Embedded system for real-time monitoring of foraging behavior of grazing cattle using acoustic signals

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Abstract

Estimating forage intake and monitoring behavior of grazing livestock are difficult tasks. Real-time detection and classification of events like chew, bite and chew-bite are necessary to estimate that information. It is well-known that acoustic monitoring is one of the best ways to characterize feeding behavior in ruminants. Although several methods have been developed to detect and classify events, their implementation is restricted to desktop computers, fact that confines their application to off-line analysis of a reduced number of animals. In this work, we present the design and implementation of an electronic system specifically developed for real-time monitoring of feeding patterns in dairy cows. The system is based on an embedded circuit to process the sound produced by the animal in order to detect, classify and quantify events of ruminant feeding behavior. The system implements an algorithm recently developed, which was adapted to be executed on a

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microcontroller-based electronic system. Only the results of sound analysis are stored in flash memory units. In addition to sound information, data from a GPS receiver is also stored, thus building a package of information. A microcontroller with power management technology, combined with a high-efficiency harvesting power supply and power management firmware, enables long operational time (more than five days of continuous operation). The system was evaluated using audio signals derived from the feeding activity of dairy cows that were acquired under normal operational conditions. The system correctly detected 92% of the events (i.e. considering them as possible events without making a classification). When the three types of events (i.e. chew, bite and chew-bite) were considered for classification, the recognition rate was about 78%. These results were obtained using reference labels provided by experts in ruminant ingestive behavior. The technology presented within this publication is protected under the international patent application PCT/IB2015/053721.

Keywords: Acoustic monitoring, real-time operation, embedded system, microcontroller.

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1. Introduction

The global dairy industry has undergone profound changes over recent decades in the world. There is a trend in dairy farming toward the automation of processes to reduce the labor and its associated costs (de Koning, 2011). This development is mainly driven by the increment of labor costs relative to capital costs. Automated systems enable dairy farmers to manage larger herds with lower labor requirements and costs (de Koning, 2011). This trend toward automation is suitable for the tendency of increasing herd sizes.

The behavior of animals is a clear indicator of their physiological and physical state (Frost et al., 1997). Eating, ruminating and resting are the main daily activities of ruminant livestock (Hancock, 1954). Monitoring these activities in the field is essential to crucial management decisions in grazing systems. This information allows herd managers to evaluate the feeding conditions of grazing cattle and make decisions about supplement and pasture management. Furthermore, accurate monitoring of foraging behavior of free-grazing cattle is necessary to ensure the welfare and health of these animals. Many efforts have been devoted to develop suitable techniques to address this problem, however the success of these developments has been limited by practical factors (Hodgson et al., 1996; Delagarde et al., 1999).

One approach for studying the grazing behavior uses acoustic monitoring. Laca et al. (1992) used acoustic monitoring to study the short-term grazing behavior of cattle, the microphone was mounted on the forehead of the animal facing inward. The head bones amplify the ingestive sounds (apprehension and chewing) produced in the oral cavity. Thus, the clarity of the signal obtained allows to detect and classify all jaw movements with high accuracy and reliability (Clapham et al., 2011; Milone et al., 2012; Navon et al., 2013; Chelotti et al., 2016). All reported applications have involved fresh herbage; obtaining promising results about estimation of intake (Laca et al., 2000; Rutter et al., 2002; Ungar and Rutter, 2006; Galli et al., 2006, 2011).

One of the most accepted ways to perform monitoring of ruminant feeding is through the detection of the three most common events of grazing activity: chew, bite and composed chew-bite. Biting includes the apprehension and saving of forage, while chewing action includes the crushing of forage. There is also another event resulting from the superposition of chewing and biting activities but made with the same jaw movement and called chew-bite. The detection and classification of these three types of events is necessary for accurate monitoring of the diet of animals. In this sense, there are few authors who have taken into account the detection and classification of these events, because of the complexity of discriminating the events, especially in noisy environments (Milone et al., 2012; Chelotti et al., 2016).

The procedure followed to monitoring the ruminant feeding activities has two steps: i) the sound is recorded and stored using a commercial sound recording device, and then ii) the recorded sounds are analyzed in a desktop computer (Clapham et al., 2011; Milone et al., 2012; Lynch et al., 2013; Chelotti et al., 2016). For short time experiments (Clapham et al., 2011; Milone et al., 2012; Chelotti et al., 2016) the recording devices are not modified. For long-term experiments the recording devices are modified to enlarge their autonomy. For example, Lynch et al. (2013) added five lithium-thionyl-chloride 3.6 V AA batteries to the commercial recorder, which allows 330 h of autonomy for each device.

