Learning About Animals and Their Social Behaviors for Smart Livestock Monitoring

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Abstract. Things are increasingly getting connected. Emerging with the Internet of Things, new applications are requiring more intelligence on these things, for them to be able to learn about their environment or other connected objects. One such domain of application is for livestock monitoring, in which farmers need to learn about animals, such as percentage of time they spend feeding, the occurrence of diseases, or the percentage of fat on their milk. Furthermore, it is also important to learn about group patterns, such as flocking behaviors, and individual deviations to group dynamics. This paper addresses this problem, by collection and processing each animal location and selecting appropriate metrics on the data, so that behaviors can be learned afterwards using machine learning techniques running on the cloud.

Keywords: Cloud computing · Learning · Internet of intelligent things · Smart livestock management · Social behaviors · Wireless sensor networks

1 Introduction

In the past, Livestock Management (LM) was based on farmer's observation, judgment and experience. Indeed, farms usually had people watching animals, which is a time consuming and expensive approach. However, due to the increasing scale of farms and the high number of animals that compose it, it is infeasible to continuously monitor the animals through visual observation during twenty four hours a day [1]. Furthermore, empirical evaluation from historical data is purely based on a human observer's experience, who cannot continuously track a single sheep 24 h a day, much less all animals on a flock of sheep.

Precision Livestock Farming (PLF) addresses such challenge, by continuously and remotely capturing measurements (e.g. position, head movement, bio-signals of animal) related with the condition of individual or groups of animals, as well as reporting this extracted data to a farm manager [2]. This paper proposes adding learning on top of it, so that livestock monitoring can be more effective than using human observation alone. Smart Livestock Monitoring (SLM) adds an extra dimension to the problem, enabling a LM system to learn from the history of such acquired data to provide added value information to a farmer.

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Animal's collars have been employed for real-time tracking of free-grazing animals' location, useful for various applications. For instance, it could be possible to deduce automatically the grazing habits of free ranging animals, which can be very useful to the farmer for making better decisions on the efficient usage of land. Additionally, it allows determining the path of the animals in a certain time, and consequently the utilized grazing area.

The real-time location of each animal may also be very useful whenever the farmer wants to fetch free-grazing animals at the end of a season, avoiding searching for them in a certain region. This is also true for animals' carcasses, since insurance companies in some countries reimburse the farmer for animal death if its body is found. Additionally, the cost of building and maintaining fences is one of the most expensive costs associated with Livestock grazing [3]. Geo-fences can be used to minimize these costs, since they do not rely on a physical fence. Furthermore, machine learning approaches can be employed to learn the geographic areas preferred by animals along different dimensions, such as weather, day time, month of the year, etc. Collecting the location of each animal can be also very interesting for detecting animals' diseases (which may affect the animals' walking pattern or behavior) employing learning strategies. This is especially important for infectious diseases, since it also enables the isolation of only those animals that had direct or indirect contact with the affected animal, avoiding the slaughtering of healthy animals.

1.1 Farm Producers: Motivation and Requirements

A requirement analysis included surveying several cattle producers, involving interviews with various experts at each location, working directly with the animals (dairy sheep) or who are directly involved on the business' management activities. Hence, requirements were gathered from three different producers:

- Queijaria Ribeira de Alpreade's offices, under the scope of Fundão's Terras do Xisto LivingLab
- Quinta do Pisão, Cascais City Council
- One of the largest farms in Portugal, with cattle and sheep, near the city of Setubal

In these farms, the dairy sheep graze freely in a large dimension pasture (tens of hectares) partially or totally covered by cellular mobile communications. They spend most of their time alternating between grazing and resting/ruminating, presenting slow movements (except during short stress periods). Sheep graze in cohesive groups and isolation is a source of stress to them. They are social animals and create strong social hierarchies between them. Typically, at the top of the hierarchy there are some leading sheep that influence the other animals, particularly their grazing movements. Therefore the other sheep tend to follow the leaders. Farmers usually tag these leading sheep with a bell on their collars to easily locate them.

