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Invited review: Cattle lameness detection with accelerometers

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ABSTRACT

Locomotion scoring is time consuming and is not commonly completed on farms. Farmers also underestimate their herds' lameness prevalence, a knowledge gap that impedes lameness management. Automation of lameness detection could address this knowledge gap and facilitate improved lameness management. The literature pertinent to adding lameness detection to accelerometers is reviewed in this paper. Options for lameness detection systems are examined including the choice of sensor, raw data collected, variables extracted, and statistical classification methods used. Two categories of variables derived from accelerometer-based systems are examined. These categories are behavior measures such as lying and measures of gait. For example, one measure of gait is the time a leg is swinging during a gait cycle. Some behavior-focused studies have reported accuracy levels of greater than 80%. Cow gait measures have been investigated to a lesser extent than behavior. However, classification accuracies as high as 91% using gait measures have been reported with hardware likely to be practical for commercial farms. The need for even higher accuracy and potential barriers to adoption are discussed. Significant progress is still required to realize a system with sufficient specificity and sensitivity. Lameness detection systems using 1 accelerometer per cow and a resolution lower than 100 Hz with gait measurement functions are suggested to balance cost and data requirements. However, gait measurement using accelerometers is rather underdeveloped. Therefore, a high priority should be given to the development of novel gait measures and testing their ability to differentiate lame from nonlame cows.

Key words: accelerometer, lameness, welfare, automated

INTRODUCTION

The debilitating effects, associated pain, and endemic prevalence make lameness a major welfare issue on dairy farms (Dolecheck and Bewley, 2018; Alsaaod et al., 2019c). Lameness, or abnormal gait, is a response to pain caused by a range of pathologies (O'Callaghan, 2002; Van Nuffel et al., 2015b; Alsaaod et al., 2019b). Lameness management consists of both prevention and treatment. Prevention is managing factors associated with lameness such as improving walking surfaces, nutrition, and genetics. For a lame cow to be treated, it must first be identified as lame by the farmer. This generally occurs in 3 ways. The first is using a locomotion scoring system to assess a herd systematically (Schlageter-Tello et al., 2014; Van Nuffel et al., 2015b). The second is routine hoof trimming. Here, legs are lifted, inspected, and if required, treated (Adams et al., 2017; Dolecheck and Bewley, 2018). The third, and most common, is ad hoc observation during other activities such as herding.

Some recommendations indicate herds should be locomotion scored at least monthly (Horseman et al., 2014). However, the regularity of locomotion scoring or routine hoof trimming is usually much rarer with some farms never performing either (Adams et al., 2017; Dolecheck and Bewley, 2018). Contrary to the expert consensus, many farmers are satisfied with ad hoc detection (Horseman et al., 2014). Ad hoc detection is ineffective at detecting mild and even moderate lameness. Farmers thus appear to be only cognizant of severe cases detected by ad hoc observation (Leach et al., 2010; Fabian et al., 2014; Sadiq et al., 2019). Ad hoc approaches also do not provide herd statistics which may be generated as part of routine hoof trimming and locomotion scoring. Measurement is often required to inform management with idioms such as "you can't manage what you don't measure" appearing pertinent in this case.

Automated lameness detection could provide useful cow and herd level information addressing an information gap, particularly regarding mild and moderately lame cows. Earlier detection and automatic drafting

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could reduce the time from onset to treatment preventing cases becoming severe, speeding up recovery, increasing production, and improving welfare (Leach et al., 2012; Groenevelt et al., 2014). Monitoring recovery after treatment (returning to normal locomotion) would also be facilitated. With these herd level statistics, the value of prevention and treatment would also then become more tangible to farmers, potentially providing motivation for increased efforts to reduce lameness (Horseman et al., 2014). By systematically recording lameness, breeding for lameness resilience could also be supported (Heringstad et al., 2018; Croué et al., 2019; Sánchez-Molano et al., 2019).

The estimated cost of lameness varies significantly between studies and pathology. On the higher end, a sole ulcer case has been estimated to cost USD $960 (Dolecheck and Bewley, 2018). On the lower end, a case of foot rot has been estimated to cost as low as USD $136 (Dolecheck and Bewley, 2018). Despite the benefits of detection and the significant costs of lameness, the returns from automated lameness detection may still be marginal (Van De Gucht et al., 2017a,c). This is because failure to detect is only part of why lameness causes economic losses. Though the benefits of prompt treatment are well documented (Leach et al., 2012; Thomas et al., 2016), some farmers perceive the treatment of moderately lame cows to be nonurgent (Horseman et al., 2014). Even after a cow has been identified as lame, it may be several weeks until treatment (Alawneh et al., 2012; Leach et al., 2012). Inadequate facilities, lack of skills, and time make treatment challenging on many farms (Horseman et al., 2014; Dutton-Regester et al., 2019). On farms with inadequate facilities, automated detection's value is curtailed as it does not necessarily make treatment easier, cheaper, or more effective. The economic viability of lameness detection technology thus depends not just on low cost and high accuracy, but also a farmers facilities, tools, expertise, and willingness to promptly treat cows identified as lame (Van De Gucht et al., 2017a,c).

Several review papers have documented the progress toward such a system (Schlageter-Tello et al., 2014; Van Nuffel et al., 2015c; Alsaaod et al., 2019c). These reviews have been broad in scope assessing a wide range of potential technologies such as load cells, pressure-sensitive mats, computer vision techniques, and accelerometers. A major consideration in creating an automated lameness detection tool is choosing a type of sensor system to focus on. Two studies (Van De Gucht et al., 2017a,c) reported that farmers preferred cow-attached sensors such as accelerometers. Accelerometers are also already relatively widely used for heat detection purposes (Mottram, 2016). For these reasons, complementing and differing from previous reviews, we focus specifically on accelerometers. Furthermore, this review informs the design choices involved in developing accelerometer-based lameness detection systems. In particular, the variables most likely to be useful are examined. The choice of an accelerometer(s), how data has been aggregated, and which classifiers have been used are also discussed. The findings are organized in a systematic manner to be useful as a reference.

Figure 1 illustrates a generic lameness detection system from raw data to lameness alert, including potential variables and lameness classifiers. Many options are available for creating such a system and the most common in the literature are included. In this example, a variety of variables form the input for 3 potential classifiers and 3 forms of output a farmer might receive are included.

After the methodology, the findings of this review are presented in 4 parts. First, to aid the interpretation of subsequent sections, how lameness detection performance is compared and assessed is discussed. Second, variables indicative of lameness are presented. Third, data aggregation approaches and statistical methods of classification are summarized. Fourth, the commercial farm application potential of several accelerometer system configurations are discussed.

METHODOLOGY

The key words lameness, automated, lameness classification, locomotion scoring, accelerometer, dairy, and cattle in various combinations were entered into Google Scholar (https://scholar.google.com/) and Web of Knowledge (http://wokinfo.com/). The final search occurred in November 2019. References within papers were also examined in a snowball technique to find additional relevant papers. The inclusion criteria were (1) cattle were the studied animal, (2) accelerometer-derived data were used, and (3) assessment of lameness/locomotion was reported or summary data about differences associated with lameness were reported. The papers were reviewed to identify several attributes. These included measures indicative of lameness, the statistical classification method, and the reported accuracy.

FINDINGS

Assessing Lameness Detection Performance

The degree a model's variables are indicative of lameness underpin the efficacy of lameness detection systems, and so are a major focus of this review. It is discussed here at the start of the findings to inform subsequent sections. To assess a variable or model's performance at identifying lame cows, appropriate statistical analysis should be performed and reported. The specific analysis reported has varied in the literature. The most common measures reported are receiver operator characteristic curve, area under the curve (Kamphuis et al., 2013; Alsaaod et al., 2017), confusion matrices (Martiskainen et al., 2009; Van Hertem et al., 2013), and specificity, sensitivity, positive predictive value, and accuracy (de Mol et al., 2013; Van Hertem et al., 2013).

Receiver operator characteristic curve and area under the curve are graphical ways of assessing binary classifiers. These are generally used for model assessment and model comparison. For binary classification, confusion matrices present the proportion of accurately and inaccurately detected cases for both actual positives and actual negatives against the prediction in a 2 × 2 grid. This illustrates the relative numbers of true positives, true negatives, false positives, and false negatives. Ratios of these values have names such as specificity (true negative rate), sensitivity (true positive rate), positive predictive value (precision), and accuracy (percentage

