Wearable device to monitor sheep behavior

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***Abstract*—Monitoring sheep activity can be crucial for improving productivity and animal welfare. This work presents the design, manufacture, and test of a collar-type device to monitor sheep behavior. The device consists of an MSP-EXP432P401R microcontroller from Texas Instruments, a Bosch Sensortec's BMI160 3-axis accelerometer, and a Narrowband-IoT BG96 modem from Quectel that includes a global positioning system. The device has 2 operating modes: Validation Mode (VM) to test and validate algorithms for characterizing sheep activity and Research Mode (RM) to support multi-day animal experiments to study their behavior. In VM, it sends accelerometer data, the animal's state (run, walk, stand, or head down), and the location to the Central System every 20 seconds. VM has an autonomy of 51 hours. In RM, the device transmits the animal's state and the location every 2 or more minutes to extend the autonomy to more than ten days. The microcontroller identifies the sheep's states (every 5 seconds) using real-time accelerometer data processed with an algorithm based on the Linear Discriminant Analysis method. We trained a classifier on a PC using a public dataset, and then we ported it to the microcontroller. Preliminary tests show that the sheep's state identification has a prediction success rate of 88 %, opening exciting possibilities for developing an applicable device.**

***Index Terms*—low power embedded application, animal behavior, accelerometer signal processing**

I. Introduction

The sheep agro-industrial complex is part of the agro-export sector, the leading industrial sector of Uruguay. There are 6.3 million sheeps in Uruguay, and the exports of wool and meat correspond to 2.4 % of the total agricultural exports [1]. The low reproductive efficiency is one of the main limitations for its development. The main reason for this is the high mortality of lambs [2], [3], which occurs in most cases in the first 72 hours of life [4]. The consequences are varied: 1) animal welfare, both lambs who die and their mothers who use part of their limited energy to produce a lamb that does not prosper; 2) inefficient use of resources: animals, materials, facilities, and human resources; and, 3) low productive results, at the farmer and country level, with consequences for the entire production chain. Predicting the time of birth would be an essential tool for farmers to prevent this problem.

Prior work reports changes in the activity of the sheep before birth. Nevertheless, it is still under research to adequately characterize these changes [5]. As far as we know, [5] is the only study on behavioral changes and changes in social dynamics and cohesion around birth using automatic monitoring methods. However, this work could not predict the birth 48 hours in advance with accelerometers placed on the sheep's ears. Consequently, this area is a fertile field for transdisciplinary research. In the medium term, we aim to generate a tool to study sheep behavior to anticipate whether a sheep is close to giving birth (48 hours in advance) using changes in behavior and geographical location.

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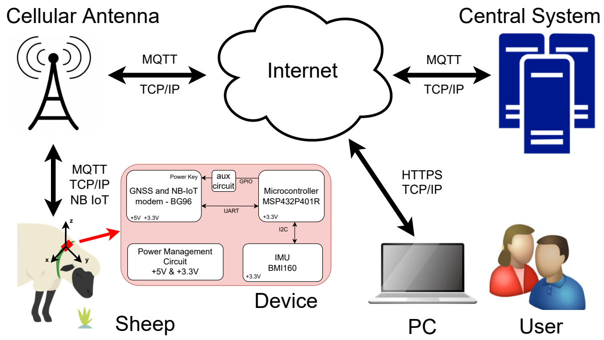

Fig. 1. Proposed system.

As a first step towards this goal, this work presents the design, manufacture, and test of the prototype of a system (see Fig. 1) capable of displaying in real-time on a PC the geographical location of a sheep and signals from an accelerometer that characterize its activity. Location is introduced to improve the data processing capacity at the server level. The system consists of a collar-type electronic device placed on the sheep's neck (the "device") that acquires, processes, and transmits the targeted information to a Central System. The communication protocol between the device and the Central System is MQTT. The Central System receives data from the device, stores it in a database, and provides a user interface to view and process the data. The device has 2 operating modes, Validation Mode (VM) and Research Mode (RM). The first seeks to serve as a platform to test and validate algorithms for characterizing sheep activity. The RM aims to support multi-day animal experiments focusing on studying animal behavior. In both operating modes, the microcontroller is in charge of identifying the sheep's states (run, walk, stand, or head down) using real-time accelerometer data.

