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Behavioral classification of data from collars containing motion sensors in grazing cattle

L.A. González [a,e,*], G.J. Bishop-Hurley [b,e], R.N. Handcock [c,e], C. Crossman [d,e]

[a] CSIRO Animal, Food and Health Sciences, PMB PO, Aitkenvale, Queensland 4814, Australia
[b] CSIRO Animal, Food and Health Sciences, 306 Carmody Road, St. Lucia, Queensland 4067, Australia
[c] CSIRO Animal, Food and Health Sciences, Private Bag 5, Wembley 6913, Western Australia, Australia
[d] CSIRO Information and Communication Technologies Centre, Pullenvale 4069, Queensland, Australia
[e] CSIRO Sustainable Agriculture Flagship, Australia

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ABSTRACT

Remote monitoring of animal behavior offers great potential to improve livestock management however technologies able to collect data at high frequency and accurate data classification methods are required. The objective of this study was to develop a methodology capable of performing unsupervised behavioral classification of electronic data collected at high frequency from collar-mounted motion and GPS sensors in grazing cattle. Two independent trials were conducted, one for developing the classification algorithm (4 groups of 11 steers) and a second for its evaluation (14 steers). Each steer was fitted with a collar containing GPS and a 3-axis accelerometer that collected data at 4 and 10 Hz, respectively. Foraging, ruminating, traveling, resting and 'other active behaviors' (which included scratching against objects, head shaking, and grooming) were observed and recorded continuously at the nearest second in animals wearing collars. Collar data were aggregated to 10-s intervals through the mean (indicative of the position of the neck and travel speed) and standard deviation (SD; indicative of activity level) and then log-transformed for analysis. The histograms of travel speed showed 3 populations and observations revealed these populations represented stationary, slow and fast travel behaviors. The histograms of the accelerometer *X*-axis mean showed populations corresponding with behaviors of head down or head up. The histograms of the accelerometer *X*-axis SD showed 3 populations representing behaviors with high, medium and low activity levels. Mixture models were fitted to data from each animal in both trials to calculate threshold values corresponding to where behaviors transitioned between different states. These thresholds from the 3 sensor signatures were then used in a decision tree to classify all 10-s data where behaviors were unknown into 5 mutually exclusive behaviors. The algorithm correctly classified 85.5% and 90.5% of all data points in the development and evaluation datasets, respectively. Foraging showed the greatest sensitivity (93.7% and 98.4%) and specificity (94.6% and 99.4%) followed by ruminating (sensitivity 97% and 87%, and specificity 90% and 95%) for development and evaluation trials, respectively. Major advantages of mixture models include computational efficiency suitable for large data sets (e.g. >2 million data lines), minimal requirement for training datasets, and estimation of threshold values for individual animals under unknown and varying environmental conditions. The technology and methodology allows for the automatic and real-time monitoring of behavior with high spatial and temporal resolution which could benefit livestock industries beyond the research domain for improved animal and ecological management.

1. Introduction

Measuring animal location and behavior across different spatial and temporal scales can facilitate understanding of the factors that drive resource selection (Owen-Smith et al., 2013), growth, reproduction and survival (Gaillard et al., 2010), response to disease (González et al., 2008) and coping mechanisms with environmental conditions (Anderson et al., 2013). Therefore, monitoring behavior in near real-time can enable more accurate and timely management decisions to optimize animal performance, welfare and environmental outcomes. In grazing systems, Global Positioning Systems (GPS) and motion sensors (e.g. accelerometers) can monitor animal

* Corresponding author at: The University of Sydney, Centre for Carbon, Water and Food, Faculty of Agriculture and Environment, 380 Werombi Road, Camden, NSW 2570, Australia. Tel.: +61 2 4601 9834.
E-mail address: Luciano.Gonzalez@sydney.edu.au (L.A. González).

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behavior in near real-time when integrated into wireless sensor networks (Wark et al., 2007; Handcock et al., 2009; Nadimi et al., 2012). However, the challenge in using sensor data is to automate the differentiation of behavioral activities. Several methodologies have previously been used to classify sensor data into behavioral states (Martiskainen et al., 2009; Ungar et al., 2005). However, those methodologies require a training dataset (e.g. direct observations) in every experiment or condition and do not account for differences among individual animals and devices. A methodology that is robust for use on data collected from different devices would also reduce the need to calibrate sensors and to fit collars with the same tension (Anderson et al., 2013). Mixture models address these constraints by allowing unsupervised classification of data using probability density functions (PDF; McLachlan and Peel, 2000; Tolkamp et al., 2000). Characterizing the structure of behavior using mixture models combined with observations in one experiment allows estimation of parameters describing the PDF without the need of direct observation in subsequent experiments.

The objective of the present study was to develop and evaluate a methodology to characterize the structure of electronically obtained data and classify such data into behavioral activities including foraging, resting, ruminating, traveling and ‘other active behaviors’ using GPS and motion sensor data from collars worn by steers. The goal was to characterize these behaviors from raw data once a dataset had been ‘fingerprinted’ based on observations and then apply the method to an independent dataset.

