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Improving the power of activity-based heat detection using additional automatically captured data

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ABSTRACT

The purpose of this study was to determine the current performance of activity monitoring devices on New Zealand pasture-based farms and investigate the potential for improved detection using additional automatically captured data. The data consisted of heat events that were assigned from pregnancy diagnosis and mating records, and from milk progesterone levels collected twice weekly during mating period. Daily milk production, milking order, milk flow rate and milk conductivity records were also collected during the mating period. The best single predictor of oestrus was 24 hour milk yield difference ($P < 0.01$) for Herd 1 and normalised milking order ($P < 0.01$) for Herd 2. The normalised pedometer data was the next best predictor of oestrus in both herds ($P < 0.01$). A linear logistic regression model was fitted within each herd. The best model included normalised milk production, milking order, milk flow rate and pedometer variables. Machine learning models with balanced bagging were also fitted to the data. The machine learning models provided a better fit than traditional statistical models. Pedometer data can aid in the detection of cow oestrus, however the power of detection improves significantly with the addition of milk yield, milk flow and milking order data.

Keywords: pedometer; fertility; oestrus; dairy cows.

INTRODUCTION

Reproductive management is an important component in profitable dairy farming. In particular, timely oestrus detection is critical for farm systems that operate in a seasonal environment. Seasonal farming systems require a concentrated spring calving pattern, which is achieved by a high submission rate combined with a high conception rate to artificial insemination (Xu & Burton, 1996). Submission rates are a function of both heat detection efficiency and the proportion of cows cycling. There is considerable variation between herds in the rate of heat detection. Good heat detection is an important component in achieving a compact calving spread in seasonal dairy herds, as the decision to breed a dairy cow is predominantly dependent upon observational heat detection. Heat detection in the modern dairy cow is hampered by lower oestrus intensity and a shorter oestrus duration. This is further compounded by increases in herd size and fewer farmers recording pre-mating heat events. Observational heat detection requires observations to be undertaken consistently every milking throughout the artificial insemination period, which is usually four to six weeks in length. Observational heat detection is aided by the use of tail paint or similar devices that allow the farmer to detect the signs that a cow in oestrus has been mounted by other cows. The period of mounting activity lasts on average six hours, however, some cows only stand to be mounted once or twice per heat cycle (Brehme *et al.*, 2008). Observational heat detection requires an experienced individual and is labour intensive.

Current animal monitoring technologies provide automatic detection of events, such as illness, mastitis and oestrus. Commercially available activity sensors that use pedometer or accelerometer technologies have been shown in a number of studies to be capable of identifying oestrus events. These devices are generically known as pedometers.

Pedometers provide the opportunity to identify cows coming into oestrus while reducing the dependency upon labour and the need for observational heat detection when used in conjunction with automatic drafting of cows using electronic identification. A pedometer is mounted by a strap around a cow's lower leg or neck and is used to detect and record motion such as walking or mounting. There are varying levels of sophistication in the data captured by different brands of pedometers. Some pedometers capture just the total number of steps while others can record a time series of the activity over a 24 hour period. Electronic readers located in the farm dairy capture the pedometer data at each milking, and the data are recorded in a computer database for analysis. Software is used to compare the activity of each cow over previous time periods. Cows show increased activity prior to the onset of standing heat by a factor of two to four times normal activity (Eradus *et al.*, 1992). Cows identified as having increased activity by the pedometer system are considered candidates for breeding within a 12 to 24 hour period of being identified. A number of studies reviewed by Firk *et al*. (2002) have shown that pedometers are capable of identifying oestrus events but that they can be prone to an unacceptably high number of false positives.

An important factor in assessing the performance of the pedometers is to have records of actual oestrus events. It is possible to use pregnancy diagnosis data combined with mating records to assign oestrus events for a mating that results in a pregnancy. However, conception rates per mating can be as low as 50%, meaning that other measurements, such as, progesterone levels during the mating period are also required to get a complete data set. The level of progesterone in blood or milk has a strong correlation with oestrus (Friggens *et al.*, 2005). Capturing this information provides a viable method to determine actual oestrus events.

The purpose of this study was to determine the current performance of activity monitoring devices on New Zealand pasture-based farms and investigate the potential for improved oestrus detection using additional automatically captured data.