II. Proposed solution

A. Hardware

The device consists of an MSP-EXP432P401R microcontroller from Texas Instruments, a Bosch Sensortec's BMI160 inertial measurement unit (IMU), and an LTE IoT 2 click board from Mikroe (see Fig. 1).

MSP432P401R is a 32-bit ARM Cortex M4F microcontroller with a hardware floating-point unit, power consumption of 4.6 mA in Active Mode, and several low power operation modes. BMI160 includes a 16-bits triaxial accelerometer featuring a current consumption of 180 μA. LTE IoT 2 click board integrates a Narrowband-IoT (NB-IoT) Quectel BG96 modem with a global positioning system (GNSS). We use an active antenna (ANN-MS from U-Blox) for the GNSS. Its main disadvantages are its current consumption (8 mA) and size. However, this antenna is much more reliable and faster to locate satellites and find the location (which results in less consumption than passive ones).

The microcontroller communicates with the accelerometer using I2C at 400 kHz, and with the modem and GNSS using UART (Universal Asynchronous Receiver-Transmitter) at 115,2 kbps.

B. Determining the sheep's state on a PC

The Linear Discriminant Analysis (LDA) method [6] assigns a d-dimensional attribute vector $x = \{x_1, ..., x_d\}$ to one of the k classes into which it is possible to partition the data applying a linear decision boundary. In our case, the classes are the sheep's states, and the attribute vector contains parameters that depend on the acceleration values. Thus, the method assigns the attribute vector x to the class that maximizes Eq. 1 (and therefore has the highest probability). For this, it is necessary to evaluate for each class k the Eq. 1.

$$log(P(y = k|x)) = \omega_k \cdot x + \omega_{k0} + Cst \quad (1)$$

where $P(y = k|x)$ is the probability that, given an attribute vector x, the class y to which it belongs is equal to the class k; ω_k and ω_{k0} are matrices obtained from the training; and, Cst is a class-independent constant. We chose this technique for its simplicity and low computational cost since it involves matrix multiplications and finding a maximum (see Eq. 1).

[7] studies the trade-off between the number of attributes and the prediction success rate when using an LDA classifier (prediction is successful if it matches the observed one). [7] selects a vector of 12 attributes (maximum value, minimum value, mean value, and standard deviation for all 3 axes) to classify inside the microcontroller. In that scenario, their prediction success rate is 82,4 %. According to [7], achieving a prediction success rate higher than 80 % with fewer attributes than twelve is possible. However, they did not implement the analysis on the collar; they did it offline on a PC.

To reduce computation requirements in the embedded system and its impact on processing time and power consumption, we propose a variant of [7], which reduces the dimension of the vector attributes to 4: x-axis minimum value (Min_X), y-axis minimum value (Min_Y), z-axis standard deviation (σ_Z), and z-axis variance (σ_Z^2).

We performed the test on a publicly available dataset [8]. Said dataset contains information obtained from an accelerometer (among other sensors) recorded with a collar in 2 sheep. The data is labeled with time and 9 activities performed by the animal. We selected the following states: walk, stand, graze (head down), and run (includes trot). We took 80 % of the

TABLE I
CONFUSION MATRIX (STATE OBSERVATIONS VS PREDICTIONS).

