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Automatic Monitoring of dairy cows' lying behaviour using a computer vision system in open barns

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Abstract. Precision Livestock Farming offers opportunities for automated, continuous monitoring of animals, their productivity, welfare and health. The video-based assessment of animal behaviour is an automated, non-invasive and promising application. The aim of this study is to identify possible parameters in dairy cows' lying behaviour that are the basis for a holistic computer vision-based system to assess animal health and welfare. Based on expert interviews and a literature review, we define parameters and their optimum in form of gold standards to evaluate lying behaviour automatically. These include quantitative parameters such as daily lying time, lying period length, lying period frequency and qualitative parameters such as extension of the front and hind legs, standing in the lying cubicles, or total lateral position. The lying behaviour is an example within the research context for the development of a computer vision-based tool for automated detection of animal behaviour and appropriate housing design.

Key words: animal welfare; computer vision; dairy cow monitoring, lying behaviour, precision livestock farming.

INTRODUCTION

Surveys of the European Union show an increasing interest and concern of citizens about animal welfare (European Commission, 2016). As a result, there is an ongoing controversial discussion about the conditions under which farm animals are kept (Vanhonacker & Verbeke, 2013). The evaluation of animal husbandry systems and the assessment of animal welfare are thus becoming increasingly important.

To date, there is no uniform indicator system for evaluating animal welfare in dairy farming. In practice, the evaluation of animal welfare is based on environmental parameters like available space or cubicle design and management-related parameters like feeding. As these parameters are related to the needs of the animals describing barn circumstances and management, they ensure good housing conditions for animals.

However, they deliver only indirect information on animal welfare (EFSA, 2012). Thus, parameters related to animal behaviour can provide further relevant insights, since animal behaviour is closely related to the physiological status (Neave et al., 2018) and animal welfare (EFSA, 2012).

One relevant behavioural parameter to assess animal welfare, health status and comfort of dairy cows is their lying behaviour (Vasseur et al., 2012; Tucker et al., 2021). In particular, changes in lying time can indicate management problems (Drissler et al., 2005), stall design problems (Gaworski, 2019; Gaworski, 2021), injuries (Ito et al., 2010; Nechanitzky et al., 2016) or a certain physiological condition (Westin et al., 2016). Since any alteration from the optimum can have a negative impact on health and reproductive capacity, several studies analysed its effect on milk production (Norring et al., 2012; Lovarelli et al., 2020), the impact on lameness (Solano et al., 2016), the association with mastitis (Cyples et al., 2012; Herskin et al., 2020) and the oestrus detection (Zebari et al., 2018). Insufficient lying time is associated with poor recovery and frustration and increases the risk for health problems (Welfare Quality Reports, 2009).

Usually, skilled operators carry out the assessment of dairy cow behaviour. However, a continuous direct observation of animal behaviour by the farmer requires a large amount of time and is therefore not feasible in practice. A variety of sensors supports the evaluation of animal behaviour. These can basically be divided into attached and non-attached sensors. Attached sensors mainly detect behaviour and range from acceleration sensors to body temperature measurement. These sensors have a high precision (Stygar et al., 2021; Fan et al., 2022), but are subject to strong mechanical influences or the penetration of dirt and moisture. In the group of non-attached sensors, a promising application for continuous monitoring of animal behaviour is computer vision technology (O' Mahony et al., 2019). The application of computer vision in dairy cow barns allows studying the behaviour of several animals as well as different behavioural patterns at the same time. In the last years, a wide range of studies investigated several use cases and methods for automatic behaviour recognition with machine vision. Determining lameness through automatic gait analysis (Van Hertem et al., 2018; Kang et al., 2020; Wu et al., 2020), location in the stable (Salau & Krieter, 2020), drinking (Tsai et al., 2020; Wu et al., 2021), eating (Porto et al., 2015; Bezen et al., 2020) and chewing behaviour (Wu et al., 2021) as well as lying (Porto et al., 2013; Adriaens et al., 2022), standing (Porto et al., 2015) and social interaction (Guo et al., 2020; Ren et al., 2021) are just some applications for machine vision. Computer vision-based detection enables non-invasive, automated and cost-effective quantification of behavioural patterns.

