Monitoring the Behavior of Cattle through Wireless Sensor Networks

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Abstract: Cattle monitoring is an important demand in precision livestock and crossbreed quality control. Previous studies and products have been proposed to approach this problem, although several factors pose challenges for real-time data acquisition and analysis. In this work, we present a proof of concept prototype for a cattle crossbreed monitoring system based on wireless sensor networks. The hardware implementation, the sensor data acquisition system and the field tests are described in detail. Supervised machine learning algorithms are applied for copulation detection and the classification metrics show that some of the proposed models have good sensitivity, suggesting promising directions for future steps and optimization.

Keywords: Cattle monitoring; Wireless sensor networks; Machine learning; Supervised learning.

1. INTRODUCTION

Agribusiness has become one of the most important sectors of the Brazilian economy in recent decades. In 2019, it represented about 21% of the Brazilian GDP, where approximately 23% of this is related to livestock production (CEPEA (2021)). This significance does not occur only in Brazil, making livestock an important part of the world economy. Thus, livestock becomes an interest on studies aiming at improvement and new technologies, in the context of precision livestock. When directed to cattle, precision livestock can be used to monitor each animal, making it possible to create a database of herds, gathering information such as breeding activities and general health of the animals. This data allows for analysis regarding activities of food ingestion, rumination and rest, as well as crossbreed quality control (Garcia et al. (2018)).

The purpose of animal monitoring is to improve the livestock production process efficiency, reducing manual activity and providing automatic event detection capability. Among events of interest, what stands out the most is reproduction. Much of the optimization of this stage is obtained from artificial insemination in herds. However, this technique shows many problems that compromise the effectiveness of this process, such as inefficiency in the estrus detection (the animal's reproduction cycle) or even the long term for reproduction in the postpartum period (Baruselli et al. (2012); Menegassi et al. (2011)).

In this context, this work proposes a cattle crossbreed monitoring system based on Wireless Sensor Networks (WSN). The purpose of the system is to collect real-time data of each individual and automatically detect copulation events between monitored individuals. Some practical constraints have been considered during the system development. Bovine breeds such as zebu cattle represent a large percentage of the Brazilian herd, and are characterized by shyness in the presence of humans. Thus, monitoring should take place with minimal human intervention - hence the use of a WSN to remotely collect the data from sensors attached to the individuals. For this purpose, a physical hardware device is proposed to be attached to animals. Each device has three types of inertial sensors: an accelerometer, a gyroscope and a magnetometer, in addition to an ambient temperature sensor. These devices collect and transmit each individual's data, which is received and stored in a central unit where event detection algorithms can be applied.

This article is organized as follows. In Section 2, some related works are presented. Section 3 system model and methods are described. Data acquisition and case study are presented in section 4. Results are presented in section 5 and conclusions of this work are described in Section 6.

2. RELATED WORKS

A system for the detection of sheeps' copulation is proposed in Bocquier (2005). It considers a set of wearable sensors dressed in the male individuals and an RFID communication system. Furthermore, it uses passive RFID tags in female individuals. During the mating event, the males system activates the female's passive device, reads its code and registers the mating event in the male's vest device. It is necessary to physically remove the male's vest in order to collect and read the data.

In Smith et al. (2006), the author's present a bovine monitoring system. The system is composed by a set of sensors to monitor the animal's temperature, heartbeat, position and movements. Data is acquired with a microcontroler and transmitted to a central unit via ZigBee wireless communication. Also, a data storage system was implemented in the microcontroller, so that data can be collected when the animals are in the range of the communication network. Even though the data is made available without preprocessing, graphical analysis can be used to evaluate the individual's behavior over a day of monitoring. Results of Smith et al. (2006) suggest that this system can be used to improve animal's welfare.

