COMMUNAUTÉ FRANÇAISE DE BELGIQUE
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CATTLE GRAZING DYNAMICS UNDER CONTRASTED PASTURE CHARACTERISTICS AT TEMPORAL AND SPATIAL SCALES

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Essai présenté en vue de l'obtention du grade de docteur en sciences agronomiques et ingénierie biologique

Promoteurs: Jérôme Bindelle (Precision Livestock and Nutrition, GxABT, ULg)
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ABSTRACT

Grassland constitutes an important and a low-cost food source for grazing livestock. Optimal management should consider both forage resource productivity and animal needs. For cattle, grazing is a normal behavior displayed in an attempt to eat the amount of forage to fulfill their nutritive requirements for maintenance and production. It is the most time-consumed activity of cows reared in pasture-based systems. With the increase of herd size, on one hand, farmers have been constrained to integrate innovative tools and techniques, such as milking robot, to improve the production system in particular to reduce the labor cost. On the other hand, such change might reduce time allocated for grazing on pasture. However pasture-based systems constitute a real pillar for sustainability as they are socially acceptable and environmentally profitable as they play an important role on ecosystem services and biodiversity provision. Studying grazing processes at individual level, which finally is the key point of animal-plant interactions, is a valuable research domain to enhance the knowledge about this mechanism and to feed decision support tools.

This thesis aimed to link the changes in pasture characteristics to the grazing behavior of cattle in order to better understand the grazing strategy under different pasture characteristics and forage allowances. To allow an individual monitoring, sensor technology has integrated within farms and livestock researches to monitor many physical variables, inducing the emergence of precision livestock farming approach. Different types of sensors were designed, and already commercialized for some, primarily for physiological status detections such as heat, parturition or diseases. Grazing behaviors could be monitored using pressure, electromyography, acoustic or accelerometric sensors by classifying posture and movements of the animal into unitary behaviors (grazing, ruminating, resting, walking, etc.) and finer behavior such as chews and bites through jaw movements' detection. When compared to real observation, detection accuracies of these behaviors were variable according to the type of sensor, its position on the animal during data acquisition on pasture, the data recording frequency, the time-window and the method dedicated to the post-recording data analysis.

State-of-the-art analysis demonstrated a great performance of accelerometers for unitary behaviors and bites detection.
An inertial measurement unit, integrating accelerometer, gyroscope and location sensors, was used for recording cattle movements during grazing at high sampling rate (100Hz). It allows a correct detection of grass intake and rumination behaviors with an average accuracy of 91% using 1-second time-window when calibrating and validating the detection algorithm.
Deeper analysis of accelerometric signal allowed us to detected bites and chews performed during grazing and ruminating. Effects of pasture heights on grazing bites characteristics were differentiated by a higher frequency when pasture is at a lower height. Finally when combined to geographical information, a similar pattern was observed for cattle grazing on the same spot confirming their herd movement during grazing in terms of bites location. Differences were visible under different pasture heights but not significant.
Such bites location, combined with continuous monitoring of cattle behaviors, through use of sensors, should be furtherly linked with more pasture characteristics, if possible with the same accuracy, and monitored on longer period in order to obtain a complete coverage of cattle grazing strategy and the effect of contrasted environment in order to purpose valuable tool for a better grazing management.

Keywords: Grassland, precision livestock farming, sensors, inertial measurement unit, cattle, behaviors, grazing, ruminating.

RÉSUMÉ

La prairie constitue une importante ressource alimentaire, et à moindre coût, pour les ruminants. Une gestion optimale de cette ressource doit considérer à la fois la productivité du fourrage et les besoins des animaux. Pour les bovins, le pâturage est un comportement normal d'ingestion de fourrage dans le but de satisfaire leurs besoins nutritionnels d'entretien et de production. Il s'agit du comportement qui occupe le plus de temps parmi les activités journalières des bovins en prairie. Avec l'augmentation de la taille des troupeaux, d'une part, les éleveurs ont été contraints d'intégrer des pratiques innovantes, telles que le robot de traite, par exemple, pour améliorer le système de production et notamment pour diminuer le coût en main d'œuvre. D'autre part, de tels changements ont eu tendance à réduire le temps alloué au pâturage des animaux. Cependant les systèmes de production à base de pâturage sont actuellement perçus comme un pilier du développement durable. En effet, ils suscitent un regain d'intérêt au niveau de la société et surtout sont bénéfiques pour l'environnement sachant que la prairie joue un rôle important dans la fourniture de services écosystémiques et de biodiversité.

Etudier le processus de pâturage à l'échelle de l'individu, qui est un point-clé dans l'interaction plante-animal, constitue un domaine de recherche d'intérêt pour approfondir les connaissances à propos de ce mécanisme et pour développer des outils d'aide à la décision.

La présente thèse a pour but de déterminer les liens entre les changements des caractéristiques du pâturage et le comportement des bovins afin de mieux comprendre les stratégies adoptées par les vaches dans un environnement prairial contrasté. Pour permettre un suivi individuel des animaux, diverses technologies de capteurs ont été utilisées à des fins pratiques en ferme et au niveau de la recherche scientifique pour contrôler différentes variables physiques, induisant notamment l'émergence du domaine de l'élevage de précision. Plusieurs dispositifs ont été conçus, dont certains ont déjà été commercialisés, principalement pour la détection de paramètres relatifs au statut physiologique ou à la santé de l'animal, notamment la détection de la chaleur, des signes de la mise-bas ou des maladies telles de la boiterie et les mastites. Les comportements liés au pâturage peuvent être détectés avec des capteurs de pression, acoustiques (microphone), électromyographiques ou accélérométriques en classifiant la posture et les mouvements adoptés par les animaux lorsqu'ils expriment des comportements unitaires (pâturage, rumination, repos, marches, etc.) et des comportements plus fins tels que la mastication ou la bouchée en classifiant les mouvements de la mâchoire. En comparaison avec les observations réelles, les précisions de détection de ces comportements varient selon le type de capteur, sa position sur l'animal, la fréquence d'acquisition des données, la méthode d'analyse des données ainsi que la fenêtre de calcul y afférente. L'état de l'art a notamment montré la performance des accéléromètres pour la détection des comportements unitaires et des bouchées.

Une centrale inertielle composée d'accéléromètre, de gyroscope et de capteur de localisation, a été utilisée pour enregistrer les mouvements et les postures des vaches en prairie avec une fréquence de 100Hz. Un algorithme booléen a été élaboré afin de détecter les comportements d'ingestion de fourrage et de rumination et une précision moyenne de 91% a été obtenue en utilisant une fenêtre de calcul d'une seconde lors de la validation de celui-ci. Une analyse approfondie des signaux accélérométriques a permis de détecter les mouvements de la mâchoire effectués lors du pâturage et de la rumination.

Confrontées à différentes hauteurs de prairie, les vaches présentaient des fréquences de bouchée supérieures lorsque la hauteur est basse. Enfin, grâce à l'exploitation des données de localisation, il a été observé que le comportement de pâturage des vaches présentait des modèles similaires en termes de mouvement confirmant un mouvement de troupeau existant au sein d'un groupe de vaches présentes sur une même prairie. Cependant les vaches présentaient des stratégies différentes en termes d'occupation de l'espace selon qu'elles entrent dans une prairie à modalité haute ou basse.

Le suivi continu des comportements des vaches en prairie utilisant des capteurs et conduisant à de telles localisations des bouchées, doit être combiné avec des données sur la distribution spatiale des plantes au niveau de la prairie, en termes d'espèce, de densité et de qualité, si possible avec les mêmes précisions, pour permettre de couvrir totalement le processus de pâturage et les stratégies des animaux quand ils sont confrontés à des environnements contrastés et de proposer des outils déterminants pour optimiser la gestion des prairies.

<u>Mots-clés</u> : Prairie, élevage de précision, capteurs, centrale inertielle, bovins, comportements, pâturage, rumination.

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ABBREVIATIONS

°C, Celsius degree

A, Accuracy

AKM, Asahi Kasei Microdevices

AM, Ante meridium

ART-MSR, Agroscope Reckenholz-Tänikon – Modular Signal Recorder

AvDist, Average distance

Ax, Ay, Az, Acceleration on x, y and z-axis

B, bites

BF, bite frequency

C, chews

CA, classification accuracy

CB, chew-bites

CLG, Corroy-le-Grand

CorrDetect, correct detection

CRA-W, Centre wallon de Recherches Agronomiques

d, distance between two peaks

DGB, duration of grazing bouts

DM, dry matter

DOR, Dorinne

ER, error rate

ESRI, Environmental Systems Research Institute

FFT, fast Fourier transform

FN, false negative

FP, false positive

FVS, faculty of Veterinary Science

g, acceleration of gravity ($g=9.8 m.s^{-2}$)

GBX, Gembloux

GIS, Geographic Information System

GPS, Global Positioning System

GRA, grass intake behavior

Gx, Gy, Gz, Gravitational component of the acceleration on x, y and z-axis

h, minimum amplitude of a peak

HM, head movements

HSH, high sward height

Hz, Hertz

IGER, Institute of Grassland and Environmental Research

IMU, Inertial Measurement Unit

JM, jaw movements

kHz, kilohertz

LLC, Limited Liability Company

LSH, Low sward height

$m.s^{-2}$, meter per square second

m , square meter

mAh, milli-ampere-hour

Max, Maximum

MD, Matrix of detection

Meas., Measured

mGx, mean of Gx

Min, Minimum

MO, Matrix of observation

NBh, Number of bites per hour

NBu, Number of bites per unique longitude and latitude coordinates

NGB, Number of grazing bouts

Obs., Observed

OTHERS, other behaviors not classified as grass intake or rumination

P, Precision

PLF, Precision Livestock Farming

PM, Post meridium

Qx,Qy,Qz,Qw, Quaternion on x, y, z and w

rad.s^{-1}, radian per second

RP, dry red-pied Holstein cows

RPc, dry red-pied canulated Holstein cows

RUM, Rumination behavior

Rx, Ry, Rz, Rotation rate on x, y and z-axis

SAS, Statistical Analysis Software

SD, standard deviation

Se, Sensitivity

sGx, standard deviation of Gx

Sp, Specificity

sRx, standard deviation of Rx

sRy, standard deviation of Ry

TGIT, Total Grass Intake time

TN, True Negative

TNB, Total number of bites

TON, Tongrinne

TP, True Positive

ULg, University of Liège

Ux, Uy, Uz, User component of the acceleration on x, y and z-axis

V, Volt

CHAPTER 1

GENERAL INTRODUCTION

1. Context

Grasslands cover 26% of total land and 69% of agricultural areas in the world supporting grazing livestock as the least expensive way to feed ruminants such as cattle for both milk and meat productions (Peyraud and Delaby, 2005; Boval and Dixon, 2012; O'Mara, 2012). In the European Union, of the 5.4% of usable agriculture area cultivated under organic agriculture, 45% are permanent pastures and a significant share of the cultivated fields include temporary pastures in their rotation. Grazed pastures display multiple roles that can benefit the sustainability of dairy production, such as lower feeding costs (Dillon et al., 2005), higher animal welfare (Burow et al., 2013) and lower occurrence of lameness and mastitis, good public image and increased milk quality (Burow et al., 2011). In addition, grasslands play an important part in the provision of social and environmental services (Boval and Dixon, 2012). Pastures can be a source of increased biodiversity on the farm through an adequate choice of more diverse grass and legume species and varieties supporting a wider range of micro fauna and auxiliaries. Moreover, pastures, and especially permanent pastures, can play a significant role in mitigating greenhouse gas emissions by trapping atmospheric carbon (Boval and Dixon, 2012). This list is not a mere acknowledgement of the multiple services ensured by grasslands as such multifunctionality of the pastoral resource constitutes a main target of nowadays dairy speculation (Carvalho et al. 2011).

Efficient management of grasslands should consider both forage resource productivity and animal requirements. Grazing management aims at maximizing grass part in the animal diet and simultaneously producing sufficient forage of good quality along the grazing season (Peyraud and Delaby, 2005). It includes the concept of balance between the number and the species of animals present in the pasture and the spatial homogeneity of forage calculated over the year (Carvalho et al., 2009; Laca, 2009). Grazing is controlled essentially by manipulating stocking rate, the type of animal, the foraging method, the distribution of water point and mineral licks as pasture home (Holechek et al., 2011). Stocking rate is an important component as it considers, on the one hand, the animal performance by limiting the accessibility to an area and, on the other hand, the productivity, sustainability and composition of the forage (Hickman et al., 2004). The choice of grazing methods (rotational vs continuous grazing) depends on the farmer's decision and according to available area although rotational grazing seemed to offer better pasture conditions (Laca, 2009). Another types of grazing method namely rotatinuous (Carvalho, 2013) matches sustainable use of forage without any kind of supplementation. Thus all of these tools and methods are based on the optimization of productivity at the herd scale, prioritizing the animal productivity, inducing some problems relative to a possible imbalance between the forage productivity and the animal requirements at the individual level . This situation is nowadays coupled with the enlargement of the herds at the level of the farms and the emergence of automation to reduce labor costs and hardness. With the spreading of automatic milking system or milking robots in dairy farms increases the risk of a reduction in time allocated to grazing. In addition, it is considered that grazing cattle spend more energy when grazing compared to non-grazing cattle (Dohme-Meier et al., 2014). Nevertheless, for consumers' point of view, grazing becomes socially critical to consider when it comes to choosing dairy products (e.g. Garric 2014), as exemplified with the increase in organic agriculture, which oblige farmers to provide minimum 60% of grazed or locally harvested forage in the diet of dairy cows. Reconciliation with grazing is needed to enhance profitability and sustainability of dairy farming, including social acceptance. Hence, a better understanding and monitoring of the grazing processes is call for and one way forward is to consider the herd at its individual level to optimize the pasture use of each individual animal.

For this purpose, precision livestock farming concept has emerged over the past decade to propose efficient tools and methods to monitor individuals at any time. The use of sensors is becoming rather common in livestock farming as it can assist the farmers' eyes to monitor mostly invisible parameters such as estrus or calving signs, early detection of disorders like mastitis or lameness and animal welfare in general (Berckmans, 2014). From sensors, using dedicated data analysis, majorly with a black-box approach, detection of grazing, ruminating or idling behaviors is accurate and averages 90% of correct classification. Different kinds of sensors are used: microphones (Ungar et al., 2007), pressure sensors inducing changes in electrical resistance (Rutter et al., 1997; Rutter, 2000), electromyography sensors (Rus et al., 2013), location sensors (Schelcht et al., 2004) and accelerometers (e.g. Martiskainen et al., 2009; Oudshoorn et al., 2013). Nonetheless monitoring cattle behaviors is not enough as it concerns only the larger scale of grazing process and covers only the daily intake scale corresponding to grazing time (Nams, 2005; Carvalho, 2013). Within grazing time, the finest scale of the grazing mechanism which is the bite should be considered. It is the atom of forage intake (Carvalho et al., 2015) and the formation of meal. Combination of time spent grazing and bite characteristics, in particular bite rate and bite mass, converges to the estimation of intake which is still a big challenge in grazing animal studies and for on farm management. It is essentially due to the complexity of strategy adopted by individual cow facing the pasture resource. On one side, the grazing process, through the choices of the animal at the feeding station level induced by the energy requirements needed by the animal, will induce some heterogeneity on the pasture. On the other side, the presence of an heterogeneity on the pasture will influence the spatial and temporal distribution of grazing inducing a dynamic and mutual interactions between the animal and the pasture.

The use of grassland resource regains a high interest nowadays. To propose more efficient decision support tools aiming a better management of the feeding, we need to better understand the grazing mechanisms of cattle under different pasture characteristics from grazing behavior to grazing bites scale.

2. Objectives

The aim of the thesis is to link the changes in pasture characteristics to the grazing behavior of cattle in order to better understand their grazing strategy under different pasture characteristics by (1) continuously monitor cattle grazing behaviors through the use of sensor technology, (2) decomposing these behaviors to attain the bite scale, (3) identifying the parameters involved facing the changes of pasture characteristics and (4) spatially determine pattern of bites distribution under contrasted pasture heights at the entry of the pasture.

Four research questions have been defined to achieve this goal:

- which sensors are available for the monitoring of cattle grazing behaviors and jaw movements?
- how sensor data could be useful to decompose unitary grazing and ruminating behaviors into their finest scale?
- what are the key parameters affecting temporal activity pattern of cattle under contrasting pasture heights?
- and how spatial distribution of the grazing process is affected by the pasture characteristics?

3. Research strategy

To answer these questions, we began this research with a literature review focusing on the use of sensor to detect and differentiate grazing jaw movements. This review highlighted the relevancy of using sensors to monitor behaviors at bite scale to replace human observations (Chapter 2). It was published in *Biotechnology, Agronomy, Society and Environment*, in 2016. The first step of the research was the calibration and the validation of the use of sensor data from an inertial measurement unit to allow accurate detection of grazing and ruminating behaviors (Chapter 3). It has been submitted for publication to *Computers and Electronics in Agriculture* and is waiting actually for final decision after a minor revision. Different results of the calibration and part of validation processes were also presented at two different conferences (International Conference on Precision Agriculture 2014, Sacramento, USA; Joint International Symposium on Nutrition of Herbivores and Ruminant Production, Canberra, Australia).

Following the validation of the detection algorithm, the grazing and rumination behaviors were decomposed through the analysis of data in frequency domain in order to identify the interesting signals to allow accurate differentiation of bites and chews and related usefulness for mechanism understanding on pasture (Chapter 4). For ruminating, the results were presented at European Grassland Federation Conference 2014 (Aberystwyth, Wales, UK). Concerning grazing bites detection, the results were published in a peer-reviewed special edition of *Precision Livestock Farming* (2015, European Conference on Precision Livestock Farming, Milan, Italy) knowing the importance of studying grazing behavior during the thesis. Validation of the biting behaviors detection initially determined in the previous chapter and their spatio-temporal changes on pasture is studied in Chapter 5. The research will be submitted for publication in *Applied Animal Behavior Science* journal.

A general discussion closes this thesis. It discusses the future of sensors in grazing management and the importance of bite scale and spatio-temporal study to provide feed decision support tools.

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CHAPTER 2

CHAPTER 2

This work starts with a review of sensors used to detect cattle behaviors at bite scale. As the thesis followed from the beginning a precision livestock farming (PLF) approach, researches focusing on use of sensors will be outlined in order to understand (1) the type of sensor, (2) the sampling and on-field data recording, (3) the data analysis methods in particular the time-windows and reached accuracies when compared to the reality.

Review on the use of sensors for jaw movements' detection

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1. Abstract

Introduction. Precision Livestock Farming (PLF) is spreading rapidly in intensive cattle farms. It is based on the monitoring of individuals using different kinds of sensors. Applied to grazing animals, PLF is mainly based on the recording of three parameters: the location, the posture and the movements of the animal. Until now, several techniques have been used to discriminate grazing and ruminating behaviors with accuracies over 90% on average, when compared to observations, providing valuable tools to improve the management of pasture and grazing animals. However, bites and jaw movements are still overlooked, even though they are of utmost importance to assess the animal grazing strategies for various pasture types and develop future techniques allowing better estimation of their intake.

Literature. The goal of this review is to explore the possibility of monitoring the individual jaw movements and the differentiation of bites in grazing animals. For this purpose, (1) the mechanisms of forage intake in cattle are explained briefly in order to understand the movements performed by the cow, especially during grazing; (2) the various sensors that have been proposed to monitor jaw movements of ruminants such as mechanical sensors (pressure sensors), acoustic sensors (microphone) and electromyography sensors are compared and (3) finally the relationship between jaw movements, biting behavior and forage intake is discussed.

Conclusions. The review clearly demonstrated the ability of mechanical, acoustic and electromyography sensors to classify the different types of jaw movements. However, it also indicated a wide range of accuracies and different observation windows required to reach these accuracies when compared to the observed movement. This classification purpose could lead to a better detection of more specific behavior, e.g. bite detection, and their exact location on pasture.

Keywords: precision agriculture, livestock management, cattle, sensors, movements, forage.

2. Introduction

Sensors enable the monitoring of many physical variables. Their use in Precision Livestock Farming (PLF) has increased rapidly over the past decade for research purposes and also in on-farm applications. Unlike more traditional livestock management methods which focus on the herd, PLF is based on (1) the monitoring of variables at the individual level (Hostiou et al., 2014) and at an appropriate frequency with reliable sensors; (2) the development of predictive models describing the animal's responses to environmental stimuli for each measured variable and (3) the comparison of the prediction models with what is actually measured through the sensors. The ultimate goal is to suggest managerial options to the farmer. Measuring such variables requires trade-offs between upstream data acquisition at high frequency, while preserving battery life and considering memory limits which are specific to the sensors that are used, and downstream output accuracy obtained using adequate data treatment methods.

In this respect, sensors can be used individually or in combination to track, detect, classify, manage and possibly control animal movements and behaviors. Monitoring ruminant behavior is a key to understanding how animals fulfill their requirements in pastoral systems by grazing a dynamic vegetation to achieve optimal plant production, animal forage intake and performances (Carvalho, 2013). Traditional managerial tools are limited to adjusting stocking rates and occupation times in rotational grazing, supplementing the animals and controlling concentrate intake at herd or individual level and indirect monitoring of forage intake through milk production, growth performance, or pasture disappearance (Holechek et al., 2011; Carvalho, 2013). PLF opens a wide range of new perspectives in both intensive pasture and extensive rangeland management by focusing on the individual instead of the whole herd. For example, Laca (2009) proposed a system in which both animal health and plant-animal interactions are monitored by combining animal position and behavior data to remotely manage individual health and feeding.

Controlling individual animal foraging behavior on pasture means the monitoring of grazing, rumination and resting behaviors, which all together occupy 90% to 95% of the daily time budget. During the last 5 to 10%, animals are busy displaying social behaviors, walking, drinking, eating supplements, etc. that might also provide interesting insights in terms of animal management (Walker et al., 2008). Focusing on feeding behavior, individual monitoring of grazing animals is based on the recording of three main parameters:

- the location of the animal: where it is in the paddock, in order to identify grazing stations;

- the posture of the animal, the static element composing a behavior such as the position of the head or the back;
- the movement of the animal, the dynamic element composing a behavior such as moving legs or jaw.

Tracking location on pasture was made possible by the large dissemination of Global Positioning System (GPS) sensors. GPS has been successfully used to detect static or dynamic unitary behaviors differentiated through changes in path speeds: foraging or grazing, resting and walking (Anderson et al., 2012). Nonetheless, accuracies of behavior classification based on GPS sensors, with sampling frequency lower than 10Hz, remain poor, i.e. < 80% when compared to visual observations based on time windows of 5-minutes each (Schlecht et al., 2004; Larson-Praplan et al., 2015). Posture analysis has been more recently developed through the use of accelerometers and based mainly on the position of the head: up or down. This information, in combination with GPS-based data, allowed discrimination between several kinds of feeding related behaviors for grazing animals with high accuracies (>90%). Those accuracies were obtained with a short time window of 5 to 10-seconds while the data acquisition from the GPS and the accelerometer ran between 4Hz and 10Hz (Dutta et al., 2015, González et al, 2015).

Finally, monitoring of cattle movements is mainly obtained using accelerometers. Through diverse analysis methods, accelerometers recording data at 10Hz could be used to classify behaviors, as done for example by Mangweth et al. (2012) when they classified lame and non-lame cows using a basic statistical methods, reaching an average accuracy of 91%. Similarly Martiskainen et al. (2009) classified multiple behaviors using a machine learning method with accuracies ranging from 29% to 86% with samples windowed for 10-seconds for all behavior classifications.

The online detection and classification of the behaviors are essential for the development of remote and automatic monitoring of cattle on pasture. However, other components of animal movements, like jaw movements are presently overlooked while they are of utmost importance to assess animal grazing strategies when grazing various types of pastures and to develop new methods to better estimate their intake. Nonetheless, bite mass and subsequent intake rate are the most variable components of the feeding behavior, thus the most difficult to predict. Bite mass and intake rate are influenced by sward height, sward bulk density, botanical family and species, animal characteristics and motivation duration of the previous starvation period, grazing system, pasture allowance, concentrate and forage supplementation level, daily time of access to pasture, hour of day, etc. (Rook et al., 1994; Gibb et al., 1997; Barrett et al., 2001). Therefore direct determination of bite mass from jaw movements is still a real challenge today. Bonnet et al. (2015) recently studied the possibility of doing a continuous bite monitoring with acoustic sensors coupled to direct observation with trained observers. Combined with preliminary estimates of bite mass performed by the hand-plucking method (Bonnet et al., 2011), they could estimate bite mass with an accuracy ranging between 80% and 94%, in a short-term intake rate (approximately 10 min). Although not applicable for PLF purposes, such methods suggest that combining information provided by different sensors, for example location, head position and acceleration, and jaw movements, may help overcome the everlasting challenge of intake estimation on pasture.

The main goal of this review is to assess the technologies available for the monitoring of individual jaw movements in cattle for research and PLF uses and to discuss the mechanisms of bite mass constitution and their links with jaw movements. For this purpose, we will (1) discuss the mechanisms of forage intake, (2) detail various sensors that have been proposed to monitor jaw movements of ruminants, and (3) outline the link between jaw movements, biting behavior and forage intake, focusing mainly on cattle.