Staff interviews revealed the need for learning different pieces of information based on sheep motion, behavior, or other features, according to priority requirements to be complied by the system prototype, which are illustrated in Fig. 1:

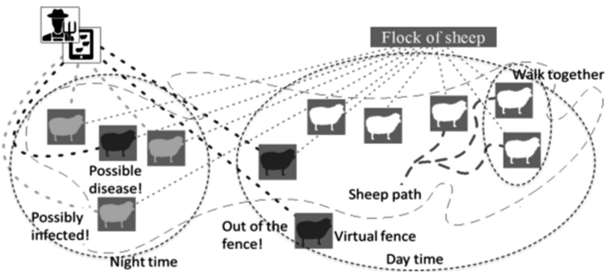

Fig. 1. Learning requirements for smart livestock management.

1. Alterations in the normal bustle of an animal may indicate to the farmer valuable information, therefore the farmers want to be informed when an individual animal presents movement values that are significantly different than the average, taking into account the history of that specific animal (based on distance travelled, velocities, erratic behavior, or any other relevant feature;
2. Whenever an animal picks an infectious disease, it is often necessary to slaughter the whole flock of sheep. Therefore it is crucial to infer the direct or indirect interactions between the various animals, based on the historical contact distances between them, to isolate solely the infected sheep, thereby avoiding slaughtering healthy ones that were not in danger of contagious;
3. Learning geographic patterns from sheep locomotion (e.g. relative to weather, hour of the day, month of the year, etc.). Learning common routes taken by a sheep or flock of sheep, to clearly identify sheep grazing habits, the used pastures, as well as the ones with better quality. Because sheep freely grazing sometimes surpass the farm limits, need also to implement a geo-fencing functionality that sends an alarm to the farmer staff indicating such occurrence;
4. Learn to detect a collar cut, indicating a possible theft;
5. Learning the percentage of fat on a sheep's milk based on previous history, such as the sheep grazing times and regions, weather conditions, time of the year, as well as using history data from other sheep.

Although these functionalities are specific to this pilot farm, some of them are transversal to the branch of the farm animals monitoring and even common to other sectors of our society. This paper will address mainly requirement 1, although compliance with some other requirements, such as 2 and 3, are also briefly discussed). Several metrics are considered aiming at the identification of the most relevant ones.

2 Related Work

Hereafter it is reviewed the most relevant previous work in the application of learning techniques for smart livestock monitoring using WSNs systems. A more extensive survey was presented by Sheikh [4], which reviewed machine learning techniques for WSN based livestock monitoring.

Nadimi et al. [5] propose a system to monitor the behavior of a herd in Denmark, capable of monitoring behavioral parameters of individual animals and transforming them into the corresponding behavioral mode, using for that an Artificial Neural Network (ANN). Farm animal's behavior and physiological responses provide important information about their health status and welfare. The behavior mode varies within five types: grazing, lying down, standing, walking and other modes. This animal behavior classification can be very useful to the farm's management.

Sikka et al. [6] deployed a large WSAN on a farm (a cattle breeding station at Belmont, in Australia) to understand the animals' behavior, improve the farms management as well as to maximize the farm production. Besides tracking animals, they also considered haptic and audio feedback to the animals. Based on the animal position, the system applies various stimuli (such as sound, vibration as well as low-level controllable electric shock) to the animal in order to change his behavior. This autonomous farm management system will automatically determine the areas more suitable for grazing based on soil moisture sensors. Such information is used to build accordingly the virtual fences, which will contain the animals that are automatically guided to these locations through stimuli.

In a related field, namely forest fire detection, Yu et al. [7] proposed a WSN solution employing a neural network for data processing. System evaluation was however through simulations.