The relevance of recording data, in term of resource management and animal welfare, for long periods of time has lead to the development of devices and wireless sensor networks for agriculture applications (Abbasi et al., 2014). In the recent years, several devices have been developed. For example, Greenwood et al. (2014) discussed the challenges of hardware and software for wireless sensor networks development required for the collection of data from different types of sensors, the management and analyses of the very large volumes of data. Then, they developed pasture intake research platform to provide detailed estimates of pasture consumption by individual animals through chemical markers and biomass disappearance, reinforced with video recordings of animal behaviors. Panckhurst et al. (2015) developed a position tracking system for livestock compose by a solar-powered sensor tag and a base station. The system is able to provide a configurable wireless connection triggered and managed by the base station, reducing the overall power consumption of the tags and allowing typical transmission range of 500 m.

In spite of all these recent developments, to the best to our knowledge, there is no portable device able of analyze in real-time the sounds produced by ruminants to detect and classify grazing events. Given the high cost involved in storing and transmitting large volumes of data, there is a need for a system capable of performing on-line processing and storing the statistical results in text files. Therefore, there exists a need to develop sensor technology for monitoring animal feeding activities in real-time while withstanding their environment. Following advances in electronics we developed and built an electronic device, consisting of a directional electret microphone, a solar panel, rechargeable batteries and an electronic circuit with small form factor that can be stored in a small case, and it is also able to operate long-terms under any weather condition. The embedded device introduced in this work has the advantages of easier mounting to the animal, lack of complex wiring between sensors and device, low weight and small form factor.

The paper is organized as follows: Section 2 introduces the developed embedded system, describing the hardware architecture and software organization. The implementation of the algorithm is discussed at the end of this section. The database used and methods employed to validate the system operation are introduced in Section 3. The results obtained from the operation of the embedded system are presented and discussed in Section 4. Finally, the conclusions are given in Section 5.

2. Material and methods

An embedded processing system was developed to estimate the representative parameters of animal feeding behavior by processing the sounds produced by the animal during its feeding activities (i.e., ruminating and grazing) and storing the corresponding statistical results. The signal processing and analysis are performed in a microcontroller that implements the detection and classification algorithm proposed by Chelotti et al. (2016) in combination with signal processing for signal conditioning. The microphone capture the sound that is conditioned and processed within the microcontroller and the information obtained is stored in a flash memory. The microphone is placed on the forehead of the animal, covered by a rubber band that protects the microphone from adverse weather conditions (e.g., wind, rain) and attenuates the external noises. The device is located on the neck just behind the head, to prevent the impacts from another animal, while the connection with the microphone is short (Figure 1).

The parameters of animal feeding activity are obtained by detecting and then identifying the type of event (chew, chew-bite or bite) and quantifying its parameters (number of events, duration, energy, amplitude). These information is accumulated during a period of five minutes and integrated with the time and position of the animal into a package of information. Then,

(a) (b)

Figure 1: (a) Microphone and device location and (b) the developed device.

this package is stored into a flash memory and communicated to the system through a configurable wireless connection managed by a base station, thus reducing the overall power consumption of the tags and allowing typical transmission of 500 m.

2.1. The embedded design

A microcontroller (MCF51JM128, NXP Semiconductors) was chosen for this application based on its availability in the local market, power consumption, computational power, analog ports, communication resources (SPI, USART and USB), internal clocking resources and a real-time clock module. The sound produced by the animal is sensed with an electret microphone facing inward on his forehead (Figure 1.a). The signal produced by the microphone is conditioned by an analog circuit that limits the signal bandwidth, in order to maximizes the signal-to-noise ratio (SNR). This circuit is comprised three stages (Figure 2):

1. A low-pass filter that limits the signal bandwidth to 1 kHz, in order to be able to subsample the signal and reduce the computational load of subsequent stages. It is implemented through a cascade of four second order filters (TLV2784, Texas Instruments Inc) following a Sallen-key topology,
2. An amplifier with AGC (MAX9814, Maxim Integrated) applies an automatic controlled amplification to signal in order to maximizes the SNR, avoiding signal distortions and clipping produced by high gain amplifications. The value of gain is available through an analog pin and it allows to normalize to obtain the true value of energy, and
3. A level shifter (TLV2781, Texas Instruments Inc) that changes the mean of the signal from 0 V to 1.65 V, to obtain a signal in the range between 0 V and 3.3 V, that can be processed by an analog-to-digital converter (ADC).

