Computers and Electronics in Agriculture 139 (2017) 126–137

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

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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ARTICLE INFO

Article history:
Received 27 July 2016
Received in revised form 16 May 2017
Accepted 17 May 2017

Keywords:
Dairy cattle
Grass intake
Behaviors
Inertial measurement unit
Open algorithm

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);

☆ Results were partially presented at the International Conference on Precision Agriculture (Sacramento, USA, July 2014) and the European Conference on Precision Livestock Farming (Milan, Italy, September 2015) and published in the respective conference proceedings.

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http://dx.doi.org/10.1016/j.compag.2017.05.020
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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.

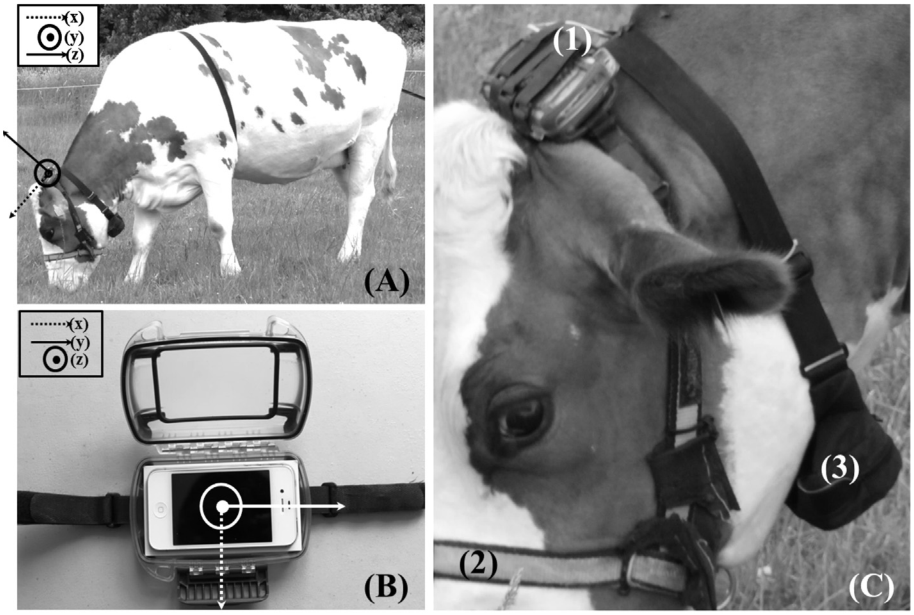
2.1. Animals

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



(1) Box containing the iPhone, (2) Halter, (3) Bag containing a supplementary battery

Fig. 1. Inertial measurement unit (IMU) device description, (A) IMU 3-D axis representation on a grazing cow, x-axis is aligned with the tail to head symmetry Ax of the animal, y-axis describes lateral movements, and z-axis gives up and down movements; (B) iPhone 4S and its IMU placed in a waterproof box; (C) all equipment components including the iPhone box (1), the halter (2) and the supplementary battery (3).

(Apple, Cupertino, CA, USA) which captures and stores data from the IMU of the iPhone at 100 Hz. The IMU of the iPhone 4S uses STMicro STM33DH 3-axis as an accelerometer, STMicro AGDI 3-axis as a gyroscope (STMicroelectronics, Geneva, Switzerland) and AKM 8963 3-axis electronic compass as a magnetometer (Asahi Kasei Microdevices Corporation, Tokyo, Japan).

To extend the data recording duration from 8 to 24 h, the original 3.7 V 1420 mAh Li-Polymer battery was connected to an additional external battery (Anker Astro E5 16000mAh portable charger, 150 × 62 × 22 mm, 308 g, Anker Technology Co. Limited, CA, USA) and attached as a collar around the neck of the animal (Fig. 1C).

Choice of this anatomical position was made because it has already proved effective in detecting cattle behaviors (e.g. Martiskainen et al., 2009), ensured minimal disturbance to the animal, and limited risk of the animal removing or damaging the device by scratching or smashing. Velcro tape was stitched on each halter and the waterproof box fixed onto the halter using Velcro straps as shown in Fig. 1C.

The SensorData application captures acceleration and gyroscope data along three axes (as showed in Fig. 1B) as well as magnetometric and GPS information, providing a total of 40 signals (Table 1).

Table 1
List of signals captured by the iPhone 4S using SensorData application (Wavefront Labs).

Sensors	Measured signals	Unit
Accelerometer	Acceleration on x (Ax), y(Ay) and z (Az)	g[a]
Gyroscope	Euler angles (pitch x, roll y, yaw z)	radian
	Attitude quaternion on x, y, z and w (Qx, Qy, Qz, Qw)	radian
	Rotation matrix (3 × 3 matrix of rotation)	
	Gravitational component of acceleration (Gx, Gy,Gz)	g
	User component of acceleration (Ux,Uy,Uz)	g
	Rotation rate (Rx,Ry,Rz)	radian s^{-1}
Magnetometer	Magnetic data (x,y,z)	μTesla
	Magnetic and true heading	degrees
Location	Latitude and longitude	degrees
	Altitude and accuracies	m
	Course	degrees
	Speed	m s^{-1}
	Proximity sensor	not defined

[a] g, acceleration of gravity (g = 9.81 m s^{-2}).

2.3. Data acquisition, calibration and validation of the detection algorithm

The Fig. 2 illustrates the whole process from observations to algorithm validation. This comprised four major steps: (1) data acquisition, (2) animal observation through recorded videos, (3) calibration and construction of a behavior detection algorithm and finally (4) its validation.

2.3.1. Data acquisition

The algorithm development began by constructing a behavior database that combined visual observations and related measured signals. For this purpose, animals wearing the equipment were set to graze ryegrass (*Lolium perenne*) and white clover (*Trifolium repens*)-based pastures, while being video recorded as reference for behavior detection. The mobile devices' IMU and the operators' video cameras were time synchronized beforehand for further data analysis. In the experimental farm (GBX), three data acquisition sessions were performed over three years. The first, fall 2012 and spring 2013, were performed on two red-pied dry Holstein cannulated cows (RPc1 and RPc2) grazing a 0.19 ha pasture, disregarding sward characteristics. The second session, summer and fall 2014, was performed on 1.4 hectare pasture with four red-pied Holstein dry cows (RP1, RP2, RP3 and RP4), with three pre-grazing forage allowances measured using a rising plate meter with an in-house calibration (1000, 2000 and 3000 kg DM ha^{-1}). Finally, in summer