The cognitive subject of our research is the identification of parameters, which allow the development of an automatic computer vision-based monitoring-system of dairy cows' lying behaviour. Besides the quantitative parameters, we also focus on the qualitative assessment of the lying behaviour. On this basis, we pursue the utilitarian goal of providing information for a non-invasive and automatic approach, that describes the current status of the animals' well-being and gives recommendations for farmers. Thus, we define the following research problem:

Which parameters are suitable for a computer vision-based quantitative and qualitative assessment of the dairy cows' lying behaviour?

In order to address this research question, we conducted expert interviews and a literature review.

RESEARCH APPROACH

This study is part of the SmartMILC project, which aims to develop a holistic system for monitoring animal health and welfare of dairy cows. The project identified five use cases: 'lying behaviour', 'heat stress monitoring', 'work diary', 'barn and herd monitoring' and 'animal health tracking'. This study focusses on the analysis of the 'lying behaviour'. The theoretical framework for each use case is a combination of gold standards and expert knowledge backed up by knowledge from literature (Fig. 1).

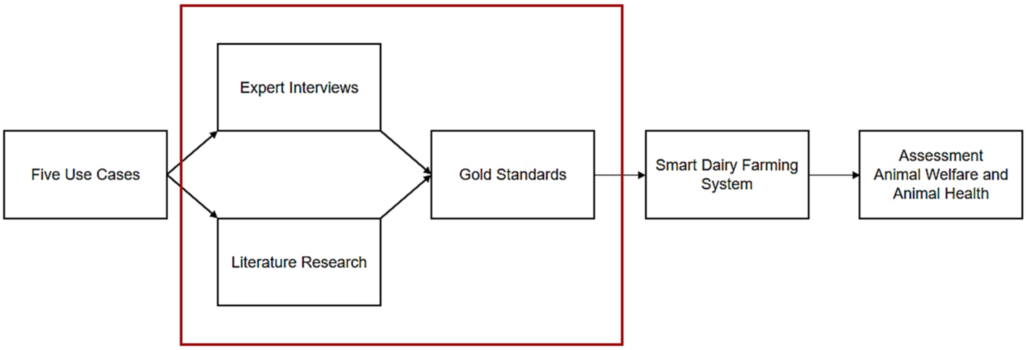

Figure 1. Research approach.

Expert interviews are widely used in qualitative empirical research. These can be used to gain an insight into the expertise of an expert and aim to capture previously undocumented knowledge. For the use case 'lying behaviour' we conducted four interviews, based on a guideline that included an introduction of the interview partners, background information on the project and use case specific information. The aim was to identify how lying behaviour is evaluated in practice, how this behavioural pattern is recorded and what kind of information the experts judge as relevant for automatic vision-based monitoring. The interviews were recorded, subsequently transcribed and key statements were identified.

Based on the literature research we identified descriptors of lying behaviour and their threshold values to derive possible methods for a computer vision-based automatic detection of the lying behaviour and a comparison with gold standards. In the context of our work, we use the term gold standard to refer to the best possible quality criterion or method for evaluation. In this paper, the gold standards are based on the results from the literature research.

RESULTS AND DISCUSSION

Expert interviews

The interviews revealed that lying behaviour is of great importance for assessing the health status of a cow. However, in practice there are clear deficits in both direct and automatic monitoring of lying behaviour. The observation is only selective and mostly carried out during barn work on the farms because direct observation is very time-consuming and subjective. Thus, acceleration sensors attached to the animals are a common alternative to direct observation, but they require a high material input.

