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DESIGN OF AN AUTOMATED SYSTEM FOR CONTINUOUS MONITORING OF DAIRY COW BEHAVIOUR IN FREE-STALL BARNS

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1 Abstract

Change in cows' behaviours is one of the indicators useful to help identifying when animals become ill. The need to analyse a large number of animals at a time due to the increase in the herd dimension in intensive farming has led to the use of automated systems. Among automated systems, inertial sensor-based systems have been utilised to distinguish behavioural patterns in livestock animals.

In this field, the overall aim of this thesis work, which was inherent to the field of the Precision Livestock Farming, was to contribute to the improvement of the systems based on wearable sensors that are able to recognise the main behavioural activities (i.e., lying, standing, feeding, and walking) of dairy cows housed in a free-stall barn. This objective was achieved through different steps aimed at producing an advance in the state of the art.

A novel algorithm, characterised by a linear computational time, was implemented with the aim to improve real-time monitoring and analysis of walking behaviour of dairy cows. The algorithm computed the number of steps of each cow from accelerometer data by making use of statistically defined thresholds. Algorithm accuracy was carried out by computing total error (E equal to 9.5 %) and Relative Measurement Error (RME between 2.4% and 4.8%).

A new classifier was assessed to recognise the cow feeding and standing behavioural activities by using statistically defined thresholds computed from accelerometer data. The accuracy of the classification was assessed by computing of the Misclassification Rate (MR equal to 5.56%).

A new data acquisition system assessed in a free-stall barn allowed the acquisition of data from different sensor devices, *with a sampling frequency of 4 Hz, during the animals' daily routine. It required a simple installation into the building and it did not need any preliminary calibration. The performance of this system was assessed by computing a Stored Data Index (DSI) that resulted equal to 83%.*

Finally, the overall design of an automated monitoring system based on wearable sensors was proposed.

2 Sommario

L'alterazione del comportamento degli animali è uno degli indicatori utili per identificare l'insorgenza di malattie. La necessità di controllare un numero sempre maggiore di capi negli allevamenti intensivi ha portato all'utilizzo di sistemi automatizzati per il loro monitoraggio. Tra questi, i sistemi basati su sensori inerziali sono stati recentemente proposti per classificare i pattern comportamentali degli animali negli allevamenti.

In questo ambito, che è inerente al campo della Precision Livestock Farming, il lavoro svolto durante il Dottorato di ricerca e descritto nella presente tesi si propone di contribuire al miglioramento di tali sistemi per il riconoscimento delle attività di lying, standing, feeding e walking delle bovine da latte allevate in una stalla a stabulazione libera.

Sulla base di un'ampia analisi dello stato dell'arte, tale obiettivo è stato conseguito tramite la definizione di nuovi approcci di applicazione della ICT (Information and Communications Technology) alla zootecnia intensiva.

In particolare, è stato realizzato un nuovo algoritmo, caratterizzato da un complessità computazionale lineare, che effettua il calcolo del numero di passi di ogni bovina dai dati di accelerazione, facendo uso di soglie definite statisticamente. L'accuratezza dell'algoritmo è stata valutata sulla base dell'errore totale, pari al 9.5%, e del Relative Measurement Error, compreso tra il 2.4% e il 4.8%.

Inoltre, è stato definito un nuovo classificatore per distinguere l'attività del feeding dallo standing, utilizzando soglie calcolate statisticamente dai dati accelerometrici.

L'accuratezza della classificazione è stata valutata sulla base del Misclassification Rate, pari al 5.56%.
L'applicazione in stalla di un nuovo sistema di acquisizione dei dati ha permesso di migliorare la raccolta dei dati da differenti sensori durante la routine giornaliera degli animali. Il sistema proposto richiede un'installazione facilitata e non necessita di calibrazioni preliminari. La sua prestazione è stata valutata mediante lo Stored Data Index che è risultato pari all'83%.
Infine, viene proposto il progetto di un sistema complessivo per il monitoraggio in automatico dei comportamenti delle bovine basato su sensori indossabili.

3 Introduction

3.1 Preface

In this century, public concern over industrial methods of rearing animals and their impact on farm animal welfare have increased (Miele and Lever, 2013). At the consumers' level, there is a growing realisation of a link, direct or indirect, between animal welfare and food safety and quality (Rowbotham and Ruegg, 2015). Scientific research is also involved in assessing whether animal welfare could influence productivity (Coignard et al., 2014). This growing interest towards animal welfare in intensive farming, which is also diffuse among the stakeholders, has joined with other current arising problems related to livestock farming management. Among these, the increase of herd dimension that has reduced the farmer's capability of visually controlling the animals and the need to decrease the livestock management expenditures due to the labour cost.

These issues have contributed to produce an increasingly spread and shared adoption of automated computational procedures for the analysis of animal behaviour.

Different kinds of innovative systems and automated tools have been proposed or assessed for the observation of animal behaviours. Among these, the automated visual recognition of cow's lying, standing, and walking behavioural activities by using a computer-vision based system (Mattachini et al., 2011; Mortensen et al., 2016; S. M. C. S. M. C. Porto et al., 2013; Song et al., 2008), the automated sound recognition (Ferrari et al., 2010; Fontana et al., 2015; Vandermeulen et al., 2016), the outdoor animal localisation by using Global Positioning Systems (Barbari et al., 2006; Godsk and

Kjærgaard, 2015) and the in-door animal localisation by using Radio Frequency Identification tags (Barbari et al., 2013; Maselyne et al., 2016; Porto et al., 2012; Voulodimos et al., 2010) and Ultra-Wide Band tags (Ipema et al., 2013; Porto et al., 2014). Some drawbacks of these systems are their high cost and the need to have highly specialised operators to calibrate them when a modification of the system within the monitored areas of the breeding environment or an extension of the system are required.

Therefore, in recent times, innovative systems and automated computational procedures based on inertial wearable sensors have been adopted to provide effective and accurate monitoring and analysis of cow behaviour to improve animal's health and welfare and respond to different issues related to the high cost of the systems, effectiveness of the outcomes, and completeness of the behaviours analysed. In these systems, the sensors attached to the animals are suitable to detect events or measure changes in some physical quantities (e.g., acceleration, pressure, air relative humidity, and air temperature).

Research studies on wearable sensor-based systems can be broadly categorised into two groups of works, which depend on the system proposed. It can be a commercial system or a prototype built by the research team. When a commercial system is tested, in the work there is usually no information on the algorithm due to patent rights, therefore researchers cannot contribute to its improvement and the work is mainly aimed at assessing the accuracy of the results compared to other systems considered as the '*golden standard*'. When a prototype of the system is proposed, the algorithm as well as software and hardware specifications are usually provided and this facilitates comparisons with other algorithms and the

advance of the research in the field. With reference to wearable sensors, most of the studies in this field have been focused on hardware improvement (Darr and Epperson, 2009; Kumar and Hancke, 2015; Nadimi et al., 2012; Pastell et al., 2009), while few research studies have been conducted to improve algorithms and implement the related software (Alsaaod et al., 2015; Nielsen et al., 2010). Furthermore, there is the need to cope with the difficulties related to the conduction of a thorough analysis of all the monitored behavioural activities of the animal.
Therefore, challenges still exist in this field of research, in which the thesis work was developed and aimed at contributing to the increase of knowledge.
On this basis, in the following Sections, an extensive analysis of literature is carried out (Section 3.2) to investigate the state of the art, which constitutes the knowledge base of this thesis work, and subsequently the objectives of the thesis work (Section 3.3) are described with reference to the highlighted issues in the field.

3.2 State of the art

3.2.1 Research studies on ICT applications to the analysis of livestock behaviour

In past times, animal observations were carried out by skilled operators either directly within the breeding environment by filling in a checklist, or by the visual analysis of images acquired from video-recording systems. Certainly, when these tasks are performed in a continuously way for a long time they became costly and time consuming (Alsaaod et al., 2015; Chanvallon et al., 2014; Nielsen et al., 2010; Robert et al., 2009). For these reasons, in the literature, these

techniques of animal observation are often used only as the 'golden standard' for the validation of automated monitoring system of animal behaviours.
A type of *automated* monitoring system regards the *automated visual recognition* of animal behaviours (Cangar et al., 2008; Mattachini et al., 2011; Mortensen et al., 2016; Porto et al., 2013; Song et al., 2008).
In this field, a *computer vision-based system* (*CVBS*) was used and validated in two research studies (Porto et al., 2013; Porto et al., 2015) concerning the automated classification of cow's lying, standing, and feeding activities. The authors demonstrated the suitability of the *Viola-Jones algorithm* for image discrimination of the cow's shape from the floor background. The proposed system based on automated image recognition required an accurate calibration phase of both the cameras and the algorithms that process the digital images. This required activity increases the complexity of the installation in the free-stall barn and the maintenance of the system when the farmer adopts any change in the observed breeding area.
Another type of *automated* system, which analyse health status of animals from activities other than behaviours, used *automated sound recognition* to predict the chicken's growth (Fontana et al., 2015), the monitoring of pig's cough (Guarino et al., 2008) or cow's coughing frequency to recognise Bovine Respiratory Disease (Ferrari et al., 2010; Vandermeulen et al., 2016).
These kinds of monitoring systems do not allow the identification of each animal.
Other *automated* systems for the monitoring of livestock animals allows for both *identification* and *localisation* of each

animal in the breeding environment and the recognition of its behaviours.
When the cows are at pasture or during outdoor activities (e.g., transport), *Global Positioning Systems* (GPSs) enable continuous and automatic tracking of an animal's position (Barbari et al., 2006; Ungar et al., 2005) and an accurate recognition of cow's activities (Godsk and Kjærgaard, 2015). However, GPSs are not easily applicable indoor due to signal weakening. Therefore, other kinds of monitoring systems have been proposed in the last decades such as those based on *radio frequency identification* (RFID) technology. They make use of two main electronic components (tags and readers) that exchange information through radio waves. Among automated systems based on RFID technology, those based on *ultra-wide band* (UWB) technology can identify and locate animal inside the livestock buildings with a higher accuracy then those based on high frequency (HF) and ultra-high frequency (UHF) technologies (Ilie-Zudor et al., 2011; Ipema et al., 2013; Porto et al., 2014, 2012). Although these types of monitoring systems make it possible to track each animal of the herd, they have a high cost that is not always sustainable for farmers. Moreover, their setting up within the breeding environment is often complex in relation to the layout and building characteristics of the barn to be monitored.
Recently, other monitoring systems based on *wearable sensors* have been more and more widely utilised due to their low cost and easy integration with other ICT devices (e.g., computers and wireless networks). These sensors are able to measure difference in physical quantity (e.g., acceleration, pressure, air temperature, and air relative humidity). For instance, accelerometer sensors implemented in smart

devices were used to monitor human behaviour and health (Mathie et al., 2004). Later, in a pilot study, they were also applied to livestock (Martiskainen et al., 2009) in order to classify dairy cow's behavioural activities by using a *Support Vector Machine* (*SVM*).

In literature, the classification of standing and lying was already successfully assessed by using an accelerometer fixed to the cow’s leg (Arcidiacono et al., 2015; Darr and Epperson, 2009). In fact, an acceleration threshold value equal to 0.5 g was found suitable to recognise standing from lying. Different systems to recognise walking and feeding are still currently under study, and their features will be described in the following sub-sections.

3.2.2 The dairy cow's step counting through wearable sensors

Concerning the monitoring of walking behaviour of dairy cows within free-stall barns, the most frequently adopted wearable sensor is the accelerometer. The pedometer attached to cow’s leg is the most used device that is equipped with an accelerometer. It provides a valuable and complete information (e.g., activity indices and step counting) about the periods spent by the animal in ‘*rest*’ and in ‘*restless*’ activities during its daily routine.

It is well know that this information is relevant for early detection of oestrous in dairy cows (Chanvallon et al., 2014; Firk et al., 2002; Silper et al., 2015) as well as for lameness (Alsaaod et al., 2012; Mazrier et al., 2006). However, the analysis of walking activity by using pedometers needs refinement to improve the accuracy of the step count and obtain its real-time acquisition. Actually, the information provided by pedometers is not available in real time, because the pedometer data is downloaded by the monitoring system only during the milking process (e.g., twice a day). Due to the current widespread use of pedometers, any technical improvement would be valuable for farmers and could be a significant step forward in the enhancement of systems based on wearable sensors.

In this field, there has been an increased focus on real-time cow's step counting. However, technical specifications of this kind of systems as well as the code of the step counting algorithm are seldom included in the literature.

The IceTag3D^{TM} (IceRobotics Ltd, Edinburgh, UK) is a new device which is based on three-dimensional acceleration technology (Figure 1).

Figure 1. The IceTag3D pedometer.

It works at a sampling frequency of 16 Hz (Kokin et al., 2014). This device was validated by Nielsen et al. (2010) and it provided information at 1-second intervals about the posture of a cow (standing vs. lying), whether the leg to which the sensor is attached was moving or not, and the number of steps taken per time unit. The aim of their study was to develop an algorithm for predicting the duration of walking and standing periods based on a moving average of the output from the IceTag3D^{TM} device. Moreover, the step count and lying/standing prediction of the IceTag3D^{TM} device were also validated against video recordings. The authors reported that accurate results were achieved from their experiments conducted on 10 cows, yet since the IceTag3D^{TM} is a commercial product supplied with a proprietary software, no information about the step counting algorithm was found.

Likewise, in a new version of the algorithm of RumiWatch pedometer (ITIN+HOCH GmbH, Fütterungstechnik, Liestal, Switzerland), proposed by Alsaaod et al. (2015), the authors provided no information about the code of the algorithm, whereas the outcomes of the application of the proposed algorithm on 21 cows were reported in detail as well as other technical features of RumiWatch pedometer (Figure 2). Among these, the sampling frequency of the accelerometer for monitoring walking behaviour, which was equal to 10 Hz, was considered very high by the authors.

Figure 2. The RumiWatch pedometer.

3.2.3 The feeding behavioural activity

According to one of the principles of animal welfare, 'good feeding' improves animal's comfort and well-being and indicates whether a management system is well designed or not (Burow et al., 2011; Grant and Albright, 2000; Praks et al., 2011). Since changes in feeding behavioural activity are increasingly recognised as a useful indicator of cow's health and welfare, the monitoring of changes in feeding activity may be useful in early detection and prevention of diseases.
The observation of feeding behaviour of animals is usually carried out directly by operators within the breeding environment or by the visual analysis of images acquired from video-recording systems. Since these two monitoring systems are usually costly and time consuming when they are

not automated (Abdanan Mehdizadeh et al., 2015; Berckmans, 2004), other kinds of systems, such as those based on radio frequency identification (RFID) technology, have been proposed in the last decades. They utilise transponder tags that identify each animal individually and localise it during the feeding activity (e.g., during the visit at the feeding alley). Among automated systems based on RFID technology, a higher accuracy is achieved by those based on ultra-wide band (UWB) technology compared to those based on high frequency (HF) and ultra-high frequency (UHF) technologies (Frondelius et al., 2015; Ipema et al., 2013; Porto et al., 2014, 2012; Schwartzkopf-Genswein et al., 1999; Tullo et al., 2016). The main disadvantages of the application of these systems are their high cost, which is not always sustainable for farmers, as well as the complex setting up in relation to the layout and building characteristics of the barn. Feeding behaviour is studied also during the animal outdoor activities by using Global Positioning Systems (GPSs) that enable continuous and automatic tracking of an animal's position (Ungar et al., 2005) and an accurate recognition of cow's activities (Godsk and Kjærgaard, 2015). However, GPSs are not easily applicable for the indoor analysis of feeding behaviour due to signal weakening.

Recently, other monitoring systems based on wearable sensors are being utilised more and more widely due to their low cost and easy integration with other ICT devices (e.g., computers and wireless networks). Wearable sensors are suitable for detecting events related to animals (e.g., change in acceleration, change in angular velocity, and change in sound waves or pressure due to chewing activity) or changes in the microclimate of the animal occupied zone (e.g., air

temperature and relative humidity, and atmospheric pressure).
With regard to the analysis of feeding behaviour of dairy cows, the most used wearable sensors are pressure sensors and accelerometers.
With reference to pressure sensors, in two experimental tests that were carried out by Ruuska et al. (2015) dairy cows were equipped with a RumiWatch noseband sensor (Figure 3).

Figure 3. RumiWatch noseband sensor.

The data acquired by the sensor were compared with those obtained by two other monitoring systems, i.e., a system for continuous recording of cow's behaviours (Experimental test 1) and a system suitable for the control of the visits to the automated feeders (Experimental test 2). In these tests the output of the RumiWatch algorithm was assessed, however

no information was provided about its features. Moreover, since the pressure sensor was placed in the noseband of the halter, the system was more invasive than other wearable sensors.
As concerns accelerometer-based systems, Martiskainen et al. (2009) carried out data acquisition from an accelerometer fixed to the collar of 30 cows in order to classify their behavioural activities by using a Support Vector Machine (SVM). However, the use of the SVM requires a training phase to reach a high level of accuracy in behaviour recognition.
In a later study, other researchers (Ueda et al., 2011) utilised a uniaxial accelerometer, named Kenz Lifecorder Ex (LCEX; Suzuken Co. Ltd., Nagoya, Japan), which was fixed to the collar of 8 Holstein dairy cows in a grazing production system. The feeding behavioural activity was studied by using the intensity of the movement recorded by the device in order to determine the eating time (min/d) that is one of the factors, together with biting rate (bite/min) and bite mass (g of DM/bite), utilised to compute DMI (Dry Matter Intake). In a recent study, Delagarde & Lamberton (2015) assessed the Plus version of the Lifecorder device (Figure 4) by fixing it to the collar of six cows in order to measure the following activities: grazing, ruminating and so-called ‘other activities’, i.e., drinking, walking without biting or searching, resting, and social interaction.