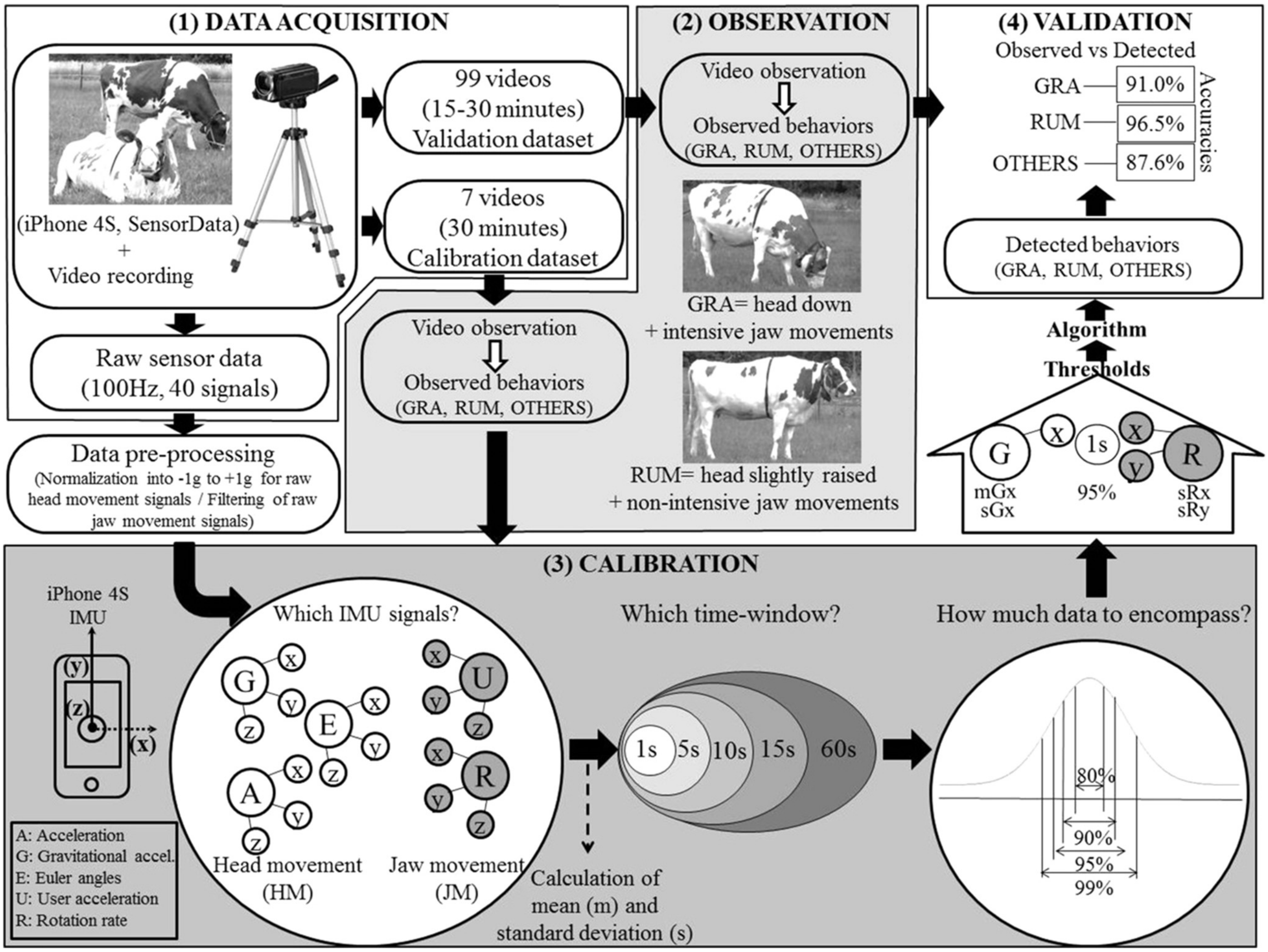


Fig. 2. From observation to detection algorithm: summary of the 4-steps process used for the construction of cattle behavior detection algorithm.

and fall 2015, a third data acquisition session was performed on seven red-pied Holstein dry cows (RP1 to RP4 and RP5, RP6, RP7) on 1.4 ha-pastures with two pre-grazing forage allowance (1000 and 3000 kg DM ha^{-1}).

Four additional data recording sessions were performed in commercial and experimental farms with ten cows (dry and in milk) in four different locations (DOR1 and DOR2 in fall 2013, CLG1 and CLG2 in summer 2014, FVS1 and FVS2 in summer 2014, TON1, TON2, TON3 and TON4 in fall 2015). These were with Belgian White and Blue, Holstein and Blonde d'Aquitaine pure or crossbred cows as indicated above.

A total of 106 videos of 15–30 min were obtained from all these periods and used to calibrate and validate the detection algorithm. For each animal, video sequences where shot in daylight in such a way that they covered all desired behaviors. No video was shot at night. For each video, a coded behavior matrix was built using CowLog 2.0 (Hänninen and Pastell, 2009) at a frequency of 1 Hz, i.e. every second, and the behavior vector was synchronized and merged with the corresponding signal matrix obtained with the IMU. Following the definition of Gibb (1996), observed behaviors from the videos were coded as grass intake (GRA) when the animal was acquiring herbage into the mouth. GRA comprises acquisition of herbage into the mouth, its mastication and subsequent swallowing, short periods of searching or moving from a feeding station to another are not considered as in this activity. Behaviors were coded RUM when the animal was ruminating, either standing or lying including bolus mastication, as well as bolus regurgitation and swallowing. Activities not corresponding to either GRA or RUM were coded as OTHERS, and included standing and walking without grazing, resting, drinking, grooming, social activities, etc. During each video sequence, only three different behaviors (GRA, RUM, OTHERS) were coded.

2.3.2. Methods for data analysis

The complete dataset was then divided into two, one for calibrating the detection algorithm exclusively and the other for its validation. Seven video sequences were chosen from each period of data collection and used for calibrations (for grazing, RPc1 in fall 2012, RPc2 in fall 2012, RP5 in fall 2014 and CLG1 in summer 2014; for rumination, RP5 in summer 2014 and CLG1 in summer 2014). The other 99 sequences were used to validate the algorithm by comparing detected behaviors with observations from the videos. Signal analyses were performed in MatLab R2013b (Mathworks, NL) and followed the steps explained in the next section, illustrated in Fig. 2.

(a) Data preprocessing and choice of the signals describing GRA and RUM movements on pasture

First, the choice of the signal was based on the observation of cattle posture and movements decomposed into head and jaw movements (HM and JM). Animal movements were observed on the 7 calibration database videos and their translation into IMU

Table 2
Data pre-processing and algorithm quality evaluation criteria.

