New Commercial Representation for Cattle Information Gathering

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Abstract: As the development of Wireless Sensor Networks improves, new applications of Internet of Things are emerging in sectors as diverse as military, environmental, health or food. In many of these applications, the autonomy of the devices is an essential element in order to make reasonable use of them. For the cattle domain, there is a need for an efficient use of energy by sending few messages that accumulate as much information as possible. This paper proposes a new strategy for sending summarized information from devices that are commercially used in cattle to analyze animal behavior. Experiments using 120 different daily time series related to animal behavior have been performed. The obtained results show that the proposed strategy highly improves the current operation mode of the equipment.

1 INTRODUCTION

Given the rapid growth that Internet of Things (IoT) has experienced over recent years through the development of Wireless Sensor Networks (WSNs), there is a clear interest from society in the development of technologies that favor the communication between people and devices (Tan and Wang, 2010). This communication allows to control at any time certain processes that may be key for some sectors such as military, environmental, health or home applications among others (Akyildiz et al., 2002).

Within the wide range of sensors available for different IoT applications, accelerometers have been widely used for activity recognition purposes (Ravi et al., 2005; Brezmes et al., 2009). In the livestock industry, accelerometers have allowed to record information about animal status in a myriad of studies (Martiskainen et al., 2009; Diosdado et al., 2015).

In addition, for processes in which devices are hardly accessible, it is of crucial importance to provide long-term autonomies to users of the system (Duarte-Melo and Liu, 2002). Consequently, there must be a compromise between the amount of data sent by WSNs and the expected battery life of the devices used to gather information within the system. Animal monitoring in extensive livestock farming is a clear example of this type of systems. The more information gathered and sent, the more energy consumption from wireless devices. However, reducing the amount of data sent in order to improve the life of the devices may result in situations in which the information collected does not faithfully reflect animal behavior.

Hence, there is a need to design information submissions as efficient as possible, collecting data that gather the maximum possible knowledge about animal behavior in each submission. More accurate representations of animal behavior could improve real-time problems detection, speed up the reaction of farmers and reduce the number of potential animal losses or health issues.

This need is one of the main goals sought by the Digitanimal project (Digitanimal, 2019). Digitanimal commercializes several IoT-based devices and services specially designed to gather and analyze information about animal behavior in extensive raising. With the combination of these devices and services, Digitanimal offers their customers a system for monitoring animal welfare that can be translated into an increase in the productivity.

The development of these services and devices is carried out in collaboration with multiple research centers and experimental farms within European projects such as CattleChain (CattleChain, 2019). As a result of this collaboration, Digitanimal receives information related to events of interest that have happened to monitored animals, such

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as calvings or heats, through the commercialized devices. The combination of these sources of information, collaborations and devices, has allowed the publication of different studies in the area of IoT and WSNs (Navarro et al., 2019; Pérez et al., 2019).

In this work a dimensionality reduction technique and a distance function are combined to analyze accuracy in the representation of time series. The major goal is to improve the quality of cattle information gathering with WSNs.

The remainder of this paper is organized as follows. Section 2 presents a review of studies and different techniques used for representation and comparison of longitudinal data related to animal behavior as well as a detailed description of the problem to be solved. In Sections 3 and 4 a new strategy is proposed for data gathering and evaluated achieving promising performance improvements. The results obtained are analyzed and discussed in Section 5. Finally, Section 6 presents the main conclusions of the study.

2 RELATED WORK

2.1 Background

The analysis of longitudinal data has been a growing research area during the last years. The wide variety of sectors in which time series analysis is necessary has resulted in a large amount of new techniques for time series representation such as Discrete Fourier Transformation (Faloutsos et al., 1994), Discrete Cosine Transformation (Korn et al., 1997) or Discrete Wavelet Transformation (Chan and Fu, 1999).

The Symbolic Aggregate aproXimation (SAX) (Lin et al., 2003) is a time series representation widely used by the community (Lkhagva et al., 2006; Notaristefano et al., 2013). SAX is a dimensionality reduction technique that allows the transformation of numerical time series into a group of symbols or letters, reducing its size and discretizing its values.

