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Cows becoming clinically lame differ in changes in behaviour and physiology compared to cows that do not become clinically lame

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Abstract

The hypothesis that sensors can detect changes in behaviours and physiologies associated with cows becoming clinically lame was tested by comparing trends of sensor data from lame cows with non-lame cows. Sensor data included data from live weighing scales, pedometers (average steps per hour) and milk meters collected between November 2010 and June 2012 on five Waikato dairy farms. Farmers were trained in detecting and diagnosing lame cows. For each lameness event ($n = 318$ events affecting 292 cows) a time period of 14 days prior to the day of detection was randomly matched by farm and date to 10 non-lame cows. In this period, lame cows decreased in weight, steps taken per hour, milk yield in the first two minutes of milking, total milk yield, and milking duration. Lame cows also entered the milking platform later. In comparison, non-lame cows had no change in sensor data trends. These differences ($P < 0.05$) in sensor data trends imply potential value of sensor data in detecting lameness automatically. Large variations in sensor data values between and within lame and non-lame cows indicated that future research should focus on combinations of variables that show the best potential to detect lameness automatically.

Keywords: dairy cow; lameness; sensor data patterns; detection

Introduction

Lameness is considered a significant health issue in the New Zealand dairy herd (Sauter-Louis et al. 2004; Chesterton et al. 2008). It is often grouped with mastitis and infertility in the top three dairy cow health issues (Gibbs & Laporte 2007). The condition affects the cow's welfare as shown by abnormal behaviour (Juarez et al. 2003; Walker et al. 2008) and loss of body condition (Walker et al. 2008) and its association with pain (Whay et al. 1997; Bicalho et al. 2007). Lameness also influences farm profitability as it negatively affects reproductive performance and milk production and increases treatment costs and culling risk (Tranter & Morris 1991; Sprecher et al. 1997; Green et al. 2002).

In spite of the negative consequences of lameness, farmers do not perceive lameness as a major health issue (Leach et al. 2010) because they tend to underestimate the prevalence of lameness on their farm (Whay et al. 2002). Lame cows are usually detected by visual observation, for example by looking at a cow's gait and back posture (Sprecher et al. 1997). However, Whay et al. (2002) reported a mean prevalence of lameness estimated by farmers of 5.7% whereas a trained observer recorded a mean prevalence on these farms of 22.1%. In this case approximately 74% of the lame cows were undetected by farmers. It is unclear what causes this low detection rate but possible explanations include the time-pressure that is put on farm staff, or that other health issues with more obvious costs, such as mastitis, attract farmer's attention at the expense of lameness, or that farmers lack skills in detecting and controlling lameness (Leach et al. 2010). However, with herd sizes increasing (DairyNZ 2012) detecting

lame cows visually is becoming more challenging. As automated technologies that monitor animal health are likely to become increasingly popular (Cuthbert 2008) automatic detection of lame cows may be a viable alternative to reliance on visual detection.

Sensors are available that monitor behavioural aspects such as activity and milking order, as well as physiological aspects such as live weight, milk yield and milking duration of cows at each milking. These data may be useful in automating the detection of lame cows. For example, given that lameness negatively affects milk yield (Green et al. 2002) it can be expected that milk yield would decline during the days before lameness became clinical, whereas one would not expect a decline in milk yield for non-lame cows. This study hypothesised that sensor data can be used to detect changes in behaviour and physiology associated with cows becoming clinically lame compared to non-lame cows.

Materials and Methods

This study was approved by the Ruakura Animal Ethics Committee.

Data collection

Data were collected on five Waikato dairy farms with a mean herd size of 770 cows, (range 432–1628) between November 2010 and June 2012. All five pasture-based farms had a rotary milking platform (Waikato Milking Systems, Hamilton, New Zealand) fitted with electronic cow identification systems, live weighing scales (Afikim, Kibutz Afikim, Israel) and electronic milk meters. All cows were fitted with pedometers (Afikim, Kibutz Afikim, Israel). All

Table 1 Total number of lameness events with a recorded observation date and sensor data that were recorded per farm, and the number of lameness events included in the statistical analyses and their assigned Lameness Score. The Lameness Scores represent the severity of the recorded lameness event with Score 2 = Mildly lame, Score 3 = Moderately lame, Score 4 = Lame and Score 5 = Severely lame. Lameness events without a Lameness Score assigned by the farmer were considered as missing.

