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Development of an open-source algorithm based on inertial measurement units (IMU) of a smartphone to detect cattle grass intake and ruminating behaviors ☆

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ABSTRACT

In this paper, an open algorithm was developed for the detection of cattle's grass intake and rumination activities. This was done using the widely available inertial measurement unit (IMU) from a smartphone, which contains an accelerometer, a gyroscope, a magnetometer and location sensors signals sampled at 100 Hz. This equipment was mounted on 19 grazing cows of different breeds and daily video sequences were recorded on pasture of different forage allowances. After visually analyzing the cows' movements on a calibration database, signal combinations were selected and thresholds were determined based on 1-s time windows, since increasing the time window did not increase the accuracy of detection. The final algorithm uses the average value and standard deviation of two signals in a two-step discrimination tree: the gravitational acceleration on x-axis (Gx) expressing the cows' head movements and the rotation rate on the same x-axis (Rx) expressing jaw movements. Threshold values encompassing 95% of the normalized calibrated data gave the best results. Validation on an independent database resulted in an average detection accuracy of 92% with a better detection for rumination (95%) than for grass intake (91%). The detection algorithm also allows for characterization of the diurnal feeding activities of cattle at pasture. Any user can make further improvements, for data collected at the same way as the iPhone's IMU has done, since the algorithm codes are open and provided as supplementary data.

1. Introduction

Over the past decade precision livestock farming (PLF) has been developed for use on commercial farms and several tools are now available in animal monitoring applications. Recent technological developments have eased the use of sensors to monitor many physical variables both for animal science research and in practical farm level applications (Berckmans, 2014). Many researchers now focus on analyzing behaviors using sensor-based technologies and various data analysis approaches (Andriamandroso et al., 2016). Monitoring the specific behaviors of ruminants, particularly grazing and rumination, is important because these behaviors occupy much of the grazing cattle's time-budget. However, duration varies greatly: over a 24-h period, grazing occupies 25–50% of cow's daily time-budget and rumination 15–40% (Kilgour, 2012).

The ability of sensors to detect cattle behaviors though movements is based on recording three main parameters:

- location, using mainly global positioning system (GPS) and geographic information system (GIS) (e.g. Ganskopp and Johnson, 2007; Swain et al., 2008);

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- posture of the animal, which is the low frequency component of behavior such as the position of the head or back (e.g. Poursaberi et al., 2010; Viazzi et al., 2013);
- movements, which are the high frequency elements of a given behavior (e.g., Rutter et al., 1997; Nydegger et al., 2010).

Different types of sensors have been tested to record these parameters and can be used either alone or in combination. GPS and its incorporation into GIS is generally used to track wild (e.g. Forin-Wiart et al., 2015) and domestic animals (e.g. de Weerd et al., 2015), and, using changes in path speed, to detect unitary behaviors, such as grazing, resting and walking. Nevertheless, successful behavior classification remains poor varying between 71 and 86% calculated from 3-min data segments (Schlecht et al., 2004; Godsk and Kjærgaard, 2011; Larson-Praplan et al., 2015). Other types of sensors, which measure pressure or changes in electrical resistances, have pioneered movement analysis by focusing on jaw types to detect chewing behaviors. This has led to correct classification of eating and ruminating behaviors with over 91% of exactness based on 5-min time windows (for example, IGER Behaviour recorder, Rutter et al. (1997) and ART-MSR by Nydegger et al. (2010)). Acoustic sensors (microphones) use sounds made by jaw movements and swallowing/deglutition to differentiate grazing and ruminating which have been successfully detected at a rate of 94% based on 1–5-min time windows (Clapham et al., 2011; Navon et al., 2013; Benvenutti et al., 2015). Movement measurements that detect or quantify animal behaviors now mostly use accelerometers.

Pressure and tension-based sensors seem to have yielded the highest possible information they can provide on feeding behavior or estimated intake (Nydegger et al., 2010; Pahl et al., 2015; Leiber et al., 2016) and acoustic sensors suffer from interferences with other animals (Ungar and Rutter, 2006). Therefore, accelerometers seem the most promising tool for PLF applications for research relative to grazing cattle (Andriamandroso et al., 2016). Behavior classification precisions from accelerometers differ according to the recording frequency (commonly varying between 0.1 and 20 Hz), to the method used for data processing and to the objective. For example, accelerometers are successfully used in the automated detection of lame animals. Based on a descriptive statistical classification method, lame and non-lame cows can be correctly classified with an average precision of 91% using data analysis with 10-s time windows (Mangweth et al., 2012). Detection of other behaviors such as walking, standing or lying, with accelerometers placed on the neck (e.g. Martiskainen et al., 2009), legs (e.g. Robert et al., 2009; Nielsen et al., 2010) or ears (Bikker et al., 2014) is accurate to between 29% and 99% using machine learning (Martiskainen et al., 2009) or a classification tree method (Robert et al., 2009; Nielsen et al., 2010) with 5-s to 5-min time windows.

