Chapter

Aiming to Improve Dairy Cattle Welfare by Using Precision Technology to Track Lameness, Mastitis, Somatic Cell Count and Body Condition Score

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Abstract

Specific animal-based indicators that may be used to predict animal welfare have been at the basis of techniques for monitoring farm animal welfare, such as those developed by the Welfare Quality project. In addition, the use of technical instruments to accurately and immediately measure farm animal welfare is obvious. Precision livestock farming (PLF) has enhanced production, economic viability, and animal welfare in dairy farms by using technology instruments. Despite the fact that PLF was only recently adopted, the need for technical assistance on farms is getting more and more attention and has resulted in substantial scientific contributions in a wide range of fields within the dairy sector, with a focus on the health and welfare of cows. Among the most important animal-based indicators of dairy cow welfare are lameness, mastitis, somatic cell count and body condition, and this chapter aims to highlight the most recent advances in PLF in this area. Finally, a discussion is presented on the possibility of integrating the information obtained by PLF into a welfare assessment framework.

Keywords: animal welfare, behaviour, body condition score, dairy cattle, infrared thermography, lameness, mastitis, precision livestock farming, somatic cell count

1. Introduction

Animal welfare with several legislative initiatives from the late 1980s to the present day has long been considered a high priority within the European Union (EU) [1]. In addition, as part of a policy-oriented strategy to find methods to enhance animals' lives, the EU has made major investments in research into the welfare of farm animals [2, 3]. For the improving the standard of animal welfare the important part is an animal observation. In this regard, attempts have been undertaken to investigate science-based welfare indicators as assessment methods [4, 5]. For example, the Welfare Quality® project contributed with protocols to assess animal welfare in cattle, pigs, and poultry [6, 7]. A few years later, the AWIN® project developed indicators for animals not included in Welfare Quality®, including horses, donkeys, turkeys, sheep, and goats [8]. However, there are several practical problems in implementing these protocols, preventing them from having the greatest influence on farm animals' quality of life [9–11]. However, the advancements made in precision livestock farming (PLF) during the past 20 years, with strong cooperation between engineering and livestock sector experts, have led to a considerable change in how animal welfare is assessed. PLF has developed rapidly in recent years, and animal welfare can be objectively assessed in real-time using a wide variety of indicators [12]. This analysis of welfare indicators is already achievable, and it is anticipated to make significant advancements for cattle production in the near future. Applying the most recent advancements in information, communication, and sensor technologies will be necessary to achieve this [13]. Through data from image, sound, and movement sensors coupled with algorithms, it is possible to monitor the welfare of cows, their production, and management techniques [14, 15]. At the moment, there is strong evidence pointing to the feasibility of automatically monitoring and evaluating welfare with outputs that can be included into welfare protocols [12, 16, 17]. Furthermore, a suitable data presentation is required so that farmers embrace and use the technology in PLF solutions effectively [18]. This chapter will examine PLF current work in assessing lameness, mastitis, and body condition, all of which are considered welfare indicators for dairy cows. This chapter also aimed to identify future opportunities for PLF solutions, such as automatically incorporating animal-based indicators into a dairy farm welfare framework, enabling for the establishment of superior welfare for the animals and value for the farmer.

2. Welfare of dairy cows and precision livestock farming

There are presently three methods for evaluating the welfare of dairy cattle, farmers ensuring responsible management in USA [19], the code in New Zealand [20], and welfare quality in Europe [21]. The latter approach has received significant criticism in a number of studies [22–24], which offered a number of recommendations for lowering the number of assessed parameters to get around the time-consuming observations, which is a limitation that prevents its normal deployment in dairy farms. Along with limiting the assessment processes, the scoring methodology was also altered and made more flexible so that measures may be modified or added as considered appropriate [23]. According to Krueger et al. [25], another welfare evaluation system under development is the integrated diagnostic welfare system (IDWS). Because it uses technology to assist farms in evaluating animal welfare and identifying any reasons of poor welfare, this method may alleviate some of the problems of the other three systems. However, a significant quantity of data and records are required to document animal behaviour, health, and welfare conditions; and the use of sensors and technology can assist in this situation (**Figure 1**) [26]. According to Knight [27], study on dairy cattle sensors has been very dynamic for detecting lameness, mastitis, and body condition, which will be the target of this work. Moreover, sensors are being used for a wide range of different purposes, including fertility (e.g., oestrus cycle and parturition), nutrition, health, and general management of dairy animals. As a result, the primary monitoring systems in dairy farms give complete information in several areas and demonstrate their appropriateness and practicality for dairy farm implementation [26].