3. Mechanism of forage intake by cattle

Grazing is a complex combination of various movements and activities performed at different temporal and spatial scales as shown in Figure 1. The single bite is the elementary component of the grazing process (Ungar et al., 2006; Carvalho, 2013). Its frequency ranges from 0.75 to 1.2 bites per second and its size is mainly determined by the mouth of the animal as well as some vegetation characteristics such as sward height, tensile strength and density (Griffiths and Gordon, 2003, Oudshoorn et al., 2013 and Oudshoorn and Jorgensen 2013). Several bites performed in a row by an animal on a single feeding station without interruption compose a grazing bout (Gibb, 1996) that will cover a few square meters and last between 10 to 100 seconds (Andriamandroso et al., 2015). Several grazing bouts are performed during each grazing event or meal (Gibb, 1996) that occurs each day for several minutes to hours during which a significant portion of the paddock is explored. Finally, the paddock is occupied for some days to several months and covers an area that is usually over one hectare. Only the two highest levels in Figure 1, i.e. grazing event and paddock, are discussed in most of research on the detection and classification of grazing behavior.

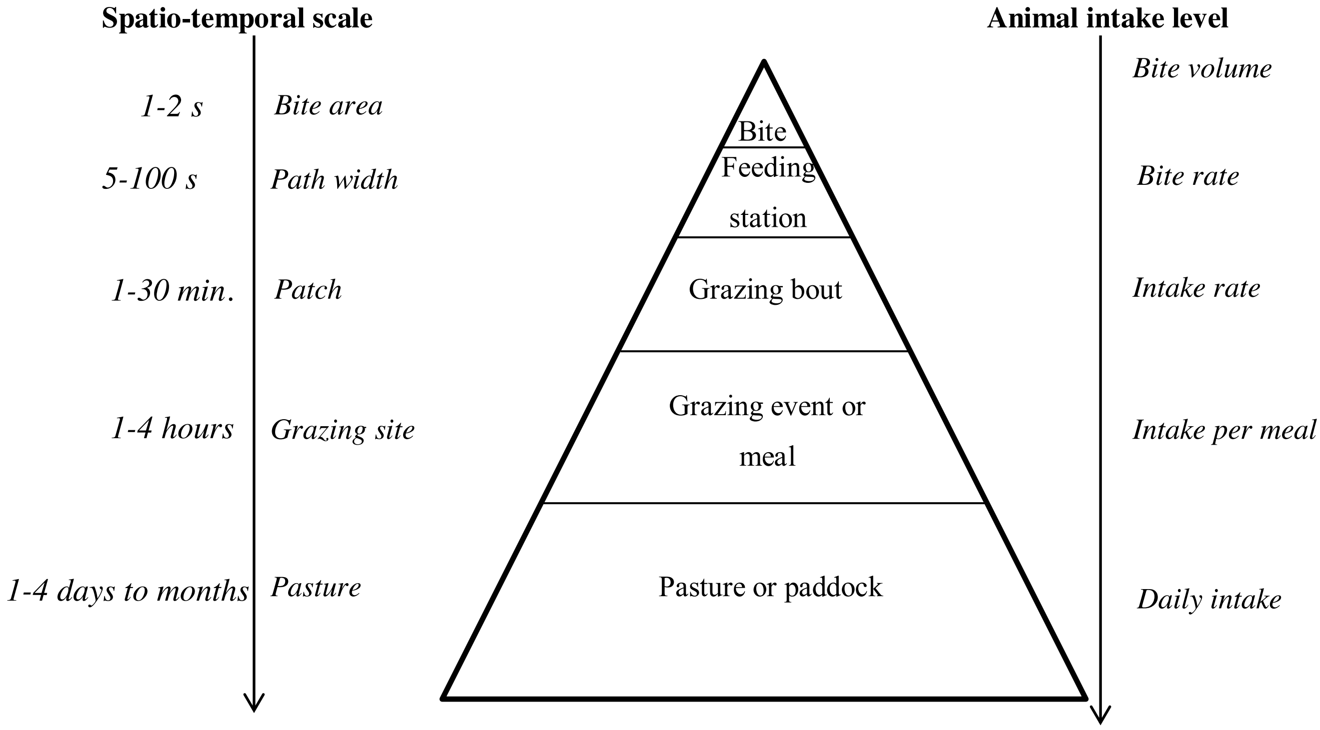

Figure 1 : Spatio-temporal components of grazing behavior (adapted from Gibb, 1996, Gregorini et al., 2006 and Carvalho, 2013)

A detailed observation of cattle movements at individual bite level (Figure 2) shows that foraging requires mainly jaw and accessorily tongue movements that can be broken down into four phases. Firstly, during prehension, cows surround a bunch of grass using their tongue and lips (Frames 1 and 6, Figure 2) and take it into their mouth (Frame 11, Figure 2). Then the grass is grabbed between the lower jaw and the gum (Frame 16, Figure 2) and it is finally cut with a sudden movement of the lower jaw usually accompanied by a movement of the whole head to perform the proper defoliation (Frames 21 and 25, Figure 2). This abrupt head movement is marked by an upward thrust of the mouth visible by the increase in distance between the mouth and the baseline and is usually considered as the actual bite (Gibb, 1996) (Figure 2). The whole forage intake is ended by chewing and swallowing the plant biomass (Vallentine, 2001).

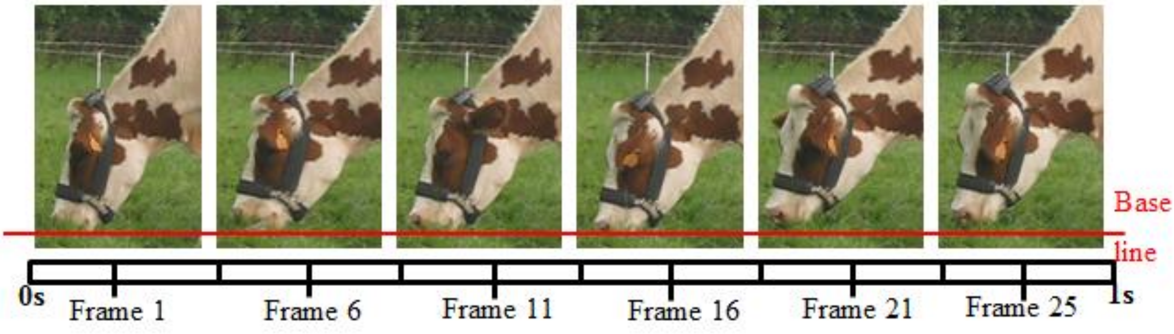

Figure 2 : Visualization of cattle mouth movements (25 frames per second video)

Rumination jaw movements are more quiet and regular. They are composed of a cyclic process which begins with the regurgitation of a rumino-reticular bolus followed by semi-circular jaw movements with a specific frequency of 1.06 ± 0.06 bites.second^{-1} during mastication and ends with the deglutition. Deglutition is described as a pause between two bouts of mastication while the mastication cycle lasts between 15-seconds and 60-seconds (Andriamandroso et al., 2014).

In order to detect bites, various techniques have been developed to monitor jaw movements of ruminants (Figure 3). Before the early 1980's, tools for counting jaw movements were strictly mechanical. Jaw movements were recorded on paper rolls or disks (e.g. Balch, 1958) or counted via built-in electrical circuits used as recorders (e.g. Stobbs and Cowper, 1972). However such devices cannot be properly considered as sensors since a sensor is a device that detects events or measures changes in a physical property such as light, force and sounds in its environment and transforms them into a usable signal, usually an electrical output, for further analysis (Kenny, 2005). According to a literature survey (Figure 3) pressure and microphone sensors are the most used sensors for monitoring cattle jaw movements with 35 and 14 references, respectively. While only 4 references mention acceleration sensors, their use is rising rapidly. Electromyography sensors are also sometimes cited (2 references), while the two last references compared different types of sensors.

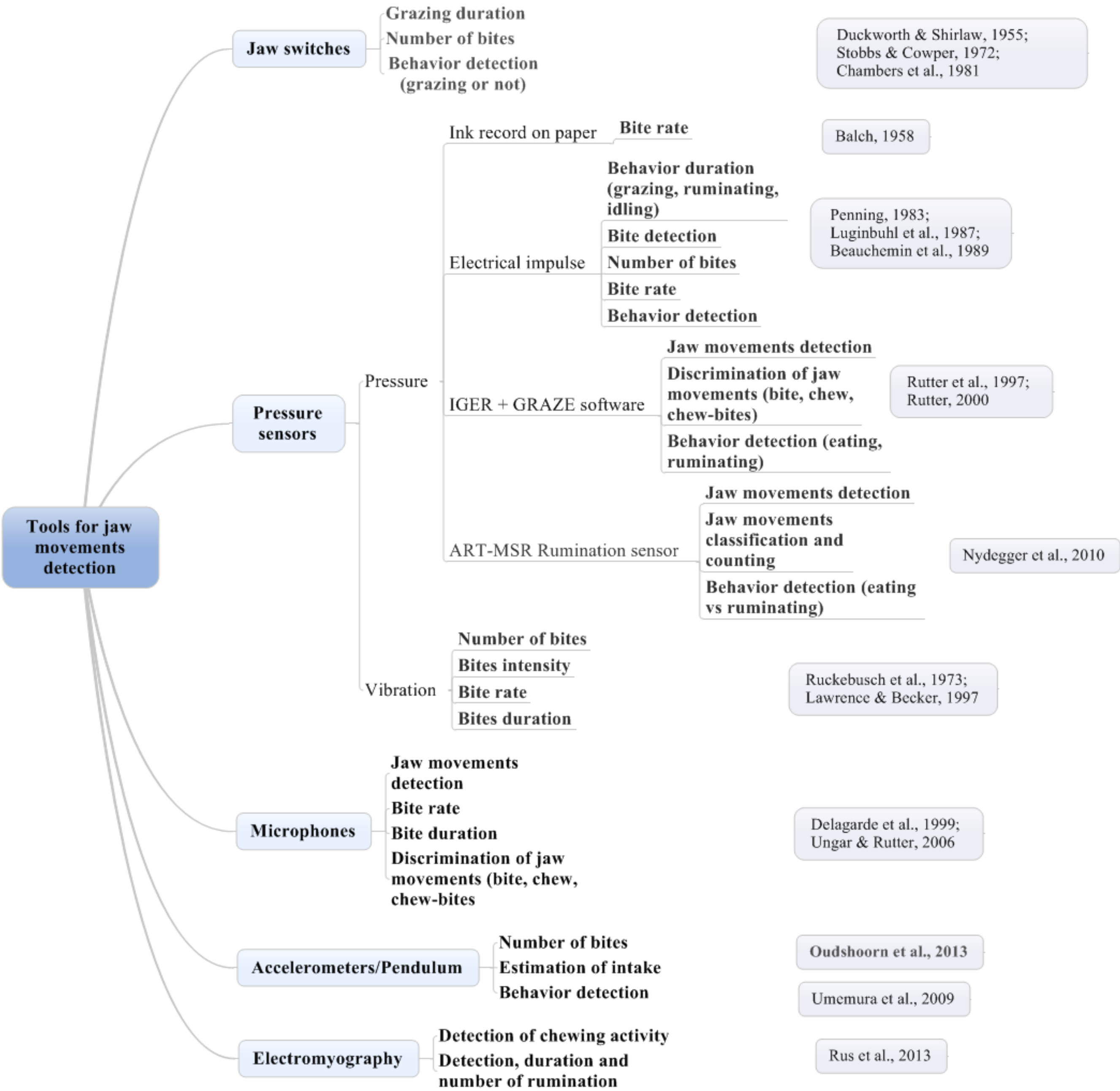

Figure 3: Principal tools used to characterize jaw movements of cattle: references used in this section came from research in Scopus (www.scopus.com, Elsevier, The Netherlands, 31/07/2015) using combination of three groups of keywords (total of 57 references):

a- "bite" OR "chewing" OR "mastication" OR "jaw movements" OR "jaw"

b- "cattle" OR "cows" OR "heifer" OR "heifers" OR "calves"

c- "sensor" OR "electronic device" OR "tool"

4. Use of sensors for jaw movements detection and quantification in cattle

Devices dedicated for jaw movements detection can be classified in five groups (Figure 3):

- jaw switches, where a switch is activated at each jaw movement;
- pressure sensors, where a jaw movement corresponds to a change in pressure or length in a tube around the nose;
- microphones, where sound patterns allow jaw movement detection;
- accelerometers, to detect movements operated during a jaw movement; and
- electromyography, transducing a jaw movement to an electrical signal from the movement of the muscle.

In the following section, only the last four sensors will be discussed, because jaw switches are not actual sensors as previously explained, since the collected information is printed directly and is not transformed into a digital or electrical signal output (e.g. Balch, 1958).

4.1. Pressure sensors

The use of pressure sensors in bite monitoring began with the pioneering works of Penning (1983). His instrument was composed of a halter fitted with a silicon noseband connected to two electrodes. When the noseband stretched from a jaw movement, it changed the electrical resistance between the electrodes placed at both ends of the tube. This induced a change in voltage which produced a signal which was proportional to the extent of the jaw movement and waving (Harman, 2005). It was used successfully to differentiate grazing and ruminating behaviors and to measure time spent grazing, ruminating and idling, achieving a 95% agreement with visual observations over a time window of 3-minutes (Penning, 1983). Several variations of the method exist, including initially the use of a rubber tube or balloon placed just under the lower jaw (Luginbuhl et al., 1987) but enhanced later as a tube encircling the nose (Penning, 1983; Rutter et al., 1997; Nydegger et al., 2010) or under the jaw (Dado and Allen, 1993).

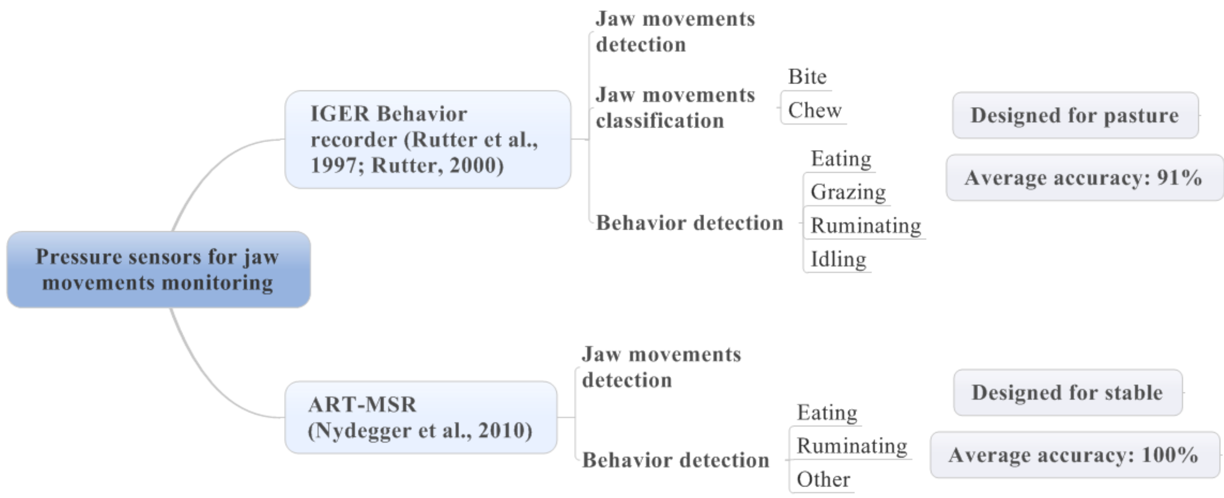

Figure 4: Comparison of the two most-used pressure sensors to monitor jaw movements of cattle

Building on this technology, two systems were developed which were used exclusively in research and not applied in PLF (Figure 4). The IGER Behaviour recorder (Institute of Grassland and Environmental Research, Okehampton, UK, Rutter et al., 1997) and the ART-MSR pressure sensor (Agroscope Reckenholz-Tänikon ART Research institute, Modular Signal Recorder MSR145, MSR Electronics GmbH, Switzerland, Nydegger et al., 2010) were designed for pasture and for stable use respectively. Both devices are able to make a 24-hours continuous data recording, with a maximum of 40 hours for ART-MSR (Nydegger et al., 2010). The IGER Behaviour recorder consists of a noseband and an electronic interface including a rechargeable battery connected to a computer board allowing a memory card to record, analyze and store data at 20Hz. A jaw movement is recognized as a pressure peak through the transmission of the movement to the halter and the change in the tube pressure. The software installed on the computer board (Rutter, 2000) is able to classify jaw movements (bites or chews), identify jaw movement bouts and determine the behavior associated with each bout with defined thresholds based on the analysis of the peaks shape. Peaks are considered as bites when they are a combination of a major long peak followed by a smaller sub-peak or a non-symmetrical peak in the absence of the sub-peak (Nadin et al., 2012). Conversely, a chew contains only one peak of symmetrical shape (Champion et al., 1997). The detection accuracy reaches an overall concordance of 91% with 95% for eating and 93% for ruminating when compared to the observations on a 5-minutes time window-basis with a maximal sampling rate of 20Hz (Rutter et al., 1997). Those accuracies decreased for cattle

grazing a tropical pasture and confronted with more heterogeneous grazing conditions, as it was difficult to clearly differentiate biting from other jaw movements (Nadin et al., 2012).
Several studies (12 references) used the IGER Behaviour recorder to investigate the effect of different factors such as the time of grazing (Abrahamse et al., 2009), the sward height (Gibb et al., 1999; Fonseca et al., 2013), the physiological state of the animal (Gibb et al., 1999) or the milking frequency (O'Driscoll et al., 2010) on grazing behavior or on grazing intake. The latest study was done by Fonseca et al. (2013) who used grazing bites detected and counted by the IGER Behaviour recorder to estimate bite mass and bite rate for determining the effect of sward height and level of herbage depletion on these bite features.
In the ART-MSR system (Nydegger et al., 2010) the tube encircling the mouth is filled with oil and the sensor records the pressure change when the jaw is moving. When the cow opens her mouth, an increase in pressure alters the electrical resistance, resulting in a signal in the sensor corresponding to one chew (Braun et al., 2014). Apart from the jaw movements features as described for the IGER Behaviour recorder, it is also possible to estimate the feed intake from the number of chews and duration of eating time with reasonable correlation coefficients (R =0.6 to 0.9) (Pahl et al., 2016). Accuracies in detecting eating and ruminating activities approached 100% while counting jaw movements performed during each behavior gave disagreement rates of 12% and 0.24% respectively compared to observations performed over 5 min (Nydegger et al., 2010).Thus, this tool is more accurate when counting ruminating jaw movements, probably due to the regular pattern of this behavior compared to eating.
To conclude, pressure sensors derive their power in detecting jaw movements by identifying patterns that are different during eating and rumination. The silicon tube encircles the nose as a normal halter, so it does not alter the normal behavior of the cow. Misclassifications in this method usually arise from practical considerations. Variation in the tightening of the halter on individual animals can generate different pressure values, modifying discrimination thresholds. The analysis of the output wave signal based on the peak detection is compromised if the halter is mounted too tightly or too loosely (Nydegger et al., 2010). Moreover, automated transmission of data is not yet developed.

4.2. Acoustic monitoring of jaw movements using microphones

The miniaturization and accessibility of different kinds of sensors increased the use of microphones for the detection and characterization of cattle jaw movements. In a microphone, sounds are going through a flexible diaphragm and cause vibrations. The output electrical signal is proportional to the intensity of these vibrations as well as their frequencies.

Microphones used for recording jaw sounds of a grazing ruminant can be used to discriminate bites or chews. This allows the classification between grazing or ruminating behavior to be achieved over time with a succession of bites or chews (Navon et al., 2013, Benvenutti et al., 2015).

Acoustic analysis allows differentiation of three types of jaw movements: chew, bite and chew-bite. Bite refers to a ripping sound while chew refers to a grinding sound, easing the differentiation between these two types of jaw movements. Chew-bite corresponds to an intermediate between chew and bite sound, i.e. during this jaw movement the herbage already in the mouth is chewed and simultaneously a new mouthful of herbage is severed; these two movements are performed within a single jaw movement (Ungar and Rutter, 2006).

Methods using sound recordings for jaw movement classification differ according to the location of the microphone, the processing of the acoustic signal and the aim of classification (Table 1). Some methods are only able to detect jaw movements. For example, based on 10 min of grazing session recorded by a camera, the simple detection of jaw movements using a machine learning technique reaches an accuracy of 94% when compared to the aural analysis of sounds by a trained operator (Navon et al., 2013). The machine learning algorithm uses four properties of the signal pattern: the shape to determine jaw movements interval, the intensity of each jaw movement represented by a peak in the time domain, the duration and their integration in a sequence of behavior (Navon et al., 2013). Clapham et al. (2011) used similar parameters (frequency, intensity, duration and time between events) calculated during sound segments of 1 to 5-minutes to detect and analyze bites, reaching an overall behavior classification accuracy of 94%. Using a discriminant function, bite and chew could also be differentiated with an accuracy of 94% (Clapham et al., 2011). The discriminant analysis is based here on three parameters determined from the signal pattern of the sound produced during biting and chewing inside a 1 kHz sound window: peak frequency, peak intensity, average intensity and their duration. (Laca and DeVries, 2000).

Table 1: Methods for jaw movements classification based on acoustic recordings, type of jaw movements differentiated (bites, B; chews, C; chew-bites, CB) and classification accuracy (CA, %) or error rate (ER, %) over required sampling time window

Type of microphone	Location	Audio signal processing before classification	Jaw movements classification method	Conditions	Accuracy	Time window	References
Shure VP wireless microphone (Shure Incorporated, Niles, USA)	Forehead	None	Quadratic discriminant function using 3 sets of variable	*Setaria lutescens* pasture (tall vs short turves) 4 Hereford cross-bred steers	For C and B, CA= 94%	not reported	Laca and DeVries, 2000
Shure VP wireless microphone (Shure Incorporated, Niles, IL, USA)	Forehead	Transformation into frequency domain (FFT) + normalization + extraction of 6 features	Discriminant analysis	*Lolium perenne* and *Trifolium repens* pasture 6 cows	Total number of peaks (CA=67%) Total number of peaks + frequency bandwidth + frequency skewness (CA=81.8%)	not reported	Ungar et al., 2007
			Logistic regression		CA=86.7%		
			Neural networks		B: CA=25-63% C: CA=65-80% CB: CA=70-90%		
Lavalier microphone (Sennheiser ME 2-US, Wedemark, Germany)	Mouth	High pass filter with cutoff frequency of 600Hz	SIGNAL software: detect bites with frequency, intensity, duration and time between those events	*Festuca arundinacea*, *Dactylis glomerata*, *Poa pratensis* and *Trifolium repens* pasture Angus steers	B: CA=95% Automated bite counts: ER=9.1%	1-5 minutes	Clapham et al., 2011
Nady microphone (Nady 151 VR, Nady Systems, Oakland, USA)	Forehead	None	1-feature extraction using Hamming window 2-Hidden Markov Model	*Festuca arundinacea* and *Medicago sativa* (tall vs short) 2 Holstein cows	B: CA=76%-90% C: CA=88%-99% CB: CA=61%-94%	13 minutes	Milone et al., 2012
Shure VP wireless microphone (Shure Incorporated, Niles, USA)	Forehead	None	Machine learning from time domain features: shape, sequence, intensity, duration	*Lolium perenne* and *Trifolium repens* pasture 12 Holstein-Friesian cows	Jaw-movements identification: CA=94% (tolerance=0.2s)	10 minutes	Navon et al., 2013

Finally, detection and classification of the three types of jaw movements (bite, chew and chew-bite) are possible using the Hidden Markov model. This model estimates sequences of bites or chews or chew-bites, called hidden states, which are not observable directly, using their acoustic spectrum characteristics i.e. the energy produced, in decibels, by each sound. Using different frame lengths (20 to 80 milliseconds) correct classification of those three jaw movement types ranged between 61% and 99% and is influenced by the pasture type and grass height (Milone et al., 2012). Using discriminant analysis, logistic regression and neural networks as classification methodologies yielded 67% to 82%, 87% and 25% to 90% of correct classifications respectively, while the time window used in the calculations was not reported (Ungar et al., 2007).

In addition, Nadin et al. (2012) showed no significant differences between visual observations and microphone-based detection methods in studies demonstrating the performance of acoustic sensors to monitor grazing jaw movements of cattle. Moreover, since grazing corresponds to a succession of bites and chews with accessorily chew-bites and rumination corresponds to a succession of chews, it is also possible to differentiate those behaviors using microphones (Navon et al., 2013).

To summarize, microphone-based methods reach good accuracy for jaw movements detection. In addition, they are able to differentiate three different kinds of jaw movements: two visible movements corresponding to chew and bite, and one intermediate difficult to detect visually (chew-bite). However, outdoor applications are disturbed by environmental noises, so extending sound recording and interpretation techniques acquired under ideal experimental conditions to an on-farm level tool recording and analyzing sounds automatically for PLF applications still requires significant development.

4.3. Acceleration sensors

An accelerometer is an electronic sensor transforming physical acceleration from motion or gravity into waveform voltage signal output. It can measure both static acceleration due to gravity, the low-frequency component of the acceleration and the dynamic acceleration due to movements imprinted by the animal (Almeida et al., 2013; Brown et al., 2013).

