Developments on real-time monitoring of grazing cattle feeding behavior using sound

Luciano S. Martínez Rau*, Nestor N. Deniz*, José O. Chelotti*,
Leonardo L. Giovanini* and Pablo A. Kler† *Research Institute for Signals, Systems and Computational Intelligence, sinc(i), FICH-UNL/CONICET
Email: {lmrau, ndeniz ,jchelotti,lgiovanini}@sinc.edu.unl.ar †Research Center for Computational Methods (CIMEC, UNL–CONICET)
Email: kler@cimec.unl.edu.ar

Abstract

Estimating forage intake and monitoring the foraging behavior of grazing livestock are difficult tasks. Detection and classification of jaw movements are very useful to obtain that information. In a similar way, the monitoring and analysis of long-term activities such as rumination and grazing provide useful insight. Several works have demonstrated that acoustic monitoring is an adequate way to analyze ruminant feeding behavior. In this work, we present a complete system for monitoring ruminant foraging behavior. As components of such a system, a review about two own methods based on the analysis of acoustic signals is included: i) a short-term analysis system that automatically detects and classifies jaw movements, and ii) a long-term analysis system for the recognition of grazing and rumination activities. Both systems use simple concepts and tools derived from signal processing and pattern recognition areas. A description of an ad-hoc electronic platform is also included.

Index Terms

feeding behavior, signal processing, pattern recognition, embedded system

I. Introduction

The world dairy industry has undergone profound changes over recent decades. A trend exists in dairy farming toward the automation of processes to reduce labor and labor costs [1]. This development is partly driven by the economic reality of increasing labor costs relative to capital costs. Automated systems enable dairy farmers to manage larger herds with lower labor requirements, which means that the application of automated systems fits with the trend of increasing herd sizes.

Animal behavior is a clear indicator of its physiological and physical state [2]. Eating, ruminating, and resting are the main daily activities of ruminant livestock. Monitoring these activities is key to many important management decisions in free-grazing systems [3]. Such information enables farmers to check the living conditions of cattle in the pasture and make effective decisions about food supplement and pasture management. Therefore, accurate monitoring of the feeding behavior of free-grazing cattle is necessary to ensure the welfare and health of these animals, which will improve quantity and quality of livestock products.

Monitoring of foraging behavior is key to ensure the fulfillment of the basic health and welfare requirements of grazing cattle and to improve the efficiency of pasture-based production systems [3]. Thus, the continuous monitoring of such behavior can help retrieve individual status information for each animal [4], [5], build a log, detect emerging diseases [6] or the onset of estrus, and optimize pasture and animal management.

Cattle foraging behavior is mainly composed of grazing and rumination bouts. Grazing can cover from 25% to 50% of the day and rumination, from 15% to 40% [7]. Grazing involves searching, apprehending,

Preprint submitted to the IEEE International Conference on Industrial Technology (ICIT) 2020

chewing, and swallowing herbage. Rumination includes bolus regurgitation, chewing, and deglutition. While grazing, the animal moves its jaw with no predefined sequence of jaw movements, a typical rumination involves chewing for 40–60 s followed by a 3-to-5 s interruption due to bolus deglutition and regurgitation [3], [8], [9]. During both activities, jaw movements (JM) are performed rhythmically with a frequency that ranges from 0.75 to 1.20 events per second. JMs are: biting, when herbage is apprehended and severed; chewing, when herbage is comminuted; and a compound movement called chew-bite, when herbage is severed and comminuted in the same JM [10]–[12]. JMs length is around 1 s, whereas activity bouts can last from minutes to hours. Thus, foraging behavior is characterized by JMs (short timescale) and activities (longer timescale).

An approach to measure feeding behavior is acoustic monitoring [13]. Laca et. al. [10] instrumented an inward-facing microphone on the forehead of steers to register stronger and readily distinguishable sounds of bites, chews, and chew-bites. Consequently, acoustic monitoring proved to be a more effective methodology to discriminate sensitive differences in feeding and rumination than previous jaw recorders or visual observation methods [11], and since then it has been increasingly applied as a research tool to study different aspects of grazing behavior in sheep and cattle [14].