Figure 1.
Collars in dairy cows provide relevant data, save time, and give proper needed information.

2.1 Lameness

After mastitis and reproductive problems, lameness is the third leading cause of economic losses on dairy farms. Mastitis, metabolic problems, and decreased fertility are more common in lame cows [28]. Lameness in dairy cows can vary significantly in incidence and can appear weeks or even months after a metabolic disorder, making it difficult to determine the cause of the lameness [29]. Lameness is typically diagnosed at an advanced stage of the disease, when it is most seriously and expensively treated. An animal in such conditions may require several weeks to recover, costing dairy farmers a lot of time and money in the form of calls to the veterinarian, medication, and therapeutic interventions [30]. The dairy farmer's time constraints are one element that contributes to the under-detection of lameness issues. Therefore, behaviour of the cows must thus be recorded using flexible and reasonably priced sensor-based devices in order to detect the beginning of lameness [31]. Treatment and prevention are important parts of lameness management. Improvements in walking surfaces, diet, and genetics are only a few of the factors that are connected to lameness and may be managed through prevention. The farmer must first identify a cow as lame before treating it. There are typically three ways that this occurs. The first is performing a systematic evaluation of the herd using a locomotion scoring system [32]. The second is regular trimming of the hoofs. Legs are lifted here to be examined and, if necessary, treated [33]. The third and most typical method is casual observation while performing other operations, including herding. Unfortunately, mild and even moderate lameness cannot be detected through ad hoc detection. Automated lameness identification has the potential to fill in information gaps regarding the cow and herd, for cows that are mildly to moderately lame. The period from the onset of lameness to treatment might be shortened with earlier detection and automated drafting, avoiding instances from becoming severe, hastening recovery, boosting productivity, and enhancing welfare [34]. In addition, lame cows tend to spend less time eating, with shorter bouts, and eat less during the day [35, 36]. Depending on the technology, the expenses of automated lameness identification may be too expensive. However, in order to improve the sensor detection performance and further improve the system for various physiological states like oestrus, illness, calving, or body condition score (BCS), it is required to go forward with the downscaling of the present systems [37]. A single accelerometer per cow is a particularly cost-effective technique, but there are still a number of barriers to overcome before this technology is widely used on farms. Schlageter-Tello et al. [38] state that most automated locomotion scoring devices measure and analyse cows' movement and behaviour parameters using sensors and mathematical algorithms in an attempt to mimic human observers. The employed technologies can be divided into three categories: kinetic (ground reaction force systems, force-scale weighing platforms, and kinetic variations of accelerometers); kinematic (pressure plate/load cell solutions, image processing techniques, and activity-based techniques); and indirect methods, which primarily include behaviour technologies and individual cow milk production measuring technologies. **Table 1** summarises scientific efforts for detecting lameness in dairy cows using kinematic and kinetic techniques.

2.2 Mastitis

Mastitis is one of the most important disease affecting dairy cows. It leads to pain in contaminated animals and has been shown to be harmful to their welfare and the profitability of dairy farms on a worldwide scale [54, 55]. Since the adoption of robotic milking systems (**Figure 2**), dairy farmers have been concerned with developing adequate mastitis control strategies in their herds. The creation and application of control strategies that includes pre and post-milking teat immersion, proper milking practices, and the limited use of antibiotics in drying only in affected cows has led in a considerable drop in infectious microorganisms. However, when mastitis pathogens occurred, researchers tried to limit the use of antimicrobial drugs while protecting animal welfare and adhering to uniform standards for unnecessary usage. Thus, despite significant improvements in mastitis management over the previous decade, mastitis will continue to be a major focus of future studies [56].