The output of the level shifter is coupled with one analog input of the microcontroller connected to a 8 bits ADC. The number resulting from the conversion includes information of the sign of the signal and its range goes from -128 for the minimum voltage and +127 for the maximum voltage of the signal. This data is used by the detection and classification algorithms. The GPS provides the time, date and position to tag each package of information.

A primary regulated 3.6 V power supply is provided to the system through a high-efficiency buck/boost charge pump regulator (TPS63000, Texas Instruments Inc). This converter was chosen because of its ability to regulate

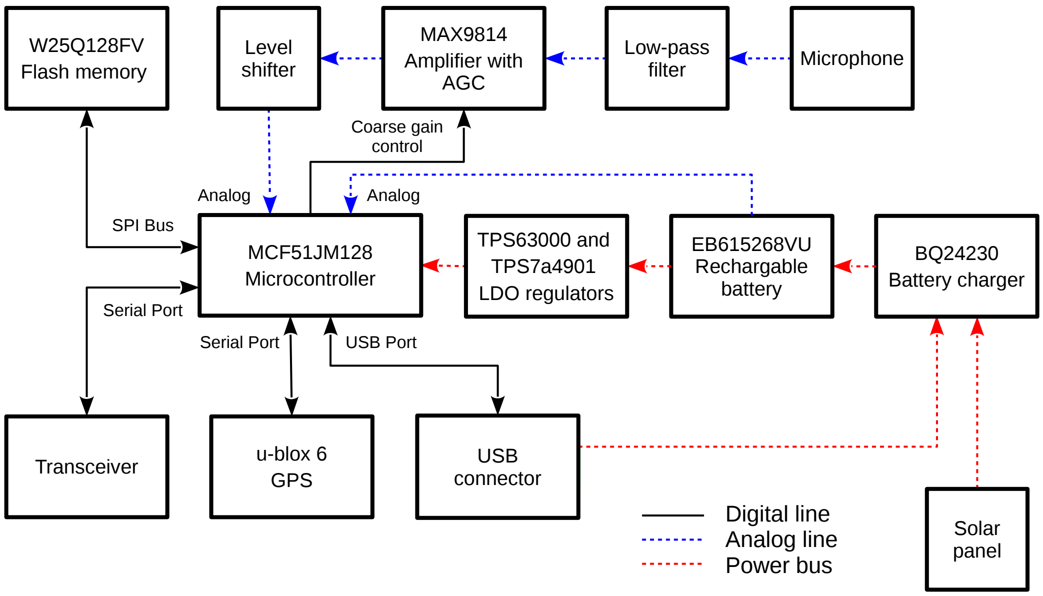

Figure 2: Block diagram of the embedded system modules.

input voltages from 1.8 V to 5.5 V and its extremely low quiescent (50 uA) and shutdown (1 uA) currents. Finally, the digital and analog voltages of system power supply are provided by a high-efficiency and low dropout voltage regulators (TPS7a4901, Texas Instruments Inc). This configuration allows to achieve a high quality voltage (low ripple and stable) and long-term autonomy of the device (more than 5 days with only the fully charged batteries). The battery power is supplied by two polymer litio-ion 3.7 V rechargeable batteries of 2500 mAh (EB615268VU, Samsung). The batteries are charged using a 1 W solar panel (5.5 V open circuit voltage and 170 mA short-circuit current) during the field operation and the USB port when the device is connected to a computer or an electric energy source. The battery charge and power-path management are provided by a high-efficiency device with input overvoltage and overcurrent protections (BQ24230, Texas Instruments

Inc). These features reduce the number of charge and discharge cycles on the batteries and enable the system to run with a defective or absent battery pack. The devices operate from either a USB port or AC adapter, supporting charge currents between 25 mA and 500 mA and input voltages up to 28 V. The microcontroller is able to monitor the true battery voltage at all times by interfacing with an analog input line without conditioning (Figure 2).

In data logging, position stamping is carried out through the host microcontroller interfacing with two 128 Mbits serial Flash memory chips (W25Q128FV, Winbond Electronics) through a serial peripheral interface (SPI). Storing in text files only the results, the flash memory capacity allows to store about two years of recordings. Regarding time, the internal microcontroller real-time clock and a GPS receiver (NEO-6M, u-blox) are communicated to host microcontroller through a serial interface. The GPS provides accurate time and position information used to tag each package of measurements. A 3 V and 20 mm coin cell battery is incorporated as a backup power supply to ensure accurate time and position, as well as a fast startup of the GPS, in the event of primary battery failure.