3 Smart Livestock Management

The proposed architecture was developed for learning useful information for farm management, based on collected data from monitoring livestock animals (e.g., horses, cows, sheep, etc.), especially when they are freely grazing. Low energy consumption, storage and processing resources scalability is achieved using the cloud. Intelligent data processing makes use of machine learning and statistical methods for inferring additional valuable information. The monitoring is centered in the collection of the animal's geographical information through WSN nodes, to be fed into the learning services. Using this information, the system should make relevant deductions about the actual status of each animal, and of the entire flock, based on historical data.

This architecture is divided into three relevant components (see Fig. 2): the WSN infrastructure, the Cloud Computing platform responsible for event detection and data processing (including animal tracking, geofence and the learning services), and a Web application for the farmer to visualize the status of the system as well as to interact with it. This way, the heavy processing occurs on the Cloud Computing platform where learning should take place.

The leader sheep will correspond to the sink nodes of the WSN as they tend to have more sheep close to them. The other sheep will correspond to mesh nodes that will send its data through multi-hop to the sink nodes, using for that a short-range radio.

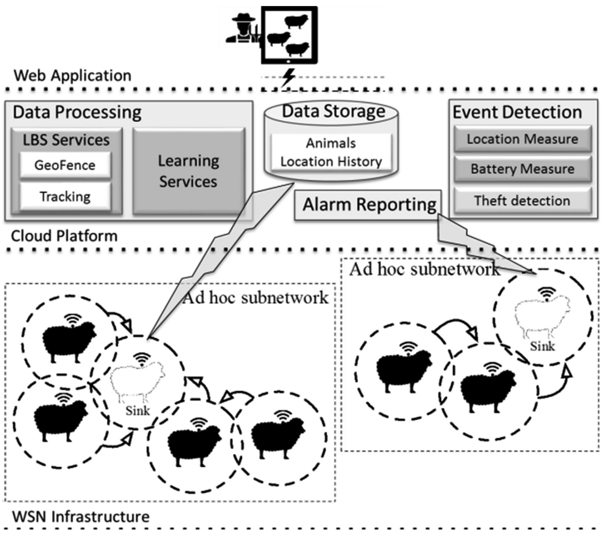

Fig. 2. System's architecture.

3.1 WSN Infrastructure

Each node of the WSN infrastructure corresponds to an animal that is equipped with a device providing sensing, computation as well as communication capabilities. Therefore, each animal will correspond to a mobile node that communicates wirelessly with the other system nodes.

Sensor Nodes. Sensor nodes are based on the eZ430-RF2500 module from Texas Instruments combined with Sensefinity's Butterfinger. The Butterfinger combines the MSP430F5419A MCU with a SIM908 module from SIMCom Wireless Solutions. It includes a GPS unit for collecting location data and a GPRS module for data transmission. In addition, it is possible to acquire as well its current battery status. As the Butterfinger has not a short-range radio (for communications within the WSN), it was necessary to combine it with an eZ430-RF2500 module, which provides the CC2500 transceiver. The sensor node (Fig. 3) is attached on the animals' collars.

Fig. 3. The final version of the hardware, its protective case, and installation on a sheep collar.

Network Protocol. A gradient-based routing protocol was implemented, appropriate for convergent traffic in mobile large-scale networks where the data packets flow to sink nodes, which aggregate all the information collected by the network. It was chosen a single-path routing approach in order to forward the data packets to the sink nodes, sending them through the most adequate neighbor (the one-hop neighbor that is closer in hops to a sink node, i.e. the neighbor with lower height). It was also used a point-to-point message delivery confirmation. Each network node adjusts its radio communication signal strength according with the targeted neighbor for communication, allowing to saving energy and reducing the network interference.

Routing. The monitored animals form a Mobile Ad-Hoc Network (MANET), providing high scalability and robustness to the network. For instance, in the cows' monitoring field, some authors [6] support this model by showing evidence that the animals on a cattle remain close to each other (typically herd together), so that overall connectivity between them was maintained using a multi-hop approach.