Farm	Number of lameness recordings	Number of lameness events analysed	Number of lameness events in each Lameness Score group				
			Score 2	Score 3	Score 4	Score 5	Missing
1	164	138	38	66	22	4	8
2	24	22	8	6	6	1	1
3	66	54	11	27	10	1	5
4	73	57	11	24	19	3	0
5	58	47	6	22	18	0	1
Total	385	318	74	145	75	9	15

farms except one applied a seasonal spring calving regime; one farm had cows calving in spring and autumn. The New Zealand Crossbred was the predominant breed being >75% of the herd on three farms. Two farms had a herd comprising 50% Friesian Holstein and 50% New Zealand Crossbred.

Individual cow and sensor data from each milking session were transferred automatically to a central database at DairyNZ each evening. Cow data included cow identification number and days in milk. Sensor data at the cow level included live weight, activity expressed as the average number of steps per hour, milking order, milk yield in the first two minutes after teat cup attachment, total milk yield and milking duration. Criteria described in Edwards *et al.* (2013) were used to identify outlier values for the four milking variables. Sensor values for live weight and activity were plotted and conservative threshold values set based on visual judgement. Values for live weight of less than 250 kg or more than 750 kg were set as missing. This applied to <0.5% of the recorded measurements. Activity measurements of less than 25 steps per hour or more than 1,100 steps per hour were set as missing. This also applied to <0.5% of the recorded measurements.

Sensor data measured at morning and afternoon milkings were averaged to get one value per day for each cow in milk. If sensor data were available for one milking only, that value was used for that cow for that day.

In addition to sensor data, data on lame cows were collected by farmers who were trained (Healthy Hoof Program, DairyNZ) before the study commenced to standardize detection and diagnosis of lame cows. Cows were checked for symptoms of lameness at each milking session in accordance with normal farm procedure. Whenever a cow was observed lame, farmers were asked to record cow identification number, date of observation, affected limb and severity of lameness using a five-point lameness scoring system adapted from Sprecher *et al.* (1997) where 1 = Normal, 2 = Mildly lame, 3 = Moderately lame, 4 = Lame and 5 = Severely lame.