Cost - effective monitoring of mastitis by automated technologies gives an ideal chance to carry out early therapeutic interventions and reduce antibiotic misuse, so boosting cow health and welfare, reducing discomfort and pain, improving recovery rates, and enhancing farm economic sustainability [57, 58]. Effective diagnostic techniques can speed up and improve the management of mastitis and encourage the proper use of antimicrobials [59]. It is also important to be able to properly evaluate the severity of clinical mastitis in terms of addressing treatment success [60] and adopt treatment safety protocols as needed.

2.3 Somatic cell count (SCC)

Health management is necessary for sustaining economical and sustainable dairy farming. The most common udder health indicator for dairy cows is somatic cell

Approach	LS	n	Locomotion test layout	SE (%)	SP (%)	Accuracy (%)	Reference
Kinematic							
Gaitwise	1–3	159	Alley 4.88 m long and 0.61 m wide	76–90	86–100		[39]
Gaitwise	1–3	40	Active surface of 4.88 m long and 0.61 m wide.				[40]
Gaitwise	1–3	36	Active surface of 4.88 m long and 0.61 m wide	88	87		[41]
Kinetic							
3D Accelerometer	1–5	12 + 36	13 m long and 1.3 m wide passageway			>60	[42]
Ground force reaction	1–5	610	Stepmetrix system	35	85	—	[43]
Ground force reaction	1–5	83	Two parallel force plates	90	93	AUC = 0.98	[44]
Ground force reaction	1–5	105	Four-force plate-balanced system	50–100	91–100	—	[45]
Ground force reaction	1–5	261	Two parallel force plates cow walks over	100	100	AUC = 0.70–0.99	[46]
Ground force reaction	1–5	346	Two parallel force plates cow walks over	52	89		[47]
Ground force reaction		6	Two parallel floor-plates loading platform–126 × 122 × 18 cm	91–97			[48]
Load cells and platform	1–5	57	Four force plates cow stands on			AUC = 0.64–0.83	[49]
Load cells and platform	1–5	57	Four force plates cow stands on			AUC = 0.67	[50]
Load cells and platform	0–13	42	Platform with 4 independent sealed load cells	75–97	60–90	AUC = 0.84–0.87	[36]
Load cells and platform	1–5	73	Four force plates cow stands on	100	58	86–96	[51]
Motion sensor		10	Motion sensor attached hind left limb	74.2	91.6	91.1	[52]
Motion sensor		65	Dairy cow individual sensor			AUC = 0.71	[53]

LS, locomotion score; n, number of cows; SE, sensitivity = True Positive/(True Positive+False Negative) × 100; SP, Specificity = True Negative/(True Negative + False Positive) × 100; AUC, area under the curve.

Table 1.
Summary of research findings for detecting lameness in dairy cows using kinematic and kinetic techniques.