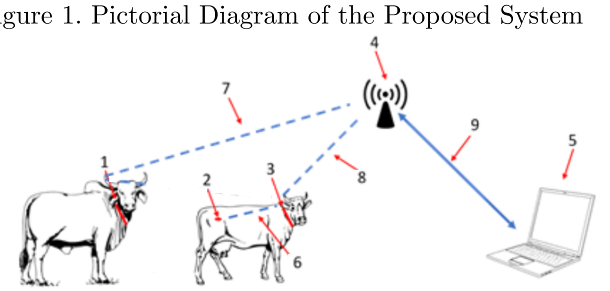
The model patented by Lisboa et al. (2017) also proposed a system for detecting copulations which was developed mainly for cattle. Using sensors with RFID coding on the female's tails and on the bull's loins, the system sends the sensor data wirelessly to a data concentrator. The concentrator device also performs the signal processing to identify the event occurrences and the involved individuals.

This work has the proposal of animal monitoring, more specifically reproductive monitoring, using WSN and an intravaginal device, with identification of events through supervised learning. Comparing with the related works: Bocquier and Lisboa have a proposal for animal and reproductive monitoring, however they do not have the other aspects of this work; Smith has the proposal to use WSN for animal monitoring, does not perform reproductive monitoring and does not use other resources.

3. SYSTEM MODEL AND METHODS

As a proof of concept, this work considers a particular scenario depicted in Fig. 1, in which the proposed WSN is mainly composed by three monitoring devices: a male collar (1), an intravaginal device (IVD) (2) and a female collar (3). A data aggregator node (4) collects sensor data and relays it to a computer system (5) through a wired link for data processing and event detection. LoRA technology is used for the wireless communication links (6), (7) and (8).

Figure 1. Pictorial Diagram of the Proposed System



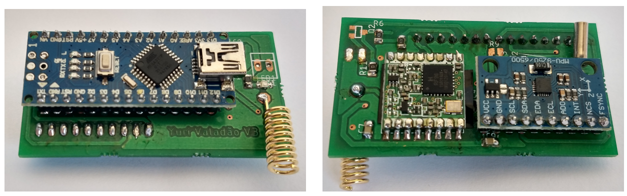
Note that the male device (2) collects and transmits data in a single-hop communication link with the aggregator (4). However, the female collar (3) acts as a wireless relay node for the IVD (2) in a store-and-forward manner. This is due to the absorption of the signal through organic tissue, causing significant reduction to the coverage radius of the IVD node (Müller and Menegassi (2018)).

3.1 Hardware Development

Since the animals' monitoring devices are wearable, it is critical to design them to be small and lightweight. This requirement leads to the choice of components with a certain degree of miniaturization for the application.

For inertial sensing of the devices, the MPU-9250 sensor was chosen (InvenSense (2020)). The choice is mainly due to its high integration, since it has integrated accelerometer, gyroscope, magnetometer and temperature sensor. Due to the long distance communication requisite, radio frequency in the 900 MHz ISM band was chosen, since it is unlicensed in many world regions and it allows long distance communication links using communication with radio LoRa (HopeRF (2020)). Aiming at the need for communication synchronism, the DS1307 real-time clock was added to the hardware, to provide synchronous timestamps (Dallas Semiconductor (2020)). Finally, for basic signal processing of the collected signals, the ATmega328P microcontroller, clocked at 20MHz, was the choice to manage the sensors (Microchip (2020)). One of the implemented prototypes can be seen in Fig. 2.

Figure 2. Developed PCB, (a) Top Side, (b) Bottom Side



(a) (b)

3.2 Network Communication Firmware

A communication protocol firmware was developed for the hardware proposed in the previous section. It is based on a finite-state machine concept and time-slot resource allocation.

The device startup state is a procedure in which it waits for configuration, which is received before deployment with a software developed for this function. The initial settings provide the individual device a category label (male collar, female collar or IVD) and an unique identification number. Furthermore, the configuration step syncs the device with the WSN by setting the sample rate of the sensors and the assigned timeslot for uplink transmission. Upon receiving the configuration data, the device performs the internal settings steps and is ready for data acquisition.

After the configuration, the device's state is changed to deployment operation, where it starts collecting data from the sensors with an internal timer interrupt service routine. Each device collects as many data as possible (with a fixed sample rate) and buffers it until its assigned periodic timeslot. This time-slotted resource assignment protocol is similar to a Time Division Multiple Access (TDMA) framework, hence the need for a real-time clock in each device.