Figure 4. Lifecorder Plus activity monitor.

However, no information was provided about the features of the algorithm and no accelerometer data were available in both studies (Delagarde and Lamberton, 2015; Ueda et al., 2011).

Differently from these studies, Oudshoorn et al. (2013) reported the accelerometer data related to cow's feeding behavioural activity. In detail, an accelerometer device combined with bite count was proposed to evaluate the grass intake of dairy cow at pasture. Acceleration threshold values during feeding activity were defined. However, these outcomes were related to grazing cows, which show different postures during feeding activity compared to cows bred inside a barn.

According to several researchers, in the near future accelerometers are the most ‘promising’ sensors among the devices studied in the literature because they are commercially available and low-cost products. However, there is still work to be done in this field in order to design models and systems that fully comply with Precision Livestock Farming (PLF) principles (Berckmans, 2004) and

are suitable for discriminating all the animal's behavioural activities with a good accuracy.
Accelerometer-based monitoring systems that utilise acceleration threshold values to study feeding behaviour are valuable because they have several advantages. Among them, they do not require a training phase as for SVM-based systems, they are not invasive for the animal if the sensor is applied to the collar and, finally, once the thresholds values are determined the computational cost of the classifier for automated monitoring is lower. Until now, acceleration threshold values during the feeding activity have been defined only for grazing cows (Oudshoorn et al., 2013).

3.3 Objectives of the thesis work

The main objective of this study was to contribute to the improvement of the scientific knowledge in the field of ICT applications to livestock farming, which is essential to deal with the issues and challenges highlighted in the preface (Section 3.1). To this aim, this thesis work involved the design of an effective *automated system* suitable for the recognition of the main dairy cows' behavioural activities, i.e., *lying*, *standing*, *walking,* and *feeding*. This objective (*objective* 1) is a relevant aspect of the *Precision Livestock Farming* (*PLF*), which offers the possibility to achieve economically, environmentally and socially sustainable farming through continuous automatic observation, real time data interpretation and active control on the smallest possible group of animals (Berckmans, 2011).
The proposed automated system was not based on any commercial ready-to-use product specifically designed for PLF application. In fact, the hardware components were

general-purpose devices and all high-level software needed for data acquisition and data elaboration was developed using open source operating system and software library that are free available on the Web.
Following this approach, a module of the proposed system was constituted by a new *data acquisition system* (*DAS*) based on low-cost technology and open-source software. Since DAS was designed and implemented taking into account the complexity of structural components, materials, and layout of functional areas of a free-stall barn, it guaranteed a simplified installation into the breeding environment. Two main elements, the sensors and the receiver, interconnected by a wireless network, composed it and they did not require any calibration or other preliminary operation before or during the registration process.
With regard to cow's *standing* and *lying* behaviours, the literature concerning the recognition of *these behaviours* by using wearable sensors fixed to dairy cows' body is already well-established. On the contrary, different methods and systems aimed at recognising *walking* and *feeding* behaviours are still currently under study. Undoubtedly, these two behavioural activities are relevant for detecting some specific state (oestrous and lameness) of the animal and its interaction with the barn building and the feeding management system. For instance, the increasing in walking activity when cows are in oestrus was reported in some studies (Firk et al., 2002; Chanvallon et al., 2014). Other researchers (DeVries et al., 2003; DeVries and von Keyserlingk, 2006) studied different typologies of feeding management system to improve building characteristics of the barn. Since thermal comfort of the animals would also have an effect on their behaviours,

research on the use of new sustainable materials would be valuable (Barreca and Fichera, 2013a, 2013b).
With the aim of achieving an advance in the state of the art, a relevant part of my research was dedicated to the study of cows' *walking behaviour* in a free-stall barn. This analysis allowed the development and the implementation of an open-source step-counting algorithm based on acceleration thresholds, which were statistically determined (*objective* 2).
Moreover, the systematic study of cows' *feeding behaviour* in a free-stall barn was conducted. This knowledge made it possible to define acceleration thresholds suitable for the automated discrimination of cows' feeding activities from standing ones (*objective* 3).
Finally, during the activities developed in my study, further results were achieved:

- The performance of the sensor devices was improved by using a new version of the firmware.
- The data retrieved by gyroscope sensors and the accelerometer sensors, during cows' walking activities, was analysed and compared.
- The data retrieved by gyroscope, barometer, and accelerometer sensors, during the cows' feeding activities, was analysed and compared.

3.4 Work organisation

The materials and methods used to achieve the animal behaviour detection are reported in Section 3 of this thesis. The whole sub-section 4.1 contains detailed information and specifications of the new data acquisition system, while the case study is presented in Section 4.2.

Section 5 focuses on the results achieved by the novel step-counting algorithm (sub-section 5.1) and the new classifier for the feeding and standing activities (sub-section 5.2). These subsections are followed by the overall design of the automated monitoring system (Section 5.3) and the results of a feasibility study on the gyroscope and barometer sensors (Section 5.4).
In Section 6, the results are discussed and compared with other studies in the literature. Moreover, considerations on new improvements for future work are also reported.
In the field of PLF, the advance in the state of the art achieved in this PhD study is highlighted in Section 7.

4 Materials and methods

4.1 The data acquisition system

A period of my PhD work was devoted to the analysis of the most up-to-date *data acquisition systems* (*DAS*), specifically on data retrieving from sensors, which are embedded in last-generation *MEMS* (*Micro Electro-Mechanical Systems*) devices. It is well known that a data acquisition system, which is capable of converting the measure of a physical variable acquired by a sensor into the related numerical value in digital format, is implemented within MEMS smart devices and thus it provides data ready to be elaborated. Differently from this kind of embedded data acquisition system, in this study the term DAS refers to an high-level ICT-based system designed to be installed in a barn and equipped with modules that allow simultaneous connections between the different wearable devices, fixed on animal's body, and a unit for data control and storage. The modules that compose the system are the sensors, a communication channel, and the unit for data control and storage.

In this phase of my PhD activity, the analysis was focused on the features of the most recent ICT technologies and on their integration, particularly taking into account the following aspects:

- How it is invasive for cows, in view of '*avoiding animal stress*'.
- Costs of hardware and software components.
- Ease of installation in relation to the building characteristics of the barn.
- Ease of interaction with the software.
- Possibility to remote control the system.

- Reduction of the periods of disconnection, which cause data loss.
- Portability of the data files between different software applications.
- Consistency and usability of data, i.e., using and showing data in different ways without changing the structure.
- Storage of log files related to the events occurred during data acquisition.
- System scalability, to improve the performance of the system, when the monitoring of a higher number of animals is required or the increasing of the surface of the monitored area is needed.

With regard to the communication between the devices fixed to the cow's body and the unit for data control and storage, *Wireless Sensor Networks* (*WSN*), which are currently and widely considered in several studies (Huircán et al., 2010; Kwong et al., 2012; Nadimi et al., 2012) were utilised in the experiments. This choice made it possible to reduce the invasive aspect of the system for the animals and simplified the system installation in the barn, still allowing for continuous acquisition of the data in real time. With reference to sensors, low-cost MEMS smart devices were selected. They are equipped with various sensors (accelerometer, gyroscope, magnetometer, thermometer, barometer, and hygrometer), a control unit for the internal memory management and data communication, and a module for the wireless connection. Finally, the unit for data control and storage was made of a single board computer that was suitably configured and programmed by using the Phyton language in order to handle the connections with the smart devices and store the data on a non-volatile memory.

4.1.1 The wireless network

The *wireless networks* are classified according to various topologies. Depending on the distance to be achieved (extension of the network), the categories are the following:

- *Wireless Personal Area Network* (*WPAN*), which has a short range (7 – 10 meters) and connects two or a few devices with *low power consumption* (IEEE 802.15.x standards).
- *Wireless Local Area Network* (*WLAN*), which consumes more power yet extends the connection to about 100 meters in the same building (IEEE 802.11x standards).
- *Wireless Metropolitan Area Network* (*WMAN*), which extends the range to a larger geographic area, such as a city or suburb.
- *Wireless Wide Area Network* (*WWAN*), which provides connectivity over a wide geographical area. Usually WWANs are networks used for mobile phone and data service and are operated by carriers.

Since my field of study was focused on the monitoring of cows in a restricted area, which is the area of a free-stall barn, my interest was focused on *WLAN* and *WPAN* categories.

In the *WLAN* field, the standard adopted from *IEEE* (*Institute of Electrical and Electronic Engineers*) is 802.11 and the term commonly used is *WiFi* network. The wireless networks (802.11, 802.11a, 802.11b, 802.11g and 802.11n) typically have a frequency of 2.4 GHz and the stream data rate is from 1-2 Mbit/s to 600 Mbit/s.

A sub-type of wireless connection is the *WPAN*, in which two or more devices are interconnected using a low-power wireless technology within a range of about 10 meters. The most commonly used *WPAN* networks are *Infrared Data Association (IrDA)*, *ZigBee*, and *Bluetooth low energy* (*BLE* or *Bluetooth Smart*).

The *IrDA* protocol requires the so-called *Line of Sight* (LoS), i.e., the devices have to be in mutual visibility, and within a distance of few meters. Therefore, the *IrDA* network was not kept into consideration in my research activity.

ZigBee is a *wireless mesh network* of low-cost and low-power nodes, developed to increase the battery life of the devices. Since each node of a network with a mesh topology is able to carry data for the network, the devices can transmit data over a long distance, from 10 to 100 m, and the availability of the network is assured because it can reconfigure itself around broken paths. Zigbee belongs to IEEE 802.15 class family and, typically, its radio bands is of 2.4 GHz with a data transfer rate from 20 Kbit/s to 250 Kbit/s. All these features and its low latency make the ZigBee network a good choice for monitoring applications. Unfortunately, during my PhD it was not possible to find accelerometer sensors implemented into a ZigBee smart device.

BLE is a technology designed and marked by the *Bluetooth Special Interest Group* aimed at novel applications in the healthcare, fitness, beacons, security, and home entertainment industries. Compared to ‘classic’ Bluetooth, *BLE* is intended to provide considerably reduced power consumption and cost while maintaining a similar communication range.

BLE is more efficient for transferring very small quantities of data, because this technology supports very short data packets

that are transferred at 1 Mbps. These and more features make *BLE* a great option for applications where the maximum bit rate is of just a few hundred bits-per-second, or less.
In Table 1, a comparison between the most relevant features of ‘classic’ Bluetooth and BLE is reported.

Table 1. A comparison between 'Classic' Bluetooth and BLE.

Technical Specification	*Bluetooth*	*BLE*
Distance/Range (theoretical)	100 m	100 m
Over the air data rate	1–3 Mbit/s	1 Mbit/s
Active slaves	7	Not defined
Latency (from a non-connected state)	Typically 100 ms	6 ms
Minimum total time to send data	100 ms	3 ms
Power consumption	1 W	0.01 to 0.5 W
Current consumption peak	< 30 mA	< 15 mA

The total time of sending data is generally less than 6 ms, and as low as 3 ms (compared to 100 ms with ‘classic’ Bluetooth). This enables an application to form a connection and send data for a short communication burst before quickly tearing down the connection.
Thanks to an increased modulation index, *BLE* technology offers a somewhat improved range with respect to ‘classic’ Bluetooth, theoretically up to 200 feet (60 m) and beyond. However, the technology is still suited for mainly small-range applications. Usually, in fact, the range of the BLE is used with the typical 30-foot (10 m) range of ‘classic’ Bluetooth.

4.1.2 The accelerometer sensor and the Texas Instruments SensorTag device

An *accelerometer* is an electromechanical device that measures acceleration forces. These forces may be *static*, like the constant force of gravity, or they could be *dynamic*, caused by moving or vibrating the accelerometer. The accelerometer measures the acceleration force in meters per squared second (m/s^2) or in G-forces (g).

There are different types of accelerometer. One of these utilises the *piezoelectric effect*, i.e., a microscopic crystal structures built in the sensor that get stressed by accelerative force and this causes the production of a voltage.

Another type is able to sense changes in *capacitance* (i.e., the ability of a body to store an electrical charge). In this case, the device contains two microstructures next to each other and they have a certain capacitance between them. When an accelerative force moves one of the structures, then the capacitance will change. A circuitry, which converts from capacitance to voltage, is needed to get a measurement of the acceleration.

An accelerometer with a piezoresistive effect uses a semiconductor or a metal that is able to change its electrical resistivity when a mechanical force is applied.

Technologically advanced methods are based on the detection of temperature variations due to convective heat exchange. They utilise an 'activation current' in the device to produce the development of small hot air bubbles. The application of a force along the accelerometer axis causes the bubble movement and the subsequent temperature variation, which is detected by the sensors. This temperature variation is transformed into an acceleration variation.

The advantages of these kind of sensors are compactness, weight, sensitivity to small acceleration, and low cost of construction.
The development of the technology of microscopic devices, which contains moving parts, is increasing more and more. Nowadays, *Microelectromechanical systems* (*MEMS*) and *Nanoelectromechanical systems* (*NEMS*) are the most used devices in this field.
Texas Instruments produces a specific *MEMS* device, named *SensorTag*, that includes several sensing unit for: air relative humidity, pressure, position/motion and air temperature. Table 2 shows an overview of its hardware.

Table 2. SensorTag hardware overview.

Component	*Supplier*
TMP006 Contactless IR Temperature Sensor	Texas Instruments
SHT21 Humidity Sensor	Sensirion
IMU-3000 Gyroscope	Invensense
KXTJ9 Accelerometer	Kionix
MAG3110 Magnetometer	Freescale
T5400(C953H) Barometric Pressure Sensor	Epcos
CC2541 Bluetooth Low Energy Radio SoC	Texas Instruments
TPS62730 Ultra Low Power DC/DC Converter	Texas Instruments

The data measured from each sensor unit can be sampled to different rates and it can be send via *BLE* to a receiver. Acceleration sensing is based on the principle of a differential in capacitance. The SensorTag has not a built-in memory unit, so it is not able to store data permanently. Moreover, to save battery live it has the ‘*sleep mode*’ activated in its firmware, i.e., after 180 seconds, without any exchange of data, the SensorTag is disconnected from the master device and it is impossible to get a new connection without switching on the device by using its button. To avoid this type of disconnections, a new update firmware was uploaded and installed on each device.

4.1.3 The single-board computers and the Raspberry Pi

A control component, which was able to handle the acquisition process as well as to store consistent data from SensorTag devices, was needed and at this regard the single-board computers were an excellent choice. A *single-board computer* (*SBC*) is a complete computer built on a single circuit board, with microprocessor(s), memory and input/output interfaces. A *SBC* reduces the system's overall cost, by reducing the number of circuit boards required. Moreover, it eliminates the problems due two connectors, since they are source of reliability problems.

The installation of a *SBC* in a free-stall barn is simplified and facilitated, because it has a low volume compared to a standard PC and its protection with a robust case is easily carried out when utilised in a hostile environment. Moreover, the installation requires only one cable, i.e., the power cable. The *SBC* adopted in the proposed data acquisition system was the *Raspberry Pi 1 Model B* (Raspberry Pi Foundation, UK). The Table 3 shows the hardware features of the Raspberry Pi Model B.

Table 3. Raspberry Pi hardware features.

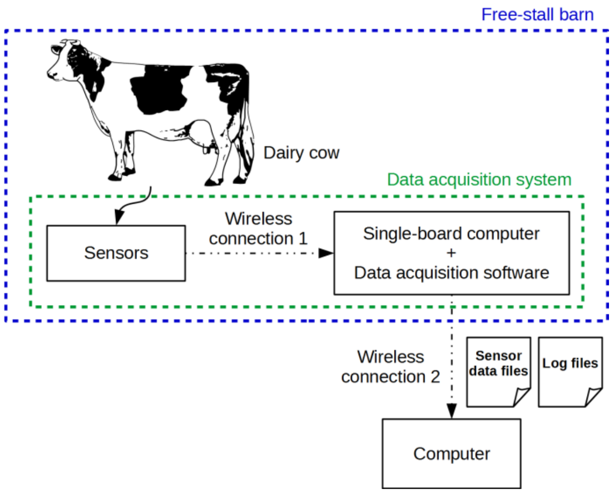
Component	Description
SOC	Broadcom BCM2835
CPU	700 MHz single-core ARM1176JZF-S
GPU	Broadcom VideoCore IV OpenGL ES 2.0 1080p30 H.264 high-profile decoder and encoder
Memory	512 MB
Number of USB Ports	2
Video input	15-pin connector MIPI Camera Interface (CSI)
Video output	RCA connector HDMI
Audio input	I²S serial bus
Audio output	3.5 mm Jack HDMI
Network	Ethernet 10/100 Mbit/s
Current (Absorbed power)	700 mA (3.5 W)
Power supply	5 V via MicroUSB

The Raspberry Pi was equipped with the following software: Raspbian Operating System and Python v2.7.6. The BLUEZ v5.4 libraries and the Pexpect v3.3 Python module were subsequently added. This software stack was needed to run the Python software module that managed the *BLE* connection as specified in the following of the text.

4.1.4 The proposed data acquisition system

In the literature, it is widely acknowledged that the continuous monitoring of each animal is a fundamental issue in the field of *PLF*. To achieve this aim, a robust *data acquisition system* (DAS) was required; it acquired the data during all the daily behavioural activities performed by the dairy cows bred in the free-stall barn. The Figure 5 shows the proposed data acquisition system.

Figure 5. Data Acquisition System.



