Automatic Classification of Eating and Ruminating in Cattle Using a Collar Mounted Accelerometer

J. Konka[1], C. Michie[1,2] & I. Andonovic[1,2]

[1]University of Strathclyde, Department of Electronic and Electrical Engineering, Glasgow G1 1XW, UK
[2]Silent Herdsman Ltd., Glasgow G51 1PR, UK

Abstract

Within the past ten years, methods for automating the process of monitoring the behaviour of cattle have become increasingly important. Within the UK, there has been a steady decline in the number of milk producers and increased commercial pressures have forced increasing consolidation within dairy farming. As a result the average farm size has grown from around 90 to 160 cows. A direct consequence of these trends is that the farmers have less time to observe their herd and are increasingly reliant on technology to undertake this function, most readily underlined with the growth in the use of oestrus or 'heat' detection collars to assist in the optimisation of fertility. There is also a desire to derive additional information for collars that have to date been utilised solely to indicate the onset of heat

The paper reports on the analysis of signatures obtained from an accelerometer based collar (Silent Herdsman) to identify both eating and rumination signatures, identified through a combination of frequency and statistical analysis. A range of post processing methods have been evaluated in order to determine the most appropriate for integration within a low power processor on the collar. Trials have been carried out using a rumination sensing halter to provide verification data. Analysis of this data over a period of several days, on a minute by minute basis has shown that it is possible to recover eating and rumination with sensitivity and positive predictive value greater than 85%.

Keywords: eating, ruminating, cattle, machine learning, accelerometer

Introduction

Within the past ten years, methods for automating the process of monitoring the behaviour of cattle have become increasingly important. In the UK, there has been a steady decline in the number of milk producers. The number of dairy cows in the UK has declined from 3.2 million in 1980, to 1.8 million in 2010 (Hawkins, 2011). Similarly the number of dairy producers has fallen from 35,741 in 1995 to 15,716 in 2010. In tandem with this the average herd size has risen, as those holdings with smaller herds have left the industry. In 2009 the average number of cows per herd was 113, compared to 80 in 1999 (Hawkins, 2011). Commercial pressures on farms has forced an increasing amount of consolidation meaning that the average farm size has grown accompanied by an increase in milk average yield per cow.

A direct consequence of this has been that more farms operate intensively in order to optimise production and operation profit. As a result, the time available to farmers for observing their herd has reduced and increasingly farmers are relying on technology to undertake this function. This is underlined by the growth in the use of oestrus or, 'heat', detection collars (NMR, 2012; Fabdec, 2011) and pedometers (Fullwood, 2011) used to assist in the optimisation of fertility. More recently heat detection collars that monitor also for rumination signatures using a microphone have become available (Lely, 2014). Here the use of an accelerometer based collar that can identify both eating and rumination signatures is reported for the first time. Trials carried out using a rumination halter

(ITIN+HOCH, 2014) in order to provide verification data have shown that the collar can recover signatures with accuracy in excess of 90%. This methodology is more reliable than using video analysis since it does not rely on a human interpretation of images.

Background

The use of automated measurement methods to monitor the behaviour of animals is becoming increasingly widespread. Key features that have been identified include restlessness (as an indication of oestrus) and rumination. Here the potential for eating and rumination signatures to be recovered using a three axis accelerometer is examined. Such information provides useful indicators of animal welfare that can be directly integrated within a herd management platform. Analysis of signatures derived from accelerometer suspended below a halter mounted on cattle (Watanabe et al., 2008) has been reported to show significant differences in the accelerometer signatures that could in principle lead to a platform that can predict eating, rumination and standing/lying behaviours (among others). A similar analysis of collar mounted accelerometers (Scheibe and Gromann, 2006) confirms significant difference in the variance of accelerometer data between standing and eating and also between eating and ruminating. However, the variance in accelerometer reading during rumination is similar to that when the cow is standing and when the cow is drinking. Unique identification of each of these parameters therefore becomes problematic using simple statistics alone. Martiskainen *et al.* (2009) reported the use of support vector machines in order to recover a range of features including rumination, eating, standing and lying. The approach produced reasonable results displaying sensitivities and positive predictive values (S, PPV) of: rumination (75%, 96%), eating (75%, 81%), standing (80%, 65%) and walking (79%, 79%). However the approach used 28 variables derived from the raw accelerometer readings and a support vector machine to classify the variables into behaviour categories. This approach is complicated and is not readily compatible with the constraints of a low power processor such as routinely available on a collar mounted system. Furthermore, the approach is essentially a supervised learning method and may be vulnerable to signature changes over time. Here a collar based methodology that simplifies the data set such that it becomes compatible with low power processing platform is reported.

