in the case of unusual mixed-species composition, makes it challenging to compare the evolution of vegetation between different pastures or crops. To avoid this limitation, a further treatment of UAV images that can be carried out, especially on multispectral images to extract information, is to work with texture, by assigning a defined value and resolution to the image's primitives (Haralick, 1979). This is conducted in two steps: (1) create a nuanced matrix of several classes, represented by shades of grey (grey level co-occurrence matrix (GLCM) (Haralick, 1979)), (2) then apply a second layer to obtain data on the spatial interrelationships of the matrix (Haralick, 1979). This second layer allows to extract many different indexes that reflect heterogeneity, homogeneity, entropy, etc. The objective in this work was to verify the possibility to use the GLCM technique to extract normalised, quantified, and comparable information between the fields concerning the heterogeneity of the grazing process without any measurement of the vegetation other than multispectral imaging.

Material and methods

Experimental data

Measurements were carried out between the 2nd and 30th of March 2021 on four 84 x 14 m² experimental fields of the ECOFOODSYSTEM platform of AgricultureIsLife from Gembloux Agro-BioTech (University of Liège, Belgium). The cover crop was sown on 3 December 2020 with the following grain density: oats (*Avena sativa*, 20 kg ha^{-1}), Phacelia (*Phacelia tanacetifolia*, 4 kg ha^{-1}), Crimson Clover (*Trifolium incarnatum*, 10 kg ha^{-1}) and Berseem clover (*Trifolium alexandrinum*, 10 kg ha^{-1}). The crops were partially damaged due to freezing temperatures between the 7th and 14th of February, when snow was present.

Ground sampling indicated that the dry above-ground biomass before grazing reached a mean (±standard deviation) of 1333 ± 193 kg ha^{-1}. Each field was grazed during 7 consecutive days by three four-year old crossbred French Texel ewes. For each paddock, two flight surveys with UAV were planned with a DJI Phantom 4 Pro (DJI, Shenzen, China) equipped with both an optical sensor (RGB) and a multispectral camera Micasense RedEdge (MicaSense, Seattle, USA). One flight was conducted on the day before the commencement of the grazing and the second on the day after the end of the grazing. Flight height was set to 30 m with cameras oriented to the nadir, with 80% front overlap and 85% side overlap. Ground control points (GCPs) were placed at each corner of each plot to calibrate the received imagery with the accuracy of an Emlid Reach RS+ GPS (EMLID, St Petersburg, Russia).

Data analysis

The collected multispectral images were processed with the QGIS software (OSGeo, Chicago, USA) as seen in Figure 1. Firstly, the multispectral images were processed following the NDVI formula (Raster calculator NDVI). Then the difference between NDVI values before grazing (BG) and after grazing (AG) was calculated.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \tag{1}$$

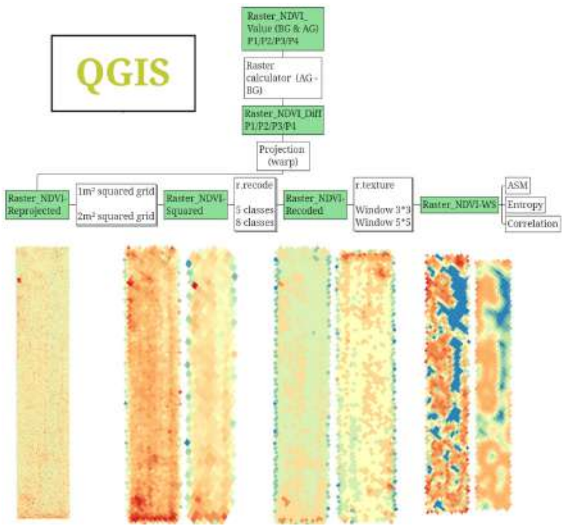

Figure 1: List of the operations and intermediate rasters used to determine the most accurate way of describing grazing heterogeneity. All raster examples are for the paddock N°3

During the process of data analysis through QGIS, several features have been tested to get the most relevant results.

Firstly, quadrats used the nearest neighbour method, then recode classes, GLCM window sizes, and finally indexes were extracted. For the choice of quadrat's resolution, the tests were run between 1and 2 m²resolution. Then, the recoding process involved the setting of a reduced number of grey levels by sorting the data into a predetermined number of classes. During the exploration of the different possibilities of data processing, we tested working with 5 and 8 classes (Figure 2).

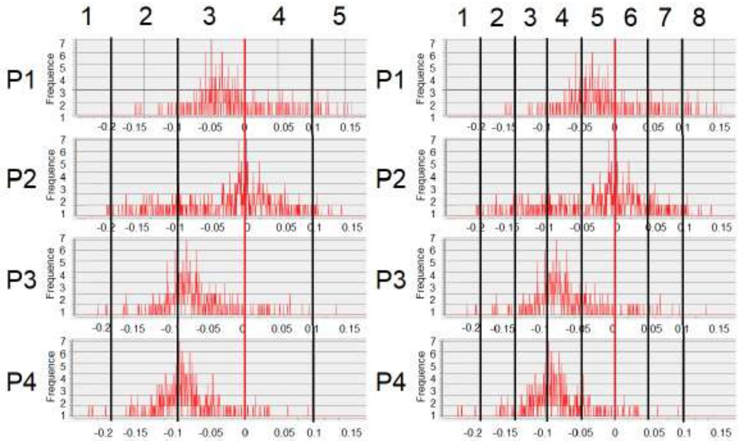

Figure 2: separation of the NDVI into 5 or 8 classes. The values represent the difference of NDVI between After Grazing (AG) and Before Grazing (BG)

As shown on Figure 3, GLMC calculates indexes based for each quadrat and the neighbouring quadrats disposed at 0°, 45°, 90° and 135° clockwise. The window size determines the number of quadrats taken into account for every orientation. For this survey we used 5×5 windows. This allowed the opportunity to observe areas with distinctive heterogeneity features, where 3×3 windows give many isolated quadrats. In our case the surface of the paddocks and 1m² resolution did not allow to test 7×7 windows.

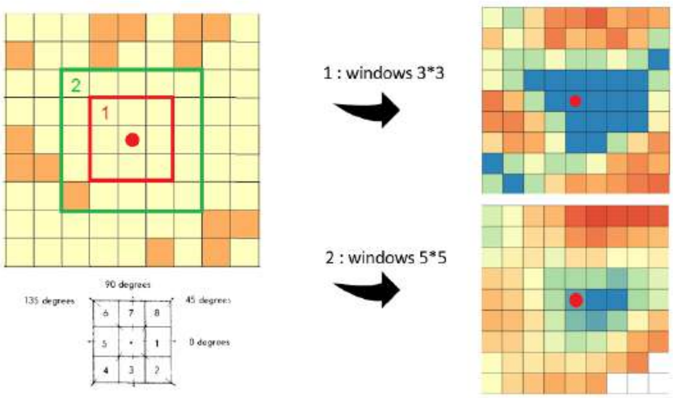

Figure 3: Representation of GLCM index calculation for two different sizes of windows

Many different indexes based on relative distribution frequency have been proposed in the works of Haralick (1793). Three of them have been observed in this survey: ASM, contrast and entropy.

$$AngularSecondMoment(ASM) = \sum_i \sum_j \{p(i,j)\}^2 \quad (2)$$

$$Contrast = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{\substack{i=1 \\ |i-j|=n}}^{N_g} \sum_{j=1}^{N_g} p(i,j) \right\} \quad (3)$$

$$Entropy = -\sum_i \sum_j p(i,j) \log\ (p(i,j)) \quad (4)$$

Where p(i,j) is the $(i,j)_{th}$ entry in a normalized grey-tone spatial-dependence matrix and N_g is the number of grey levels in the image (Haralick, 1793).

Results and Discussion

The results obtained encouraged the use of 1m² sized quadrats for resolution. Two m² quadrats led to less precise analysis. One m² is a good compromise from a grazing process perspective as it can be almost assimilated to the area of one feeding station (Andriamandroso *et al*., 2016). The recoding into 5 classes allows the opportunity to make the result of GLCM analysis more consistent and setting the NDVI interval to 0,1 between the classes, or 8 with 0,05 intervals. The results for 8 classes recoding showed mainly high levels of heterogeneity as well as isolated quadrats, which were more difficult to interpret than the 5 classes system which allows the observance of patches of different heterogeneity levels.

The three indexes observed (ASM, contrast, entropy) gave very similar information. The ASM had the advantage over the other two in only giving values between 0 and 1; this facilitates information on homogeneity that is both easily comparable between different paddocks, and quantified (Figure 4). We also observed that the first paddock, smaller than the other 3 (75m of length instead of 84), also had more homogeneous tendencies. This corresponds to the previous statement that more intensive grazing leads to more homogeneity (Nunes et al., 2019). A similar process was followed for the NDVI Before Grazing (BG) and After Grazing (AG) and showed that the homogeneity had indeed increased on paddock 1 (average ASM : 0.176±0.048 BG, 0.291±0.099 AG) and it had decreased on paddock 4 (average ASM : 0.186±0.056 BG, 0.171±0.044 AG). The ground observation matched those results.

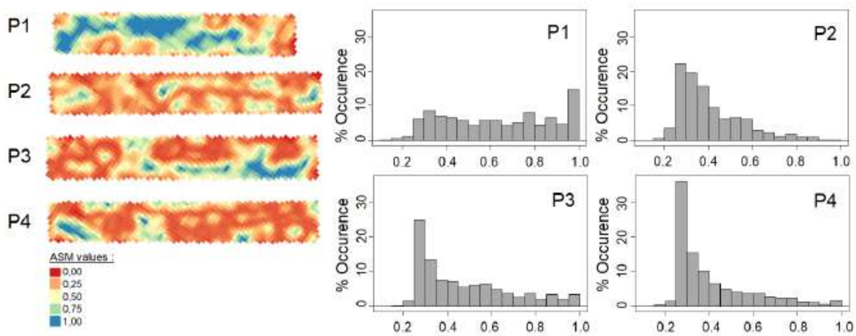

Figure 4: ASM symbology and percentage repartition for each paddock's difference of NDVI. High values represent high heterogeneity

This use of multispectral imagery to quantify and observe grazing heterogeneity could be of use in different situations. First, in the case of rotational grazing management, homogeneity at the end of a grazing session is a sign that the animals made use of most of the paddock. More heterogeneity can lead to higher intake rates at the beginning of grazing (Pontes-Prates et al., 2020) but is a risk to heading of ungrazed grasses and thus losses of nutritional value for the pasture. Also, if the homogeneity gets too high, it becomes an indicator of overgrazing (Nunes et al., 2019). The fact that this imagery treatment allows distinct zones of heterogeneity to be distinguished, then general evolution of the vegetation could be combined with sensors to monitor behaviours and geolocation of the animals through the division of the paddocks in zones of equivalent surfaces (Riaboff, 2020). Lastly, in the case of ICLS, heterogeneity of grazing is an important indicator because it is linked to (1) the possibility to put a new crop after the cover without too much additional work having to be done (2) fertiliser allowance (manure) and (3) the general behaviour of the animal.