In this work, we review previously published algorithms based on the acoustic method: i) one related to the recognition of JMs [15] and the other ii) related to the recognition of grazing and rumination activities [16]. The concept and results of each method are presented. Also, the design and evaluation of an ad-hoc embedded system are presented.

II. Sensor system for feeding behavior

A. Jaw movement recognition

Since the 1980s, a lot of work has been put into developing sensors that measure parameters of individual cows. A sensor system consists of devices plus the software that processes the data (see Fig. 1):

- **Transduce and record** the signal of interest;
- **Analyze** the data to explain the changes to produce information about the state of the cow;
- **Integrate** the information provided by sensor with supplementary data to improve the quality and accuracy of animal information; and
- **Make a decision** using the information obtained by the system to advise the farmer.

The stages defined here describe the abstraction level of information provided by the sensor system. The sensor itself is only the first stage. The second stage is to process the sensor data with algorithms that provide information about the state of each individual cow. In this stage, it is possible to combine sensor data with data about cow history. The algorithm produces information about the cow's state by determining changes in the sensor data. The third stage uses this information in a decision support model that uses economic information to produce advice about how to act upon the detected events. Finally, the fourth stage is the decision regarding the change in the health status of the cow, as detected by the sensor.

In this work, we focused on the initial stages of the system for the case of real-time monitoring of the feeding behavior of grazing cattle (left side in Fig. 1). The proposed system is based on acoustic sensors and algorithms capable of achieving good performance in the detection and classification of feeding activities with a low computational cost, which allows its real-time execution. Therefore, a group of measurable properties should be found to characterize the sounds produced by JMs.

III. The algorithms

A. Jaw Movement Recognition

A pattern recognition system is an automatic process that aims at classifying input data into a set of specific classes [17]. This system can be described by a series of generic stages that allow: (i) the input signal description, which facilitates the extraction of distinctive features, and (ii) its classification, which

sinc(i) Research Institute for Signals, Systems and Computational Intelligence (sinc.unl.edu.ar)
L. Rau, J. O. Chelotti, S. R. Vanrell & L. Giovanini; "Developments on real-time monitoring of grazing cattle feeding behavior using sound"
2020 IEEE International Conference on Industrial Technology (ICIT), pp. 771-776, 2020.

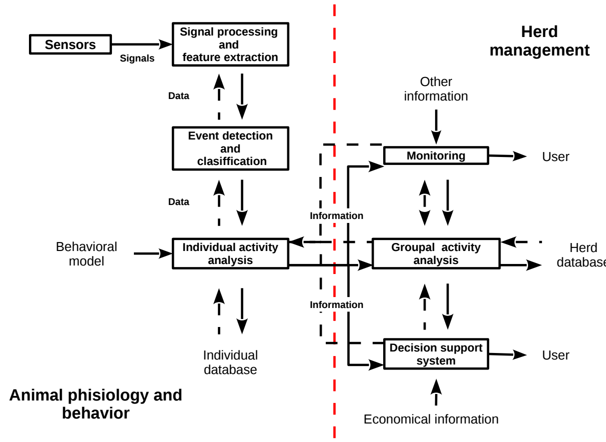

Fig. 1. Structure of a sensor system for animal monitoring

enables identification of patterns. A block diagram of the jaw movement recognition algorithm (called CBIA in the original work) is shown in Fig. 2.

Fig. 2 shows the relationship between a typical pattern recognition system and the different stages of the algorithm: signal conditioning, preprocessing, event detection, feature extraction, and event classification. The input of the system is the digitized sound, whose numerical representation is normalized and its range is matched with the range of the computer in the signal conditioning stage. Sound signals sometimes show slow time-varying noises added to the target signal, especially in barn environments. Therefore, CBIA uses a detrending technique that removes the non-stationary noises at the signal conditioning stage. Within the pre-processing stage, the sound signal follows two paths:

- A maximum detector computes the maximum amplitude of the sound signal over a sliding window whose length is half of the duration of a typical chew-bite event.
- An envelope detector computes the sound envelope using synchronous demodulation and a low-pass filter.