Obs\Pred	Walk	Stand	Head down	Run	Total
Walk	166	0	65	0	231
Stand	3	652	32	1	688
Head down	47	118	664	1	830
Run	3	0	0	180	183
Total	219	770	761	182	1932

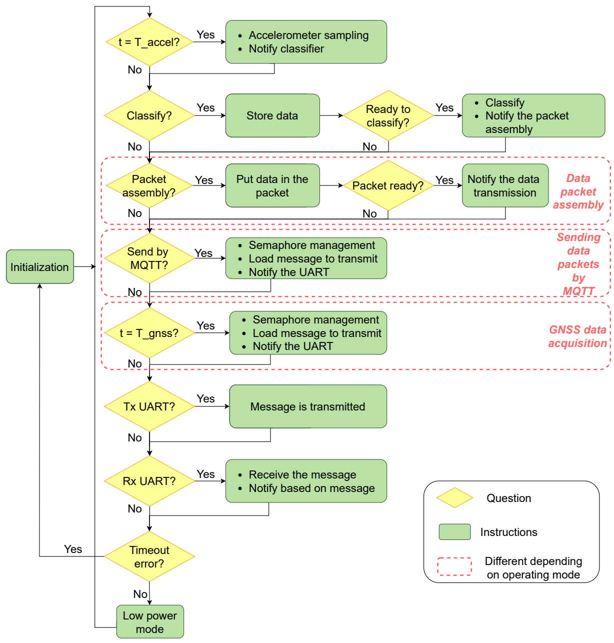

Fig. 2. Main module flow chart.

available data for training and 20 % for verification. Then, we processed the data in windows of 500 samples (5 seconds). The prediction success rate of our proposal is 85,7 %. Table I shows the confusion matrix, where each column represents the number of predictions of each class, while each row represents the observed ones. The major confusions occur between the head down and stand states.

C. Embedded software

The software was coded in Code Composer Studio (Texas Instruments) using C language. The architecture is Round-Robin with interruptions [9], Fig. 2 shows the main's flow chart. Firstly, the program checks if T_accel (accelerometer sampling period) has elapsed. After accelerometer sampling, the acquisition function notifies that there is new data to the classification function. Next, it stores the data, and every 500 samples it performs the classification and notifies the function that assembles the packets. Packet assembly adds the new data to a buffer and reports the uart module when is ready to be sent to the Central System (by MQTT). When T_gnss elapses, the microcontroller queries the GNSS, acquires and stores the data, and notifies the uart module. Finally, the microcontroller transmits the packets to the modem via UART.

Interruptions generated by the Timer set the sampling flags. Also, UART communication with the modem and GNSS

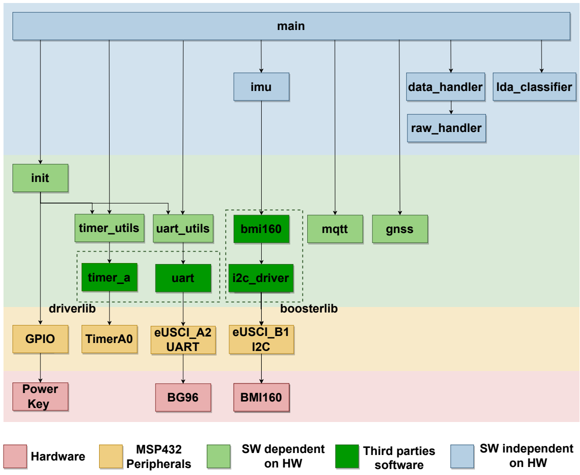

Fig. 3. Hardware/Software modules diagram.

works with interruptions. Additionally, communication with the accelerometer operates through I2C interruptions. Once the microcontroller has no actions to execute, it goes into low power mode and exits after an interruption wake up event.

The modem and GNSS share the same UART to communicate with the microcontroller. To avoid simultaneous access, we protect the UART with a semaphore.