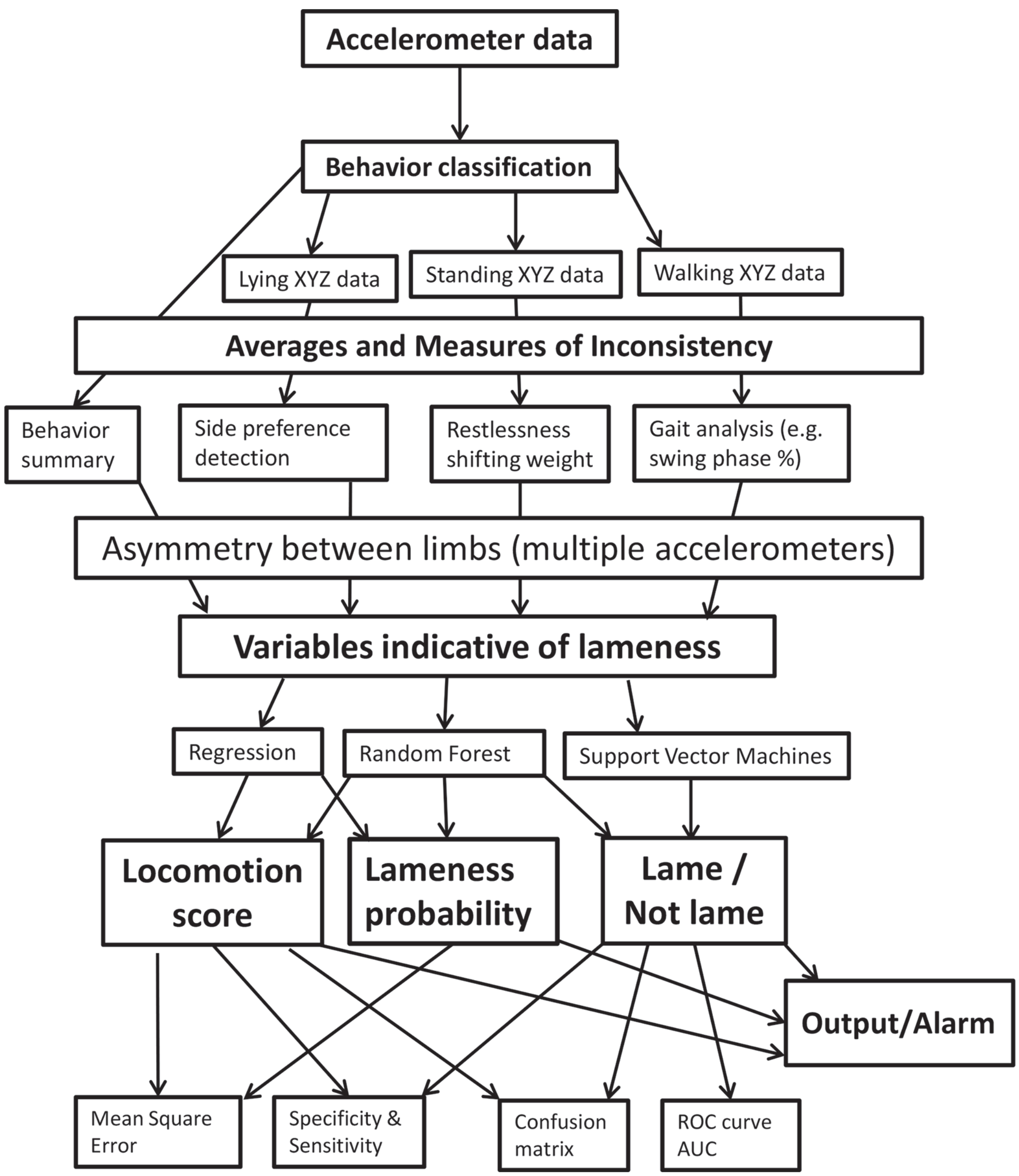

Figure 1. A schematic diagram of how lameness classification could be implemented using accelerometers. This figure is intended to be illustrative of a potential system. Other system configurations are discussed in the text. ROC = receiver operating characteristic; AUC = area under the curve.

correct). Within the context of lameness detection, specificity refers to the percentage of truly nonlame animals that are identified as nonlame. Conversely, sensitivity is the percentage of truly lame animals that are identified as lame. Positive predictive value is the probability an animal identified as lame is truly lame.

The importance of these ratios depends on the costs of the outcomes and the typical ratio of actual positives and actual negatives. Lame cows are usually a small minority in a herd creating an imbalance. A system that classifies most cows as nonlame regardless of lameness status, might be considered accurate, as most classifications would be correct. For this reason, accuracy or the percentage of correct classifications is of limited value. A consensus on the most appropriate performance statistics would facilitate comparisons between studies. We suggest specificity, sensitivity, and positive predictive value are the most informative in the context of automated lameness detection.

Variables Indicative of Lameness

In this section, the foundations of a lameness detection system, the variables that differentiate lame and nonlame cows are summarized. We categorize these variables into 2 broad categories: behavior and gait measures. We further categorize these variables into 3 statistical types. The first is standalone summary measures, typically averages but also including measures such as minimums and maximums (e.g., lying time per day). The second statistical type is measures of variance as measured on one limb (e.g., acceleration standard deviation). If a variable in this second category is to be useful, then lame cows would be less (or more) consistent on a measure than nonlame cows. The third statistical type is measures of gait asymmetry using 2 or more accelerometers per cow. Here, differences between limbs distinguish lame from nonlame cows.

Lying and Eating Behavior Measured by Accelerometers. Lying behavior has been the most studied measure in relation to lameness detection (Tables 1, 2, and 3). Lame cows tend to lay for longer and generally have fewer but longer lying bouts (Tables 1, 2, and 3). Table 1 details the literature where lying time, activity, and eating at specific times of the day (diurnal analysis) were investigated in relation to lameness. There are some indications that the increased lying time is more pronounced during the day for lame cows (Van Hertem et al., 2013), but most of the reported temporal differences relate to eating. Lame cows tend to spend less time eating (Grimm et al., 2019), with shorter bouts (Nechanitzky et al., 2016), and eat less during the day (Barker et al., 2018). Reacting slower when feed is delivered has also been reported (Blackie et al., 2011; Yunta et al., 2012; Weigele et al., 2018). However, only moderately accurate models have been reported using such temporal patterns with sensitivity and specificity results tending not to exceed 90% (Table 1).

Most of the reviewed studies have been from indoor herds milked in a conventional milking system (Tables 1, 3, and 4). Table 2 summarizes the studies from automatic-milking-systems and grazing-based systems. The findings relating to lying time using automatic milking machines are broadly consistent with conventional systems. However, grazing-based systems tend to differ to an extent. Thompson et al. (2019) indicated that precipitation and parity need to be controlled for if lying time is to be indicative of lameness when cows are grazing. Other variables correlated with lying time include parity, milk yield, DIM, grazing or zero-grazing, lying surface, standing surface, and type of lameness (Tables 1, 2, and 3). These are likely to confound lameness detection based on lying time measures.

However, in some studies, lying variables have been reported to not differ to a statistically significant extent. For example, daily lying time was only marginally different between lame and nonlame cows in 3 studies (Chapinal et al., 2011; Charlton et al., 2016; Blackie and Maclaurin, 2019). Longer lying bouts by lame cows have generally been reported (King et al., 2017; Schindhelm et al., 2017; Weigele et al., 2018), whereas one study with Jerseys reported shorter bouts (Blackie and Maclaurin, 2019). Westin et al. (2016) concluded that only a small proportion of variation in lying time could be explained by lameness. In aggregate, measures of lying time are not reliable indicators of lameness, in part because lying time is influenced by many factors other than lameness. For these reasons, further research focusing on measures of lying time alone for the purposes of supporting automated lameness detection is unlikely to be successful.

Other Behaviors Measured by Accelerometers. The most prominent behaviors other than lying time associated with lameness are activity, rumination, and eating. Rumination appears to be less indicative of lameness than activity (Van Hertem et al., 2013), and rumination and feeding are generally measured with neck-worn accelerometers. The most accurate systems reviewed have been leg worn. Eating and rumination are thus unlikely to contribute to lameness detection systems.

Activity has been operationalized in several ways. Gross acceleration measures from neck worn accelerometers have been labeled as activity (Van Hertem et al., 2013; Weigele et al., 2018). Similar leg-derived measures have been called motion index (Thorup et

Table 1. Studies reporting variation in lying time, activity, and eating within the day were indicative of lameness using accelerometers

Reference	Variables associated with lameness	Other variables	Sample and context	Timeframe	Statistical approach	Performance
Barker et al. (2018)	Lame cows spent less time eating, less likely to eat during the day	N/A[1]	10 nonlame and 10 lame cows	5 d	Wilcox rank-sum test, decision tree	N/A
Blackie et al. (2011)	Lame cows were slower to feed, stood more at night	Milk yield	59 cows on 1 UK farm	4 d, once a month for 3 mo	ANOVA	N/A
Blackie and Maclaurin (2019)	Lame cows had shorter lying bouts; total lying time did not differ	Yield did not differ	35 zero grazing Jerseys	5 d	1-way ANOVA	N/A
Garcia et al. (2014)	Activity in the morning, variation throughout the day	Parity, yield	150 Holstein, Danish Red and crosses	Two 5-wk periods, hourly data analyzed	Partial least square discriminant analysis	80% sensitivity and specificity
King et al. (2017)	Longer lying time and bout duration; higher night to day ratio for neck motion	Fetching, stocking density	41 AMS[2] farms, 30 cows each	6 d	Logistic regression	N/A
Nechanitzky et al. (2016)	More lying, less standing over 12 h at night; bouts are similar	N/A	10 nonlame and 32 lame Holsteins	Scored 3 d in a row; mean used	*t*-Test between lame and sound cows	Area under the curve = 0.71
Schindhelm et al. (2017)	Lying time ratio (day/night); lying bouts and duration longer	Feeding time, milk yield	60 Simmental cows on AMS system	1 yr	Regularized elastic net regression	Area under the curve = 0.84, specificity = 0.8, sensitivity = 1
Weigele et al. (2018)	Longer lying time and longer bout duration, preferred lying side	Neck activity, feed push-up time	17 farms, nonlame and 66 lame cows	Two 48-h windows	Generalized mixed-effects models	Summary values
Yunta et al. (2012)	Lame cows rose 13 min later after feeding, and lay down 19 min earlier after	DIM, feeding	10 farms, 10 to 15 cows each farm	10 d	Mixed-effects model	NS
Van Hertem et al. (2013)	Night/day activity ratio rumination at night associated with lameness	Milk yield preceding 10 d	118 Holsteins (44 lame)	±3 wk from diagnosis	Logistic regression, cross validation, confusion matrix	Sensitivity 77%, specificity 84%

[1]N/A = not applicable.
[2]AMS = automated milking machine.