Since the sound envelope only has low-frequency components, the signals computed by both detectors are down-sampled to reduce the amount of data processed by the remaining stages. The events are detected by comparing the sound envelope with a time-varying threshold [18]. Then, the sound envelope

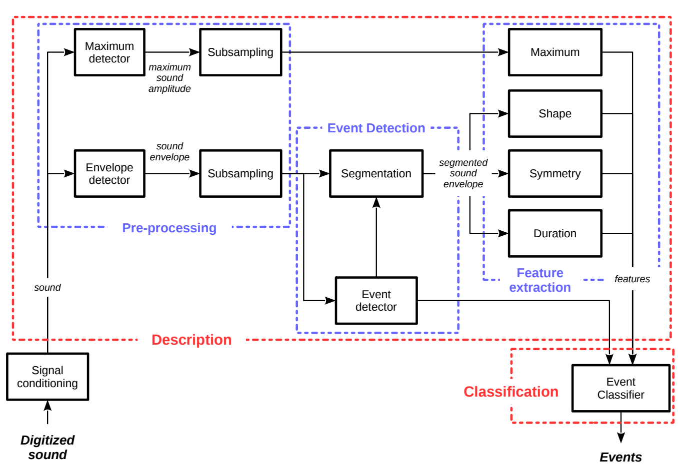

Fig. 2. Block diagram of the JM recognition system (CBIA).

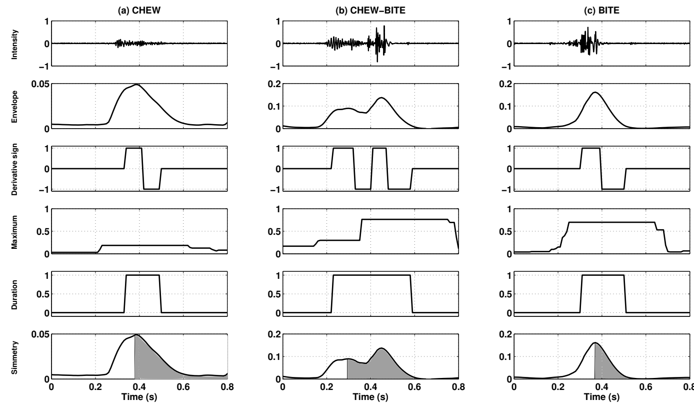

Fig. 3. Acoustic events, jaw movements, and derived signals.

is segmented and it is used to compute the features. Once the candidate JMs are detected, their features are extracted over a time window centered at the sample where the event was detected. Four temporal features that are low-cost and with discriminative power for this problem are extracted:

- **Shape index**: is computed as the number of zero-crossings in the sign of the derivative signal obtained from the envelope signal (third row in Fig. 3). This calculation is performed only if the envelope amplitude exceeds a noise threshold. This feature provides useful information to differentiate simple JMs (chews and bites) from combined JMs (chew-bites).
- **Maximum intensity**: provides information to differentiate low-amplitude JMs (chews) from high-amplitude ones (bites and chew-bites). This feature is extracted directly from the sound signal over a sliding window with length equal to the period of a typical chew-bite event (fourth row in Fig. 3).
- **Duration**: is calculated as the time in which the envelope amplitude is greater than a given threshold. In general, the duration of compound events (chew-bites) is larger than simple events (chews or bites), which are similar (fifth row in Fig. 3).
- **Symmetry**: is computed as the ratio between the left area and the total area of the event. Left and right event areas are divided at the first peak of the event (last row in Fig. 3). It can provide discriminative information because events have different symmetries.