Parameters	Equation
Data pre-processing	
Normalization (E1)	E1 = [input − minimum(input)]/[maximum(input) − minimum(input)]
Filter design (E2)	Parameters: [b,a] = butter (order, [frequency minimum/(sampling_frequency/2) frequency maximum/(sampling_frequency/2)], 'bandpass')
	Filtering: filtered signal = filter (b, a, input signal)
Algorithm quality evaluation	
True positive (TP)	A behavior is correctly detected as it is in the observation
True negative (TN)	A behavior is correctly undetected as it is in the observation
False positive (FP)	A behavior is incorrectly detected as another behavior (type I error)
False negative (FN)	Another behavior is incorrectly detected instead of the right behavior (type II error)
Sensitivity (Se)	Se = TP × 100/(TP + FN)
Specificity (Sp)	Sp = TN × 100/(TN + FP)
Precision (P)	P = TP × 100/(TP + FP)
Accuracy (A)	A = (TP + TN) × 100/(TP + FP + TN + FN)

signals was then assessed. The hypothesis is that GRA and RUM behaviors combine different HM and JM. Grazing is characterized by the head being down with active JM, while during rumination the head is slightly raised and JM are quieter and more regular (Vallentine, 2001). In order to differentiate GRA from RUM, these parameters for HM and JM were chosen to describe how movements are translated into signals along the 3 axes of the IMU. To reduce signal noise before further analysis, HM magnitude along the 3 axes was normalized using 'min-max normalization' (E1 in Table 2, Kotsiantis et al., 2006). This normalization transformed each recorded signal value into a value between 0 and 1, and also allowed minimized the biases of morphological difference amongst cows and differences in the positioning of the IMU on the animal. For JM, signal data was filtered between 1 and 2 Hz to isolate repetitive JM searched during GRA and RUM. This frequency range was isolated by a second order Butterworth bandpass filter (E2 in Table 2). Finally, in order to limit the number of combination that were to be tested in the development of the detection algorithm, a cluster and histogram analysis of the signals along the 3 axes was used to select the signals expressing the highest discrimination potential between GRA and RUM.

(b) Thresholds determination, time windows and detection algorithm

Following the step described above, nine acceleration and gyroscope signals were considered out of 40 candidate signals: the 3-D gravitational component of the acceleration (G), the 3-D user component of the acceleration (G), the 3-D rotation rate (rad s^{-1}), each on the three axes. Data from the seven calibration database sequences were merged. Descriptive statistics were calculated for each of the 9 signals considered for each of the 3 behaviors being discriminated: GRA, RUM and OTHERS. To allow detection of activity change at a high rate, minimum and maximum values were calculated for each signal to encompass 80% (from percentile 0.100 to percentile 0.900), 90% (from percentile 0.050 to percentile 0.950), 95% (from percentile 0.025 to percentile 0.975), and 99% (from percentile 0.005 to percentile 0.995) of the data for both the mean and the standard deviation calculated over the shortest time window possible (i.e. 1-s). Mean was calculated to determine the average position of the head of the animal when moving to perform GRA or RUM while standard deviation was calculated to detect changes in the signal during GRA or RUM expressing in particular differences in jaw movements: intensive for GRA and non-intensive for RUM. Indeed, while signal sampling was performed at 100 Hz, behavior observation using video recordings was done at 1 Hz (i.e. each second). These minimum and maximum values encompassing 80, 90, 95 and 99% of the data were then used as thresholds to discriminate behaviors in the tested algorithms, combining different signals as described before. For this purpose, simple Boolean algorithms were built (shown in Fig. 3), in the form of a one- or two-step decision tree based on different signal combinations and minimum/maximum threshold values. The ability of each Boolean algorithm to discriminate behaviors was assessed.

The first step of the calibration was to use the calibration dataset to test different combinations of signals and threshold levels for the corresponding signals. The following combinations of signals were tested, which are those that in the previous step had best reflected the changes in HM and JM: mGx, sGx, sRx, sRy, (mGx, sGx), (mGx, sRx), (mGx, sRy), (mGx, sGx, sRx), (mGx, sGx, sRy), (mGx, sGx, sRx, sRy). For the different algorithms, namely signal combinations, detection accuracies were compared depending on the threshold levels (80%, 90%, 95%, and 99%) for prediction of GRA, RUM and OTHERS. The final algorithm, used later in the validation step, was constructed with the most accurate threshold values and signal combinations. All parameters used in the different algorithms were calculated using 1-s time windows. Finally, to assess how important it was to use the shortest time window (1-s) to calculate average and standard deviations of the different signals used in the best classification algorithm (mGx, sGx, sRx and sRy), the classification's accuracy was calculated using extended time windows (1 s, 5 s, 10 s, 15 s, 30 s, 60 s) and the detection accuracies of GRA, RUM and OTHERS were then compared for the calibration dataset.

(c) Validation of the algorithm

To validate the algorithm that had been developed, data from the remaining 99 video sequences of the validation database were processed by the algorithm. This estimated detection quality using the different formulas set out in Table 2. To explore the usefulness of the algorithm, its ability to describe daily behavior patterns over a 24-h time period was also tested on one cow grazing swards with two contrasted forage allowances (1000 and 3000 kg DM ha^{-1}).

3. Results

3.1. Algorithm calibration

3.1.1. Choice of signals for adequate HM and JM description

Regarding head movements (HM), due to the position of the IMU device on cows, three IMU parameters were considered good candidates to reflect changes in head position: acceleration, Euler angles and gravitational component of acceleration. When cows

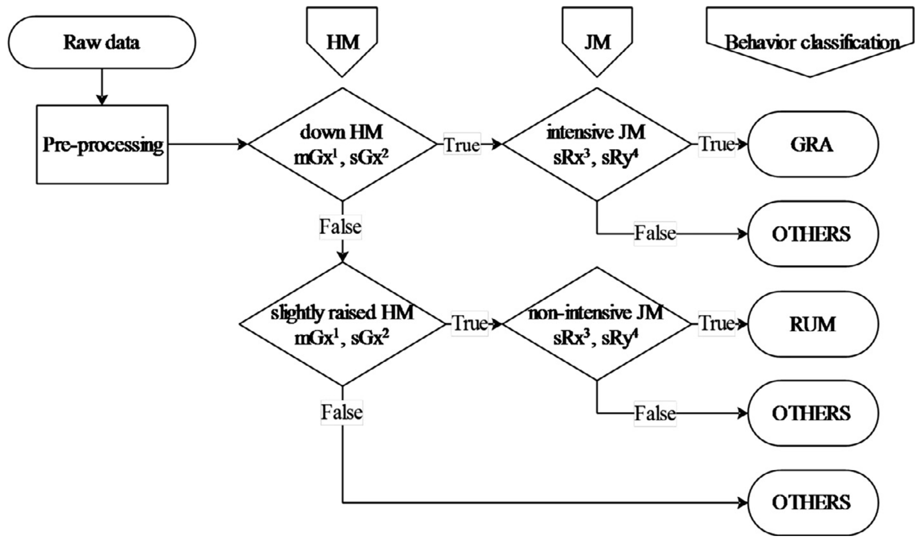


Fig. 3. Structure of a Boolean algorithm allowing the automated classification of GRA and RUM based on means and standard deviations levels of gravitational acceleration and rotation rate signals (mGx, sGx, sRx and sRy) related to head (HM) and jaw movements (JM) measured on cows wearing the iPhone 4S IMU on the neck. [1]mGx: mean of gravitational acceleration on x-axis. [2]sGx: standard deviation of gravitational acceleration on x-axis. [3]sRx: standard deviation of rotation rate on x-axis. [4]sRy: standard deviation of rotation rate on y-axis.