To implement this system, *Texas Instruments SensorTags* were used as wearable sensors attached to cow's body (e.g., leg and neck). Each SensorTag has a *unique ID number* that is used to distinguish each dairy cow during the data acquisition process and the next phase of the data analysis.
Since these sensor devices have not a memory unit, they are not able to store the acquired data. Therefore, a second component is needed, i.e., a control unit that manages connections to the devices and stores consistent data into a memory storage unit by using files. Since the free-stall barn is a 'hostile' environment for the electronic devices, the *SBC Rasberry Pi* was considered in the design and in the implementation of the data acquisition system.

The '*Wireless Connection 1*' of Figure 5 was achieved by BLE wireless connections because a BLE communication module was provided in both Raspberry Pi and TI SensorTags.
Finally, the '*Wireless Connection 2*' was implemented by using the WiFi-USB adapter installed on the Raspberry Pi. When used with a desktop computer, this wireless connection allowed the following tasks:

- The managing of the Raspberry Pi, i.e., login, logout, restart, and shutdown;
- The managing of the data acquisition process, i.e., start, stop, and monitoring of disconnected sensors;
- The downloading of the data files (`.cvs` text file);
- The downloading of the log files (`.txt` text file).

The software module of the data acquisition system was developed using the Python programming language. This module, named *PLFRecorder*, had the following purposes:

- establish and maintain *BLE* connections to SensorTag devices;
- retrieve data from sensors;
- store the received data in consistent file (`.csv` format);
- attempt to re-establish *BLE* connections to disconnected SensorTag devices;
- store every occurred event, for each SensorTag device, in a log file.

The software module was composed by the following Python scripts:

- `settings.xml`;
- `sensor_calcs.py`;
- `PLFRecorderSettings.py`;

- `PLFRecorderSensorTag.py`;
- `PLFRecorderStart.py`;
- `PLFRecorderStop.py`;
- `PLFRecorderDisconnectedSensors.py`;
- `PLFRecorderShared.py`.

The *XML* (*eXtensible Markup Language*) file named `settings.xml` contained all the parameters needed by the *PLFRecorder* module to work correctly. A set of these parameters was, for instance, the duration of the registration (the number of seconds or an indefinite time option), the sample rate of the measurements, the list of all the activated SensorTag devices during the registration and identified by a *MAC address* (*Media Access Control address*), and, the sensors to be activated for each SensorTag.

The Python file `sensor_calcs.py` was a utility library that performed low-level computation and numeric conversion. It was freely available on the Internet (`https://github.com/mvartani76/RPi-Ble-Sensor-Tag-Python/blob/master/sensor_calcs.py`).

PLFRecorderSettings.py is a utility script that reads the raw parameters from the file settings.xml and stores their values into well-defined variables, which are reusable by the other Python scripts.

The `PLFRecorderSensorTag.py` was the middle component of this software module. Its aim was to be an interface between low-level tasks (e.g., contained in `sensor_calcs.py`) and the high-level script that controls the registration process.

The file `PLFRecorderStart.py`, was the high-level main script. It runs the preliminary tasks, i.e., reading preference files, initialising global variables, and allocating memory

working area. Then, it starts to establish connections with the SensorTag devices. It managed a list of the disconnected SensorTag using a *queue*. In computer science, a *queue* is a particular kind of abstract data type with a linear structure where a *FIFO* (*First In First Out*) criterion is adopted. At the beginning (first), all of the SensorTags were registered in the disconnected queue. When a connection was established, the respective SensorTag was pulled out from the queue and the process started to register the data coming from the device. If a connection between the Raspberry Pi and a SensorTag was lost, the process put the SensorTag in the disconnected queue. During the registration process, a thread tried continuously to empty the disconnected sensor queue.
Finally, three auxiliary scripts, named `PLFRecorderStop.py`, `PLFRecorderDisconnectedSensors.py`, and `PLFRecorderShared.py`, were considered. The first script was useful when it was necessary to stop the registration before the established time or stop a registration that started with an indefinite time. When invoked, the second script wrote the list of the disconnected sensors in a text file. The file `PLFRecorderShared.py` contained shared code such as the definitions of the global variables as well as the global procedures used in the others scripts.
The performance of the DAS was computed by using the total quantity of data stored in the SD Card of the single board computer at the end of the acquisition process. This criterion was expressed by the indicator:

$$SDI = \frac{\sum_1^n sd_i}{TSD} \times 100 \qquad (1)$$

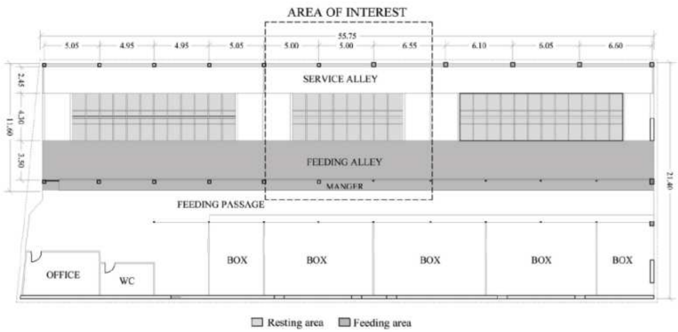
where sd_i is the amount of *stored data* during the data acquisition process by the *i-th* SensorTag and *TSD* is the *Theoretical Storeable Data*, which is the maximum amount of data that *DAS* can acquire during the time interval of the acquisition process. A *SDI* (*Stored Data Index*) equal to 100% means that no disconnection and neither system latencies nor system delays occurred during the process.

4.2 The case study

4.2.1 The free-stall barn area under study

The experiments were carried out during June 2015 and June-July 2016 in a free-stall barn for dairy cow housing located in Sicily, in the territory of the municipality of Vittoria (province of Ragusa), at 234 m.a.s.l. The main building of the barn is 55.75 m long and 21.40 m wide (Figure 6) and it is completely open on three sides. Only the south-western front of the building is made of a load bearing masonry wall. The building is asymmetric with respect to the feeding passage from a point of view of both geometry and functionality of the breeding areas.

Figure 6. The plan of the free-stall barn.



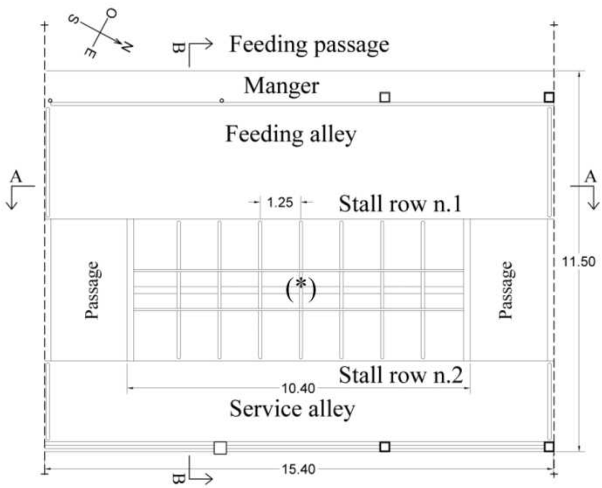
The area north-east of the feeding passage has an overall width of 10.16 m and includes the resting area, the feeding alley, and a service alley. During the experiment, this area housed 53 Holstein dairy cows. The area south-west of the feeding passage has an overall width of 6.71 m and includes five multiple pens for calves' and steers' fattening by age, a room for farming tools storage, a space subdivided into two rooms, i.e., an office and a WC, and a convex-shaped manger adjacent to the feeding passage.
The barn is equipped with two different air-cooling systems, i.e., an evaporative one and a shower type with fans. The feed is supplied once a day by a mixer-wagon at about 6:30 a.m., and, during the day, feed that poured out is moved into the manger. Milking is carried out twice a day at 6:00 a.m. and 5:00 p.m., with three shifts and an overall milking duration of about two hours. The cleaning of the feeding and the service alleys is performed once a day by a scraper. The manure is stored in a manure-pit located outside the barn in front of the south side.

Within the barn there were three groups of cows that were composed of 20 cows, 14 cows, and 19 cows. In this study, the second group of 14 cows, which were bred in the central pen of the barn, was selected (Figure 6).

4.2.2 The installation of the data acquisition system

The activity described in this sub-section was included in the thesis work to demonstrate how easy is the installation of the proposed acquisition system in free-stall barns. Figure 7 shows the area of interest, where the experimental trials were conducted.

Figure 7. Plan of the study area (*) and the position of the Raspberry Pi.



The Raspberry Pi was installed at the centre of the study area, fixed to a 2.5 m-high stake (see (*) on Figure 7). A power cable was fixed to the beams of the bearing structure of the

barn. It started from the office within the free-stall barn to the Raspberry PI position. Since the Raspberry Pi was equipped with a WiFi-USB adaptor, other cables were not needed to establish a network connection with it.
In Figure 8 the Raspberry Pi setting is reported.

Figure 8. The Raspberry Pi position.

The computer located in the office of the barn, which was used as a module of the validation system (See Section 3.2.3), was equipped with the '*Bitvise SSH Client*' free software. This software provides a free *SSH* (*Secure Shell*) client, able to establish a connection, between the computer in the office and the Raspberry Pi situated in the centre of the area of interest. This connection was utilised to monitor the data acquisition process during the experiments, e.g., sensor disconnections, failures, and power-off events. Moreover, since the computer was provided with *TeamViewer* remote control software, it was possible to monitor the data acquisition system activity from the University department.

4.2.3 The validation system

The barn was equipped with a video-recording system composed of 10 IP Vivotek FD7131 video-cameras (Figure 9), which were fixed to roof beams, two Digicom switches with 16 ports (including eight PoE ports), and a computer equipped with an Intel Core (TM) 2 Quad 2.66 GHz CPU Q6700 processor, Windows Vista Business 64 bit Service Pack 2 operative system, and 4 GB RAM.

Figure 9. Vivotek FD7131 video-camera.

Both the video cameras and the computer were connected to the switches by Ethernet cables. The software installed on the computer allowed for the synchronised acquisition of the 10 snapshots recorded by the video cameras. From those acquired snapshots, a unique panoramic image of the area of interest with a 1280 × 1960 pixel resolution was generated (Figure 10).

Figure 10. Synchronised acquisition of the 10 snapshots recorded by the video cameras.

A panoramic top-view image of the observed area was crucial in order to obtain images that showed the true shape of cow's body when walking activity occurred. The video-recording system was successfully applied for cow lying recognition and the discrimination of feeding from standing by using the Viola-Jones algorithm (Porto et al., 2014, 2015; Porto et al., 2013).

4.2.4 The walking analysis and the step counting

The experiment was carried out during June 2015. The duration of the experiment was established by considering the daily time budget usually spent by a dairy cow bred in a free-stall barn (Grant and Albright, 2000). Since the aim of the proposed algorithm is to count steps of dairy cows, the data acquisition system was operated for about 5 hours during the time intervals characterised by standing or walking activities (Porto et al., 2016), i.e., between 13:00 and 18:00.

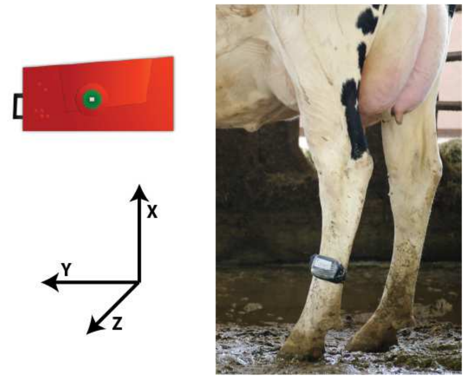
Since each cow of the herd could show differences in walking activity, in this study five cows (named with an identification number, i.e., ID 1, ID 2, ID 3, ID 4, and ID 5, in the following of the text) were selected from the observed group of 14 animals in order to consider differences in acceleration data. Therefore, the walking activity of each cow constituted the reference population from which acceleration samples were extracted and statistically analysed for each cow individually. Then a group comparison method was carried out in order to test any difference in acceleration data among the considered populations.

The five cows were randomly selected and their behaviour was not forced during the experiment. These two conditions assured that independent samples could be extracted from the walking activity of each cow.

The walking samples selected were: 25 for the cow with ID 1, 39 for the cow with ID 2, 25 for the cow with ID 3, 37 for

the cow with ID 4, and 27 for the cow with ID 5; therefore, a total of 153 samples were collected.
To acquire acceleration values, a SensorTag was fixed to the left hind leg of each animal (Figure 11).

Figure 11. SensorTag fixed at left hind leg.



Each SensorTag was protected by inserting it into a bubble wrap and, in turn, into a water-resistant plastic case, which was equipped with a belt and a Velcro closure. An adhesive label, which contained the identification code of the SensorTag, was fixed on each case.
The position of the SensorTag on the cow's leg was decided based on the findings of Firk et al. (2002). They found that, when the device is positioned at the collar, a higher number of false positives are likely to be obtained in oestrus detection than when it is fixed at the leg, whereas no significant differences were reported in their study between the choice of the left hind leg and that of the fore-leg.

Figure 11 shows the coordinate system of the SensorTag in relation to the cow's leg. Consequently, the leg motion during walking activity of the cow essentially developed in the x-y plane.
Each cow was marked with a unique visible sign to enable visual assessment of behavioural activity by using the images collected by the video-recording system described above (see Section 4.2.3).
Before starting the data collection, the clock of the Raspberry Pi was synchronised with the one of the existing video-recording system that was utilised as validation system.
The data acquired by the two systems, i.e., accelerometers and video-recording systems, were analysed at the end of the experiment in the barn. The walking activity of the five cows was extracted from the accelerometer recordings with the support of the video-recording system image visualisation.
According to Alsaaod et al. (2015), a walking period was defined as a period of at least three consecutive steps to avoid that isolated movements (e.g., a flick of the leg) could be misinterpreted as steps. Moreover, when the time interval between two steps exceeded 4 s, the two steps were attributed to two different periods of *walking*.
In order to decide which duration of walking samples is more suitable for cows' *walking* activity, literature was analysed. Some authors (Nielsen et al., 2010) obtained the most accurate results by using walking samples of at least 5 s, whereas Robert et al. (2009) reported a more accurate behaviour classifications with samples of 3 s and 5 s than with samples of 10 s, for the recognition of standing, walking, and lying behaviours.
Therefore, based on the literature outcomes, in this study, the cows' walking activity was subdivided into samples of 5 s;

since the system used in this study operated at 4 Hz frequency, each sample included 20 instantaneous measurements of the acceleration. In the following discussion, the term 'observation' will be used to refer to a single measurement of acceleration. Furthermore, at each walking sample a univocal alphanumeric code was assigned by joining the cow's ID, the symbol '_', and the progressive number of the sample.
In literature, different variables have been considered to study the accelerometer signals. In this study, according to Robert et al. (2009), two vector variables were utilised to measure the accelerometer data: the *Signal Vector Magnitude* (*svm*), named *mod* hereafter, and *Signal Magnitude Area* (*sma*). They were defined as follows:

$$mod_{xy} = \sqrt{acc_x^2 + acc_y^2} \qquad (2)$$

$$sma_{xy} = |acc_x| + |acc_y| \qquad (3)$$

where acc_x and acc_y represent the components of acceleration in the x and y directions, respectively. In this study, the two variables mod_{xy} and sma_{xy} were utilised independently.
Since leg motion during this activity essentially developed in the x-y plane, the accelerometer data related to the z axis was neglected in the analysis of cow walking behaviour.
Successively, two versions of an innovative algorithm for step counting, which utilises two thresholds, were developed.
A first version, named Alg_{mod} hereafter, used the main threshold th_{mod}, which was an acceleration and was suitable for detecting the presence of a step in the sample. In this regard, the observations having an acceleration value mod_{xy} higher than the fixed threshold th_{mod} were termed *peaks*. A second threshold, named th_{offset}

hereafter, was defined to detect if two *peaks* should be assigned to the same step or else to two different steps. Therefore, the parameter $offset(p_1, p_2)$ was defined as the number of observations between two peaks, p_1 and p_2. The detailed description of the algorithm Alg_{mod} is reported in Figure 12.

Figure 12. The threshold-based algorithm proposed in the study.

```
START

input:     sample, set of n records
           th_mod, accelerometric threshold
           th_offset, offset threshold
output:    step_counter, calculated steps in sample

    current_observation <- 0;
    last_peak <- 0;

    step_counter <- 0;

    for row in sample do

           acc_x <- row['acc_x'];
           acc_y <- row['acc_y'];

           mod_xy <- sqrt(acc_x^2 + acc_y^2);

           current_observation <- current_observation + 1;

           if mod_xy > th_mod then
                  if last_peak = 0 then
                         step_counter <- step_counter + 1;
                  else
                         if current_observation - last_peak > th_offset then
                                step_counter <- step_counter + 1;
                  last_peak <- current_observation;


    write step_counter;

END
```

By following the same methodology, a second version of Alg_{mod}, named Alg_{sma} hereafter, was defined. It uses the variable sma_{xy} instead of mod_{xy} with the corresponding thresholds th_{sma} and th_{offset}.

With the aim to determine the values th_{mod} and th_{sma}, the walking samples were used twice to compute the variables mod_{xy} and sma_{xy}. They constituted initial datasets of the two versions of the step counter algorithm.