In both operating modes, the accelerometer sample rate is 100 Hz. In VM, the microcontroller sends this data, the animal's state (computed every 5 seconds), and location (sampled every 10 seconds) to the Central System every 20 seconds. The software assembles 4 packets with each classified state (500 samples per axis, 1500 bytes total). One packet has the location, the animal's state, and a time stamp, and the other 3 have the raw data from the accelerometer. Having so many packets, requires sending them within the shortest delay, increasing transmissions and consumption. Its main advantage is that it allows us to analyze raw data offline. The modem and the GNSS are always on in this operating mode. In RM, the device continuously calculates and stores the animal's state (every 5 seconds), and the modem and GNSS are off. Every 2 or more minutes, the device turns the modem and GNSS on and sends the location and the animal's states to the Central System. This approach drastically reduces the transmitted data and energy consumption.

The software contemplates differences in the code flow according to the operating mode, particularly the assembly of packets, the sending of packets by MQTT, and obtaining data from GNSS (red dotted in Fig. 2).

Fig. 3 shows the module diagram of the software, and the relationship between the microcontroller and peripherals (internal and external hardware modules). Each module in Fig. 3 makes use of those that are linked to by arrows. The names of the modules are descriptive of their functions and will not be detailed, except for the following. Firstly, *data_handler* includes the functions that assemble data packets (receive data from *raw_handler*). Secondly, *raw_handler* implements a method of escaping raw data for the forbidden binary bytes in UART communication. Finally, *lda_classifier* implements the functions in charge of classifying the sheep's state from the accelerometer data. These functions include calculating the attribute vector and multiplying it by the classifier matrix afterward. The data window has 500 samples per axis. The module has pre-loaded the matrices and vector obtained in the training stage (see Section II-B). Algorithm 1 performs the classification and determines the animal's state from the vector of attributes.

Algorithm 1: State classifier

Input: vec (attribute vector)
Output: state
`// Standardize the attribute vector`
for $i \leftarrow 0$ ***to*** vec_size **do**
  $std\_vec_i \leftarrow (vec_i - mean_i)/std\_dev_i$
end
`// Search the state`
$prob\_state \leftarrow \omega_k \times std\_vec + \omega_{k0}$
$state \leftarrow 0$
for $i \leftarrow 1$ ***to*** $state\_size$ **do**
  if $prob\_state_i > prob\_state_{state}$ **then**
    $state \leftarrow i$
  end
end
return *state*

III. Experimental Results

A. Behaviour monitoring

We tested our system in a flock of 20 Corriedale rams in a pen of $300\,\mathrm{m}^2$. The test consisted of putting the collar to a ram for 3 hours. The activity of the ram was video-recorded, performing *focal observations* [10]. The observed behavior is compared with the one reported by the device in real time.

Between 8:00 and 9:00 AM (Range 1), animals were eating forage (alfalfa hay and ration) on the floor, thus remaining standing and walking little with their heads down. Between 9:35 and 10:15 AM (Range 2), interventions were made in the flock, so that the animals walked and ran. There was no intervention in the rest of the experiment, and regular interactions occurred.

Range 1 presents the highest change frequency between the stand and head down states. Table II presents the confusion matrix. The diagonal of the table represents the states correctly classified, while the rest are the misclassified ones. Table III presents the algorithm's accuracy and sensitivity (maximum value is 1). The state with the worst accuracy and sensitivity is head down. The prediction success rate is 87.7 %.

In Range 2, we find the walk and run states. Table IV presents the confusion matrix, and Table V shows the algorithm's accuracy and sensitivity. The difference between a run and a brisk walk is hard to identify visually. This might lead to mislabeling the state and thus explain why the run state's sensitivity is not good. The prediction success rate is 89.0 %.

TABLE II
CONFUSION MATRIX OF RANGE 1 (EATING)

Obs\Pred	Walk	Stand	Head down	Run	Total
Walk	1	0	0	0	1
Stand	2	311	15	0	328
Head down	0	34	52	0	86
Run	0	0	0	0	0
Total	3	345	67	0	415

TABLE III
RANGE 1 ANALYSIS (EAT)

	Walk	Stand	Head down	Run	Total
Accuracy	0.33	0.90	0.78	—	0.87
Sensitivity	1	0.95	0.60	—	0.88

B. *Geographical location*

Fig. 4 shows 500 GNSS samples (blue dots) on a satellite image map. The orange rectangle shows the pen. There is a high density of dots where animals were eating, and the dots that leave the rectangle correspond to the ram entering the pen.