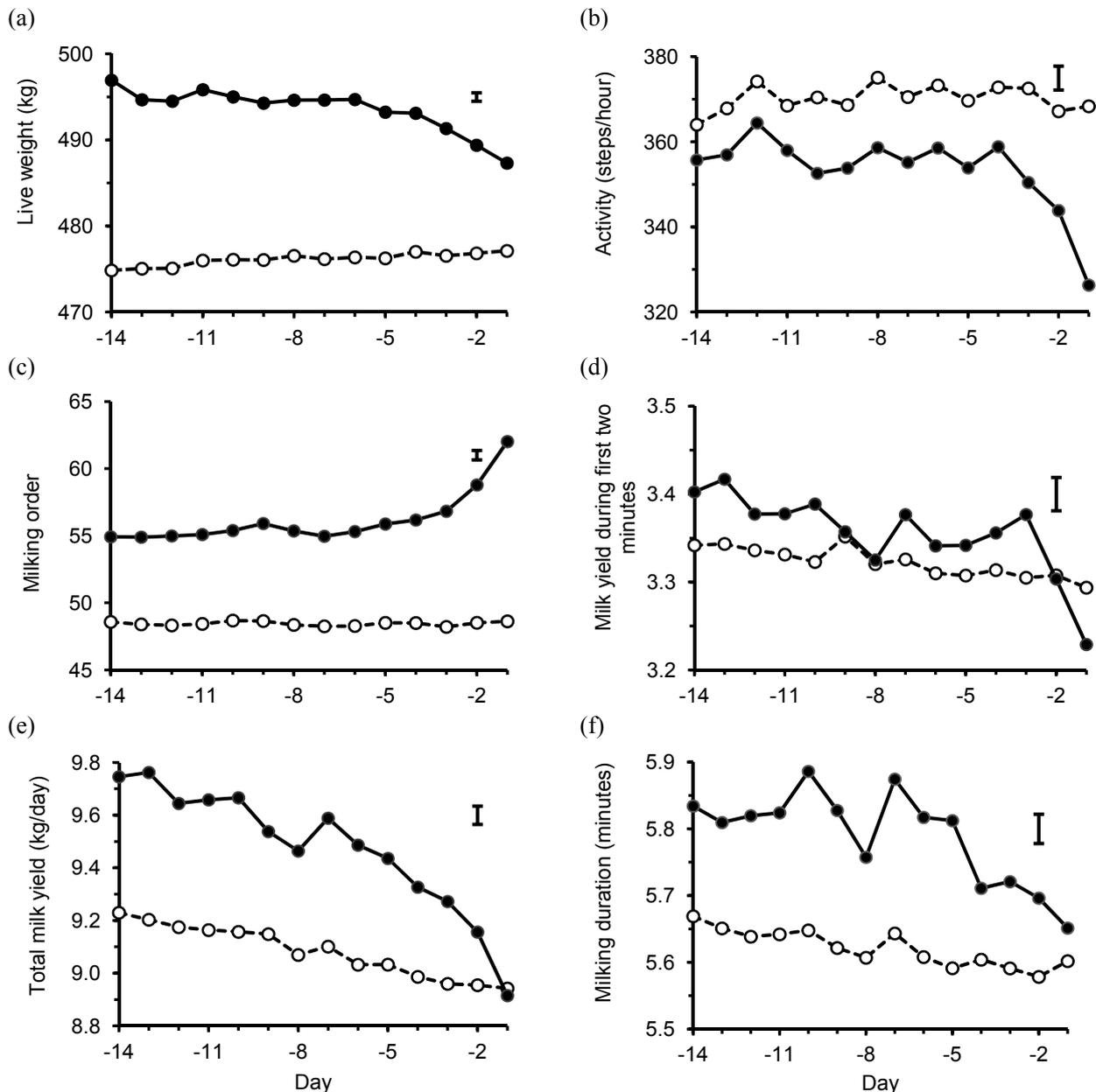
In total, 466 lameness events were recorded. Lame events recorded without date of observation were excluded ($n = 39$). Separate lameness events for the same cow for the same affected limb were defined when the time lag between two lameness events was >31 days; if the period was ≤ 31 days then the second lameness event recording was excluded ($n = 12$). Records on other health events including cow identification number, date of health event and type of health event such as clinical mastitis, artificial insemination and natural breeding ($n = 43,047$ records) were collected at the end of the study by extracting this information from the herd management software.

Farmers were visited every month to collect data on lameness. During these visits, lameness scoring forms were discussed with the farmer to ensure standardised recording throughout the study period. Sensor data and records of lameness and health events were merged within farm, cow identification number and date. After merging the data sets, records of lameness ($n = 30$) and health events ($n = 12,295$) without sensor data were excluded.

Definition of lame and non-lame episodes

Lame cows were defined as cows with at least one lameness event recorded. To ensure that sensor data were not affected by health events other than lameness or by calving events, lame events were excluded from further analyses when the cow was recorded to have another health event occurring from 14 days prior to the date of detection (D-14) recorded on Day 0 (D0) till seven days after detection (D7) ($n = 27$), and when D-14 fell within the first 30 days in milk ($n = 34$). This 22 day time period from D-14 to D7, was considered a lameness episode. Lameness episodes with less than 10 days of sensor data from D-14 through D0 were excluded ($n = 6$). Each lameness episode was randomly matched by farm and date with 10 non-lame cows, creating lameness blocks. Non-lame cows were defined as cows without recorded lameness events during the entire data collection period, without any health event recorded

Figure 1 Daily means for Lame (●; n = 318) and Non-lame (○; n = 3,180) cows for (a) live weight, (b) activity, (c) milking order, (d) milk yield during the first two minutes, (e) total daily milk yield and (f) milking duration from Day -14 till Day -1 of lameness detection. The vertical bars in each plot represent the maximum standard error of the difference for time comparisons within the Lame group. Sensor data trends through time of Lame cows differ significantly ($P < 0.05$) from Non-lame cows for all six sensor-based variables.



during the matched time period and with at least 10 days of sensor data from D-14 through D0. Each lameness block therefore contains sensor data from one lame cow and 10 non-lame cows. The selection procedure ensured that lame cows were never eligible to contribute as a non-lame cow. Non-lame cows could contribute sensor data to more than one lameness block.