are grazing, their heads stay down but when ruminating, the IMU points slightly upwards. Consequently, as shown in Fig. 4, the gravitational component along the x-axis increases when cows take grass and move the head down, getting closer to 1 g. The opposite occurs on the z-axis: gravitational acceleration decreases when switching from RUM (head up) to GRA (head down). Logically, changes along the y-axis are not of concerned. As Fig. 4 shows, Euler angles can also reflect such changes, although for these signals, the response seems to be more dependent on the individual animal, making the choice of thresholds for this criterion less universally discriminating. Total acceleration, combining both user (U) and gravitational components (G), was not accurate enough because the values caused by the back and forth HM associated with GRA were too dispersed. Normalized gravitational acceleration (G) presented the best potential for discriminating between GRA and RUM behaviors on the x and z axes (Fig. 4), and the mean and the standard deviation of this normalized signal distribution were therefore used to characterize cattle head movements (respectively mGx and sGx).

Although head position seems sufficient to discriminate grazing from rumination, the range of values in Fig. 4 indicates that this single criterion does not allow for discrimination between RUM or GRA from OTHERS. This is due to overlap in frequencies. Therefore, a second discrimination step was necessary using the remaining information related to HM and JM. Intensities of such movements can be characterized by the standard deviation of user

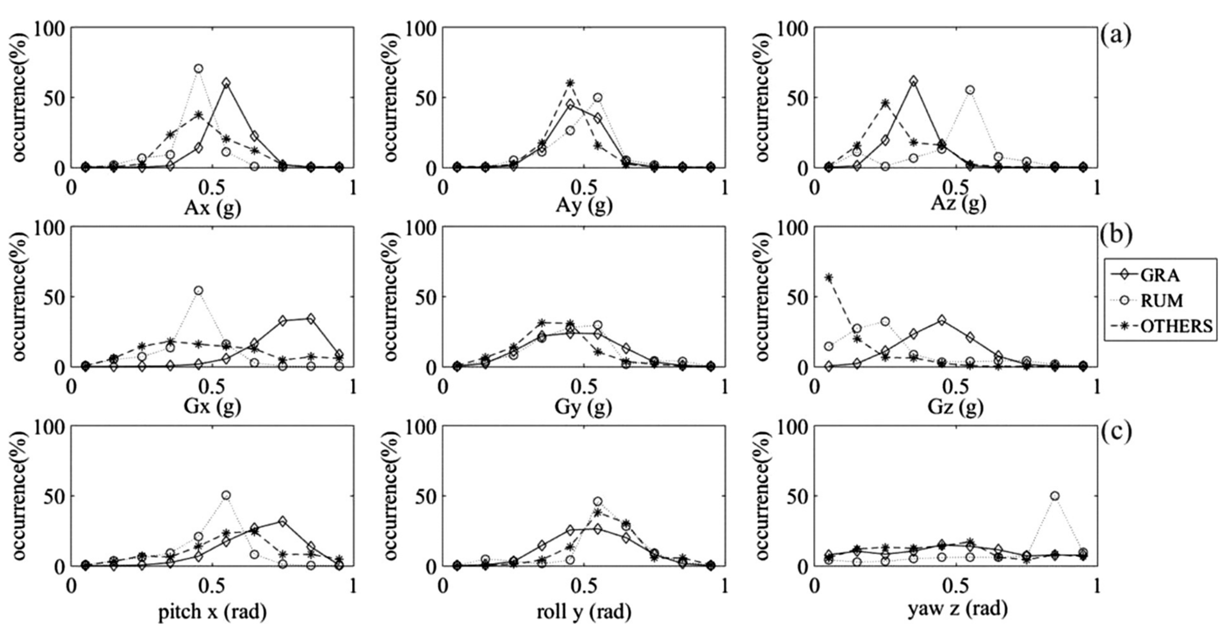


Fig. 4. Frequencies distribution of normalized values along the 3 axes of the IMU signals expressing head movements during tagged sequences of GRA, RUM and OTHERS activities. With (a) the acceleration (Ax, Ay, Az) expressed in g (acceleration of gravity, g = 9.81 m s^{-2}), (b) the gravitational component of the acceleration (Gx, Gy, Gz) expressed also in g and (c) the Euler angles (pitch, roll, yaw) expressed in Rad (Radian), all on the (x,y,z) axes of the IMU. Gx is the most relevant signal to discriminate head movements occurring during GRA and RUM.

acceleration particularly along the x-axis (as displayed in Fig. 5). During grazing and rumination, cows show a typical rotation movement with their jaws when chewing and with their heads when taking grass into the mouth. Therefore, candidate signals to reflect such movements were rotation rates along the x and y axes of the IMU. The average algebraic value of those signals always equals to 0 when the time window is over 1-s because the jaw and the head return regularly to their original position and so useful information from these signals must be based on squared values, such as standard deviations (sRx and sRy).

Subsequently, a total of 40 possible combinations were tested in a Boolean algorithm, when associating four threshold levels encompassing either 80%, 90%, 95% or 99% of the observations with 10 possible combinations of signals using the mean of the gravitational component of the acceleration along the x-axis (mGx), its standard deviation (sGx), and the standard deviation of the rotation rate around the x- (sRx) and the y-axis (sRy) as explained above.

3.1.2. Choice of threshold values

For each set of observations, the different threshold values (80%, 90%, 95% and 99%) that were calculated from the normalized calibration database are shown in Table 3.

For every combination, detection accuracies for GRA, RUM and OTHERS were lower when using threshold values that encompassed 80% and 99% of the observations compared to those for 90% and 95% (Fig. 6). Apart from single signals which also provide lower detection accuracies than combinations, thresholds for 95% of encompassed data, gave the best percentage of correctly detected behaviors, although the difference to 90% was rather low.

After considering those results, the algorithm was built using thresholds that include 95% of all calibration dataset observations.