Conclusions

This paper shows the possibility of using texture as an indicator for local heterogeneity of the grazing intensity using UAV, which are a way less time-consuming and more precise tool than traditional "on the ground" means. Moreover, this technique uses the ASM index, which gives quantified information and can be used without any previous measurement of the average NDVI values for the studied vegetation.

This advance could be very useful in grazing management, for ICLS or more classical application, if combined with other PLF devices such as behavioural monitoring sensors based on accelerometers and/or GNSS systems to track the animal's trajectory and favourite or avoided parts of the paddock, and behaviour. From there we could evaluate the correlation with biomass evolution, its intensity and heterogeneity. For example, in pasture composed of mixed species or to evaluate different duration of grazing in a rotational system.

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Kinetic energy harvesting potential of grazing livestock

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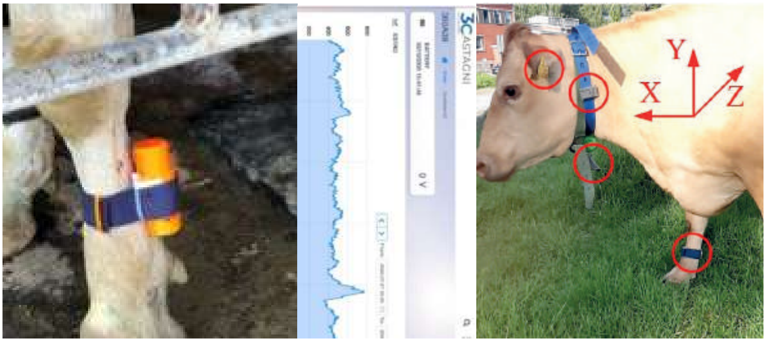
Abstract
The potential of using farm animal kinetic energy for powering wearable precision livestock farming devices has not been researched thus far. Kinetic energy harvesting is a process in which vibration or locomotion is converted by a transducer into electrical energy. This process could potentially enable autonomous livestock wearables. In this paper an approach for measuring and analyzing farm animal locomotion is detailed. By using triaxial accelerometers, free grazing Finncattle locomotion is logged at different cattle body parts and analyzed in MATLAB for future kinetic energy harvesting designs.

Keywords: accelerometer measurements, animal locomotion, kinetic energy harvesting

Introduction
In this paper we present details of locomotion measurements performed on Finncattle during project ENTRAP (CORDIS 2019). These measurements were performed to determine locomotion characteristics, like acceleration amplitudes, directions of excitation, or specific frequencies present in irregular livestock locomotion. This data was then employed to design and prototype a kinetic energy harvesting (KEH) device, as presented in another paper at this conference ('Cow locomotion energy harvester for powering IoT wearables'). KEH devices are designed to convert energy of vibrations or locomotion into electrical energy for enabling low power devices with autonomous power (Siang, J. *et al*., 2018). In the case of a precision livestock farming application, a KEH device would power an animal wearable with electrical energy produced by the animal itself.

The use of accelerometers to characterize animal locomotion specifics has long been employed by animal scientists and ethologists. Most commonly the research has been utilized to determine certain animal health or life cycle events. In this frame accelerometers have been used for lameness detection either from change in activity or gait differentiation, estrus cycle detection and detection of various metabolic disorders (Eckelkamp, E. A. 2019). More specifically cattle (Pastell, M. *et al.* 2009, Rahman, A. *et al.* 2018), sheep (Barwick, J. *et al.* 2018) and geese (Spink, A. *et al.*) locomotion has been previously measured and characterized by tri-axial accelerometers. Usually, data sampling frequencies bordering the Nyquist frequency of animal locomotion have been used. These are inadequate to log a complete locomotion characteristic like a step or ear flap or to capture the exact number of high acceleration events during grazing. Here we propose a very robust measurement apparatus and innovative, simple and easy to use attachments based on 3-D printed casings or commercially available adhesive tapes capable of withstanding several hours of free grazing activity while logging data.



a) b) c)

Figure 1: a) Axivity AX3/6, b) 3D printed sensor casings, c) Sensor locations and axes

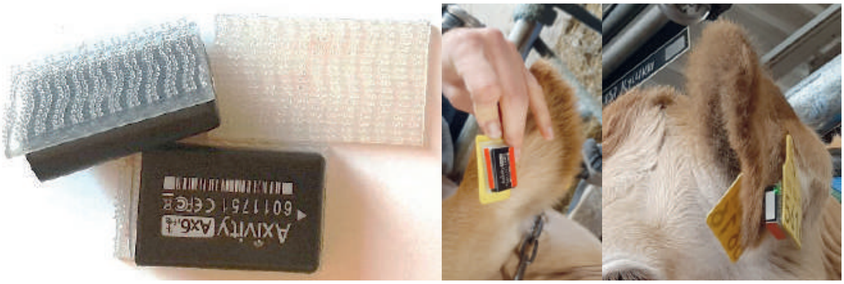
Material and methods

This section will describe in detail the design of the experiment and the measurement apparatus employed during experiments. In the end, the tools for PSD data analysis will be presented.

Measurement apparatus and set-up

For the purpose of experiments presented here, two AX3 triaxial acceleration loggers and one AX6 triaxial accelerometer/gyroscope logger were chosen (manufactured by Axivity, Figure 1, a). These devices are small (23x32.5x8.9 mm) and lightweight, weighing 0.011 kg (important considering ear measurements). They can also be easily configured and synchronized via a USB hub and the AX3/AX6 OMGUI Configuration and Analysis Tool. Both sensors are specified with measurement resolutions of up to 16-bit, configurable accelerometer ranges - ±2/4/8/16 g, and sampling frequencies in the range of 12.5 Hz – 1600/3200 Hz (AX6/AX3) (Axivity 2015). Logging time depends on the configuration but is specified at 14 days configured to a 100 Hz sampling frequency. The sensors themselves do not provide a suitable means of attachment. To equip the animals with the sensors, suitable casings had to be manufactured which could then be used with standard collars and pedometer leg straps (through specifically designed slots) (Figure 1, b). Casings were at first 3D printed with PLA filament on a Prusa I3 MK3 3D fused deposition modelling printer in the FabLab facility of Tampere University. After the PLA cases broke or dismantled due to screws coming loose during grazing, they were replaced with stronger PETG filament printed cases which were also semi-transparent allowing the sensor LEDs to be checked for operation. Also, antivibration nuts were used to secure the casings and these modifications proved to increase robustness.

For the first set of the experiments the following locations were chosen for acceleration measurements: front leg (lateral outer side of the metacarpal just above the fetlock), collar (left side of the neck) and pendant (a casing fitted to freely hang from the marking weight akin to a bell pendulum) (Figure 1, c). Casings were designed to be robust and contoured for animal comfort (especially the front leg position). In the second set of experiments both ears were equipped with the sensors and again the collar sensor was used for control (Figure 2, b & c). Self-adhesive 3M SJ3560 Dual Lock reclosable fasteners were used to attach the sensors to the ears. First part of the Dual Lock was cut to size and glued to the back side of the ear tags (which were scrubbed clean with alcohol to achieve high level of adhesiveness). Second part of the Dual Lock was glued to the Axivity sensors themselves (Figure 2, a). In the initial set of cow experiments the devices were then mounted to the animals with a collar (equipped with two sensors, neck and pendant) and a leg strap. In the second set of experiments both ear sensors were simply mounted with Dual Lock's easy click snapping mechanism (release with peeling motion) while a collar was used again for the neck measurement like in the initial experiments. The collars and leg straps have been fitted with a regular degree of tightness, collar thus being quite loose and the leg strap being a snug comfortable fit while the Dual Lock fasteners inherently provide a snug fit to the ear tag.



a) b) c)

Figure 2: a) Sensors fitted with Dual Lock, b) Sensor on right ear, c) Sensor on left ear

Measurement experiments

Eight free grazing cow locomotion measurements have been performed in August and September of 2020 at a dairy farm, Ahlman (Ahlmanin koulun saatio, Tampere, Finland). Five consecutive experiments were performed as a part of the 'Set 1' (collar, pendant and leg) with a four-year-old Eastern Finncattle cow Neilikka, while in the 'Set 2' (collar and both ears) three consecutive measurements were completed with a five-year-old Western Finncattle cow Miilu. Even though three experiments were compromised with faulty casings each data set resulted with more than 1 h of active grazing time with all sensors present on the animal. Experiment logs for measurement Set 1 & 2 are listed in Table 1.

Signal analysis

The data sets comprising of sampling time and acceleration level in units of gravity were recorded in Axivity's binary format which were all retrieved from the sensors upon experiment completion with the Open Movement OMGUI Tool installed on a laptop. The data sets were then directly imported into MATLAB matrices with Open Movement's recommended import function CWA_readFile.m (Open Movement, 2022). All data was passed through a low-pass filter included in the MATLAB's Signal Analyzer App with the passband frequency set to 20 Hz to filter out the high frequency measurement noise. To remove the effects of sensor positioning with respect to the direction of gravity and its influence on the values, mean values of acceleration were calculated and subtracted for each axis. For ease of identifying overall levels of energy present at each measurement location, the resultant magnitude was first calculated as

$$|\vec{a}| = \sqrt{a_X^2 + a_Y^2 + a_Z^2} \tag{1}$$

Table 1: Experimental logs per day of measurement in August and September 2022.

Set 1					
	Exp. 1	**Exp. 2**	**Exp. 3**	**Exp. 4**	**Exp. 5**
Date	11.08.	12.08.	13.08	14.08	15.08.
Subject	Neilikka	Neilikka	Neilikka	Neilikka	Miilu
Length	5 h	4 h	6.5 h	5.5 h	5 h
Collar	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 8 g	800Hz / 8 g
Pendant	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 16 g	800 Hz / 16 g
Leg	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 8 g
Casing fault	–	pendant	pendant	–	collar

Set 2			
	Exp. 1	**Exp. 2**	**Exp. 3**
Date	11.09.	14.09.	15.09.
Subject	Miilu	Miilu	Miilu
Length	6.5 h	6 h	4.5 h
Collar	400 Hz / 8 g	200 Hz / 8 g	400 Hz / 8 g
Right Ear	400 Hz / 8 g	200 Hz / 8 g	800 Hz / 8 g
Left Ear	400 Hz / 8 g	400 Hz / 8 g	800 Hz / 8 g
Casing fault	–	–	–

Power spectral density of the data sets

To assess the levels of available energy and obtain frequency information of the recorded locomotion, power spectral density (PSD) estimations were used. Using a PSD estimation allows for quick identification of characteristic process frequencies and the levels of energy associated with each frequency emerging from random locomotion. To obtain a PSD, at first MATLAB's fast fourier transform algorithm is used to compute a discrete fourier transform (DFT) of the signal, defined as where the $x[n]$ is the sampled signal, N is the signal length, K is the number of points in the frequency domain (usually $K = N$), $f_k = kf_s / K$ is the normalized frequency where f_s is

$$X(f_k) = \sum_{n=0}^{N-1} x[n] e^{-j2\pi kn/K} \tag{2}$$

the sampling frequency of the recorded signal. For signals acquired at frequencies two times greater than the maximum frequency of the signal, the Nyquist frequency, the PSD can be estimated with a DFT (Pierre J. and Kubichek R. F. 2002) and easily computed in MATLAB as

The following approach was used to obtain the results: 1) inspection of time series, 2) PSD estimation of $|\vec{a}|$ for a single day record, 3) isolate 1 h of active grazing data,

$$P(f_k) = \frac{2}{f_s N} |X(f_k)|^2 \tag{3}$$

4) PSD estimate of $|\vec{a}|$ during 1 h, 5) PSD estimate for each separate axis during 1 h to obtain directional data. Each PSD was smoothed with a Savitzky-Golay finite impulse response smoothing 3rd order filter and a frame length of 101 samples.