Other methods have combined different kinds of sensors to increase detection precision. For example, González et al. (2015) combined GPS and accelerometers to achieve an overall correct classification of grazing behaviors between 85 and 91% using a decision tree and based on the analysis of 10-s time windows. Dutta et al. (2015) combined accelerometers with magnetometers to reach precisions ranging between 77% and 96% with different supervised classification methods on 5-s time windows such as binary tree, linear discriminant analysis, naïve Bayes classifier, k-nearest neighbor and adaptive neuro- fuzzy inference.

Nonetheless, because all these methods are either based on black-box statistical approaches or in-lab made prototype devices, an open detection algorithm that can be easily used for research purposes across various grazing conditions is not yet available. Commercial PLF systems designed for on-farm use incorporate accelerometers and gyroscopes that are similar, if not identical, to the ones used in smartphones. However, these commercial systems are designed for on-farm use and generally do not provide raw data that can be used by PLF researchers. Invariably, they also sample accelerometers at a fixed rate limiting the potential for data mining for ruminant ethology, especially that related to feeding behavior on pasture.

By offering an open method for the detection of grazing cattle behaviors that can be shared, this paper proposes a flexible platform for PLF researchers to collect accelerometer data and process it to extract useful behavior information. The algorithm should comply with three criteria: (1) be based on an open approach in order to allow further development and improvement by users, (2) be valid across a wide range of grazing conditions regarding both the animal as well as the pasture condition, and (3) using sensors that are easily available to users without any need for hardware development. For the third criteria, the choice was made to work with the inertial measurement unit (IMU) of an iPhone (Apple, Cupertino, CA, USA). IMUs generally comprised two or three sensors which measure velocity, orientation and gravitational force using an accelerometer for inertial acceleration and gyroscopes for angular rotation. In recent devices, a magnetometer has also been added to measure magnetic deviation and improve gyroscopic measurements. After internal calibration, IMUs can measure many physical parameters within three axis, such as linear acceleration, rotation angle (pitch, roll, and yaw) and angular velocity (Ahmad et al., 2013). To fulfill our objective, the work was divided into (1) assessing the individual and combined capabilities of IMU-acquired signals to detect cattle movements on pasture, and (2) constructing and evaluating a decision tree based on a simple Boolean algorithm to classify grass intake and rumination unitary behaviors.

2. Material and methods

All experimental procedures performed on the animals were approved by the Committee for Animal Care of the University of Liège (Belgium, experiment n°14-1627). Measurements were carried out over three years between 2012 and 2015, in four different locations in Wallonia (Belgium) and with different breeds in order to achieve a more representative and variable dataset.

2.1. Animals

A total of 19 cows of different breeds across four different farms were used, aged between 4 and 12 years, and with estimated weights between 450 and 650 kg:

- 9 dry red-pied Holstein (Gembloux, Gembloux Agro-Bio Tech, University of Liège experimental farm, 50°33′54.6″N 4°42′04.6″E, GBX);
- 2 black-pied Holstein (Liège, Faculty of Veterinary science, University of Liège experimental farm, 50°34′45.4″N 5°35′14.1″E, FVS);
- 2 Blonde d'Aquitaine x Belgian White and Blue cross-bred (Corroy-le-Grand, commercial farm, 50°39′43.4″N 4°40′43.0″E, CLG);
- 6 Belgian White and Blue cows (Dorinne, commercial farm, 50°18′43.9″N 4°57′58.1″E, DOR and Tongrinne, commercial farm, 50°30′37.4″N 4°36′12.6″E, TON).

2.2. Materials

Each cow was fitted with a halter containing an iPhone 4S (Apple, Cupertino, CA, USA) inside a waterproof box (Otterbox Pursuit series 20, 152.4 × 50.8 × 101.6 mm, 142 g, Otter Products, LLC, USA) (Fig. 1B). Each mobile phone was equipped with an application (SensorData, Wavefront Labs) downloaded from Apple Store