Statistical analyses

Sensor data measured at D0 through D7 were excluded from all cows to prevent sensor data being influenced by management practices after a cow was observed lame. This left a time period running from D-14 through D-1 for each cow within each lameness

episode to be included in the statistical analyses. Differences in sensor data trends for each variable were analysed for D-14 through D-1 using a mixed model where the repeated measurements of each cow through time were modelled using an autoregressive order 1 covariance structure. The mixed model included Day, Lameness and the interaction of these two terms as fixed effects and Lameness Block, Cow within Lameness Block and Day within Cow as random effects. Differences in sensor data trends between Lame and Non-lame cows are indicated by the interaction term Day within Lame. To test differences in Lameness Score within the Lame group, Lameness Score, for values of 2 to 5 inclusive, and the interaction between Day and Lameness Score

Figure 2 Box plots for the difference in activity (steps/hour) between Day -4 and Day -1 before lameness detection for Lame and Non-lame cows on each farm. The length of each box represents the interquartile range (distance between 25th and 75th percentile) with the group median presented by the horizontal line within the box. Each whisker indicates the range of values on that side of the median.

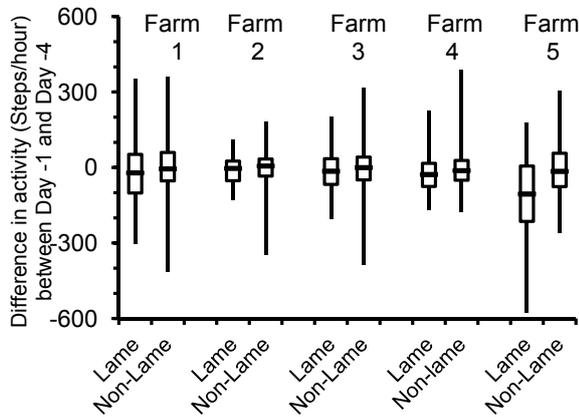
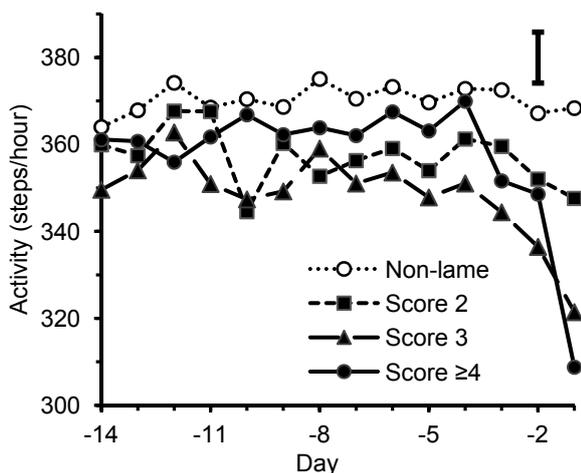


Figure 3 Average daily values for activity (steps/hour) for Non-lame cows and Lame cows that received a Lameness Score where Score 2 = Mildly lame, Score 3 = Moderately lame and Score ≥ 4 = Lame and Severely lame, from Day -14 till Day -1 of lameness detection. The vertical bar represents the maximum standard error of the difference for time comparisons within the Lame group. The sensor data trend through time differs significantly ($P < 0.01$) between Lameness Scores.



were added to the first model as fixed effects. Differences in sensor data trends between Lameness Score groups within the Lame group are indicated by the interaction term Day within Lameness Score. Lame cows without a Lameness Score ($n = 15$; Table 1) were excluded from this second analyses. Data cleaning and preparation was done using SAS (Version 9.2, SAS Institute Inc., Cary, North Carolina, USA). Statistical analyses were conducted using GenStat (Payne et al. 2009).