3.3 Rare Event Detection Problem

Cattle copulation detection is framed in this work as a rare event detection problem in time series data. Some challenges for the detection algorithm can be highlighted:

- packet losses during communications in the WSN, result in missing data over time;
- the event is rare, that is, most of the time it is not ocurring, and when it happens, it lasts for a very short time (a few seconds).

Let n be the discrete-time index for the sampling moments and i be an index for one of the devices (collars and IVD). At time n, the device i collects one scalar measurement of each sensor. Additionally, each of the three inertial sensors has data from three independent space dimensions. Thus, along with ambient temperature, each device is collecting 10 measurement per sample.

Let $\mathbf{x}_{i,n} \in \mathbb{R}^{10}$ be the sample data of device i at time n, for $i = 0, 1, 2$ and $n = 0, 1, \ldots, N-1$. Once the aggregator collects the buffers from all individuals over a large enough period, it forms a time series $\mathbf{X} = \{\mathbf{X}_0, \ldots, \mathbf{X}_{N-1}\}$, where each sample $\mathbf{X}_n$ corresponds to data from the three devices: $\mathbf{x}_{0,n}$, $\mathbf{x}_{1,n}$ and $\mathbf{x}_{2,n}$. Note that $\mathbf{X} \in \mathbb{R}^{N\times 30}$, and it is denoted here as a dataset with N samples of 30 features (10 sensor data measured simultaneously from 3 individuals).

In general, when working with raw datasets, it is necessary to first apply some transformations and preprocessing to assist in time series analysis methods. The normalization of features (orthogonal dimensions) in datasets with multidimensional samples can be very helpful to machine learning estimators. A widely used technique is to transform the scale of the different variables of the system into a common range of values. Thus, for this work it was decided to use a standard scaler normalization (Guralnik and Srivastava (1999); Goodfellow et al. (2016)). It standarizes the data of each feature by removing its average value and scaling it to result in an unitary dispersion (standard deviation), as described by Eq. 1:

$$\mathbf{z}_k = \frac{\mathbf{x}_k - \mu_k}{s_k}, \tag{1}$$

where μ is the sample average, s is the sample standard deviation and k is the feature index of $\mathbf{X}_n$, for $k = 0, \ldots, 29$ (Morettin and Toloi (2018); Fernandes (1995)).

3.4 Label Annotations and Windowing of the Time Series

In order to apply supervised learning algorithms, there is a need to label the reproduction events, which are the target variable that must be estimated (classified) In this work, the sampling time of each row (sample) of the dataset is 500 ms. Although the target event is short-lived, its signature in the data can be visually characterized for a longer time. With the preliminary analysis of the collected dataset, it was established that a sufficient window length of 2.5 seconds could be enough to characterize the event. Hence, this corresponds to a frame of 5 consecutive samples (rows) of the dataset $\mathbf{X}$. The window is shift in steps of one sample each time. Thus, for each window, a binary value is labeled to indicate the ocurrence of the event in that window (0 for it not ocurring and 1 indicating a signature window of the copulation). Remark that due to this stride length, there are overlapping windows labeled as 1 (or "True") for the same event.

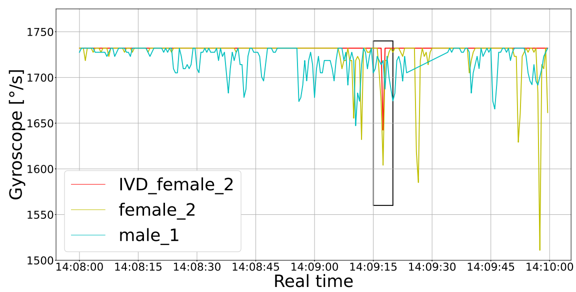
4. DATA ACQUISITION AND CASE STUDY

In field tests of the system depicted in Fig. 1, temperature, magnetic field (magnetometer), angular velocity (gyroscope) and acceleration (accelerometer) data of the devices were collected with a sampling time of 500 ms during approximately 2 hours. All the tests were made under supervision of a veterinary physician responsible for the well-being of the animals. In this period, only 3 copulation events have occurred, which is consequence of the challenges of field testing close to the animals and the low rate of occurrence of the event.