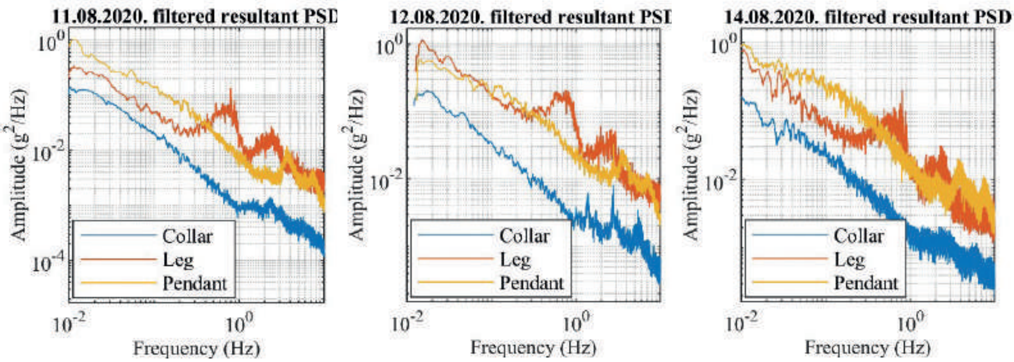
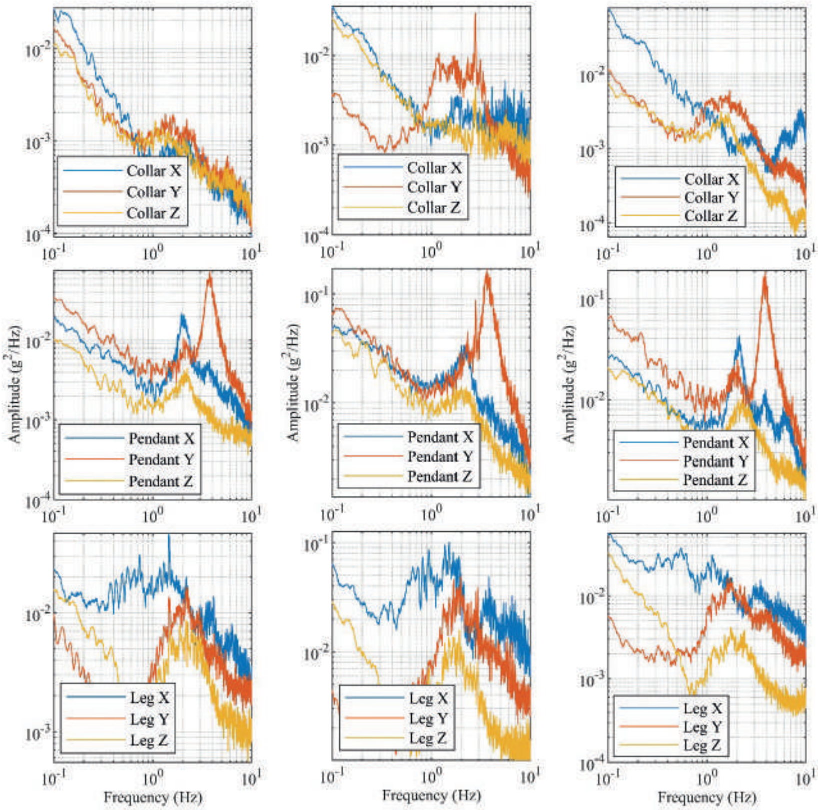


Figure 3: PSDs of the resultant magnitude of acceleration from Set 1 – complete day logs

Table 2: Characteristic cattle locomotion frequencies, Hz

Position	$f_{\|\vec{a}\|}$	f_X	f_Y	f_Z
Collar	2.5	1.5	1.5	1.5
Pendant	3.6 / 7.2	2	2 / 3.7	2
Leg	0.8 / 2.5	1.7	1.7	1.7
Right ear	3.3 / 5.5	2.7	5	2.7
Left ear	3.3 / 5.5	2.7	5	2.7



a) b) c)

Figure 4: PSDs estimated from individual axis records from selected 1 h of active grazing time in Set 1 - a) 11.08., b) 12.08. and c) 14.08

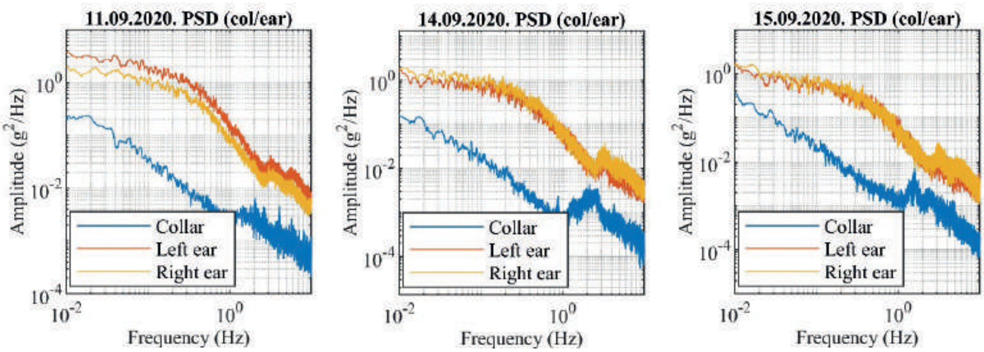
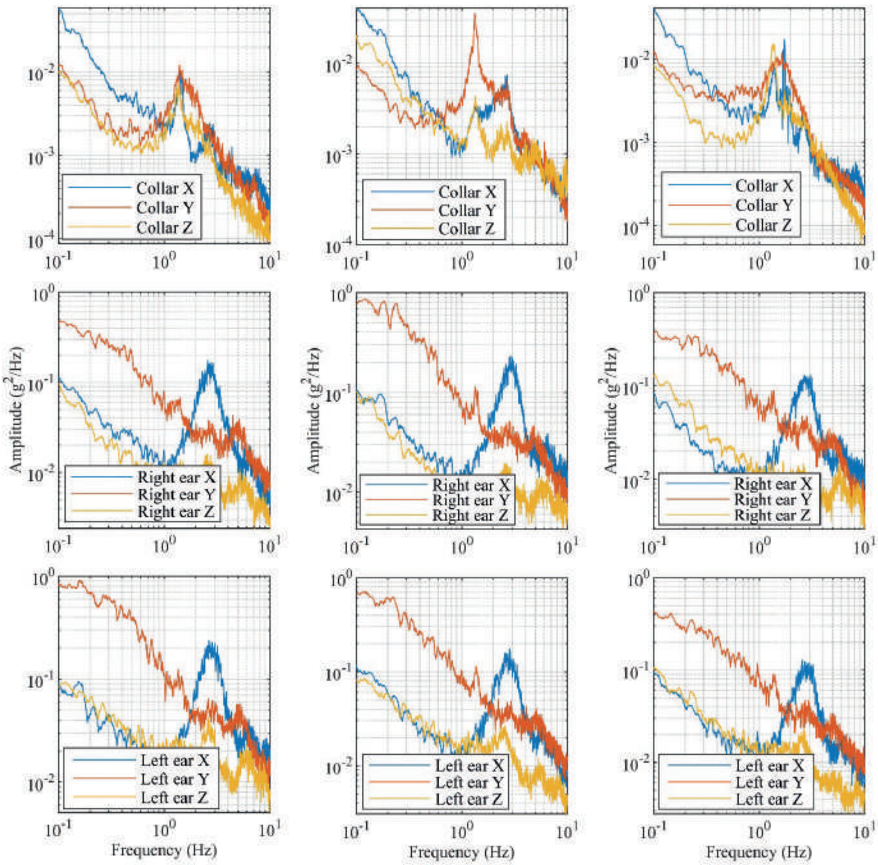


Figure 5: PSDs of the resultant magnitude of acceleration from Set 2 - complete day logs



a) b) c)

Figure 6: PSDs estimated from individual axis records from selected 1 h of active grazing time in Set 1 – a) 11.08., b) 12.08. and c) 14.08

Results and Discussion

In both Figure 3, (three days of Set 1) and Figure 5, (three days of Set 2) whole day resultant $|\vec{a}|$ was used for PSD estimations (idling included). Both figures show the largest power density amplitudes, in units of squared gravitational constant (g2) per frequency (Hz), present at low frequencies and aperiodic, random events (below 1 Hz) decreasing with frequency. The collar logs resulted with the lowest average amplitudes in both sets. In Set 1 (Figure 3), the first identifiable low frequency of leg motion with the largest amplitude occurs at ~0.8 Hz (first peak on orange curves close to 1 Hz). This can be interpreted from the time series as the response of walking motion. Walking motion is transferred also to the collar, the effect of which can be seen in the ~2.5 Hz peak both in the collar and leg (more pronounced in the orange curves - leg, less but still present in blue curves - collar). The pendant has a higher frequency response, ~3.6 Hz / ~7.2 Hz (two peaks in the yellow and orange curves closer to the right side). In Set 2 (Figure 5), both ear sensors display two frequencies, ~3.3 Hz and ~5.5 Hz (first and second peak seen from the overlapping yellow and orange curves to the right side). Results from the collar are identical as in Set 1. When using acceleration magnitude $|\vec{a}|$ as the basis of a PSD estimate, the directional information is lost. To preserve this information and gain insight for potential KEH device locations, individual estimates were performed for each axis during 1 h of grazing. Figure 4 displays individual axis PSD estimates during three days of Set 1. The most easily noticeable peak in all of three days, with the highest power density is the pendant's vertical Y axis at ~3.7 Hz (first high orange curve peak) and the pendant's X forward motion axis at ~2 Hz (first peak in the blue curve). Leg locomotion peaks in X, Y and Z at ~1.7 Hz, while the leg's forward X motion shows higher average power density (blue leg curve). The collar response is again coupling closely with leg locomotion at ~1.5 Hz (identifiable in Figure 4 b). Individual cow step durations were measured from the time series data, lasting 700-800 ms in average (cause of the identified leg frequency). Same principle of analysis has been applied to data from Set 2 (Figure 6), where the forward ear flapping motion peaks (the X axis, blue curves) are instantly noticeable in the right and left ear displaying the largest amplitude at ~2.7 Hz. Second component of the flapping motion is the lateral Z axis (yellow curves) peaking at the same frequency. Second interesting occurrence in the ear harmonics is the prominent peak of ~5 Hz in the vertical Y axis direction of locomotion (orange curve peak close to the right side of individual ear graphs) which could be attributed to free vibration ear response.