B. *Activity recognition*

Grazing and rumination are activities with quasi-periodic characteristics. In addition, each activity has a different proportion of JMs. The proposed activity recognition algorithm aims to use this discriminative information to provide grazing and rumination bouts [16]. To achieve a low computational cost, tasks within each stage have been simplified whenever it was possible. The input of the system is the sound signal produced during foraging activities. Three activities are considered: rumination, grazing, and other activities. The latter category includes any activity other than rumination or grazing (i.e. from silence to different noises).

Detection and classification of JMs are performed with the algorithm presented in Section III-A. Then, the feeding activity is recognized by analyzing fixed-length segments of the acoustic signal. JMs that are detected and classified within a segment are stored in a segment buffer. The rate of JMs in a segment and the proportions of their types are computed to feed the last processing stage. At this point, activity classification could be seen as a simple task, but an exploratory data analysis on the training set has shown a complex underlying distribution of the segment features (rate, %c, %b, %cb). The rate of recognized JMs during rumination and grazing is expected to be in the range from 0.75 to 1.40 Hz (Fig. 5). By contrast, the rate of JMs identified during other activities presents a lower frequency. The overlapping among rate distributions of activities is part of the problem.

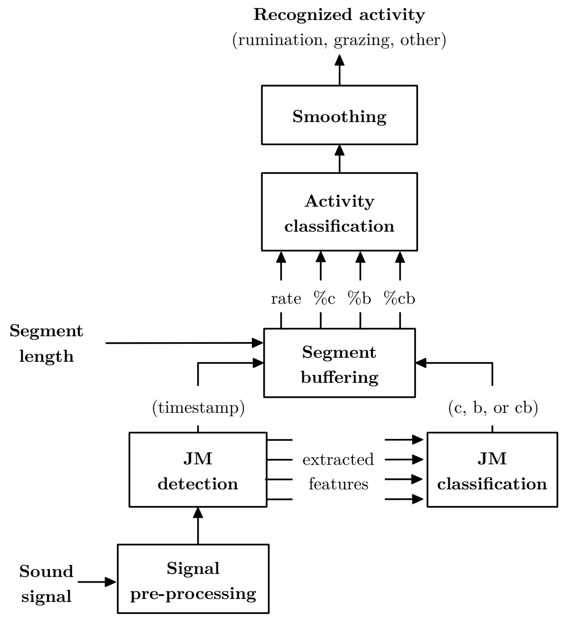

Fig. 4. General diagram of the activity classification algorithm.

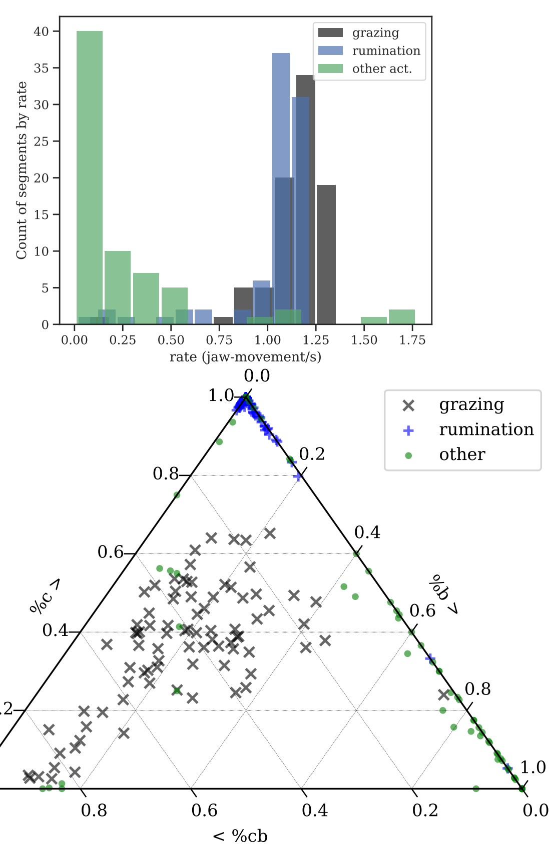

Fig. 5. Distribution and proportions of jaw movements.