Table 2. Studies regarding lying/standing time when grazing or in automatic milking systems[1]

Reference	Variables associated with lameness	Other variables	Sample and context	Timeframe	Statistical approach	Performance
Byabazaire et al. (2019)	Cows classified as dormant, normal, or active using lying time; prediction reported for normal group only	Step and swap counts	146 grazing cows, 32 lameness cases in 6 mo	Daily classification based on hourly summaries	K nearest neighbors, random forest	87% accuracy for lame/nonlame 3 d before scoring
de Mol et al. (2013)	Lying bouts and time, 7 variables; if 2/7 trends were consistent with lameness, alert issued	Yield and concentrate leftovers	100 Holstein cows, automatic milking system	23 mo of data; daily models	Cow specific quadratic trend model; training and test sets	80% sensitivity, 89% specificity
Navarro et al. (2013)	Pasture or housing did not affect lying; housed cows had more lying bouts	Yield, parity, type of lameness	400 cows, 20 farms; half grazing, half zero grazed	3 d	Mixed effect model	N/A[2]
Sepúlveda-Varas et al. (2014)	Multiparous cows lay for 1.7 h more if lame; lame cows had fewer lying bouts	Parity	274 grazing cows	21 d starting at calving	Mixed models with repeated measures	N/A
Thompson et al. (2019)	Lying time indicative of lameness; rain reduces lying time, especially for lame cows	Rain, parity	252 grazing cows from 6 farms for 4 wk	Scored 4 times in a month	Linear mixed-effects models	Lame (>2) or nonlame
Westin et al. (2016)	Lame cows lay down for longer (0.6 h/d) in fewer bouts	Parity, BCS, DIM	1,377 cows on automated milking system	4 d of observation	Simple linear regression and linear mixed-effects model	N/A

[1]Automated milking system studies presented in Table 1 (King et al., 2017; Schindhelm et al., 2017; Grimm et al., 2019).
[2]N/A = not applicable.

Table 3. Other behavior-related studies not focusing on gait

Reference	Variables associated with lameness	Other variables	Sample and context	Timeframe	Statistical approach	Performance
Alsaaod et al. (2012)	Activity and lying time changes from baseline more indicative than absolute values	N/A[1]	30 cows, freestall barn	549 labeled days	Support vector machines	75% for within cow changes
Chapinal et al. (2009)	Speed did not differ; lying time longer when cows had ulcers, not dermatitis or hemorrhages	Parity, type of lameness	Experiment 1 (of 2) 53 cows	Cows monitored for 5 d	Mixed and generalized linear models	Cows with ulcers lay for 13.8 h, those with no lesions 12.6 h
Chapinal et al. (2010)	Rear leg weight shifting, lying bouts and walking slower indicative of lameness	N/A	57 multiparous Holstein cows, 28 lame	Observed for 10 d	Mixed model with repeated measures	Area under the curve (AUC) = 0.83
Charlton et al. (2016)	Lying time and lying-bout duration indicative of herd lameness prevalence	N/A	100 tiestall farms, 40 cows each	5–10 d	Canonical discriminant analysis	Lying time per cow not significant
Ito et al. (2010)	Lying time associated with lameness on deep-bed-straw housing, not with mattress stalls	Stall surface (deep-bedded and mattresses)	1,319 cows 28 farms in British Columbia	5-d lying behavior	Logistic regression, receiver operator curve	Reasonable specificity (>89%) but poor sensitivity
Grimm et al. (2019)	Increasing yield plus low lying time associated with lameness; lying time alone not indicative	Parity, milking interval	100 Simmental cows milked by a robot	1 yr, hourly summaries	Stepwise logistic regression. Elastic net regression	Specificity 83%, sensitivity 92%
Kamphuis et al. (2013)	Steps per hour, live weight, and milking order	N/A	4,904 cows, 318 lame, on 5 grazing farms	Change from diagnosis to 14 d prior	Additive logistic regression; decision tree, logit boost	Binary classification of ≥3 AUC = 0.74
Proudfoot et al. (2010)	Cows with lesions in mid lactation stood more during prior transition period	Feeding time	55 Holstein cows	Observed for 9 mo	GLM, logistic regression	AUC = 0.81
Solano et al. (2016)	Longer lying time with fewer, longer bouts	Parity	40 cows, 141 freestall farms	4 d observation	GLMM, logistic regression	Low sensitivity and specificity, maximum 69%
Thomsen et al. (2012)	Lying-bout duration associated with skin lesions (digital dermatitis and so on), not horn lesions (white line and so on)	Parity	1,340 cows in 42 Danish dairy herds	5 d lying behavior	Odds ratio, 95% CI, *P*-values	Summary

[1]N/A = not applicable.

Table 4. Non-behavior-focused studies including gait measurement using accelerometers

Reference	Variables associated with lameness	Sample	Sensors	Statistical approach	Performance
Alsaaod et al. (2017)	Gait measures, the cow pedogram, swing and stance phase, peak acceleration at toe-off and -on	Holstein Friesian, Red Holstein, Swiss Fleckvieh, and Rhaetisches Grauvieh	Two 400-Hz accelerometers per cow	Thresholds for differences between legs	Perfect accuracy using thresholds for several variables such as stance phase and swing phase (%)
Alsaaod et al. (2019b)	Cows treated with pain relief medication had reduced differences in the "relative duration of stance phase" between legs.	41 cattle with unilateral limb pathologies; 5 males, 35 females, 7 breeds	Two 400-Hz accelerometers per cow	Logistic regression	Not applicable
Beer et al. (2016)	Standing bouts (behavior) and walking speed (gait), stride distance (gait)	61 German Holsteins	Mean of 2 daily summaries	Logistic regression	Sensitivity 90.2%, specificity 91.7%
Chapinal et al. (2011)	Five pedometers, variance between legs indicative	12 (on concrete) and 24 (concrete and rubber) lactating Holsteins	5 accelerometers per cow at 33.3 Hz	Correlation and mixed models	Summary values; Pearson's r = 0.71 for front leg asymmetry
Haladjian et al. (2018)	Placed a block on nonlame cows and compared with and without block; peak acceleration and stride duration	10 German Holstein/ Fleckvieh and crosses of both	100 Hz	Butterworth low-pass filter, support vector machine	Per step classification 91.1% accuracy
Mangweth et al. (2012)	X, Y, Z average root mean square of acceleration most predictive	16 nonlame, 26 lame cows, 15 cows before and after digit amputation	100 Hz attached on spine near tail	Root mean square, decision tree	Sensitivity 0.94, specificity 0.8
Martiskainen et al. (2009)	Collar-based detections of several behaviors including lame walking behavior	30 Ayrshire and Holstein Friesian cows	10 Hz	Support vector machine	Lame/nonlame, 65% sensitivity/66% specificity
Pastell et al. (2009)	Gait characteristics; total acceleration and variance; forward and vertical axis the most informative, in particular, the period when the foot strikes the ground	12 Ayrshire cows	4 accelerometers (each leg) 25 Hz	Maximal overlap wavelet transformation	Summary values; lame cows walked more carefully with lower variance in measures
Thorup et al. (2015)	Total activity, activity per second while walking, walking duration, step frequency; motion index while standing indicating restlessness	348 Holstein Friesian cows on 4 farms	>30 d of consecutive data	Principal component analysis	Almost classification; could distinguish mildly lame cows

al., 2015), total acceleration (Pastell et al., 2009), or pedogram (Alsaaod et al., 2017). Thorup et al. (2015) reported associations between locomotion score and motion index while walking, walking duration per day, motion index while standing, and variance in lying. Steps per hour alone was reported to be marginally predictive of lameness with an area under the curve of 0.6 by Kamphuis et al. (2013). Byabazaire et al. (2019) reported lying time, step count, and swaps (changes in behavior) as a basis for a detection model with a classification sensitivity of 89.7% and a specificity of 72.5%. Beer et al. (2016) reported greater sensitivity (90.2%) and specificity (91.7%) when using standing bouts and speed, a measure of gait, not behavior. Equivalent performance with behavior measures alone has not been reported.

Behavior measures that could contribute to a lameness detection system include gross measures of acceleration, the ratio of day to night time activity (Pastell et al., 2009; Kamphuis et al., 2013; Thorup et al., 2015; Beer et al., 2016; Grimm et al., 2019), activity while standing (Thorup et al., 2015), standing bouts, total lying time, and lying bouts (de Mol et al., 2013; Beer et al., 2016). However, these results have generally not been replicated with each study reporting unique sets of indicators. Behavior measures do not appear to be reliable indicators of lameness. They are thus likely to be only useful for complementing other indicators of lameness such as measures of gait.

Gait. Gait describes how an individual walks. Painful pathologies of the limbs often result in gait abnormalities (lameness). This is due to cows changing their gait to minimize pain in the affected limb (O'Callaghan, 2002; Gleerup et al., 2015; Alsaaod et al., 2019c). Manual observation of locomotion is based on observing these abnormalities. In a PhD thesis, Jones (2017) reported the results of a survey of 32 lameness experts assessing their views on which abnormalities are most important for locomotion scoring. She reported the relative importance of 6 variables as follows: symmetry (25%), tracking or placing the rear foot on the same spot the corresponding front hoof was (20%), spine curvature (19%), head bobbing (15%), speed (12%), and abduction/adduction (9%). If these variables, which are used for locomotion scoring, can be measured by accelerometers, then they are likely to be indicative of lameness. To inform how abnormal gait might be used to detect lameness, we now describe normal gait.