External communication with a computer is provided by an Universal Serial Bus (USB) port embedded within the microcontroller, which can also be used to charge the battery of the device when it is powered by the external device. The USB module provides an On-The-Go (OTG) dual-role controller, fully compliant with USB 1.1 and 2.0 specifications. All these features simplify the hardware and software required for communication. Finally, a wireless link operating at 2.4 GHz is implemented using a XBee XB24 module with wire antenna that enables wireless data transfer up to

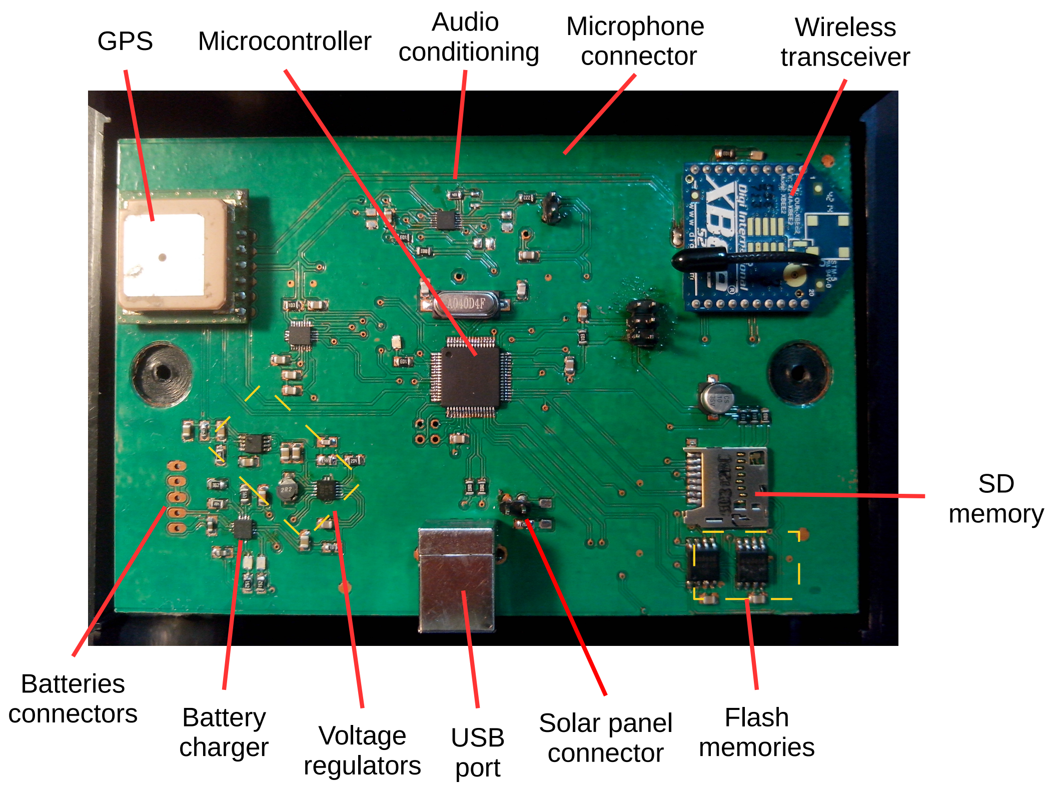

Figure 3: Printed circuit board design of the embedded system.

250 kbit/s for a range up to 500 m. All components were assembled onto a printed circuit board that has a full ground plane to reduce electrical noises in analog and digital circuits (Figure 3).

2.2. Device functionality

The goal of this embedded system is monitoring the grazing behavior of livestock by estimating the indicative attributes of feeding activity from the sound. To fulfill this task, it is necessary to detect and classify the ingestive events produced during the cattle feeding. There are several algorithms that can detect and classify ingestive events (Milone et al., 2012; Navon et al., 2013; Chelotti et al., 2016), but the only one that can be executed in real-time in a low-performance microcontroller is the one proposed by Chelotti et al. (2016).