It is used a convergent protocol to route the data to the back-end infrastructure using a multi-hop approach. All system nodes use the short-range radio with low power consumption to communicate with the other animals inside the WSN. Due to this system's natural mobility constraints, some nodes eventually may become disconnected from each other, therefore forming independent and isolated ad hoc networks [8]. Our SML solution addresses this challenge by following a modified Full Cloud Connectivity model, employing data buffering and opportunistic routing of information in cases whether cellular coverage is inexistent.

3.2 Cloud Platform Services

The Machinates Cloud Computing platform provides the back-end infrastructure that supports the WSN, offering: data processing, data storage, event detection as well as alarm reporting. The Cloud Computing resources can be easily and automatically adjusted according to new application's demands, or as the application's requirements grow, without the farmer having to invest more in back-end infrastructure. The Cloud Computing platform is also in charge of sending digests to the end-user (via email) containing a monitoring summary during a period of analysis (day, week, month, etc.)

Location Tracking. A sensor node acquires its current geographic location, through GPS or other localization method, following a time-driven data reporting model. All this sensed information is aggregated in a sink node and then uploaded to a back-end infrastructure to be later processed. To accomplish these functionalities, each animal uses a technological device robust to the surrounding environmental conditions.

Geofence. Each time a position message is delivered to the Machinates® back-end, the geo-fencing algorithm will compare the new received animal's location with the existing virtual fence coordinates. Therefore, it is possible to determine if an animal is inside or outside the virtual fence, and erase or trigger accordingly an alarm. A simple geo-fencing algorithm was therefore implemented based on the Jordan Curve Theorem,

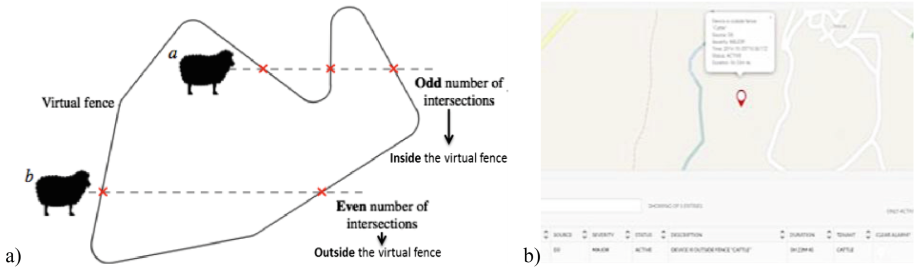

Fig. 4. (a) Example of the Jordan Curve Theorem; (b) Geo-fencing alarm on the Web application.

as follows. It is first necessary to draw a straight line from a given point (i.e., the sheep's location) to the outside of the whole drawing (i.e., outside the virtual fence). If the line meets the curve (i.e., the virtual fence) an odd number of times, that point (i.e., the sheep) is on the interior, otherwise if the line meets the curve an even number of times, that point is on the exterior. Figure 4a illustrates the application of the Jordan Curve Theorem. The line that intersects sheep a meets the virtual fence line 3 times (i.e., an odd number of times), therefore this sheep is on the interior of the virtual fence. The line that intersects sheep b meets the virtual fence line 2 times (i.e., an even number of times), therefore this sheep is on the exterior of the virtual fence.

Alarm Reporting, Storage and Event Detection. The farmer can use a Web app to visualize the last reported system (and its nodes) states, consult historical information that have been saved, access the events detected by the platform (see Fig. 4b), as well as interact with the system.

3.3 Pattern Learning Services

Machine learning approaches can be employed to add intelligence to the Internet of Things [9]. Running on the cloud, pattern learning aims at identifying healthy from non-healthy animals based on individual and group metrics (see Fig. 5a).

It was considered statistical and machine learning functionalities given by MATLAB tool (and libraries) in order to implement the two components of this module. The first component consists of feature extraction from geo-location data. It comprises, for each day of data, the extraction of statistical features, such as average and standard deviation values, and signal entropy, to feed such data into a learning algorithm (also employing matlab toolboxes). According to Fig. 5b, it was initially considered both supervised and non-supervised learning, namely clustering and neural networks, respectively. For supervised learning, the learning algorithm is first trained with inputs, for which the desired outputs for such data are known in advance (e.g. using data from known healthy and non-healthy animals). After the training process, and once the algorithm were fed with the inputs, it estimates the appropriate output. For unsupervised approaches, only the classification process takes place.