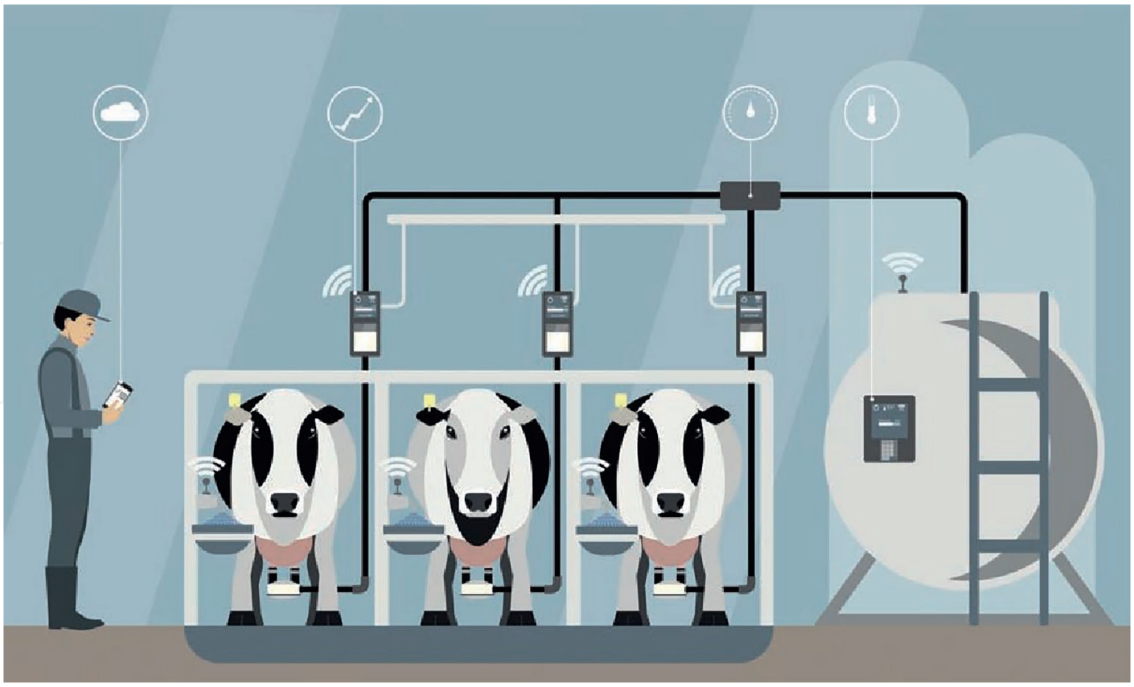

Figure 2.
A schematic of a robotic milking facility in which dairy cows can decide the time and frequency of milking.

count (SCC), which is tested at the quarter, cow, and bulk tank levels. In automatic milking systems (AMS), completely automatic online analysis devices are available to monitor SCC at the farm during each milking [61]. Moreover, from the results of the online SCC, a number of additional cows and quarter level factors important for udder health are recorded in these systems [62]. The SCC may be used to monitor intramammary infection to some extent, and the industry has progressed toward inventing novel sensors that are specifically developed for udder health monitoring. This provides a considerable increase in the quantity of data available for udder health management, for example, which may also use as phenotypes for breeding programmes. In addition to SCC measurements taken on a regular basis, a number of additional cow level and quarterly parameters judged important for udder health are recorded in the AMS at each milking [63].

2.4 Infrared thermography

Infrared thermography (IRT) is a non-invasive method that permits reliable temperature assessment from a distance and has several applications in animal science [64, 65]. Early mastitis detection in dairy production has been achieved with the use of IRT. Despite its demonstrated ability to diagnose mastitis, manual animal analysis has limits because it is time-consuming and needed a trained examiner [66]. In order to discriminate between cows with normal and increased SCC, Zaninelli et al. [67] applied software that detected the udder thermogram pixel with the highest temperature. When compared to the current gold standard of manual evaluation, the findings of automatic analysis of the thermograms of bovine udders that had suffered intramammary *E. coli* exposure indicated encouraging signs of clinical mastitis. We assume that the high temperatures seen with manual analysis occurred because warmer areas, including the udder-thigh cleft, were included, whereas these regions are omitted by automatic segmentation [68]. This technique may also be used to identify changes in internal body temperature, such as fever. However, infrared thermography should not take the place of an individual animal examination and is only intended to be used as a tool for automated health surveillance [69].

2.5 Body condition scoring

Body condition is an important factor for herd management and welfare. The dairy cow's body condition is highly correlated with their health, metabolic activity, and the composition of the milk during lactation [70]. Assessment of body condition is an indirect measure of the level of body reserves, and deviations from show the overall variation in the energy balance [71, 72]. Regular measures of body condition are based on visual observation and palpation of particular body parts to provide a score that evaluates the adipose tissue and muscle mass deposits [73]. This evaluation method, commonly referred to as the body condition score (BCS), has captured attention as a useful technique for managing dairy herds [74].