Conclusions

This paper proposes a method for measuring animal locomotion considering design practices for KEH devices and standard PLF wearables. The goal of the research was to identify positions and directions on a cow's body which would be suitable for conversion of kinetic into electrical energy either by strong impacts or by tuning the harvester to operate at a specific animal locomotion frequency. Measurement locations - leg, collar, pendant and ear - were chosen considering the frequent forms of PLF wearables (ear tags, leg straps, collars or bells). Power spectral density estimations have been performed from which it could be seen which body parts provide stronger excitations. In general, all PSD plots show that the largest power densities occur aperiodically due to random animal motion or at low frequencies. Specific frequencies have been identified related to walking, pendant swinging, or ear flapping (Table 2). Leg, pendant and ear motion have been identified to have the largest power densities at specific axial directions while the collar position displays the lowest average power densities. Some locations for animal KEH are more feasible than others. Legs and ears, with higher power density, cannot handle bulky devices which hinder movement, while the collar with smaller average power densities can be equipped with a larger device with a heavier moving mass. Designing a low frequency KEH device is not a simple task due to an increase in sizes of the moving masses. Nonlinear and impact energy harvesting mechanisms will have to be considered as well as higher frequency components of the here identified basic frequencies to decrease size and weight. In the future this data will be used to calculate theoretically obtainable KEH powers using a finite element model of a 1D electromagnetic KEH device. The presented measurement data, although acquired with KEH in mind, is objectively quantified with 3D accelerometers and frequency analysis methods and can used to bring further insight into research of animal locomotion. The conclusions will also be important in developing a new class of farm animal kinetic energy harvesting devices.

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Measuring learning progress in conditioning procedures in livestock husbandry

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Abstract

The automation of stimulus-controlled operant conditioning gains more and more relevance in management applications for farm animals. Recent examples are solutions for virtual fencing and latrine training. Such systems need to assess the learning progress of the animals in order not to overburden their adaptive capacity. Classically, the learning progress is evaluated based on the displayed behaviour using metrics for classification performance. However, the preconditions for applying these metrics, such as clear behavioural motivation and free access to the training device, are no longer given if the training is conducted with group-housed animals. In this case, such metrics may only serve as a heuristic for the learning progress and have to fulfil certain plausibility criteria to be applicable. These properties were investigated in a study based on an exemplary signal discrimination task. This task was used to condition adult sows under three training conditions that differed in group size and the number of training opportunities. The study evaluated the suitability of sensitivity and precision - two metrics commonly used to measure classification performance. The results indicate that both metrics do not provide plausible results whereas a newly developed metric called normalized precision does.

Keywords: cooperative livestock farming, precision livestock farming, animal learning, performance heuristics, classification metrics

Introduction

Cooperative livestock farming (CLF) as a sub-discipline of precision livestock farming (PLF) has the potential to significantly reduce the complexity and cost of animal-specific husbandry solutions. This can be achieved by complementing technical solutions and the practical experience of the herd managers by the sensory and cognitive abilities of farm animals. The fundamental concept dates back to Kilgour (1978). Recent examples are virtual fencing (Lomax et al., 2019), animal toilets for pigs (Tillmanns et al., 2022) and cattle (Dirksen et al., 2021) and signal feeding (Kirchner et al., 2014). All these approaches have in common that they use instrumental learning to elicit operant behaviour depending on a stimulus. In sophisticated learning tasks, metrics for the individual learning progress are necessary to avoid overburdening the animals. Under practical conditions of livestock farming, the training conditions can be very variable *e.g.* with regard to group size, group composition or the number of training opportunities. Thus, appropriate metrics for learning progress have to be applicable in such a way that they allow universal learning criteria even under very diverse training conditions.

To measure learning progress in stimulus controlled operant conditioning tasks, the animals are taken as classifiers and their classification performance is inferred from their displayed behaviour *i.e.* their reaction to the stimulus (Marston, 1996). This approach is based on the assumption that the reward or punishment is sufficiently motivating to elicit the operant behaviour and that this is the only behavioural motivation for the animals. In most laboratory settings, these preconditions are enforced e.g. by fastening the animals in case of a feed reward and by using single animals in standardised test apparatuses. However, these preconditions are no longer guaranteed if the training is conducted under practical conditions in group-housed farm animals. Here, effects especially from social rank and the different accessibility of the training device may prevent that the expected behavioural reaction is displayed when the stimulus is recognised (Manteuffel et al., 2010). In this regard, the conditioning can be interpreted as a behaviour economic test (Dawkins, 1983) for the strength of the animal's preference not to react as intended.

As a consequence, the applicability of common metrics for classification performance such as the true positive rate (*sensitivity*) or the positive predictive value (*precision*) as an estimate for the learning progress has to be questioned. The present work is based on the hypothesis that these metrics cannot be utilized to directly measure the learning progress of group-housed animals. They may be useful as a heuristic if they fulfil a number of plausibility criteria. Given that a training procedure is working it can be assumed that all animals have a low learning status when the training starts. The learning status is improved during the training and reaches under all training conditions a comparable level once all animals consolidated their conditioning. Thus, the value of a suitable learning metric needs to be low for all naive animals regardless of the conditions. Furthermore, the metric must reflect the improvement due to the training and eventually result in similar high values for fully trained animals.

The present work evaluates *sensitivity* and *precision* as established metrics for signal classification performance with regard to these plausibility criteria. In addition, the novel *normalized precision* is proposed as a heuristic that may be better suited for practical applications. The suitability of these three metrics was compared using signal feeding as an exemplary signal discrimination task. Here, adult sows learned to enter a feeding station contingent upon the emission of individual acoustic signals (spoken names). To allow an evaluation of the transferability of the learning metrics under different training conditions, the conditioning was performed in groups of different sizes and with different numbers of reaction opportunities (feedings) per day. This conference article is a shortened and adjusted version of Manteuffel et al. (2021)

Material and methods

Experimental setup

Groups of gestating and nulliparous sows were automatically conditioned to identify individual acoustic signals (Manteuffel et al., 2011). Subsequently, these signals were used to selectively call single sows to an electronic feeding station. The training was performed for seven weeks in groups with *few* (<8) and *many* (<36) sows. The number of feedings per day varied between one to four (*rarely*) and up to eight feedings (*often*). The factors group size and feeding frequency formed the basis for a 2×2 trial design. However, the combination (many × *often*) was not feasible as the daily activity period of the sows would have been too short to supply all sows.

Of the *many* × *often* setup, the initial learning progress of 17 gestating sows was analysed. These 17 sows were selected because their training was not interrupted by farrowing and mating. In the *few* × *often* setup the data from seven sows and in the *few* × *rarely* setup, data from 14 sows was analysed. After three weeks of training, a few sows left the training occasionally due to injuries or for re-insemination so that data of in total 28 sows was available for the whole observation period.

In small groups, the conditioning was performed simultaneously for all sows, while no more than eight sows were conditioned in the large groups at the same time. Hence, in each setup approximately the same number of sows were conditioned simultaneously, regardless of the group size. The sows in the small groups had to learn to interact with the feeding station during the first week of training because they were not familiar with this feeding system whereas sows in the large group were. The training consisted of scheduled feedings by which the learning progress was estimated and spontaneous feedings that were initiated autonomously by the animals. The autonomous feedings served the purpose to ensure sufficient feed supply regardless of the training progress. Based on the training progress and training duration, the probability for autonomously obtaining feed was continuously reduced. Difficulties in applying this mechanism in differently sized groups provided the motivation to develop the novel *normalized precision* learning metric.

Data analysis

Behaviour data was autonomously recorded by the feeding station. It formed the basis for the data analysis. Reactions of the animals were detected by means of their radio frequency identification (RFID) ear-tags. The evaluation of the learning progress was solely based on scheduled feedings where the system used the acoustic signals to call a sow. Here, own feedings formed the class of positive events (P) and feeding of con-specifics the class of negative events (N). In the following, errors are denoted by the letter F (false) and correct reactions by the letter T (true). Correctly reacting to the own feeding signal is hence a true positive reaction (TP).

The statistical analysis evaluated the fixed factors *training condition* with the levels (many × rarely (mr), few × often (fo) and few × rarely (fr)) and the fixed effect *training duration* in weeks with the levels (start (0), 1, 2, 3, 4, 5, 6). Response variables were the learning metrics with a [0, 1] value domain. A quasi-binomial generalised linear model was utilized to estimate least-square means and confidence intervals and the effect of the factors using the logit link function. Repeated measurements were incorporated by taking the sows as random factor and assuming a temporal autocorrelation. All calculations were performed using the R statistics software (R Core Team, 2013). Sources and data used to create the presented results can be acquired from https://doi.org/10.17632/ngbxmgddz6.2 .

Results and Discussion

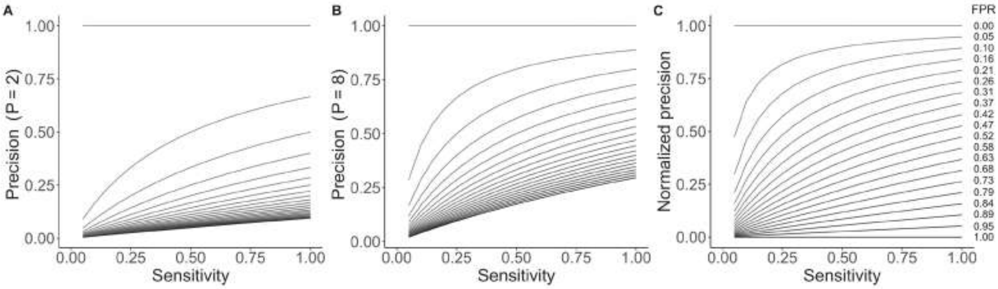

Figure 1: Hypothetical learning curves based on conventional and normalized precision (NP_-) for different error rates in relation to signal recognition. The graphs depict which learning progress would be indicated depending on the proportion of recognized signals (sensitivity = TPR) and the number of classification errors in terms of false-positive rate (FPR). All graphs assume a cardinality of N = 19 for the negative event class. Each of the curves represents different scenarios for FPR, starting from zero (topmost) and ending at one (lowest curve). (A) Precision given a cardinality P = 2 for the positive event class. (B) Precision given a cardinality P = 8. (C) Normalized precision. This metric is independent of the cardinality of the event classes as it uses their cardinality for normalization. This figure was adapted from Manteuffel et al. (2021).

Theoretical properties

Figure 1 demonstrates how the precision metric (= $TP/(TP + FP)$) gives different results for positive classes of different sizes. Depending on the context of the learning task, it evaluates the learning progress different even though the actual learning progress is identical. This dependency of the precision metric on the balance of the event classes can be eliminated by normalisation with the cardinality of these classes. Equation 1) shows a proposal for such a metric – the normalized precision.

$$NP_- = \frac{TPR}{TPR + \frac{FP}{TN}} NP_+ = \frac{TNR}{TNR + \frac{FN}{TP}} \tag{1}$$

Besides being independent from class cardinality this metric satisfies more plausibility criteria. Its value is zero if either TPR (= TP/TP) or FPR (= FP/N) approach zero *i.e.* if many errors are made or few signals are responded. Its value is reciprocal to FPR if all events from P are responded. In turn, the metric value increases hyperbolically with sensitivity (TPR) if FPR approaches zero. Thus, erroneously reacting to events from N has a larger weight than reacting correctly to events from P. The rationale behind this design decision is that there are much more events in N than in P. This assumption can be inverted by exchanging the classes in the formula (NP_+). A balanced metric can be calculated from the mean of NP_- and NP_+.