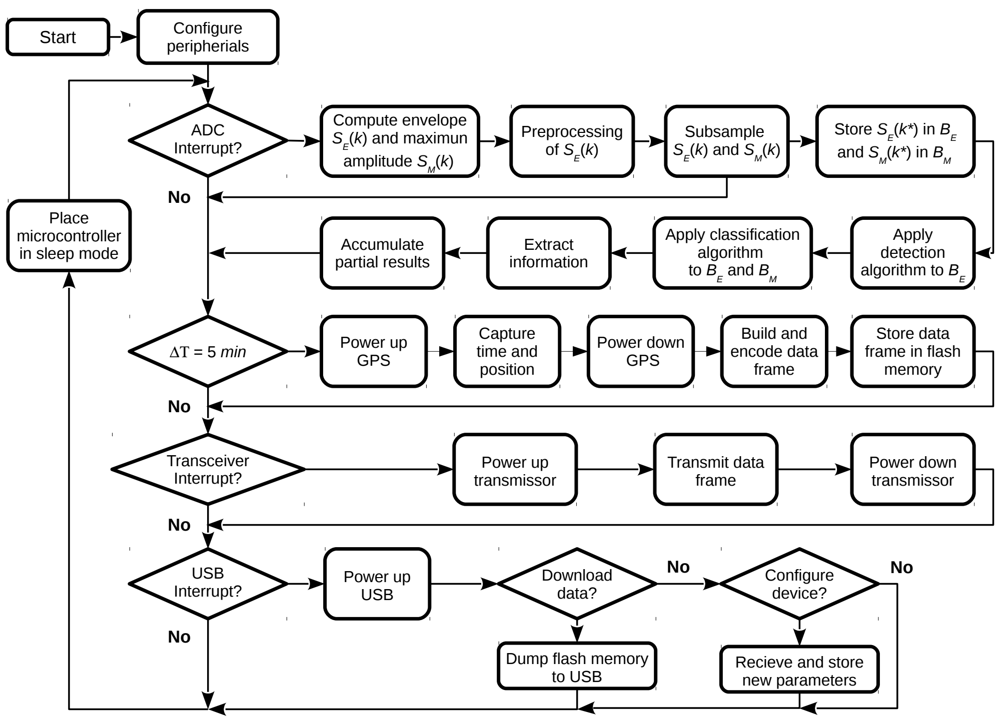

Figure 4: Flowchart of the embedded system firmware.

The embedded system proposed in this work implements the algorithm proposed by Chelotti et al. (2016) and the software for data logging and communication with the base station. The embedded software is organized in four tasks: i) signal preprocessing, event detection and classification, ii) data logging, iii) communication and iv) device configuration. The software architecture is driven by interrupt that switches between full power and sleep modes between interrupt events (Figure 4). Four main interrupt functions are: i) 500 us ADC interrupts (single conversion of audio signal at 2 kHz), ii) 5 min timer interrupts (information package), iii) wireless transceiver interrupts and iv) USB port communication interrupts. Each of these interrupts wake up the microcontroller into active power mode, and a routine is used to determine which function caused the interrupt event.

At each 500 us time interval, the microcontroller is woken up by the ADC when it finished the current conversion and then it computes the envelope of the signal $S_E(k)$ and the maximum on the window $S_M(k)$, removes the offset and decimate the envelope to 100 samples/s. These tasks correspond to the preprocessing task of the acoustical analysis system (Chelotti et al., 2016). If decimate samples of $S_E(k^*)$ and $S_M(k^*)$ are available, the software updates buffers B_E and B_M. In a first step, the possible ingestive events are detected on the envelope of the signal (Figure 5) and then classified according to a set of heuristic rules. In the opposite case, the microcontroller is set into sleep mode to save energy. The details of the detection and classification algorithm are described in Chelotti et al. (2016). Once the events are detected and classified, the software extract the information that characterized the ingestive activities and accumulates the partial results. Finally, the microcontroller is set into sleep mode.

At each five minutes interval (30.000 samples of subsampled signal) a data frame is built. The data frame is integrated by: i) the information that characterized the feeding activities (number of chews, chew-bites and bites, average time of chewing and biting, average chew and bite energy, average chew and bite amplitude), ii) the time and iii) position where the sound is recorded. This information is organized in a self-contained data frame,

