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Cattle behaviour classification from collar, halter, and ear tag sensors

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A B S T R A C T

In this paper, we summarise the outcome of a set of experiments aimed at classifying cattle behaviour based on sensor data. Each animal carried sensors generating time series accelerometer data placed on a collar on the neck at the back of the head, on a halter positioned at the side of the head behind the mouth, or on the ear using a tag. The purpose of the study was to determine how sensor data from different placement can classify a range of typical cattle behaviours. Data were collected and animal behaviours (grazing, standing or ruminating) were observed over a common time frame. Statistical features were computed from the sensor data and machine learning algorithms were trained to classify each behaviour. Classification accuracies were computed on separate independent test sets. The analysis based on behaviour classification experiments revealed that different sensor placement can achieve good classification accuracy if the feature space (representing motion patterns) between the training and test animal is similar. The paper will discuss these analyses in detail and can act as a guide for future studies.

1. Introduction

Animals alter their behaviour to enable them to deal with stressors such as infection, satiety, or social and environmental changes. This behaviour is often consistent and predictable but cannot be measured at scale because of the labour required to physically monitor large numbers of animals continuously. Wearable sensor technologies offer a possible solution to this problem enabling measurement at scale but this can only be successful if sensor outputs can be interpreted accurately and in real time. Monitoring cattle behaviour using wearable sensors is becoming an important option for farm management and genetic selection programs and a greater emphasis on individual wellbeing and performance rather than a more traditional herd based approach. Examples of precision agriculture (PA) management and genetic improvement strategies are seen across the agricultural spectrum including cropping [1,2], dairy/beef [3] and the aquaculture industry [4–6].

In the livestock sector behaviour analysis can provide insight into (i) Animal health: animal behaviour patterns can be linked to animal health [9–13], an early detection of sickness was identified when rumination and general activity decreased below expected levels; (ii) Feed intake and satiety:

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behaviours like grazing, chewing and feeding are indicators of feed intake. Percentage of time spent on grazing related behaviours can assist in understanding the amount of feed intake compared to amount of pasture or supplements offered, animal preference and satiety state [14–16]; (iii) Heat/Estrus event: this refers to the period of sexual receptivity and fertility in female mammals. The heat event has been shown to be detectable through changes in restlessness (activity) [12]. The detection of periods indicate the appropriate time for artificial insemination.

Commercial and research systems presented in [9–21] continuously and automatically monitor the rumination time [9–11], grazing time [10] and activity intensity [9–13] of individual animals. Current behaviour monitoring systems are commonly comprised of: (a) an individual sensor or combination of sensors that are fitted to each animal (Fig. 1) - these sensors can include accelerometers, magnetometer, gyroscope, compass, GPS, pressure and microphone; (b) a sensor node to process, store and transmit sensor observations; and (c) a model or set of models [17,18] to infer an animal's behaviour from the raw sensor observations.

Sensors can be placed on different parts of the animal and it is not known if, or how, location might influence classification accuracy. We therefore devised an experiment to better understand how sensor placement influences behaviour classification accuracy? In this study, we collected data simultaneously from accelerometers placed on three different parts of the animal body: neck (collar), head (halter) and ear (using an ear tag). We developed separate behaviour classification models based on sensor data from these three locations. We utilised two different testing approaches: (i) Training on data from a set of animals and testing models on data from animals that are not part of the training process and (ii) Mix data from all the animals, training on data on part of mixed data set and testing models on data are not part of the training process. Analysis results reveal that feature distribution between training and test data is an important factor for accurate behaviour classification for any sensor placement.

Fig. 1 – Collar, halter and ear tag sensors used for cattle behaviour monitoring.

2. Feature extraction for classification

In previous studies, machine learning based cattle behaviour classifiers [17,18] employed a standard approach to model development without considering the potential value of state of the art classifiers and feature representations. The standard workflow (Fig. 2) in developing behaviour models involves partitioning time series data into short time windows, and for each window, extracting a small set of statistical features (i.e. first to fourth order statistical moments). The combination of statistical features and corresponding behaviour annotations were used to train a classifier. A set of statistical features were computed from the time series sensor data in [19–21] and showed potential to classify cattle behaviour with high accuracy. In this study we computed statistical features only for classification experiments.

An important step in a classification framework (Fig.2) is feature extraction. For the experiments conducted as part of this study, a set of statistical features were computed from the time and frequency representations associated with each window of the input series. Frequency domain representations of the time series data were obtained using Discrete Fourier Transformation (DFT). Let x_t be the $t-$ th element of the time series. In DFT $k-$ th element of the frequency domain representation is obtained as:

$$f_k = \sum_{t=0}^{n-1} x_t e^{-2\pi i t k/n} \qquad (1)$$

where n is the length of the vector. The interpretation is that x represents the signal level at various points in time and f represents the signal level at various frequencies. The DC component of the DFT (f_0: component corresponding to 0 frequency) is retained as a feature. The remaining statistical features are then computed from the spectrum after its DC component has been removed. The statistical features used include the mean, standard deviation, skewness, and kurtosis as presented in Table 1.

We also used minimum and maximum of the series x_t and f_k as features (with $k > 0$). The standard deviation, minimum and maximum features were used to represent the motion intensity. Along with these features, the period of the signal within each time window was computed in time domain using the method presented in [6]. The period feature is included because some behaviours, such as grazing, walking and ruminating, have repetition within their motion patterns. A total of fourteen statistical features were computed.

3. Sensors for data collection

The results presented here are based on trial data collected at FD McMaster Laboratory in Armidale, NSW, Australia in November 2014. Accelerometer sensors were placed in a collar, ear tag, and halter at the same time and data from these three different sources. A video camera recorded the animal's behaviours. A domain expert coded the videos to identify a range of time-stamped data from the three sources were

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