Methodology

The RumiWatch^{TM} halter (Zehner *et al.*, 2012) uses a pressure sensor to directly measure cow jaw movements and hence derive an understanding of the time evolution of eating and rumination. Over a period of several weeks, a halter was used to measure the eating and ruminating behaviour of beef and dairy cattle fed using a total mixed ration. The forage component of the complete diet consisted of grass silage, maize silage and whole crop. Each cow monitored was fitted with a RumiWatch^{TM} halter and a Silent Herdsman collar containing a three axis accelerometer.

An example of a trace from the RumiWatch^{TM} halter is shown below in Figure 1.

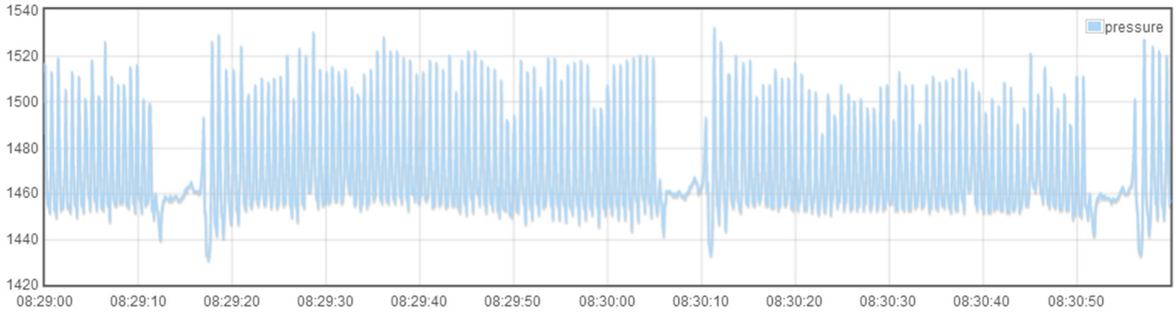

Figure 1. RumiWatch halter output while a cow is ruminating.

The rumination signature is characterised by two features. Firstly the raw movements are highly regular and are very consistent; secondly, every 40 seconds or so the process stops while the cow swallows a bolus and regurgitates a fresh bolus. The corresponding trace derived from a collar mounted accelerometer is shown Figure 2. Although the signal to noise ratio of the measurement is not as high as obtained using the jaw mounted pressure sensor, the regularity of the motion and the occurrence of bolus swallowing and regurgitation are clearly identifiable.

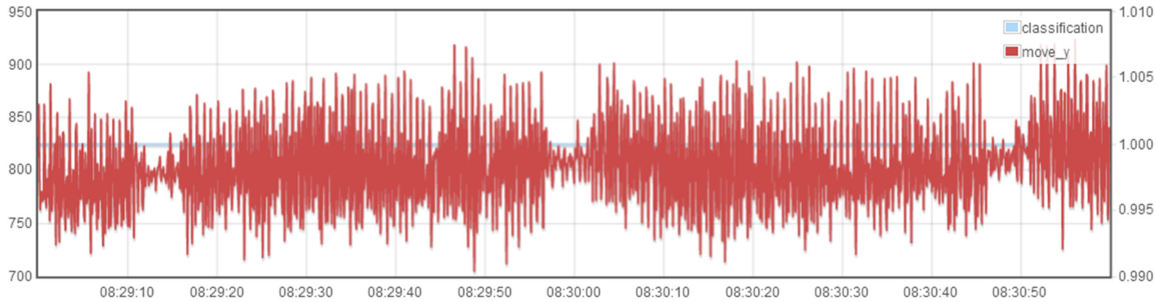

Figure 2. Rumination signature measured using a neck mounted collar.

The jaw movements exhibited during eating are significantly larger than those during rumination. Furthermore, eating signatures are also accompanied with a wider range of head movements. This enables the two to be separated in feature space.

Results

Using the above metrics as input data, the performance of four machine learning algorithms: Gaussian Mixture Model (GMM) K-Means methodologies using Euclidean and Taxi-Cab distance estimation methods, and Hidden Markov Model (HMM) approach was executed. The performance was tested over a period of 7 days, and measured in 5 complementary ways: Sensitivity and Positive Predictive Value (PPV) in detecting ruminating events, Sensitivity and PPV in detecting eating events, and overall accuracy.