3.1.3. Choice of signal combinations in the algorithm

The usefulness of combining signals was also compared. Fig. 6 clearly shows the need to use signals representing HM (mGx and/or sGx) and JM (sRx or sRy). These combinations gave the

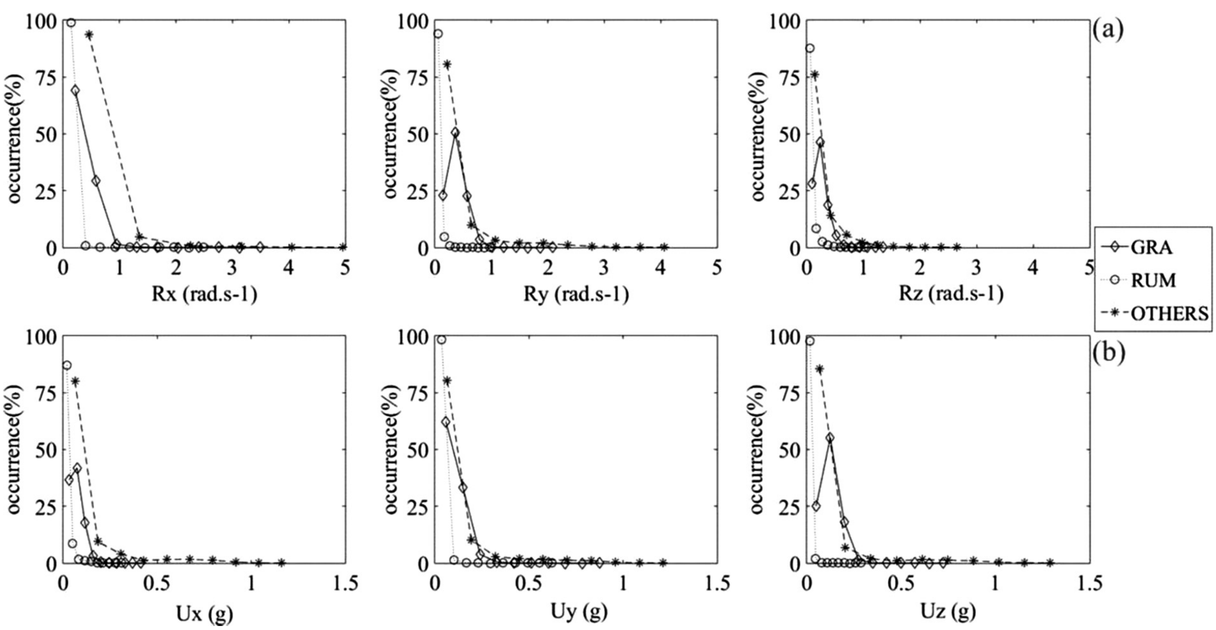


Fig. 5. Frequencies distribution of the values of standard deviation of amplitude signals of (a) rotation rate (Rx, Ry, Rz) expressed in rad s^{-1} (radian per second) and (b) user-acceleration (Ux, Uy, Uz) expressed in g (acceleration of gravity, g = 9.81 m s^{-2}) on the (x,y,z) axes of the IMU, during tagged sequences of GRA, RUM and OTHERS activities. Rx and Ry are the most relevant signals to discriminate jaw movements intensities between GRA and RUM.

Table 3
Minimum and maximum value windows for mGx, sGx, sRx and sRy calculated with 1-s time windows to encompass 80%, 90%, 95% and 99% of the observations in the calibration dataset.

Considered data percentage	Behaviors	Mean of the gravitational acceleration along x (mGx) (g)		SD[a] of the gravitational acceleration along x (sGx) (g)		SD of the rotation rate along x (sRx) (rad s^{-1})		SD of the rotation rate along y (sRy) (rad s^{-1})	
		Min	Max	Min	Max	Min	Max	Min	Max
80%	GRA	0.716	0.922	0.006	0.036	0.151	0.605	0.140	0.619
	RUM	0.111	0.478	0.003	0.012	0.062	0.157	0.029	0.092
90%	GRA	0.693	0.945	0.005	0.052	0.134	0.793	0.116	0.734
	RUM	0.099	0.493	0.002	0.018	0.056	0.185	0.025	0.145
95%	GRA	0.600	0.950	0.005	0.060	0.134	0.793	0.116	0.734
	RUM	0.100	0.490	0.003	0.018	0.032	0.185	0.025	0.145
99%	GRA	0.581	0.963	0.002	0.151	0.060	1.214	0.047	1.069
	RUM	0.066	0.559	0.002	0.067	0.014	0.290	0.017	0.466

[a] SD: standard deviation.