The triangle plot in Fig. 5 shows the proportions of the identified JMs for several segments of the training set. Proportions of a single segment always sum to 1.0. The top corner corresponds to 100% of chews, the bottom left corner corresponds to 100% of chew-bites, and the bottom right corner corresponds to 100% of bites. Points inside the triangle correspond to segments composed by more than one type of JMs. For example, while rumination is mainly composed of chews, grazing has a diversity of JMs compositions. During other activities, bites are the most assigned type of JMs.

Distributions of segment features show that the recognition of JMs within grazing and rumination activities is not perfect. For example, CBIA detects a few bites during rumination, which is not actually true. Thus, the problem of distinguishing between activities requires a powerful method to handle these errors. In this study, the use of a simple method of machine learning is proposed. Activity classification is performed by a trainable model, such as a multilayer perceptron or a decision tree, which assigns an activity label to the segment. In this way, at the end of the processing stages, each segment of the input signal has a label that indicates if it corresponds to rumination, grazing, or other activity. Finally, a smoothing process is applied over the sequence of labeled segments to remove short gaps and thus reduce fragmentation of activity bouts. Thus, long recognized bouts are encouraged, which mimics the typical length of activity bouts.

IV. The embedded system

The design of a battery-powered embedded system requires a detailed analysis of each subsystem to minimize size, cost, and, principally power consumption. The sensor unit device has been designed as a trade-off between minimizing power consumption and parameter estimation accuracy. It is located on the neck of the animal, just behind the head. The embedded device was built around a microcontroller (MCU) and it comprises four interconnected modules: i) the signal conditioning, ii) the data-logging and communications, iii) the power supply and energy harvesting, and iv) the digital processing, as shown in Fig. 6.

The MCU for this application (MCF51JM128, NXP Semiconductors) was chosen 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.

A. *Signal conditioning*

The signal conditioning module acquires and conditions the animal feeding sound. It senses the sound with an electret microphone facing inward on his forehead. The signal bandwidth is limited to 2 kHz to minimize the quantization noise with an eighth-order Butterworth low pass filter. An automatic gain control (AGC) amplifier is used to maximize the signal-to-noise ratio. The AGC output is connected to one of the analog input channels of an 8 bits A/D converter in the MCU. The AGC applied gain level is delivered to the MCU through another analog input channel. The AGC output is also connected to a low pass filter to detect when an acoustic signal is present. It is compared with a defined threshold reference voltage to detect when there is feeding activity and to wake-up the MCU (IRQ input).

B. *Digital processing and data-logging*

The embedded firmware is organized into four tasks: i) signal conditioning and preprocessing, event detection, and classification, ii) data logging, iii) internal and external communication, and iv) device configuration. The software architecture is driven by four possible interrupts to wake-up the MCU from sleep mode and execute one of these tasks.

When the voltage comparator detects a sound level above a threshold, an A/D conversion begins. Every 500 μs a finished A/D conversion wake-up the MCU and execute the algorithm to detect and classify JMs. The software extracts the information that characterized the ingestive activities and accumulates the partial results, and the MCU is set into sleep mode until the next A/D conversion is completed. Finally, after 5 minutes since the last sound level activation, the device is hibernated.

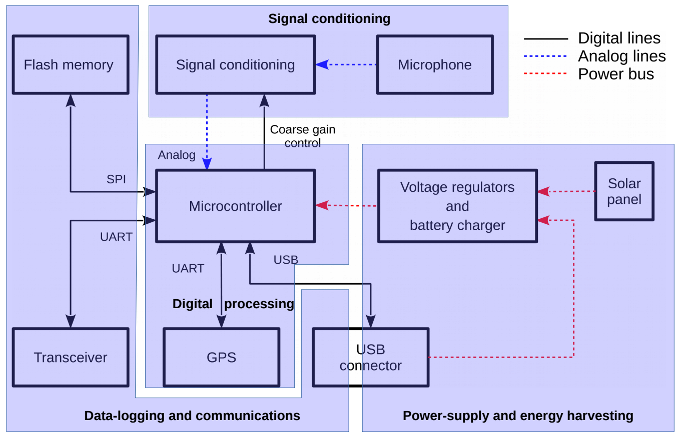

Fig. 6. Block diagram of the embedded system.