Before carrying out threshold computation, for each reference population of walking activity it was verified that mod_{xy} values of the walking samples, as well as sma_{xy}, were not statistically different among them in the time interval of data acquisition. This test was useful to check for mod_{xy} and sma_{xy} outliers.
To obtain a unique acceleration threshold for each version of the algorithm, suitable for counting the steps of all the cows, a method was adopted to test the equality of accelerations obtained from the considered cows. Since the two variables mod_{xy} and sma_{xy} did not follow a normal distribution, the non-parametric *Kruskal-Wallis test* was used as group comparison test. This test made it possible to verify the equality of acceleration medians for the reference populations, i.e., the walking periods of the five cows analysed, and produced two new datasets for Alg_{mod} and Alg_{sma}. These new datasets were used in the analysis and testing phases of the algorithms. In detail, the datasets were subdivided as follows: 75% of the walking samples constituted the datasets $analysis\_dataset_{mod}$ and $analysis\_dataset_{sma}$ which were used to compute th_{mod} and th_{sma}, respectively; the remaining 25% of the walking samples composed the datasets $test\_dataset_{mod}$ and $test\_dataset_{sma}$, which were used to test the two versions of the algorithm, Alg_{mod} and Alg_{sma}.
The threshold values th_{mod} and th_{sma} were computed as the maximum of the five acceleration medians in their respective datasets.
The determination of the th_{offset} was based on considerations regarding the acceleration time plots. It included, for instance, the duration of a cow's step and the number of observations occurring between two consecutive steps (typically 2 observations). The th_{offset} value depended on the 4 Hz sampling frequency; in fact, a higher sampling frequency will cause a higher value of th_{offset}.

In the testing phase, the number of cow's steps (N_{step}^{c}) computed by the algorithm were compared with the number of steps observed in the video-recordings (N_{step}^{v}).
The indicators selected to evaluate the accuracy of the two versions of the algorithm were the following:

$$E = \frac{\sum_i^k \left(N_{step_i}^{c-} + N_{step_i}^{c+} \right)}{\sum_i^k N_{step_i}^{v}} \times 100\% \qquad (4)$$

$$RME = \frac{\left| \sum_i^k N_{step_i}^{v} - \sum_i^k N_{step_i}^{c} \right|}{\sum_i^k N_{step_i}^{v}} \times 100\% \qquad (5)$$

where k is the number of walking samples in the datasets $test\_dataset_{mod}$ or $test\_dataset_{sma}$.
The first indicator (*E*) takes into account the total error when an overestimation (N_{step}^{c+}) or an underestimation (N_{step}^{c-}) of the number of steps occurred. The second indicator named *Relative Measurement Error* (*RME*) takes into account the compensation between N_{step}^{c+} and N_{step}^{c-} and allowed the comparison with another study (Alsaaod et al., 2015).
Furthermore, different values of the thresholds th_{mod}, th_{sma}, and th_{offset} were applied to conduct a sensitivity analysis suitable for determining how different values of the thresholds affected the error produced by the two versions of the algorithm. In detail, ±5% and ±10% variations of th_{mod} and th_{sma} were applied and the values 1, 3, and 4 were considered for th_{offset}.

4.2.5 The feeding classifier

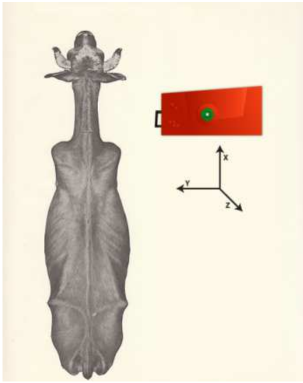
The field experiments were carried out during June 2015 in a free-stall barn for dairy cows located in Sicily. In this study, the central pen of the barn, which housed a group of 14 primiparous cows, was selected.

Based on the daily time budget usually spent by a dairy cow breed in a free-stall barn (Grant and Albright, 2000), the data acquisition system was operated for about 5 hours during the time intervals when cows are in standing or feeding (Porto et al., 2016), i.e., between 13:00 and 18:00.
The SensorTags were shielded prior to be installed on the animals by providing a water-proof protection, which was composed of a bubble wrap and a water-resistant plastic bag. The protected tag was inserted into a plastic case equipped with a Velcro closure, a belt loop, and an adhesive label, which contained the identification code of the SensorTag.
Five cows of the considered group were selected for the experiment and a plastic case, which contained the activated SensorTag, was fixed to the collar of each cow through the belt loop (Figure 13), similarly to what done in other research studies (Martiskainen et al., 2009; Oudshoorn et al., 2013).

Figure 13. SensorTag fixed to the collar of the cow.

The placement of the SensorTag at the collar of the cow was carried out in order to have the *x*-axis of the coordinate system of the SensorTag aligned with the cow's neck axis (Figure 14).

Figure 14. Coordinate system of the SensorTag fixed to the collar.



With the aim of monitoring the group of cows in the central pen of the barn, the Raspberry Pi was installed at the centre of the study area, fixed to a 2.5 m high stake. This height was suitable for maintaining the data connection in the whole area of interest and keeping the Raspberry Pi above the area of influence of the air cooling system.
Before starting data collection, the Raspberry Pi clock was synchronised with that of the existing video-recording system, which was utilised as validation system.
The visual recognition, carried out on the images collected by the video-recording system was facilitated by drawing different signs on cows' back with livestock paint crayons.

During the experiment, changes in cows' behaviours were not forced.

Data collection for the analysis of feeding and standing behavioural activities of the five cows was carried out from the accelerometer recordings related to periods of feeding and periods of standing which were observed by using the video-recording system. In this study, a '*period of feeding*' was defined as an activity that began when the cow put its head down into the manger (Martiskainen et al., 2009; Nielsen, 2013) and ended when the cow raised the head up for at least 5 s. A '*period of standing*' was defined as a 'moment of rest' in which the cow kept all its four hooves on the ground, did not make steps forward nor backwards, and kept its head still without movements or rotations (Martiskainen et al., 2009).

In our study, the accelerometer data acquired during the feeding and standing periods were considered as the reference population. Therefore, five reference populations of feeding and standing activity were statistically analysed, i.e., one for each cow.

Each period, both for feeding and for standing, was subdivided into *samples* of 5 s. A single instantaneous measurement of the acceleration data within a sample was named *observation*. Since a sample had a 5 s duration and the device was set at 4 Hz sample rate, there were 20 observations in each sample.

Since the cows were randomly selected from the observed group of animals and their behaviour was not forced during the experiment, independent samples were extracted from the reference populations.

No filtering or other pre-processing activity was carried out on the data acquired by the sensors, as done in other studies (Ruuska et al., 2015).

To facilitate the data management, an identification number was associated to each cow (Cow's ID) and a univocal alphanumeric code was assigned to each of the 5-seconds intervals of the feeding or standing samples. This code was defined by joining the letter 'F' for feeding or the letter 'S' for standing to the symbol '_', the cow's ID, the symbol '_', and the progressive number of the sample.
In this study, the accelerometer data obtained from the y-z plane was neglected in the analysis of cow feeding behaviour, since the head motion during this activity essentially developed along the x-axis, as already found in other studies (Delagarde and Lamberton, 2015; Ueda et al., 2011). This acceleration was named acc_x in the following of the text.
Based on statistical analyses of the accelerometer data, the proposed method was developed in order to define thresholds suitable for real-time discrimination of cow feeding activity from standing activity by the use of a specific classifier.
With the aim of determining an accelerometer value that could be used as threshold in such an automated classifier, 30 samples from the feeding periods and 30 samples from the standing periods were collected for each of the 5 cow. Therefore, 300 samples were obtained and randomly subdivided into 8 datasets: 7 datasets (i.e., 210 samples) were used for the analysis and the computation of the threshold and one dataset (i.e., 90 samples) for the testing of the classifier. Each of the 7 *analysis datasets* (named AD_1, …, AD_7) included 30 randomly selected samples, obtained by selecting 3 feeding samples and 3 standing samples for each of the 5 cows. The same method was applied for the *test dataset* (*TD*): for each of the 5 cows, 9 feeding samples and 9 standing samples were considered. By this procedure, the two

behavioural activities and the five cows were equally represented within each dataset.
After verifying that the variable acc_x did not follow a normal distribution, parametric tests were applied to obtain statistical information on the acceleration medians computed on the 7 analysis datasets. The *Kruskall-Wallis Test* showed a low robustness since the z-value was highly variable even when computed on samples of the same activity. On the contrary, the non-parametric *Mood's Median Test* was suitable for providing information on each of the 7 analysis datasets. For each dataset AD_1, …, AD_7, this test computed the 'overall median' (i.e., the median of the whole dataset) and for each sample it provided both the number of observations having acc_x values lower or equal to the 'overall median' and the number of observations with higher values. The mean of the 7 'overall medians', named th_{feed} in the following of the text, was proposed as the acceleration threshold in order to discern feeding from standing.
The classifier processed the *TD* as follows: for each of the *TD* samples the number of observations having acc_x value lower or equal to the th_{feed} value was computed. This number was named *score*. The samples having a *score* lower than 10, which is half of the number of observations, were classified as feeding, the remainder as standing.
With the aim of assessing the classifier accuracy and compare the results with those obtained in other research studies (Nielsen, 2013; Porto et al., 2015), the indicators *Misclassification Rate* (*MR*), *Sensitivity*, *Precision*, *Specificity*, *Quality Percentage* (*QP*), *Branching Factor* (*BF*), and *Miss Factor* (*MF*) were considered. They are defined as follows:

$$MR = \frac{FN+FP}{TP+TN+FN+FP} \times 100 \qquad (6)$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \qquad (7)$$

$$Precision = \frac{TP}{TP+FP} \times 100 \qquad (8)$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \qquad (9)$$

$$QP = \frac{TP}{TP+FN+FP} \times 100 \qquad (10)$$

$$BF = \frac{FP}{TP} \qquad (11)$$

$$MF = \frac{FN}{TP} \qquad (12)$$

where *TP* are the *True Positives*, *FN* the *False Negatives*, *FP* the *False Positives*, and *TN* the *True Negatives*.
Furthermore, the slope, intercept, and determination coefficient R^2, obtained by applying a linear regression between the real observed behaviours and those predicted by the classifier, were computed to allow for comparison with other studies.
Finally, the classification of cow's feeding activity, obtained in this study, was further analysed by computing the frequency histograms of the two behavioural activities, i.e., feeding and standing, and comparing their distributions for the whole datasets, the *TD* dataset, and the dataset of each cow.

5 Results

5.1 *The walking activity and the step counting*

5.1.1 *Data analysis through the mod_{xy} variable*

For each observation included in a walking sample, the variable mod_{xy} was computed. In Table 4, the walking sample number 20 of the cow with ID 5 is reported as an example.

Table 4. Sample n. 20 of cow with ID 5.

Cow sample	*Date*	*Time*	*acc_x* [*g*]	*acc_y* [*g*]	*acc_z* [*g*]	*mod_xy* [*g*]
5_20	05/06/2015	17:48:18	-1.0625	0.0000	0.1250	1.0625
5_20	05/06/2015	17:48:18	-1.0000	0.0625	0.1250	1.0020
5_20	05/06/2015	17:48:18	-1.0625	0.1250	0.0625	1.0698
5_20	05/06/2015	17:48:18	-1.0000	0.1250	0.1250	1.0078
5_20	05/06/2015	17:48:19	-1.1250	0.0625	0.2500	1.1267
5_20	05/06/2015	17:48:19	-1.0000	0.1875	0.3125	1.0174
5_20	05/06/2015	17:48:19	-1.2500	-0.0625	0.2500	1.2516
5_20	05/06/2015	17:48:19	-0.4375	-0.5000	1.2500	0.6644
5_20	05/06/2015	17:48:20	-2.3750	2.9375	0.2500	3.7775
5_20	05/06/2015	17:48:20	-1.0000	-0.4375	0.2500	1.0915
5_20	05/06/2015	17:48:20	-1.0000	-0.3125	0.2500	1.0477
5_20	05/06/2015	17:48:20	-1.0000	-0.1250	0.3750	1.0078
5_20	05/06/2015	17:48:21	-1.1250	-0.2500	0.2500	1.1524
5_20	05/06/2015	17:48:21	-1.0625	-0.7500	-0.0625	1.3005
5_20	05/06/2015	17:48:21	-0.0625	-0.7500	0.0625	0.7526
5_20	05/06/2015	17:48:21	-1.6250	1.8125	0.1250	2.4343
5_20	05/06/2015	17:48:22	-1.0000	-0.4375	0.2500	1.0915
5_20	05/06/2015	17:48:22	-1.0000	-0.2500	0.2500	1.0308
5_20	05/06/2015	17:48:22	-1.0000	-0.0625	0.0000	1.0020
5_20	05/06/2015	17:48:22	-0.9375	0.1875	0.3125	0.9561

Three walking samples of cow with ID 2 were recognised as outliers and discarded, since accelerations were shown to be statistically different by applying Kruskal-Wallis test.
The remaining 150 samples were subject to the test for group comparison (Kruskal-Wallis test) and other 13 samples were discarded. The resulting dataset, which was composed of 137 elements, was randomly divided into two sub-dataset. The first one, $analysis\_dataset_{mod}$, contained 75% of the data (103 samples) and was utilised to compute the values of the threshold th_{mod}, whereas the second one, $test\_dataset_{mod}$, included 25% of the data (34 samples) and was utilised for testing the step counter algorithm Alg_{mod}. The statistical analysis on the samples are reported in Table 5.

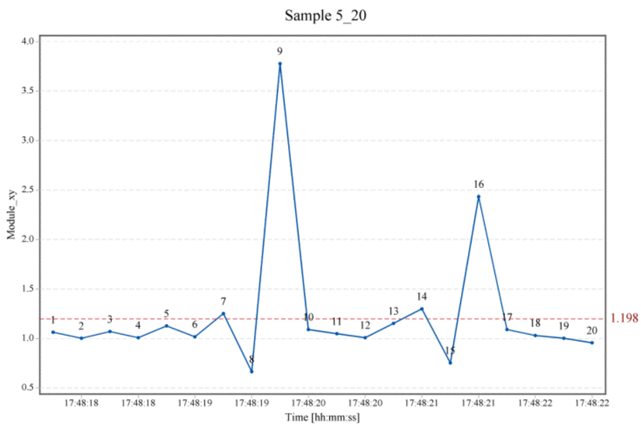
Table 5. Results of group comparison test on mod_{xy} variable.

Cow ID	*Initial samples*	*Samples discarded by the Kruskal-Wallis test*	*Remaining samples*
1	25	0	25
2	39	3	36
3	25	0	25
4	37	0	37
5	27	0	27
Overall dataset	153	3	150
Samples discarded by the Kruskal-Wallis test			13
Filtered dataset			137
Analysis dataset (75%)			103
Test dataset (25%)			34

The value of th_{mod}, which is necessary to establish the minimum acceleration intensity in order to recognise a step, was obtained as the maximum of the medians of the

$analysis\_dataset_{mod}$ samples and resulted equal to 1.198 g. The value of th_{offset} between two peaks was fixed to 2 on the basis of the sampling frequency of 4 Hz and the comparison between the graphs of the accelerometer signal of the walking samples and the corresponding sequence in the video-recordings. In fact, the example reported in Figure 15 shows that four out of twenty observations were *peaks*. The *peak* 7 and the *peak* 9 have an *offset*(7, 9) = 1 < 2, therefore, they referred to two accelerations occurred in the same step. In this regard, the video-recordings showed that in a free-stall barn it is not possible for a cow in walking to make two steps within 0.5 s, i.e., in three observations. The same remarks apply for *peaks* 14 and 16. Instead, the *peaks* 9 and 14 have an *offset*(9, 14) = 4 > 2 and, thus, they belong to two different steps.

Figure 15. Plot of Signal Vector Magnitude (mod_{xy}) of sample 5_20 showing threshold value 1.198 g.



The step counter algorithm, which was coded in Python language, was executed on the 34 samples of the $test\_dataset_{mod}$, and the results were compared with the number of steps obtained from the visual recognition of the same samples in the video-recordings (Table 6).

Table 6. Performance of *Alg_{mod}* and *Alg_{sma}* algorithms in comparison with video recorded data.

	N_{step}^{v}	N_{step}^{c}	N_{step}^{c+}	N_{step}^{c-}	*Total errors*	*E*	*RME*
Alg_{mod}	84	88	6	2	8	9.5%	4.8%
Alg_{sma}	84	82	3	5	8	9.5%	2.4%

The overall number of steps observed in the video-recordings were 84. The algorithm Alg_{mod} computed 88 steps and produced an error of ±1 step in 8 samples, with a total error of 8 (E = 9.5%). The compensation between overestimation (N_{step}^{c+}) and underestimation (N_{step}^{c-}) of the number of counted steps produced a difference of 4 steps compared to the number of steps observed in the video-recordings (N_{step}^{v}) and, therefore, a *RME* of 4.8%.

5.1.2 Data analysis through sma_{xy} variable

The procedure of data analysis was repeated by using the 153 samples available and substituting the variable mod_{xy} with the variable sma_{xy}. The final dataset, which was composed of 146 samples, was subdivided into 110 samples (75%) for the analysis ($analysis\_dataset_{sma}$) and 36 samples (25%)

for the testing ($test\_dataset_{sma}$) of the algorithm Alg_{sma} (Table 7).

Table 7. Result of group comparison test on *sma_{xy}* variable.

Cow ID	*Initial samples*	*Samples discarded by the Kruskal-Wallis test*	*Remaining samples*
1	25	3	22
2	39	4	35
3	25	0	25
4	37	0	37
5	27	0	27
Overall dataset	153	7	146
Samples discarded by the Kruskal-Wallis test			0
Filtered dataset			146
Analysis dataset (75%)			110
Test dataset (25%)			36

The threshold value th_{sma} was computed as the maximum of the medians of the $analysis\_dataset_{sma}$ samples and resulted equal to 1.75 g. The value th_{offset} between two peaks was fixed to 2. The statement 18 of the algorithm was substituted with the computation of the variable sma_{xy} (Figure 12).

The algorithm Alg_{sma}, coded in Python language, was executed on the 36 samples of the $test\_dataset_{sma}$ and the results were compared with the number of steps obtained from the video-recordings of the same samples (Table 6).