Despite the depth of literature surveyed, only four references used this type of sensor to identify and classify jaw movements, among which three described different methods of classification. In stables, Tani et al. (2013) coupled a 1-axis accelerometer to a microphone to classify cattle chewing activities by matching 1 minute segment waveform patterns to observed eating and ruminating behaviors. Intake and chewing activities were highly distinguished at 90%, reaching 99% when the sensor was attached to the cow's horn.

On pasture, a 3-axis accelerometer was used by Oudshoorn and Jorgensen (2013) to record cow bites. A visualization of recorded signals from the three individual orthogonal axes (*x*, *y*, *z*) was done first, in order to determine which one matched best with the observed bites. To determine each bite, a series of thresholds were tested to determine the peak which had the best correlation to the observation. The average correlation coefficient was 0.65 indicating the difficulty to count bites using an accelerometer this way. Finally, Umemura et al. (2009) modified a pedometer into a pendulum under the lower jaw to monitor cattle jaw movements. The data could be wirelessly downloaded from the sensor which had a lifespan of one year. This system was able to count jaw movements with an accuracy of 90% compared with manual counts over 10-minutes segments. This bite count was correlated with a coefficient of 0.7 to pasture disappearance estimated indirectly by a rising plate meter.

Accelerometer sensors thus provide interesting options to automatically count cattle jaw movements. As for sound sensors, interference may be present in the signal recorded by the sensor. Bites are the result of jaw and head movements while chew imprints mostly jaw movements. The sensitivity of accelerometers could provide undesirable signals during recording sessions due to ear movements or sudden head turns to drive flies or other insects away. Thus, a pre-processing of the signal is probably required to isolate the signal relative to the jaw movements in order to consider this method for actual PLF uses on farms. In terms of material, the use of an inertial measurement unit (IMU) which is a combination of accelerometers, gyroscope, magnetometer and location sensors might offer a real advantage knowing that all these variables can be recorded simultaneously at a high sampling frequency (100Hz). For example, Andriamandroso et al. (2015) used smartphone IMUs to count the number of bites through frequency pattern of 1-axis acceleration data. As for pressure sensors, if the accelerometer is mounted in a halter, the tightening also plays an important role in the transmission of the movement to the sensor.

4.4. System based on electromyography

While the noseband pressure sensor quantifies changes in tube pressure and translates it into an electrical impulse, electromyographic sensors quantify the electrical potential of masticatory muscles during contractions (Rus et al., 2013). Two electrodes are fixed on a halter and measure electrical signals occurring during a jaw movement with a contraction of the Masseter muscle. This sensor, coupled to a 3-axis accelerometer and a wireless transmission of data in real time, constitutes the DairyCheck sensor (Rus et al., 2013). This system is able to detect ruminating and feeding behavior on the basis of the regularity and irregularity of signal pattern respectively. The DairyCheck system yielded an overall concordance of 87% compared to visual observations over 1 minute, when detecting feeding time and rumination time (Büchel and Sundrum, 2014).

Finally, when the different above-mentioned techniques are compared, noseband pressure sensors and microphones are best able to detect jaw movements with high accuracy (over 94%) and differentiate biting and chewing jaw movements with fair accuracy (61% to 95% for microphone) (Table 2). Accelerometers can identify jaw movements with less than 90% of accuracy but discrimination of the different types of jaw movements is not mentioned yet. Authors using the electromyography method did not give any information about the accuracy of the detection of specific jaw movements.

Table 2: Comparison of different type of sensors to detect and classify jaw movements.

Type of sensor	Jaw movements detection accuracy[1] (%)	Jaw movements classification (accuracy[1] in %)	Required sampling time window (min)	References
Noseband pressure sensors	91-95	Bite Chew	5-minutes	Rutter et al. (1997) ; Nydegger et al. (2010)
Microphones	94-95	Bite (76-95) Chew (88-94) Chew-bite (61-94)	1-13 minutes	Ungar et al. (2007) ; Clapham et al. (2011); Milone et al. (2012) ;
Accelerometers	65-90	(data not provided)	10-minutes	Oudshoorn et al. (2013)

[1] Comparison with visual observations

5. Estimation of grazing intake through bites quantification

For many years, various methods have been used to quantify forage intake of grazing herbivores, including the measurement of pasture biomass before and after grazing, changes in animal bodyweight, digestive markers, or fecal near-infrared reflectance spectroscopy (reviewed by Decruyenaere et al., 2009) (Figure 5).

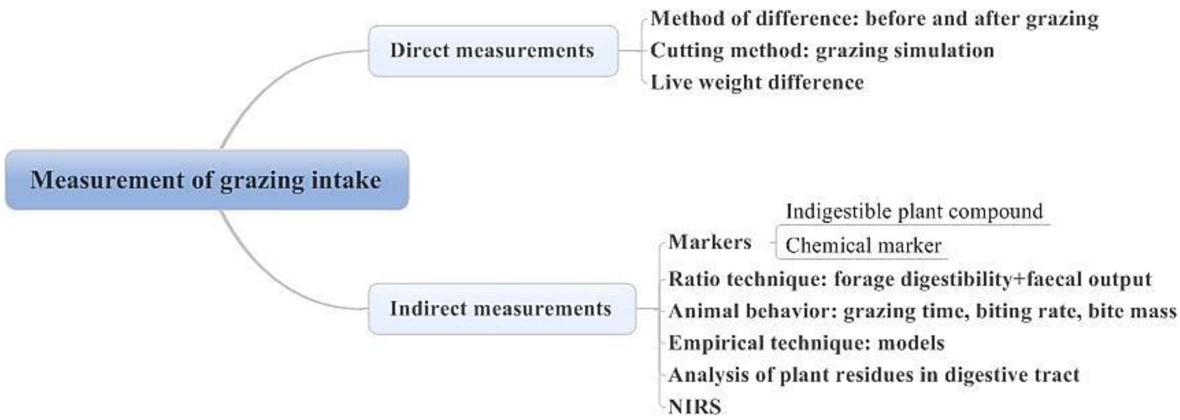

Figure 5 : List of techniques for grazing intake measurement (from Decruyenaere et al., 2009)

Among these techniques, animal behavior can also be used as a measurement of grazing intake by combining grazing duration, biting rate and bite mass. Knowing that a bite is the elementary and indivisible unit of the whole grazing process, this technique stresses the need to properly quantify bites, to estimate the intake along with the mass of each individual bite or their average mass.

This method is based on the determination of bite mass (quantity, in grams, of grass taken in each bite) and bite rate (number of bites per minute) as per the following formula (Vallentine, 2001):

$$\textit{Forage intake (gram.day}^{-1}\textit{)} = \textit{bite mass (gram.bite}^{-1}\textit{)} \times \textit{bite rate (bite.minute}^{-1}\textit{)} \times \textit{grazing activity duration (minute.day}^{-1}\textit{)}$$

To efficiently use this formula, accurate detections of grazing behavior and individual bites are essential. As already mentioned, several sensors are able to quantify these parameters with various accuracies. Oudshoorn et al. (2013) correlated intake for grazing cattle from grazing time estimated by an accelerometer and bite frequency with a prediction precision of less than 1.4 kilograms of dry matter per cow per day. In this experiment, grass intake was initially measured using an indigestible marker and the difference in net energy balance between energies offered by the grass and required for animal needs. This paper shows that prediction of intake from grazing behavior and bites counts is still beyond reach due to the lack of accurate bite mass estimation. Indeed, beyond bite rate, forage intake of grazing animals depends on pasture characteristics (sward height and bulk density) as expressed by the bite mass formula (Carvalho et al., 2015):

$$\textit{Bite mass (gram.bite}^{-1}\textit{) = Bite area (centimeter}^{2}\textit{)} \times \textit{Bite depth (centimeter)} \times \textit{Bulk density (gram.centimeter}^{-3}\textit{)}$$

In this formula, the bulk density and the bite area are calculated from empirical models using, sward height and relative bite depth (sward height/2), tiller density and forage biomass per area unit, and the size of the dental arcade. Such predictive models yield acceptable bite mass estimates in short-term experiments with very homogenous vegetation characteristics (Carvalho et al., 2015), but fail in more complex vegetation units. Until now, the best method available remains hand-plucking. It simulates a bite by mimicking grass prehension by hand and bite mass estimation accuracies can be as high as 95% for cows and goats with trained operators. This accuracy corresponded to the correlation between the amount of grass taken by the animal per bite and those plucked manually (Bonnet et al., 2011). While this method seems useful to calibrate bite masses for intake measurements for research purposes, it is time-consuming and no sensors can perform a similar task, hence it seems useless from a PLF perspective.

Therefore, monitoring intake in grazing ruminants using PLF approaches is still out of reach. Nonetheless, from a research perspective, the bite mass formula provides interesting directions for future research on the quantification of bite mass using a combination of promising technologies such as: (1) accurate monitoring of the pasture with for example distance meters and/or time-of-flight cameras, (2) animal positioning with Wifi triangulation or centimeter-accurate GPS,(3) rigid body attitude estimation from accelerometer data to reconstruct head movement and (4) jaw monitoring using sensor-based technologies described in this paper.

6. Conclusion

Most sensors mentioned in this review were primarily designed for research. Although some sensors such as accelerometers (e.g. SensOor®, CowManager, Utrecht, The Netherlands) are already used for behavior classification in farm situations, their use as on farm tools for jaw movements' monitoring of grazing animals still requires significant hard- and software developments, especially regarding the automation process and real-time data acquisition, as well as ease of installation and use. For example, whether based on mechanical (pressure or acceleration), electrical, or acoustic signals, most sensors require the use of a halter, and the way it is mounted is extremely important in the recording of jaw movements. A pre-processing of the signal may also be required to eliminate existing noises around the animal or during the movement. Combining different sensors, for example accelerometers to microphones, may be a solution for a better monitoring of bites. Dedicated signal processing also requires significant development. For example, using frequency domain signal processing approaches on acceleration data might provide useful progress. Accuracies mentioned in this document were obtained using short time windows and different calculation methods which could affect the percentage values. Longer time step should be considered to cover one or several days in order to show if the detection would change significantly or not. Finally, PLF requires the system to be robust and adaptable to a wide range of situations. Most techniques presented here were applied under strict controlled conditions for research and their implementation in the farms would also require some ability for auto-calibration of the device or tools to overcome differences in individual physiological states, morphologies or grazing conditions according to the season and pasture.

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CHAPTER 3

CHAPTER 3

From the previous chapter, the relevancy of using sensor-based techniques to detect and classify particular behaviors of grazing animals was shown as an important tool for their monitoring. Besides the common objective of detecting jaw movements, the choice of the sensor, its sampling frequency, the data analysis method and the choice of time-windows for all calculations have an impact on detection accuracy. Most of the reviewed studies used a "black-box" approach to achieve the classification. This chapter will describe in detail a tool developed in this thesis for an accurate detection of cattle grazing behaviors starting from the data collection method and the related data analysis which follows specifically an open approach as opposed to the majority of the techniques described in the previous chapter.

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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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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1. 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-second 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.

Keywords: dairy cattle, grass intake, behaviors, inertial measurement unit, open algorithm.

2. Highlights

- An iPhone 4S can be used to automatically monitor the behavior of grazing cattle using its built-in inertial measurement unit (IMU).
- A Boolean classification tree using the IMU signals in the phone reached similar accuracies for grass intake and ruminating to already available devices
- The classification algorithm codes have been made available to any user for further development.

3. 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-hours period, grazing occupies 25% to 50% of cow's daily time-budget and rumination 15% to 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 & Johnson, 2007; Swain et al., 2008);
- 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-minutes data segments (Schlecht et al., 2004; Godsk & 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-minutes 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 to 5-minutes 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 & 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-seconds 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-seconds to 5-minutes 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-seconds 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-seconds 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, California, 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.

4. 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.

4.1. Animals

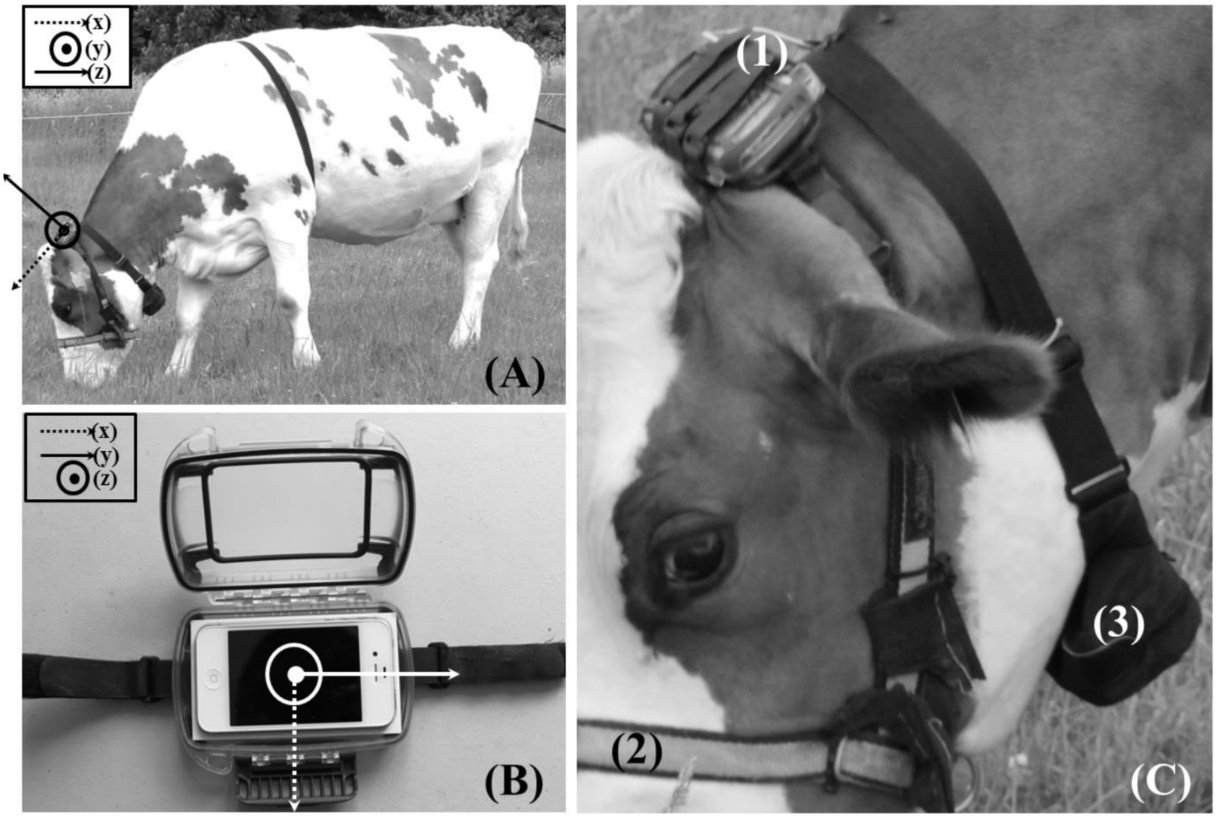
A total of 19 cows of different breeds across four different farms were used, aged between 4 to 12 years, and with estimated weights between 450 and 650 kilograms:

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

4.2. Materials

Each cow was fitted with a halter containing an iPhone 4S (Apple, Cupertino, California, USA) inside a waterproof box (Otterbox Pursuit series 20, 152.4 × 50.8 × 101.6 millimeters, 142 grams, Otter Products, LLC, USA) (Figure 6B). Each mobile phone was equipped with an application (SensorData, Wavefront Labs) downloaded from Apple Store (Apple, Cupertino, California, USA) which captures and stores data from the IMU of the iPhone at 100Hz. 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 hours, the original 3.7V 1420mAh Li-Polymer battery was connected to an additional external battery (Anker Astro E5 16000mAh portable charger, 150 × 62 × 22 millimeters, 308 grams, Anker Technology Co. Limited, California, USA) and attached as a collar around the neck of the animal (Figure 6C).



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

Figure 6: 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 axe 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).

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 on Figure 6C.

The SensorData application captures acceleration and gyroscope data along three axes (as showed in Figure 6B) as well as magnetometric and GPS information, providing a total of 40 signals (Table 3).

Table 3: 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[1]
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	meter
	Course	degrees
	Speed	meter. $second^{-1}$
	Proximity sensor	not defined

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

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

The Figure 7 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.

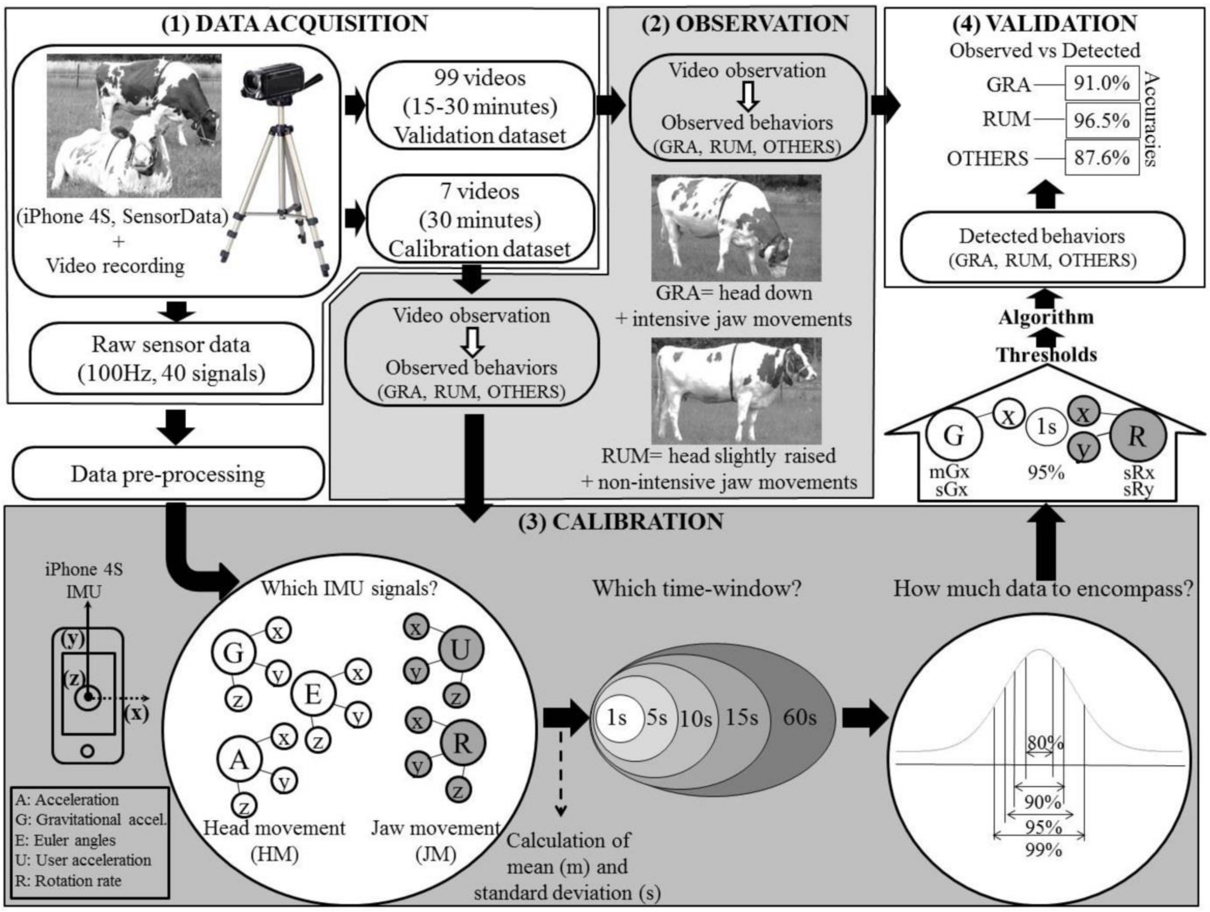


Figure 7: From data acquisition to detection algorithm: summary of the 4-steps process used for the construction of cattle behavior detection algorithm.

4.3.1. 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 hectare 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 kilograms of DM.hectare^{-1}). Finally, in summer 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 hectare-pastures with two pre-grazing forage allowance (1000 and 3000 kilograms of DM.hectare^{-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 to 30 minutes 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 & 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, several different behaviors could be observed (GRA, RUM, OTHERS).

4.3.2. 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 Figure 7.

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 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 4, 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 4). 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.

Table 4 : 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	A behavior is correctly undetected as it is in the observation

(TN)	
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 x 100 / (TP + FN)
Specificity (Sp)	Sp = TN x 100 / (TN + FP)
Precision (P)	P = TP x 100 / (TP + FP)
Accuracy (A)	A = (TP + TN) x 100 / (TP + FP + TN + FN)

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-second). 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 Figure 8), 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.

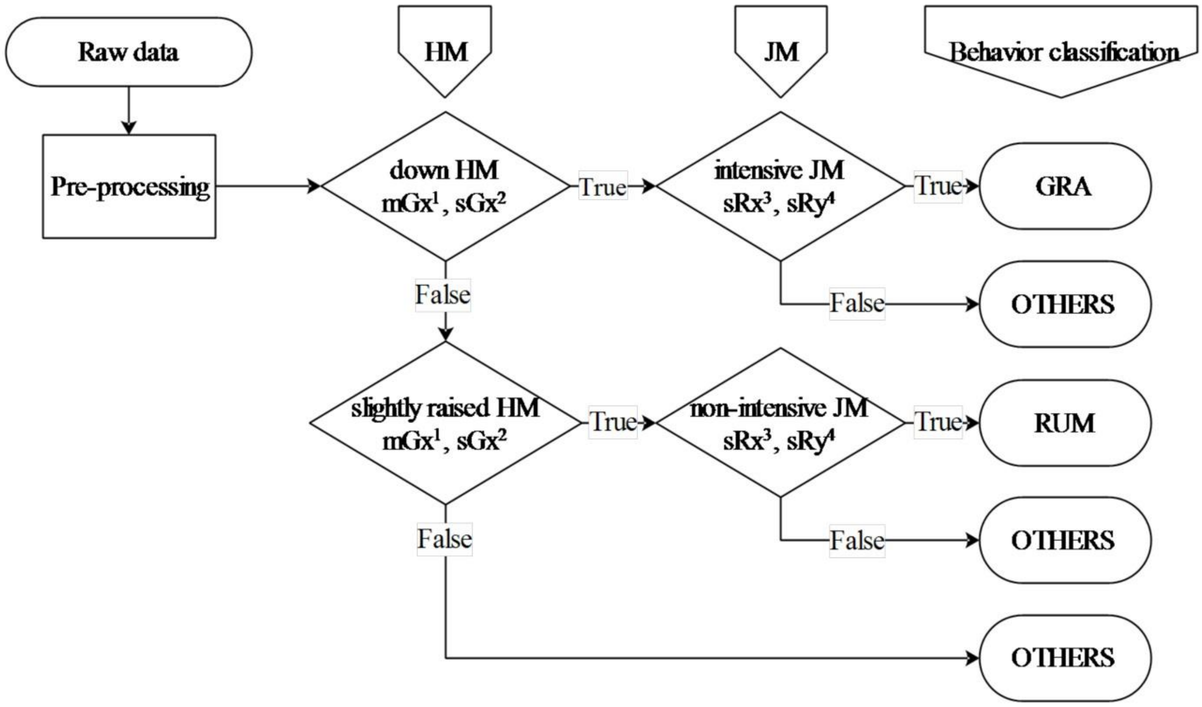


Figure 8: Structure of a Boolean algorithm allowing the automated classification of GRA and RUM based on means and standard deviations levels of gravitational acceleration and rotation rate signals (mGx, sGx, sRx and sRy) related to head (HM) and jaw movements (JM) measured on cows wearing the iPhone 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

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-second time windows. Finally, to assess how important it was to use the shortest time window (1-second) 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 (5-seconds, 10-seconds, 15-seconds, 30-seconds and 60-seconds) 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 4. To explore the usefulness of the algorithm, its ability to describe daily behavior patterns over a 24-hours period was also tested on one cow grazing swards with two contrasted forage allowances (1000 and 3000 kilograms of DM.hectare^{-1}).

5. Results

5.1. Algorithm calibration

5.1.1. 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 are grazing, their heads stay down but when ruminating, the IMU points slightly upwards. Consequently, as shown in Figure 9, 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 Figure 9 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 (Figure 9), and the mean and the standard deviation of this normalized signal distribution were therefore used to characterize cattle head movements (respectively mGx and sGx).