Results

Farmers recorded 385 lameness events with an observation date and sensor data available; the number of cases ranged from 24 cases at Farm 2 to 164 cases at Farm 1 (Table 1). After cleaning and preparing the data, 318 lameness episodes affecting 292 cows (5.9% Jersey 29.7% Holstein, 64.4% New Zealand Crossbred) were included for statistical analyses. The largest proportion (46%) of these episodes involved cows that were moderately lame (Lameness Score 3) showing an abnormal gait and an arched back while walking and standing. Another 23% of cows were mildly lame (Lameness Score 2) showing a slightly abnormal gait and an arched back while walking only. Twenty-six per cent were lame or severely lame (Lameness Score 4 and 5).

Figure 1 plots the daily means for the six sensor-based variables for Lame ($n = 318$) and Non-lame ($n = 3,180$) cows during the time period of interest (D-14 through D-1). Over time, lame cows tended to lose weight, decreased their activity, entered the milking parlour later, with a decreased milk yield in the first two minutes and a decreased total milk yield, as well as taking a shorter time to milk. These sensor data trends through time differed significantly ($P < 0.05$) between Lame and Non-lame cows for all six sensor-based variables.

Figure 2 shows the variation in the difference in activity between D-4 and D-1 for the Lame and Non-lame cow groups on each farm separately. The mean difference in activity for Lame cows is lower or similar compared to Non-lame cows on all five farms. The data indicate a wide range in activity within Lame and Non-lame cows on all farms and that there is a large overlap in activity differences between Lame and Non-lame cows across all the farms. Box plots for the other variables showed similar results with large variation in sensor values within and between the Lame and Non-lame groups of cows.

Weighted daily Activity averages by Lameness Score are plotted in Figure 3. On average, lame cows decreased their activity in the four days leading up to visual detection (D-4). This drop in activity was more pronounced with higher Lameness Scores. This trend of decreasing activity through time differed significantly ($P < 0.01$) between Lameness Scores. Similar statistically significant patterns ($P < 0.05$) between Lameness Scores were observed for all other production variables, except total milk yield ($P = 0.15$).

Discussion

Previous studies have reported that lameness affects a cow's normal behaviour patterns. Lame cows increase their lying time (Juarez et al. 2003), spend less time walking and enter the milking parlour later (Walker et al. 2008) than non-lame cows. Lameness also negatively affects milk production (Green et al. 2002) and body condition (Walker et al. 2008). The current study agrees with results reported

in these previous studies demonstrating that lame cows start showing these reported negative effects before they were actually observed as being lame. In addition, the current study demonstrated that these negative trends through time for Lame cows are significantly different compared to Non-lame cows for all the six sensor-based variables and that these negative trends differ significantly, except for total milk yield, between Lameness Scores within the Lame group. With these results we have proved the hypothesis that sensor data can be used to detect changes in behaviour and physiology associated with cows becoming clinically lame compared to non-lame cows.

Our data also demonstrated that there is a wide variability in sensor data measured within and between the Lame and Non-lame cow groups (Figure 2). Part of this variation is attributable to the fact that sensors were not calibrated for study purposes. It could be debated whether it was better to use calibrated data from validated sensors. However, this study focussed on the potential of currently commercially available sensors as used on-farm for the automated detection of lameness, regardless of whether these sensors were calibrated often, as a normal maintenance practice, or not calibrated at all. The large variation in sensor data implies that sensor-based detection models using one variable are unlikely to be a sufficiently accurate predictor of lameness to identify cows requiring treatment. As a consequence 'a one variable' procedure is likely to miss too many lame cows and/or indicate too many non-lame cows as becoming lame; a false alert. This result is important because it means that predicting or detecting individual lame cows will be difficult. The accuracy of the procedure can be improved by combining sensor data. Combining sensor data to improve model performance has proven to be valuable in the field of automated detection of clinical mastitis (Kamphuis et al. 2008). Future research should focus on the combinations of variables that show the best potential to develop an automated lameness detection model.

Conclusion

Lame cows have significantly different behavioural and physiological sensor data trends compared to non-lame cows. Sensor data trends also differed significantly between a Lameness Score within lame cows for all variables except total milk yield. These differences imply potential value of using sensor data to predict lame cows. However, the large variation of sensor data values between and within the Lame and Non-lame groups of cows suggests that single variable detection models are unlikely to be accurate enough for predicting lameness. Therefore, future research should focus on combinations of variables that show the best potential for developing an automated lameness detection model.

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