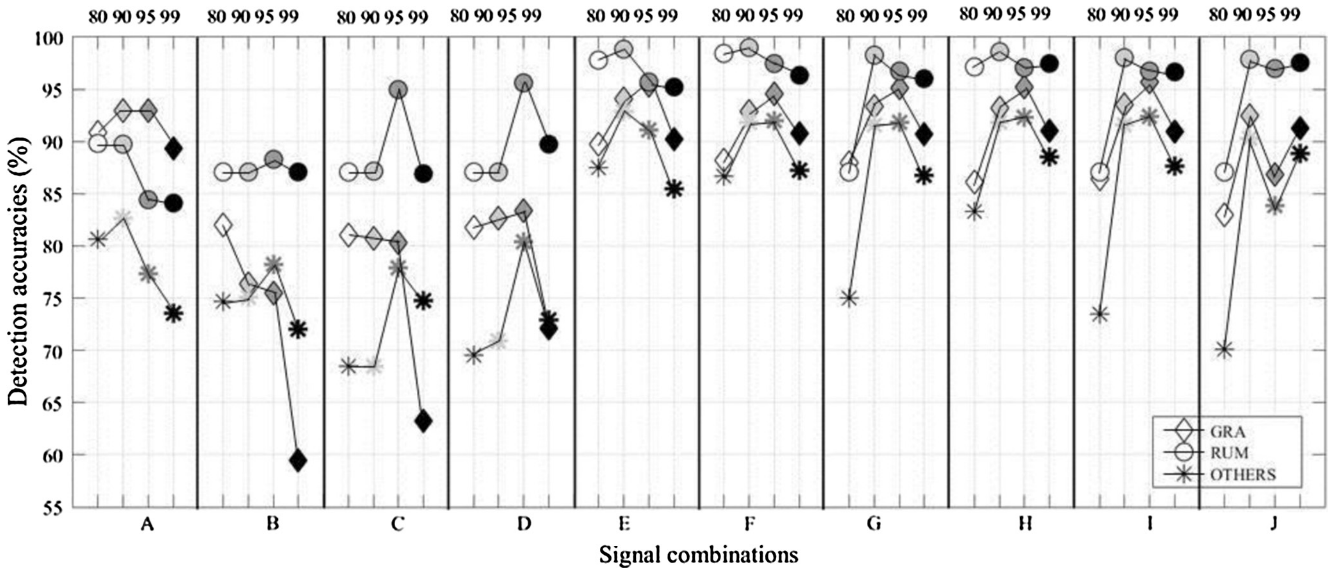


Fig. 6. Detection accuracy (% of exact prediction) of feeding activities (GRA, RUM and OTHERS) with algorithms based on a single or combination of signals given by the IMU when using value windows that encompass 80–99% of the calibration dataset observations. With (A) mGx: mean of gravitational acceleration on x-axis; (B) sGx: standard deviation of gravitational acceleration on x-axis; (C) sRx: standard deviation of rotation rate on x-axis; (D) sRy: standard deviation of rotation rate on y-axis, and with six different combinations (E) (mGx, sGx), (F) (mGx, sRx), (G) (mGx, sRy), (H) (mGx, sGx, sRx), (I) (mGx, sGx, sRy) and (J) (mGx, sGx, sRx, sRy).

highest detection accuracies especially for grazing and ruminating behaviors with average accuracies of up to 93%. Detection accuracy using sRx to translate JM was slightly higher (94.5%) than when using sRy (94%). The most accurate algorithm, with an average accuracy of 92%, was therefore built on the combination of mGx, sGx and sRx (i.e. the H combination on Fig. 6).

3.2. Testing the algorithm with different time window lengths

When the precision of the algorithm was evaluated according to the size of time window used to calculate mGx, sGx, sRx and sRy, the highest accuracy found was with a 1-s time window (Fig. 7). When comparing detected behaviors with the observation for longer time windows (>1-s) the "cleanliness" of each observation matrix of was assessed and every sequence of 5, 10, 15, 30, 45 and 60-s which did not contain only GRA, only RUM or only OTHERS was discarded from the database. Obviously the longer the time window, the higher the percentage of unused sequences (up to 38%) as shown in Fig. 7.

The final algorithm (Fig. 8) therefore uses a 1-s time window and considers mGx, with sGx and sRx parameters following threshold values encompassing 95% of the calibration data in a 2-step discrimination tree. The MatLab code and user's guide are provided in Supplementary Data 1.

3.3. Algorithm validation

The validation dataset included 99 sequences with a total of 38.5 h of video (N = 138332 of 1-s sequences, with 79244 s of GRA, 5350 s of RUM and 53738 s of OTHERS). When the algorithm was applied to the validation dataset, the average detection

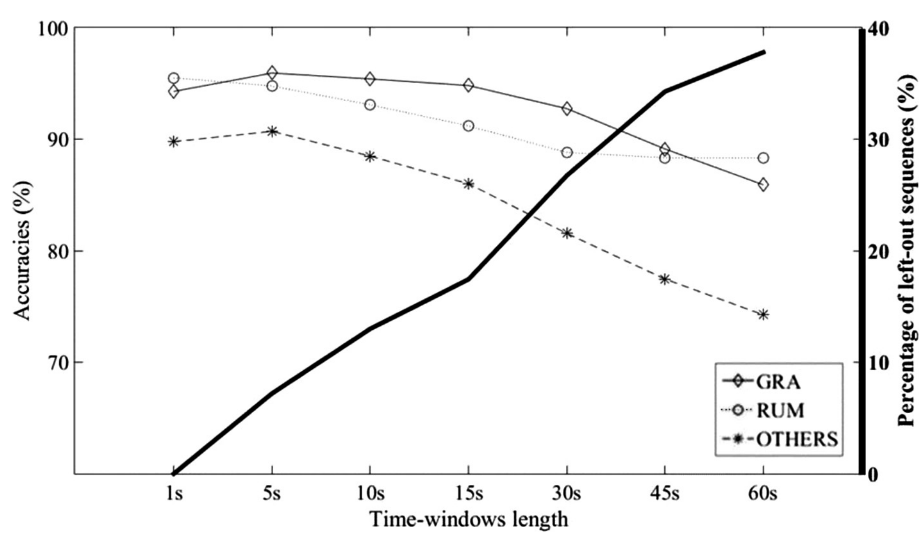


Fig. 7. Comparison of detection accuracies of GRA, RUM and OTHERS when all the parameters of the algorithm are calculated with 1, 5, 10, 15, 30, 45, and 60-s (respectively 1 s, 5 s, 10 s, 15 s, 30 s, 45 s and 60 s) time windows, and percentage of calibration database sequences discarded for not containing pure GRA, RUM or OTHERS behaviors.

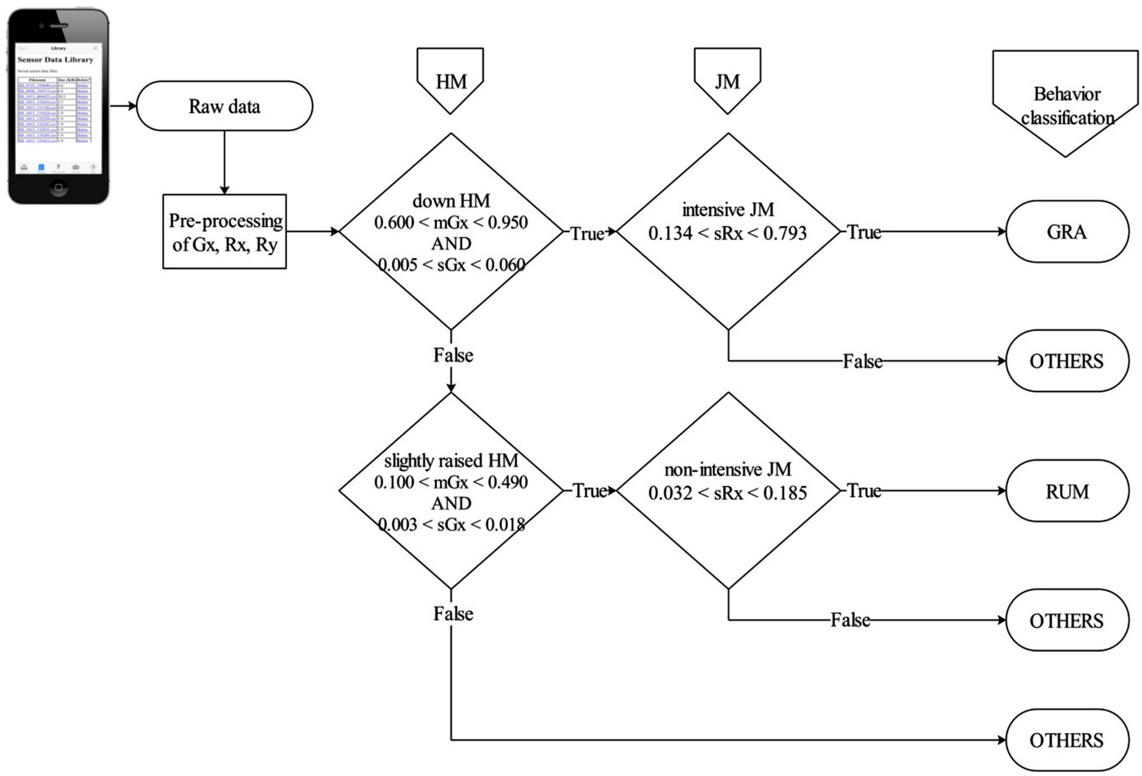


Fig. 8. Final structure of the detection algorithm including the thresholds to differentiate GRA from RUM following the algorithm built in Fig. 3.