MATERIALS AND METHODS

Data collection and preparation

Data was collected from 750 (Herd 1) and 655 (Herd 2) cows from two herds in the 2008 season over seven and six weeks of artificial breeding, respectively. The total number of steps between each milking was recorded by the pedometers. Oestrus event data was based on an analysis of milk progesterone levels collected twice weekly during the mating period, and on the analysis of pregnancy diagnosis and mating records. The frequency of progesterone recording was limited by the cost of sampling and analysis. Daily milk production, milking order, milk flow rate and milk conductivity records were also collected at each milking by the automatic sensors in the milking plant. The pedometer, milking order and milking data were normalised at each milking to remove the effects of paddock location, feeding level and time of milking on the measurements. Different pedometers were used in each herd. Herd 1 used the Rescounter (Westfalia Landtechnik, Oelde, Germany) and Herd 2 used the Afitag (S.A.E. Afikim, Kibbutz Afikim, Israel). The normalisation process involves replacing the raw values with their calculated z-score, using the average and standard deviation of the relevant milking session. This means that all values of the same type are projected onto a common scale.

Time lag variables were calculated as the difference between the current and previous milking, and between this milking and the milking 24 hours earlier. The time lag variables were calculated for all the normalised milking data as well as pedometer data resulting in a total of 15 explanatory variables. The actual oestrus events were represented as binary records.

Methods of analysis

A simple rule based model was developed for the pedometer data for each herd. A single rule was developed using a decision tree model using a single split and two branches. The rule would divide cows in to an oestrus group and a non-oestrus group. The decision tree model analysis differs from regression analysis by allowing each continuous explanatory variable to be treated as a series of discrete variables (Witten & Frank, 2005).

A second analysis was undertaken using a linear logistic regression within each herd. First, each of 15 explanatory variables calculated previously, were fitted individually to determine best single predictor of oestrus. Second, each of 15 explanatory variables were fitted simultaneously. The best combination of variables for predicting oestrus was determined by finding the model with the maximum Bayesian information criterion (Weakliem, 1999).

A third analysis undertaken was a machine learning approach, which used the WEKA toolset (Witten & Frank, 2005). This approach was used to see if it was possible to overcome the problems presented by having datasets that were overwhelmingly unbalanced where only 5% of instances are positive for oestrus. In this situation standard statistical methods and machine learning algorithms can do no better than always predicting the negative class. That is a cow that is not in oestrus. A common technique used to deal with this in machine learning is known as "bagging", where instances are randomly sampled into bags. Each bag is used to train one model. The dataset becomes balanced by ensuring that equal numbers of both classes are selected for each bag using replacement.

It is also possible to augment this procedure by balancing the dataset before bagging begins. Balancing is achieved by copying the dataset a predetermined number of times, then randomly deleting instances from the majority class until the number of instances matches the minority class. This ensures all the data from the minority class are present in each copy, along with a different subset of data from the majority class. Each copy is used to train a separate bagging model. A prediction for a new instance is simply the majority vote from all the trained models. The overall effect of balancing in this way is that more weight is given to the minority class by ensuring all of its data is used for each model.

The datasets were used to train separate balanced-bagging models, then tested using ten-fold cross-validation. Cross-validation divides the data into equal subsets or "folds", in this case ten, and in each step trains the model using all but one fold, then tests it using the held out fold. Each model used ten copies for every balancing step, since experimentally this was found to be a sufficient number of copies to obtain good accuracy. Each herd's data was used to train WEKA's bagging classifier using ten repetitions and un-pruned decision trees.

RESULTS AND DISCUSSION

Herd 1 had 750 cows with 1,106 oestrus events recorded over seven weeks of mating. Herd 2 had 655 cows with 672 oestrus events recorded over six weeks of mating. Cows with an oestrus event had on average an increase of 0.32 and 1.24 in normalized pedometer steps compared to cows without an oestrus event for Herd 1 and Herd 2, respectively. Also the change in normalized steps over the previous 24 hours was 0.16 and 0.90 units greater for cows experiencing an oestrus event in Herd 1 and Herd 2, respectively. The oestrus cows in Herd 1 on average were closer to the rear of the herd in terms of their milking order. The opposite behaviour was observed in Herd 2 where the oestrus cows on average were closer to the front of herd and also closer to the front relative to their position 24 hours previously.