For size reduction, SAX relies on the use of Piecewise Aggregate Approximation (PAA) (Keogh et al., 2001) which normalizes, i.e., transform to mean zero and standard deviation one, and splits time series into equi-length sections computing the average value of each one. Once PAA is applied, SAX discretizes values of the PAA result by mapping the averages computed to some predefined equiprobable levels. These levels are identified with symbols and calculated through different breakpoints, as seen in Table 1, that produce equal-sized areas under a Gaussian curve. This can be done thanks to the

Table 1: Breakpoints (γ) in a Gaussian distribution. From 4 to 8 equiprobable levels (α).

γ \ α	4	5	6	7	8
γ_1	-0.67	-0.84	-0.97	-1.07	-1.15
γ_2	0	-0.25	-0.43	-0.57	-0.67
γ_3	0.67	0.25	0	-0.18	-0.32
γ_4	——	0.84	0.43	0.18	0
γ_5	——	——	0.97	0.57	0.32
γ_6	——	——	——	1.07	0.67
γ_7	——	——	——	——	1.15

fact that normalized time series have a Gaussian distribution (Larsen et al., 1986). SAX offers multiple advantages against other time series representation techniques such as dimensionality reduction or lower bounding of the true distance between the represented and the original time series (Lin et al., 2003).

Besides time series representation, measuring distances between time series has also been of relevance for the scientific community. Thus, different similarity metrics and distances have been proposed like Euclidean distance (Faloutsos et al., 1994), Dynamic Time Warping (Berndt and Clifford, 1994), Longest Common Subsequence (Vlachos et al., 2002) or Edit Distance with Real Penalty (Chen and Ng, 2004).

2.2 Problem Description

Digitanimal commercializes several IoT devices specially designed to analyze animal behavior. This work is based on the use of two kind of these devices: Digitanimal's core product and a prototype developed for research purposes. The main aim of the presented work is to improve the quality of the information sent by the commercial product through the data gathered with the research prototype.

The core product of Digitanimal is a collar (see Figure 1) equipped with a GPS system, a surface temperature sensor and a 3-axis accelerometer. This device, placed on the neck of the animal, sends a message with information captured by its sensors to the servers of the company, at a fixed time rate of 30 minutes.

The message sending is realized through an IoT-based communication technology, Sigfox (Sigfox, 2019). This technology introduces important restrictions regarding the amount of information to be sent: 12 bytes per message at most and no more than 140 messages per day or a message every 11 minutes. Currently, the 12 bytes are distributed in the

Figure 1: Digitanimal collar placed on an animal.

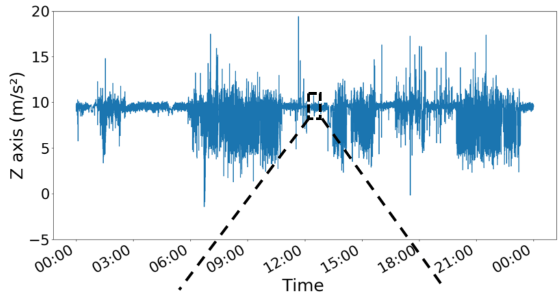
following way: 42 bits for GPS coordinates, 6 bits for temperature and 48 bits for accelerometer data (16 bits per axis).

A time rate of 30 minutes allows to ensure that collars have a battery life for over a year without the need of replacement. This is one of the main competitive advantages of Digitanimal and, thus, this study has not contemplated the possibility of reducing this rate. Besides, Digitanimal considers 30 minutes as an appropriate time rate for monitoring animal behavior through one-off GPS and surface temperature measurements. For this reason, the way GPS and temperature sensors information is sent has neither been part of this study.

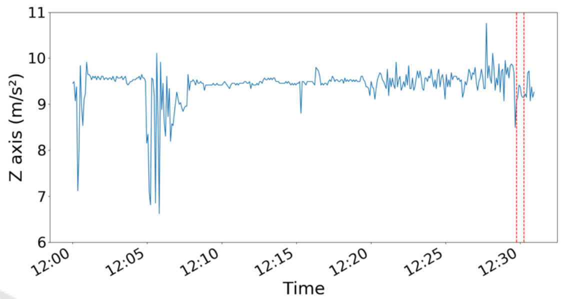
The gathering of accelerometer information is carried out differently than the GPS and surface temperature. Several measurements are taken in a time window of 30 seconds for each of its axis instead of just one measurement. Then, average (AVG), standard deviation (SD) and maximum excursion (EX) variables are computed from the recorded measurements. Hence, is essential to increase the amount of information captured by the accelerometer within the 30 minutes between each sent message, taking into account that Digitanimal considers the AVG variable of greater importance than SD or EX.