BCS observations can be done by visually or using a combination of visual signs with bone structure palpation, and the amount of subcutaneous fat. The backbone, pins, tail head, long ribs, short ribs, hips, and rump are the key segments for BCS assessment [75]. Different scoring scales have been developed all around the world throughout the years. In the United States, for example, a five-point scale method was mostly used, proposed by Windman et al. [76]. Ferguson et al. [77] suggested a scale of 0 to 5, subdivided into 0.25 centesimal intervals, to measure body condition, namely the adipose tissue of the cow's lumbar and pelvic parts. Despite widespread agreement among dairy farmers, nutritionists, and herd management regarding the benefits of BCS assessment, various reasons restrict its adoption [78], subjectivity in judgement can result in different scores for the same cow, and on-farm technician training is difficult and time-consuming [79]. Furthermore, in order to obtain useful data, cow measurements must be recorded every 30 days across the lactation period [80], increasing the extra cost and difficulty of obtaining BCS data. To address these limitations, different alternatives solutions have been developed within the approach of the PLF, with extremely promising outcomes. The most innovative options use image capture and recording as vision-based body condition score systems, which resemble traditional BCS assessments in some ways. Ultrasound is another imaging technique that has been used to determine body and carcass composition [81]. This approach is commonly used to monitor body condition in small ruminants [82, 83], swine [84], and cattle [85]. Recent studies [86, 87] demonstrated the utility of applying ultrasound to examine the body reserves of cows by scanning the body areas associated with the BCS assessment, such as the ribs, pin, tail-head, and lumbar spine. Despite its excellent accuracy for BCS prediction, the cows must be individually confined to obtain the ultrasound pictures, making this technology less ideal for evaluating large numbers of animals over time. Therefore, larger farms with hundreds of animals should not use this method. In order to achieve a BCS evaluation of animals in motion, the ultrasonic technique is only used for timely analyses or the validation of other approaches, such as those supported by cameras [88, 89].

2.5.1 Vision-based body condition scoring systems

Currently, many vision-based BSC monitoring systems, including thermal imaging [90], 2D imaging [91], and 3D imaging technology [92, 93], have been developed and tested. With examples like Fourier transformation [94] and machine learning

Sensor	N	Sensor position	Accuracy	Accuracy within BCS points deviation (%)			Reference
				0	0.25	0.5	
2D Sensors							
Black-and-white	2571	60 to 70 cm above the cows' backs			93	100	[97]
AXIS 213 PTZ	286	3 m above ground	Error = 0.31				[78]
Sony, DCR-TRV460	46	3 m above ground	R2 = 90				[98]
Hikvision DS-2CD3T56DWD-I	8972	2.6 m the ground. Milking passage	R2 = 98.5				[75]
Hikvision DS-2CD3T56DWD-I	2231	Cows walk below the camera			65	95	[97]
3D Sensors							
Mesa 3D ToF	40	Hand-held setup			79	100	[99]
SR4K time-of-flight	540	Above electronic feeding dispenser	R2 = 89				[100]
ToF MESA SR4000	1329	Above DeLaval AWS 100	R = 84				[101]
Asus Xtion Pro	82	2 m above ground	R = 96				[102]
PrimeSense™ Carmine	116	1.5 m from the cows' backs			71	94	[103]
Microsoft Kinect v2	1661	2.8 m above ground-milk parlour		40	78	94	[65]
Intel RealSense D435	480	3.2 m above ground			77	98	[100]
Microsoft Kinect v2	38	3 m above the ground		56	76	94	[93]
3D ToF	52	3.4 m above ground-rotary parlour	MAPE = 3.9				[101]

n, number of cows; ToF, time of flight; BCS, body condition score; R, correlation coefficient; R2, coefficient of determination; MAPE, mean absolute percentage error.

Table 2.
Summary of study measuring cow body condition score with 2D and 3D sensors.