Practical properties

The results for the *sensitivity* metric (Fig. 2a) indicate that after five weeks the sows were under all three training conditions able to correctly respond to their acoustic signals (sensitivity > 0.75). This metric was, hence, suited to indicate the equivalence of the final learning status in all three conditions. On the other hand, it indicated significant differences in the initial learning status, even though all sows had by definition an equivalent status at the training start (mr0 < fo0: $t_{35} = -4.0$; $p = 0.036$ / mr0 < fr0: $t_{35} = -7.0$; $p < 0.001$). The increase in learning progress was reproduced in groups that were fed often as well as in large groups (mr0 < mr1: $t_{1480} = -4.0$; $p = 0.009$ / fo0 < fo2: $t_{1480} = -3.8$; $p = 0.023$). However, it was not reproduced in small groups that were fed rarely (fr0 < fr1: $t_{1480} = -3.3$; $p = 0.12$).

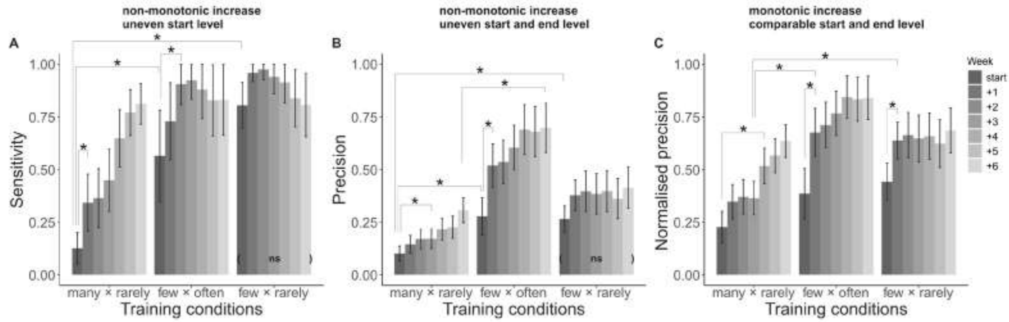

Figure 2: Learning progress over seven weeks for three different classification performance metrics and three different training conditions. (A) Proportion of detected events (sensitivity). (B) Proportion of correct detection (precision). (C) Proportion of correct detection normalized by the number of events in each category (normalized precision). Training conditions are represented by tuples characterizing group size and number of training events. Here, rare stands for one to four events per day while often represents up to eight events per day. The term many refers to a training group of up to eight animals that was embedded into a group of up to 35 animals, while few stands for overall group sizes of up to seven animals. (Data is presented as least square mean estimates ± confidence intervals. The headlines indicate the main properties found for the respective metric. $n \leq 38$; significance limit $P < 0.05$; Transitive differences are not indicated.) This figure was adapted from Manteuffel et al. (2021).

The *precision* metric produced values that systematically violated the plausibility criteria for the start and end of the training as well as the training progress. It estimated a significantly higher learning progress at the start in small groups (mr0 < fo0: $t_{35} = -4.2$; $p = 0.019$ / mr0 < fr0: $t_{35} = -4.7$; $p = 0.005$). In addition, the metric detected no learning progress in the small groups that were fed rarely (fr0 < fr6: $t_{1480} = -2.9$; $p = 0.28$).

For the same training condition, the *normalized precision* (NP.) metric indicated a significantly improved classification performance in the first two weeks of training (fr0 < fr1: $t_{1328} = -4.0$; $p = 0.011$). Similarly, the increase in learning performance was detected in the other groups (mr0 < mr4: $t_{1328} = -5.7$; $p < 0.001$ / fo0 < fo2: $t_{1328} = -4.3$; $p = 0.003$). This metric did not indicate differences in the classification performance of the initially naive sows especially with regard to the large groups (mr0 < fo0: $t_{35} = -2.3$; $p = 0.73$ / mr0 < fr0: $t_{35} = -3.6$; $p = 0.08$). According to this metric, the learning progress in the large groups was reduced from week one to week four (mr1 < fo1: $t_{35} = -4.4$; $p = 0.013$ / mr1 < fr1: $t_{35} = -4.6$; $p = 0.006$) but equivalent again from week five on (mr5 < fo5: $t_{35} = -3.3$; $p = 0.17$ / mr5 < fr5: $t_{35} = -0.8$; $p = 0.99$). Hence, the normalized precision indicated an equivalent learning progress in the animals of all groups once they had consolidated their conditioning.

Discussion

In the present study, it took five weeks until the sows from all three training conditions consolidated their training. This very long training period was necessary because the implementation of the signal discrimination task was oriented toward the limitations of practical husbandry conditions. The main limitation was here the utilisation of common electronic feeding stations that were only slightly modified in order to be able to interact with the signal-feeding module. Such feeding stations usually use low-frequency RFID readers to identify animals at the trough and station entry. LF-RFID has a reading range of just a few centimetres and a reading rate of several seconds. In addition, only one ear-tag can be read at a time if several ear-tags are in the range of the antenna. Therefore, it could take up to 30 seconds or even longer until the correct reaction of a sow was recognised by the reward routine. Other sows nearby could prolong this period further or push forward into the station after the correct reaction of a different sow was detected. This prevented the rewarding of some correct reactions leading to uncertainty in the animals. Thus, the link between reaction and reward was relatively indirect compared to laboratory setups. In a previous study in small groups of up to ten sows, the training duration was up to 14 days (Kirchner et al., 2014). A similar learning speed was observed in the small groups of the present study.

Previous studies on signal-feeding (Ernst et al., 2005) and studies on other species in different experimental setups suggest (Erskine et al., 2019; van Horik et al., 2019) that 20 to 60 interactions with the training setup are necessary to consolidate the conditioning. Therefore, the overall training duration in the different setups was to a large extent governed by the number of feedings per day. In this regard, the training period of 49 days can be assumed to be sufficient to finish the training of most animals in the large group with only one scheduled feeding per day. Thus, a transferable learning metric should have indicated an equivalent learning progress at the end of the present study. This was not the case for the *precision* metric, which was clearly affected by the differences in the number of feedings. The *sensitivity* metric on the other hand seemed to be affected by the reduced accessibility of the feeding station in the large group. It could not reproduce the equivalent learning status of the sows at the beginning of the training but confirmed an equivalent signal recognition at the end of the training in all groups.

The only metric that fulfilled all plausibility criteria in this study was the novel *normalized precision* metric. This does not mean that there are no other metrics that can be used as a heuristic for learning progress and it does not imply that normalized precision is indispensable to evaluate learning tasks in group-housed animals. However, six more metrics for machine learning and for the evaluation of the effectiveness of medical treatments were shown to be not transferable with regard to the exemplary signal discrimination task (Manteuffel et al., 2021).

Conclusions

Transferable metrics for the learning progress of group-housed animals need to fulfil a number of plausibility criteria in order to achieve comparable results under different training conditions and allow the definition of universally applicable learning criteria.

In particular, they should indicate low progress if an animal does not react or makes many errors. They should give the same value regardless of whether the event classes are balanced. Furthermore, they should comply with the intuitive shape of the learning curve of an effective training which starts from a low plateau in naive animals and rises to a higher plateau when the conditioning is consolidated.

The present study conditioned adult sows on an exemplary signal discrimination task under three different training conditions to evaluate the suitability of different metrics for classification performance in this regard. The differences in group size and the number of training opportunities significantly affected the learning speed of the sows but also led to differences in the evaluation of objectively equivalent training levels by some learning metrics. Of the investigated metrics, only the novel *normalized precision* metric fulfilled all plausibility criteria.

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Temperature measurements during animal transports

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Abstract
Livestock is transported by road in order to move towards the next location in the production process. The climate in the vehicle is of interest especially due to the variable transport conditions in Europe. Temperature is an easy to measure indicator for climate and of great importance for the welfare of animals. Exposure to either too high (heat stress) or too low temperatures (cold stress) can lead to an impairment of welfare, exhaustion and in some cases even to death. In this research, temperature sensors were applied inside and outside animal transport vehicles during eight periods of commercial Dutch livestock transports. In each period several transports were followed, the number of transports per period varied from one to twenty-three. Data was obtained from a total number of seventy-nine transports. Seven different animal categories were distinguished: newborn calves, weaner calves, veal calves for slaughter, piglets, pigs for slaughter, bulls and broiler chickens for slaughter. Temperature sensors were installed and started at the beginning of a period, measuring with a frequency of 10[1] minutes during the whole period and were stopped and removed at the end of a period. The number of temperature sensors per period (and transport) varied between six and seventy-six. It was concluded that it is possible to measure temperature continuously during animal transports under varying circumstances. Measured temperatures were compared with legal temperature limits. The effects of location (length, width, height) of the sensor in the vehicle, animal species and outside temperature were estimated with a statistical model.

Keywords: animal transport, temperature, REML model

Introduction
Livestock is transported by road in order to move towards the next location in the production process, including the slaughterhouse as the last location. During transport animals are exposed to various circumstances that can differ from those prior to or after transport, including sounds, movements, handling, deprivation from water or food, driving skills of the transporter, and climatic conditions. Those circumstances can influence physiological functioning of animals and are potential stressors and threats to homeostasis and welfare (Broom, 2003, Van De Water *et al.* 2003, Terlouw *et al.*, 2008, Visser *et al.*, 2014, Goumon & Faucitano, 2017).

Temperature is an easy to measure indicator for climatic conditions and of great importance for the welfare of animals. Environmental temperature has a direct effect on the body temperature of an animal. When an animal fails to keep the body temperature constant, homeostasis is compromised first resulting in an uncomfortable situation for the animal and ultimately in damage to the body (Beakley & Findlay, 1955, Silanikove, 2000). Exposure to either too high (heat stress) or too low temperatures (cold stress) can therefore lead to an impairment of welfare, exhaustion and in some cases even to death. As a result of climate change, extreme temperatures occur more often during spring and summer. Tropical conditions with accompanying heat waves will be present more often in regions with temperate climates including north and central Europe and especially southern Europe. During these heat waves, temperatures inside livestock transport vehicles can rise to 30 °C or higher. In contrast to the above, in winter temperatures inside transport vehicles can reach below the lower limit set by regulations. Transport of animals under these extreme circumstances is not allowed by European law. By improving transport vehicles and climate control systems the livestock transport sector responds to climatic challenges. Up to now there is no independent proof that using these innovations ensures climatic comfort for the transported animals and that transport companies are complying with regulations when lower and higher environmental temperatures occur. The Dutch government and livestock transport sector express concerns regarding the welfare of transported animals during more extreme environmental conditions and the continuation of animal transport during these periods. It is established by regulation in the EU that the temperature inside the livestock transport vehicle must be maintained withing 5 °C and 30 °C (± 5 °C tolerance) for all transported animals during the entire journey (Council Regulation (EC) No 1/2005). Based on EU regulations the Dutch Ministry of Agriculture, Nature and Food Quality formulated new regulations in 2020 regarding the transport of livestock during heat waves (expected outside temperatures of above 35 °C for national transports and above 30 °C for international transports). The enforcement takes place at any moment of the journey, including stationary periods.