C. *Power Consumption / Autonomy*

We measured the device current consumption with Qoitech's OTII Arc. We measured it for 2 cases in VM: when GNSS searches satellites and when it tracks them. In the first case, the device consumed 156.4 mA, and with GNSS tracking, it consumed 137.4 mA. Given the device's battery, the autonomy is 51 and 58 hours, respectively. We considered 3 duty cycles to measure the current consumption in RM. If the device turns the modem and GNSS on every 2 minutes the autonomy is 14 days (it consumes 24.5 mA), every 5 minutes is 25 days (13.1 mA), and every 10 minutes is 37 days (8.9 mA). The shortest period in RM mode is enough for birth surveillance.

IV. CONCLUSION

We presented the design, manufacture, and test of a wearable electronic device to monitor sheep behavior. The device reports the sheep's location and signals from an accelerometer that characterizes its activity to a Central System. The device has 2 operating modes. In VM, it reports data every 20 seconds, and the battery lasts 51 hours. In RM, it can report every 10 minutes, and the autonomy is 37 days. In both operating modes, the microcontroller identifies the sheep's state using real-time acceleration data. We performed an experiment on a single male animal on a single day. More tests are required to reach definitive conclusions, particularly on animals of different sexes, sizes, breeds, ages, and larger time slots. Likewise, preliminary tests are promissory since the state identification has a prediction success rate of 88 %, and the overall device's performance is well in line with the state-of-the-art (see Table VI). These results offer solid ground to develop a system based on our proposal to study sheep behavior to anticipate whether a sheep is close to giving birth.

TABLE IV
CONFUSION MATRIX OF RANGE 2 (WALK AND RUN)

Obs\Pred	Walk	Stand	Head down	Run	Total
Walk	26	0	6	0	32
Stand	0	160	11	0	171
Head down	0	1	3	0	4
Run	5	0	1	5	11
Total	31	161	21	5	218

TABLE V
RANGE 2 ANALYSIS (WALK AND RUN)

	Walk	Stand	Head down	Run	Total
Accuracy	0.83	0.99	0.14	1	0.85
Sensitivity	0.81	0.93	0.75	0.45	0.79

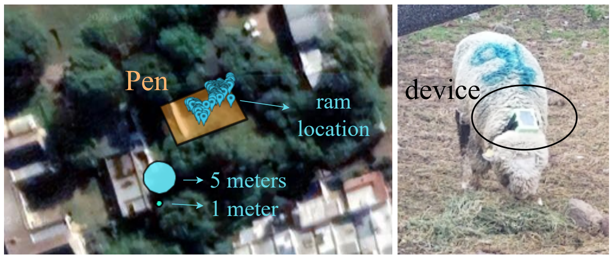

Fig. 4. Left: satellite image of pen's surroundings. Right: ram with the collar.

TABLE VI
STATE-OF-THE-ART COMPARISON

	[7]	[5]	[11]	This work
# States (activity)	5	4	3	4
Classification accuracy	82.5 %	76.9 %	85.2 %	87.7 %
On-device classification	no	no	hybrid	yes
Accelerometer samp rate	100 Hz	12.5 Hz	16 Hz	100 Hz
GNSS samp period (s)	n/a	no	no	10 - 120
Autonomy (days)	n/a	30	2.4	2 - 10
Microcontroller	MSP430	PIC24	Quark	MSP432
Wireless comm tech	RF	no	LPWA	NB IoT
External memory	2 GB	512 MB	n/a	no
Device type	collar	ear tag	ear tag	collar

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