The experts rate an automatic recording of animal health parameters, including lying behaviour, as a valuable support in their daily work. Parameters such as 'lying time per day', 'length of lying period' and 'lying period frequency' were named and enable a quantitative assessment of lying behaviour. According to the practitioners, these parameters should also be put into context with environmental parameters such as air temperature, humidity and wind speed and with animal-related indicators such as rumen pH, ruminant activity, milk yield, etc. Two of the four experts placed a high value on the rising behaviour, which, in contrast to horses, begins with raising of the hindquarters. In addition, the quality of lying comfort can be determined by behavioural parameters such as stretched out front or hind leg, side lying, hindquarter outside the cubicle or head resting. The experts also deduce the quality and acceptance of the cubicles from the animal behaviour: if many cows stand with two or four legs in the cubicles, it can indicate an inappropriately adjusted neck rail or an uncomfortable or dirty cubicle.

The small number of interviews is of course a limiting factor, however, the interviewees are to be seen as additional experts to the smartMILC consortium.

Derived Parameters from Literature Research

Different studies record the analysis of lying behaviour of dairy cows by computer vision. Porto et al. (2013) investigated lying behaviour using a multi-camera system and the Viola Jones algorithm. The cameras were mounted above the cubicles and provided panoramic top-view images. As the Viola Jones algorithm cannot recognize rotated images, two classifiers had to be used to recognize the cows in the opposing cubicles. Both classifiers showed a true positive rate of 0.9 but had problems with changing lighting and background conditions. Yin et al. (2020) used the Convolutional Neural Network (CNN) 'EfficientNet' for spatial feature extraction and the BiFPN (bidirectional feature pyramid network) to extract the features of behavioural information. Finally, the video images are aggregated into a time series by the BiLSTM (bidirectional long-term memory) module so that behavioural patterns (feeding, drinking, lying, standing and walking) could be detected quickly and accurately. The lying behaviour is detected with a precision of 98.60%. Lighting had little influence on the algorithm, the usability at night is not researched yet. Wu et al. (2021) monitored the basic behaviours drinking, ruminating, walking, standing and lying with the CNN-LSTM algorithm. The algorithm VGG16 is the skeleton of the network and is used to extract the feature vector sequences. They also used subsequently the Bi-LSTM to detect the behaviour. VGG16 is then compared with five algorithms (VGG19, ResNet18, ResNet101, MobileNet V2 and DenseNet201). The accuracy for lying behaviour was almost 0.98. Environmental factors like illumination change, rain or wind had no significant impact on the algorithm. Adriaens et al. (2022) used a cow detection and tracking algorithm (YOLOv5 for detection of changes in bounding boxes and DeepSORT for tracking) with bounding boxes to capture lying down and getting up events. The recognition of the lying down and standing up behaviour is based on changes in the bounding boxes. It has been shown that there are no uniform criteria for the best possible detection; however, the potential of this application has been demonstrated.

These studies show that lying behaviour can be successfully detected using machine vision, but a quantitative and qualitative assessment of this behavioural pattern has not been researched yet. The derivation of parameters for the evaluation of the lying behaviour requires a profound understanding: a typical lying down process begins with selecting a suitable resting location and an olfactory check of the lying place. The first front leg is bent, followed by the second one so that the cow knees on the carpal joint while the hind leg of the intended lying side is placed under the body. This is followed by lowering the body first onto the chest and then onto the hind limbs (Chaplin & Munksgaard, 2001; Pelzer et al., 2012).

Related research used the 'daily lying time', 'lying period length' and 'lying period frequency' as parameters in the lying behaviour context (Mattachini et al., 2019; Lovarelli et al., 2020). The daily lying time ranges from 8 to 13 hours with the most common average of 10 to 12 hours. This behavioural pattern is divided into 9 to 11 lying periods per day of 60 to 99 minutes (Tucker et al., 2021). However, the lying behaviour is subject to numerous influencing factors (Fig. 2).