Table 4
Predictive quality evaluation of the final algorithm when applied to the validation dataset using (1) Sensitivity = true positive/(true positive + false negative), (2) Specificity = true negative/(true negative + false positive), (3) Precision = true positive/(true positive + false positive) and (4) Accuracy = (true positive + true negative)/(true positive + false positive + true negative + false negative) as indicators. The number N represents the length of viewed sequences, in second, within validation dataset containing each behavior.

Behaviors	Sensitivity (1) (%)	Specificity (2) (%)	Precision (3) (%)	Accuracy (4) (%)
GRA (N = 79244)	91.1	90.9	93.5	91.0
RUM (N = 5350)	53.1	99.4	84.5	96.5
Others (N = 53738)	87.6	87.5	79.1	87.6

accuracy was 92.0% (Table 4). It was more accurate when detecting RUM (96.5%) than GRA (91%).

3.4. Effect of the different sward heights on 24 h allocation of cattle activities

With overall detection accuracies of unitary behaviors namely GRA and RUM above 91%, practical uses of this algorithm to characterize cattle feeding activities during a complete day can be expected. In Fig. 9, 24-h activities of the same cow grazing a sward with two different pre-grazing heights (i.e. 1000 and 3000 kg DM ha^{-1}) in two different seasons (summer 2015 and fall 2015) were plotted using this algorithm. Based on the 1-s detection output of the algorithm, the proportion of detected behavior was calculated per minute. At first glance, the usefulness of the algorithm could be verified, because in this instance it highlighted that grazing bouts depend on forage allowance (they were not even in both forage allowances) and that only a few GRA events are observed at night, leaving more time for RUM and OTHERS.

4. Discussion

The aim of this paper was to propose an open method for detecting grazing cattle behaviors using readily accessible devices with little requirement for hardware development. For this purpose, smartphones were used, more specifically the iPhone, which was preferred because of the standardization of models and the accurate description of their inner components, particularly their inertial measurement units (IMU). As expected, an IMU placed on the neck of an animal was able to record changes in posture and movements in all directions. This is not surprising given that the speed and acceleration one would expect a cow to relay to the device fits into the ranges of human user exertion. Other smartphones equipped with IMUs or even tailor-made devices could also be used with the same algorithm, assuming they provide the same characteristics in terms of sensitivity and recording frequency and have an appropriate application installed to record IMU signals. The approach used to build the algorithm based on observation of cattle movements proved an efficient strategy to build an algorithm since validation on a completely independent database reached high accuracies for detecting GRA and RUM behaviors using a very short time window (1-s). Dutta et al. (2015) chose 5-s time windows when combining GPS recording at 4 Hz sampling frequency and 3-D accelerometer at 10 Hz to detect grazing behaviors and attained 96% accuracies using a neural network method. Similar experiments by González et al. (2015) using 10-s time windows reached an average detection accuracy of 90.5%. To detect JM, other published works have used longer time windows, between 1 to 15-min (e.g. Oudshoorn et al., 2013 with 10-min). With our algorithm changes in behavior can be measured at a very high rate, thanks to the high frequency of data acquisition that the IMU allows (100 Hz) compared to previous studies that sampled signals from 1 to 20 Hz, and for which accuracies ranged between 65 and 90% (e.g., Oudshoorn et al., 2013). In these previous studies, increasing the time windows to up to 10–15-s was shown to significantly increase the specificity and sensitivity of classification (González et al., 2015; Smith et al., 2016). As shown in Fig. 7, this was not the case using the algorithm proposed here, notwithstanding that a number of sequences had to be discarded from the database because an increasing proportion of sequences were comprising more than one behavior, especially GRA and OTHERS. These differences stem from the behavior classification method based on visual observation. In our experiment, animal behavior was video recorded while in previous works, animal behavior was observed on the spot. The latter method does not allow the detection of the very short term changes in activity that can occur when grazing, for example discriminating grass intake (classified as GRA in the present work) from searching for a feeding station with the head still pointing downwards (classified as OTHERS) .As showed by Hämäläinen et al. (2016), high frequency sampling allows for better data acquisition, greatly improving detection accuracy with small time windows. This is especially so when it comes to distinguish specific behaviors (for example, different phases of grass prehension to investigate grazing strategies). In addition, the high sensitivity of the IMU leads a rapid change of the rotation rate signal on x-axis, and has given poorer results when the time-windows was increased unlike in other researches where different kind of variables were used for classification and use of longer time-window had given better result.

In future, a precision grazing management application might need to detect changes in grazing behavior as accurately as possible, and so an automated detection algorithm should aim to reach the highest accuracy possible with the shortest time window.

When comparing different detection accuracies among unitary behaviors, the algorithm shows better performances with GRA, where corresponding sensitivity (89.3%) and specificity are highest (87.0%). This is logical since it is the only behavior for which the cow puts her head down for a long time. The only possible confusing behaviors are when the cow has her head in a similar position, for example when drinking or searching for a feeding station