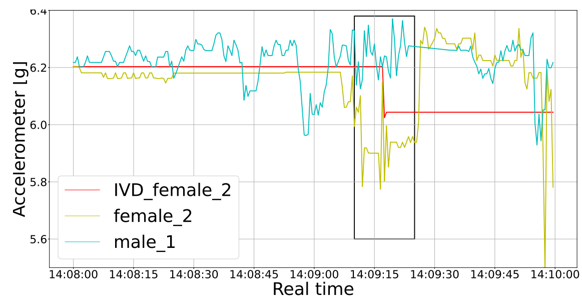
During these field activities, timestamp of copulation event was manually annotated. Subsequently, as a means of verification, data was analyzed within a short period before and after these timestamps, double-checking the signature of occurrence of the event and labeling the corresponding windows.

To illustrate the signature of the event, Figure 3 shows a slice of the data for the absolute value of the vector sum of angular velocities and acceleration during a copulation moment. Each device's curve has a different color according to the plot legend.

Figure 3. Identified copulation 1 (a) Gyroscope (b) Accelerometer



(a)



(b)

4.1 Data Augmentation

In the collected data, less than 1% of the samples is related to the occurrence of the copulation. Thus, it was decided to artificially add more samples to better balance the training data. In the machine learning literature, this procedure is called data augmentation (Goodfellow et al. (2016)). In the case of this work, we are only interested in increasing the sample windows labeled as 1. A simple strategy to increase the number of samples of the data would be to copy them and slightly modify the scale of the variables (multiplying by a scalar, for example). However, this maintains a very strong correlation with the original data. Therefore, it was decided to add noisy copies of the true events. After train/test data split, Gaussian noise was added to copies of the copulation windows to increase the size of the training data. The signal-to-noise ratio of these copies is controlled with a noise power parameter, varying in ranges from -30 dB to -1 dB with 50 different intensity levels. This augmentation results in a percentage of approximately 23% of copulation events (real plus noisy copies) in the training set.

4.2 Parameters for Train/Test Splits

The training and test splits were separated with 20% of the test data in a cross-validation evaluation method. However, since the original data has few samples of positive events (disregarding augmented data, used only after the training split is available), it is ensured that half of these positive samples (50% of the copulation windows) is always separated for training and the other half for testing. A randomized repeated K-fold function with 200 repetitions and 2 splits is used for cross-validation.

5. RESULTS

In this supervised learning framework, four classification models have been evaluated for this problem: logistic regression (LR), Gaussian Naive Bayes (GNB) classifier, Decision Tree Classifiers (DTC) and Support Vector Classifiers (SVC). In conjunction with the models, a class weight $w \in (0.5, 1)$ is used for the samples with label 1 and $1 - w$ for the samples of label 0. This weighting acts as a penalty in the calculation of the objective function during the fit of the models, punishing more strongly "false negative" type of errors. For all the results herein, it is assumed $w = 0.8$.

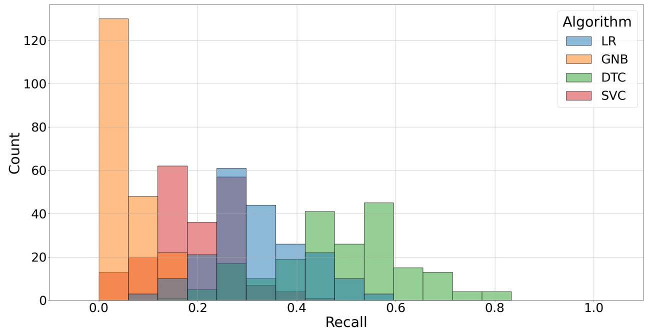
Considering all the parameters described in preliminary sections, a few scenario are reported here to compare the performance of the different models. The most important metrics that have been considered here are the recall (or sensitivity), which decreases proportionally to the false negative errors, and the false alarm rate, which decreases proportionally to the false positive errors.