Currently, livestock transport vehicles are equipped with one temperature sensor per level on the inside of the side wall of the vehicle and one on the outside of the vehicle. Data from these standard sensors gives limited insight into the different temperatures in the vehicle that animals are exposed to. To get a more complete picture of temperatures at animal level, more measurements need to be taken on different locations inside and outside the vehicle. This research focussed on measuring temperatures continuously on different locations in livestock transport vehicles to answer the following questions:

- What is the effect of the location of the sensors on measured temperatures?
- Are temperatures affected by the animal species that are transported?
- What is the relation between the outside and inside temperature?
- Are temperatures during transport in compliance with legal requirements?

In this report we describe findings from research performed during commercial Dutch livestock transport (see also Hoorweg *et al.*, 2021).

Material and Methods

Temperature data was collected during eight periods ranging from July 2020 till August 2021 (Table 1) for seven different animal categories: newborn calves, weaner calves, veal calves for slaughter, bulls, piglets, pigs for slaughter and broiler chickens for slaughter. The length of the periods ranged from one day to two weeks. Temperature was measured with iButton sensors (Maxim Integrated, San Jose, USA) every twenty minutes with a resolution of 0.5 °C and an accuracy of ± 1 °C. For transport company 1 and 2 (cattle and pig transports), these devices were attached to fences separating different compartments within the truck or trailer. For transport company 3 (broiler transports) these devices were attached to the transport containers. The location of the devices was coded in four digits: first digit for truck (1) or trailer (2), second digit for height (1 for lowest level up to 2, 3 or 4 for the highest level; 0 for device outside vehicle), third digit for length (1 for front fence up to 3 or 6 for hindmost fence) and fourth digit for width (1 for leftmost up to 3 or 5 for rightmost location).

Furthermore, temperature was measured routinely by three (truck) and four (trailer) sensors attached to inner side of the left wall of the vehicle, and one outside the vehicle of transport company 1 and 2. Besides temperature, these standard sensors also recorded data on driving speed of the vehicles. Standard data was not available for company 3.

Table 1: Survey of periods where temperature data was collected during animal transports: period, transport company, number of transports in period, animal categories, number of installed temperature sensors, availability of data from standard temperature sensors

Period	Transport company[1]	No of transports	Animal categories[2]	No of sensors	Standard sensors
1: July '20	1	9	calves, weaners, veals	23	yes
2: Aug. '20	1	22	calves, weaners, veals	28	yes
3: Aug. '20	2	17	calves, weaners, veals, piglets, pigs	50	yes
4: Sept. '20	2	15	weaners, veals, piglets, pigs	48	yes
5: Feb. '21	3	1	broilers	73	no
6: July '21	2	13	calves, veals, bulls, piglets, pigs	56	yes
7: Aug. '21	2	1	pigs	6	yes
8: Aug. '21	3	1	broilers	76	no

[1] transport company 1 = mechanically ventilated truck & trailer without isolated walls, transport company 2 = mechanically ventilated truck & trailer with isolated walls, transport company 3 = truck & trailer for broiler transport with containers

[2] calves = newborn calves, weaners = weaner calves, veals = veal calves for slaughter, pigs = pigs for slaughter, broilers = broiler chickens for slaughter

Sensor data was available by reading the devices offline after the ending of each period. The CSV files were imported into a Microsoft Access database and combined with other data like the placement codes and the standard data. Further processing of the data was done with the MATLAB software (version 9.9.0 (R2020b). Natick, Massachusetts: The MathWorks Inc). Only sensor data from locations where animals were present during a transport were used in the analysis. Sensor data from strongly deviating sensors (apparently defect sensors) was excluded. The median value per transport and sensor was used instead of the average to compensate for possible outliers. The medians were explored in a restricted maximum likelihood (REML) analysis using the statistical software package GenStat for Windows (VSN International Ltd., Hemel Hempstead, United Kingdom).

Results and Discussion

Most transports concerned cattle and pigs, there were only two broiler transports (Table 1). Therefore results were analysed separately for broilers and cattle/pigs. There was one transport of bulls, this transport is not included in the results.

<u>Broiler transports</u>

Two periods, 5 and 8, concerned each one broiler transport in different weather conditions. Data from 73 (Period 5) and 76 (Period 8) temperature sensors was available during these transports (Table 1). Broilers were transported in containers on a truck and trailer, a tarpaulin covered the outer walls during the transport in Period 5. The location of the sensors was coded by: vehicle (truck/trailer), height (low-high in four steps), length (front-back in six steps) and width (left-right in five steps). Period 5 was in winter (average outside temperature -4.0 °C) and transport 8 was in summer (average outside temperature 22.4 °C). To illustrate the measured temperature levels during Period 5, the temperatures per sensor in the trailer are depicted in Figure 1. There was a large range in the temperatures, some sensors hardly reached temperatures above 0 °C, where other sensors reached the level of 30 °C. During Period 5, an average temperature range of 24 °C between the lowest and highest temperature was measured. The average range was lower (8 °C), but still considerable during the broiler transport in Period 8.

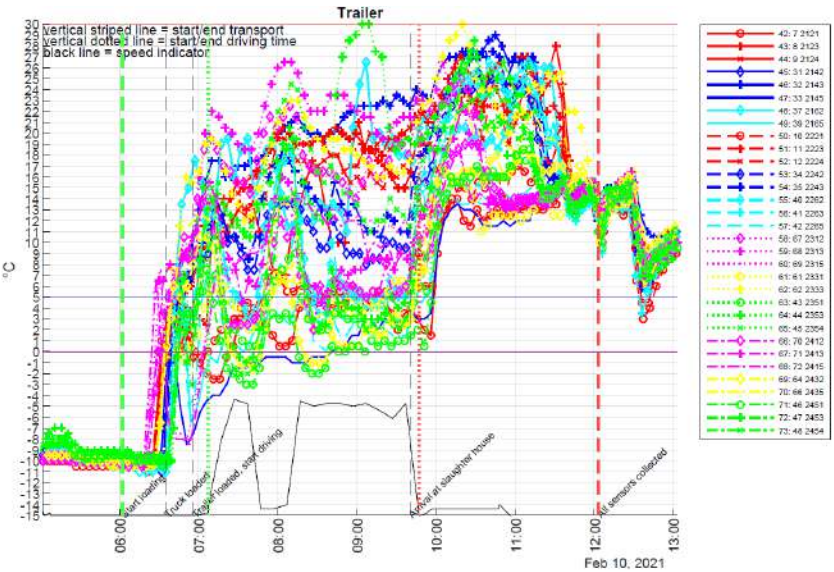

Figure 1: Temperature per sensor on the trailer during the broiler transport in Period 5 on February 10, 2021 from a broiler farm to the slaughterhouse (approx. 150 km); the solid black line in the lower part is an indication of the speed of the vehicle

The average temperature depended on the location of the sensor. This is illustrated in Figure 2 where a heat map is given for the average temperature per location. Lowest temperatures occurred in the corners and the highest temperatures occurred in the centre of the trailer. Because of the low number of transports, no further analysis of the temperatures during the two broiler transports has been done.

<u>Cattle and pig transports</u>

Six periods concerned cattle and pigs transports. Two periods with a mechanically ventilated truck and trailer without isolated walls (transport company 1), and four periods with a mechanically ventilated truck and trailer with isolated walls (transport company 2).

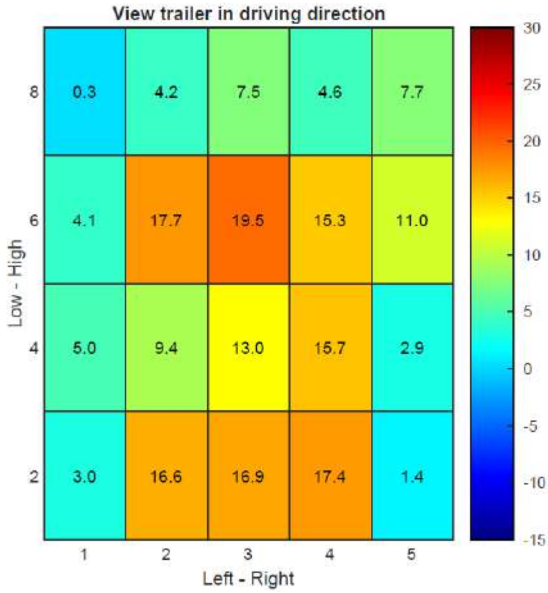

Figure 2: Heat map of the average temperature of all sensors in the trailer in the low-high direction and left-right direction during the broiler transport in Period 5 on February 10, 2021 from a broiler farm to the slaughterhouse (approx. 150 km)

The location of these sensors was coded by: vehicle (truck/trailer), height (low-high), length (front-back is two steps) and width (left-right in three steps). The height coding depended on the transport company, for transport company 1 the truck had only two low-high levels and the trailer three; for transport company 2 both the truck and the trailer had four low-high levels. As an example the temperature measurements during a transport in Period 3 (transport company 2) of veal calves for slaughter are shown in Figure 3. This transport was during a heat wave in The Netherlands. In this case, but also in general, the temperature range is much lower for cattle and pigs, compared to broilers. This is illustrated by a heat map for the temperature for the same transport (Figure 4).

The median of the inside temperature during each transport was used as response variable in a REML model with average outside temperature, animal category, transport number, vehicle and other location variables as predictors. Most predictors were factors, only average outside temperature is a quantitative variable. The other location variables were coded by height (low-high with three levels), length (front-back with two levels) and width (two levels: side or centre). This implies that some transformations were done for height and width.

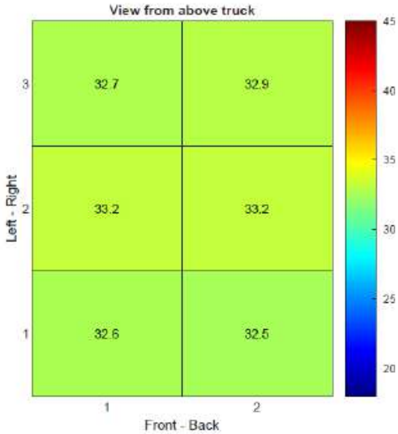

Figure 4: Heat map of the average temperature of all sensors in the front-back direction and left-right direction during the transport of veals for slaughter in Period 3 on August 10, 2020 from a veal farm to the slaughterhouse (approx. 75 km)

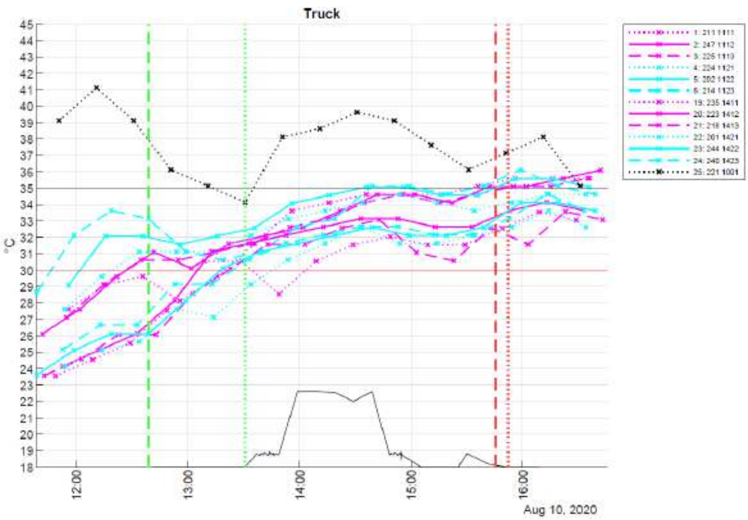

Figure 3: Temperature per sensor on the truck during the transport of veal calves for slaughter in Period 3 on August 10, 2020 from a veal farm to the slaughterhouse (approx. 75 km); the solid black line in the lower part is an indication of the speed of the vehicle

In a first step a complete model was tested with all variables and all two-way interactions. Non-significant terms were not used in the final model, with outside temperature, animal category, height, width (with two-ways interactions) as fixed effects and transport number, vehicle (with two-ways interactions) as random effects.