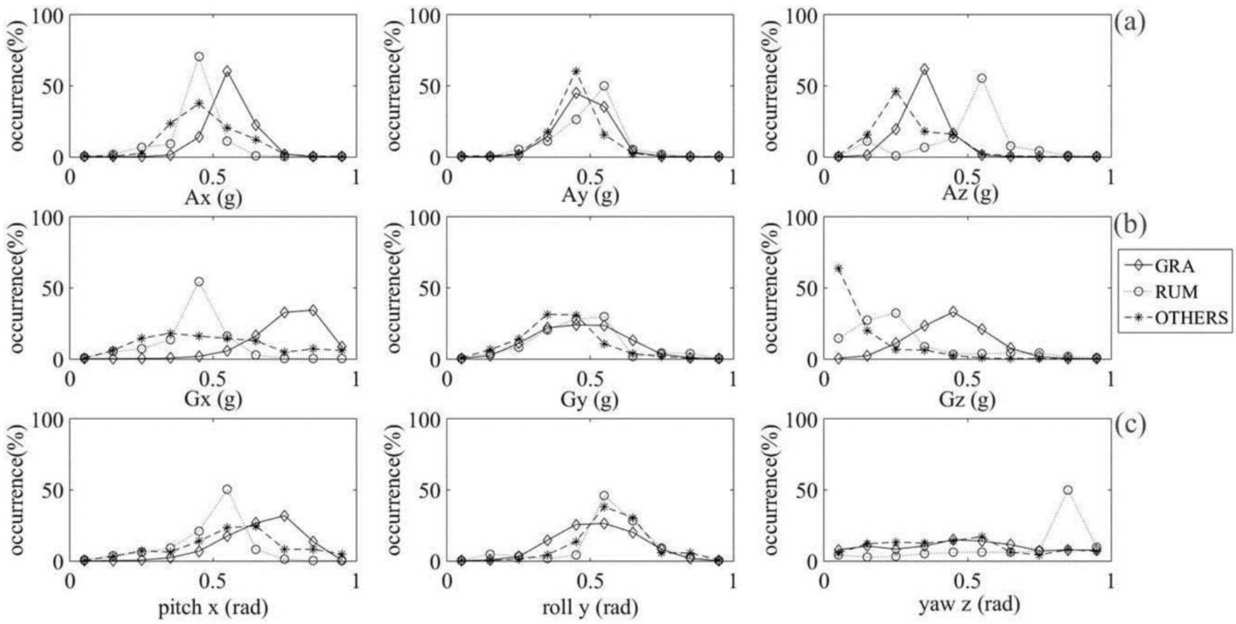


Figure 9: Frequencies distribution of normalized values along the 3 axes of the IMU signals expressing head movements during tagged sequences of GRA, RUM and OTHERS activities. With (a) the acceleration (Ax, Ay, Az) expressed in g (acceleration of gravity, g=9.81 m.s^{-2}), (b) the gravitational component 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.

Although head position seems sufficient to discriminate grazing from rumination, the range of values in Figure 9 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 acceleration particularly along the x-axis (as displayed in Figure 10). 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-second 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).

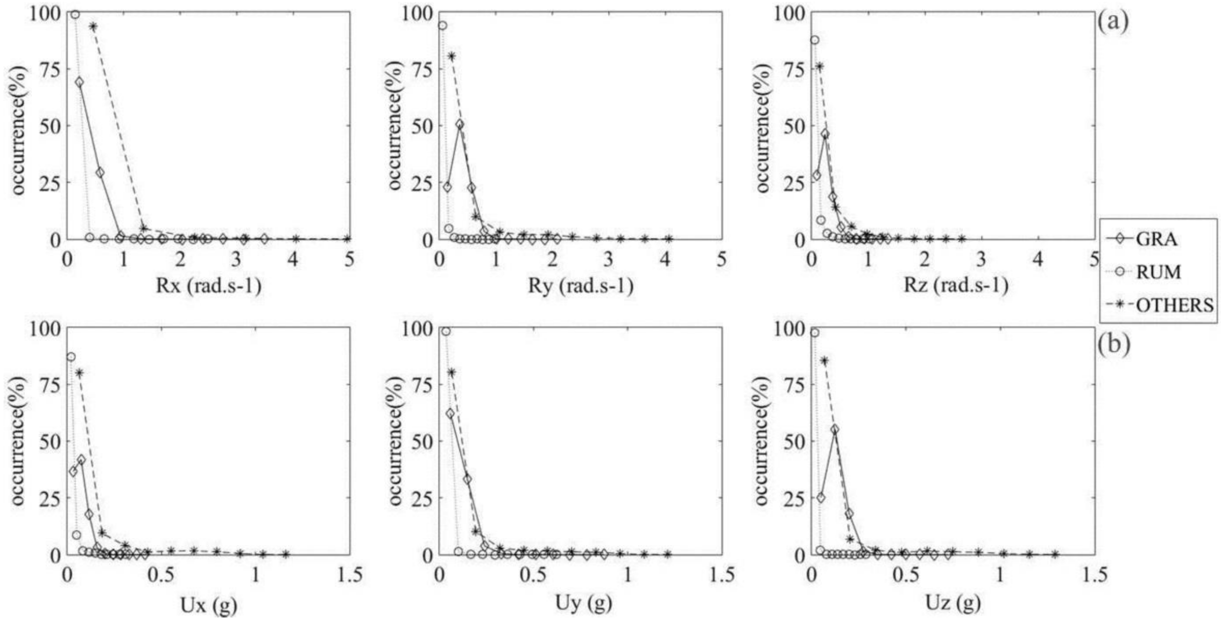


Figure 10: Frequencies distribution of the values of standard deviation of amplitude signals of (a) rotation rate (Rx, Ry, Rz) expressed in rad.s^{-1} (radian per second) and (b) user-acceleration (Ux, Uy, Uz) expressed in g (acceleration of gravity, g=9.81 m.s^{-2}) on the (x,y,z) axes of the IMU, during 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.

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.

5.1.2. 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 5.

Table 5: Minimum and maximum value windows for mGx, sGx, sRx and sRy calculated with 1-second 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[1] 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

[1]SD: standard deviation

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% (Figure 11). 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.

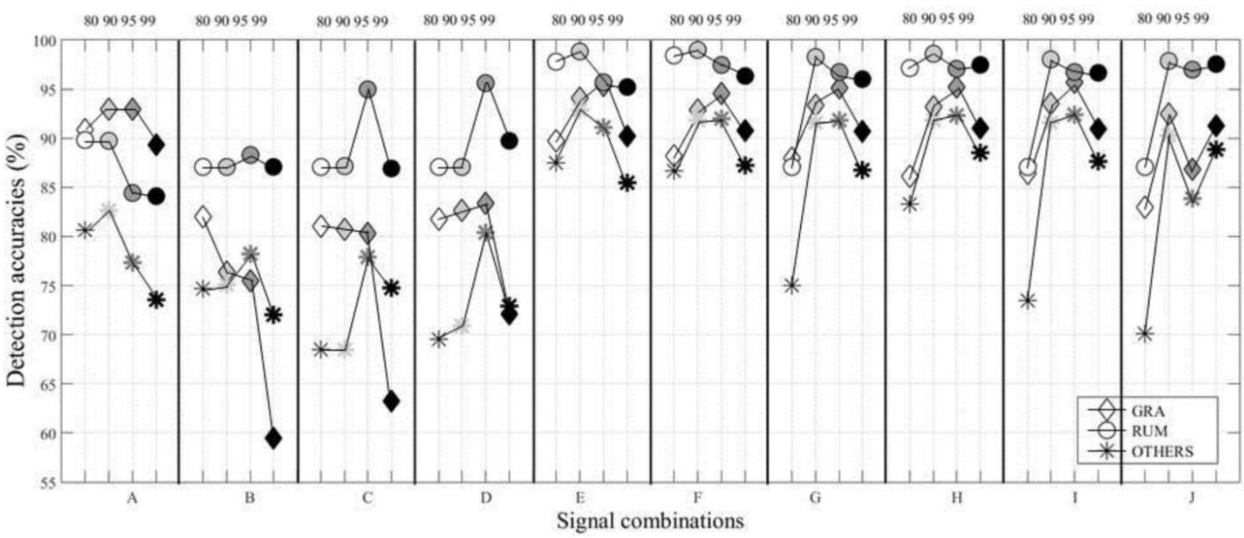


Figure 11: Detection accuracy (% of exact prediction) of feeding activities (GRA, RUM and OTHERS) with algorithms based on a single or combination of signals given by the IMU when using value windows that encompass 80% to 99% of the calibration dataset observations. With (A) mGx: mean of gravitational 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).

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

5.1.3. Choice of signal combinations in the algorithm

The usefulness of combining signals was also compared. Figure 11 clearly shows the need to use signals representing HM (mGx and/or sGx) and JM (sRx or sRy). These combinations gave the 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.

5.1.4. 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-

second time window (Figure 12). When comparing detected behaviors with the observation for longer time windows (> 1-second) the “cleanliness” of each observation matrix of was assessed and every sequence of 5, 10, 15, 30, 45 and 60-seconds 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 on Figure 12.

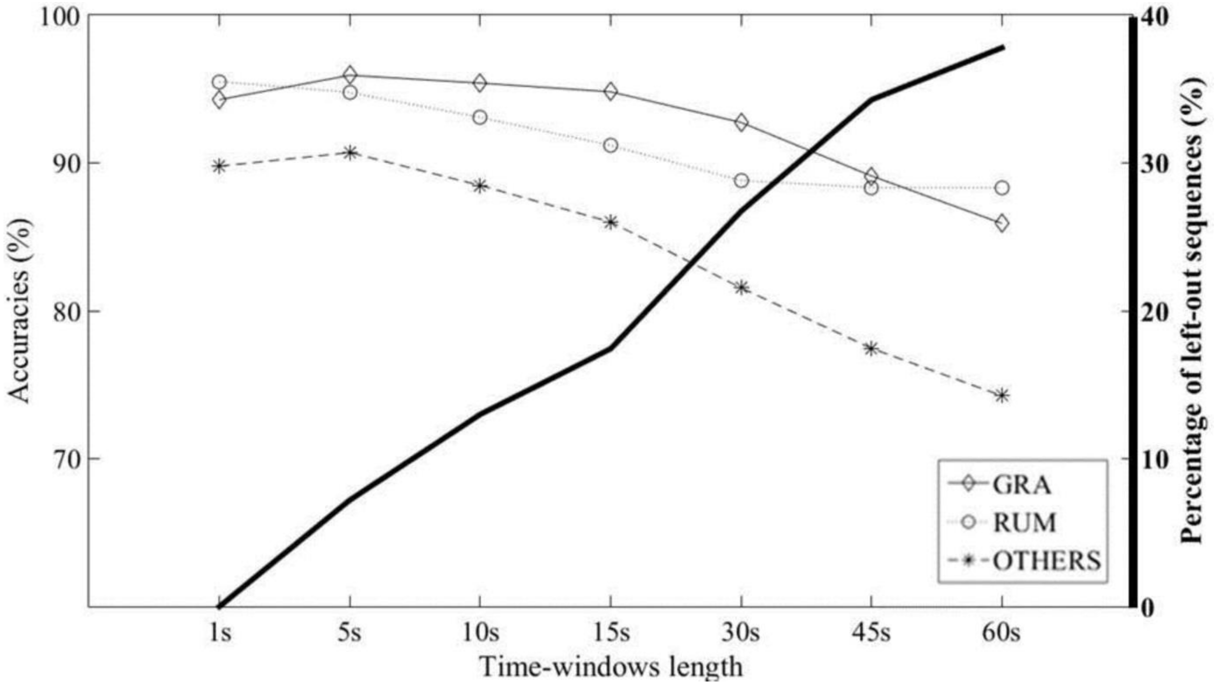


Figure 12: Comparison of detection accuracies of GRA, RUM and OTHERS when all the parameters of the algorithm are calculated with 1, 5, 10, 15, 30, 45, and 60-seconds (respectively 1-second, 5-seconds, 10-seconds, 15-seconds, 30-seconds, 45-seconds and 60-seconds) time windows, and percentage of calibration database sequences discarded for not containing pure GRA, RUM or OTHERS behaviors.

The final algorithm (Figure 13) therefore uses a 1-second time window and considers mGx, with sGx and sRx parameters following threshold values encompassing 95% of the calibration data in a 2-steps discrimination tree. The MatLab code and user’s guide are provided in Supplementary Data 1 (page 120).

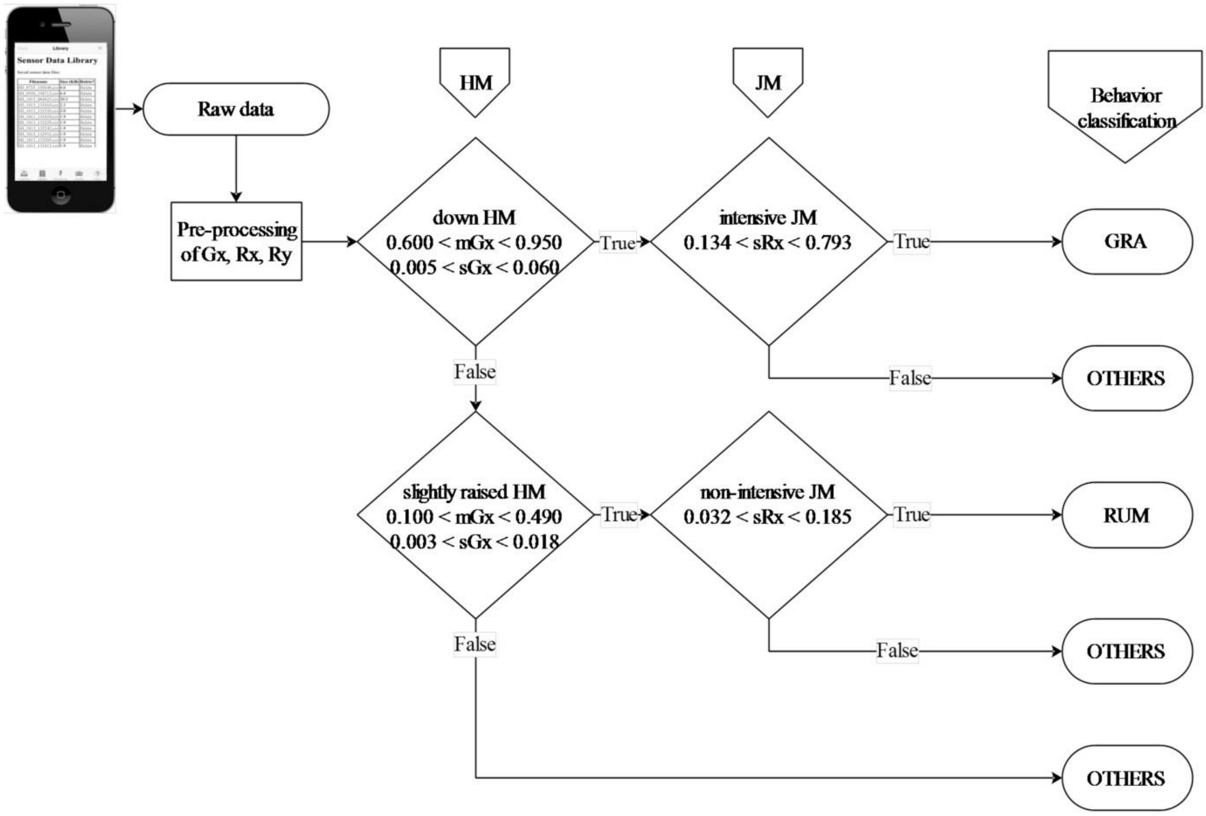


Figure 13: Final structure of the detection algorithm including the thresholds to differentiate GRA from RUM following the algorithm built in Figure 8

5.2. Algorithm validation

The validation dataset included 99 sequences with a total of 38.5 hours of video (N=138332 of 1-second sequences, with 79244 seconds of GRA, 5350 seconds of RUM and 53738 seconds of OTHERS). When the algorithm was applied to the validation dataset, the average detection accuracy was 92.0% (Table 6). It was more accurate when detecting RUM (96.5%) than GRA (91%).

Table 6: 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

5.3. Effect of the different sward heights on 24h 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 Figure 14, 24-hours activities of the same cow grazing a sward with two different pre-grazing heights (i.e. 1000 and 3000 kilograms of DM.hectare^{-1}) in two different seasons (summer 2015 and fall 2015) were plotted using this algorithm. Based on the 1-second 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.

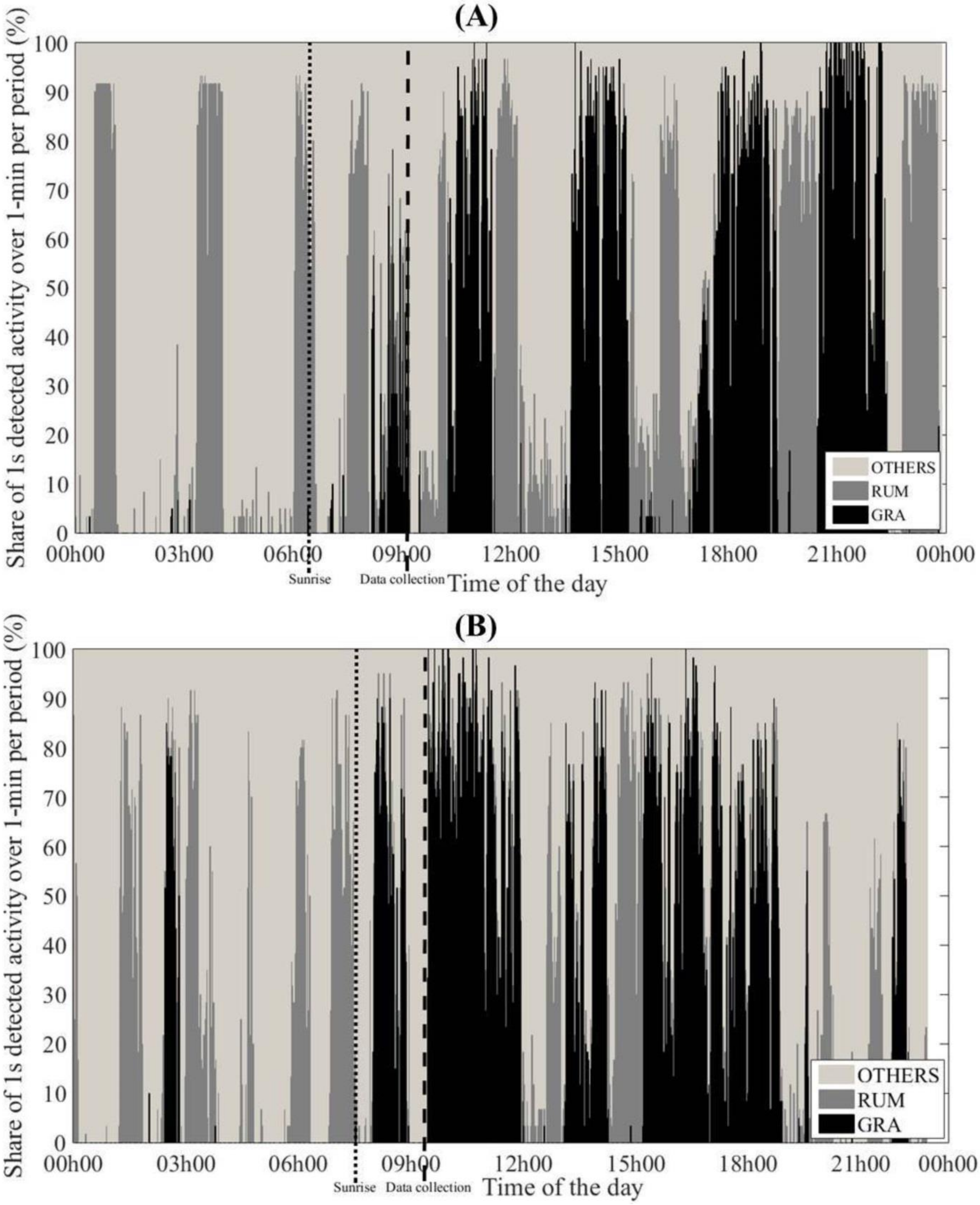


Figure 14: Allocation of activities during 24-hours for a non-supplemented cow grazing the same pasture at two different times of the grazing season and with two different forage allowances: 1000 kilograms of DM.ha^{-1} (A) and a 3000 kilograms of DM.ha^{-1} (B).

6. 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-second). Dutta et al. (2015) chose 5-seconds 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-second 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-minutes (e.g. Oudshoorn et al., 2013 with 10-minutes). 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 to 15-seconds was shown to significantly increase the specificity and sensitivity of classification (González et al., 2015, Smith et al. 2016). As shown in Figure 12, 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 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 Figure 14, 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).

7. 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.

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CHAPTER 4

CHAPTER 4

In Chapter 3, an algorithm was built to detect accurately cattle grass intake and rumination unitary behaviors using the IMU of an iPhone. As one of the goals of the thesis is to analyze grazing processes at the bite scale, Chapter 4 will decompose the detected unitary behaviors into bites for grass intake and chews for ruminating. By using an open approach, recorded signals relative to these behaviors will be decomposed to define the right signals which hypothetically correspond to bites and chews. Then an automated detection of these jaw movements will be performed and compared to the real observation.
This step is important for moving from pasture scale with the unitary behaviors to the scale of feeding stations with the bites since bites are the elementary units of the intake process of cattle on pasture.

Decomposing grazing and ruminating behaviors to increase their monitoring

1. Accurate monitoring of the rumination behaviour of cattle using IMU signals from a mobile device

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1.1. Abstract

Improving the monitoring of rumination in cattle could help in assessing the welfare status and their risk of acidosis. In this work, the monitoring of cattle's behaviour was performed using the inertial measurement unit (IMU) present in smartphones mounted on the neck of cows. The processing of both time and frequency domains of the IMU signals was capable to detect accurately the main behaviours (grazing, rumination and other) and highlight the characteristics of the rumination process. The algorithm for analysis of rumination was more accurate for grazing cattle than for silage-fed cattle in stables.

Keywords: Cattle, behaviour, rumination, signal processing, IMU

1.2. Introduction

All animal species display behaviours that indicate their physical, physiological, and welfare status (Frost et al., 1997). For ruminants, grazing, ruminating and resting behaviours occupy more than 90% of the time budget of the animal on pasture (Kilgour, 2012).

Rumination represents 5 to 9 $hours.day^{-1}$ for cattle (Vallentine, 2001). It is a cyclic process which completes the chewing of fibrous ingested feed after it underwent anaerobic fermentation by microbes in the rumen. A cycle begins with the regurgitation of a rumino-reticular bolus followed by semi-circular jaw movements and ends with the deglutition (Jarrige et al., 1995). Rumination routines are influenced by pasture quality, intake quantity especially in fibrous content (Jarrige et al., 1995; Fustini et al., 2011), physiological status and the level of stress and anxiety of the animal (Soriani et al., 2012; Braun et al., 2013). In dairy cows, high-yielding individuals are fed high level of concentrates leading to a low level of insoluble fibre intake. This low level of fibre puts them at risk for both acute and chronic acidosis since it induces a decrease in the duration of the rumination in the daily cycle (De Vries et al. 2009). Characterising rumination is therefore an interesting indicator of health and welfare in ruminants.

Recent developments in sensors technology lead to their possible use for automated detection of domestic ruminants' main behaviours, such as rumination or grazing using mainly GPS and accelerometers (Swain et al., 2008). The present work aimed at developing a white-box approach to detect differences in rumination patterns in order to enable its accurate monitoring based on signal processing of a mobile device's IMU fixed on cows.

1.3. Material and methods

Two red-pied dry cows were fitted with an iPod Touch 4G or an iPhone 4S on their neck. Nine recording sessions were performed between September 2012 and November 2013: 7 with the cows grazing a rye grass-white clover pasture, 2 in stables when cows were fed silage-based diets. Each session included: (1) 100Hz data acquisition from the 3-D accelerometer and the 3-D gyroscope of the IMU by means of Sensor Data software (Wavefrontlabs), and (2) simultaneous video recording of the cows to allow accurate observation of the behaviours and their decomposition as sets of movements of the head or the jaw. The dataset was divided in 2 independent sets, one for calibration (the 3 first fields' data) and one for validation of the procedure (the 6 other data).

The data analysis included 2 steps and was performed using MatLab R2013a. The first task was to create an algorithm for the detection of the main behaviours: grazing vs. ruminating vs. other. This algorithm was based on criteria from the movements' decomposition on 3D-accelerometer and gyroscope signals. The results of the classification were compared with the observed behaviours on the validation dataset to calculate the detection accuracies. The second part of the work focused on rumination. The duration and the number of bites were counted on the video files. The interesting IMU signal, chosen according to the most discriminative movement for the rumination process, was analysed on time and frequency domain using fast Fourier transform (FFT) and its inverse. A first filtration process was performed by choosing the most recurrent frequency between 1Hz and 6Hz to eliminate noise waves from the raw data to bring out the actual signal from rumination. Two algorithms were developed to characterize the deglutition and the mastication (number and duration of deglutition, number and duration of bites). The deglutition was described as a pause between two bouts of mastication (mobile standard deviation of a 2-seconds sample of the selected signal<0.03 $rad.s^{-1}$ at deglutition) while the mastication was known by its duration ranging between 15-seconds and 60-seconds. For the mastication bouts, a second filtration between 1 and 2 Hz corresponding to normal frequency of bites during rumination was done. The number of mastication is counted with the number of zero crossing waves on the filtered signal.

The foreseen results were compared with the observed data from the validation dataset.

1.4. Results and discussion

The detection accuracies for the grazing (on pasture) or feeding (on stable) and rumination ranged between 90% and 100% on pasture and between 80% and 84% in stable. The worse detection in stable is probably due to the different ration fed to the cows. In addition, the algorithm developed for the detection was calibrated on cows on pasture, because designed for them, and not on stabled cows which means that a new calibration for stabled animals should be necessary to increase the detection of stabled cows behaviors and in particular feeding activities.