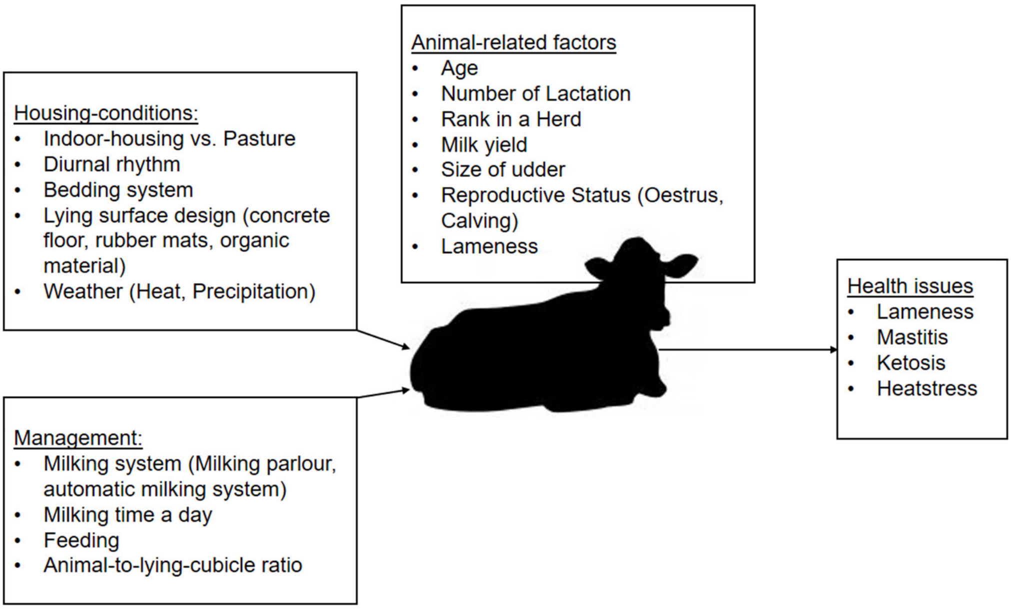

Figure 2. Lying behaviour and its influencing factors.

The lying behaviour of cows is influenced by the daily rhythm (Overton et al., 2002) and daily lying times are significantly longer for cows kept indoors than on pasture due to higher time expenditure for foraging and eating of the latter (Tucker et al., 2021). Another important influencing factor is the cubicle design. Improperly adjusted neck rails or lateral boundaries make it difficult or impossible for a cow to lie down. This is mainly manifested by cows standing with two or four legs in the cubicles (Pelzer et al., 2012). The comfort of the lying surface also has a significant influence on the daily lying time: while lying processes are shortest on pure concrete floors, they increase when the floor is equipped with organic materials or rubber mats (Solano et al., 2016). However, De Palo et al. (2006) observed that with increasing THI, cows prefer lying surfaces that allow good heat dissipation (e.g. sawdust). A lack of bedding as well as wet lying surfaces reduce lying times (Fregonesi et al., 2007; Westin et al., 2016; Schütz et al., 2019). Numerous studies investigated the influence of heat on lying behaviour using the THI. Daily lying times decrease with increasing THI (Cook et al., 2007; Allen et al., 2015). Tresoldi et al. (2019) found that daily lying time is reduced by about 20 minutes for a 1 °C increase in temperature. Besides the housing-conditions, there are management-factors, like the animal-to-lying space ratio, that also influence the lying behaviour. With increasing stock density, average lying times decrease significantly and the variability of lying times increases (Tucker et al., 2021). This effect is more pronounced in lower-ranking animals. The milking management also influences lying behaviour. Whereas in automatic milking systems the cows themselves decide when to be milked, in milking parlours the entire group is driven to get milked. This interrupts lying down processes and with increasing milking times, the animals are forced to stand for longer periods, which in turn reduces lying times (Gomez & Cook, 2010). After a long period of forced standing, cattle show a high preference for lying and neglecting of other important behaviours such as feed uptake (Munksgaard et al., 2005). Some studies show that increasing age and numbers of lactations increase daily lying times (Westin et al., 2016; Henriksen & Munksgaard, 2019) while others found no or moderate influence. A direct relationship between lying time and oestrus has been demonstrated by numerous studies (Silper et al., 2015; Zebari et al., 2018). Silper et al. (2015) found a 37% reduction in lying time on the day of oestrus. Even high milk yields have a negative influence on lying behaviour (Vasseur et al., 2012; Stone et al., 2017). Changes in lying behaviour can be both an indication of disease and a cause of it: while uncomfortable cubicles increase the risk of lameness due to reduced lying time (Thomsen et al., 2012; Bouffard et al., 2017), lameness simultaneously implies longer lying times and lying periods, but a lower lying frequency (Westin et al., 2016). In addition, a shortened lying period can be a sign of mastitis or, if it occurs shortly after birth, of ketosis (Itle et al., 2015). Due to the multiple interpretation possibilities, lying behaviour should always be seen in context with other parameters.