[95], data analysis techniques have been used to track the development of sensors, which boost the capability of working systems. There are still limitations to completely automated systems, despite the advancements that have previously been made. However, with the advancement of cameras and software, we are getting closer to an automated and objective BCS. The guesswork and errors associated with conventional scoring are eliminated by vision-based approaches, while the efficiency may be significantly increased. These factors clearly act as the foundation for developing machinery that producers consider to be effective [96]. The study on measuring cow body condition score using 2D and 3D sensors is summarised in **Table 2**.

The Welfare Quality standards now incorporate BCS as an animal-based indicator connected to livestock feed [102]. Similarly to what is currently being done with other species (e.g., Eye Namic for Poultry and Swine [17]), by continuously monitoring health and welfare in real time, PLF technologies have shown to be a step forward in the individual assessment of cows [14, 103].

3. The potential of PLF for assessing welfare animal-based indicators of dairy cattle

Because welfare is a complicated multi-dimensional phenomena, assessing the welfare of dairy cows and other farm animal species usually involves time-consuming and costly audits [102]. On the other hand, with recent advances in sensor technology, the sole purpose of PLF, which is continuous real-time on-farm monitoring of individual animals to enhance production/breeding, health and welfare, and environmental sustainability, is already being approached in different aspects of dairy cattle production [103]. As with the Welfare Quality® protocol, the implementation of dairy cow welfare evaluation has considerable constraints, as it is time-consuming [23] and lacks interaction with trained users on the value of various welfare criteria [104]. In addition to shortening the evaluation period, many researchers proposed changes to the calculations, such as the one described by Van Eerdenburg et al. [22] for drinking water. Furthermore, the welfare calculations required more adjustable techniques, mainly for the total score [23, 104]. As a result, the ability to use PLF solutions to assess the animal-based indicators of lameness, mastitis, and body condition presented in this review could well be much appreciated. Because of the recent development and validation of different PLF solutions, as shown by the discussed advances, it is now possible to address the three animal-based indicators listed by commercial PLF technologies. In addition, a recent review [13] noted that in order to properly use the continuous measurement and individual monitoring of cows, some of the protocol criteria would need to be modified. This modification can rely on animal-based welfare measures, such as those examined in this paper and others, as explained by Tuyttens et al. [23], who reviewed the Welfare Quality Protocol and discovered a more user-friendly, time-efficient approach in assessing dairy cattle welfare with the inclusion of only six animal-based indicators. Various farm animal welfare frameworks, such the five domains model [101], will also have room. Researchers studying farm animal welfare are becoming more interested in the five domains model, and they are also discussing about the possibility of using the PLF with this model. With the advancement of PLF technologies, it is now unquestionably possible to monitor cow welfare in real time with the use of animal-based indicators. Therefore, based on recent scientific research and technological advancements (e.g., Stygar et al. [14]), significant PLF developments are assumed to occur soon, opening the window of opportunity for monitoring and improving the welfare of dairy cows.

4. Challenges for the future

Precision livestock farming is recognised as key for future dairy producers since it allows for regular monitoring of animal health and welfare during production. The advancement of applying technology for monitoring lameness, mastitis, and body condition in dairy cows is highlighted in this chapter. Accurate continuous monitoring systems that eliminate false alarms are required for farmers to accept and implement these technologies for these challenges, which have been identified as animal-based indicators. Therefore, a detailed early warning system is required to monitor the health of dairy cows in order to prevent the development of more serious diseases and welfare issues. Finally, research into dairy cow welfare technologies has provided various indications that might be automatically monitored and integrated into an evaluation framework.

5. Conclusion

Farm animal welfare is an increasing problem all over the world. There is a considerable need in milk production to analyses the welfare of dairy cows. The Welfare Quality project's procedures have been used in one of the most sound assessment initiatives. These methods primarily assist in the examination of cow welfare using animal-based indicators. However, analysing these indications takes time and money, thus adopting precision livestock farming (PLF) technologies is a viable option that is becoming a reality in the dairy sector. This chapter discusses advancements in PLF solutions, generally in the previous 5 years, along with animal-based indicators of lameness, mastitis, and body condition in dairy cattle farming.

Conflicts of interest

The authors disclose that they have no conflicting interests.

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