5.1 Scenario 1

Here, all features are considered as input values to the model. Since each input window has $N = 5$ samples, the input dimensionality is flattened to an array of length $5 \times 30 = 150$.

In Fig. 4, a histogram of recall is presented. The algorithm which is performing the best is the DTC, with an average recall of 48.44%. Since the results of all models were very poor in this scenario, the false alarm rate will not be analyzed.

Figure 4. Histogram of the recall of the algorithms considering all elements.

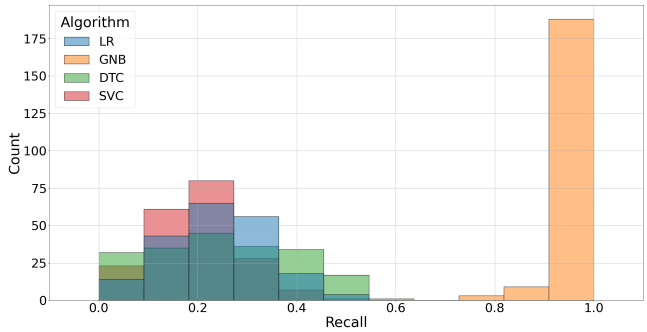


5.2 Scenario 2

Herein three new features are added to the dataset: the absolute values of the vector sum of the 3-axis inertial sensors. They can be viewed as feature engineering of values of magnetic fields, accelerations and angular velocities. The original features of independent spacial axis are dropped from the dataset. Moreover, after a few tests, the ambient temperatures features were also removed, since it was noticed that it was worsening the prediction power of all models. The modified dataset now has only $3 \times 3 = 9$ input features (3 from each device).

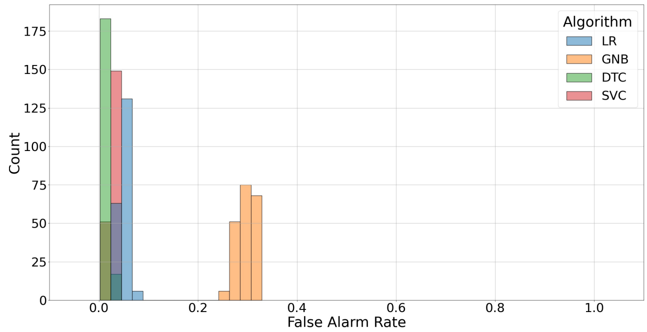
Fig. 5 shows the recall histograms for each model. There is a significant improvement in the GNB model with an average recall value of around 92.7% and with a confidence interval between 82 and 100%. The other models failed to achieve a very good performance, causing their recall averages to be reduced.

Figure 5. Histogram of the recall of the algorithms considering absolute values without temperature data.



In Figure 6, the false alarm rate of this scenario is also shown. This histogram is complementary to the previous histogram, since for the GNB model to have a high recall performance, it generates more false positives than before, between 19 and 27% while the other algorithms keep the expected (due to the unbalaced dataset) low false alarm rate.

Figure 6. Histogram of the false positive rate of the algorithms considering absolute values without temperature data.



Another benefit of this scenario is the reduced dimensionality of the input signals, which may decrease the complexity order of the algorithms, eliminate strongly correlated variables (since this can bring multicollinearity problems) and further facilitate communication in the sensor network (in future refactor of hardware and firmware).

6. CONCLUSIONS

This work has proposed a cattle crossbreed monitoring system with automatic copulation detection. Hardware and firmware have been developed and a wireless sensor network has been implemented for field tests in a case study. Results show that the supervised learning approach is promising and that feature engineering can bring benefits both for dimensionality reduction and future system's optimizations.

In future work, a more methodical analysis of the selection of features is important, using techniques such as SHapley Additive exPlanations (SHAP), select Kbest or Recursive Feature Elimination (RFE), enabling a better performance of the algorithms. Also, using a model that is capable of dealing with sequential data predictions, such as recurrent neural networks or Long Short-Term Memory (LSTM), can be an evolution of the parameters over time.

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