The results of the REML analysis indicated that:

— Inside temperature for newborn calves and weaner calves was lower than for veal calves for slaughter, piglets and pigs for slaughter (if the outside temperature is 20 °C).
— For all animal categories, inside temperature increased with higher outside temperature. This effect was lowest for piglets and the strongest for newborn calves and weaner calves. Furthermore, this effect was strongest at the side, which implies that inside temperature was more increased at the side of the vehicle on warmer days.
— Inside temperature was lower on the side of the vehicle for weaner calves, veal calves for slaughter and pigs for slaughter. This was not the case for piglets and newborn calves.
— Differences in inside temperature in height depended on animal category: for example, the middle level was warmer in case of piglets and pigs for slaughter.
— Inside temperature is lower at the back side; this effect was strongest for pigs for slaughter.
— The effect of width depended on height (apart from animal category). Inside temperature was higher at the lower level at the side. At the middle level this effect was negative.
— For transport company 1, the inside temperature of the trailer was warmer than the truck; on the other hand for transport company 2 the trailer was cooler.
— The other effects did not interact with the vehicle, with depth as an exception. This was lower in the trailer.

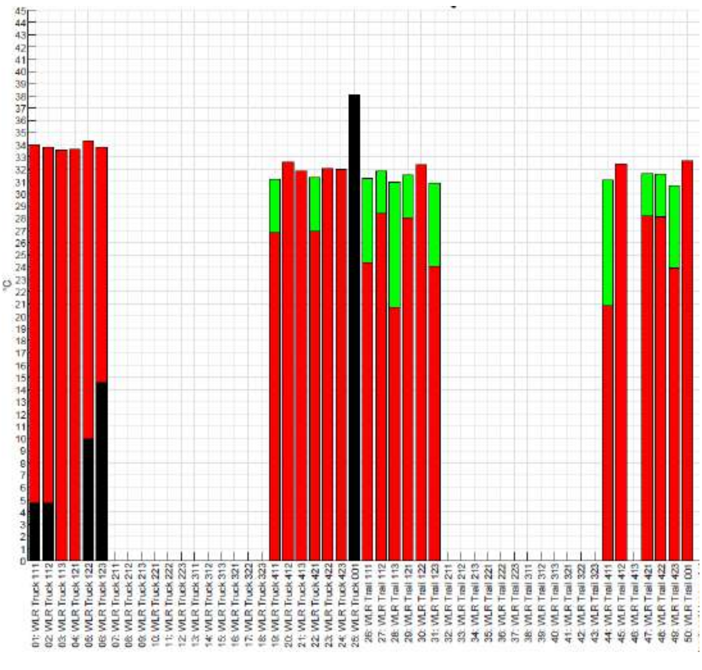

Figure 5: Bar graph of the temperature per sensor during the transport of veals for slaughter in Period 3 on August 10, 2020 (during a heat wave) from a veal farm to the slaughterhouse (approx. 75 km); the height of a bar represents the average temperature, green represents the proportion of time with temperature between 5 °C and 30 °C, red between 30 °C and 35 °C and black above 35 °C; data from sensors without bar was excluded for this transport as the related level was not used

Inside temperature during animal transports should be maintained within 5 °C and 30 °C (± 5 °C tolerance). This goal was not always reached, for example in Figure 5 temperatures per sensor are depicted during a transport during a heat wave in Period 3. For this transport temperatures in the vehicle were mostly between 30 and 35 °C. The highest temperature was reached by the sensors outside the vehicle (when the first code is '0'). Temperatures outside the allowed range were also found in the broiler transport during wintertime (Figure 1 and 2) where the temperature sometimes was below the lower limit. The temperature range was bigger during broiler transports than during cattle and pigs transports, this is also found in similar research (Burlinguette *et al*. 2012).

The main goal of this project was to get experience with sensor measurements during animal transports. In follow-up experiments, more transports will be followed, including more animal categories. More sensors might be used, for example relative humidity sensors are candidates as they make it possible to calculate the temperature–humidity index (THI) which is of great importance for heat stress (Fiore *et al*., 2012).

The results make is possible to decide where to place sensors in follow-up research so that extreme values will be included.

Conclusions

It is possible to measure temperature inside and outside the vehicle during animal transports. Application of a high number of sensors makes it possible to analyse the effects of location, animal category and other influences on temperature inside the vehicle. This makes it possible to better quantify the risks of violating temperature limits during animal transports and to develop appropriate measures to prevent those extremes.

Acknowledgements

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The application of Social Life Cycle Assessment to dairy cattle farms equipped with PLF technology

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Abstract

Over time, the increasing interest in animal-based product has led consumers to require that the production processes are performed in an ethical way and that food quality is assured. In this context, PLF may be a useful tool as a technology that can help farmers in monitoring the herds and improving animal welfare and health, as well as increase the productivity and enhance the welfare of farmers and workers. However, no methodology is currently available for the evaluation of the social performance of livestock activities implementing PLF. This paper proposes a preliminary methodological framework for the assessment of the social impact of PLF in dairy cattle farms through the Social Life Cycle Assessment (S-LCA) methodology (type I), to evaluate with a life cycle perspective the impacts generated on the well-being of stakeholders by the activities of the studied system.

Keywords: PLF, welfare, ethic farming, health, sustainability

Introduction

In recent years, the demand for animal-based products has increased considerably. In 2020, in Europe the value of the animal-based products achieved 172 bn €, the 40% of the total agricultural output. Here, the dairy sector has always had a crucial importance in socio-economic terms. According to the data provided by the EU, the volumes of milk produced and intended for dairies involved 12.000 plants and employed 300.000 people. In 2018, the sector accounted for 12% of total agricultural outputs in the EU, thus confirming it as the second largest agricultural sector in terms of outputs (Brie, 2018). Also in Italy, where in 2020 the dairy cows number was estimated to be around 1,521,000 cows distributed in about 25915 Italian farms, the sector is confirmed to be of remarkable relevance (Ismea, 2022). Furthermore, according to some estimates, Italian milk production is expected to increase by 10-15% and the trend could persist until 2030 (Ismea, 2022).

In parallel with the growth faced in recent and coming years, the market for animal products needs to face significant changes to meet the new consumers' habits and the new political frameworks that regulate production processes. Consumers are increasingly demanding transparency in production, not only in terms of food quality but also in relation with the social and environmental impact of food production, and of social and ethical aspects in animal-based food production (Lovarelli et al., 2020).

Consistently, similarly to what has happened with "Farm to Fork strategy", new rules are expected for dealing with social sustainability and animal welfare. In the light of social pressures and the policy adopted by the EU, the dairy cattle sector is called to a big challenge to implement its environmental and social sustainability.

At that end, there is an urgent need to develop analytical tools to assess the social sustainability of the sector in a common and uncontroversial way. In this context, the aim of this contribution is to evaluate the social impact of Italian dairy cattle farms through the analysis of a set of social indicators on the different categories of stakeholders selected: workers, local communities, society and animals.

Material and methods

Of the methodologies useful for assessing the social sustainability of production processes, the social life cycle assessment defined by the United Nations Environmental Program guidelines is undoubtedly one of the most widely used.

Following the guidelines of the United Nations Environment Program (UNEP, 2019), the Social-Life Cycle Assessment (S-LCA) has been structured in 4 phases: definition of objectives and scope, inventory analysis, impact assessment and interpretation of results.

The analysis aims to assess the negative and positive social impacts related to the activities carried out in two dairy cows' farms in Italy in 2021 for the following stakeholders: Workers, Society, Local Communities and Animals. The "Value Chain Partners" stakeholder was not considered because the analyzed farms are not large enough to impose vexatious conditions on their commercial partners.

The chosen functional unit is the farm. As for the system boundaries, due to the lack of available data for S-LCA studies in the upstream processes, a gate-to-gate perspective was selected to assess the actual (and not only potential) social impacts.

The "Reference Scale" approach was chosen as the methodology for assessing the social impacts. As alternative, the UNEP guidelines defines the "Impact Pathway" as a possible assessment methodology, however this option was discarded since the characterization factors needed to translate inventory data into quantified social impacts are still to be defined. The "Reference Scale" methodology, on the other hand, does not quantify social impacts (whether positive or negative), but it aims to assess the social performance of organizations operating within the system boundaries by comparing data for each chosen indicators to the selected reference values; these values may refer to sector average values (e.g., the average wage of agricultural workers), to legal provisions (e.g., hours of training for workers) or to international conventions (e.g., the International Labour Organization's maximum limit of 44 working hours per week).

The "Reference Scale" approach involves the following steps:

1. Identification of indicators, carried out by adopting a participatory approach. Stakeholder representatives were asked to prioritize the list of indicators reported in the UNEP guidelines. The list was further implemented to define appropriate indicators for the "Animal" stakeholder.
2. Evaluation scale definition for each selected indicator. The definition of the threshold values of the rating scales was carried out on the basis of an analysis of literature and/or public databases (e.g., ISTAT, Eurostat).
3. Social sustainability analysis by comparing values collected and/or selected from the literature with identified threshold values.