The rumination process was analysed using the rotation rate signal along the x-axis of the mobile device which is aligned with the cows nose to tail axis. This signal shows the particular jaw movement of the cattle during rumination best, showing a discriminant peak between 1 and 2 Hz on the frequency domain (Figure 15). This behaviour is characterized by succession of 32 to 48-seconds of mastication and 2 to 4s of pause for deglutition. As shown in the Figure 16, correct measurements were high for both duration and number of mastication in which over estimation is not respectively greater than 7s and 7 bites for fields' data. For the number of mastication, a bite corresponds to four zero crossing waves. The average mastication rate equals to 1.06 ± 0.06 bites.second^{-1}. For the stable sessions, the correct measurement yielded from the field data was much lower. The deglutition's standard deviation is lower than 0.03 rad.s^{-1}. The duration of mastication is also more scattered (between 15-seconds and 40-seconds). This situation is explained by the difference of the diets fed to the animals and requires further data processing to improve the algorithm.

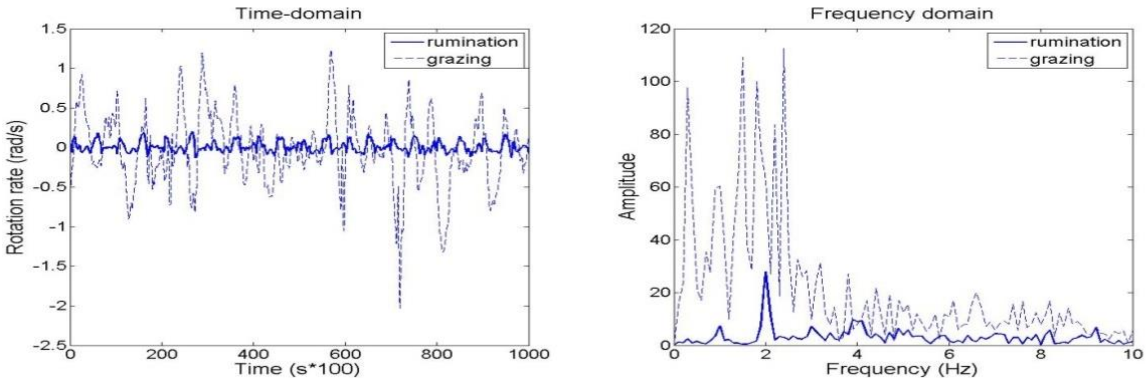

Figure 15 : Time and frequency domain patterns for 10-seconds mastication periods during rumination and grazing for field data along rotation rate on x-axis.

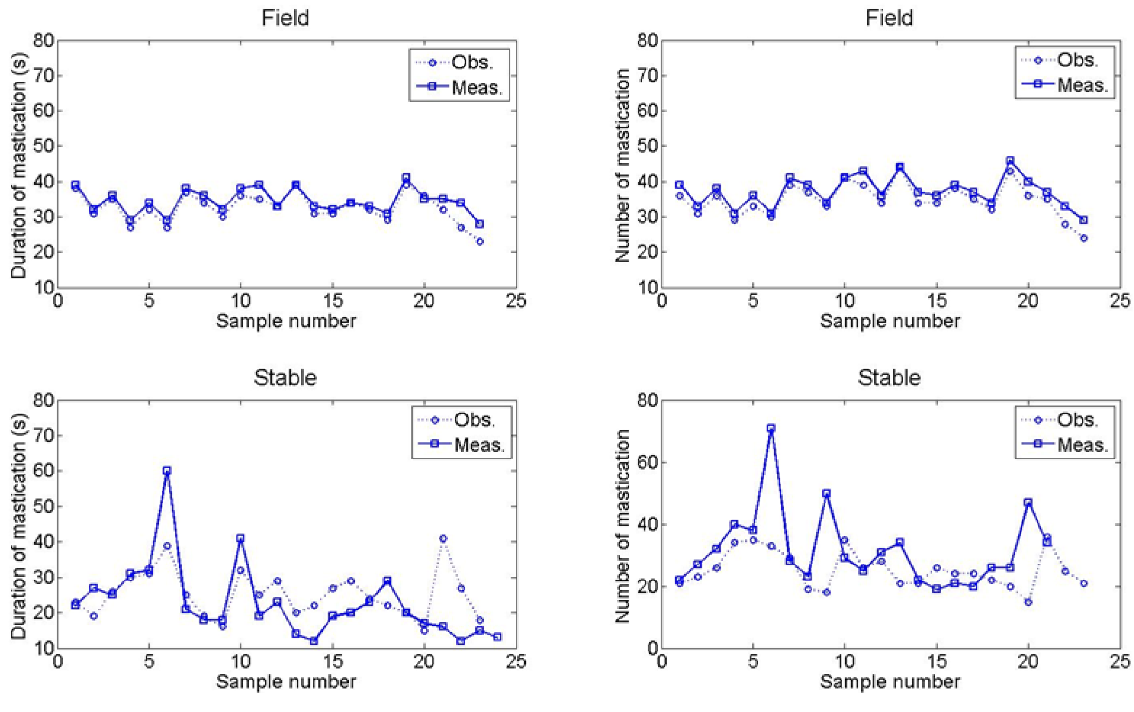

Figure 16: Comparison between the observed (Obs.) and the measured (Meas.) duration and number of mastication for field and stable validation data

1.5. Conclusion

The signals recorded from the IMU of iPhones and iPods offered an accurate detection of the behaviours of cattle. Deeper analysis about the rumination could measure its principal characteristics such as the duration and the number of mastication but the approach requires further improvements to account for major changes in rumination patterns induced by differences between pasture and silage-based diets.

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2. Changes in biting characteristics recorded using the inertial measurement unit of a smartphone reflect differences in sward attributes.

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2.1. Abstract

Accurate monitoring of grazing activity at individual cow level would provide useful information to farmers to improve the management of their animals and pastures in intensive dairy systems. Pasture attributes, starting with sward height, influence grazing behaviour and bites characteristics. In an attempt to link sward height to an individual automated detection of biting behaviour, a series of recording sessions of 4×3 days were realized on a ryegrass pasture with two contrasting heights (5 and 15 centimeters) over the grazing season (from July to October) with 4 dry red-pied cows equipped with the inertial measurement unit (IMU) of a smartphone on a halter, recording acceleration data at 100Hz. The behaviours were video-recorded. The number of grazing bouts performed during grazing tends to increase when the grass is highest. Fourier transforms of acceleration data showed that grazing bouts were characterized by a distinctive acceleration peak which frequency ranged between 1.02 Hz and 1.46 Hz whatever the sward height. It corresponded to the grass defoliation frequency in the biting movement when compared with the observation in the video recordings and it could be used to improve automated grazing behaviour detection and to remotely characterize bites. These results show that some bite characteristics are influenced by sward height and automated individual monitoring of grazing behaviour is possible. An extension of this methodology should allow analysing more deeply the grazing behaviour of cattle in order to determine number of bites and possibly to link it to biomass intake.

Keywords: cattle behaviour, inertial measurement unit, bite frequency

2.2. Introduction

Recent developments in sensor technology enable promising tools that will prove useful to farmers and contribute significantly to the coming of precision grazing management. Several studies demonstrate the capability of individual or combined sensors to classify and quantify animals' behaviors. Such classification could be done for example by equipping animals with a three-axis accelerometer and statistically analyzing data with support vector machines (Martiskainen et al, 2009). More recently, Larson-Praplan et al (2015) studied cattle grazing strategies using global positioning sensors under different seasonal contrasted environments. Accurate monitoring of grazing and biting activity at individual cow level would be a considerable help to enhance animal performances and pasture management (Carvalho et al, 2015). The mechanism of grazing is based on intensive jaw movements and is composed of 3 steps: prehension of the grass, its defoliation and its mastication before swallowing; it is the biting process (Gordon and Benvenutti, 2006). Counting bites leads to determining their frequency which, combined to their weight (i.e. quantity of forage taken per bite) and the time spent grazing, would allow to calculate the grass intake (Vallentine, 2001). Continuous monitoring of the biting process is also a prerequisite to address the 'precision biting' issue paving the way to precision grazing management (Carvalho et al., 2009).

Accelerometer and gyroscope sensors are presently used in biomechanical studies to assess gait disturbance in Humans (e.g. Leardini et al, 2014). Since cattle movements are similar in terms of frequency and magnitudes to Humans, using a combination of accelerometer and gyroscope sensors making the Inertial Measurement Unit (IMU) (Hazry et al, 2009) which is integrated in most smartphones, in addition to location sensor (GPS), provided promising results in the detection of grazing and ruminating behaviors (Andriamandroso et al, 2014). Accuracies ranged between 87% and 100%.

Pushing this technique further, the aim of this study was to assess whether IMU integrated in a smartphone could provide information at the bite level when cattle graze pastures differing in sward height.

2.3. Material and methods

2.3.1. Data collection on field

All experimental procedures performed on the animals were approved by the Committee for Animal Care of the University of Liège (Belgium). Four red-pied dry cows were fitted with a halter containing an iPhone 4S (Apple inc., Cupertino, California, USA). The mobile phones ran an IMU which signals from 3-D accelerometer, gyroscope, and GPS were collected at 100Hz using the Sensor Data application (Wavefront Labs, available on App Store, Apple inc., Cupertino, California, USA) for 9 hours from 8.00AM to 5.00PM daily.

After 6 weeks of adaptation to the equipment, the 4 cows were set to graze in one group the experimental pasture in July-August and in September-October 2014. The 1.8 ha pasture located on the farm of Gembloux Agro-Bio Tech in Belgium (50° 33' 54.162" North, 4° 42' 7.945" East) consisted of newly established ryegrass and clover (*Lolium perenne*, 0.935; *Trifolium repens*, 0.065). The pasture was divided in different paddocks differing in sward heights (5centimeters = low sward height – LSH, 15centimeters = high sward height – HSH) obtained by varying post-mowing time from 7 to 21 days. Sward height and biomass availability was controlled before and after grazing by means of a rising-plate meter using an in-house calibration. Each paddock was divided in 3 sub-paddocks providing each approx. 80 kilograms of DM.cow^{-1}.day^{-1}.

The animals were grazing each sub-paddock for one day and moved subsequently to the next sub-paddock before 8.00AM the next morning. The 1st day was discarded form the database to let the animal adapt to the new sward height, while the 2nd and the 3rd days were used for data collection and analysis.

Animals were continuously video recorded during all data collection days by 2 observers. The experimental scheme was as follows: 4 cows × 2 days × 2 sward heights × 2 grazing periods.

2.3.2. Data analysis

Since pasture height decreased quickly during the morning grazing, only the first 30 min. were considered as typical for the given sward height. Video records were coded into a behavior matrix using CowLog 2.0 (Hänninen and Pastell, 2009) with a specific focus on grazing behavior.

Actual grazing bouts were visually analyzed and jaw movements were counted and classified. A grazing bout is an uninterrupted repetition of the sequence of grass prehension and defoliation spaced by mastication and swallowing. Two different analyses will be done with collected data. First analysis concerns comparison of grazing bouts duration ($y_{i,j}$) by means of a general linear model in the mixed procedure of SAS (Cary, North Carolina, USA) where sward height (LSH and HSH), season (summer and fall) and their interaction were used as mixed factor of variation. Individual cows were considered as experimental units.

Secondly, in order to allow a Fourier Transform of the signals, the bite grazing bouts under 20 s were discarded since they did not allow further frequency-domain analysis as described below. The total number of grazing bouts (longer than 20-seconds) during the first 30-minutes of grazing varied between 11 and 24 bouts.cow^{-1}.day^{-1} for LSH and 17 to 26 for HSH, expect when IMU signals were not properly acquired.

Knowing that jaw movements' patterns can be measured using the user acceleration on x-axis of the IMU (Andriamandroso et al, 2014), this signal was used to count each jaw movements within each grazing bout. A fast Fourier transform (FFT) was performed to detect peak frequency in this signal using the 'periodogram' function in MatLab R2014a (MathWorks, Natick, Massachusets, USA).

Finally observed and detected movements on each grazing bouts were compared with calculation of detection errors.

2.3.3. Results and Discussion

a) Effect of sward heights on duration of grazing bouts

No interaction was found between the influence of sward height and season on the analyzed parameters. The duration of grazing bouts was shorter when cows grazed under HSH than LSH ($p<0.01$, **) (Table 7). When observing video records, grazing bouts are spaced with prolonged mastication and/or swallowing events. In addition, grazing bouts were shorter in summer than in fall ($p<0.01$, **).

Table 7: Effect of sward height on grazing bouts duration

Factor of variation	**Sward height**		**Season**	
	LSH	HSH	Summer	Fall
Mean ± Standard dev. (seconds)	44.85±51.52^{a*}	32.21±32.66^{b*}	31.37±35.48^{b*}	45.12±47.44^{a*}
Minimum (seconds)	1	1	1	2
Median (seconds)	29	20.50	19	30
Maximum (seconds)	413	237	237	413

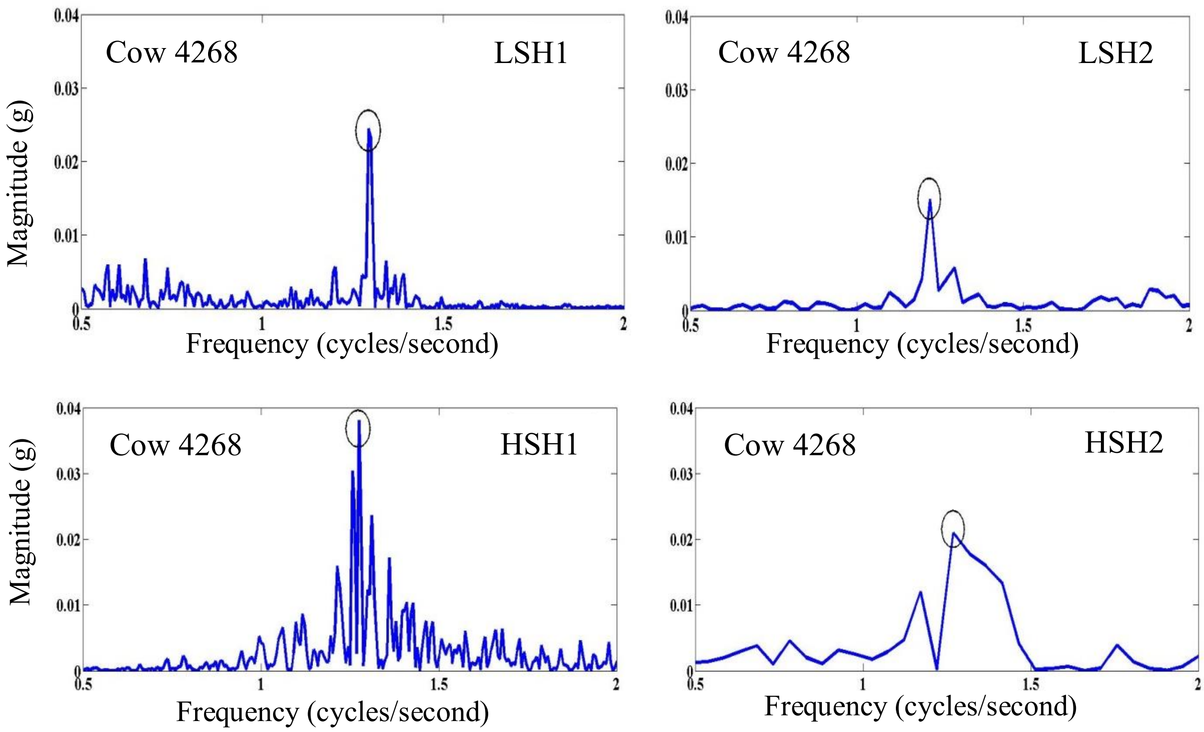
*For one factor of variation, means followed by different letters differ at a significance level of 0.05.

b) Detection of a peak in frequency domain corresponding to the defoliation bites

Analysis of the Fourier Transform of the user acceleration signal along the x-axis (expressed in g, 1g=9.81m.s^{-2}), which corresponds to the movement transmitted along the anterioposterior axis of the animal's head, allowed to identify a very distinctive repetitive peak between 1.02Hz and 1.46Hz within grazing bouts whatever the season and the grazing height (e.g. on Figure 17).

When comparing to visual observations, acceleration peaks matched exactly the frequency of jaw movements during defoliation of the grass (defoliation bites) with a mean error of 4% to 5% (Figure 18 and Table 8). There was no effect of the sward height in the defoliation bites frequency (p=0.410) which could be explained by a constant DM intake per defoliation bite (Carvalho et al, 2015).

The frequency range observed here (60 to 88 bites.$minute^{-1}$) is slightly higher than bite frequencies of 30 to 70 bites.$minute^{-1}$ reported previously by Oudshoorn and Jorgensen (2013).



LSH1 and HSH1 for July/August 2014, LSH2 and HSH2 for September/October 2014

Figure 17 : User acceleration on x-axis signal in the frequency domain for one cow

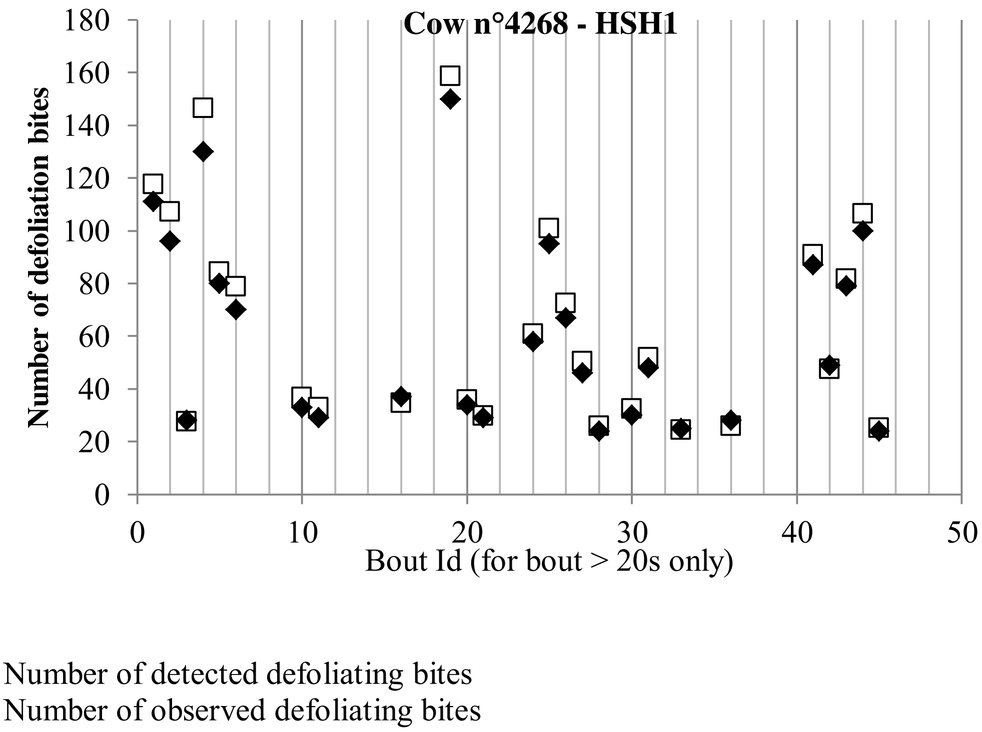


Figure 18 : Comparison between observed and automatically detected defoliation bites using the IMU signals within single grazing bouts for one cow grazing a high sward height pasture in August.

Although detection errors were limited (Table 8), the number of defoliation bites was essentially overestimated when using the dominant peak in the frequency domain. However, one cannot rule out that some defoliation bites were not identified as such during visual observations which explain some misdetection.

Table 8: Defoliation bites detection errors compared to visual observation

Sward height	Error min.	Error max.	Mean ± standard dev.
LSH1 (summer 2014)	0	9	5%±2%
LSH2 (autumn 2014)	0	16	4%±4%
HSH1 (summer 2014)	0	16	5%±5%
HSH2 (autumn 2014)	0	10	4%±2%

These maximal errors concerned less than 1% of estimation for the whole grazing bouts in each sward height.

2.4. Conclusion

Considering these results, adding the frequency domain peak analysis to the time-domain based Boolean algorithm of detection of grazing behavior proposed by Andriamandroso et al (2014) which determines head postures by gravitational part of the acceleration (μ=[0.2g; 0.85g], 1g=9.81m.s^{-2}) and jaw movements by the acceleration transmitted by the cow on the IMU (σ=[0.0175g; 0.05g]) could enhance its detection accuracy.

This range of peak frequency would be interesting to differentiate grazing from other behaviors performed with the same posture such as drinking or looking for forage on pasture. In addition, since contrasting sward heights gave easily detectable change in grazing bouts, a deeper analysis of the length of the different phases within grazing bouts combined to measurements of bite weights under contrasting pasture attributes might help in assessing forage intake of ruminants on pasture.

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CHAPTER 5

CHAPTER 5

Detection of bites and chews were possible using specific pattern of, respectively, grass intake and ruminating behaviors under the frequency domain as stated in Chapter 4. Hence, it seems possible to move from monitoring animals at the pasture scale to the individual bites on specific feeding stations. As the main concern of the thesis is the study of grazing mechanism and strategy of cattle under contrasted environment, the validation of the automation of bites detection will be the first objective of Chapter 5. Then, different parameters will be calculated to identify which are influenced by changes in pasture characteristics over the day and over the season to identify relevant animal-based indicators related to the grazing process.
In addition, information about bites will be coupled with geographical data in order to assess their spatial distribution on pasture.

How cattle grazing behaviors change under contrasted pasture attributes: identification of the key indicators using bite characteristics and their spatial distribution

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1. Abstract

Bites constitute the elementary level of the interaction between grazing animals and the forage. The automated detection of defoliation bites performed during grazing were possible using a simple peak finder function derived from an detection algorithm of grass intake unitary behavior, using the inertial measurement unit (IMU) of a smartphone recording data at

100 Hz as sensor. Using two videos as calibration dataset, observations of slow-speed video revealed the relevancy of detecting bites by means of the rotation rate along the y-axis signal of the smartphone for each single bite corresponds to a distinctive peak. Hence, using a simple peak finder function, using 0.10 rad.s^{-1} as minimal amplitude and 0.40-second as minimal interval between two peaks, detection accuracy of defoliation bites averaged 89.8% using a different validation dataset with 3.6% and 6.6% of false positive and false negative rates respectively. This defoliation bite detection method was used as basis of calculation of different parameters such as total time dedicated to grass intake, total number of bites, duration of grazing bouts and bites frequency and impacts of different sward heights (low vs high) and the season were investigated. Two experiments were set up: (1) (Exp 1) to test the direct effect of the two different sward heights (low vs high) and the three grazing seasons grazing (spring vs summer vs fall) by performing 8-hours (from 9AM to 5PM) and 24-hours experiments on two different paddocks with the same forage allowance; and (2) Exp 2 to introduce the spatial distribution of bites on pasture and their evolution in time by performing a grazing down experiment starting from high or low sward height and ending when average height of 3 centimeters was attained after 3 and 5 days of continuous grazing, for low and high sward height respectively.

Temporal evolution of cattle behaviors on pasture showed an important period of grass intake between 5PM and sunset when compared to other periods of the day. During Exp. 1, the difference in sward height affected significantly bite frequency while the seasonal changes affected more the time dedicated to take grass on pasture and thus the total number of bites with longer period of foraging during fall than during summer and spring.

In Exp. 2, distance traveled and spatial distribution of bites were the essential variables of interest. In terms of distance, cows covered longer distance when the sward was at a low status while no effect was observed along successive days of depletion. In terms of bites performed on each Longitude-Latitude coordinate position (within a square of 25 m), no significant pattern was observed along the successive days. Nevertheless, an increase in the number of bites performed on the same place was observed, especially when the sward height was low at the beginning of the experiment.

Keywords: cattle, grass intake, pasture, bites, sward height, spatio-temporal analysis.

2. Introduction

Grasslands occupy 50 million square kilometers representing 37% of the emerged land area on earth excluding Greenland and Antarctica (O'Mara, 2012). In the European Union, of the 5.4% of usable agriculture area cultivated under organic agriculture, 45% are permanent pastures and a significant share of the cultivated fields include temporary pastures in their rotation. Following the strict regulations of organic agriculture which oblige dairy farmers to allow a permanent access to the pasture for cows during grazing season and at least 60% of locally grazed or harvested forage in the cattle diet (European Union Council Regulation, 1999; von Borell and Sorensen, 2004) and the increasing trends in keen interest for organic farming, in particular for food safety and environmental reasons (Rossi, 2013), this resource is nowadays placed in the top of essentiality in particular for dairy farming. Considered as a low-cost food source for grazing ruminants (Dillon et al., 2005), grasslands are also considered as key biodiversity and ecosystem services providers by inducing spatial heterogeneity (Rook et al., 2003; Boval and Dixon, 2012; Dumont et al., 2012). Thus, an efficient grazing management is of utmost importance to maintain the balance between socio-economic demands and a sustainable production.