A gait cycle can be said to begin with a back leg lifting, swinging forward, and striking the floor. The corresponding front leg begins swinging before the back foot has landed. This allows the back foot to land where the front foot was (tracking). The opposite rear leg and opposite front leg follow before the cycle restarts (Flower et al., 2005; Van Hertem et al., 2014; Alsaaod et al., 2017). During this cycle 2 or 3 legs are bearing weight and this is referred to as double or triple support, respectively (Flower et al., 2005; Van Hertem et al., 2014; Alsaaod et al., 2017). While a leg is in motion, the leg is in the swing phase. During normal walking, approximately 36% of a whole step cycle in nonlame cows is step phase with a standard error of the mean of 0.68% (Alsaaod et al., 2017). The remainder is considered the stance phase (support). Here the claw is stationary on the ground and the leg is pivoting forward upon it, propelling the body forward.

Gait Analysis Using Accelerometers. Several studies have reported the characteristics of typical steps as measured by leg-worn accelerometers (Pastell et al., 2009; Alsaaod et al., 2017; Haladjian et al., 2018). Alsaaod et al. (2017) manually delineated stages of the gait cycle by referencing video acquired using a high-speed camera. Haladjian et al. (2018) automated the process by using peak detection to delineate aspects of the gait cycle. This included stride duration and the range of acceleration on several variables resulting in 66 attributes per step. Both studies used relatively high-resolution accelerometers (400 and 100 Hz, respectively, denoting the records per second). In addition to documenting a typical step, these studies also examined measures when the cow's gait was abnormal.

Haladjian et al. (2018) attached a block typically used to treat lameness to the base of a digit, creating abnormal gait. A support vector machine model for each cow had been created using a subset of data from when she was nonlame. Individual steps from normal and block attached walking were then classified by the model as normal or anomalous and reported an accuracy of 91%. A similar approach to simulating lameness has been reported in sheep where one leg was taped in such a way to restrict locomotion (Barwick et al., 2018). However, it has not been tested if these are valid proxies for the abnormal locomotion typically associated with lameness.

Differences in measures between hind legs (asymmetry) have been reported indicative of lameness (Pastell et al., 2009; Alsaaod et al., 2017). These measures included stance phase and pre-swing phase %, total acceleration at toe-off, and foot-load (foot striking the ground) and heel-off. Differences between legs for lame cows for these measures were much higher than nonlame cows and 100% accurate lameness detection was achieved using difference thresholds (Alsaaod et al., 2017). For example, when a 2.53% or greater difference in stance phase between rear legs was recorded, the cow was always lame in that study (Alsaaod et al., 2017).

Beer et al. (2016) reported that lame cows walked slower, with shorter stride lengths than nonlame cows using only data from one 10-Hz accelerometer per cow. A sensitivity of 90.2% and a specificity of 91.7% were reported using both gait and behavior measures. Chapinal et al. (2010) also supported the predictive value of walking speed, but Chapinal et al. (2009, 2011) did not. Given these mixed results, walking speed may be a useful variable and warrants further investigation. Table 4 summarizes the studies that did not look at specific behaviors or focused on measures of gait. As can be seen by comparing Table 4 to Tables 1 to 3, relatively few studies have focused on gait. Furthermore, those studies that have focused on gait have been relatively more successful with regard to lameness detection.

Gait Analysis Using Nonaccelerometer Technologies. Given the relative paucity of accelerometer-based research examining gait, findings from research that measure gait using other technologies may provide useful insights for accelerometer-based research. If these technologies identify a variable as indicative of lameness, then investigating if that can be measured using accelerometers may be of value. Van Nuffel et al. (2015c) reported that stride length (meters) and duration (seconds) were indicative of lameness using the Gaitwise pressure mat system, a research tool described in Maertens et al. (2011). Using the Gaitwise system, stance time (weight-bearing) for the nonlame leg was also found to be longer in lame cows (Van Nuffel et al., 2013, 2015a). Lame cows are relatively cautious or careful about affected foot placement as this action is thought to be painful (Van De Gucht et al., 2017b). Van De Gucht et al. (2017b) reported that the duration of foot placement and foot lifting was relatively longer for lame cows. Volkmann et al. (2019) examined sound generated by cows walking past microphones. Less forceful gait for lame cows was inferred from audio analysis having lower standard deviation. Pluk et al. (2012) found that lame cows' legs tended to have a decreased range of motion. In particular, at the time the hoof lifted, the angle was steeper for front hooves. Walking speed has been identified using several methods as being indicative of lameness (Chapinal et al., 2009; Thorup et al., 2014; Zillner et al., 2018; Volkmann et al., 2019).

These variables were generally averages. Measures of inconsistency have also been proposed by some researchers citing its use in human gait research (Van Nuffel et al., 2015a). Inconsistency in this context is the extent a step varies from one to the next. Inconsistency has been operationalized as the coefficient of variation (standard deviation divided by the average value; Van Nuffel et al., 2015a). In that study, most of the studied inconsistency measures had incremental predictive value over the basic variables. Stance time asymmetry as measured by the Gaitwise pressure sensor (Van Nuffel et al., 2015a) and a 3-dimensional force plate measurements of hind legs (Thorup et al., 2014) have been identified as being indicative of lameness.

The relevance of these findings to accelerometers depends on if an accelerometer can measure related variables, and there are some examples of similar variables being measured with accelerometers. Approximations of walking speed have been developed with accelerometers, for example. Chapinal et al. (2011) reported a Pearson's correlation coefficient of $r > 0.7$ between acceleration and walking speed. Beer et al. (2016) reported relatively accurate lameness detection based on an accelerometer-based estimation of speed, stride length, and duration. They calculated speed based on the variables stride distance and stride duration. In univariate analysis, speed outperformed stride distance, and stride distance outperformed stride duration at differentiating lame from nonlame (area under the curve 90.6, 88.7, and 75.5, respectively). Variables similar to tenderness have been measured as acceleration peaks by high-resolution accelerometers (Pastell et al., 2009; Alsaaod et al., 2017). Accelerometers combined with a gyroscope would measure pitch (Haladjian et al., 2018), which could be a proxy of range of motion and leg to floor angle, which Pluk et al. (2012) identified as indicative of lameness.

That asymmetry between limbs is greater for lame cows has also been well documented using accelerometers (Chapinal et al., 2011; Alsaaod et al., 2017, 2019a). Foot load acceleration magnitude and peak value asymmetry between legs were found to differ between lame and nonlame cows (Alsaaod et al., 2017, 2019a). It is interesting to note the focus on asymmetry in accelerometer studies (Alsaaod et al., 2017, 2019a) and the focus on averages and inconsistency for the pressure mat studies (Van Nuffel et al., 2013, 2015a; Van De Gucht et al., 2017b). It may be advantageous for accelerometer-based research to focus more on measures of inconsistency. One relative strength of accelerometers is their continuous recording, and so, accelerometers may be the most appropriate technology for measuring inconsistency.

Variable Summary. Several behavior variables were identified as indicative of lameness. These were activity/walking duration (Thorup et al., 2015), step count (Byabazaire et al., 2019), the ratio of day to night time activity (Van Hertem et al., 2013; Schindhelm et al., 2017), standing bouts and swaps (changes in behavior; de Mol et al., 2013; Beer et al., 2016; Byabazaire et al., 2019). Behavior variables that are not listed here were judged to have evidence that showed them insufficient or too inconsistent (i.e., lying time) to warrant inclusion.

The key gait variables measurable by accelerometers were walking speed (Chapinal et al., 2011; Beer et al., 2016), stride distance (Beer et al., 2016; Alsaaod et al., 2017), weight shifting while standing (Chapinal et al., 2011; Thorup et al., 2015), and tenderness measures such as foot placement and lifting duration (Alsaaod et al., 2017; Van De Gucht et al., 2017b). Gait-based approaches have been less studied (Table 4) compared with behavior-based approaches (Table 1–3). Gait measures also offer incrementally predictive ability beyond behavior measures alone (Beer et al., 2016; Alsaaod et al., 2017). In addition to averages, 2 forms of analysis appear to be relatively promising. The first is measures of inconsistency that measure one limb with one accelerometer. The second is measures of asymmetry between limbs using 2 or more pedometers. Measures of asymmetry have been the basis of the only studies to report perfect accuracy (Alsaaod et al., 2017, 2019a), which may be unsurprising given that asymmetry is the most prominent feature in manual locomotion scoring (Jones 2017).

System Design

Timeframes and Aggregation of Data. The variables identified in the previous section are recorded by sensors at different frequencies which can be aggregated and summarized in various ways (400 Hz, 10 Hz, per step, per hour, per day, or per week). Weekly behavior summaries were reported by Garcia et al. (2014); daily behavior summaries were reported by Kamphuis et al. (2013); Beer et al. (2016); King et al. (2017), and Byabazaire et al. (2019); and within day behavior information was reported by Garcia et al. (2014) and Grimm et al. (2019). Other studies have reported variables specifically from when cows were walking (Thorup et al., 2015), standing (Thorup et al., 2015), and lying (Kokin et al., 2014). There is no clear indication as to which of these is the most appropriate, except to observe that the most successful of these behavior-based studies in terms of lameness detection performance used daily summaries (Beer et al., 2016; Byabazaire et al., 2019).

The most granular aggregation has been measures of individual steps that are appropriate for measuring gait variables as per Martiskainen et al. (2009) and Haladjian et al. (2018). In the case of a 10-Hz sensor being used to create per step values, about 12 to 13 readings would be aggregated for each step, which lasts approximately 1.2 to 1.3 s each. Averages, measures of variance, measures of asymmetry, and changes over time can then be calculated. Assessing the efficacy of per step measures aggregated at multiple resolutions for their ability to predict lameness (e.g., per hour, per day, and so on) would be of interest. Such an assessment would allow the minimization of hardware and computational demands on devices. Limiting the need to process, store, and transmit data, will extend battery life and ultimately reduce costs. Decandia et al. (2018) reported a similar study assessing sheep behavior classification. They found that aggregating to 30 s was most accurate having tested aggregations from 5 to 300 s. The collected data and the reference or gold standard also need to be aligned. The gold standard in lameness detection is usually manual locomotion scores or sometimes claw inspections (Lambertz, 2019). For example, 24-hourly behavior summaries may be aggregated as averages and measures of variance to create daily variables which then could be matched to a single daily or weekly locomotion scoring event.