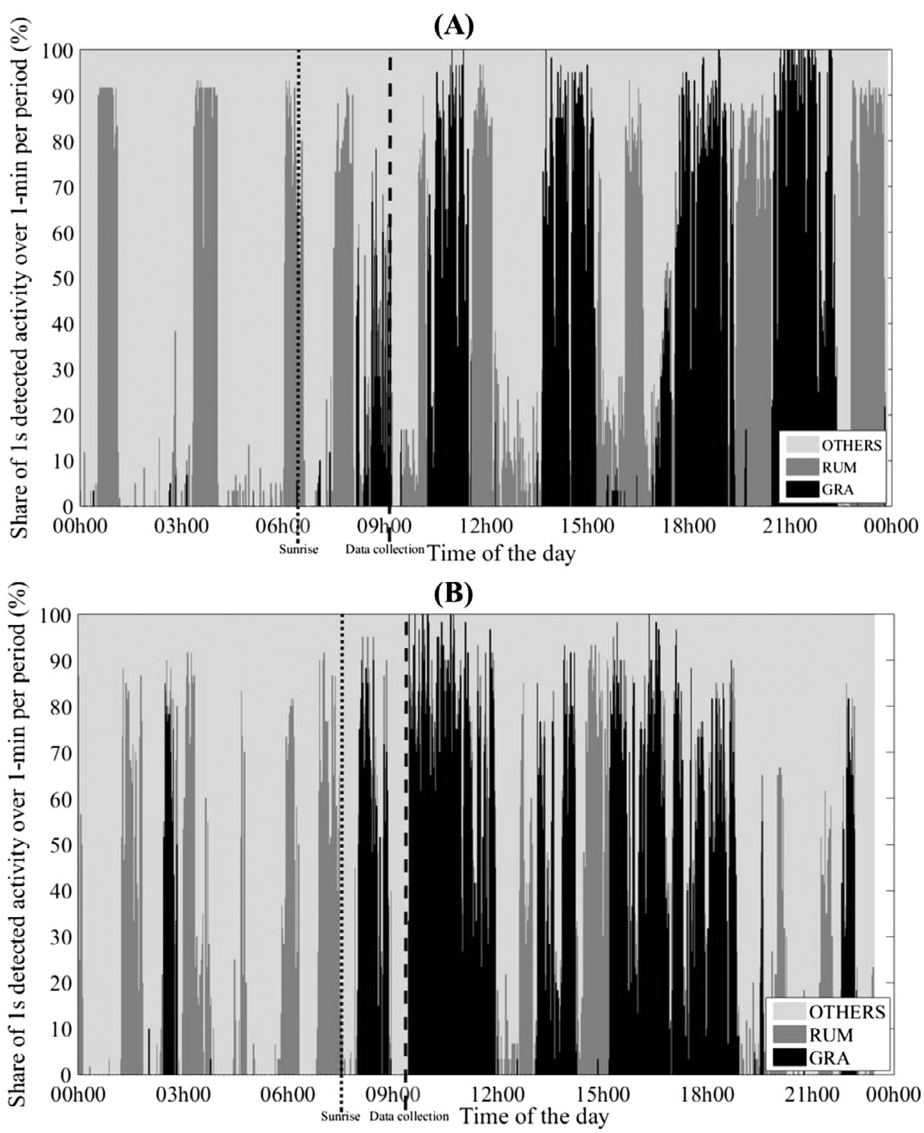


Fig. 9. Allocation of activities during 24-h for a non-supplemented cow grazing the same pasture at two different times of the grazing season and with two different forage allowances: 1000 kg DM ha^{-1} (A) and a 3000 kg DM ha^{-1} (B).

without eating and therefore not performing any specific JM considered part of grazing behavior (Gibb, 1996). But the intensity of these movements is much lower resulting in lower standard deviations, and the time allocated to these behaviors is not as important as for grazing (Vallentine, 2001). For RUM, high specificity (99.4%) combined with low sensitivity (53.1%) results in a high false negative rate. This can be ascribed to possible confusion between RUM and resting periods, standing or lying down without rumination which are included in OTHERS. These behaviors are only differentiated by the JM performed during RUM and by detecting sequences of chewing and regurgitation phases which occur approximately once per minute. Since even with longer time windows the accuracy was not improved, an option would be to improve the algorithm to detect regurgitation from chewing within the rumination phase. The signal representing jaw movement was filtered between 1 Hz and 2 Hz where a characteristic peak could be shown in the frequency-domain for RUM. When toggled in the time-domain for the Ry analysis, RUM bouts are composed of a succession of chewing peaks interrupted by a stop period during the swallowing and regurgitation of the bolus (Gibb, 1996). For better monitoring of RUM patterns in cows, a discrimination loop considering the detection of typical patterns in the Rx or Ry signal could be added to improve the detection of RUM and at the same time to allow counting the numbers of chewing movements, for example, as it is done by the IGER behavior recorder (Rutter et al., 1997; Rutter, 2000).

Finally, the algorithm was tailored to be as general as possible. The normalization step of raw signals allowed for high accuracy levels for a range of cattle of different weights and conformation (dairy and beef) and under various sward heights. Although the algorithm was not built to detect differences in grazing conditions, using it to reconstruct different daily feeding activity kinetics is one possible prospect of further use, which could provide useful information for grazing management research. Nevertheless, such approaches still require proper validation and should be compared to studies of factors influencing grazing and eating behaviors of cattle under similar pasture conditions such as time of day (Gibb et al., 1998), sward height (e.g. Gibb et al., 1999; Orr et al., 2004) or bulk density (Mayne et al., 1997). The example given in Fig. 9, describes how grazing periods are more 'grouped' in a paddock with a higher sward height, suggesting that cows perform longer grazing bouts when more grass is available. Griffiths et al. (2003) have shown similar results with a longer residence time when the sward is high. However, quantifying the whole grazing duration is not enough since additional information about intake such as bite characteristics are an essential part of improving the understanding of cattle grazing processes under different contexts, preferably under long-term experiments (Chilibroste et al., 2015).

5. Conclusions

Using a smartphone with an efficient IMU that is readily available worldwide, it was possible to detect grass intake (GRA) and rumination (RUM) behaviors of cattle fed on pasture based on observations assuming that cows perform different group of head and jaw movements when performing these behaviors. Different signals recorded by the IMU were then chosen to describe these physical movements and to define thresholds used for GRA and RUM behaviors classification. Data collection is possible by simply installing an application on the smartphone, which allows for recording many signals from the accelerometer, gyroscope or location sensors at different sampling rates. Average accuracies ranged between 90 and 95% when detecting grass intake and ruminating behaviors, and 86% for others.

Until now, raw data is transferred and analyzed on a computer. Nevertheless, real-time acquisition and analysis of the data is possible and in progress in the scope of Precision Livestock Farming approach.

The developed algorithm was coded in MatLab and is available in the supplementary data of this manuscript. It can be used by others for research or teaching purposes, or to further improve it highlighting the open character of the algorithm. Obviously, before being used, in the tropics for example, the algorithm should be validated for more diverse conditions with more heterogeneous vegetation and with more breeds, especially zebus. Using similar method with other domestic species and pets could also be possible but there is a need to find the best anatomical place for the device before testing the method itself. Finally, deeper analyses of each behavior through peak or frequency signal analysis are needed to further explore potential of accelerometer-based behavior monitoring methods.

Acknowledgement

This work was supported by TERRA – AgricultureIsLife [Project 1B] of Gembloux Agro-Bio Tech (Université de Liège, Belgium).

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.compag.2017.05.020.

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