Traditional pasture management uses static tools. It is based on the balance between productivity and dynamics of pasture plants and their usage by the animals by manipulating different variables such as stocking rate, type of animals or types of grazing methods (Carvalho et al., 2009, Holechek et al., 2011) leading to a management focused on the herd. However, since both the plants and the animals are complex dynamic components on the grazing process, both components should be monitored simultaneously and, if possible, at the same level of accuracy. Thus, farmers who rely on pastures require new tools to help farmers eyes, knowledges and experiences, specifically targeted at the accurate measurement of pasture biomass, its nutritional value and valorization by ruminants and how they change in time (French et al., 2015). The monitoring of grazing behavior at the individual level is thereby a key as it potentially allows grasping the complexity of the plant-animal interaction at its atomic level: the bite.

This monitoring of the individual grazing behaviors of cattle is surging in the literature thanks to advances in sensor technology allowing a remote monitoring of many physical variables for research or practical farm level applications (Berckmans, 2014). Different type of sensors are proposed to transform recordings of posture, movements and location of animals into behaviors such as grazing, ruminating, resting, walking, etc. (Andriamandroso et al., 2017 submitted). As grazing combines spatially and temporally variable movements and activities, more attention should be paid to the smallest scale of this process, namely the bite, as it determines intake regulation of the animal from the short term intake on a feeding station to the exploitation of an entire paddock over a whole grazing season (Ungar et al., 2006; Carvalho, 2013; Andriamandroso et al., 2016).

On the time scale, the combination of bite characteristics, bite rate and bite mass in particular, and time spent grazing allows the calculation of intake which is actually the least accurately measured variable in the whole grazing process (Hills et al., 2016). To identify bites and chews, jaw movements can be detected over time-windows ranging from seconds to minutes using pressure, associated with changes in electrical resistance (Rutter et al., 1997; Rutter, 2000), acoustic (e.g. Navon et al., 2013), electromyography (Rus et al., 2013) or accelerometer sensors (e.g. Oudshoorn et al., 2013).

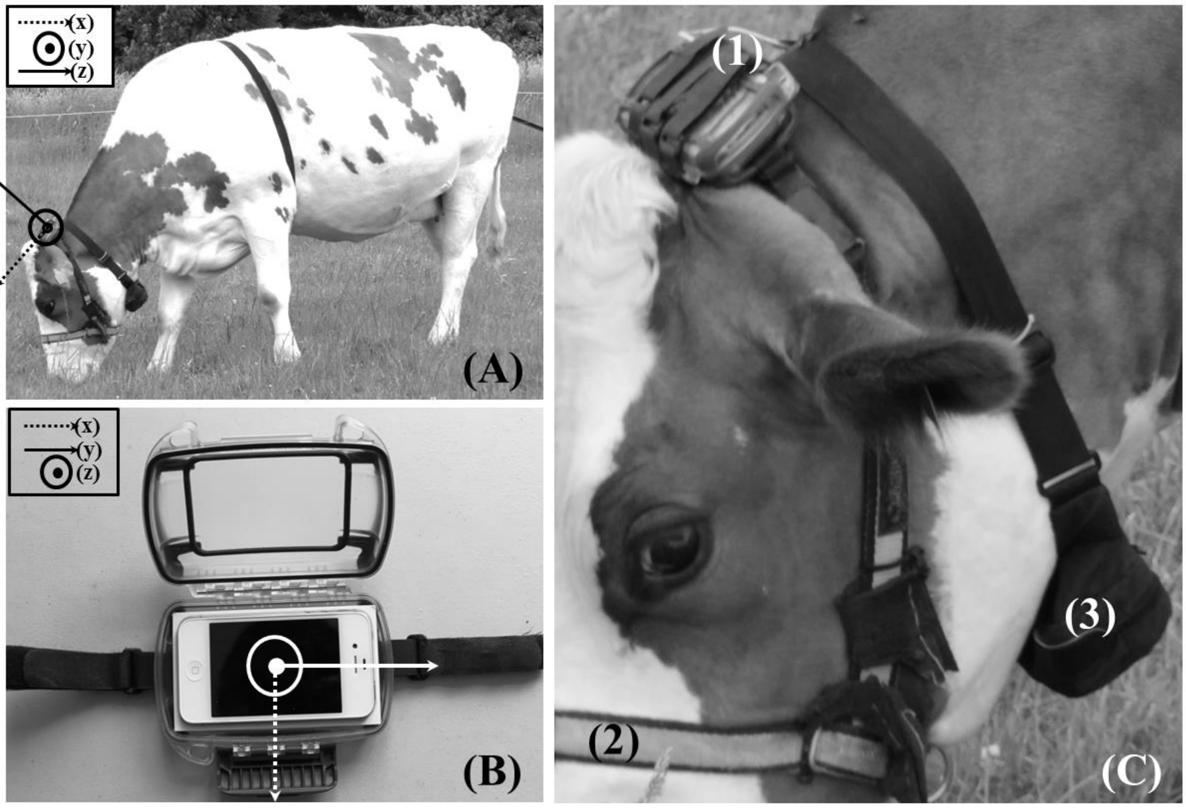
On the spatial scale, the use of location sensors such as GPS and related Geographical Information System (GIS) are used to track animal preferences on pasture (Putfarken et al., 2008; Handcock et al., 2009), but also to detect their movements or even discriminate their behaviors mainly grazing, walking and resting (Schlecht et al., 2004; Ungar et al., 2005). The monitoring of behavior alone is not enough to improve pasture management. The spatial distribution of the vegetation, including species composition, physical parameters (height, density) and inherent quality, influences also the movement patterns of cattle which modulate their preferences and thus their grazing strategy (Chapman et al., 2007; Larson-Praplan et al., 2015). Understanding grazing processes must involve a multiple scale analysis of grazing behavior starting from the largest scale of pasture, by determining the unitary behaviors, especially grazing, down to the finest scale of bites and their evolution in time and in space in order to link these spatiotemporal changes to the pasture plant attributes.

For this purpose, this paper investigates the variation and the spatial distribution of bites performed by grazing cattle under different pasture forage allowances and across seasons. For this purpose, building on an open-source algorithm classifying grazing and ruminating behaviors of cattle based on signals acquired from an inertial measurement unit (IMU) (Andriamandroso et al., 2017), a complementary analysis protocol was developed to detect automatically defoliation bites performed when grazing. This was later used to investigate at the individual level the effect of pasture height on biting pattern and, using the location sensor of the IMU, their spatial distribution on the grazed paddock.

3. 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 done in 2014 and 2015 in the experimental farm of ULg-Gembloux Agro-Bio Tech (50°33'54.6"North 4°42'04.6"East Belgium). Nine dry red-pied cows, aged between 4 and 12 years old and with estimated weights between 450 and 650 kilograms were grazed on *Lolium perenne-Trifolium repens* mixed pasture. Six cows (RP1 to RP6) were used during 2014 grazing season. After a detected lameness on RP3, she was removed from the group in summer 2015 and three other cows (RP7, RP8 and RP9) entered the group.

As described by Andriamandroso et al. (2017, submitted), during all experiments, each cow was fitted with a halter containing an iPhone 4S (Apple, Cupertino, California, USA) inside a waterproof box (Otterbox Pursuit series 20, 152.4 × 50.8 × 101.6 millimeters, 142 grams, Otter Products, LLC, USA) (Figure 19B). Each mobile phone was equipped with an application (SensorData, Wavefront Labs) downloaded from Apple Store (Apple, Cupertino, California, 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 hours, the original 3.7V 1420mAh Li-Polymer battery was connected to an additional external battery (Anker Astro E5 16000mAh portable charger, 150 × 62 × 22 millimeters, 308 grams, Anker Technology Co. Limited, California, USA) and attached as a collar around the neck of the animal (Figure 19C).



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

Figure 19: 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 axe 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).

3.1. Data acquisition and grazing experiments

Two independent grazing experiments, named Exp. 1 and Exp. 2, were performed during two consecutive grazing seasons (2014 and 2015).

The objective of Exp. 1 was to investigate the behavioral pattern of cattle allowed to graze two contrasted pasture with similar forage allowance but at different heights. For this purpose, two paddocks were constituted displaying two different sward heights (Low Sward Height (LSH) <=5 centimeters and High Sward Height (HSH) >=15centimeters). Each paddock was then divided into two sub-paddocks: one for the cows' adaptation and the other for the proper experiments. The sizes of the paddocks were adjusted to provide similar forage allowance per cow per day (16 kilograms of dry matter per 100 kilograms of body weight per day). To reach the adequate sward heights, the pasture was mowed at the beginning of each month (August to October for 2014 and May to October for 2015) and the experiments started once the desired average height was reached. One replication of observations on LSH and HSH was done each month, except for October 2015 where the HSH modality was not attained due to a long dry period that reduced pasture growth. For each modality, cows entered the first sub-paddock for 24 hours of adaptation and afterwards they entered the experimental sub-paddock for another 24 hours. In 2014, due to the limitation of the IMUs in terms of battery life, the data recording was made during eight hours (from 9AM to 5PM). In 2015, an additional battery was added to allow measurements during a full day of experiment. Hence, two different datasets were obtained from Exp.1, one set for 8-hour experiments from 9AM to 5PM (2014 and 2015) and another set for 24-hour (2015 only). Through the detection of grazing behaviors and bites, which will be explained in the next section, different grazing parameters, namely the number of grazing bouts (NGB), duration of grazing bouts (DGB in minutes) and total grass intake time (TGIT), bites features, such as bites frequency (BF in bite per second), number of bites per hour (NBh in bites per hour) and total number of bites (TNB in bites) were measured and compared. A grazing bout was considered as an uninterrupted sequence of grass intake (GRA) behavior during which the cow has taken grass from the ground (Gibb, 1996).

During Exp.2, exclusively done in 2015, cows also entered two types of paddock, similarly to Exp. 1, but they were allowed to graze until the pasture was depleted to an average stubble height of 3 cm. The aim of Exp. 2 was to follow the evolution of daytime grazing behaviors of cows, including spatiotemporal shifts in the most significant parameters between NGB, DGB, TGIT, BF, NBH and TNB determined in Exp 1. over the course of pasture depletion.

During both experiments, pasture heights and forage allowances, expressed in kg of forage DM available per 100 kilograms of body weight per day, were measured using a rising plate meter and dry matter content was determined after 72 hours drying at 60°C.

Video recording sessions of cattle behaviors were also performed on all the cows during both Exp.1 and Exp.2. Most of the recorded videos were used for the validation of the grazing behaviors detection algorithm (Andriamandroso et al., 2017, submitted). Ten videos were expressly taken to allow the development of the algorithm for bite detection by zooming on the head of the cows during the recording session.

3.2. Data analysis

3.2.1. Detection of grazing behaviors

Cattle grazing behaviors were determined using an open-source algorithm dedicated to interpret IMU signals from iPhone into behaviors: grass intake (GRA), ruminating (RUM) and others (OTHERS) (Andriamandroso et al., 2017, submitted). From this algorithm, patterns of activities performed by each cow were determined by calculating the share of detected behaviors per minute to define which behavior had the highest probability of occurrence during a specified minute.

3.2.2. Detection of bites

During both grazing experiments, ten two-minutes videos of four cows (RP1 to RP4) for each LSH and HSH pre-grazing heights were observed in total using CowLog 2.0 (Hänninen and Pastell, 2009) at a speed three times slower than the normal speed. Two videos filmed with one cow (RP1 at {LSH, HSH}) were used for calibration while the others were used to validate the method of bites detection (RP3 at {LSH, HSH}, RP4 at {LSH, HSH}, RP5 at {LSH, HSH}, RP6 at {LSH, HSH}). Each bite performed by the cow was recorded and it constituted the basis of the detection (matrix of observation, MO). During the experiments, a bite was considered as the action performed by the cow when she defoliates the grass from the ground (Gibb, 1996). The time and bites spent on searching, masticating and swallowing the grass were not taken into account although these activities are part of the grazing behavior. The videos used for the setup of the algorithm were selected to display only uninterrupted GRA to optimize bites detection.

The choice of the IMU signal corresponding to each observed bites was made with the two videos dedicated for calibration. A bite was observed to be represented by a peak in the time-domain series of rotation rate signal along the y-axis of the IMU (Figure 20) (Andriamandroso et al., 2015).

An automated detection of each of the hypothetical bites, thus of each peak, was afterwards performed in MatLab R2015a (Mathworks, NL) creating the matrix of detected bites (MD) using the "findpeaks" function. The parameters used in the function (peak height or amplitude noted as h and peak minimum distance noted as d) were firstly assessed with the calibration dataset. Following the determination of h and d, the main purpose of the method was the reduction of the distance between observed and detected peaks. To attribute a detected peak to an observed one, differences between MO and MD were assessed using k-nearest neighbors'

method to find the minimum delay between two peaks from MO and MD. As one observed bite had to correspond to one detected bite, all peaks with too long delay compared to the observation (>0.5-second) were eliminated and classified into false positive or false negative.
The quality of the detection was assessed with the validation dataset by comparing observed with detected bites in order to obtain the lowest delay, in absolute value, and the highest percentage of correctly detected bites. Average distance between one observed bite and one detected bite was calculated to confirm it as representation of the reality. False positive and false negative rates completed the quality assessment of the algorithm.
After validation of the algorithm, it was applied to detect each individual defoliation bite on each grazing sequence detected during Exp.1 and Exp. 2.

3.2.3. Temporal distribution of cattle behaviors

From behaviors and bites detections, pattern of temporal use of pasture day was displayed for 24-hours in Exp. 1. NBh were compared along the day using a simple mixed procedure in SAS 9.4 (SAS Institute Inc., North Carolina, USA) and using hours of the day, seasons (Spring, Summer and Fall) and sward height (LSH and HSH) as fixed variables while cow was used as random variable.

3.2.4. Statistical analysis

The effects of sward height (LSH and HSH) and season (spring, fall, summer) on NGB, DGB, TGIT, BF, NBh and TNB were assessed for 24-hour (N=18) and 8-hours (N=38) measurement sessions in Exp. 1, using mixed procedures of SAS 9.4 (SAS Institute Inc., North Carolina, USA). Cows were used in the model as random factor and the chosen experimental unit was one 24-hours or 8-hours grazing session, i.e. one cow×day.

3.2.5. Spatial distribution of bites

The spatial distribution of the bites was investigated on three cows (RP4, RP5 and RP6) during measurements in Exp. 2, so during a grazing down experiment. These cows were chosen because of their presence along the whole experiment of 2014 and 2015 and the completeness of consecutive grazing sessions database (no IMU failure). In order to be complete, 8-hours grazing experiments were chosen for the spatial analysis (9AM to 5PM). The longitude and latitude recorded in the built-in location sensor of the IMU was used to yield a spatial representation in a Geographical Information System (GIS) of the location of the detected bites using ArcMap 10.3 (ESRI, Redlands, California, USA). From the initial behavior detection algorithm, GRA, RUM and OTHERS were classified as percentage of occurrence per minute stored in a matrix of 3 columns and t lines where t corresponded to the length of the processed raw data in minute. From this algorithm, the temporal unit used in all spatial analyses was 1 minute. GRA sequences were isolated from this matrix and associated with the corresponded number of bites. Average latitude and longitude coordinates were then determined, per minute, to be linked with each number of bites. Number of bites per unique longitude and latitude coordinates (NBu), representing a point inside a square of 5meters x 5meters, performed on the paddock was calculated and classify within four classes of bites per 5meters x 5meters square (<65, 65-75, 75-85, >85 NBu) in order to determine the spatiotemporal evolution of the bites when the cows grazed on pastures at low and high pre-grazing grass heights. These classes were chosen considering that the expected average biting frequency was 70-80 per minute (Rutter et al., 2002). Number of bites performed on the same longitude and latitude coordinates was summed. Each NBu was mapped in ArcMap and occurrences of each bites class were calculated. These occurrences were useful to determine how many bites were performed on each position and, hypothetically, how many times a cow went back to the same position.

In addition, distance traveled by each cow was derived from the position of the cow recorded per minute using Haversine formula (Chopde and Nichat, 2013) which calculates distance between two longitude and latitude coordinates. Sum of all distances between two positions corresponded to the distance traveled by the cow (DIST in kilometers).

Occurrences of each bite class and DIST will be compared using mixed procedures of SAS 9.4 (SAS Institute Inc., North Carolina, USA) where factors of comparison were the day of the experiment and the initial sward height of entrance into the paddock.

4. Results

4.1. Bites detection

4.1.1. Determination of parameters for bites detection

The rotation rate on y-axis (Ry) signal was used for the detection of bites performed by cattle during grazing periods. Before detecting the potential bites, Ry was filtered between 0.5 Hz and 2Hz as done by Andriamandroso et al. (2015) in order to clean the raw signal and keep the peak related to grazing jaw movements. When compared to observations, peaks along Ry matched accurately the observed bites (Figure 20).

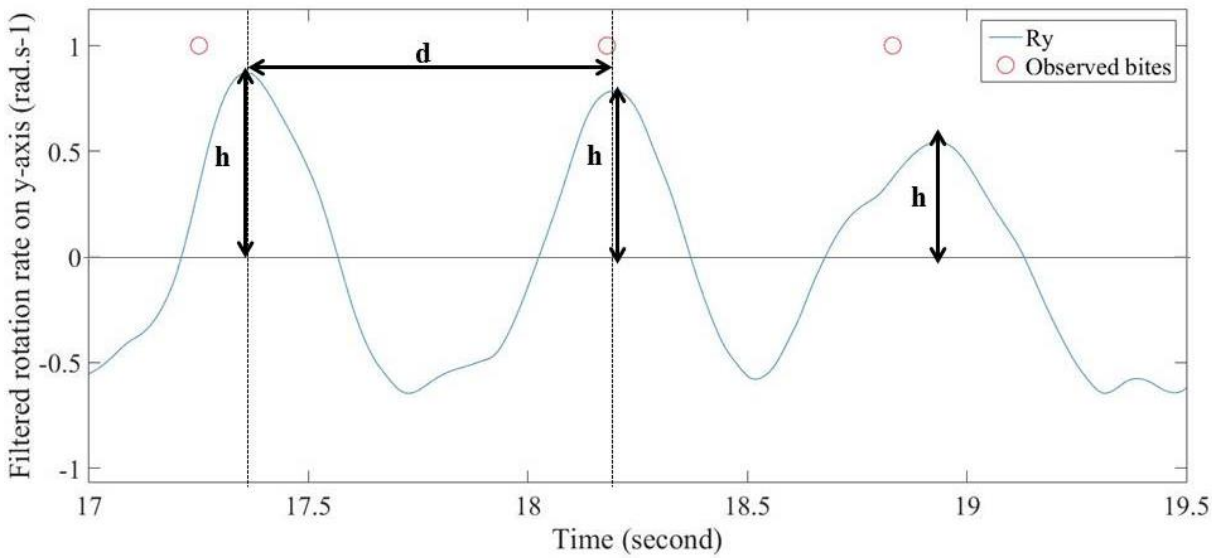


Figure 20: Example of the correspondence between location in time of observed defoliation bites and the candidate peaks observed in the rotation rate along the y-axis (Ry) of the IMU placed on the neck of a cow.

The increase observed in Ry, represented by a peak, is considered as a response to the abrupt head movement in addition to the jaw movement associated to the grass cutting and hypothetically as a bite. Although it is distinguishable at a low video speed, the exact time of a bite might have little delay. To detect the peak, the main parameters that should be considered were the distance between two candidate peaks (d) and the minimum value of each peak (h). From the observed peaks, different values of d and h were tested in order to have the highest correct detection of bite. The procedure detailing the bites detection is displayed on Figure 21.

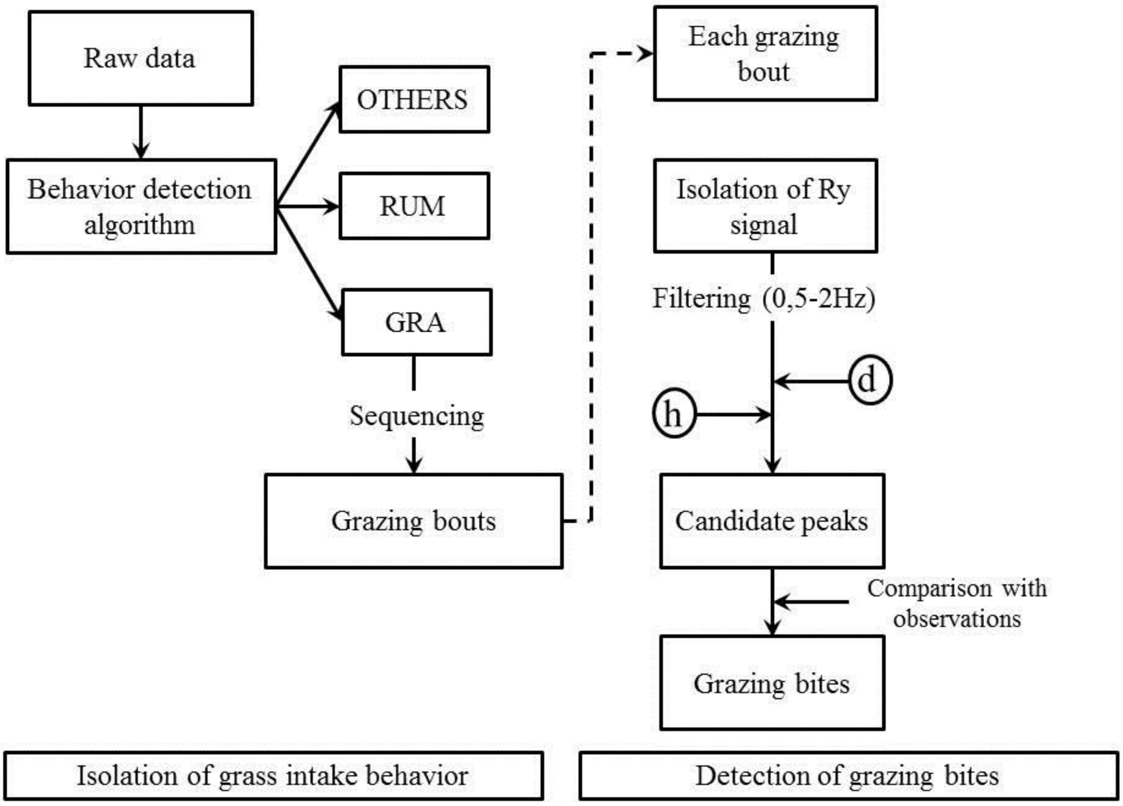


Figure 21: Grazing bites detection process starting from isolation of grass intake behavior sequences and validation by comparison with observations.

Table 9 details the percentage of correctly detected bites when compared to the reality on validation dataset. From these results, the combination of d=0.40-second and h=0.10 $rad.s^{-1}$ was used for bites detection. The values used for h were chosen starting from the lowest possible value when visualizing Ry signal of calibration data set. The lowest value observed was 0.10 $rad.s^{-1}$ and the highest was above 1 $rad.s^{-1}$. For values of d, bite rate averaged 1 bite.second-1 but to avoid in maximum the missing of a bite, we prioritized the detection of more peaks candidates to peaks and also chose the minimal possible value of distance with two peaks as half of the normal average distance of 0.80 second (Rutter et al., 2002).

Table 9: Comparison of different h (0.10 to 0.40 rad.s^{-1}) and d (0.40 to 0.60 second) values in terms of percentage of correctly detected bites when compared to observation.

		h (rad.s^{-1})						
		0.10	**0.15**	**0.20**	**0.25**	**0.30**	**0.35**	**0.40**
d (second)	**0.40**	89.8	89.4	86.0	79.5	68.8	65.2	33.1
	0.45	89.6	89.8	85.8	78.8	69.1	65.4	33.1
	0.50	88.8	88.5	85.7	78.5	68.8	44.5	-
	0.55	87.6	86.8	83.3	77.2	67.7	42.9	-
	0.60	85.0	83.9	81.1	76.7	65.7	39.7	-

4.1.2. Peak detection quality

Using previously determined parameters, the quality of bites detection from peak finding is reported in Table 10.

Table 10: Assessment of the quality of bite detection by finding peaks on Ry signal compared to observation using four parameters with the validation dataset (N=8):

(1) AvDist: average distance between observed and detected bites in seconds;

(2) FP: false positive rate representing incorrectly detected bites while there is no bite observed on the video at this moment.

(3) FN: false negative rate representing incorrectly undetected bites while they are observed on the video.

(4) CorrDetect: percentage of correctly detected bites. CorrDetect = 100-(FP+FN)

Cows	Video duration (s)	Sward height	AvDist (s)	FP (%)	FN (%)	CorrDetect (%)
RP3	135	HSH	0.19	5.84	8.44	85.7
RP4	135	HSH	0.13	3.70	2.96	93.3
RP5	135	HSH	0.15	1.16	6.94	91.9
RP6	135	HSH	0.12	5.13	7.05	87.8
RP3	135	LSH	0.12	1.57	7.87	90.5
RP4	135	LSH	0.11	1.71	0.57	97.7
RP5	135	LSH	0.19	3.13	12.50	84.4
RP6	135	LSH	0.22	6.38	6.38	87.2
Mean	**-**	**-**	**0.16**	**3.58**	**6.59**	**89.8**

An example of comparison between observed and detected bites is represented on Figure 22. It confirms the assumption that a delay might exist during the observation of the video. The maximum value of AvDist is 0.22 second when using detection of peaks at a rate of 0.40

second. With an average CorrDetect of 89.8% this method could be used for detecting grazing bites on pasture.