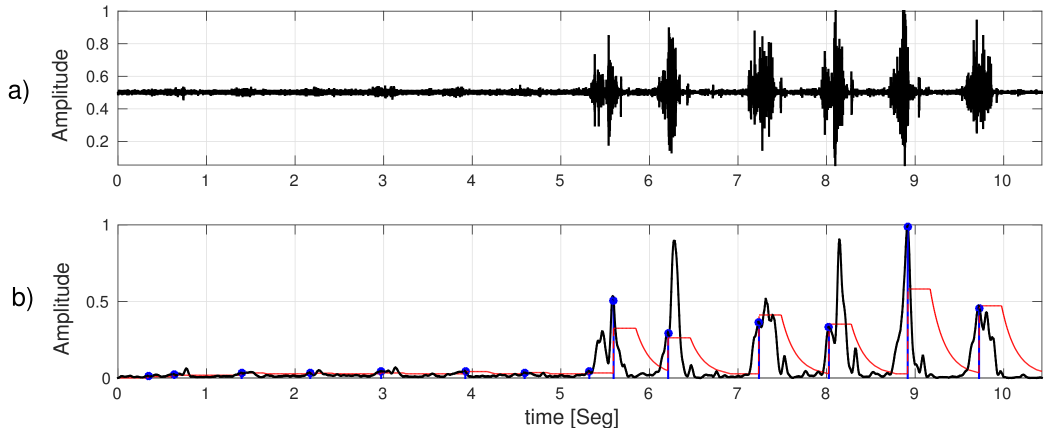

Figure 5: Signals generated by the algorithm: (a) Original sound signal and (b) signal processed by the microcontroller (variable threshold in red-dashed line and peak detection in blue line).

which is codified using a low-density parity-check (LDPC) code (Casu et al., 2015) to guarantee the integrity of the data from errors. The position is obtained from a GPS that normally operates in power safe mode and it is switched to maximum performance mode to acquire the position. This way of operating the GPS maximizes the performance while reduces the overall power consumption. Finally, the data frame is stored as a text file in the flash memory, and the microcontroller is set into sleep mode.

The text file is structured in two sections: i) one section for the time and position where the data was collected, and ii) another section for the characteristic parameters of grazing activities. The structure of the file is shown in Figure 6.a. It starts and ends with two numerals characters (#) and the data fields are separated by commas (,). This structure reduces the parsing time and avoids data loss or misleading. The first section stores the date (D), time (T), latitude (Lat) and longitude (Long) where the data was

##,D,T,Lat,Long,NC,DC,AC,EC,NB,DB,AB,EB,NCB,DCB,ACB,ECB,TNE,##

(a)

23232C3136303831362C3134353932332C333330322E31353831532C363035332E3737335
572C3132312C302E32332C302E32382C302E32362C36322C302E32362C302E37352C30E
36312C3230362C302E33372C302E37382C302E36392C3338392C2323

(b)

Figure 6: Data file used to store information: (a) general structure and (b) example for a grazing segment, where information is expressed in hexadecimal code.

collected. They are obtained from the GPS, using NMEA 0183 standard (Association et al., 2002) to communicate with the microprocessor, then the information is stored in the same format: six ASCII characters for date, six ASCII characters for time and ten ASCII characters for latitude and longitude respectively. The second section corresponds to the parameters of grazing activities. It stores the total number of events (TNE), the number of events (C, B and CB), the average duration of time (DC, DB and DCB), the average amplitude (AC, AB and ACB) and the average energy (EC, EB and ECB) of the grazing events (Chew, Bite and Chew-Bite) respectively. Each data field of this section is stored in 32 bits integer format. A dump memory of a data frame is shown on nibble-level in Figure 6.b. Figure 7 shows the file in a user-friendly interface in a personal computer.

The wireless communication between the device and the base station is initiated and controlled by the base station. It is achieved through the use of request and response packages protocol. The reception module of the transceiver is on all the time, waiting for a request package from the base

Date (D): 160816
Time (T): 145923
Latitude (Lat): 3302.1581S
Longitude (Long): 6053.7735W
Number of C (NC): 121
Average duration of C (DC): 0.23 [s]
Average amplitude of C (AC): 0.28
Average energy of C (EC): 0.26
Total number of events (TNE): 389

Number of B (NB): 62
Average duration of B (DB): 0.26 [s]
Average amplitude of B (AB): 0.75
Average energy of B (EB): 0.61
Number of CB (NCB): 206
Average duration of CB (DCB): 0.37 [s]
Average amplitude of CB (ACB): 0.78
Average energy of CB (ECB): 0.69

Figure 7: Information of file shown in user-interface.

station. When a request package is received, the software turns on the transmission module, transmits the requested data frames, waits for the reception acknowledgment of the base station and then it turns off the transmission module.