For every 30 min interval, a data frame is built gathering instant information from the GPS (time and position) and information related to the feeding activities (i.e. quantity, average time, and average energy of each potential event). Finally, the data frame is stored as a text file in one of the two flash memories, and the MCU is set into sleep mode.

Every 15 min the PC starts and controls the wireless communication with the sensor device, generating an interrupt in the MCU. The reception module is on continuously. When a request package is received from the PC, the MCU turns on the transmission module, transmits the requested data frames, waits for the reception acknowledgment and then it turns off the transmission module and the MCU is set into sleep mode. The final interrupt is triggered when a USB communication is established to transfers the data stored in the flash memories to the PC or to set a new sensor configuration.

C. Communications

Internal sensor communications are managed by the MCU. A 3 V coin cell battery is incorporated as a backup power supply for the GPS. The USB module provides an On-The-Go (OTG) dual-role controller. The additional wireless communication mode operates at 433/470 MHz with a transfer rate of up to 37.5 kbps. All these features simplify the hardware and software required for communication.

D. Power supply

The device has been designed to minimize power consumption whereas it is able of harvesting all the energy needed for its operation. Therefore, three complementary approaches were used to develop the energy management scheme: i) A combined duty-cycling and data-driven operating scheme, driven by data, to operate only when relevant information is available. It is implemented through the firmware in the MCU. ii) An energy harvesting scheme, by using a 1W solar panel able to recharge the two Li-Ion batteries when the sensor device is operating outdoors; iii) A USB port when the device is connected to a PC or an energy source.

E. Autonomy analysis

To determine the autonomy of the sensor device it is mandatory to know the time it will be on the active mode, due to the sum of the times of the rumination and grazing activities. According to the circadian rhythm of the cattle feeding behavior described in the sensor device will be on the active mode around 60% of the daily time.

The measured charge consumption per hour during active mode is 34.9 mAh. Considering the battery capacity of 5000 mAh and in the absence of the solar panel, the sensor device would have an autonomy

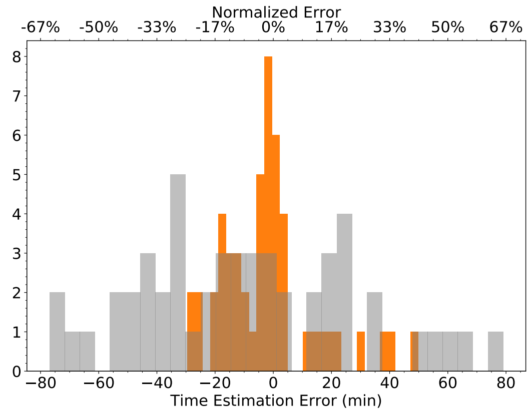

Fig. 7. Time estimation error of rumination for proposed activity recognition system (orange) and Hi-Tag (gray). Top axis is normalized with the length of segments analyzed (2 hours).

of $T_A = 143.27$ h. Otherwise, the instant current provided by the solar panel is 120 mA during daylight hours. If we suppose it is maintained during 6h, the average charge provided is $Q_{SP} = 30.0$ mAh.

According to the circadian cycle of the cattle feeding behavior, the average charge consumed per hour for a whole day is given by $Q_{CR} = 20.6$ mAh. Thus, the net charge balance is $Q_{SP} - Q_{CR} = 9.4$ mAh. This shows that the harvested power is sufficient to energize the sensor device.

To determine the worst-case conditions, the sensor device was tested in active mode during 5 days outdoors with the batteries fully charged initially. During the day, the sensor device is powered entirely by the solar panel and, at the same time, the batteries are partially recharged. However, it is not enough to accomplish a full charge of the batteries. As expected, during the night, the batteries supply the embedded system and its voltage decreases considerably. At the end of the test, the sensor device still worked properly and the voltage tends to stabilize close to 3.7 V, which is the nominal battery voltage.