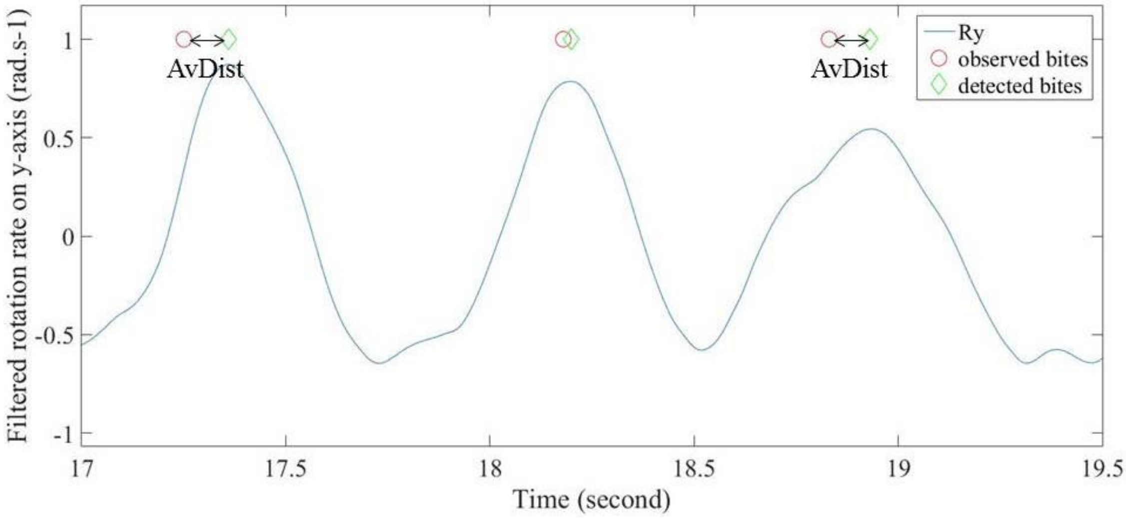


Figure 22: Comparison of observed and detected bites. AvDist is one of the quality indicators of the bite detection.

4.2. Influence of pasture height on bites characteristics (Exp. 1)

4.2.1. Exp. 1: 24-hours grazing sessions

The cumulated NBh performed by 3 cows on pasture during 24-hours grazing sessions is represented on Figure 23. This example shows that cows spent more time taking grass, and thus performing more defoliation bites between 4 PM and 8PM. Independently to the season, 50% of the total bites are performed during this period.

Average total number of bites was significantly high ($p<0.05$) on LSH pasture than on HSH pasture, and significantly high ($p<0.01$) during fall than during spring and summer.

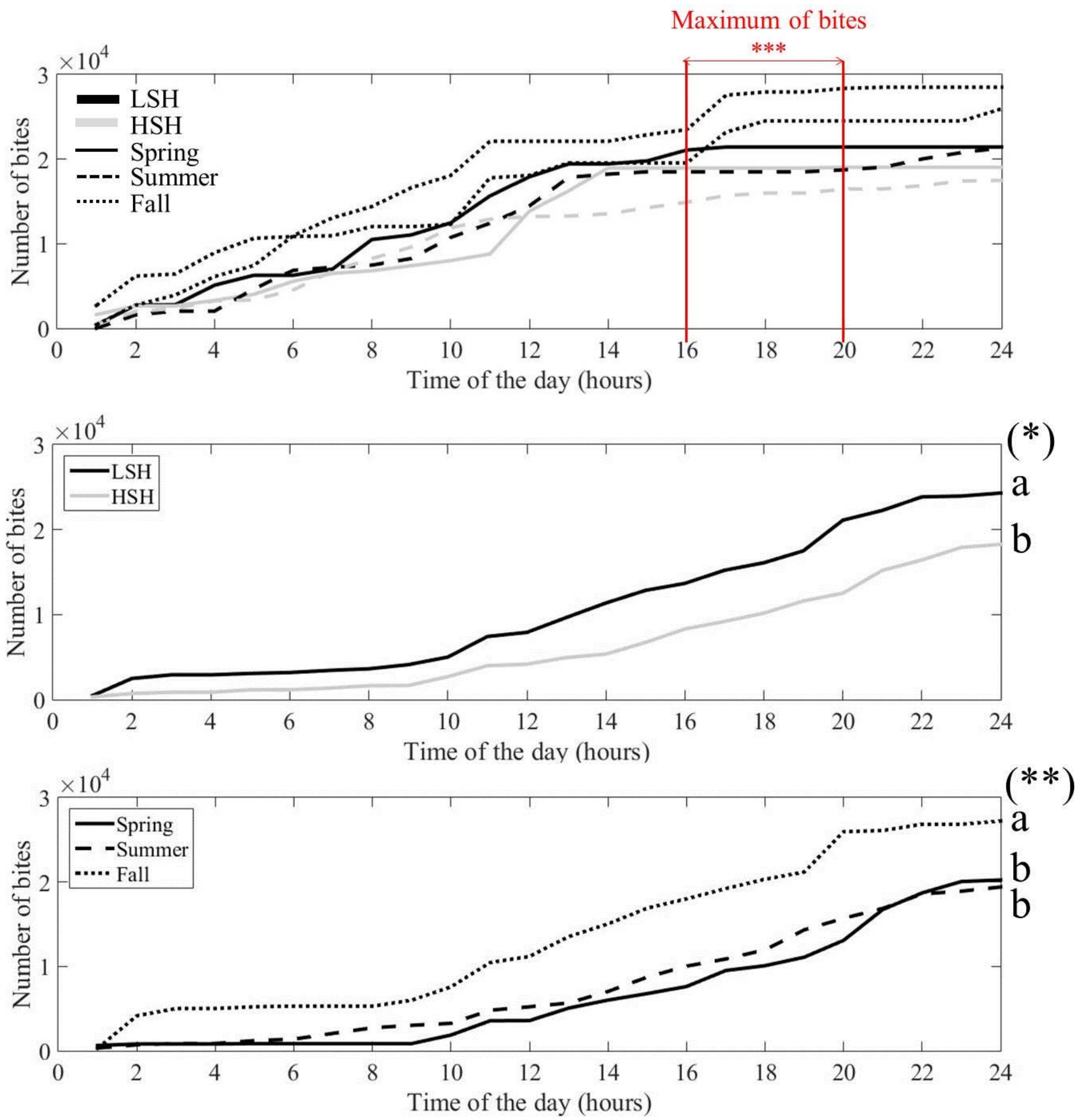


Figure 23: Variation of cumulated number of bites along the day expressing the temporal variation of NBh, according to two different sward heights (LSH and HSH) and across three different seasons (Spring, summer and fall). Independently to these factors, period between 4PM and 8PM contained the highest number of bites and thus during which cows performed more grass intake. Significant difference between two curves is represented by two different letters (a and b).

Concerning the analysis of the effect of the season (spring, summer, fall) and pasture height (LSH, HSH) no interactions were observed when for all studied variables (p>0.05).

Between the sward states, only biting characteristics (BF, NBh and TNB) were affected with higher values for LSH ($p<0.05$) (Table 11).

TGIT and TNB differed between seasons with higher value for fall compared to spring and summer ($p<0.05$). Although the instantaneous biting frequency was not different, the biting rate per hour differed with more bites performed during fall contrarily to summer.

In addition, pasture dry matter content displayed different average values within the three seasons (spring: 25%, summer: 38%, fall: 32%).

Table 11: Effect of sward heights and seasons on grazing and bites characteristics when considering the whole day (24-hours) grazing time in Exp. 1.

Variables	Sward height		Significance	Season			Significance
	LSH (n=12)	HSH (n=6)		Spring (n=6)	Summer (n=6)	Fall (n=6)	
TGIT (minutes)	369^a	265^a	NS	304^b	281^b	419^a	*
NGB	31^a	32^a	NS	25^b	37^a	32^a	*
DGB (minutes)	10.8^a	9.6^a	NS	12.5^a	7.8^a	10.9^a	NS
BF (bites.second^{-1})	1.19^a	1.10^b	*	1.18^a	1.13^a	1.18^a	NS
NBh (bites.hour^{-1})	1115^a	760^b	*	910^b	808^b	1272^a	**
TNB (bites)	26761^a	18250^b	*	21838^b	19391^b	30541^a	**

a,b: letter difference represents significant difference of means
NS: non-significant difference ($p>0.05$)
*: significant difference ($p<0.05$)
***: highly significant difference ($p<0.001$)

4.2.2. Exp. 1: 8-hour grazing sessions

From 9AM to 5PM, the trends were the same as for 24-hours grazing sessions. More grass intake time occurred during the afternoon (at least 50%) whatever the season or the sward height.

As this range of experiment concerned two consecutive years (2014 and 2015) the factor year did not significantly impact the studied variables ($P>0.05$).

Concerning the analysis of the effect of the season (spring, summer, fall) and pasture height (LSH, HSH) no interactions were observed for all studied variables, as for the 24-hours sessions ($P>0.05$). TGIT, NBh and TNB had also seasonal difference ($p<0.05$) but this time there is no seasonal effect on NGB.

When comparing LSH and HSH, the variables TGIT, TNB and NBh were significantly higher on LSH than on HSH ($p<0.05$). BF was also higher on LSH than on HSH but with higher significance ($p<0.001$) (Table 12).

Table 12: Effect of sward heights and season on grazing and bites characteristics when considering 9AM to 5PM grazing time in Exp. 1.

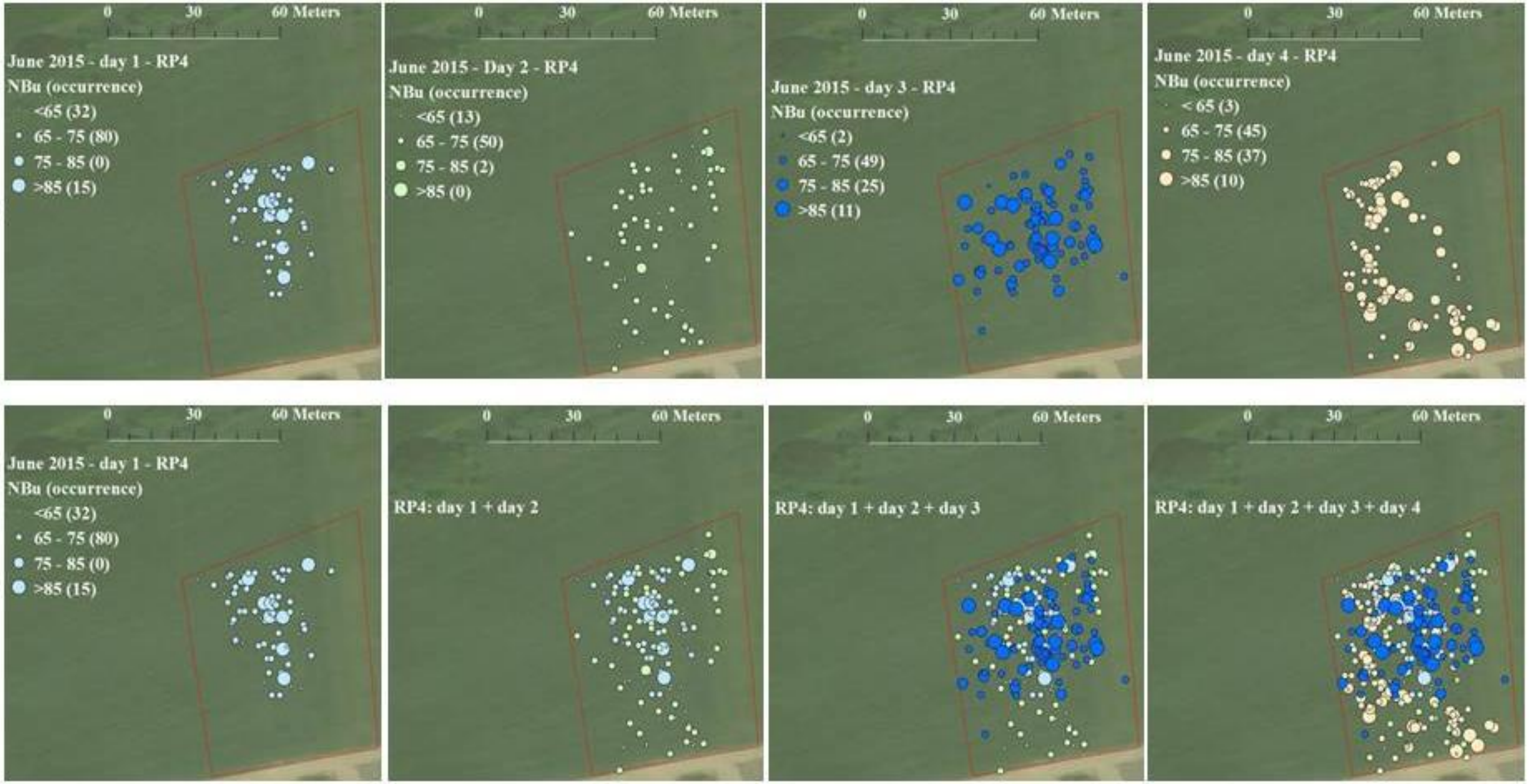
Variables	Sward height		Significance	Season			Significance
	LSH (n=22)	HSH (n=16)		Spring (n=8)	Summer (n=20)	Fall (n=10)	
TGIT (min.)	144^a	138^b	NS	122^c	141^b	157^a	*
NGB	15^a	17^a	NS	13^a	15^a	19^a	NS
DGB (min.)	9.9^a	9.8^a	NS	9.9^a	10.1^a	9.4^a	NS
BF (bites.s^{-1})	1.17^a	1.09^b	***	1.17^a	1.11^a	1.17^a	NS
NBh (bites.h^{-1})	1082^a	1035^b	NS	919^c	1060^b	1182^a	*
TNB (bites)	10398^a	9166^b	NS	8751^b	9581^b	11377^a	*

a,b: letter difference represents significant difference of means
NS: non-significant difference ($p>0.05$)
*: significant difference ($p<0.05$)
***: highly significant difference ($p<0.001$)

4.3. Exp2: Evolution over time and spatial distribution of bites

When coupling location with the number of bites performed on each longitude and latitude coordinates on pasture, differences in spatial distribution and bites density were shown according to the height of the sward when cattle entered the paddocks (HSH on Figure 24 and LSH on Figure 25). Post-grazing heights of 3 cm were attained after 3 and 5 days of continuous grazing when cows entered at LSH and at HSH, respectively.

(1)



(2)

Figure 24: Example of patterns of spatial distribution of grazing processes and related number of bites per longitude-latitude coordinates (NBu) with a cow entering at a high sward height where (1) concerns day to day evolution and occurrences of NBu class and (2) cumulates the daily evolution of NBu distribution

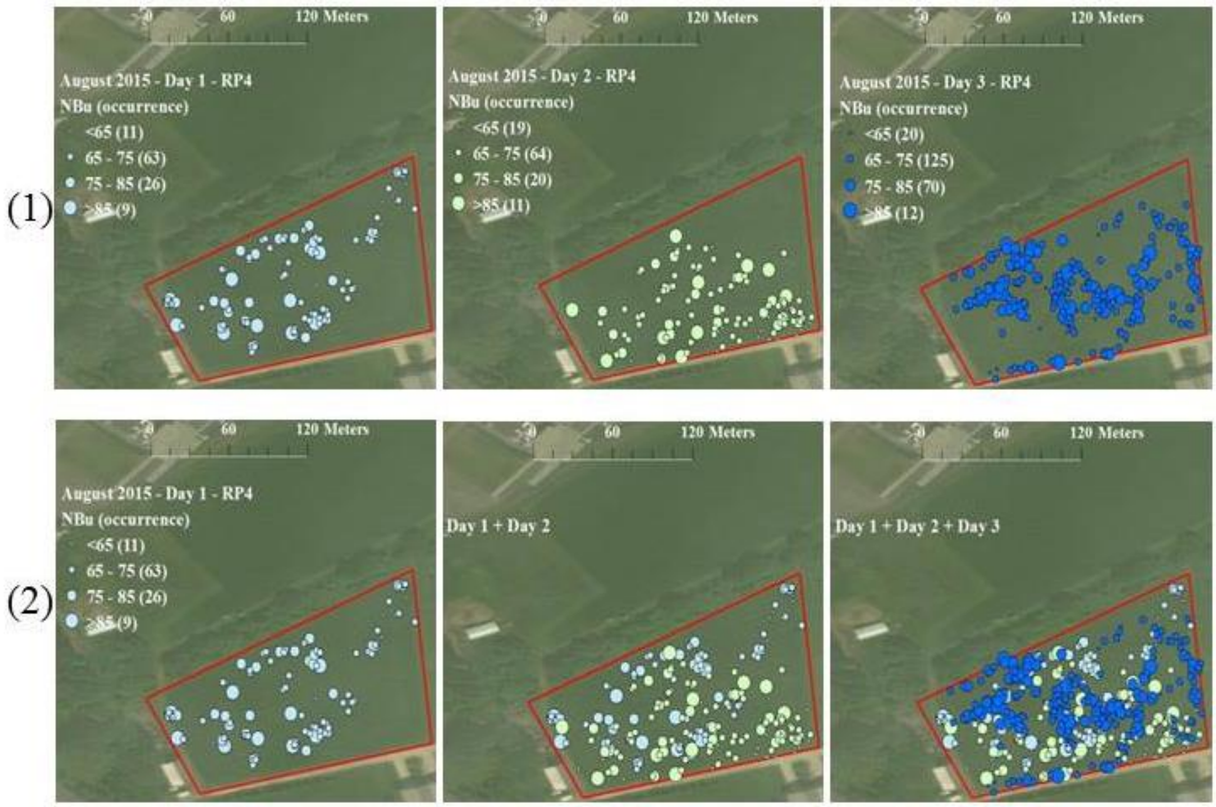


Figure 25: Example of patterns of spatial distribution of grazing processes and related number of bites per longitude-latitude coordinates (NBu) with a cow entering at a low sward height where (1) concerns day to day evolution and occurrences of NBu class and (2) cumulates the daily evolution of NBu distribution

Concerning the distance traveled, cows covered longer distances when the sward was at a low status as reported in Table 13 ($p<0.01$). When comparing NBu occurrences, 75-85 bites class was higher under LSH ($p<0.001$) while under HSH cows performed lower bites per unique longitude and latitude coordinates ($p<0.05$).

Table 13: Comparison of distance traveled by the cows and bites class occurrences per longitude and latitude coordinates under the two different sward heights (LSH and HSH) considering all days of 8 hours (9AM-5PM) of the grazing down experiment

	DIST (kilometers)	Bites class occurrences (NBu occurrences)			
		<65	65 - 75	75 - 85	>85
HSH[1]	1.78[b]	29[a]	60[a]	12[b]	10[a]
LSH[1]	2.52[a]	11[b]	76[a]	70[a]	14[a]

[1]Sward height at the entrance of the paddock

[a,b]: letter difference represents significant difference of means, NS: non-significant difference ($p>0.05$), *: significant difference ($p<0.05$), ***: highly significant difference ($p<0.001$)

Although the total area allowed to cows was different, in order to have similar forage allowance for both sward heights in Exp. 2, the animals moved around the paddock during the first day with a higher rate when the sward height was low. On Figures 24 and 25, these differences were represented by higher number of bites performed on each grazing station when the pre-grazing height of entrance was low. There were more occurrences for 65-75 NBu class at pre-grazing HSH while occurrences are more important for 75-85 NBu class at LSH. For the highest NBu class (>85), they were more performed at pre-grazing LSH suggesting that cows spend more time on different feeding station. And this NBu class was increasing along the day. These observations are confirmed by Table 14 although differences were not significant. In particular when starting from LSH, NBu occurrences increased, although it is not significant, along the day which meant that cows were returning more often to a previously explored feeding station to perform more bites when the sward height was low.

Table 14: Evolution and comparison of distance traveled by the cows and bites class occurrences per longitude and latitude coordinates along the days of 8 hours (9AM-5PM) of the grazing down experiment starting from HSH and LSH.

		Bites class occurrences ± SD[1] (NBu occurrences in number of bites per 5 meters x 5 meters square)			
HSH	DIST ± SD[1] (kilometers)	<65	65-75	75-85	>85
Day 1	2.02±0.5	56±40	67±16	2±2	10±7
Day 2	1.75±0.33	31±26	70±17	9±9	10±7
Day 3	1.50±0.49	28±26	62±26	12±10	10±8
Day 4	1.87±0.36	12±11	50±40	14±5	9±9
Day 5	1.80±0.46	19±18	51±14	22±19	13±7
Significance	NS	NS	NS	NS	NS
LSH	DIST ± SD(km)	<65	65-75	75-85	>85
Day 1	2.90±0.44	10±7	52±11	49±38	10±9
Day 2	2.30±0.95	10±9	58±16	99±73	17±14
Day 3	2.10±0.06	9±8	89±32	92±47	22±15
Significance	NS	NS	NS	NS	NS

[1]SD : Standard Deviation

NS : non-significant difference

When the cows entered a paddock with a HSH on the first day, the patterns of grazing did not follow a regular trend. Occurrences of each NBu class oscillated along the successive days supposing more contrasted spatial distribution when the grass is high.
Contrariwise, when the cows entered a paddock with a LSH on the first day, the distance covered by the animal decreased along the successive days while the occurrence of 75-85 NBu class doubled and stabilized following the first day.

5. Discussion

The technique developed here to identify bites is similar to the approach used when analyzing data from IGER with Graze software (Rutter et al., 1997; Rutter, 2000) in this way that with IGER and the IMU, candidate peaks for bites are detected using amplitude and interval criteria. Moreover, in terms of material, IGER and IMU both need a halter surrounding the mouth of the cow to allow a correct detection of jaw movements. Nevertheless as IGER recorded data relate changes in electrical resistance and IMU record signals from its built-in accelerometer, differences between the two methods concerned firstly the detection of grass intake and ruminating behaviors which was defined a priori for our method and a posteriori after putting data on Graze. Another difference concerned the form of the peaks. With the IGER, the first biting peak is followed by a subpeak related to the ingestion mastication, i.e. chews (Rutter, 2000). In our method, only a single peak is observed. However it does not seem important for us to differentiate bites from chews as, conversely to the IGER method, our method works in two steps with a detection of grass intake behavior performed before detecting individual bites each time this behavior was performed. Finally, concerning the quality of bites detection, Graze based on IGER data detects a high number of false positive (14 %), possibly because of the difficulty in identifying bites during the observation of video recordings (Champion et al., 1997). In our situation, recorded videos zoomed on head of the animal and observations were made on a really slow rate easing the identification of each bite. Other methods using sound analysis of jaw movements recorded by microphones were also performed with peak analysis but with more complex algorithms such as discriminant analysis, logistic regression or neural networks (Ungar et al., 2007). These techniques had higher ability to detect chews and chew-bites jaw movements with higher rate (87 to 91%) than bites (59 to 77%) when using the methods mentioned previously. The high accuracy in detecting bites (89%) of the method developed here confirms the important role of an a priori discrimination of unitary behaviors to detect grass intake periods pior to focusing on defoliation bites.

Concerning grazing behavior characteristics, in most cases, the total time spent grazing is used as a parameter involved in the foraging dynamics. For the majority of this researches reported in the litterature, grazing is composed by the total time spent eating, which in our case is time spent taking grass from the sward, plus the time spent searching a feeding station to take the grass (Gregorini et al., 2011). Because of this difference, the values displayed in our research were lower than those reported in other researches. Indeed, total duration of daily grazing time reaches 9 to 11 hours when it includes forage research time (Gibb et al., 1997; Abrahamse et al., 2009). As in our case, time spent actually eating turned around 4 to 5-hours on average and considering that increasing the total grazing time is limited (Benvenutti et al., 2008), it can be considered that the cows spent half of the time dedicated to grazing in searching grass, which is a major part of energy expenditure for cows (Griffiths and Gordon, 2003). However this ascertainment should be nuanced since differences in pasture conditions have not been considered.

Concerning the bites characteristics, our results match with previous studies concerning bite rate which averaged between 1 to 1.1Hz (Gibb et al., 1997; Rook et al., 2004; Mezzalira et al., 2014). When comparing LSH from HSH, higher BF was observed under lower sward heights possibly in response to a reduction in bite mass that occurred when the access to tall grass is not possible. This behavioral adaptation is considered as a compensatory mechanism translating a reduction in the time spent to take grass (Chilibroste et al., 2015). As bite mass is a function of BF, pasture height is a key parameter in the determination of amount of intake and thus can be used as a management tool (Orr et al., 2004).

The seasonal effect on total grass intake time (TGIT), number of bite per hour (NBh) and total number of bites (TNB) despite similar sward heights might be due to the variation of the dry matter content of grass between spring, summer and fall, respectively 25%, 38% and 32%, knowing that the internal water content of grass could have an impact on dry matter intake of cattle. Estrada et al. (2004) demonstrated that the voluntary intake of cattle increases when the dry matter content is higher. The higher TGIT in summer and fall might be explained by the increase in dry matter content. Some night and early grazing sessions were observed during these two seasons in our experiment. In terms of energy content, Fulkerson et al. (2007) demonstrated that the metabolisable energy of temperate rye-grass decreases from summer to fall which may induce an additional necessity for cattle to increase their grass intake in particular during fall.