The overall value of the steps observed in the video-recordings was 84. The algorithm Alg_{sma} computed 82 steps and produced errors in 7 samples with a total number of 8 (E = 9.5%). The compensation between overestimation (N_{step}^{c+})

and underestimation (N_{step}^{c-}) of the number of counted steps produced a difference of 2 steps compared to the number of steps observed in the video-recordings (N_{step}^{v}) and, therefore, a *RME* of 2.4%.

5.1.3 Comparison between Alg_{mod} and Alg_{sma}

The two versions of the algorithm, Alg_{mod} and Alg_{sma}, which were executed on two different test datasets, produced the same accuracy, since they made an error *E* = 9.5%. For Alg_{mod}, the 75.0% of the total errors *E* corresponded to an overestimation of the number of steps whereas the remaining 25.0% to an underestimation. For Alg_{sma}, instead, the 62.5% of the total errors was an underestimation of the number of steps and the 37.5% an overestimation. From the visual analysis of the video-recordings it resulted that Alg_{mod} made a higher number of N_{step}^{c+}, which were caused by little movements of the leg slightly before or after the walking activity. Alg_{sma}, instead, produced a higher number of N_{step}^{c-}, which occurred when the cow walking was characterised by steps having an acceleration intensity that did not exceed the fixed threshold. For Alg_{sma}, the best compensation between N_{step}^{c-} and N_{step}^{c+} produced a value of the relative error *RME* = 2.4%, which is lower than that of Alg_{mod}, equal to 4.8%.

5.1.4 Sensitivity analysis

In Table 8, the results of the application of the variations to the threshold th_{mod} and the parameter th_{offset} of the algorithm Alg_{mod} are reported. The choice of $th_{mod} = 1.198$ and $th_{offset} = 2$ produced the minimum number of total errors (*E* = 9.5%). The same value of *E* was obtained by fixing the threshold variation th_{offset} equal to 3. This value of th_{offset} produced a higher compensation between N_{step}^{c+} and N_{step}^{c-} with a *RME* value of 2.4% and determined the best performance of Alg_{mod}. Although a 5% increase of th_{mod} produced a lower *RME*, equal to 1.2%, the total error E was higher (15.5%).

Table 8. Sensitivity analysis on *Alg*

th_{mod}	th_{offset}	N_{step}^{c}	N_{step}^{c+}	N_{step}^{c-}	*Total errors*	*E*	*RME*
1.198	2	88	6	2	8	9.5%	4.8%
1.078 (-10%)	2	102	19	1	20	23.8%	21.4%
1.138 (-5%)	2	99	15	0	15	17.9%	17.9%
1.258 (+5%)	2	83	6	7	13	15.5%	1.2%
1.318 (+10%)	2	76	2	10	12	14.3%	9.5%
1.198	1	104	21	1	22	26.2%	23.8%
1.198	3	82	3	5	8	9.5%	2.4%
1.198	4	70	1	15	16	19.0%	16.7%

In Table 9, the results of the parameter variations for the algorithm Alg_{sma} are summarised. They showed that the initial values $th_{sma} = 1.75$ and $th_{offset} = 2$ minimised the number of the total errors (E = 9.5%). Although the same outcome was obtained by fixing th_{offset} equal to 3, the *RME* value did not decrease (2.4%). Therefore, this version of the algorithm performed best with the initial threshold values.

Table 9. Sensitivity analysis on *Alg_{sma}* algorithm.

th_{sma}	th_{offset}	N^{c}_{step}	N^{c+}_{step}	N^{c-}_{step}	*Total errors*	*E*	*RME*
1.75	2	82	3	5	8	9.5%	2.4%
1.575 (-10%)	2	89	7	2	9	10.7%	6.0%
1.662 (-5%)	2	88	6	2	8	9.5%	4.8%
1.837 (+5%)	2	80	2	6	8	9.5%	4.8%
1.925 (+10%)	2	80	3	7	10	11.9%	4.8%
1.75	1	104	24	4	28	33.3%	23.8%
1.75	3	82	3	5	8	9.5%	2.4%
1.75	4	73	2	13	15	17.9%	13.1%

Finally, a further analysis on the data was carried out with the aim of verifying that the performance of the algorithm was not affected by the reduction of the dataset due to the group comparison test, which produced a number of discarded walking samples. Therefore, a new computation of both *E* and *RME* was carried out by randomly adding the 25% of the discarded walking samples to the $test\_dataset_{mod}$. In comparison to the previous results, which were computed without all the discarded walking samples Table 5, it was observed that a slight increase of *E* to 10.9% occurred, whereas a substantial decrease of *RME* to 2.2% was registered. This result suggested that *RME* is less suitable than *E* for measuring the accuracy of the step counter because N^{c+}_{step} and N^{c-}_{step} compensated each other.

5.2 The feeding activity

5.2.1 The data analysis through acc_x variable

With the objective of discerning the feeding from the standing samples by using the acc_x variable, the Mood's

Median Test was conducted on the analysis datasets AD_1, …, AD_7. As an example, the results of the test on AD_1 are reported in Table 10.

Table 10. Results of the Mood Median Test on AD_1 analysis dataset.

```
Results for: MMT Analysis G1

Mood Median Test: acc_x versus cow_id

Mood median test for acc_x
Chi-Square = 531,29    DF = 29    P = 0,000

                               Individual 95,0% CIs
cow_id  N≤  N>  Median  Q3-Q1  ----+---------+---------+---------+-
F_1_10   0  20    0,69   0,11                             *-)
F_1_18   0  19    0,75   0,06                               *-)
F_1_21   0  21    0,69   0,06                           (-*
F_2_1    0  20    0,75   0,11                             (-*
F_2_28   0  20    0,81   0,06                                 *-)
F_2_30   0  20    0,81   0,13                               (-*-)
F_3_22   7  13    0,31   0,13              (-*--)
F_3_28   0  20    0,56   0,05                         *
F_3_7   13   7    0,25   0,11              *-)
F_4_11   0  20    0,44   0,06                   (-*
F_4_24   0  20    0,75   0,00                               *
F_4_29   0  20    0,63   0,17                       (---*
F_5_15   1  20    0,38   0,06                   *
F_5_16   0  20    0,44   0,13                   (-*)
F_5_20   0  19    0,56   0,06                       (-*
S_1_10  20   0    0,03   0,06      (*)
S_1_14  20   0    0,16   0,06          (*)
S_1_25  20   0    0,16   0,06          (*)
S_2_11  20   0    0,13   0,06        (-*
S_2_19  20   0    0,06   0,06      (-*
S_2_7   20   0    0,13   0,06          *-)
S_3_10  20   0    0,00   0,00      *
S_3_22  20   0    0,06   0,13      (-*-)
S_3_7   20   0   -0,03   0,06    (*)
S_4_17   7  13    0,31   0,06              (-*
S_4_19  20   0    0,13   0,00          *
S_4_23  20   0    0,00   0,13    (-*-)
S_5_23  19   0   -0,06   0,00    *
S_5_3   20   0   -0,06   0,06  (-*
S_5_6   18   3    0,13   0,22        (-*--)
                               ----+---------+---------+--------+-
                                 0,00      0,30      0,60      0,90

Overall median = 0,25
```

In Table 10, the ‘overall median’ of AD_1 resulted equal to 0.25 g. As it can be observed, the feeding samples are characterised by a high number of observations having acc_x greater than the ‘overall median’ of the dataset, whereas the standing samples have a high number of observations having acc_x lower or equal than the ‘overall median’ of the dataset. Unlike the other feeding samples, the sample with ID ‘F_3_7’ produced 13 observations having acc_x values lower or equal to the ‘overall median’, whereas the standing sample with ID ‘S_4_17’ had only 7 observations having acc_x values lower or equal to the ‘overall median’. Therefore, only these two samples could not be discriminated by using the 'overall median'.

Moreover, although all the SensorTags were set at 4 Hz, in some cases 3 observations or in other cases 5 were attributed to the same second. This occurrence was due to slight differences in the synchronicity between the Raspberry Pi and the BLE devices. This is the reason why, for instance, the sample ‘F_1_18’ had 19 observations, whereas the sample ‘F_1_21’ had 21 observations.

The Mood’s Median Test carried out on all the analysis datasets produced the values of the ‘overall medians’ reported in Table 11.

Table 11. Overall medians obtained by Mood's Median Test on all the analysis datasets.

Analysis dataset	*Overall median*
AD_1	0.250 g
AD_2	0.310 g
AD_3	0.250 g
AD_4	0.250 g
AD_5	0.310 g
AD_6	0.250 g
AD_7	0.313 g

In Table 11, some values of the 'overall medians' are repeated. This is due to the resolution of the sensor, equal to about 0.06 g, which affects the discrimination between two very similar angles of the cow's head.
The mean of the medians reported in Table 11, which is equal to 0.276 g, constituted the acceleration threshold th_{feed} that can be applied to distinguish feeding from standing behaviour of cows.
With regard to the test datasets *TD*, the *score* was computed on each sample (i.e., 45 feeding samples and 45 standing samples). The classifier correctly detected 42 samples out of 45 feeding samples (Table 12), whereas 3 samples were recognised as standing.

Table 12. Results (‘*F*’ as *Feeding*; ‘*S*’ as ‘*Standing*’) of the classification of feeding samples.

Sample	*Score*	*Result*	*Sample*	*Score*	*Result*	*Sample*	*Score*	*Result*
F_1_13	0	F	F_2_29	0	F	F_4_17	8	F
F_1_19	0	F	F_2_4	0	F	F_4_18	14	S
F_1_2	0	F	F_2_9	0	F	F_4_19	7	F
F_1_23	0	F	F_3_11	20	S	F_4_22	0	F
F_1_25	0	F	F_3_12	16	S	F_4_30	0	F
F_1_29	1	F	F_3_13	9	F	F_4_9	5	F
F_1_3	0	F	F_3_19	0	F	F_5_18	1	F
F_1_8	0	F	F_3_2	6	F	F_5_22	0	F
F_1_9	0	F	F_3_23	0	F	F_5_25	0	F
F_2_13	0	F	F_3_26	0	F	F_5_26	1	F
F_2_17	0	F	F_3_3	0	F	F_5_29	0	F
F_2_18	0	F	F_3_5	0	F	F_5_3	0	F
F_2_19	0	F	F_4_1	0	F	F_5_6	0	F
F_2_2	0	F	F_4_12	0	F	F_5_8	0	F
F_2_24	0	F	F_4_13	1	F	F_5_9	0	F
		Mean	1.978		*SD*	4.609		

The classifier correctly detected 43 samples out of 45 standing samples (Table 13), whereas 2 samples were recognised as feeding.

Table 13. Results of the classification of standing samples.

Sample	*Score*	*Result*	*Sample*	*Score*	*Result*	*Sample*	*Score*	*Result*
S_1_12	17	S	S_2_29	20	S	S_4_15	18	S
S_1_13	10	S	S_2_4	20	S	S_4_20	20	S
S_1_19	20	S	S_2_9	20	S	S_4_21	19	S
S_1_21	20	S	S_3_14	19	S	S_4_22	20	S
S_1_28	18	S	S_3_19	20	S	S_4_3	15	S
S_1_30	20	S	S_3_2	21	S	S_4_6	14	S
S_1_4	20	S	S_3_20	20	S	S_5_10	20	S
S_1_5	20	S	S_3_23	21	S	S_5_15	16	S
S_1_9	16	S	S_3_28	0	F	S_5_20	19	S
S_2_15	20	S	S_3_30	0	F	S_5_22	20	S
S_2_17	20	S	S_3_4	20	S	S_5_26	20	S
S_2_2	20	S	S_3_5	17	S	S_5_27	19	S
S_2_23	20	S	S_4_1	20	S	S_5_28	20	S
S_2_25	19	S	S_4_11	20	S	S_5_8	20	S
S_2_28	20	S	S_4_14	20	S	S_5_9	20	S
		Mean	18.178		*SD*	4.463		

With regard to *TD*, the following values of the indicators were obtained: *MR* = 5.56 %, *Sensitivity* = 93.33%, *Precision* = 95.45%, *Specificity* = 95.56%, *QP* = 89.36%, *BF* = 0.05, and *MF* = 0.07.
The results of the classifications were then entered in a linear regression model and produced the coefficients *slope* = 0.89 and *intercept* = 0.07, and a coefficient of determination R^2 = 78.8%.

5.2.2 The data analysis through the frequency diagrams

Besides the numerical analysis on the data described in section 3.1, data was also analysed by means of the frequency diagrams of the samples. The analysis of these diagrams confirmed the strong influence of the sensor position, in relation to the cow's neck axis, on the classifier accuracy.

In Figure 16, the comparison among the different distributions of the medians of standing and feeding samples is reported. The diagram shows a clear, though small, overlapping of the two distributions in the x-axis interval (0.15 g - 0.55 g). In Figure 17, the two distributions relative to *TD* also show an overlap. More in detail, in the x-axis interval (0.15 g - 0.45 g) an overlap of 12 samples is included, 6 of them are standing samples and the other 6 are feeding samples. This condition would cause the failure in achieving a threshold suitable for correctly classifying all the 90 samples of the *TD* considered.

Figure 16. Distributions of the medians of standing and feeding samples referred to the overall data.

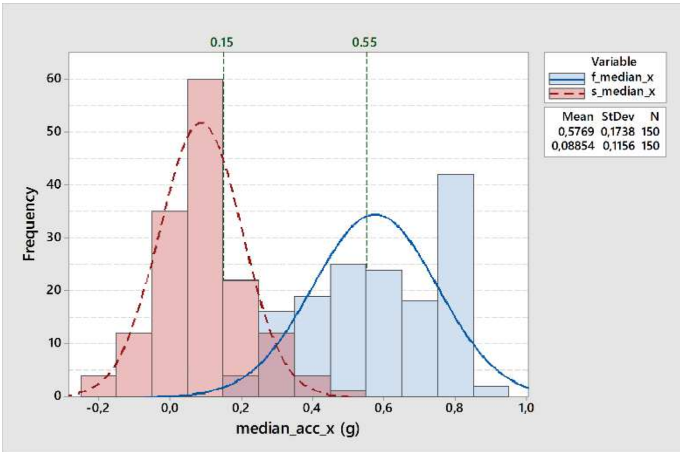
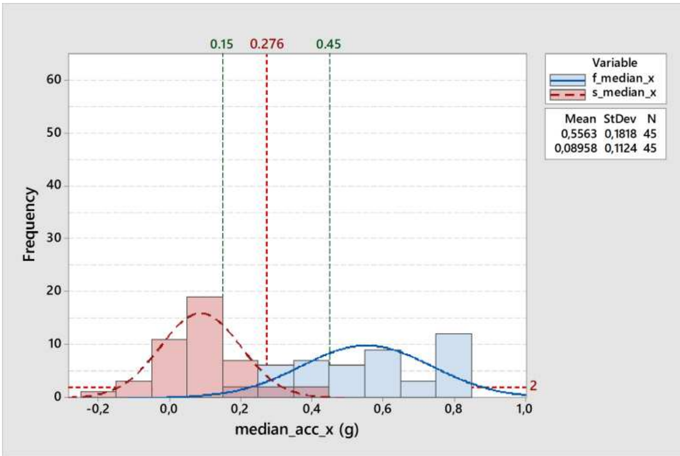


Figure 17. Distributions of the medians of the test dataset.



Starting from these considerations, a more specific analysis was carried out, based on the diagrams related to the two behaviours for each of the five cows individually (Figure 18 to Figure 22).

Figure 18. Distributions of the medians of standing and feeding samples for the cow with ID 1.

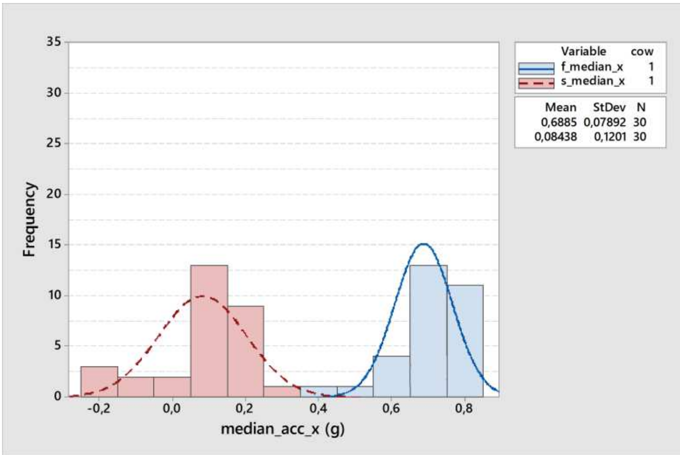


Figure 19. Distributions of the medians of standing and feeding samples for the cow with ID 2.

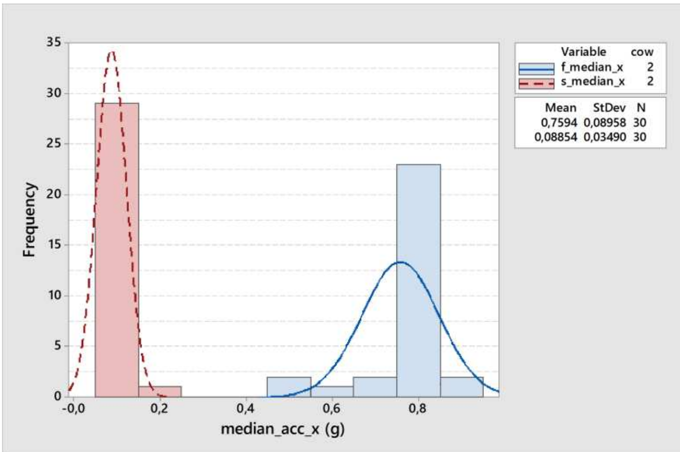


Figure 20. Distributions of the medians of standing and feeding samples for the cow with ID 3.