2. Materials and methods

All experimental procedures were approved by the institutional Animal Ethics Committee (Approval # A10/2010, A11/2010, and A8/2011). Two trials were conducted to collect data from electronic monitoring collars and direct visual observations of animal behavior. Data from one trial was used to develop an algorithm to classify collar data into behavioral categories that identify behaviors. Data from the remaining trial were used to evaluate the accuracy of the classification algorithm. Both trials were conducted at the Commonwealth Scientific and Industrial Research Organization (CSIRO) Lansdown Research Station near Townsville, Queensland, Australia (18°39′42″S and 146°51′12″E, elevation 63 m) using Brahman, Belmont Red Composites and crossbred Brahman steers. Paddocks contained tropical vegetation dominated by *Urocloa* spp., *Stylosanthes* spp., *Macroptilium* spp. and *Chloris* spp., and contained more than 2000 kg of DM/ha. Trees, woody vegetation and shrubs edible by cattle were not prevalent in trials of the present study. Steers had *ad libitum* access to one water trough in each paddock. The algorithm-development trial involved 4 groups of 11 steers with a mean initial body weight [BW] of 403 ± 30 kg and a mean average daily gain [ADG] of 0.37 ± 0.40 kg/day during 3 experimental weeks. Each steer was fitted with a CSIRO electronic cattle monitoring collar (Wark et al., 2007) for 21 days in October 2011 and each group of steers grazed a 7 ha flat treeless paddock. The evaluation trial was conducted in a 15 ha paddock and involved a single group of 14 steers (initial BW = 433 ± 32 kg; ADG = −0.63 ± 1.50 kg/day) fitted with collars for 10 days during November 2012.

2.1. Description of CSIRO cattle monitoring collars

The CSIRO collars (Wark et al., 2007) had a 20-channel GPS receiver chip (U-Blox, Thalwil, Switzerland), a GPS antennae, a microcontroller (Fleck™, CSIRO, Australia), 4 D-cell batteries in series (Duracell, Australia), a 4 GB micro Secure Digital card for data storage, a piezoelectric micro-electromechanical system (MEMS) chip containing a 3-axis accelerometer and a 3-axis magnetoresistive sensor (HMC6343 Honeywell, Plymouth, MN), and wireless network communication capability with 900 MHz radio antennae. All components except the GPS antenna were sealed in a plastic box and positioned on the animal such that the box remained below the neck when worn, and the GPS antenna remained on top of the neck to improve signal reception. The GPS measures animal location on the earth surface and calculates the speed the GPS unit is moving across the landscape on board of the collar. The accelerometer measures inertial acceleration in a 3 axis inertial and gravitational frame (fore-aft, right-left, up-down) with the *X*-axis detecting the vertical or up-down direction (tilt), the *Y* axis detecting the fore-aft and the *Z* axis the right-left direction. The collars were programmed to collect GPS data at 4 Hz (i.e. 345,000 data points/day) and accelerometer data at 10 Hz (i.e. 862,500 data points/day). Effective actual battery life was 12–14 days. After collar retrieval from the steers at the end of the trial, the memory storage cards were removed and the data downloaded.

2.2. Behavioral measurements

Direct visual behavioral observations (the gold standard method) were recorded using continuous sampling on random animals in each group for both experiments by recording the animal ID, time (to the nearest second) and type of activity at every occasion in which the steers changed from one activity to another (Altmann, 1974). Therefore, the number of animals from which data was collected and the length of the observation periods were variable for each behavioral activity. The percentage of data collected by electronic collars which had accompanying behavioral observations in the final datasets was 0.6%. Observations were made on days 2, 3, 5, 6, 7 and 8 after fitting the collars to the animals for the development trial with a total of 18 h of visual observations made during daylight hours from 1000 to 1800. The observations for the evaluation trial totaled 25 h over 5 days (days 1, 2, 3, 5 and 8 after fitting the collars). Animals got used to the collars very quickly and observations were started on the day of collar deployment. Five mutually exclusive activities (i.e. steers could only perform 1 activity at the time) were recorded: foraging, ruminating, resting, traveling and other active behaviors. Initially, grazing with the head down, browsing and searching for food were recorded separately however grazing occupied more than 95% of all foraging behaviors and it was decided to merge the 3 into the activity called ‘foraging’ for simplicity. Therefore, foraging was considered the act of searching for food while walking short distances with the head down without picking food up with the mouth, grazing with the head down while apprehending the forage with the mouth, browsing consisting of apprehending vegetation with the head held leveled with respect to the ground surface, and chewing either with the head down or the head leveled with regards to the ground surface. Ruminating was defined as chewing the cud while standing up or lying on the ground. ‘Other active behaviors’ was a category created to include vigorous head movement while standing with no forward movement of the body such as when rubbing or scratching their own body against an object (e.g. fence post), licking themselves or other herd mates with the mouth or tongue, or head shacking when attempting to get rid of insects. Traveling was defined as forward moving without foraging including walking or running and while the animal could be ruminating or not ruminating but not engaged in foraging activities. Resting was considered when the animals were stationary and not foraging, ruminating, traveling or performing other active behaviors (either in standing or lying down postures). The *WhatISee* smart phone application was used to register the activities (https://itunes.apple.com/us/app/whatisee/id332512569?mt=8) for iPhone, iPod or iPad (Apple, Cupertino, USA). Information to correct the time difference between *WhatISee* (local time) and