On the other hand, the prototype developed by Digitanimal is a continuous measurement (CM) device similar to the commercial one. The main difference between them is that the CM device only incorporates the accelerometer and it records information in another way. Every 5 seconds, this device stores the current position of the accelerometer in a memory card that is recovered once the data collection is completed. This device is placed on the neck of the animal and uses the same green casing as the commercial one.

Figure 2 shows a representation of the scarce amount of data captured by commercial devices every time window of 30 minutes. In Figure 2a, animal movement in the Z axis over 24 hours is represented in blue. In Figure 2b, a time window of 30 minutes is enlarged for displaying through red lines the time while the accelerometer reads the status of the device. Therefore, the previous 29 minutes and 30 seconds animal behavior cannot be analyzed, being this issue the major cause of this study.



(a) 24 hours of animal activity.



(b) Commercial data recording.

Figure 2: Commercial information gathering in a 30 minutes time window.

Therefore, the main goal of this study is to improve the quality of the information collected by the accelerometers of Digitanimal commercial devices respecting the constraints imposed by Sigfox technology and the expected battery life. For this purpose, a new strategy is defined to represent the time series obtained from CM devices with the highest possible accuracy.

3 METHODOLOGY

In order to achieve the improvement in the representation of accelerometer time series sought in this study, a solution based in SAX is proposed and evaluated against the current operation mode of the devices. In this section, the proposed as well as the commercial solutions are explained in detail.

The main idea behind the evaluation of all the solutions is based on the assumption that data

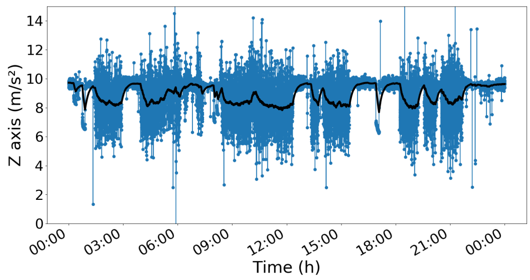


Figure 3: Application of exponential smoothing to the continuous measurement signal.

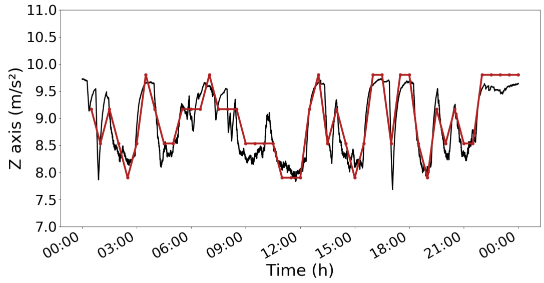


Figure 4: Commercial signal representation for 24 hours.

collected through CM devices is a close enough approximation to the real animal behavior. However, prior to applying any solution to the CM data, it is necessary to reduce its noise.

Figure 3 shows the application of an exponential smoothing to the raw CM signal. The transformed signal is represented through the black curve while the blue one is the raw data.

3.1 Commercial Solution

With the current commercial solution (CS), the device turns on automatically every 30 minutes and reads its status through its sensors. Firstly, the GPS position and surface temperature are stored to be included in the final message. Then, the accelerometer takes several measurements of its position during a time window of 30 seconds at a time rate of 100 milliseconds.

These 300 measurements are used to compute the AVG, SD and EX variables of the signal within those 30 seconds after applying a low-pass filter. Finally, all these values are sent in a message to the servers of the company using the following distribution of bits per variable: 6 bits for AVG, 6 bits for SD and 4 bits for EX. As only one measurement is sent per message, each amount of bits can be used to codify the information in different possible values following the relation stated in Equation 1.

$$Possible\,values = 2^{Number\,of\,bits} \tag{1}$$

Therefore, this bits distribution means that each variable (AVG, SD and EX) is discretized in 64, 64 and 16 different possible values, respectively. These values are computed in an equidistant way within a range from -2g to 2g, being g the gravity acceleration.