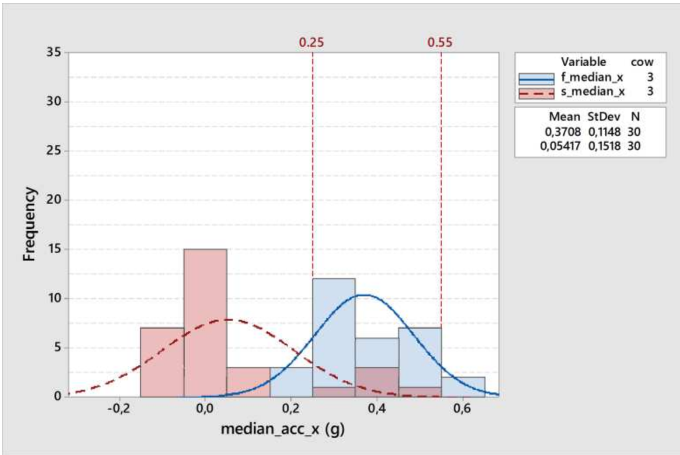


Figure 21. Distributions of the medians of standing and feeding samples for the cow with ID 4.

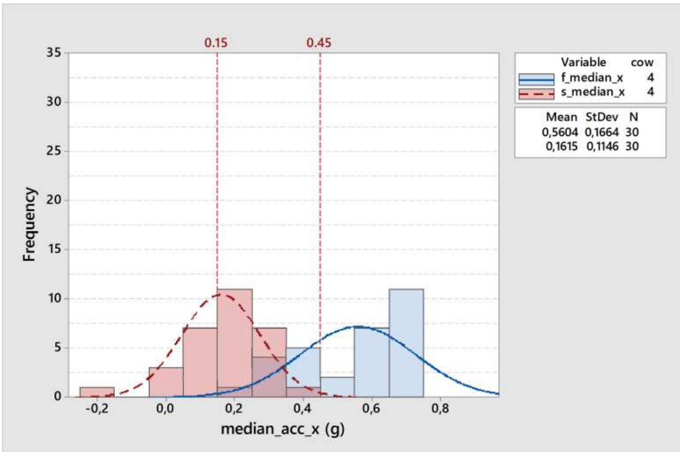
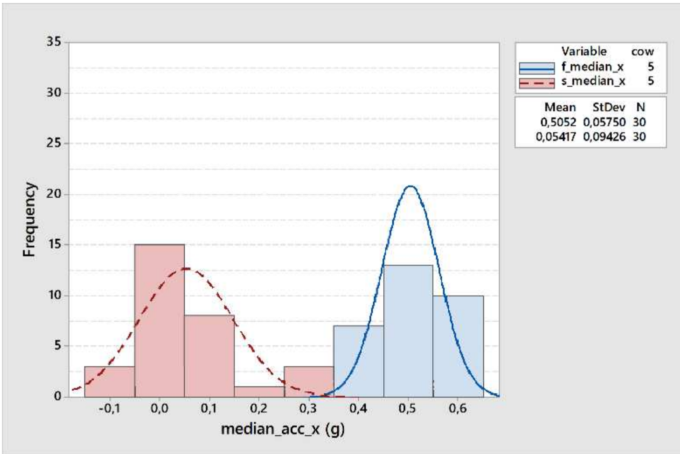


Figure 22. Distributions of the medians of standing and feeding samples for the cow with ID 5.



From the comparison of these diagrams (Figure 18 to Figure 22), it can be highlighted that there is no overlapping between the distributions of the medians of the standing and feeding samples for the cows with IDs 1, 2 , and 5, whereas overlapping is found for cows with IDs 3 and 4. In detail, five standing samples related to cow with ID 3 are contained within the x-axis interval (0.25 g - 0.55 g) and, therefore, they fall into the distribution of feeding samples. Twelve samples, of which six are related to the standing and six to the feeding, overlap in the *x*-axis interval (0.15 g - 0.45 g) for the cow with ID 4.

5.3 <u>*The design of the automated monitoring system*</u>

In the design of the automated system suitable for continuous monitoring the main behaviours of dairy cows (*objective* 1), the phase of detection of these behaviours is based on the use of acceleration thresholds. In detail, the following thresholds were considered:

- The acceleration threshold, named th_{stand} hereafter, was determined by Darr and Epperson (2009) for standing and lying behaviour discrimination.
- The acceleration thresholds, named (th_{movx}, th_{movy}, th_{movz}) and (th_{walkx}, th_{walky}, th_{walkz}) hereafter, were proposed by Arcidiacono et al. (2015) and were validated for the recognition of small movements of the cow's leg and for the recognition of walking, respectively.
- The acceleration threshold th_{mod}, computed in this PhD work, is suitable for step counting during the walking activity of the cow.
- The acceleration threshold th_{feed}, computed in this PhD work, is suitable for feeding recognition when the cow is in standing.

Besides the recognition phase, the system includes two other phases aimed at producing useful information for the farmer, by using the raw data obtained from the wearable sensors located on the cow's body. Each one of these phases was carried out by using a module of the system, which is described in the following sub-sections.

5.3.1 The data acquisition system

During my PhD studies, the first version of the data acquisition system proposed by Arcidiacono et al. (2015) was improved with new features. The new version of the firmware, uploaded into the SensorTag devices, make it possible to disable the ‘*sleep mode*’, which switches off the device after an idle period of 180 s. Furthermore, the data

acquisition software, initially implemented in a single Python script file, was totally re-engineered and developed using multi-files according to the principles of *Software Engineering*. Finally, the connection and re-connection phases were managed thorough a *queue* (*First In First Out* data structure), which allowed for a correct synchronisation of the processes.
Table 14 shows the amounts of data, measured in Mbyte, acquired and stored for each SensorTag during the time interval of the experiment (5 hours).

Table 14 . Stored data from each SensorTag and the relative percentage referred to the theoretical acquirable amount of data during the time interval of the experiment.

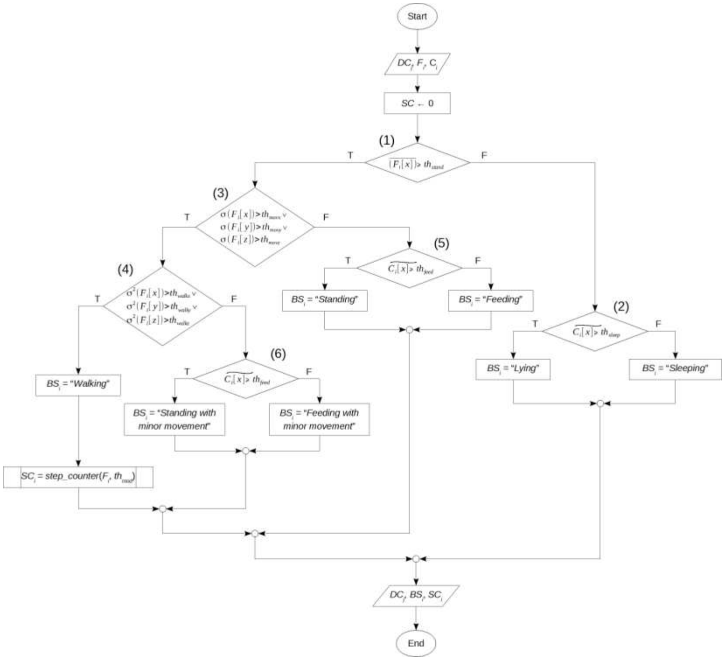
	Foot Accelerometer [MByte]	*Neck Accelerometer* [MByte]	*Total per cow* [Mbyte]
Dairy Cow ID 1	1.78 (51.3%)	2.79 (80.4%)	4.57
Dairy Cow ID 2	2.16 (62.2%)	2.87 (82.7%)	5.03
Dairy Cow ID 3	2.85 (82.1%)	2.89 (83.3%)	5.74
Dairy Cow ID 4	1.82 (52.4%)	2.89 (83.3%)	4.71
Dairy Cow ID 5	2.55 (73.5%)	2.96 (85.3%)	5.51
Total [MByte]	11.16	14.40	25.56

For each device, this amount of data is also reported in percentage referred to the theoretical amount of stored data for the whole duration of the experiment (3.47 MByte for each device). During the lying behavioural activities, the signal of the SensorTags attached to the cows' legs were often absorbed by the animal's body, therefore the amount of data acquired from the foot sensors is always less than the amount of data acquired from the related neck sensor. Since the lying activity affected the communication between the foot sensor and the single board computer for long periods, the indicator *SDI* of the performance of the data acquisition system was calculated by taking into account only the amounts of data from the collar sensors. The value of SDI was equal to 83%.

5.3.2 The algorithm for behaviour recognition

The values of the acceleration thresholds reported in the literature and those reported in this study allowed the design of a novel automated system for the recognition of dairy cows behavioural activities (i.e., *lying*, *standing*, *walking*, and *feeding*). The algorithm of this automated system is illustrated in the flow chart of Figure 23.

Figure 23. The algorithm of the automated system for the recognition of cow's behaviours.



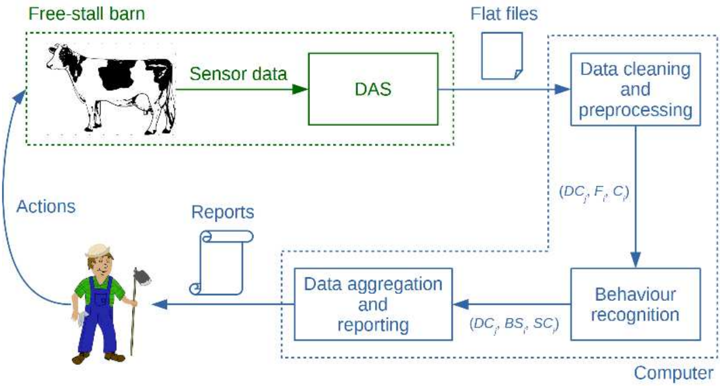
In detail, let *m* the number of cows bred in the free-stall barn and DC_j, $j = 1 \ldots m$, the *j*-th cow of the herd. The algorithm required two 5-s samples as input for each DC_j, i.e., the F_i sample (*i*-th acceleration sample acquired by the sensor fixed to the cow's leg) and C_i sample (*i*-th acceleration sample acquired by the sensor fixed to the cow's collar), where $i = 1 \ldots n$ and *n* is the number of samples acquired during one day (24 h). When the algorithm ends its computation, it will give two outputs. They are the *behavioural state* (*BS*), attributed to DC_j during the 5-s sample (i.e., '*lying*', '*standing*',

‘*standing with minor movement*’, ‘*feeding*’, ‘*feeding with minor movement*’, and ‘*walking*’) and the *step count*, *SC*, if the ‘*walking*’ behavioural state (*BS* = ‘*walking*’) was recognised.
In detail, the check of the condition (1) in Figure 23, where $\overline{(F_i[x])}$ is the mean value of the accelerations along the x-axis and th_{stand} is equal to 0.5 g, determines if the cow is in standing or in lying. If the cow is in *lying*, the sub-sequent condition (2) is also verified, where $\widetilde{C_i[x]}$ is the median value of the accelerations along the x-axis and th_{sleep} is a threshold suitable to determine if the cow is in *sleeping* or not. This threshold was defined but it has not been computed yet (Section 6.3).
If the cow is in standing, the condition (3) is used to detect minor movement of the leg (Arcidiacono et al., 2015), and the condition (4) is used to detect the walking of the cow (Arcidiacono et al., 2015). In this last case, the behaviour state was set to ‘*walking*’ (*BS* = “*walking*”) and the step counting algorithm is used to obtain the step count, *SC*, of the cow DC_j during the sample F_i by using th_{mod} equal to 1.198 g. Finally, again in the case of still standing posture, the conditions (5) and (6) were used to recognise the feeding activity by using th_{feed} equal to 0.276 g.

5.3.3 The overall design of the automated monitoring system

After the description of the two main modules, i.e., the data acquisition system and the algorithm for the recognition of cow’s behaviours, it was possible to describe the overall design of the automated monitoring system (*objective* 1) through Figure 24.

Figure 24. The design of the automated monitoring system for a free-stall barn.



In Figure 24 two other modules are the ‘*Data cleaning and pre-processing*’ and the ‘*Data aggregation and reporting*’. The ‘*Data cleaning and pre-processing*’ module performs *cleaning* and *pre-processing* activities on the flat files received from the data acquisition system, i.e. the data files in `.cvs` format and the log files.

Looking at disconnection periods reported on the log files, this module should *clean* the data files from inconsistent or partial data. For instance, if only the acceleration data from the collar sensor is available, due to a disconnection of the leg sensor for a period of time, the module should mark the samples of such period as *unknown behavioural activity*.

Furthermore, the second main task of this module is the *pre-processing* of the data stored in the flat files to achieve the integration with the next module, i.e., ‘*Behaviour recognition*’. For each cow DC_j, where j = 1 … m, the acceleration data retrieved from the SensorTag attached to the cow's leg was splitted in 5-s subsequent samples: $F_1, \ldots, F_n$. In the same way, the acceleration data retrieved from the SensorTag attached to the cow's collar was splitted in 5-s subsequent samples: $C_1, \ldots, C_n$. At this point, the process sends the tuple (DC_j, F_i, C_i) to the algorithm for cow's behaviour recognition.

Since the algorithm for behaviour recognition, reported in Section 5.3.2, gives as output the tuple (DC_j, BS_i, SC_i), i.e. the predicted behavioural activity of the cow DC_j during the i-th 5-s sample, and this result is not a valuable information for the farmer, an additional module was required: '*Data aggregation and reporting*'. The processes of this module store each one of such tuples in a data structure, i.e, a table of a database (Table 15).

Table 15. Collection of 5-s samples related to the predicted behaviours for each cow.

Cow	*BS*	*SC*
…	…	…
DC_5	'*standing*'	0
DC_5	'*standing*'	0
DC_5	'*walking*'	2
DC_2	'*standing*'	0
DC_2	'*standing*'	0
DC_2	'*lying*'	0
DC_5	'*walking*'	3
DC_2	'*lying*'	0
DC_5	'*feeding*'	0
DC_5	'*feeding*'	0
DC_2	'*lying*'	0
DC_5	'*feeding*'	0
…	…	…

After this phase, the aggregation of the data reported in Table 15 is performed by grouping per cow and behaviour, as shown in Table 16.

Table 16. Report of behaviour duration and step count for each cow.

Dairy Cow	*Lying* [s]	*Standing* [s]	*Feeding* [s]	*Walking* [*s*]	*Step count*
…	…	…	…	…	…
DC_2	15	10	0	0	0
…	…	…	…	…	…
DC_5	0	10	15	10	5
…	…	…	…	…	…

In the example shown in Table 16, the duration of each behaviour is measured in seconds. This choice was made to clarify the aggregation process, which is crucial to obtain valuable information from the data reported in Table 15. Certainly, when the information reported in Table 16 is referred to the whole day (24 h), a measure in hours (h) and/or minutes (m) for the duration of each behaviour should be more appropriate. In this way, the information presented in the final report could be compared with the typical daily time budget for a lactating dairy cow (Grant and Albright, 2000).

5.4 *Feasibility study on gyroscope and barometer sensors*

5.4.1 *The gyroscope data during cow's walking activity*

During the phases of data acquisition and data analysis (June-July 2016), the gyroscope sensor of the SensorTag devices, fixed to cows' leg, was also considered. Figure 25 and Figure 26 show a comparison between the accelerometer data and the gyroscope data during the same walking period, from 14:03:52 to 14:04:12, for the cow with ID 2.

Figure 25. Graph of *acc_sma_{xy}* variable for cow with ID 2 from 14:03:52 to 14:04:12.

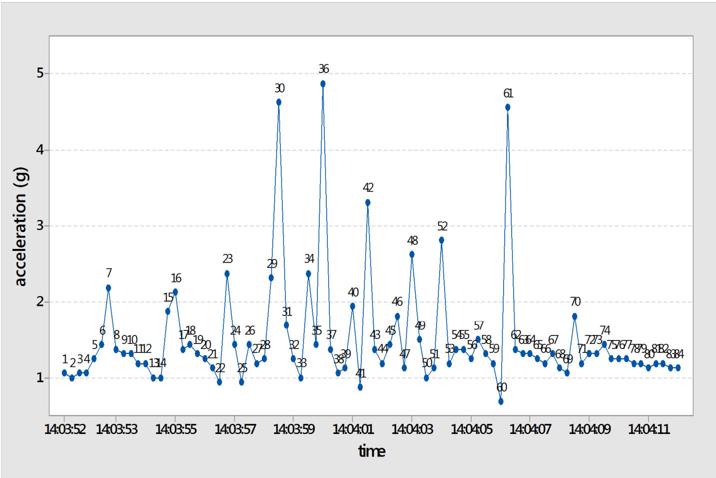
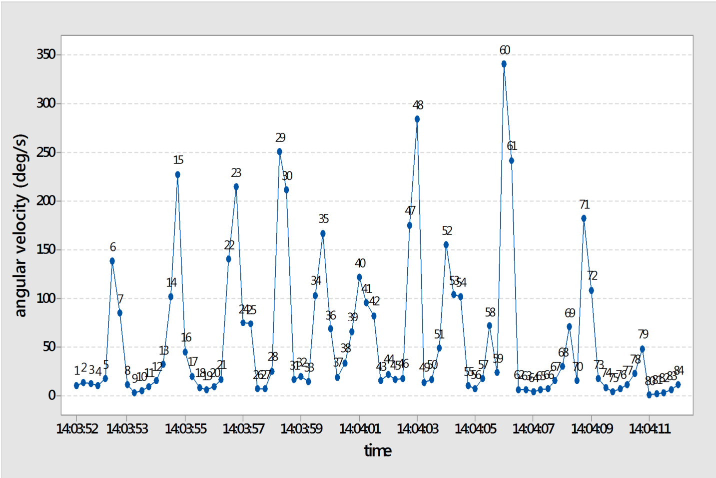


Figure 26. Graph of *gyr_sma$_{xy}$* variable for the cow with ID 2 from 14:03:52 to 14:04:12.