V. Results

A comparison of the rumination time estimation obtained by a commercial system (Hi-Tag) and the proposed system was performed. The Hi-Tag system summarizes the total time the animal spent ruminating during two-hour chunks [19]. Raw data and timestamps of rumination bouts within a two-hour chunk are not available [20]. Therefore, the estimations with the proposed system were aligned, and the total duration of rumination was summarized to match the same two-hour chunks of the Hi-Tag system. The comparison was made with a total of 53 two-hour chunks from all the recordings analyzed as it was done in [21]. Since the Hi-Tag is a commercial system, its computational cost was not available to be considered in the analysis.

The results of time estimation error for rumination are shown in Fig. 7. The medians of the distributions are -2.91 min and -13.55 min for the proposed system and the Hi-Tag system, respectively. Negative medians imply that both systems tend to underestimate the rumination time. The proposed system was more accurate and resulted in a narrower error distribution. While the error dispersion for the proposed system is in the range (-30, +50) min, the distribution corresponding to the Hi-Tag is wider and it is in the range (-80, +80) min. In practical terms, these errors are very high since they are in the same order of magnitude of the two-hour chunks analyzed [16].

Fig. 8 shows the evolution of voltage and current of the batteries. During the day, the current provided by the batteries decreases to zero, when the device is powered entirely by the solar panel and, at the same time, the batteries are partially recharged. However, it is not enough to accomplish a full charge of batteries. As expected, during the night and periods when there is no solar light incident on the solar panel, the batteries supply the embedded system and its voltage decreases considerably. During each daylight, there is a small peak in the current consumption, which corresponds to the projection of a shadow above the solar panel making that much of the current consumed by the device has to be provided by the batteries during this time. At the end of the test, the device still worked properly and the voltage tends to stabilize close to 3.7 V, which is the nominal battery voltage.

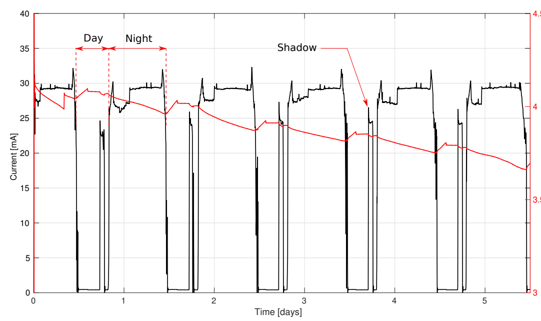

Fig. 8. Current consumption (black line) and voltage of the battery pack (red line).

VI. Conclusions

In the tests performed, the acoustic methods presented have achieved good performance rates. In addition, they provide comprehensive information (short- and long-term) of the foraging behavior of the ruminant. The low computational cost of the proposed methods allows its real-time execution in a simple embedded system. The activity recognition method showed better performance than a commercial system, under certain conditions. Robust recognition of rumination and grazing activities is another challenge to be addressed in future studies. The developed embedded system has shown suitable communication, processing and autonomy characteristics.

Acknowledgment

The authors would like to thank Julio Galli, Marcelo Larripa, Alejandra Planisich, and Martín Quinteros from Facultad de Ciencias Agrarias, Universidad Nacional de Rosario for their assistance in animal management and gathering data. This study has been funded by Universidad Nacional del Litoral, PACT CAID 2011-525, Universidad Nacional de Rosario, projects 2013-AGR216 and 2016-AGR266, Agencia Santafesina de Ciencia, Tecnología e Innovación (ASACTEI), project 2010-216-16 (2016), Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), project 2017-PUE-sinc(i).

References

[1] K M Svennersten-Sjaunja and G Pettersson. Pros and cons of automatic milking in europe. *J. Anim. Sci.*, 86(13 Suppl):37–46, March 2008.

[2] A R Frost, C P Schofield, S A Beaulah, T T Mottram, J A Lines, and C M Wathes. A review of livestock monitoring and the need for integrated systems, 1997.