As the aforementioned parameters ‘lying time’, ‘lying-period length’ and ‘lying-period frequency’ just allow statements about the appearance of the lying event, the quality of lying enables animal-related statements regarding animal welfare.

CowsAndMore is a digital tool that facilitates the objective direct recording of animal-related traits. However, the tool ‘CowsAndMore’ intends an assessment twice a year and does not provide any information about the individual. To evaluate cubicle quality, the number of cows standing in cubicles (with two or four legs), lying in a cubicle and lying in the alley is recorded. The lying positions ‘breast position’, ‘stretched front leg’, ‘stretched hind leg > 45°’, ‘sleeping position’ and ‘total side position’ allow statements about both the cubicles and cow comfort. Erp-van der Kooij et al. (2019) used these parameters to find differences in lying posture between outdoor and indoor husbandry. The duration of standing in the cubicle until lying down is also evaluated by CowsAndMore. If this time is less than 30 seconds, the lying down process is assessed as quick, between 30 and 60 seconds as hesitant and over 60 seconds as refusal or aborted (Chaplin & Munksgaard, 2001; Pelzer et al., 2012).

For the evaluation of animal welfare and cow comfort, it is useful to supplement the quantitative parameters with qualitative factors. Based on the expert interviews and the literature research, the following parameters and their gold standards were defined.

The parameters summarized in Table 1 serve as the basis for the automatic analysis of dairy cows' lying behaviour. In particular, we intend to implement a computer vision system that not only recognizes lying behaviour in terms of quantity but also provides insights on lying behaviour quality. For this purpose, we make use of both a 360-degree fisheye camera for a general overview of the barn as well as depth cameras for a more precise view of individual instances of standing, lying down, lying and standing up in the lying boxes. The installed cameras provide regular image data of the recorded barn areas and additional information from the stereo depth cameras.

Table 1. Lying parameter, its description and method of measurement

Parameter	Definition	Measurement	Reference
Lying down	Starts when one carpal joint is bent and ends when the front legs are pulled out from under the torso	< 3 seconds on the carpal joints < 30 seconds: quick 30–60 seconds: hesitant	Chaplin & Munksgaard (2001); Pelzer et al. (2012); CowsAndMore
Interrupted lying down	When the process of lying down is not finished after a period of 60 seconds	> 60 seconds	Pelzer et al. (2012); CowsAndMore
Lying period duration	Duration between the end of lying down and the start of rising	60–99 minutes	Tucker et al. (2021)
Lying time per day	Sum of the lying period duration per day	10–12 hours per day	Tucker et al. (2021)
Lying period frequency	Frequency of lying down per day	9–11	Tucker et al. (2021)
Rising	Starts with head swing and rising of the hindquarter, ends with standing on four legs	Pose estimation and classifica-tion	Pelzer et al. (2012)
Anomaly while rising	Rising like a horse: at first the forehand, followed by the hindquarter	Pose estimation and classifica-tion, < 3 seconds	Chaplin & Munksgaard, (2001)
Hindquarter outside cubicle	Hindquarter overhangs the cubicle edge	Overhang in cm	Interviews
Stretched hindleg	One hindleg is stretched more than 90° from the body	Pose estimation, angle	Pelzer & Kaufmann (2018)
Stretched frontleg	One frontleg is stretched under the head and is not under the cows body	Pose estimation and classifica-tion	Pelzer & Kaufmann (2018)
Lateral position	Lateral position, legs are not under body	Pose estimation	Pelzer & Kaufmann (2018)
Head resting	Head is lying on a front leg, the ground or on the torso	Pose estimation	CowsAndMore
Standing in cubicle	Cow is standing with two or four legs in the cubicle	Pose estimation, Location	Pelzer & Kaufmann (2018), CowsAndMore
Lying outside the cubicle	Cow lies on the walking area, not in the cubicle	Pose estimation, Location	Pelzer & Kaufmann (2018), CowsAndMore