Past Behavior, Herd Mates, or Reference Values. We categorize 3 options for framing variables indicative of lameness. First, if the variable typically varies significantly between nonlame cows, then a cow's past behavior will be more appropriate. Here, changes in variables characteristic of lameness are the basis of lameness detection (Haladjian et al., 2018; Byabazaire et al., 2019). Alsaaod et al. (2012) reported that performance increased using such measures. However, changes within a cow characteristic of lameness onset can also be caused by her environment or management. One unanswered question in accelerometer-based research is how long of a window of historical comparison is most effective. In a study developing automated lameness detection using video analysis, Piette et al. (2019) reported that a reference window of 200 d resulted in the highest performance.

Second, if a variable is influenced by environment or management, then reference to herd-mates experiencing the same conditions might be appropriate. This reference to herd-mates approach is inherent to studies studying only one cohort of cows. The assumption is that a variable will reliably differentiate lame and nonlame in a range of conditions. This assumption is particularly questionable for shorter studies when management and conditions could be relatively homogeneous. Conditions can influence variables differently in lame and nonlame cows. For example, lying time of lame and nonlames cows at pasture is differentially affected by rain (Thompson et al., 2019). Thus comparisons to herd-mates alone are problematic. Third, reference thresholds will be more appropriate in some contexts. If a variable is relatively consistent among nonlame cows and is relatively unaffected by management or environment, then reference values may be useful. One example of such is the threshold values for step phase asymmetry that distinguished lame from nonlame cows (Alsaaod et al., 2017, 2019a). Studies have generally applied only one of these 3 approaches. Identifying the approach, or combination of approaches, most indicative of lameness for each variable may improve lameness detection performance.

Classifier. A key aspect of lameness detection is the classifier or the statistical modeling approach. This is what converts the variables indicative of lameness into assessments of whether cows are lame or not. This, in turn, creates information or alerts for the farmer. A consensus has yet to emerge regarding which is the most appropriate with a wide range of classifiers reported in the literature (Tables 1, 2, 3, and 4).

The simplest classifier was reported by Alsaaod et al. (2017). The difference in values between each pedometer on each rear leg was greater for lame cows in their sample (asymmetry). Using thresholds for these differences, lame and nonlame cows could be accurately identified. Three studies used Support Vector Machines and were relatively successful (Martiskainen et al., 2009; Alsaaod et al., 2012; Haladjian et al., 2018). Support vector machine models can be described as a black box because they are difficult to interpret. What differed between lame and nonlame cows was thus not identified, just that nonnormal locomotion could be identified. Logistic regression is also relatively prominent having been used in 2 studies (Van Hertem et al., 2013; Beer et al., 2016).

de Mol et al. (2013) reported using 9 quadratic trend models and a vote count rule. If 2 or more models of the 9 indicated lameness, an alert was triggered (de Mol et al., 2013). Two studies reported using differing forms of discriminant analysis, partial least squares discriminant analysis (Garcia et al., 2014), and canonical discriminant analysis (Charlton et al., 2016). Most of the reviewed studies that reported classifying cows as lame or not reported using a binary output. Kamphuis et al. (2013) classified cows into several locomotion scores with several binary assessments. Their classifiers were built using decision trees, additive logistic regression and logit boost. Other approaches that could be or have been applied include K–nearest neighbors and random forest (Byabazaire et al., 2019), time series analysis (Maertens et al., 2011; Barwick et al., 2018), wavelet analysis (Pastell et al., 2009), and a range of machine learning approaches (Valletta et al., 2017). In summary, logistic regression and support vector machines are the 2 most prominent approaches. They have both been reasonably successful in achieving relatively higher accuracy rates compared with the other methods. How much of this variation in predictive performance, if any, can be attributed to the choice of a classifier is unclear, as these studies varied in many other ways.

Hardware Considerations. Some of the characteristics of the systems used to collect the variables identified in the previous sections may pose challenges for application on commercial farms including the resolution of the accelerometer. For measures of behavior, 10 Hz seems sufficient (Werner et al., 2017). For gait analysis, 10 (Beer et al., 2016), 33 (Chapinal et al., 2011), 100 (Haladjian et al., 2018), and 400 Hz sensors have been used (Alsaaod et al., 2017). Alsaaod et al. (2019c) classified accelerometers with a sampling rate of less than 40 Hz as low frequency and high frequency as being 400 Hz or more. With increasing resolution and granularity, more detailed assessment of gait cycles is facilitated. This indicates that high-resolution accelerometers should be the preference for researchers aiming to increase knowledge of cow gait and lameness. However, increasing resolution increases costs, data storage, and computing requirements, while shortening battery life. Thus, for commercial lameness detection application, minimizing the resolution required should also be a goal.

Another application issue is the number of accelerometers required (Pastell et al., 2009). In the literature, 2 (Alsaaod et al., 2017), 4 (Pastell et al., 2009), and 5 (Chapinal et al., 2011) accelerometers per cow have been reported. As with higher resolution, there is value in having multiple accelerometers per cow. Perfect accuracy in detecting lameness using 2 pedometers in a semi-automated manner has been reported (Alsaaod et al., 2017). The same authors further went on to report similar success in other studies (Alsaaod et al., 2019a,b). Though reducing hardware costs may make medium resolution accelerometers (40–400 Hz) possible on commercial farms, the same is unlikely to be true for multiple accelerometers per cow systems. In addition to unit cost, the labor entailed in attaching and maintaining multiple sensors per cow would likely be less appealing to commercial farms. Multiple sensors also undermine the potential for lameness detection to piggyback on systems primarily designed for heat detection that only require one accelerometer per cow. Multiple accelerometers per cow approaches are thus likely to be mainly of use in veterinary and research contexts.

However, challenges also present themselves with single accelerometer per cow systems. Van Nuffel et al. (2013) demonstrated that altered gait manifests distinctly on the affected limb and the nonaffected limbs. This contrast between affected and nonaffected limbs (asymmetry) using 2 or more accelerometers appears to be more indicative of lameness than measures indicative of lameness derived from one pedometer. This contrast between limbs is the basis of the near-perfect lameness detection achieved by Alsaaod et al. (2017, 2019a) using 2 accelerometers per cow and manual locomotion scoring (Jones 2017). Without this contrast between affected and nonaffected limbs, a single pedometer system needs to detect gait alterations originating on both the measured and the nonmeasured legs. For example, mean stance time was reported higher when the contralateral leg was lame in one study but not for the affected leg itself (Van Nuffel et al., 2013). Indicators of lameness derived from the affected limb but not from other limbs have also been reported. These include measures of tenderness and stride length (Van Nuffel et al., 2013; Van De Gucht et al., 2017b). Future research with single pedometer systems should record which leg is lame, and which leg the pedometer is attached to (Van Nuffel et al., 2013; Van De Gucht et al., 2017b; Haladjian et al., 2018). Distinct classifier models may be required to detect lameness on the measured leg and the nonmeasured legs. This could provide additional functionality if the affected leg is identified, which would likely speed up the inspection and treatment process.

Several issues relate to how research findings might translate onto on-farm applications. Previous reviews (Van Nuffel et al., 2015c) and several studies (Kamphuis et al., 2013; Van Hertem et al., 2013; Westin et al., 2016) have discussed the cumulative value of multiple sources of data. Multiple sources of data such as milk yields, milking order, and body condition do appear to increase accuracy slightly. However, while adding marginal predictive value, they are also likely to complicate application. As such, the use of supplementary data sources may be best framed as an optional addition to supplement an already adequate system. A sufficiently accurate single pedometer system with noncost prohibitive resolution (100 Hz or less) would likely encourage broader adoption on farm.

DISCUSSION

Lameness remains a significant issue on dairy farms. This is in part because the expense and difficulty of lameness detection and treatment remain prohibitive. Automated lameness detection addresses the aspect of detection, but the costs may be prohibitive depending on the system. Single accelerometer per cow approaches are particularly promising from a cost perspective, but several hurdles remain before such technology can be widely adopted on farm. Foremost is developing reliable indicators of lameness using only one low or medium resolution pedometer. Effective lameness detection using 2 high-resolution accelerometers has been demonstrated (Alsaaod et al., 2017, 2019a). However, the need for 2 pedometers and those pedometers being higher resolution than those currently widely adopted on farm are likely to be major barriers to adoption.

Behavior-based approaches have been explored relatively extensively, but gait-based measures offer the most promising avenue to increase detection performance. Measures of gait should, therefore, be the focus of future research. Inconsistency analysis of gait measures, for example, may facilitate single low-resolution accelerometer-based systems. Although behavior will be affected by management and differ significantly from farm to farm (Thorup et al., 2015), gait may generalize to novel contexts more effectively. It is likely that a combination of the relatively well-developed knowledge of behavior-based approaches along with novel gait-based measures will be required to achieve levels of specificity, sensitivity, and positive predictive value required for widespread adoption. A major milestone will be the development of a commercially viable system that accurately detects lame and nonlame cows. This system will have been independently tested in a variety of contexts (e.g., indoor/grazing-based), with a variety of breeds and systems (robotic/conventional/grazing based) and been shown to be accurate. A discussion of what level of performance is likely required for commercial application was not found in the literature.