Figure 4 shows the AVG variable of a commercial signal constructed from the smoothed CM signal. The red curve represents the commercial one while the smoothed CM signal is represented in black color. Each value of the commercial signal is computed through the average value of measurements within a time window of 30 seconds. Therefore, each one of these values is the average of 6 CM values.

3.2 Proposed Solution

The proposed solution, SAX solution (SS), is an approach based in the representation technique explained in Section 2. This solution takes into account the constraints introduced by Sigfox in order to define different possible parameter combinations of number of levels and equi-length sections for each variable maintaining the current bit distribution adopted by Digitanimal. For each combination of parameters, the amount of available bits will limit the possible number of levels and sections. Besides this limitation in the amount of bits per axis and variable, this study does not consider combinations of two levels as they reduce excessively the information sent.

Hence, this solution independently determines different parameter combinations for the representation of the AVG, the SD and the EX variables. As a result, 18 different possible combinations of levels and sections for each axis are evaluated. In this work, α and β stand for the levels and sections of the SS representation. Table 2 shows some of the final possible combinations considered (for a full view of these combinations see Appendix).

Once defined all the possible combinations, the first step of the solution is the determination of the α levels. Then, two different approaches are considered for their computation: equiprobable and equidistance levels. The normalization of the smoothed CM signal is required for the division in equiprobable levels. On the contrary, equidistance levels are computed in the same way as in the CS.

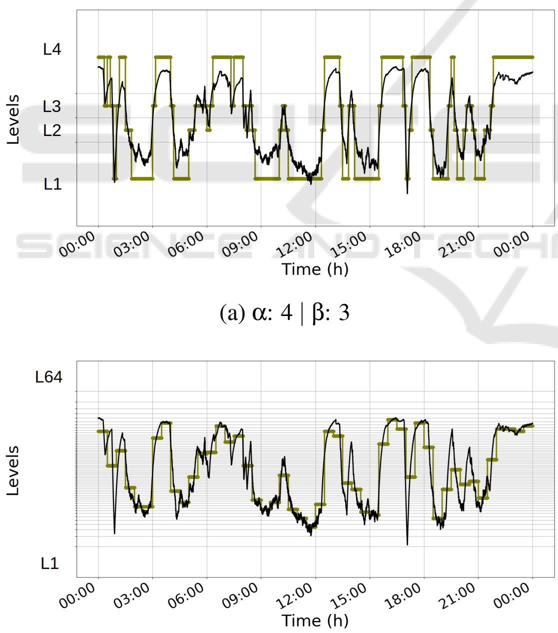
In the next step, β values are computed within time windows of 30 minutes. These values are computed through the mean, standard deviation or maximum excursion depending on the variable to be constructed. Then, each β value is mapped to α

Table 2: SAX Solution (SS) combinations of levels (α) and sections (β) for average (AVG), standard deviation (SD) and maximum excursion (EX) variables.

Combination	AVG_α	AVG_β	SD_α	SD_β	EX_α	EX_β
SS_{13}	64	1	4	3	4	2
SS_{14}	64	1	4	3	16	1
SS_{15}	64	1	8	2	4	2
SS_{16}	64	1	8	2	16	1
SS_{17}	64	1	64	1	4	2
SS_{18}	64	1	64	1	16	1

levels giving shape to the transformed signal. The defined procedure is applied using every possible combination specified in Table 4 as parameters.

Figure 5 serves as an example of the application of two possible combinations of this procedure to the CM data for representing the AVG variable. Black curves represent the smoothed CM signal, while the green ones are the transformed signal for the combinations of 4 levels and 3 sections and 64 levels and 1 section.



(a) α: 4 | β: 3

(b) α: 64 | β: 1

Figure 5: SAX solution applied to two of the possible level and section combinations.

4 EXPERIMENTAL RESULTS

In order to select the best representation for cattle information gathering, data from 8 different animals was captured for 15 days in a row. Hence, a total of 120 different CM daily time series are reconstructed using each one of the solutions proposed and compared with the original signal in order to select the optimal solution.

Next, the strategy for the performance measurement, different related problems and the final results achieved, are presented.