The video recordings showed the cow with ID 2 executed exactly 8 steps during this walking period, while the step counting algorithm, Alg_{sma}, predicted 9 steps. Figure 26 demonstrated that a similar statistical analysis used to define the accelerometer thresholds th_{mod} and th_{sma}, could be used for defining *angular velocity thresholds* (*deg*/*s*). For instance, by setting an angular velocity threshold at 100 deg/s, the algorithm will predict 10 steps for the reported period (Figure 26).

This comparison was completed with a further test regarding the measure of battery life duration in different configurations of the SensorTag (Table 17).

Table 17. A comparison of the battery life duration of the SensorTag using different combinations of sensors.

	Accelerometer	*Gyroscope*	*Accelerometer and Gyroscope*
Battery duration (days)	12	5	3

5.4.2 *The barometer data and the gyroscope data during cows' feeding activity*

Since the barometer built in the SensorTag device was able to measure the change in atmospheric pressure, it could reveal change in the height of the animal head during the feeding activity, if it was fixed to the cow's collar.
The first trial was conducted in laboratory. TablesTable 18 toTable 25 reported the *Anova tests* (Tukey test; CI = 95%) performed on 5 SensorTags placed, at the same time, at different heights from the ground, i.e., from 140 cm to 70 cm at steps of 10 cm (8 trials). All the sensors worked at 1 Hz of sampling frequency and for 1 min for each height.

Table 18. ***Anova tests* (Tukey test; CI = 95%) performed on 5 SensorTags placed 140 cm high from the ground.**

F	*M*	*G*
sAD	1000,700	A
s54	999,900	B
sCB	999,768	C
s3D	999,501	D
s2A	999,198	E

Table 19. ***Anova tests* (Tukey test; CI = 95%) performed on 5 SensorTags placed 130 cm high from the ground.**

F	*M*	*G*
sAD	1000,450	A
s54	999,534	B
sCB	999,507	B
s3D	999,141	C
s2A	998,917	D

Table 20. ***Anova tests* (Tukey test; CI = 95%) performed on 5 SensorTags placed 120 cm high from the ground.**

F	*M*	*G*
sAD	1000,600	A
s54	999,687	B
sCB	999,624	C
s3D	999,280	D
s2A	999,021	E

Table 21. ***Anova tests* (Tukey test; CI = 95%) performed on 5 SensorTags placed 110 cm high from the ground.**

F	*M*	*G*
sAD	1000,640	A
s54	999,730	B
sCB	999,728	B
s3D	999,327	C
s2A	999,119	D

Table 22. ***Anova tests* (Tukey test; CI = 95%) performed on 5 SensorTags placed 100 cm high from the ground..**

F	*M*	*G*
sAD	1000,550	A
s54	999,692	B
sCB	999,620	C
s3D	999,251	D
s2A	999,017	E

Table 23. ***Anova tests* (Tukey test; CI = 95%) performed on 5 SensorTags placed 90 cm high from the ground..**

F	*M*	*G*
sAD	1000,58	A
s54	999,708	B
sCB	999,634	C
s3D	999,247	D
s2A	999,025	E

Table 24. ***Anova tests* (Tukey test; CI = 95%) performed on 5 SensorTags placed 80 cm high from the ground..**

F	M	G
sAD	1000,60	A
s54	999,661	B
sCB	999,606	C
s3D	999,241	D
s2A	999,007	E

Table 25. ***Anova tests* (Tukey test; CI = 95%) performed on 5 SensorTags placed 70 cm high from the ground.**

F	M	G
sAD	1000,55	A
s54	999,645	B
sCB	999,619	B
s3D	999,217	C
s2A	998,994	D

The comparison of the tables shows that, in each of the eight trials, the five sensors did not belong to the same grouping, so their measures obtained at the same height are significantly different.

This investigation proceeded with a further Anova test, performed on each SensorTag individually, at the different heights analysed. The Anova test grouped measures of different heights by assigning the same label (e.g., in Table 28, the measures obtained from SensorTag ‘s2A’ at 90 cm, 120 cm, 100 cm, 80 cm and 70 were labelled with the same letter ‘C’)

Table 26. ***Anova tests*** **(Tukey test; CI = 95%) performed on SensorTag s54.**

F	*M*	*G*
140 cm	999,900	A
110 cm	999,730	B
90 cm	999,708	B C
100 cm	999,692	C D
120 cm	999,687	C D
80 cm	999,661	D E
70 cm	999,645	E
130cm	999,534	F

Table 27. ***Anova tests*** **(Tukey test; CI = 95%) performed on SensorTag sAD.**

F	*M*	*G*
140cm	1000,70	A
110cm	1000,64	B
80cm	1000,60	C
120cm	1000,60	C
90cm	1000,58	C D
70cm	1000,55	D
100cm	1000,55	D
130cm	1000,45	E

Table 28. ***Anova tests*** **(Tukey test; CI = 95%) performed on SensorTag s2A.**

F	*M*	*G*
140cm	999,198	A
110cm	999,119	B
90cm	999,025	C
120cm	999,021	C
100cm	999,017	C
80cm	999,007	C
70cm	998,994	C
130cm	998,917	D

Table 29. ***Anova tests*** **(Tukey test; CI = 95%) performed on SensorTag sCB.**

F	*M*	*G*
140cm	999,768	A
110cm	999,728	B
90cm	999,634	C
120cm	999,624	C
100cm	999,620	C
70cm	999,619	C
80cm	999,606	C
130cm	999,507	D

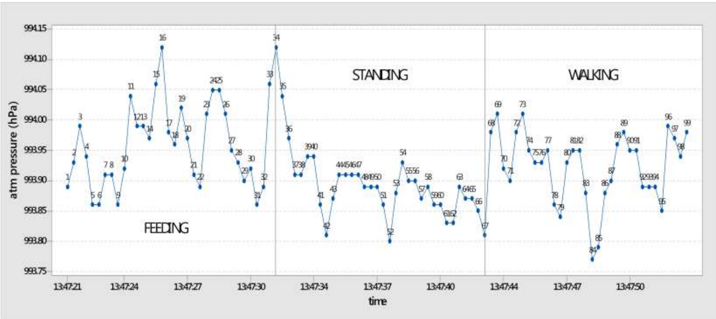
Table 30. ***Anova tests* (Tukey test; CI = 95%) performed on SensorTag s3D.**

F	*M*	*G*
140cm	999,501	A
110cm	999,327	B
120cm	999,280	C
100cm	999,251	C D
90cm	999,247	C D
80cm	999,241	D
70cm	999,217	D
130cm	999,141	E

Therefore, the tests performed in the laboratory proved that the detection of the height of the cow's head by using the barometer cannot be achieved with a single measure of the atmospheric pressure. Instead, a better approach should take into account the change in the atmospheric pressure during behaviour transitions (i.e,, from standing to feeding or vice versa).

To this aim, a test was conducted in the free-stall barn by using a SensorTag fixed to the cow's collar. In detail, Figure 27 shows 99 consecutive measures of the barometer (33 during the feeding, 33 during the standing, and 33 during the walking) collected in the time interval between 13:47:21 and 13:47:53.

Figure 27. A graph of atmospheric pressure data during transitions between different behavioural activities.



The outcomes of the Anova test (Tukey test and CI 95%) conducted on the data shown in Figure 27 were reported in Table 31. The group of measures acquired by the barometer during the feeding activity was labelled with the letter ‘A’, whereas the letter (‘B’) was assigned to both the group of measures of the standing activity and the group of measures of the walking activity.

Table 31. Anova test on the groups of measures acquired by the barometer.

Behaviour	*N*	*Mean*	*Grouping*
Feeding	33	993,958	A
Standing	33	993,920	B
Walking	33	993,896	B

The above period was also analysed through the plotting of the *x*-axis of the accelerometer (Figure 28) and the plotting of the *x*-axis of the gyroscope (Figure 29).

Figure 28. A graph of the accelerometer x-axis (acc_x) during different behavioural activities.

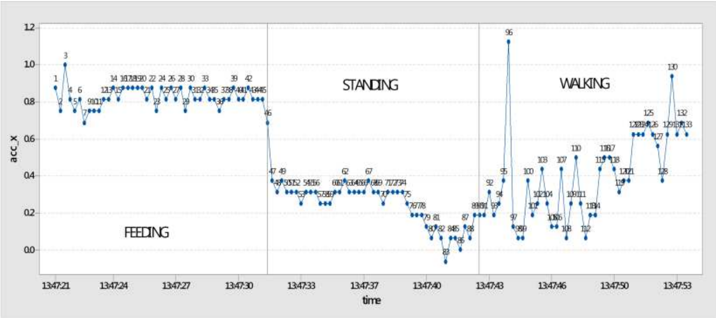
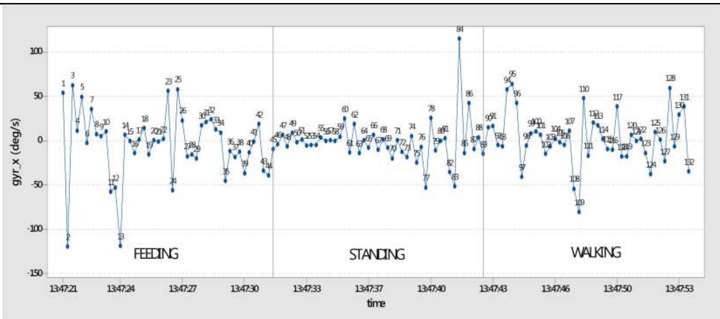


Figure 29. A graph of the x-axis of gyroscope (gyr_x) during different behavioural activities.



It is evident that the x-axis of accelerometer describes the change in behaviour, i.e. from feeding to standing and from standing to walking, more clearly than the x-axis of the gyroscope.

6 Discussion

6.1 The walking activity and the step counting

6.1.1 Memory and time complexity analysis of the algorithm

The analysis of an algorithm involves the computation of the required resources in terms of *occupied memory* and *computational time* (Cormen et al., 2001). Concerning the occupied memory, it is possible to sum up the memory size, measured in bytes, that is occupied by each variable of the algorithm (Table 32).

Table 32 - Algorithm memory usage.

Variable	*Type*	*Size* [Byte]
current_observation	int	4
last_peak	int	4
step_counter	int	4
acc_x	float	4
acc_y	float	4
mod_xy (or sma_xy)	float	4
Total		24

The results of this computation, expressed in bytes, are reported in the 'Size' column of Table 32 and were obtained by the Python instructions '`ctypes.sizeof(ctypes.c_int)`' and '`ctypes.sizeof(ctypes.c_float)`'. The total amount of occupied space resulted equal to 24 bytes.

The estimation of computational time $T(n)$ is also of interest. This is defined as the number of statements of the algorithm that are executed for the output computation, in relation to the input dimension. By utilising the asymptotic notations introduced by Cormen et al. (2001), who proposed to assign a cost to each instruction and take into account the number n of times that each instruction is executed, it was found that the algorithm has a linear computational time for high values of n, i.e., $T(n) = \Theta(n)$ where $\Theta(n)$ is the asymptotic notation.

6.1.2 Real-time application of the system

Since the methodology for the identification of cow's steps proposed in this study was specifically studied for possible applications in RTC, no data pre-processing was conducted. This phase could be avoided because data obtained by the SensorTags in the field experiment proved to be noiseless and without outliers. This condition avoided the application of filters to eliminate undesired peaks or anomalous values, during the data analysis. Furthermore, the sampling frequency of just 4 Hz reduced the amount of data to be processed for each SensorTag connected to the system. This acquisition frequency was suitable to detect each step within the 5-s walking samples as verified by visual assessment of video recordings.

Finally, in this study, the use of thresholds, which is a widely used approach in the literature, simplified the methodology in comparison to the use of *SVM* or *ANN* (*Artificial Neural Network*) models that require a higher computational complexity. Moreover, the Alg_{sma} offers the advantage of computing the intensity of the acceleration as a summation of the acceleration components in absolute value; at a computational level, this advantage involves the execution of basic operations such as switching the bit related to the sign of the variables acc_x and acc_y when necessary and execute the sum of their values.

6.1.3 Comparison with literature results

The comparison with literature results proved that the computation of the values of the acceleration thresholds, within step counter algorithms, was one of the novelties of this study, because they have not been reported elsewhere until now.
Some authors (Alsaaod et al., 2015) have recently issued the results of the validation of a new version of the RumiWatch Algorithm. Since the RumiWatch Algorithm was not reported in the study of Alsaaod et al. (2015), it was not fully possible to compare the performance of the RumiWatch Algorithm with that of the algorithm proposed in this study. The experimental activity was carried out on 21 cows, which were forced to walk and video-recorded for a time interval greater than 10 minutes in order to validate the number of cow steps computed by RumiWatch Algorithm. Therefore, their goal only partially overlapped mine because their objective was to count the steps of the cows without defining any thresholds for acceleration data. The same length of the time interval adopted to validate the RumiWatch Algorithm was not considered in this study because due to the forced walking activity the acceleration values were not representative of the daily walking activity of the cows.
In Alsaaod et al. (2015) only the *RME* was considered for analysing the error of the algorithm. Differently from this study, the *RME* values obtained by validating the RumiWatch Algorithm were grouped for each cow and then averaged in

order to obtain an *RME* value equal to 6.23%. This value is higher than that obtained in this study for both the two versions of the algorithm.

Since the RumiWatch Algorithm was not reported, it is only possible to make a hypothesis when comparing the *RME* value obtained by the algorithms. The lower values of *RME* obtained by the two versions of the algorithm proposed in this study were not affected by the group comparison test which discarded some walking samples from the initial dataset. This was proved by the results achieved in the sensitivity analysis. Probably, the *RME* values obtained in this study could be due to the computed thresholds which produced a higher compensation between N_{step}^{c+} and N_{step}^{c-}.

However, *RME* is less robust than *E* when measuring the accuracy of step counter algorithms. In fact, when adding samples that makes the algorithm commit a higher number of errors, it is expected that the values of the error indicators (*E* and *RME*) would increase. On the contrary, in the sensitivity analysis it was found that at adding discarded samples the *RME* decreased while *E* increased.

In the study of Nielsen et al. (2010) the period of standing and walking of 10 dairy cows were quantified by utilising *IceTag* sensors fixed to the hind legs of the animals. The protocol of the experiment involved the succession of standing and walking periods in sequences of about 20 s and a time interval of ~ 10 minutes for each cow. The total number of walking periods were 139 (average duration of 15 s, SD = 9 s, and range of 1-50 s). The Authors utilised the video-recordings to validate the number of steps computed by the software (*IceTagAnalyzer*) and obtained the results reported in Table 33.

Table 33. Basic statistics of the step counting obtained from the algorithms (*IceTagAnalyzer*, *Alg*$_{mod}$, Alg_{sma}) and video-recording analyses; basic statistics of the distributions of the differences between the number of steps detected by each algorithm and that obtained from video-recording (N^{v}_{step}).

		Min	*Max*	*Median*
IceTagAnalyzer	Videorecorded steps	2	20	11.5
	IceTagAnalyzer steps	1	26	7
	Difference steps	-2	+5	0
Alg_{mod}	N^{v}_{step}	1	4	2
	N^{c}_{step}	1	4	2.5
	Difference steps	-1	+1	0
Alg_{sma}	N^{v}_{step}	1	3	2
	N^{c}_{step}	1	3	2
	Difference steps	-1	+2	0

A similar analysis was also conducted in this thesis work and the results obtained by the algorithms Alg_{mod} and Alg_{mod} are presented in Table 33. Though the duration of walking periods, which were utilised in the analyses reported in Table 33, were different, it is remarkable to observe that *IceTagAnalyzer*, Alg_{mod}, and Alg_{sma} obtained medians equal to zero for the difference between the number of detected steps and corresponding ones in the video-recordings. Therefore, since the distributions of this difference had a similar central tendency, the three algorithms showed a similar accuracy.

6.2 The feeding activity

6.2.1 Behaviour misclassification

The visual analysis of the video-recordings related to the cases of feeding misclassification, i.e., samples F_3_1,

F_3_12, and F_4_18, highlighted the following concurrent events for the cows with IDs 3 and 4. In the video-recordings, it was observed that cow’s head was maintained slightly higher than the bottom of the manger; the sensor position in relation to the cow's body axis was modified compared to the initial position, and the cow rotated its head during the feeding activity. These factors affected the acceleration along the *x* axis (acc_x) and, therefore, most of the observations of these samples had lower values than the fixed threshold.
In the cases of standing misclassification (samples S_3_28 and S_3_30), the cows maintained their head down and, therefore, most of the observations of these samples had higher values than the fixed threshold.
The results described in Figure 16 and Figure 17, where all the cows were considered, showed that an acceleration threshold could not be determined without making any misclassification. In this experiment, this was determined by some standing samples that overlapped some feeding samples for cows n. 3 and n. 4, as the analysis of Figures Figure 18 to Figure 22 showed. This occurrence was thought to be depended on a modification of the acceleration values due to a slightly rotation of the sensor compared to its initial position. Actually, in Figure 30 there is evidence of this rotation of the sensor fixed to the collar of the cow with ID 4.

Figure 30. Slightly rotated position of the sensor compared to its initial position.