The final interrupt routine is triggered by a USB port data event. This is caused by messages being sent from a personal computer to the embedded system through the USB port on the microcontroller. When a download command is sent, the microcontroller transfers the flash memory data to the computer through the USB port. The downloaded data is processed by the software.

After downloading all data, the microcontroller immediately continue its normal operation. A message contained a new configuration settings can also be sent to the device. The use of interrupt driven programming is an essential component of the software to the successful implementation of this embedded system. It allowed to optimize the power consumption of the device by using low power sleep modes while ensuring a precise data sampling and processing intervals.

3. Experimental setup

Experiments performed on the developed embedded system were carried out in a laboratory environment using a database previously obtained with a commercial recorder (SONY ICDPX312). The recorded sound signals were reproduced by speakers, with a flat frequency response in the band of interest, from a desktop computer and into an acoustically isolated room. Thus, reproductions of these signals were captured by electret microphone of the device and then processed by the embedded system. The results and the information obtained from the GPS were recorded on the flash memory. This methodology allowed to compare directly the results obtained by the embedded system with the reference labeling. The reference transcription files were aurally segmented and labeled by experts in animal behavior. The database used for experiments is described in the following subsection.

3.1. Database

The signals were obtained by a field experiment conducted at the Campo Experimental Villarino (Universidad Nacional de Rosario, Zavalla, Argentina) dairy facility, during October of 2014. Project protocols were previously evaluated and approved by the Committee on Ethical Use of Animals for Research of the Universidad Nacional de Rosario. The foraging behavior of five Holstein lactating cows, weighing 570 ± 40 kg, grazing alfalfa (Medicago sativa) and fescue (Festuca arundinacea) mixed pastures were continuously monitored during six non-consecutive days. Cow halters were specially designed for experiments. The evaluation was performed with 24 h continuous sound recordings. Sounds of biting and chewing were recorded using a directional microphone mounted onto the forehead of the animal and covered by a elastic band fastened to the halter, where a recorder was attached. The signals were recorded at 44.1 kHz sampling frequency, 16-bit resolution and WAV format. The microphone/recorder devices were randomly assigned to the cows and rotated over the six days.

3.2. Performance measures

One important issue for the comparison between events recognized and classified by the algorithm and the corresponding reference labels is the synchronization time of events in both sequences. To solve this, the HTK performance analysis tool HResults was used. The comparison is based on a Dynamic Programming-based string alignment procedure (Young et al., 1997), in order to measure distance between the two sequences (reference and recognized). The outputs of this tool were: (i) the number of deletions (D), which are considered as false negatives, (ii) the number of substitutions (S), which are considered as misclassified events, (iii) the number of insertions (I), which are considered as false positives, and the total number of events (T) in the reference transcription files provided by the experts. Using this information, some performance measures can be established. Regarding the detection task, the percentage of correctly detected events is defined as

$$\delta\% = \frac{T - D}{T} \; 100\%, \tag{1}$$

where the number of substitutions was not considered, because in the detection task it only matters if an event has occurred or not, regardless of the type of event. Regarding the classification task, it is important the type of event. In this sense, two measures can be established. The percentage number of correctly recognized events, takes into account misclassified events (S) but not false positives (I) and is given by[1]

$$C\% = \frac{T - D - S}{T}\ 100\%. \tag{2}$$

The other measure is the accuracy, which is computed by

$$A\% = \frac{T - D - S - I}{T}\ 100\%, \tag{3}$$

where misclassified events (S), false negatives (D) and false positives (I) are considered for computation. In this sense, accuracy will always be less than or equal to the percentage number of correctly recognized events.

4. Evaluation of the system

Five representative segments of 10-min from a total of 24 h of continuous audio recording were aurally segmented and labeled by two experts in animal behavior. The reason for choosing segments of this length was because the labeling task performed by the expert is very tedious as it should be aurally labeled event by event within rumination and grazing activities. In order to consider different types of foraging behaviors, each segment consisted of 5-min of rumination (contain only chew events) and 5-min of grazing (contain the three types of events), which were randomly selected. The results

[1]http://htk.eng.cam.ac.uk/

achieved good performance rates for the implementation of the algorithm in the embedded system developed in this work. In addition it was shown that processing was executed in real-time. Following the definitions of performance measures used, event detection rate (without identification of the type of event) achieved high performance (about 92% on average over the segments considered). Regarding the classification task, the recognition rates obtained from the analysis can be seen in Table 1.