4.1 Performance Evaluation

For the sake of comparison, each solution is evaluated following the same performance evaluation method. The CM signal, splited in time windows of 30 minutes, is used as the reference signal. Thus, the accuracy of each representation is determined through its Euclidean distance to the reference signal. For that matter, as values of the reconstructed signals are based on some predefined levels, each point of the CM signal is compared with the middle point of the corresponding level. Notice that, the CM devices capture data in time rates of 5 seconds. Thus, every CM time series contains 48 time windows of 30 minutes made up of 360 points.

To illustrate this process, Figure 6 presents an example of the error calculation for a 30 minutes time window between the SS combination of 4 levels and 3 sections, and the CM signal. For visualization purposes, the number of points represented for the CM signal have been reduced to just a 10% of the original amount. Therefore, just 36 points from the original 360 has been represented, 12 points per section. In this case, the error is calculated as the sum of the Euclidean distances between the CM points and the SS levels.

The estimation of the representation error implies two different problems. First, the definition of a reference signal to evaluate the reconstruction of SD and EX for each solution. Next, the determination of the middle point for the first and last levels, in the proposed representations.

Notice that, in order to evaluate the accuracy of the AVG variable reconstruction, the original CM values can be directly used as reference signal. However,

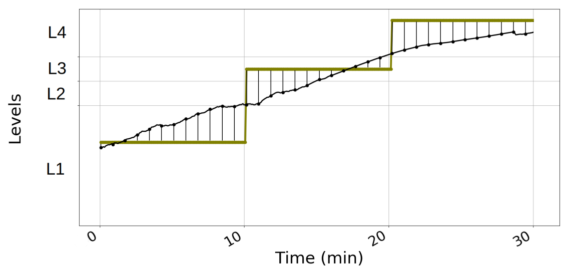


Figure 6: Error calculation within 30 minutes time intervals. CM signal in black, SS representation in green.

when dealing with SD and EX, new time series are necessary to compute the Euclidean distance. In this work, we propose to generate these time series as follows: SD and EX references are computed per time windows of 10 minutes from the original CM signal. Thus, final signals of 3 points each 30 minutes (that is 144 points per time series), are used in the evaluation.

The problem of determining the middle point of first and last levels arise because these levels cover from $-\infty$ to the first breakpoint and from the last breakpoint to $+\infty$. Therefore, choosing their middle points is not a straightforward decision. To illustrate the proposed procedure, Figure 7 explains how these middle points are selected for a SS combination of 4 levels. The 3 breakpoints needed to define the 4 levels are represented by vertical lines over the Gaussian distribution. These breakpoints correspond to the first ($Q1$) , second (median, $Q2$) and third ($Q3$) quartiles of the Gaussian distribution. Notice that the second middle point (mp_2) is related to $Q1$ and $Q2$, and it is calculated as follows:

$$mp_2 = \frac{1}{2}(Q2 - Q1) \tag{2}$$

In the same way, the third middle point (mp_3) is related to the second and third quartiles:

$$mp_3 = \frac{1}{2}(Q3 - Q2) \tag{3}$$

First (mp_1) and fourth (mp_4) middle points are related to $Q1$, $Q3$ and the interquartile range (IQR) defined as the difference between $Q3$ and $Q1$. Thus, given a boxplot, the middle points for first and last levels are the midpoint between the box and whiskers given that further values can be considered outliers. The lower whisker is defined by $Q1 - 1.5IQR$. Then, the middle point of the first level is obtained as follows:

$$mp_1 = Q1 - \frac{Q1 - (Q1 - 1.5IQR)}{2} = Q1 - \frac{3}{4}IQR \tag{4}$$

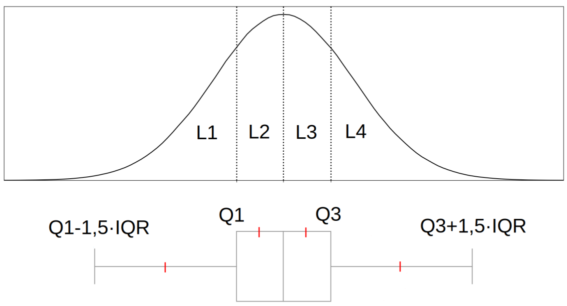


Figure 7: Middle point selection for extreme levels.