[3] J (ed) Hodgson and A W (ed) Illius. The ecology and management of grazing systems. 1998.

[4] Mette S Herskin, Lene Munksgaard, and Jan Ladewig. Effects of acute stressors on nociception, adrenocortical responses and behavior of dairy cows. *Physiol. Behav.*, 83(3):411–420, December 2004.

[5] Daniel J Bristow and David S Holmes. Cortisol levels and anxiety-related behaviors in cattle. *Physiol. Behav.*, 90(4):626–628, March 2007.

[6] J G Welch. Rumination, particle size and passage from the rumen, 1982.

[7] Robert J Kilgour. In pursuit of “normal”: A review of the behaviour of cattle at pasture. *Appl. Anim. Behav. Sci.*, 138(1):1–11, 2012.

[8] Thatianne Coutheux Trindade. Influência do controle glicêmico no potencial de crescimento fetal em pacientes com diabetes melito gestacional.

[9] M A Benvenutti, D R Pavetti, D P Poppi, I J Gordon, and C A Cangiano. Defoliation patterns and their implications for the management of vegetative tropical pastures to control intake and diet quality by cattle, 2016.

[10] E A Laca, E D Ungar, N G Seligman, M R Ramey, and M W Demment. An integrated methodology for studying short-term grazing behaviour of cattle, 1992.

[11] Eugene David Ungar and Steven Mark Rutter. Classifying cattle jaw movements: Comparing IGER behaviour recorder and acoustic techniques, 2006.

[12] J R Galli, C A Cangiano, M A Pece, M J Larripa, D H Milone, S A Utsumi, and E A Laca. Monitoring and assessment of ingestive chewing sounds for prediction of herbage intake rate in grazing cattle. *Animal*, 12(5):973–982, May 2018.

[13] Philip U Alkon, Yosef Cohen, and Peter A Jordan. Towards an acoustic biotelemetry system for animal behavior studies, 1989.

[14] Julio R Galli, Carlos A Cangiano, Diego H Milone, and Emilio A Laca. Acoustic monitoring of short-term ingestive behavior and intake in grazing sheep, 2011.

[15] José O Chelotti, Sebastián R Vanrell, Julio R Galli, Leonardo L Giovanini, and H Leonardo Rufiner. A pattern recognition approach for detecting and classifying jaw movements in grazing cattle, 2018.

[16] José O Chelotti, Sebastián R Vanrell, Luciano Martinez-Rau, Diego H Milone, Santiago A Utsumi, Julio R Galli, H Leonardo Rufiner, and Leonardo L Giovanini. An online method for estimating grazing and rumination bouts using acoustic signals in grazing cattle. *Comput. Electron. Agric. (Under review since May 2019)*.

[17] Richard O Duda, Peter E Hart, and David G Stork. *Pattern Classification*. John Wiley & Sons, November 2012.

[18] José O Chelotti, Sebastián R Vanrell, Diego H Milone, Santiago A Utsumi, Julio R Galli, H Leonardo Rufiner, and Leonardo L Giovanini. A real-time algorithm for acoustic monitoring of ingestive behavior of grazing cattle. *Comput. Electron. Agric.*, 127:64–75, 2016.

[19] K Schirmann, M A G von Keyserlingk, D M Weary, D M Veira, and W Heuwieser. Technical note: Validation of a system for monitoring rumination in dairy cows. *J. Dairy Sci.*, 92(12):6052–6055, December 2009.

[20] C Goldhawk, K Schwartzkopf-Genswein, and K A Beauchemin. Technical note: validation of rumination collars for beef cattle. *J. Anim. Sci.*, 91(6):2858–2862, June 2013.

[21] Sebastián R Vanrell, José O Chelotti, Julio R Galli, Santiago A Utsumi, Leonardo L Giovanini, H Leonardo Rufiner, and Diego H Milone. A regularity-based algorithm for identifying grazing and rumination bouts from acoustic signals in grazing cattle. *Comput. Electron. Agric.*, 151:392–402, August 2018.