In order to enable the continuous monitoring of the cows' lying behaviour visual data needs to be analyzed automatically - i.e., by computer vision. Recent strides in this domain include an increasing quality in algorithms for object detection and tracking (Redmon et al., 2016; Chandan et al., 2018) as well as pose estimation (Munea et al., 2020; Wang et al., 2021). These are mainly used for studying human behaviour in various scenarios, but approaches for computer vision in livestock farming are gaining momentum. For example, different pose estimation models for animals are available (Lauer et al., 2022) and similar models are used for analysing dairy cows (Ter-Sarkisov et al., 2017; Li et al., 2019).

Starting from this technological progress, we implemented a Cow Detection and Cow Pose Estimation which are illustrated in Fig. 3. On this basis, we intend to develop classification models. Firstly, the classification is aimed to differentiate between standing and lying as well as between the acts of lying down and standing up. Secondly, these acts can also be classified in terms of their ergonomic quality based on training data labelled by experts. Thus, we will be able to derive quantified information regarding the listed parameters in real-time.

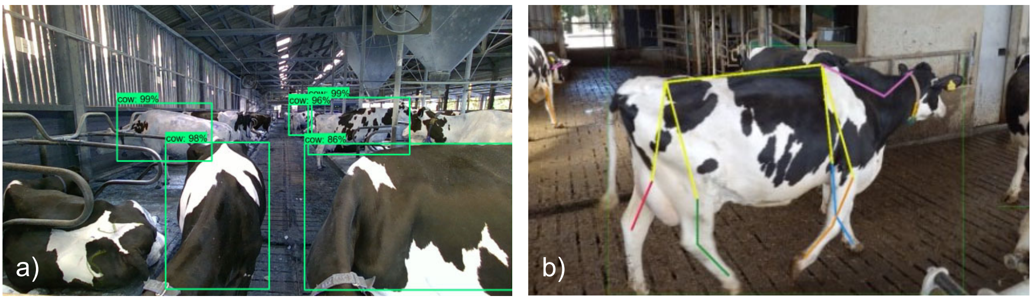

Figure 3. Example frames for (a) Cow Detection and (b) pose estimation.

However, our current challenges include reliable approaches for object detection and tracking as well as pose estimation for images in the barn environment that are characterized by visual obstructions due to overlapping cows and barn infrastructure - occlusion (Russello et al., 2022). Under these circumstances, pose estimation loses accuracy and a differentiation between lying and standing may be impossible. Here, the benefit of including additional information from the depth sensors as well as integrating information from multiple cameras becomes evident.

CONCLUSIONS

In conclusion, we identified a large number of animal-related parameters that allow a qualitative and quantitative assessment of the dairy cows' lying behaviour. This framework is the basis for the continuation of the smartMILC project. With the help of cow detection and pose estimation algorithms, first lying processes have already been successfully detected. The ongoing work includes the accuracy improvement for the detection of lying down and rising up behaviours as well as the computer vision-based detection of the derived qualitative parameters. In summary, the time-consuming direct observation of animal behaviour can be supported by computer vision and helps to improve welfare and health of animals.

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