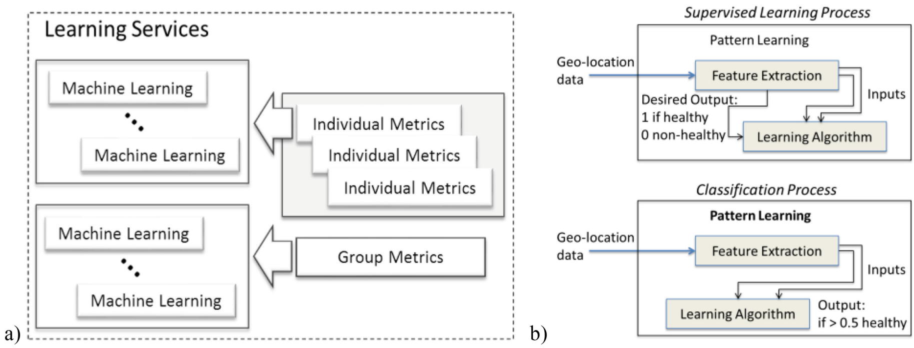

Fig. 5. (a) Metrics acquisition over acquired data for machine learning services; (b) Pattern learning strategies.

4 Pattern Learning Experiments

Experimental evaluation was performed at a large farm on the city of Setubal. Data concerning locations for two sheep is available for a two day period. A similar pair of sheep used collars, but one of them was injured. The results hereafter discussed are on (latitude, longitude) coordinates (see Fig. 6), distances and total velocities in degrees, over an equal period of nearly 6 h during daytime. Although different sheep were tracked during different day time periods, this 6 h period correspond to identical monitoring time intervals.

For each experiment, in each day and for each sheep, it was determined the velocity between two consecutive measured points. Thereafter, several features were extracted, namely average and standard deviation values, total sum of velocities (represented as d total on Table 1), and two entropy measures (corresponds to the two entropy values determined for the maximum scale according to Costa et al. [10]). In Table 1, velocities are given by $(\Delta x^2 + \Delta y^2)^{1/2}$, where $\Delta x_i = (\text{Latitude}_i - \text{Latitude}_{i-1})/\Delta T_i$ and $\Delta y_i = (\text{Longitude}_i - \text{Longitude}_{i-1})/\Delta T_i$, and $\Delta T_i = \text{timestamp}_i - \text{timestamp}_{i-1}$.

The results are shown in Fig. 7. Notice that the entropy value is smaller for the limp sheep during the two days of experiments. This may give some initial hint for a mechanism (e.g. clustering) to identify healthy from non-healthy sheep.

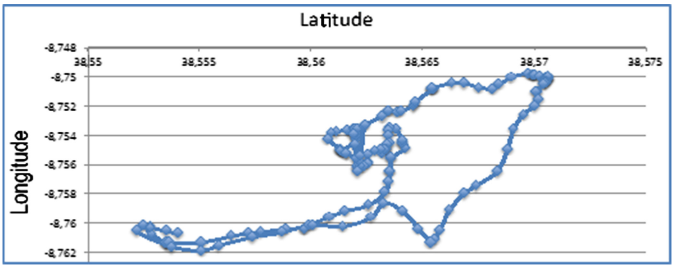

Fig. 6. Experiments in Setubal farm - Latitude/Longitude of limp sheep, day 2.

Table 1. Statistical measures for both normal and limp sheep during each day of experiments.