We suggest greater than 90% sensitivity and 99% specificity would be of significant value on most farms. The 99% specificity may seem high, but a farmer's perception of a system is perhaps most closely linked to positive predictive value. A high proportion of cows identified as lame turning out not to be lame may frustrate farmers. Concerns were raised by Van Nuffel et al. (2015c) that unnecessary drafting and hoof inspection would detract from the value of a system. Minimizing false positives is thus likely to be more important than minimizing false negatives (Van Hertem et al., 2013; Van Nuffel et al., 2015c). In a 400-cow herd with 40 lame cows (10% prevalence), this translates into 40 cows being identified as lame and drafted for inspection. Of these 40 cows, there would be 36 lame cows, and about 4 nonlame cows would be incorrectly classified as lame. There would also be 4 lame cows that would not be detected. Even though missing lame cows is undesirable, it is currently accepted by many farmers as normal (Horseman et al., 2014). This scenario would thus still represent a significant reduction in missed lame cows on many farms and it is also possible that missed cows might be later identified.

The high specificity of 99% is likely required for the broad adoption of these systems. If it is not possible to achieve both high sensitivity and very high specificity, perhaps reducing the requirements for sensitivity may be required even though more lame cows would not be detected by the system. If, however, the specificity was relaxed from 99 to 95%, then 54 cows would be identified as lame and drafted, but 18 of them would be false positives (only 67% positive predictive value). This lower specificity may still be of value on some farms, but these false positives have costs. False positives and subsequent drafting may affect the welfare of the healthy cow being restrained and examined, be frustrating for the farmer, and cost farmers time and money. It is also conceivable that farmers may lose trust in the system and ultimately not rely on it for the identification of lame cows.

Providing users the ability to adjust the sensitivity and specificity of the alerts may be one option whereby farmers can judge the appropriate tradeoff for their situation if these thresholds cannot be met. The first accelerometer-based automated lameness detection system was marketed by IceRobotics (Edinburgh, UK) in 2017 (IceRobotics, 2017) and in October 2018 locomotion scoring was marketed (IceRobotics, 2018). The system is based on a single low-resolution accelerometer per cow. They present users with the probability that a cow is lame using a traffic light system. Cows that are likely nonlame are green, those that may be lame are yellow, and those likely to be lame are red (IceRobotics, 2017). This approach is different from what has been seen in the literature but may be an appropriate solution for communicating information with less than perfect accuracy to farmers. However, as of November 2019, no published independent validation of this system was found in an online search.

The detection of lameness is only of use if that information is acted upon promptly (Dutton-Regester et al., 2019). The time delay between lameness detection and treatment can be up to several weeks (Alawneh et al., 2012; Horseman et al., 2014). Farmer beliefs such as "moderate lameness treatment is nonurgent" (Horseman et al., 2014; Croyle et al., 2019; Sadiq et al., 2019) and regarding lameness treatment efficacy (Potterton et al., 2012) will likely remain an issue. Changing farmer beliefs and attitudes is thus also important in effecting improved lameness management (Dutton-Regester et al., 2019). Another priority should be improving lameness treatment efficacy. Automated lameness assessment may facilitate this as improvements after treatment could be measured systematically.

CONCLUSIONS

This review on lameness detection using accelerometers has summarized the findings of a corpus of studies dominated by lying and standing behavior. Only a proportion of these studies have reported the efficacy of their approaches at detecting lameness. Many papers have only reported small and moderate associations insufficient for lameness detection. For these behavior-focused studies, there has also been little to no replication of these findings in similar or novel contexts. The most promising results using hardware likely to be practical on commercial farms used both behavior and gait variables. Therefore, it is recommended that a deeper understanding of gait features indicative of lameness should be prioritized as this is more likely to contribute to lameness detection. This review has highlighted several promising avenues that may inform the next steps in developing accelerometer-based lameness detection. The main recommendation is for future research to focus on single accelerometer systems with resolutions lower than 100 Hz to support the creation of systems suitable for widespread commercial application.

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REFERENCES

Adams, A. E., J. E. Lombard, C. P. Fossler, I. N. Román-Muñiz, and C. A. Kopral. 2017. Associations between housing and management practices and the prevalence of lameness, hock lesions, and thin cows on US dairy operations. J. Dairy Sci. 100:2119–2136. https://doi.org/10.3168/jds.2016-11517.

Alawneh, J. I., R. A. Laven, and M. A. Stevenson. 2012. Interval between detection of lameness by locomotion scoring and treatment for lameness: A survival analysis. Vet. J. 193:622–625. https://doi.org/10.1016/j.tvjl.2012.06.042.

Alsaaod, M., E. Bucher, M. Feierabend, M.-C. Haerdi-Landerer, and A. Steiner. 2019a. Detection and localisation of unilateral hindlimb pathologies in cattle using the cow pedogram. Vet. Rec. 184:318. https://doi.org/10.1136/vr.105014.

Alsaaod, M., M. Fadul, R. Deiss, E. Bucher, J. Rehage, J. Guccione, and A. Steiner. 2019b. Use of validated objective methods of locomotion characteristics and weight distribution for evaluating the efficacy of ketoprofen for alleviating pain in cows with limb pathologies. PLoS One 14:e0218546. https://doi.org/10.1371/journal.pone.0218546.

Alsaaod, M., M. Fadul, and A. Steiner. 2019c. Automatic lameness detection in cattle. Vet. J. 246:35–44. https://doi.org/10.1016/j.tvjl.2019.01.005.

Alsaaod, M., M. Luternauer, T. Hausegger, R. Kredel, and A. Steiner. 2017. The cow pedogram—Analysis of gait cycle variables allows the detection of lameness and foot pathologies. J. Dairy Sci. 100:1417–1426. https://doi.org/10.3168/jds.2016-11678.

Alsaaod, M., C. Römer, J. Kleinmanns, K. Hendriksen, S. Rose-Meierhöfer, L. Plümer, and W. Büscher. 2012. Electronic detection of lameness in dairy cows through measuring pedometric activity and lying behavior. Appl. Anim. Behav. Sci. 142:134–141. https://doi.org/10.1016/j.applanim.2012.10.001.

Barker, Z. E., J. A. V. Diosdado, E. A. Codling, N. J. Bell, H. R. Hodges, D. P. Croft, and J. R. Amory. 2018. Use of novel sensors combining local positioning and acceleration to measure feeding behavior differences associated with lameness in dairy cattle. J. Dairy Sci. 101:6310–6321. https://doi.org/10.3168/jds.2016-12172.

Barwick, J., D. Lamb, R. Dobos, D. Schneider, M. Welch, and M. Trotter. 2018. Predicting lameness in sheep activity using tri-axial acceleration signals. Animals (Basel) 8:E12. https://doi.org/10.3390/ani8010012.

Beer, G., M. Alsaaod, A. Starke, G. Schuepbach-Regula, H. Müller, P. Kohler, and A. Steiner. 2016. Use of extended characteristics of locomotion and feeding behavior for automated identification of lame dairy cows. PLoS One 11:e0218546. https://doi.org/10.1371/journal.pone.0155796.

Blackie, N., J. Amory, E. Bleach, and J. Scaife. 2011. The effect of lameness on lying behaviour of zero grazed Holstein dairy cattle. Appl. Anim. Behav. Sci. 134:85–91. https://doi.org/10.1016/j.applanim.2011.08.004.

Blackie, N., and L. Maclaurin. 2019. Influence of lameness on the lying behaviour of zero-grazed lactating Jersey dairy cattle housed in straw yards. Animals (Basel) 9:829. https://doi.org/10.3390/ani9100829.

Byabazaire, J., C. Olariu, M. Taneja, and A. Davy. 2019. Lameness Detection as a Service: Application of Machine Learning to an Internet of Cattle. Pages 1–6 in 2019 16th IEEE Annual Consumer Communications & Networking Conference (CCNC). IEEE.

Chapinal, N., A. M. de Passillé, M. Pastell, L. Hänninen, L. Munksgaard, and J. Rushen. 2011. Measurement of acceleration while walking as an automated method for gait assessment in dairy cattle. J. Dairy Sci. 94:2895–2901. https://doi.org/10.3168/jds.2010-3882.

Chapinal, N., A. M. De Passillé, J. Rushen, and S. Wagner. 2010. Automated methods for detecting lameness and measuring analgesia in dairy cattle. J. Dairy Sci. 93:2007–2013. https://doi.org/10.3168/jds.2009-2803.

Chapinal, N., A. M. De Passillé, D. M. Weary, M. A. G. Von Keyserlingk, and J. Rushen. 2009. Using gait score, walking speed, and lying behavior to detect hoof lesions in dairy cows. J. Dairy Sci. 92:4365–4374. https://doi.org/10.3168/jds.2009-2115.

Charlton, G. L., V. Bouffard, J. Gibbons, E. Vasseur, D. B. Haley, D. Pellerin, J. Rushen, and A. M. de Passillé. 2016. Can automated measures of lying time help assess lameness and leg lesions on tie-stall dairy farms? Appl. Anim. Behav. Sci. 175:14–22. https://doi.org/10.1016/j.applanim.2015.02.011.

Croué, I., A. Michenet, H. Leclerc, and V. Ducrocq. 2019. Genomic analysis of claw lesions in Holstein cows: Opportunities for genomic selection, quantitative trait locus detection, and gene identification. J. Dairy Sci. 102:6306–6318. https://doi.org/10.3168/jds.2018-15979.