Table 1 depicts the results of the analysis. It is clear that, for both eating and ruminating, the highest average PPV was achieved by HMM, while the lowest by GMM. The highest average sensitivity, on the other hand, was achieved by GMM. This suggests that GMM is significantly over-predicting (high sensitivity) while being imprecise (low PPV), in contrast to HMM which is less sensitive but more precise at the same time (lower sensitivity but higher PPV).

Table 1. Average Sensitivity, PPV and overall accuracy in detecting ruminating and eating events.

Algorithm	Rumination		Eating		Overall accuracy
	Avg. sensitivity	Avg. PPV	Avg. sensitivity	Avg. PPV	
Euclidean K-Means	84.44%	96.03%	93.33%	70.54%	87.57%
Taxi-Cab K-Means	85.42%	95.79%	93.42%	69.85%	87.60%
GMM	87.23%	86.75%	97.30%	53.37%	78.21%
HMM	86.12%	98.67%	86.89%	88.10%	90.68%

In terms of the overall accuracy, it is clear that HMM achieves the highest overall accuracy, while GMM, as expected, is the least accurate. The results of the analysis corroborate that it is possible to recover eating and rumination with sensitivity and PPV greater than 85%, and overall accuracy in excess of 90%.

Conclusions

An accelerometer based collar to detect both eating and ruminating signatures has been reported together with a performance comparison of four machine learning algorithms (Euclidean K-Means, Taxi-Cab K-Means, GMM, and HMM) used to recover the behaviour states of an animal. HMM was the most precise (accurate) of all the considered algorithms, while GMM the most sensitive and least precise. Using these techniques, it is possible to recover eating and rumination with sensitivity and positive predictive value greater than 85%, and accuracy in excess of 90%.

List of References

Fabdec, 2011. Fabdec's Cow Management Systems. [Online]. Available: http://fabdec.com/productlist/Cow-Management-Systems [Accessed Jan. 31, 2014].

Fullwood, 2011. CRYSTA ACT+ – the most accurate pedometer on the market. [Online]. Available: http://www.fullwood.com/news/content/128 [Accessed Jan. 31, 2014].

Hawkins, O., 2011. Dairy industry in the UK: statistics, Standard Note: SN/SG/2721. [Online]. Available: http://www.parliament.uk/briefing-papers/sn02721.pdf [Accessed Jan. 31, 2014].

ITIN+HOCH, 2014. RumiWatchSystem: Measurement system for automatic health monitoring in ruminants. [Online]. Available: http://www.rumiwatch.ch/downloads/99_Diverses/RumiWatch_E.pdf [Accessed Jan. 31, 2014].

Lely, 2014. Lely Qwes HR–Rumination activity. [Online]. Available: http://www.lely.com/en/milking/detection-system/qwes-h--hr/rumination-activity#tab [Accessed Jan. 31, 2014].

Martiskainen, P., Jarvinen, M., Skon, J.-K., Tiirikainen, J., Kolehmainen, M., Mononen, J., 1 June 2009. Cow behaviour pat- tern recognition using a three-dimensional accelerometer and support vector machines. Applied Animal Behaviour Science 119 (1), 32–38.

NMR, 2012. Silent Herdsman. [Online]. Available: http://www.nmr.co.uk/silentherdsman/ [Accessed Jan. 31, 2014].

Scheibe, K. M., Gromann, C., 2006. Application testing of a new three-dimensional acceleration measuring system with wireless data transfer (was) for behavior analysis. Behavior Research Methods 38 (3), 427-433.

Watanabe, N., Sakanoue, S., Kawamura, K., Kozakai, T., 2008. Development of an automatic classification system for eating, ruminating and resting behavior of cattle using an accelerometer. Grassland Science 54 (4), 231-237.

Zehner, N., Niederhauser, J. J., Nydegger, F., Grothmann, A., Keller, M., Hoch, M., Haeussermann, A., Schick, M., 2012. Validation of a new health monitoring system (RumiWatch) for combined automatic measurement of rumination, feed intake, water intake and locomotion in dairy cows. In: Information Technology, Automation and Precision Farming. International Conference of Agricultural Engineering—CIGR-AgEng 2012: Agriculture and Engineering for a Healthier Life, Valencia, Spain, 8-12 July.