Sheep	Day 1					Day 2				
	avg vel	std vel	d total	Entropy 1	Entropy 2	avg vel	std vel	d total	Entropy 1	Entropy 2
Normal	0,211	0,149	23,9	1,56	1,63	0,221	0,157	22,3	2,44	1,87
Limp	0,176	0,168	19,9	1,42	1,12	0,213	0,241	21,6	1,8	1,34

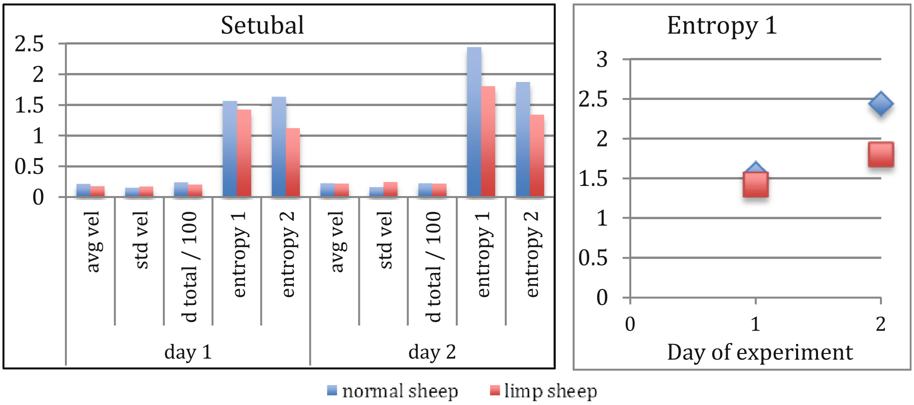

Fig. 7. Empirical results for the two monitored sheep at Setubal, for each of the two days of experiment. Several statistics are shown: average velocity and its standard deviation, two entropy values according to Costa et al. [10], and total distance during one day (scaled by 0.01).

The hypothesis concerning learning animal's health remains however to be tested upon the future availability of more training data to infer statistically relevant metrics (just two collars were available for experimental evaluation). It concerns the variation of the entropy value over several days, namely if for non-healthy individuals the entropy value over several days gets consistently lower than for healthy individuals. On a neural network, the inputs could be the entropy values of an animal over several days, and the output a value giving the probability of an animal being healthy, or not.

However, given the extremely small dataset available, no meaningful conclusions can yet be extracted concerning (i) the best features to extract from the data in order to feed a learning mechanism, either for clustering of a neural network approach; and (ii) the capability, or not, of identifying healthy animals from non-healthy ones using their patterns of motion. Concerning this last point, Costa et al. [10] have shown that the fractal property of organisms, such as given by a multi-scale entropy measure, gives a measure of an organism healthy, and have shown this strategy applied to ECG signals, as well as motion data. However, on their experiments the sampling frequency is significantly higher than 5,55 MHz (corresponding to 3 min in our system), and windows of analysis contain thousands of points (compared to nearly 100–200 data points for 6–8 h collection of sheep location data). Hence it is arguable if such approach could contribute in the future for the problem at hand.

5 Conclusions and Future Work

This paper proposed a learning architecture for a WSN system based on a Cloud Computing platform specifically designed for Livestock monitoring and management, centered on the periodical reporting of the animals' geographical location, and correspondent extraction of useful information for farm management from statistics and patterns detected on historical data.

A prototype was elaborated based on interviews with farm experts, and tested in a real scenario application, in particular for the monitoring of free-ranging dairy sheep. Although experimental evaluation evidenced the usefulness of this solution to a producer, further improvements will be pursued since real data statistical relevance is still rather weak, due to the small number of collars available for the experiments. We are however evaluating the learning system with sheep at two other farms.

Future work will continue to address the identification of the relevant features for each learning problem and algorithm. Moreover, features that were not completed in this first prototype system should be implemented (such as detect and report cuts in the sheep's collars). According to requests by experts at Queijaria Ribeira de Alpreade, the system should be upgraded in the future for monitoring other components of the business, namely predicting the percentage of fat on a sheep's milk, for aiding the farm's milking system.

Finally, experiments should be made with a higher number of monitored animals in different health conditions for a longer period of time in order to test the solution's effectiveness in detecting and distinguishing between healthy and non-healthy sheep. We are currently working on applying machine learning strategies to detect certain abnormal behavioral patterns that may suggest possible animal diseases.

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