Croyle, S. L., E. Belage, D. K. Khosa, S. J. LeBlanc, D. B. Haley, and D. F. Kelton. 2019. Dairy farmers' expectations and receptivity regarding animal welfare advice: A focus group study. J. Dairy Sci. 102:7385–7397. https://doi.org/10.3168/jds.2018-15821.

de Mol, R. M., G. André, E. J. B. Bleumer, J. T. N. van der Werf, Y. de Haas, and C. G. van Reenen. 2013. Applicability of day-to-day variation in behavior for the automated detection of lameness in dairy cows. J. Dairy Sci. 96:3703–3712. https://doi.org/10.3168/jds.2012-6305.

Decandia, M., V. Giovanetti, G. Molle, M. Acciaro, M. Mameli, A. Cabiddu, R. Cossu, M. G. Serra, C. Manca, S. P. G. Rassu, and C. Dimauro. 2018. The effect of different time epoch settings on the classification of sheep behaviour using tri-axial accelerometry. Comput. Electron. Agric. 154:112–119. https://doi.org/10.1016/j.compag.2018.09.002.

Dolecheck, K., and J. Bewley. 2018. Animal board invited review: Dairy cow lameness expenditures, losses and total cost. Animal 12:1462–1474. https://doi.org/10.1017/S1751731118000575.

Dutton-Regester, K. J., J. D. Wright, A. R. Rabiee, and T. S. Barnes. 2019. Understanding dairy farmer intentions to make improvements to their management practices of foot lesions causing lameness in dairy cows. Prev. Vet. Med. 171:104767. https://doi.org/10.1016/j.prevetmed.2019.104767.

Fabian, J., R. A. Laven, and H. R. Whay. 2014. The prevalence of lameness on New Zealand dairy farms: A comparison of farmer estimate and locomotion scoring. Vet. J. 201:31–38. https://doi.org/10.1016/j.tvjl.2014.05.011.

Flower, F. C., D. J. Sanderson, and D. M. Weary. 2005. Hoof pathologies influence kinematic measures of dairy cow gait. J. Dairy Sci. 88:3166–3173. https://doi.org/10.3168/jds.S0022-0302(05)73000-9.

Garcia, E., I. Klaas, J. M. Amigo, R. Bro, and C. Enevoldsen. 2014. Lameness detection challenges in automated milking systems addressed with partial least squares discriminant analysis. J. Dairy Sci. 97:7476–7486. https://doi.org/10.3168/jds.2014-7982.

Gleerup, K. B., P. H. Andersen, L. Munksgaard, and B. Forkman. 2015. Pain evaluation in dairy cattle. Appl. Anim. Behav. Sci. 171:25–32. https://doi.org/10.1016/j.applanim.2015.08.023.

Grimm, K., B. Haidn, M. Erhard, M. Tremblay, and D. Döpfer. 2019. New insights into the association between lameness, behavior, and performance in Simmental cows. J. Dairy Sci. 102:2453–2468. https://doi.org/10.3168/jds.2018-15035.

Groenevelt, M., D. C. J. Main, D. Tisdall, T. G. Knowles, and N. J. Bell. 2014. Measuring the response to therapeutic foot trimming in dairy cows with fortnightly lameness scoring. Vet. J. 201:283–288. https://doi.org/10.1016/j.tvjl.2014.05.017.

Haladjian, J., J. Haug, S. Nüske, and B. Bruegge. 2018. A wearable sensor system for lameness detection in dairy cattle. Multimodal Technol. Interact. 2:27. https://doi.org/10.3390/mti2020027.

Heringstad, B., C. Egger-Danner, N. Charfeddine, J. E. Pryce, K. F. Stock, J. Kofler, A. M. Sogstad, M. Holzhauer, A. Fiedler, K. Müller, P. Nielsen, G. Thomas, N. Gengler, G. de Jong, C. Ødegård, F. Malchiodi, F. Miglior, M. Alsaaod, and J. B. Cole. 2018. Invited review: Genetics and claw health: Opportunities to enhance claw health by genetic selection. J. Dairy Sci. 101:4801–4821. https://doi.org/10.3168/jds.2017-13531.

Horseman, S. V., E. J. Roe, J. N. Huxley, N. J. Bell, C. S. Mason, and H. R. Whay. 2014. The use of in-depth interviews to understand the process of treating lame dairy cows from the farmers' perspective. Anim. Welf. 23:157–165. https://doi.org/10.7120/09627286.23.2.157.

IceRobotics. 2017. COWALERT Lameness Detection Highly Commended. Accessed Jun. 28, 2018. http://www.icerobotics.com/news/cowalert-lameness-detection-highly-commended/.

IceRobotics. 2018. Tweet "Come and See How CowAlert Can Help Your Dairy Herd, at #WelshDairyShow... ... And We Have a Heater! #lyingtimes #AutomaticMobilityScoring." Accessed Nov. 14, 2018. https://twitter.com/Ice_Robotics/status/1057197386097934337.

Ito, K., M. A. G. Von Keyserlingk, S. J. Leblanc, and D. M. Weary. 2010. Lying behavior as an indicator of lameness in dairy cows. J. Dairy Sci. 93:3553–3560. https://doi.org/10.3168/jds.2009-2951.

Jones, B. W. 2017. Behavioral Gait Change Characterization and Detection using Precision Dairy Monitoring Technologies. PhD Thesis, College of Agriculture, Food, and Environment, University of Kentucky, Lexington, KY.

Kamphuis, C., E. Frank, J. K. Burke, G. A. Verkerk, and J. G. Jago. 2013. Applying additive logistic regression to data derived from sensors monitoring behavioral and physiological characteristics of dairy cows to detect lameness. J. Dairy Sci. 96:7043–7053. https://doi.org/10.3168/jds.2013-6993.

King, M. T. M., S. J. LeBlanc, E. A. Pajor, and T. J. DeVries. 2017. Cow-level associations of lameness, behavior, and milk yield of cows milked in automated systems. J. Dairy Sci. 100:4818–4828. https://doi.org/10.3168/jds.2016-12281.

Kokin, E., J. Praks, I. Veermäe, V. Poikalainen, and M. Vallas. 2014. IceTag3D^{TM} accelerometric device in cattle lameness detection. Agron. Res. (Tartu) 12:223–230.

Lambertz, C. 2019. Using cluster analysis to differentiate degrees of lameness in cattle. Vet. Rec. 184:218–219. https://doi.org/10.1136/vr.l572.

Leach, K. A., D. A. Tisdall, N. J. Bell, D. C. J. Main, and L. E. Green. 2012. The effects of early treatment for hindlimb lameness in dairy cows on four commercial UK farms. Vet. J. 193:626–632. https://doi.org/10.1016/j.tvjl.2012.06.043.

Leach, K. A., H. R. Whay, C. M. Maggs, Z. E. Barker, E. S. Paul, A. K. Bell, and D. C. J. Main. 2010. Working towards a reduction in cattle lameness: 1. Understanding barriers to lameness control on dairy farms. Res. Vet. Sci. 89:311–317. https://doi.org/10.1016/j.rvsc.2010.02.014.

Maertens, W., J. Vangeyte, J. Baert, A. Jantuan, K. C. Mertens, S. De Campeneere, A. Pluk, G. Opsomer, S. Van Weyenberg, and A. Van Nuffel. 2011. Development of a real time cow gait tracking and analysing tool to assess lameness using a pressure sensitive walkway: The GAITWISE system. Biosyst. Eng. 110:29–39. https://doi.org/10.1016/j.biosystemseng.2011.06.003.

Mangweth, G., J. P. Schramel, C. Peham, C. Gasser, A. Tichy, C. Altenhofer, A. Weber, and J. Kofler. 2012. Lameness detection in cows by accelerometric measurement of motion at walk. Berl. Munch. Tierarztl. Wochenschr 125:386–396. https://doi.org/10.2376/0005-9366-125-386.

Martiskainen, P., M. Järvinen, J. P. Skön, J. Tiirikainen, M. Kolehmainen, and J. Mononen. 2009. Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines. Appl. Anim. Behav. Sci. 119:32–38. https://doi.org/10.1016/j.applanim.2009.03.005.

Mottram, T. 2016. Animal board invited review: Precision livestock farming for dairy cows with a focus on oestrus detection. Animal 10:1575–1584. https://doi.org/10.1017/S1751731115002517.

Navarro, G., L. E. Green, and N. Tadich. 2013. Effect of lameness and lesion specific causes of lameness on time budgets of dairy cows at pasture and when housed. Vet. J. 197:788–793. https://doi.org/10.1016/j.tvjl.2013.05.012.

Nechanitzky, K., A. Starke, B. Vidondo, H. Müller, M. Reckardt, K. Friedli, and A. Steiner. 2016. Analysis of behavioral changes in dairy cows associated with claw horn lesions. J. Dairy Sci. 99:2904–2914. https://doi.org/10.3168/jds.2015-10109.

O'Callaghan, K. 2002. Lameness and associated pain in cattle—Challenging traditional perceptions. In Pract. 24:212–219. https://doi.org/10.1136/inpract.24.4.212.

Pastell, M., J. Tiusanen, M. Hakojärvi, and L. Hänninen. 2009. A wireless accelerometer system with wavelet analysis for assessing lameness in cattle. Biosyst. Eng. 104:545–551. https://doi.org/10.1016/j.biosystemseng.2009.09.007.

Piette, D., T. Norton, V. Exadaktylos, and D. Berckmans. 2019. Individualised automated lameness detection in dairy cows and the impact of historical window length on algorithm performance. Animal 14:409–417. https://doi.org/10.1017/S1751731119001642.

Pluk, A., C. Bahr, A. Poursaberi, W. Maertens, A. van Nuffel, and D. Berckmans. 2012. Automatic measurement of touch and release angles of the fetlock joint for lameness detection in dairy cattle using vision techniques. J. Dairy Sci. 95:1738–1748. https://doi.org/10.3168/jds.2011-4547.