The best simple rule using the decision tree based on pedometer data alone chose to split the cows based on the change in normalised number of steps in the last 24 hours. The rules were defined as a change in normalised steps ≥0.36 and 1.98 for Herd 1 and Herd 2, respectively. The rules provided a significant ($P < 0.05$) difference in the proportions of oestrus cows in each leaf set. However, the simple rule based approach would result in over 50% of the oestrus cows being misidentified as non-oestrus cows in both herds. Also based on this rule, 148 and 25 non-oestrus cows would be drafted incorrectly as oestrus cows per day in Herd 1 and Herd 2, respectively. The poor performance of the decision tree is in part due to the unbalanced nature of the data.

The results of logistic regression of the 15 explanatory variables fitted one at a time within each herd, showed that a number of these variables explained significant variation in the probability of a cow being in oestrus. For Herd 1 the 24 hour difference in normalised milk yield explained the largest amount of variation. The variables; normalised steps, milking order, milk conductivity and milk flow, 12 hour difference in normalised steps, and 24 hour difference in normalised steps, milking order, milk yield, milk flow; each explained significant ($P < 0.05$) amount of variation. However, for Herd 2 normalised milking order explained the largest amount of variation. The variables; normalised steps, milk yield, milk conductivity and milk flow, 12 hour difference in normalised milk yield and milk conductivity, and 24 hour difference in normalised steps, milk yield, milk conductivity, milk flow; explained a significant ($P < 0.05$) amount of the variation. The normalised pedometer data was the second best predictor of oestrus in both herds ($P < 0.05$).

A summary of the estimates derived from the areas under the receiving operator characteristics curve analysis are shown in Table 1. Fitting the 15 variables simultaneously in logistic regression resulted in an optimal model (maximum Bayesian information criterion) model for Herd 1 comprising of normalised steps, milk yield, milk conductivity and milk flow, 12 hour difference in normalised steps, milk yield and milk flow, and 24 hour difference in normalised steps, milking order, milk yield and milk flow. The area under the receiving operator characteristics curve was 0.68 indicating that if the model was to achieve a high degree of sensitivity in selecting oestrus cows it would be accompanied by a large number of false positives. The optimal model (maximum Bayesian information criterion) model for Herd 2 contained normalised steps, milk yield and milk conductivity, 12 hour difference in normalised step count, milking order and milk conductivity, and 24 hour difference in normalised milking order, milk yield and milk conductivity. The area under the operator curve for Herd 2's model was 0.89, a better result than Herd 1; however, the model would still have a reasonably large number of false positives.

When the machine learning approach was applied to Herd 1, the balanced-bagging model was only able to achieve an accuracy of 74%. However, the areas under the operator curves were significantly higher for the balanced model, 0.84 for balanced-bagging and 0.77 for bagging. Furthermore, the true positive rate is also higher, 78% versus 74% for bagging. For Herd 2, an

TABLE 1: A summary of the area under the receiving operator characteristics curve for each model.

Model	Herd 1	Herd 2
Logistic regression	0.68	0.89
Bagging	0.77	0.91
Balanced bagging	0.84	0.93

accuracy of 88% was achieved, with a true positive rate of 82% for oestrus. Although the overall accuracy is poorer than bagging alone, which was 98%, the balanced bagging model was more effective at determining whether a cow was in oestrus. This is expressed through the higher true positive rate of 82% versus 21% for bagging alone. The area under the operator curve for balanced-bagging was 0.93, compared to 0.91 for bagging. For both herds the machine learning models produced were complex with a large number of branches, and were not easily interpretable. The accuracies of the machine learning models were better than those achieved from the logistic regression approach. The level of false positives from the machine learning models was still high especially in Herd 1.

The level of accuracy of the pedometer data and the level of false positive cows are within the range of values reported by a review published by Firk *et al*. (2002). The accuracies of detection obtained in this study from the multivariate analyses were similar to those reported by Nebel *et al*. (1997) and de Mol (2001).

CONCLUSIONS

Pedometer data can aid the detection of oestrus cows. Cows showing oestrus on average have greater levels of activity. In this study a simple rule set using the pedometer data alone would not provide a suitable method for determining oestrus cows as the number of false positive cows drafted per day would be too large. The power of detection improved significantly with the addition of milk yield, milk flow and milking order information. The machine learning approach using a balanced-bagging classifier gave the most promising results. However, it was not able to achieve accuracy high enough to be used as a sole method of heat detection. It is possible that more data could improve the model to a level of accuracy sufficient for sole use. Advances in pedometer design such as storing a data time series for each cow may improve the accuracy of this technology beyond the level found in this study.

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