Table 1: Workers, Local Community, Society and Animals indicators

Stakehol.	Indicator	Reference Scale	Source
WORKERS	Average Hourly Salary	Committed > 13.86 €/h Proactive < 13.86 €/h Compliant <12.65 €/ Risky < 10.86 €/h	Agriregionieuropa (2018) CCNL - OPERAI AGRICOLI E FLOROVIVAISTI (2019)
	Percentage of Workers with a Permanent Contract	>36.24= Committed <36.24% = Proactive < 30.2 % = Compliant < 24 %= Risky	Gli Operai Agricoli in Lombardia (2019)
	Injuries	0: Proactive 1: Compliant >1: Risky	Inail 2019
	Weekly Working Hours	<39h: Proactive 39h<and <44 h: Compliant > 44h: Risky	International Labour Organization, CCNL 2019
	Hours Devoted to Workers Training	>12h: Proactive 12h: Compliant <12 h: Risky	Art. 37 - D.Lgs. 81/2008, Accordo - 21/12/2011 - n. 221/CSR
LOCAL COMMUNITY	Number of Accidents in the last 2 years	0: Complaint >0: Risky	Authors elaboration
	Complaints Regarding Nuisance Issues in the last 2 years	0: Complaint >0: Risky	Authors elaboration
	Local Hiring Rate	>30%: Committed <30%: Proactive <25%: Compliant <20%: Risky	Zira et al., 2020
	Local Sourcing of Feed	>22.8%: Committed <22.8%: Proactive <19%: Compliant <15.84%: Risky	Gislon et al., 2020
	Number of Engagement Moments	>1: Proactive 1: Compliant 0: Risky	Zira et al., 2020
	Expenditure for Common Infrastructure, for the local community, or in charitable donations for the local community	>0€: Compliant 0 €: Risky	Authors elaboration
SOCIETY	Workers Younger than 30 years old	>30%: Committed <30%: Proactive <25%: Compliant <20%: Risky	Gli operai agricoli in Italia secondo i dati INPS, 2019
	Percentage of Feeds Edible for Humans	<9.56%: Committed >9.56%: Proactive >14.34%: Compliant >16.49%: Risky	Mottet et al., 2017
	Antimicrobial use	0: Proactive 4.8: Compliant >4.8: Risky	Mazza et al., 2021

ANIMALS	Oestrus events identification	>80%: Committed >75%: Proactive >50%: Compliant <50%: Risky	Reith & Hoy, 2018
	Milk production	>35kg/d: Committed >30kg/d: Proactive 30kg/d: Compliant <28 kg/d: Risky	Lovarelli et al., 2019
	Heat Stress	<68: Committed <72: Proactive 72: Compliant >72: Risky	Allen et al., 2015
	Lying Time	>12: Committed >10: Proactive 10: Compliant <10: Risky	Lovarelli et al., 2020
	Clinical Mastitis	0: Committed 1: Proactive 2: Compliant >2: Risky	Vitali et al., 2020
	Lameness	<20%: Committed <25%: Proactive 25%: Compliant >25%: Risky	Whitaker et al., 1983

Summarizing, a series of indicators have been identified for each stakeholder, and each indicator was then included in an impact subcategory suggested by the UNEP guidelines. Each subcategory refers to a specific stakeholder and it identifies a social issue that contributes to his well-being (e.g., fair wages for workers, employment rate for local communities, economic development for the company).

Methodological framework definition

Table 1 shows the selected indicators for the “Workers”, “Society”, “Local Communities” and “Animals” stakeholders.

As for the “Workers” stakeholder, 5 indicators were selected, both quantitative, all related to the following subcategories: fair wages, working hours, health and safety, and workplace safety. The “Society” stakeholder is instead represented by 3 quantitative indicators, which refer to the themes of health, economic development and food security. With regard to the “Local Communities” stakeholder, 6 quantitative indicators were selected, all included in the following sub-categories: health and safety, local economic development, access to resources and involvement of local communities. Lastly, 6 semi-quantitative indicators were identified for the “Animals” stakeholder.

A reference value was selected for each indicator. Starting from the identified reference value, an evaluation scale was defined to assess the conditions for each specific indicator (e.g., working hours, salary level, use of antibiotics, housing practices), and then to determine the impact (e.g., neutral, positive or negative) that affects the stakeholders’ “welfare”. 4 ranges have been identified in the defined rating scales. Compared with the respective reference values, different scores can be assigned to the indicators:

— “Committed” if collected data are significantly higher than the reference value (e.g., if the hourly wage paid by the company is significantly higher than the average hourly wage received by agricultural workers in Italy); the “Committed” score indicates a noticeably positive impact on stakeholder;
— “Proactive” if the data are slightly better than the reference values; the “Proactive” score indicates a fairly positive impact on stakeholder;
— “Compliant” if the data are equivalent to the defined reference value or range; this is a neutral situation, in which it is assessed that no impact is generated;
— “Risky” if the data describe a worse situation compared to the reference value; the “Risky” score indicates a negative impact on stakeholders’ well-being.

Multiple ranges rating scales were not applied to all the selected indicators. The impossibility for some indicators to generate positive effects on stakeholders was indeed taken into consideration: for instance, as for the “ *Number of Accidents in the last 2 years*” indicator, we have considered that the firm behaviour can only be defined “*Risky*”, and therefore generate a negative impact on stakeholders or “*Compliant*” if the firm can be considered conform to a standard or norm, without causing any impact.

Preliminary Results and Discussion

This analysis framework (indicators and rating scales) was preliminarily applied to two dairy cows’ farms in northern Italy which is a livestock intensive area. Farm A has a herd of 135 dairy cows in which no technological support is introduced. Farm B instead has a herd of 345 dairy cows, and it is equipped with neck collars for behavior observations and a milking system collecting data from each milking session.

Figure 1a-c shows the results obtained respectively for the “Workers”, “Local Community” and “Animals” stakeholders. The values 1- 4 in the figure refer respectively to the Risky (1), Compliant (2), Proactive (3) and Committed (4) scores.

The figures show the indicators with value for at least one of the two selected farms. For missing data, a value of 0 has been assigned. Consistently, “Antimicrobial use” and “Oestrus events identification” indicators have been excluded from the figures due to the lack of possibilities in collecting data for both farm A and farm B. Lack in data may be due to difficulties in collecting data from comparable methods (e.g., unavailability of tools useful in detecting specific data) and/or to differences in specific stakeholder category (e.g., the absence of employees in farm A).

For all stakeholder categories, farm B shows on average a lower social impact. In the category “Workers”, although several indicators are not applicable as farm A has no employees, the comparable indicators show a lower social impact. For the indicator “Weekly Working Hours”, data show substantial differences between farm A (72 working hours/week) and farm B (39 working hours/week). The gap could be the result of a greater division of labour among employees compared to the working organization of the family farm, and a greater exploitation of technologies (such as PLF) able to alleviate the workload of operators.

The “Local Community” stakeholder does not show many differences between farms A and B, except for indicator “Local sourcing of feed” since farm B self-produces about 50% of the rations given to dairy cows - against 30% self-produced by farm A.

Respect to the “Society” stakeholder only 2 indicators were analyzed from which it emerged that “Percentage of Feeds Edible for Humans” indicators resulted the same while the second indicator “Workers Younger than 30 years” old is not applicable for Farm A. The stakeholder “Animals” in farm B refers a lower social impact for the animal welfare indicators “Milk production”, “Heat stress” and “Lying Time” (n.a. in farm A due to absence of PLF technologies to monitor cows behavior). Farm A, on the other hand, shows a lower social impact for the “Clinical Mastitis” and “Lameness” indicators. However, the limited use of technologies in farm A could lead to a reduced probability of identifying mastitis and lameness than the technologies used by farm B, thus biasing data.

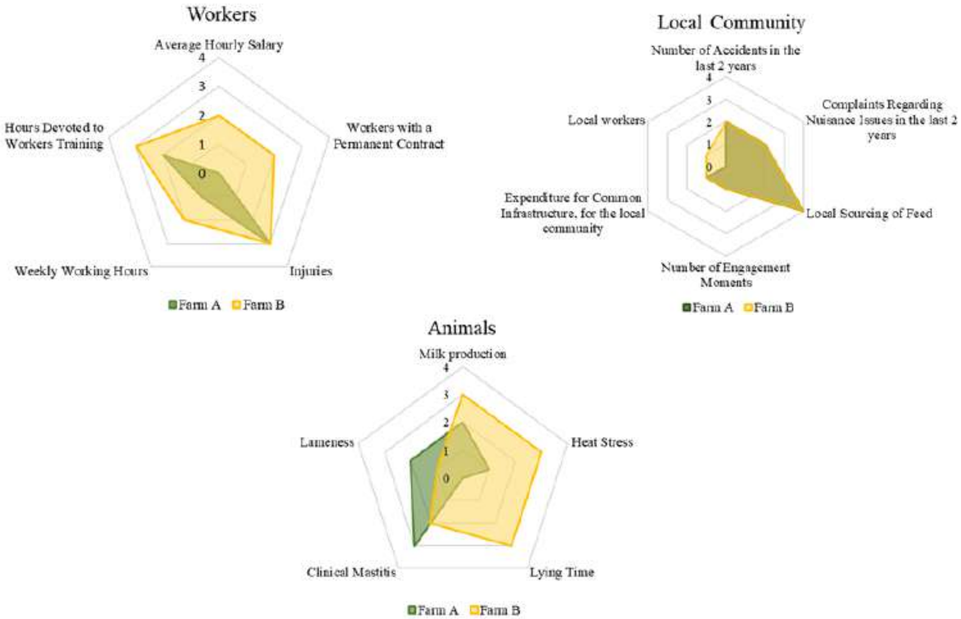

Figure 1: Social Impact on the stakeholders: (a) Workers, (b) Local Community, (c) Animals.

Conclusions

In conclusion, in dairy cows’ farms, S-LCA can be a useful analytical tool, to be integrated with other life cycle analysis methodologies (LCA and LCC). However, further improvements of the methodology are needed to develop specific analytical frameworks for the sector. The homogeneity of tools for data collection causes several difficulties in indicators selection and data comparison. Preliminary results confirm that, in this first attempt of assessing S-LCA of the sector, the application of technologies may help in reducing the social impact of dairy farming. Notwithstanding, the definition of indicators specifically designed for this sector and able to read its specificities is a fundamental aspect and more than ever necessary to make the S-LCA a useful approach to assess the social sustainability of livestock systems.

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Precision Livestock Farming as One Health Technology

The One Health concept states that infections are travelling around from water, soil and air to wildlife, next to livestock and then to humans. Planet earth counts today around 150 billion wildlife animals (not considering birds and sea animals), every year over 70 billion animals are slaughtered for the worldwide food demand and there are around 7.8 billion humans. In human diseases, more than 60 per cent of them are zoonotic and 75 per cent of new, "emerging" infectious diseases are zoonotic. While we did not yet get rid of the Covid-19 pandemic, the question is not whether another pandemic will come, the question is when.

Animal protein remains a very efficient way to feed humans. Especially in developing countries, livestock plays an important role to produce food and to give social status to people. Due to growing population and changing diets, the worldwide demand for animal products is increasing with over 65% by 2050. It is however unthinkable that we would keep more animals in the livestock sector. The worldwide livestock sector is facing huge problems such as animal health in relation to human health, animal welfare, lack of efficient process management leading to unacceptable environmental impact. Today, governments struggle with keeping a balance between the polluting livestock sector, the use of water and the protection of the nature and biodiversity. Rather than investing in technical and management solutions, in different countries legislation aims to reduce the number of farms and animals per farm while the worldwide demand for animal products is increasing.

Each of us should contribute to the solution. We need to improve the efficiency of the core process in the livestock sector: transforming feed energy, especially which is not suitable for human consumption into animal product. Here, it is particularly important to avoid unnecessary energy and product losses (meat, eggs, milk), e.g. as a result of suboptimal husbandry conditions and diseases. We need more animal product with less feed input and consequently less environmental impact. The continuous real-time monitoring 24/7 allows to realize active management solving problems when they occur, opposite to detecting problems after the facts in the slaughterhouse or once a year in a visit. The PLF technology has the potential to create a worldwide infection monitoring system for humans, for livestock and for wildlife. This will help fast detection and early warning of diseases, allowing immediate actions and reduce spreading of infections.

We are the ones to create science and knowledge required by the livestock sector and the world. Therefore, we must produce solutions by collaborating in a most professional way within and between our different research disciplines, with farmers, industrial partners and governments to bring solutions for a more sustainable planet earth.

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