Finally, the spatial distribution of grazing bites resulted from the combination of NBu and individual bite location could be an interesting starting point for an accurate study of the spatio-temporal dynamics of cattle when facing contrasted pasture environments. Complexity of finding a predictable pattern of cows' movement on pasture was assumed as they are confronted into multifactor decisions on the grazing area, not only related to their specific interface with the plant resource but also to interindividual relationships in the herd (Amaral et al., 2013). Nonetheless, the differences shown in this paper (Figure 24 and Figure 25 and Table 13 and Table 14), when performing compared grazing down starting with different pasture heights, confirmed that these decisions are more important at bite and feeding station level (Amaral et al., 2013) than on larger scale, excepted for the traveled distance. Differences between the treatments (LSH or HSH) reflected more on the number of bites performed on each position on the paddock.

In summary, our article dissected the grazing behavior of cattle on pasture into grass intake and bites in order to assume the important role of this finest scale in the determinant of cattle adaptation when facing contrasted grazing conditions. For a better analysis of this cornerstone of the plant-animal interaction, it should be linked to an accurate spatial distribution of the vegetal component in terms of species, density, height or even leaf/stem ratio and nutritive quality to offer a complete understanding of cattle grazing strategies.

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CHAPTER 6

CHAPTER 6

General discussion, perspectives and conclusion

Our research pursued a double objective: (1) to develop an original method for the monitoring and the automated detection of the behavior of grazing cattle, including at the fundamental level of bites, and (2) to use this method to identify relevant indicators of the interaction of grazing cattle with the pasture resource.

For this purpose, the grazing behaviors of cattle were continuously monitored using an inertial measurement unit of a smartphone and a dedicated algorithm was developed. The relevancy of using this kind of sensor in the detection of unitary behaviors mainly grass intake and ruminating behaviors and their decomposition into chews and bites was clearly demonstrated. During grazing, bites constitute the “atom” of this behavior and their monitoring was essential to understand the cattle strategy under contrasted conditions in time and in space. Trends of the increasing use of sensors, the different levels of measurement in grazing processes and the importance of the integration of the spatial scale are the principal subjects of this discussion as they all concern the subject of the research but they are also key points to better understand how cattle behave in front of different resources and how the stemming information could be used in the development of decision-support tools for grazing management.

1. Managing the individual to optimize the herd grass intake

Farmers traditionally manage the pasture resource and grazing animals by reacting to their visible status such as depreciation of the forage quality and quantity through its visual degradation or the discomfort of animals through bad physical condition or diseases. Farmers’ decisions are in general based on the variation of these vegetal and animal parameters at a large scale. Weakness of human observation was demonstrated (Mottram, 2015) and limited the optimization of the decisions. When combining this to the enlargement of herd size, using human observer for these tasks remains highly time-consuming and thus increases the labor cost. To assist these decisions, there is a need for associating what is actually visible and what is not visible relative to internal physiology and behaviors of both plant and animals.

From a grazing management point of view, problems emerge most of the time because of the destabilization regarding the balance between pasture productivity and animal needs resulting in overgrazing (Lyons and Machen, 2000). The grazing management is primarily based on adapting the herd size to the pasture area, known as stocking rate or stocking density (Holechek et al., 2011), and by varying the forage use under continuous or rotational system where the balance is calculated over the year (Laca, 2009). The problem with such management is that it impacts the fitness of the animals as the forage resource does not in general fit with the requirements of the animal (Lyons and Machen, 2000). The consequence in more intensive production such as in dairy farming is the need for forage and concentrates supplementation. Moreover, in order to maximize intake of grazed grass, as the cheapest feed resource for ruminant farming (Dillon et al., 2005), the structure of the sward must be carefully managed in such a way that both grass growth and the animal intake rate are close to the maximum value. The search for such an optimum led novel grazing management techniques to be developed with rotation with high sward heights and short occupation time of the paddocks (Carvalho 2013). Indeed, on pasture, strong interactions do exist between the sward characteristics and environment conditions and the grazing behaviors (Larson-Praplan et al., 2015). This large scale of behavior monitoring is the first step of continuously understand the interaction between plant and animal at any time. It mainly determines the temporal distribution of cattle activity across the day or across the seasons and the years. Through our research, this step was done to be able to detect grass intake and rumination behaviors (Chapter 3). Day time distribution and seasonal differences were investigated. Although a similar pattern of grass intake existed inside a herd, results also showed the importance of an individual management as the changes in these unitary behaviors were usually dependent to the actual physiological or health status of the animal.

However this individual scale is not enough as the main determinants of foraging process concern a finer scale in direct relation to intake which is the bite. Indeed, high grazed forage intake rates require considering the grass defoliation process through the biting behaviour. Considered as the “atom” of the grazing mechanism (Carvalho, 2013), bite characteristics vary widely with the pasture quality in particular with forage allowance and surface sward height (Gibb et al., 1998; Chilibroste et al., 2015). Chapter 4 developed a deeper analysis of particular signals recorded by the IMU we used to decompose grass intake and ruminating behaviors into bite and chews respectively. By focusing on grazing bites, our results, displayed in Chapter 5, confirmed these previous results on the high dependence of biting rate with sward height status. Although it was not measured, changes in sward height probably also affected bite mass, which is the amount of grass taken during each bite, as it was constrained by bite depth (Lyons and Machen, 2000). Coupling bite rate and bite mass with time spent grazing would be the key parameters to define intake of grazing animals (Carvalho, 2013). Under controllable conditions such as in feedlots, intake is relatively easy to monitor. On pasture, due to more heterogeneity and due to the individual decision of the animal, the estimation of the intake remains a big challenge. Direct observation of this parameter was made possible even under heterogeneous pasture by coding different biting technics known as hand-plucking (Bonnet et al., 2015). Estimation of the intake rate is also possible with utilization of the unitary behaviors and time spent eating (e.g. Barrett et al., 2001). Under monocultures of ryegrass and white clover, Rutter et al. (2002) demonstrated that intake rate was identical with a value of 12.9 grams of dry matter intake per minute for young heifers. Hence, if we associate this value to the number of bites per minute that we showed to be able to monitor automatically (Chapter 5) we can estimate the amount of pasture taken by each cow on the dedicated pasture. Nonetheless, if we want to enlarge the scope of the method, the problem of variability in bite mass remains as the biting process is not regular according to the animal and the status of the pasture offered to him. While handplucking can help in solving this issue from a research perspective, it is still a time-consuming method because it is not autonomous and it required a highly trained observer (Bonnet et al., 2011). Associating handplucking with a sensor-based system such as the one that was developed here would yield the possibility to analyze precisely the recorded data for each type of bite. Then the second step would be the estimation of the intake through a signal processing technique.

To achieve correctly the monitoring of the individual whether at a large or at a fine scale, sensors are definitely unavoidable owing to their capacity to continuously measure physical variables and to make them analyzable (Kenny, 2005).

2. Sensor data in the service of grazing management

New technologies offer substantial tools to enhance farm monitoring including data recorder such as cameras, microphones, or other sensors, data communication via radio, bluetooth and wireless connection and data storage via built-in storage within the data recording device or cloud storage (Berckmans, 2014). At the upstream of the system, besides cameras installed in the farms primarily for surveillance of the animals, microphones, pressure, electromyography and accelerometer sensors, used alone or in combination, are nowadays the most used technology in livestock farming to allow accurate and continuous measurement of animals and a reduction in labor cost with automation (De Koning et al., 2010). From the animal point of view, sensors were firstly predestined to help for early detection of disturbance in animal such as diseases like mastitis which is difficultly detectable without sensors (Hogeveen et al., 2010), lameness by gait analysis (e.g. Van Nuffel et al., 2015) or estrus which detectability increased by 70% using sensors (Mottram, 2015). Later, sensors integrated various uses such as in grazing behavior monitoring, including detection of unitary behaviors such as grazing or ruminating, numerous types of wearable sensors could be used. Some of these sensors were reviewed in chapter 2 showing their capacity in the detection and classification of jaw movements. Starting from this classification of jaw movements (e.g. Rutter, 2000; Ungar et al., 2007) or directly distinguished with most of the time black-box analysis (e.g. Martiskainen et al., 2009), the unitary behaviors could be accurately classified offering a first important output concerning the animal. The technique developed in Chapter 3 of this work, using the inertial measurement unit offered similar accurate results but in addition offered the opportunity to other users to enhance the detection algorithm for research, but possibly also for on-farm application.

Accelerometer-based information could be of high value for a more precise management of pasture resource and grazing animals and could be integrated in big data approaches, as long as capture, storage, transfer, sharing, visualization and analysis of huge amounts of information are dealt with. Animal behaviors determine their reaction in front of different situations. Changes in feeding and ruminating behaviors were valuably used for example in detection of estrus (Mottram, 2015) or lameness (Beer et al., 2016). In research as well as at farm scale, the required data streaming must be developed in a near future following the boom of the Internet of Things. Potential applications in cattle and pasture management are very diverse ranging from the management of the health, the production and the animals' welfare to the management of the pasture resource itself. Nonetheless the scale of the sensor capability should fit with the scale of the measurement and, of course, with the objective of the research or with the needs of the farmer. Although the use of I-phone is not likely to help farmers and is rather dedicated for researchers, the good performances of the open-source algorithm could lead to a quick development of on-farm decision-support tools based on low-cost tailor-made sensors.

3. Associating time-series to location sensor data to understand grazing strategies

The use of spatial information of grazing animals started with the use of GPS sensors in extensive rangelands in order to track the movements of the animals. Some research also diverted GPS data for the detection of different behaviors relative to movement. As grazing is a mobile behavior it could be easily differentiated from more static behavior such as ruminating or idling. Schlecht et al. (2004) used this system to differentiate grazing from non-grazing behaviors. In our research, although location data was available in the inertial measurement unit of smartphone (Chapter 3), it was not used for this kind of differentiation. Knowing that the diet selection of grazing cattle is associated to defoliation and the relative growth of the pasture resource (Laca, 2009), the act of taking grass from cattle regulates the spatial distribution of the grass in terms of physical status (height and density in particular) and vice versa. The importance of integrating spatial data to grazing behavior monitoring is valuable to solve the problem of determining the initiation and the end of each bite process (Chilibroste et al., 2015). An accurate grid map of the grass distribution is necessary to achieve this purpose. This grid should be coupled with the activity pattern of the cattle as done in Chapter 5. Similar accuracy between the grass and bites distribution is also an important criterion as the determination of the factor inducing each bite is finer than a simple detection of bite. In addition, the rate of regrazed area should also be determined (Larson-Praplan et al., 2015) to avoid as much as possible the occurrence of such regrazing processes that lead either to overgrazing, or depression in intake rate or both if adequate management decision is not taken such as moving the animals to another paddock or supplementing them.

In this thesis, we integrated spatial data from the location sensor of the smartphone to allow a continuous monitoring of cattle movements associated to the amount of bites performed during a minute passed on each feeding station (Chapter 5). The results showed a predominant herd movement of cattle but differences exist and should be related to more information about the vegetation which was limited to the average height and the dry matter content in our case. The originality of our research concerned the integration of detected bites with their location on pasture knowing that number of bite performed on each single feeding station could be an indicator of daily intake (Hirata et al., 2015). An additional layer such as a vegetation grid would be helpful if established to fit with the grazing strategy of cattle. For example, Feldt and Schlecht (2016) studied spatio-temporal dynamics of cattle, fitted with GPS collar, under tropical conditions and linked the grazing patterns with a local land cover classification map to understand animal itineraries. The missing layer in our spatial study was similar land cover grid describing with a maximum of precision, in terms of location, floristic composition, density, height, vegetative stage, dry matter content and relative quality indicators (metabolisable energy, fiber content, etc.) of pasture. In order to achieve an efficient monitoring of the plant-animal interaction for grazing cattle, similar precision between animal foraging behavior and vegetation mapping is necessary (Rutter, 2007). In addition such spatial analysis of behaviors is relevant in terms of grazing management as the interest in innovative range management systems such as fenceless livestock control or virtual fencing is increasing because of the reduction in cost for implementation and maintenance of actual fences (Umstatter et al., 2015).

4. Valorizing observations to enhance sensor data feeding precision grazing management tools

The future of grazing management will depend a lot on the growth of technologies including the use of sensors and faster information transfer and storage as the information that could be collected with these tools is highly valuable for the understanding of behavior mechanism. Highlights of this thesis showed the efficiency of observation-based studies of cattle behavior using sensors as a tool to automate in a continuous manner and accurately time consuming real observations instead of leaning on complex classification methodologies which are efficient but need a good correspondence with what is really observed. Nonetheless, the next step of such research needs to pay more attention to real-time data acquisition and analysis in order to achieve real precision livestock farming systems which involves live or near-live data streaming.

Zootechnical information stemming from our research should be a basis of wider scale experiments under more natural and non-induced environments in order to handle the grazing strategy of cattle on real pasture conditions. Both spatial and temporal scales are relevant when studying the plant-cattle interaction especially under contrasted conditions and precision regarding the monitoring of the animals and the vegetation should be similar fully required to propose a set of tools for precision grazing management.

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AUTHOR'S PUBLICATIONS RELATED TO THIS THESIS

1. Articles

Three articles published (peer-reviewed)

Andriamandroso, A.L.H., Bindelle, J., Mercatoris, B.C.N. and Lebeau, F., 2016. A review on use of sensors to monitor cattle jaw movements and behavior when grazing. *Biotechnology, Agronomy, Society and Environment,* 20 (1).

Andriamandroso, A.L.H., Lebeau, F. and Bindelle, J., 2015. Changes in biting characteristics recorded using the inertial measurement unit of a smartphone reflect differences in sward attributes. In: Guarino, M. and Berckmans, D.,(eds.), *Precision Livestock Farming '15*, pp. 283-289.

Andriamandroso, A.L.H., Lebeau, F. and Bindelle, J., 2014. Accurate monitoring of the rumination behaviour of cattle using IMU signals of a mobile device. *Grassland Science in Europe* 19, 631-634.

One article submitted to peer-reviewed journal and accepted with minor revision:

Andriamandroso, A.L.H., Beckers, Y., Froidmont, E., Dufrasne, I., Heinesch, B., Dumortier, P., Blanchy, G., Blaise, Y. and Bindelle, J. Development of an open-source algorithm based on inertial measurement units (IMU) of a smartphone to detect cattle grazing and ruminating behaviors. *Computers and Electronics in Agriculture*

One article to be submitted to peer-reviewed journal:

Andriamandroso, A.L.H., Lebeau, F., Beckers, Y., Castro Muñoz, E., Arnould, R., Blaise, Y. and Bindelle, J. How cattle grazing behaviors change under contrasted pasture attributes: identification of the key indicators using bite characteristics and their spatial distribution. To be submitted to *Applied Animal Behaviour Science*.

2. Conferences:

2.1. Oral presentations

Andriamandroso, A.L.H., Lebeau, F. and Bindelle, J., 2015. Changes in biting characteristics recorded using the inertial measurement unit of a smartphone reflect differences in sward attributes. Presented at: *7th European Conference on Precision Livestock Farming 2015,* Milano, Italy, 15-18 September 2015.

Andriamandroso, A.L.H., Lebeau, F., Bindelle, J. and Dumont, B., 2014. The performance of mobile devices' inertial measurement unit for the detection of cattle behaviors on pasture. Presented at: *12th International Conference on Precision Agriculture* Sacramento, CA, USA, 20-23 July 2014.

2.2. Posters

Andriamandroso, A.L.H., Bindelle, J. and Lebeau, F., 2014. Use of inertial measurement unit of a mobile device to discriminate cattle grazing and ruminating behaviours on pasture. Presented at: *1st Joint International Symposium on the Nutrition of Herbivores/International Symposium on Ruminant Physiology (ISNH/ISRP),* Canberra, Australia, 08-12 September 2014

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SUPPLEMENTARY DATA

Supplementary Data (Annex to the Chapter 3): Program code and procedure for cattle grazing behaviors detection using data collected from iPhone 4S inertial measurement unit (IMU) under MatLab

Steps to follow:

Objective Step	How to do	Input	Output in Matlab
To load the raw data	1. Open csv file recorded by the iPhone's IMU via SensorData	'SD_xxxx_xxxxxx.csv'	Matrix 'file' with all signals recorded by the IMU
To isolate the useful signals for detection	2. Isolate the desired signals for the detection (gravitational acceleration on x-axis Gx, rotation rate on x and y-axis Rx and Ry)	'file' matrix	Matrix 'imu_useful' grouping all useful signals for behavior detection
Save the detection main code into a m-file	3. Behavior detection main code (to save to a m-file)	'imu_useful' matrix	Matrix 'detected_behaviors' grouping detected behaviors at a 1Hz frequency
To run the behavior detection main code efficiently	4. Behavior detection procedure	'file' matrix and matrix length for step detection of behaviors	Matrix 'detection_total' grouping all detected behaviors by step calculation at 1Hz frequency
To plot detected behaviors with a larger time-windows	5. Graphical representation of detected behaviors	'detection_total' matrix and desired time-windows to view detected behaviors (here 1-min)	Plot containing the share of detected behaviors during a 1-min time window

1.Open csv file of recorded data on SensorData application

```
file= [];
file = csvread('SD_xxxx_xxxxxx.csv',1,0); %Change 'SD_xxxx_xxxxxx.csv' name
to the recorded data csv file name
```

2.Isolate the useful signals for further detection in a matrix using 'openfile' function

```
function [imu_useful]=openfile(file)
%%%%%%%%1-Open Sensor Data file from iPhone 4s%%%%%%%%
    Ax=[];% Acceleration on x-axis;
    Ay=[];% Acceleration on y-axis;
    Az=[];% Acceleration on z-axis;
    pitch_y=[];% Euler angles on x-axis;
    roll_x=[];% Euler angles on y-axis;
    yaw_z=[];% Euler angles on z-axis;
    Gx=[];% Gravitational acceleration on x-axis;
    Gy=[];% Gravitational acceleration on y-axis;
    Gz=[];% Gravitational acceleration on z-axis;
    Ux=[];% User acceleration on x-axis;
    Uy=[];% User acceleration on y-axis;
    Uz=[];% User acceleration on z-axis;
    Rx=[];% Rotation rate on x-axis;
    Ry=[];% Rotation rate on y-axis;
    Rz=[];% Rotation rate on z-axis;
imu_useful=[];% Useful data from IMU;
size_file=size(file); % Calculate size of the opened matrix;

%%1-For files with all 41 signals%%
if size_file(:,2)==41;
    Ax= file(:,2);
    Ay= file(:,3);
    Az= file(:,4);
    pitch_y=file(:,6);
    roll_x=file(:,5);
    yaw_z=file(:,7);
    Gx=file(:,21);
    Gy=file(:,22);
    Gz=file(:,23);
    Ux=file(:,24);
    Uy=file(:,25);
    Uz=file(:,26);
    Rx=file(:,27);
    Ry=file(:,28);
    Rz=file(:,29);
else
% %%For signals containing less than 41 signals%%
    Ax=file(:,2);
    Ay=file(:,3);
    Az=file(:,4);
    pitch_y=file(:,5);
    roll_x=file(:,6);
    yaw_z=file(:,7);
    Gx=file(:,8);
    Gy=file(:,9);
    Gz=file(:,10);
    Ux=file(:,11);
    Uy=file(:,12);
    Uz=file(:,13);
    Rx=file(:,14);
    Ry=file(:,15);
```

```
    Rz=file(:,16);
end
%%Useful IMU signals for further analysis are grouped in imu_useful
matrix%%
imu_useful=[Gx Rx Ry];
```

3. Cattle behaviors detection main code (to save into 'icowdetector.m')

```
%Fixed data
fs=100;%sampling frequency of the IMU (100Hz)
window = 1*fs; %if time window size = 1 second
[b,a]=butter(2,[1/(fs/2) 4/(fs/2)],'bandpass'); %filter design to allow
frequencies between 1Hz and 4Hz pass.

%List of signals thresholds for the behavior detection:
%mGx: mean of gravitational acceleration on x-axis
%sGx: standard deviation of gravitational acceleration on x-axis
%sRx: standard deviation of rotation rate on x-axis
%sRy: standard deviation of rotation rate on y-axis
%mingraze and maxgraze: minimum and maximum thresholds for grazing
%minrum and maxrum: minimum and maximum thresholds for ruminating.
mGx_maxgraze=0.95;
mGx_mingraze=0.6;
mGx_maxrum=0.4905;
mGx_minrum=0.1;
sGx_maxgraze=0.06;
sGx_mingraze=0.0052;
sGx_maxrum=0.0176;
sGx_minrum=0.0025;
sRx_maxgraze=0.7933;
sRx_mingraze=0.1336;
sRx_maxrum=0.1851;
sRx_minrum=0.032;
sRy_maxgraze=0.7337;
sRy_mingraze=0.1156;
sRy_maxrum=0.1445;
sRy_minrum=0.025;

%List of parameters of interest for the detection
Gx=imu_useful(:,1); %gravitational acceleration on x axis
Rx=imu_useful(:,2); % rotation rate on x axis
Ry=imu_useful(:,3); %rotation rate on y axis

%Variable initialization
norm_Gx = [];%normalized gravitational acceleration on x-axis
mGx = [];%normalized mean of gravitational acceleration on x-axis
sGx = [];%normalized standard deviation of gravitational acceleration on x-
axis
fRx = [];%filtered rotation rate on x-axis
fRy = [];%filtered rotation rate on y-axis
sRx = [];%standard deviation of filtered rotation rate on z-axis
sRy = [];%standard deviation of filtered rotation rate on y-axis

%Variable pre-processing
norm_Gx = normalize_var(Gx,0,1);
fRx = filter(b,a,Rx);
fRy = filter(b,a,Ry);

%Mean and standard deviation calculation
```

```
mGx=calculate_mean(norm_Gx,window);
sGx=calculate_std(norm_Gx,window);
sRx=calculate_std(fRx,window);
sRy=calculate_std(fRy,window);

%mGxsGxsRx is the signals combination giving the best detection accuracies.
%The algorithm is a simple Boolean algorithm in the respect to the
%thresholds mentioned previously.

detected_behaviors =[];%Matrix of detected behaviors at 1Hz frequency
for n=1:length(mGx);
    if mGx(n,1)<=mGx_maxgraze && mGx(n,1)>=mGx_mingraze &&
sGx(n,1)<=sGx_maxgraze && sGx(n,1)>=sGx_mingraze && sRx(n,1)<=sRx_maxgraze
&& sRx(n,1)>=sRx_mingraze;
        detected_behaviors(n,1)=1; %1 = Grazing
    elseif mGx(n,1)<mGx_maxrum && mGx(n,1)>=mGx_minrum &&
sGx(n,1)<=sGx_maxrum && sGx(n,1)>=sGx_minrum && sRx(n,1)<=sRx_maxrum &&
sRx(n,1)>=sRx_minrum;
        detected_behaviors(n,1)=2; %2 = Ruminating
    else detected_behaviors(n,1)=3; %3 = Others
    end
end

%Avoid ruminating and grazing behaviors which duration is less than 2s
for n=2:length(detected_behaviors)-1;
    if detected_behaviors(n,1)==2;
        if detected_behaviors(n-1,1)~=2 && detected_behaviors(n+1,1)~=2;
            detected_behaviors(n,1)=3;
        end
    end
end
for n=2:length(detected_behaviors)-1;
    if detected_behaviors(n,1)==1;
        if detected_behaviors(n-1,1)~=1 && detected_behaviors(n+1,1)~=1;
            detected_behaviors(n,1)=3;
        end
    end
end
```

4. Cattle behavior detection procedure to be more efficient

```
detection_total=[];%Matrix of detection behaviors at 1Hz frequency
fs=100; %Sampling frequency in Hz
calc_windows = 2000; %Define a calculating windows to fluidize the running
of the program. Here it is 2000s.
step=calc_windows*fs;

%Perform the icowdetector for each calculating windows size of the data.
for p=(calc_windows*fs):step:length(file);
    data=file (((p-(step-1)):p),:);
    [imu, imu_useful]=openfile(data);%open file with openfile function
    icowdetector %run icowdetector.m
    detection_total((round(p/fs)-round(step/fs-
1)):round(p/fs),1)=detected_behaviors;
end
```

5. Plotting cattle behaviors percentage occurring each minute

```
M=[];%percentage of behaviors occurring each minute
```

```
d=[];%matrix of behaviors at 1Hz frequency
d=detection_total(:,1);
for n=60:60:length(d);
    M(n/60,1)=length(find(d(n-(60-1):n)==1))*100/60; %first column concerns 
grazing behavior
    M(n/60,2)=length(find(d(n-(60-1):n)==2))*100/60; %second column 
concerns ruminating behavior
    M(n/60,3)=length(find(d(n-(60-1):n)==3))*100/60; %third column concerns 
other behaviors
end

%Plot the figure representing cattle behaviors percentage occurring each 
minute
figure,plot(M(:,1),'-bs','MarkerSize',11)%Blue is grazing
hold on
plot(M(:,2),':ro','MarkerSize',11)%Red is ruminating
plot(M(:,3),'--k*')%Black is others
legend('Grazing', 'Ruminating', 'Others')
ylabel('Share of 1s detected behavior over 1-min per period (%)')
xlabel('Time(min)')
```