From Table 1, it can be observed a similarity between the values of correct (78.2%) and accuracy (76.4%), which were calculated as the macro-average over all analyzed segments. Following the definitions given in the previous section, this evidences a low number of insertions (false positives) for the system, due to the correct value for the cut-off frequency of the low-pass filter, included in the algorithm for obtaining the envelope signal. If this frequency would be higher, higher frequency components would pass through the filter, then can be detected as possible events when in fact they are not (false positives). Conversely, if the cut-off frequency would be lower, more frequency components of the target signal would be eliminated by the filter, which would cause the correct percentage to decrease significantly. On the other hand, it can be clearly seen that the best recognized event was the CHEW event, in agreement with the results obtained by Chelotti et al. (2016). Because rumination activity is composed only of CHEW events, it is expected that such activity will be better recognized than grazing activity.

Although a very good performance is obtained, there are two important aspects to consider in order to enhance the system implementation. One aspect is related to improving the algorithm. In this sense, some signals may

Table 1: Confusion matrix and average recognition rates and accuracy for the five analyzed segments (S_i). Each row represents the distribution of true events over the categories into which they were classified by the system. For example, in S_1 9% of the bites were misclassified as chews. Bold numbers indicate the best results in recognition.

	Event	Bite	Chew	Chew-bite	C%	A%
	B	**82**	9	9		
S_1	C	1	**98**	1	**78**	**77**
	CB	10	9	**81**		
	B	**77**	8	15		
S_2	C	1	**97**	2	**83**	**81**
	CB	5	6	**89**		
	B	**81**	11	8		
S_3	C	1	**97**	2	**75**	**74**
	CB	6	11	**83**		
	B	**95**	5	0		
S_4	C	4	**84**	12	**70**	**67**
	CB	3	11	**86**		
	B	**84**	8	8		
S_5	C	1	**96**	3	**85**	**83**
	CB	3	13	**84**		
Average†					**78.2**	**76.4**

† Macro-averaging over all the segments considered.

be contaminated with low-frequency noise, which may hinder their analysis. These baseline noises are non-stationary and may be due to the presence of different sources in barn environments, such as: engines of machinery, sounds of other animals and reverberation of the place, among others. In order to remove this type of disturbances, it would be very useful to incorporate an adaptive detrending stage. The other aspect to consider is related to hardware autonomy. In spite of the good performance achieved, it would be interesting to carry out an exhaustive search for integrated circuits of better energy efficiency. Both aspects are currently being addressed.

Providing a system capable of acquiring and processing data in real-time for the monitoring of feeding behavior in ruminants is important for the livestock area. Such on-line processing and analysis of acoustic information makes it possible to store and transfer only the results of analysis instead of the sound, which improve the performance of transferring between systems. On the other hand, optimizing the power consumption of the hardware will increase the autonomy of the system, thus allowing to evaluate behaviors of the ruminant during longer temporal intervals.

5. Conclusions

An electronic system able of real-time monitoring feeding behavior of ruminants was designed and implemented. The system stores and transmits the statistical results without the need of storing the sound signal. The motivation of this work was to provide a tool to enhance the understanding of feeding activities by developing embedded technology that allows for continuous monitoring of animal feeding activities under different environmental conditions. The documented design uses a directional microphone and analog electronic circuits to acquire and conditioning the sounds, and signal processing and computational intelligence tools to detect and classify the events. All the software routines were implemented in a micro-controller using integer arithmetic.

The electronic system was implemented using micro-controller with power management technology combined with a high-efficiency harvesting power supply and power management firmware. It also includes on-board a wireless transmitter and non-volatile memories for transferring and storing data.

The system was able to correctly detect 92% of the feeding events, i.e. considering them as possible events without making a classification, while was able to correctly classify 78% of the total events in the three types of events considered (i.e. chew, bite or chew-bite). These results are similar to the results obtained by the algorithm implemented in desktop computers with floating point precision. Since the experiments of the present study and that described in Chelotti et al. (2016) were performed on different databases (different recording conditions), the results are similar but not directly comparable to each other.

As a future work, the device will be tested in field operational conditions for continuous operation, where the weather and the power supply system will play important roles. On the other hand, we will evaluate the use of machine learning techniques to replace the set of heuristic rules. The use of automated methods will help to explore more complex decision boundaries in the search of the best solution, which is expected to improve current results. In order to maintain real-time execution, such techniques must have a low computational cost.

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