The modification in the direction of the x-axis of the sensor determined a lower sensibility of the device along this axis, which was able to cause an overlap of the two behaviours in some cases. Therefore, this would explain how most of the classifier’s errors occurred for the behaviours of cows with IDs 3 and 4.

At this regard, Oudshoorn et al. (2013) observed that slight movements of the accelerometer device could increase errors and solved the problem by fixing a threshold for each cow, for the estimation of grazing time. In mine experiment, this choice would not have thoroughly solved the problem since the distributions, reported in Figure 20 and Figure 21, would not allow for fixing a suitable threshold for the samples.

Based on these considerations, the aim of achieving a higher accuracy of behaviour classification would be facilitated by selecting a cow's collar capable of avoiding or at least reducing the rotations of the sensor relative to cow's neck.

6.2.2 Comparisons with the research studies in the field

Several studies have regarded the recognition of cow's feeding activity, however the different environmental conditions of the experiments, different typologies and configurations of the adopted devices make difficult to perform a direct comparison. The experiments were often carried out on grazing animals, i.e., out of a free-stall barn, which was instead considered in this study. Furthermore, in a number of studies stationary systems were utilised, whereas in other studies that considered accelerometer sensors data were acquired with higher sampling frequencies than that proposed in this study (4 Hz).

By using an accelerometer sensor located at the cow's neck and a sampling frequency of 10 Hz, the model presented by some authors (Martiskainen et al., 2009) for the recognition of behavioural patterns obtained lower values of Sensitivity and Precision, respectively equal to 75% and 81% for feeding, compared to the values found for this model. In their experiment, one sensor for each cow was utilised to classify the various behaviours (standing, lying, ruminating, feeding, walking normally and lame walking) by means of a *SVM*. In this field of application where modularity of the system is usual, the use of an *SVM* could reduce the flexibility of the system. For instance, in the hypothesis of utilising two sensors, e.g., one fixed at the collar and the other to the hind leg, the aim of improving the precision of the recognition could be achieved only by training the SVM again. Instead, the choice of a classifier that utilises accelerometer thresholds, as the one proposed in this study, would simplify the use and management of two sensors used to obtain a higher accuracy for the results.

With regard to the utilisation of uniaxial accelerometer devices, Ueda et al. (2011) applied the Kenz Lifecorder EX commercial device (LCEX; Suzuken Co. Ltd., Nogoya, Japan) to eight grazing cows subdivided into three groups. The device, which costs about 245 $, has a sampling frequency of 32 samples/s and produces an output of activity levels from 0 to 10, through a 11-values proprietary scale. The researchers utilised the level 1 (AL_1) as a threshold for 'eating' activity and obtained, in the best case, a misclassification of 5.5%. Therefore, the *MR* of the model proposed in this study was comparable to the best performance of device used by Ueda et al. (2011).

Oudshoorn et al. (2013) determined the accelerometer threshold values based on the analysis of the acceleration time series related to the horizontal forward axis. The experiments were conducted on dairy cows at pasture and the resulted thresholds ranged from -0.40 to -0.48 g with an average value of -0.445 ± 0.025. These results are slightly different from those obtained in this study (th_{feed} = 0.276 g). The opposite sign was due to the different orientation of the *x*-axis of the sensor when applied to the collar while the difference in acceleration threshold value caused by the dissimilar position of the cow's head in the two experiments. Specifically, in this study during the feeding activity cow's head position was higher than for grazing cows due to the building characteristics of the barn. In fact, in the barn there is a difference in the height between the ground of the feeding area, where the cow was in feeding, and the ground of the manger, where the feed was located. The higher position of the head of the cows considered in this study determined a lower value of the acceleration threshold than those obtained by Oudshoorn et al. (2013).

In the study by Ruuska et al. (2015), a new system based on a commercial pressure sensor, named RumiWatch noseband (Itin + Hoch GmbH, Liestal, Switzerland) was assessed by estimating the duration of the 'eating', 'rumination' and 'drinking' activities of dairy cows. The results of the 'eating' activity obtained in the experiment 1 showed a coefficient of determination R^2 = 94% which is higher than that computed in our study. However, since the classified behavioural activities were different from those analysed in this work, it was not fully possible to make a direct comparison of the results. Although Rumiwatch noseband sensor is designed for the classification of cow's behavioural activities that involve chewing and swallowing (eating, rumination and drinking), it could be integrated with other types of sensors to recognise other behaviours such as standing, lying, and walking. However, the implementation of a system that utilises a number of sensors of the same typology to recognise the different behaviours, as the system proposed in this study, would surely be facilitated since it would require a lower effort in the development of the software for the communication module.

By applying a different approach, Porto et al. (2015) carried out a study on the discrimination between feeding and standing activities by using an image recognition system. In this work, the animals did not wear sensors and the recognition of the two behavioural activities was performed by the automated elaboration of the digital images acquired through a video-recording system. The accuracy of the system was assessed by computing the indicators *Sensitivity*, *QP*, *BF*, and *MF*. The values of these indicators for the two systems are compared in Table 34.

Table 34 – Indicators for the image recognition system and the sensor-based system.

	Sensitivity	*QP*	*BF*	*MF*
Porto et al. (2015) *Image recognition system*	87.00%	81.00%	0.08	0.15
This study *Sensor-based system*	93.33%	89.36%	0.05	0.07

The higher *Sensitivity* and *QP* of the sensor-based system compared to those of the stationary system indicated that a higher number of *TP* was found in relation to the real number of samples of the considered behaviour and to the number of classified samples as that behaviour, respectively. The lower *BF* and *MF* implied that a lower number of *FP* and *FN* was respectively found in relation to the *TP*. Therefore, the sensor-based system had a higher accuracy in detecting cow's feeding activity.
Besides a higher accuracy, the proposed system allows for the identification of the animals individually, whereas the image recognition system was unable.

6.3 The automated system proposed

In the literature, several approaches assessed wearable sensors, e.g. the accelerometer, to recognise dairy cows' behaviours. Frequently, such studies aimed at recognising specific behaviours (e.g., standing or lying; standing or feeding; walking analysis) by fixing the sensors to the animal's leg or to the animal's head or neck. Rarely, they attempted to recognise all the main behaviours as done by Martiskainen et al. (2009). Likely, the use of only one sensor per each cow makes difficult to deal with this challenge. For instance, the accelerometer fixed to the cow's leg did not give valuable information about the feeding activity, instead its data was very useful to detect the standing and the lying cow's postures, the period of walking activity, and the step counting. On the other hand, the accelerometer fixed to the animal's head was successfully utilised for the feeding analysis, even if it was not able to detect with accuracy the posture of the animal, i.e., standing or lying, or the step counting. For all these reasons, the automated monitoring system reported in this study was based on two accelerometer sensors per cow.

During the research activities in the free-stall barn, a novel *data acquisition system* was assessed. It revealed robustness and user-friendliness, in fact the installation in a free-stall barn was simpler in comparison to other systems (e.g., systems based on UWB technology), and no calibration was needed. The hardware was *not expensive* since a cost of about 350 € is evaluated for the monitoring of five cows by using two sensors for each of them (in all, ten sensors). Moreover, the Python libraries, which were *free available* on the Web, made easier the implementation of the BLE communication within the software.

The data acquisition system was used with ten SensorTags, which were operating at the same time. No experiment was carried out with a greater number of these devices. At this regards, the *scalability* of the system is an important feature: in fact, when a greater number devices is required, another single board computer could be added to this system. The two single board computers should cooperate by subdividing the tasks needed to retrieve data from a larger number of devices. Moreover, the scalability should also involve the increase of the area of the free-stall barn covered by the *BLE* network. In

this way, when a cow is moving away from the receiver and the devices attached to its body lose the connection with the single board computer, a new connection with another single board computer, closer to the animal, should be established.
Due to the low sampling frequency (4 Hz) of the data acquisition, the *memory occupation* of the proposed system was not high. For instance, by using the results reported in Table 14, the required memory for storing raw data acquired by the ten sensors, which operate simultaneously, for one day (24 h) is around 170 MByte. Therefore, the proposed system allows for a continuous data acquisition for around 30 days by using these settings and an 8 GByte SD Card into the single board computer, where about 3 GByte was already allocated for the operating system. Furthermore, Table 14 shows that for each cow the amount of data acquired by the accelerometer sensor attached to the collar is greater than the amount of data acquired by the accelerometer sensor attached to the leg. This difference was due to two aspects. The first one regards the effect of cow's body on system communication; when the cow was in lying on the its left side, its body absorbed the SensortTag signal, avoiding the communication with the Raspberry Pi. The second one regards pen crowding in intensive farming; when the cow is in standing, the body of the other cows could absorb the signal along the line of sight between the SensorTag fixed to its leg and the Raspberry Pi, thus interrupting the communication.
Of course, some feature of the system can be improved. The ZigBee network, assessed by (Huircán et al., 2010; Nadimi et al., 2012, 2008), appeared to be more robust than the BLE network for this kind of application. Specifically, in a mesh network each node is able to carry data for the network,

therefore the devices can transmit data over a longer distance, from 10 to 100 m, and the availability of the network is assured because it can reconfigure itself around broken paths. Another improvement could be obtained by reducing the sampling frequency of the accelerometer sensor fixed to the cow's collar. In fact, since it was used only to detect the inclination of the animal's head and the data was not used in other analysis, the 4 Hz frequency sample could be decreased to 1 – 2 Hz. This improvement will reduce of around 25 % the memory usage required by the data acquisition system, but also speed-up the next data elaboration performed by the '*Behaviour recognising*' module.
In Section 5.3.3 the overall design of the proposed system was reported. The algorithm for behaviour recognition (Figure 23) used in this system was able to detect the main cow's behaviours (i.e., lying, standing, feeding, and walking) by using acceleration thresholds, which were previously determined through a statistical method. In the literature, such an algorithm was not reported until now. The values of the thresholds (th_{stand}, th_{movx}, th_{movy}, th_{movz}, th_{walkx}, th_{walky}, th_{walkz}, th_{mod}, th_{feed}) were reported either in literature (Darr and Epperson 2009; Arcidiacono et al. 2015) or in this study. However, the value of the threshold th_{sleep} has not been computed yet. At this regard, some authors (Hokkanen et al., 2011) developed a small, neck-based, wireless accelerometer system, fixed to the collar of 10 calves, suitable for measuring the sleep and lying time of calves. The authors extracted 7 feature from each epoch (20 s) and they used a support vector machine classifier (SVM) to predict different sleep stages (REM and NREM) and lying behaviour based on behavioural observations. According to the authors, '*NREM sleep*' is when the calf was resting head up, being still, and '*REM*

sleep' is when the calf was resting neck relaxed, with the head against the floor or flank. Total sleep was a sum of REM and NREM. These definitions could be the basis of a new study for the determination of a new acceleration threshold, th_{sleep}, able to recognise a resting activity with the head against the floor. To achieve this recognition, the branch of the algorithm in Figure 23 will involve the condition (1), with the threshold th_{stand}, to predict the lying posture and then the condition (2), related to th_{sleep}, to determinate the '*REM sleep*' activity.
In the design of the overall system reported in Figure 24, a 'black-box approach' was used to describe each module of the system. Some further considerations can be added about the assessment of an effective hardware setting of the system. Definitely, the setting-up of a single board computer in the data acquisition module was the better choice, considering both the structural and the environmental characteristic of a free-stall barn. The remaining modules, drawn with a blue line, were allocated in a desktop computer sited in another building, e.g. an office room. The desktop computer should receive the data files from the single board computer through a WiFi connection. Nevertheless, with the aim of reducing the cost of the system, another setting up could be considered. In the case of monitoring few animals (a small herd), where the data acquisition process do not require high computational resources, it could be possible to implement the '*Data cleaning and pre-processing*', '*Behaviour recognising*', and '*Data aggregation and reporting*' modules into the single board computer. In this case, the desktop computer is not needed for data elaboration and the '*Data aggregation and reporting*' module should present the information by publishing the reports in a 'web service' installed in the *SBC*.

The farmer should use a mobile device or its own desktop computer to browse these reports.
Finally, an additional discussion could be done for the '*Data aggregation and reporting*' module.
As shown in Figure 24, it receives atomic information, such as a tuple for each 5-s sample per cow, from the '*Behaviour recognising'* module, and then it performs an aggregation process to obtain valuable information. The *granularity* of the data aggregation has a high relevance for the farmer, who carries out actions and processes to maintain a good health state of the dairy cows. Undoubtedly, the daily (24 h) report produces accurate information on the daily animal routine when compared to the typical daily time budget for a lactating dairy cow (Grant and Albright, 2000), but other time intervals for data aggregation could be considered. For instance, the 3 h – 6 h reporting could be useful for the following objectives:

- Detect a very long resting activity of the animal (e.g., lying) due to any illness or disease (e.g., lameness);
- Detect an intensive and increasing restlessness of the animal due to the arising of a physiological state (e.g., oestrus) or social interactions with other cows.

In all these situations, the system should send an alert (i.e., a mobile phone message or an e-mail message) to the farmer.

6.4 The gyroscope and the barometer sensors

The *gyroscope sensor* and the *barometer sensor* were also investigated during my PhD activity (June-July 2016). The graphs reported in Figure 25 and Figure 26 show the signal *SMA* computed on the x-axis and y-axis of the acceleration data and the angular velocity data during the cow's walking activity, respectively. The graph of Figure 26 shows that the

gyroscope data appears suitable to detect the steps of a dairy cow. Unfortunately, this sensor device has a higher power consumption than the accelerometer and it is likely that for this reason no study was reported in the literature on the use of a step counting algorithm based on the gyroscope sensor.
With the aim to investigate the use of the *barometer sensor* for achieving the recognition of different heights of the cow's head during the feeding and standing activities, an experimental data analysis was conducted (Table 31). The results of the statistical test, i.e. group comparison test (Anova test), show a different labelling between the 'feeding group' and the 'standing group'. Of course, this single test cannot demonstrate that the barometer sensor is able to recognise the feeding activity from the standing activity, yet these results encourage for a further more extensive statistical analysis on the data coming from the barometer sensor.
Finally, the graph reported in Figure 29 shows the data acquired from the *x*-axis of the *gyroscope sensor* during the same period. It can be observed that angular velocity variations during feeding activity are similar to the angular velocity variation during walking activity and this similarity made unsuitable the use of gyroscope sensor for detecting the 'feeding' activity from other standing activities (i. e., 'still standing' and 'walking').

7 Conclusions

The main objective of the research activity, which was conducted during my PhD studies, consisted in the design of an automated system for continuous monitoring of dairy cow's behaviours in free-stall barns. It was achieved through the definition of new ICT approaches.
A new data acquisition system, which was based on accelerometer sensors fixed to the dairy cows' body (i.e., neck and hind leg), was developed and assessed in a free-stall barn located in Sicily. It allowed the acquisition of data from different sensors (accelerometer, gyroscope, and barometer), with a sampling frequency of 4 Hz, during the animals' daily routine. The performance index (*SDI*) of this system was equal to 83 %. Moreover, it required a simple installation into the building and it did not need any preliminary calibration. During the data acquisition process the sensor devices did not cause any stress to the animals and their behavioural activities were not forced or influenced by the researchers or by other farm operators.
The walking activity of the dairy cows was analysed by applying rigorous statistical methods on the data that described the change in acceleration values of the cows' leg. This phase of the research made it possible to develop a novel step counting algorithm, based on acceleration thresholds, which was reported in an open source code. The indicator of the total committed error of the algorithm was equal to 9.5%. The same rigorous approach was repeated to the analysis of the feeding activity of the dairy cows, using the acceleration values of the animals' neck. This phase allowed the definition of a classifier, based on acceleration threshold, able to

recognise the feeding activity from the standing activity. The misclassification rate of the classifier was equal to 5.56%.
The automated system for continuous monitoring of dairy cow, proposed in this thesis work, was designed by using low cost devices, such as wearable sensors and single board computers, and open source software. These features of the system would have a crucial relevance in developing countries. Furthermore, the application of two accelerometer sensors per each dairy cow allowed for the recognition of the main behaviours (lying, standing, feeding, and walking). Instead, systems based on the use of a pedometer are not suitable for acquiring accurate information about the feeding activity. Similarly, other systems based on wearable sensors attached to the cow's head, though attempting to give information on walking activity, do not generally give accurate information and are not suitable for step counting. A unique system able to monitor different behaviours would give relevant benefits to the farmer. Among the main advantages of this kind of systems, the ability of the system to acquire and store useful data as well as send alerts for the early detection of any unusual event or disease would provide a reduction of the time spent for observing the animal and a decrease of the management costs. The criticalities of a unique system would regard the discrimination of other specific behaviours, such as chewing with bite counting, rumination, and drinking. Future enhancements of a unique system would regard the recognition of these specific behaviours. Further improvements of the proposed system would involve the utilisation of a different wireless communication protocol.
In this thesis work, ICT was applied to livestock farming by exploiting the integration of my knowledge in Computer

Science with the research studies in the PhD course of '*Agricultural, food and environmental science*'. In multi-disciplinary studies in this fields, other scenarios open up, such as the new emerging computing concept, based on a new level of networking, i.e., machine-to-machine (M2M) communications. In these scenarios, smart objects and a wide variety of devices will be able to exchange information and share computing services. Sensors, actuators, RFID tags, Real-Time Location Systems, and mobile devices will become the resources for new uses, new computation approaches, and a new way of farming. Since the animal welfare and quality of livestock production take primary relevance in PLF, new ICT services as well as micro/nano electronic devices will support the decisions of the farmer and other stakeholders to achieve the requested standards. In this context, the research activity that I developed and completed during my PhD is tightly connected to the most up-to-date applications of ICT to animal housing. It attempted to provide elements of innovation and make advances in the field by addressing the most crucial issues of the stakeholders and the needs of the farmers.

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