Potterton, S. L., N. J. Bell, H. R. Whay, E. A. Berry, O. C. D. Atkinson, R. S. Dean, D. C. J. Main, and J. N. Huxley. 2012. A descriptive review of the peer and non-peer reviewed literature on the treatment and prevention of foot lameness in cattle published between 2000 and 2011. Vet. J. 193:612–616. https://doi.org/10.1016/j.tvjl.2012.06.040.

Proudfoot, K. L., D. M. Weary, and M. A. G. von Keyserlingk. 2010. Behavior during transition differs for cows diagnosed with claw horn lesions in mid lactation. J. Dairy Sci. 93:3970–3978. https://doi.org/10.3168/jds.2009-2767.

Sadiq, M. B., S. Ramanoon, W. Shaik Mossadeq, R. Mansor, and S. Syed Hussain. 2019. Dairy farmers' perceptions of and actions in relation to lameness management. Animals (Basel) 9:E270. https://doi.org/10.3390/ani9050270.

Sánchez-Molano, E., V. Bay, R. F. Smith, G. Oikonomou, and G. Banos. 2019. Quantitative trait loci mapping for lameness associated phenotypes in Holstein–Friesian dairy cattle. Front. Genet. 10:926. https://doi.org/10.3389/fgene.2019.00926.

Schindhelm, K., I. Lorenzini, M. Tremblay, D. Döpfer, S. Reese, and B. Haidn. 2017. Automatically recorded performance and behaviour parameters as risk factors for lameness in dairy cattle. Chem. Eng. Trans. 58:583–588. https://doi.org/10.3303/CET1758098.

Schlageter-Tello, A., E. A. M. Bokkers, P. W. G. G. Koerkamp, T. Van Hertem, S. Viazzi, C. E. B. Romanini, I. Halachmi, C. Bahr, D. Berckmans, and K. Lokhorst. 2014. Manual and automatic locomotion scoring systems in dairy cows: A review. Prev. Vet. Med. 116:12–25. https://doi.org/10.1016/j.prevetmed.2014.06.006.

Sepúlveda-Varas, P., D. M. Weary, and M. A. G. Von Keyserlingk. 2014. Lying behavior and postpartum health status in grazing dairy cows. J. Dairy Sci. 97:6334–6343. https://doi.org/10.3168/jds.2014-8357.

Solano, L., H. W. Barkema, E. A. Pajor, S. Mason, S. J. Leblanc, C. G. R. Nash, D. B. Haley, D. Pellerin, J. Rushen, A. M. de Passillé, E. Vasseur, and K. Orsel. 2016. Associations between lying behavior and lameness in Canadian Holstein-Friesian cows housed in freestall barns. J. Dairy Sci. 99:2086–2101. https://doi.org/10.3168/jds.2015-10336.

Thomas, H. J., J. G. Remnant, N. J. Bollard, A. Burrows, H. R. Whay, N. J. Bell, C. Mason, and J. N. Huxley. 2016. Recovery of chronically lame dairy cows following treatment for claw horn lesions: A randomised controlled trial. Vet. Rec. 178:116. https://doi.org/10.1136/vr.103394.

Thompson, A. J., D. M. Weary, J. A. Bran, R. R. Daros, M. J. Hötzel, and M. A. G. von Keyserlingk. 2019. Lameness and lying behavior in grazing dairy cows. J. Dairy Sci. 102:6373–6382. https://doi.org/10.3168/jds.2018-15717.

Thomsen, P. T., L. Munksgaard, and J. T. Sørensen. 2012. Locomotion scores and lying behaviour are indicators of hoof lesions in dairy cows. Vet. J. 193:644–647. https://doi.org/10.1016/j.tvjl.2012.06.046.

Thorup, V. M., O. F. do Nascimento, F. Skjøth, M. Voigt, M. D. Rasmussen, T. W. Bennedsgaard, and K. L. Ingvartsen. 2014. Short communication: Changes in gait symmetry in healthy and lame dairy cows based on 3-dimensional ground reaction force curves following claw trimming. J. Dairy Sci. 97:7679–7684. https://doi.org/10.3168/jds.2014-8410.

Thorup, V. M., L. Munksgaard, P. E. Robert, H. W. Erhard, P. T. Thomsen, and N. C. Friggens. 2015. Lameness detection via leg-mounted accelerometers on dairy cows on four commercial farms. Animal 9:1704–1712. https://doi.org/10.1017/S1751731115000890.

Valletta, J. J., C. Torney, M. Kings, A. Thornton, and J. Madden. 2017. Applications of machine learning in animal behaviour studies. Anim. Behav. 124:203–220. https://doi.org/10.1016/j.anbehav.2016.12.005.

Van De Gucht, T., W. Saeys, A. Van Nuffel, L. Pluym, K. Piccart, L. Lauwers, J. Vangeyte, and S. Van Weyenberg. 2017a. Farmers' preferences for automatic lameness-detection systems in dairy cattle. J. Dairy Sci. 100:5746–5757. https://doi.org/10.3168/jds.2016-12285.

Van De Gucht, T., W. Saeys, S. Van Weyenberg, L. Lauwers, K. Mertens, L. Vandaele, J. Vangeyte, and A. Van Nuffel. 2017b. Automatically measured variables related to tenderness of hoof placement and weight distribution are valuable indicators for lameness in dairy cows. Appl. Anim. Behav. Sci. 189:13–22. https://doi.org/10.1016/j.applanim.2017.01.011.

Van De Gucht, T., S. Van Weyenberg, A. Van Nuffel, L. Lauwers, J. Vangeyte, and W. Saeys. 2017c. Supporting the development and adoption of automatic lameness detection systems in dairy cattle: Effect of system cost and performance on potential market shares. Animals (Basel) 7:77. https://doi.org/10.3390/ani7100077.

Van Hertem, T., E. Maltz, A. Antler, C. E. B. Romanini, S. Viazzi, C. Bahr, A. Schlageter-Tello, C. Lokhorst, D. Berckmans, and I. Halachmi. 2013. Lameness detection based on multivariate continuous sensing of milk yield, rumination, and neck activity. J. Dairy Sci. 96:4286–4298. https://doi.org/10.3168/jds.2012-6188.

Van Hertem, T., S. Viazzi, M. Steensels, E. Maltz, A. Antler, V. Alchanatis, A. A. Schlageter-Tello, K. Lokhorst, E. C. B. Romanini,

C. Bahr, D. Berckmans, and I. Halachmi. 2014. Automatic lameness detection based on consecutive 3D-video recordings. Biosyst. Eng. 119:108–116. https://doi.org/10.1016/j.biosystemseng.2014.01.009.

Van Nuffel, A., W. Saeys, B. Sonck, J. Vangeyte, K. C. Mertens, B. De Ketelaere, and S. Van Weyenberg. 2015a. Variables of gait inconsistency outperform basic gait variables in detecting mildly lame cows. Livest. Sci. 177:125–131. https://doi.org/10.1016/j.livsci.2015.04.008.

Van Nuffel, A., J. Vangeyte, K. C. Mertens, L. Pluym, S. De Campeneere, W. Saeys, G. Opsomer, and S. Van Weyenberg. 2013. Exploration of measurement variation of gait variables for early lameness detection in cattle using the GAITWISE. Livest. Sci. 156:88–95. https://doi.org/10.1016/j.livsci.2013.06.013.

Van Nuffel, A., I. Zwertvaegher, L. Pluym, S. Van Weyenberg, V. M. Thorup, M. Pastell, B. Sonck, and W. Saeys. 2015b. Lameness detection in dairy cows: Part 1. How to distinguish between non-lame and lame cows based on differences in locomotion or behavior. Animals (Basel) 5:838–860. https://doi.org/10.3390/ani5030387.

Van Nuffel, A., I. Zwertvaegher, S. Van Weyenberg, M. Pastell, V. M. Thorup, C. Bahr, B. Sonck, and W. Saeys. 2015c. Lameness detection in dairy cows: Part 2. Use of sensors to automatically register changes in locomotion or behavior. Animals (Basel) 5:861–885. https://doi.org/10.3390/ani5030388.

Volkmann, N., B. Kulig, and N. Kemper. 2019. Using the footfall sound of dairy cows for detecting claw lesions. Animals (Basel) 9:78. https://doi.org/10.3390/ani9030078.

Weigele, H. C. C., L. Gygax, A. Steiner, B. Wechsler, and J.-B. Burla. 2018. Moderate lameness leads to marked behavioral changes in dairy cows. J. Dairy Sci. 101:2370–2382. https://doi.org/10.3168/jds.2017-13120.

Werner, J., L. Leso, C. Umstatter, M. Schick, and B. O'Brien. 2017. Evaluation of precision technologies for measuring cows' behaviour. Pages 82–84 in Grassland Science in Europe, Alghero, Italy.

Westin, R., A. Vaughan, A. M. De Passillé, T. J. Devries, E. A. Pajor, D. Pellerin, J. M. Siegford, E. Vasseur, and J. Rushen. 2016. Lying times of lactating cows on dairy farms with automatic milking systems and the relation to lameness, leg lesions, and body condition score. J. Dairy Sci. 99:551–561. https://doi.org/10.3168/jds.2015-9737.

Yunta, C., I. Guasch, and A. Bach. 2012. Short communication: Lying behavior of lactating dairy cows is influenced by lameness especially around feeding time. J. Dairy Sci. 95:6546–6549. https://doi.org/10.3168/jds.2012-5670.

Zillner, J. C., N. Tücking, S. Plattes, T. Heggemann, and W. Büscher. 2018. Using walking speed for lameness detection in lactating dairy cows. Livest. Sci. 218:119–123. https://doi.org/10.1016/j.livsci.2018.10.005.

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