In the same way, the upper whisker is defined by $Q3 + 1.5IQR$. Thus, the middle point of the last level is obtained as follows:

$$mp_4 = Q3 + \frac{(Q3 + 1.5IQR) - Q3}{2} = Q3 + \frac{3}{4}IQR \tag{5}$$

4.2 Final Results

Once the procedure for error calculation has been defined, the final results are computed through the average error for each one of the 120 available time series. As the AVG is fixed for the cattle domain experts as the most relevant variable, a weighted average is used for the global error calculation. The final error per time series representation is computed using weights proposed by domain experts as follows:

$$error = 0.4 \cdot \varepsilon_{avg} + 0.3 \cdot \varepsilon_{sd} + 0.3 \cdot \varepsilon_{ex} \tag{6}$$

Table 3 presents the error results (per axis) for the six best SS solutions and for the CS representation (see the Appendix for a complete table with all the results). The best overall results are obtained for the combination SAX_{15} (see Table 4 in the Appendix for the definition of this combination). Regarding the CS solution, error reductions of 31%, 68% and 31% are achieved for x, y and z axis, respectively, when the proposed best solution is used.

Figure 8 shows an example of this improvement for one of the 120 time series. It can be seen that the SAX solution fits the original CM signal. In addition, it is possible to detect situations when the CS solution underfit the CM signal. For instance, at time $10:30$. In general, the CS solution seems more sensitive to abrupt changes in the original signal, than the SAX solution.

Table 3: Average and standard deviation error rates per axis for best solutions.

Solution	$\bar{x}_{error}$	$\bar{y}_{error}$	$\bar{z}_{error}$
CS	3.99±0.52	8.72±1.50	3.56±0.41
SS_{13}	2.79±0.27	2.88±0.85	2.51±0.26
SS_{14}	3.15±0.34	3.12±0.92	2.79±0.33
SS_{15}	2.75±0.27	2.82±0.86	2.45±0.27
SS_{16}	3.11±0.34	3.06±0.93	2.74±0.34
SS_{17}	2.79±0.28	2.84±0.86	2.48±0.28
SS_{18}	3.15±0.35	3.09±0.93	2.77±0.36

5 DISCUSSION

The proposed solution for the representation of cattle information is a valuable alternative to the current operation mode of devices and, thus, an improvement in the quality of cattle information gathering. However, further analysis has been done revealing that there is still room for improvement.

Figure 9 shows the Probability Density Functions (PDF) of the errors computed for the AVG variable in axis X and Y. For the first case (X axis), the best combination (lower errors) is the combination of 64 levels and 1 section for equidistant levels. For the Y axis, the best combination is the combination of 64 levels and 1 section for equiprobable levels.

This issue is explained through Figure 10. The blue curve represents the PDF of the measurements recorded by one of the devices during the 15 days of the experiment in the X axis, while the orange one represents the measurements recorded in the Y axis. Notice that the X axis presents an uni-modal distribution, that is, a unique type of behavior is detected. However, the Y axis shows a bi-modal distribution, that is, two type of behaviors are presented. This fact is the main reason why the equiprobable distribution of levels represents in a more accurate way the animal behavior.

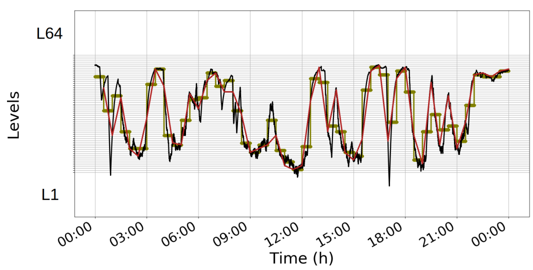
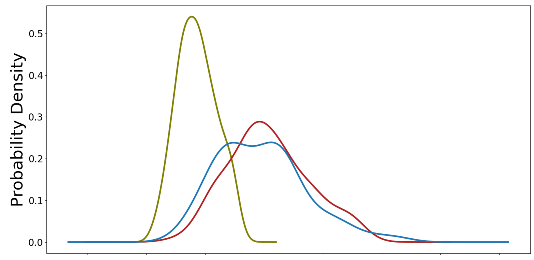
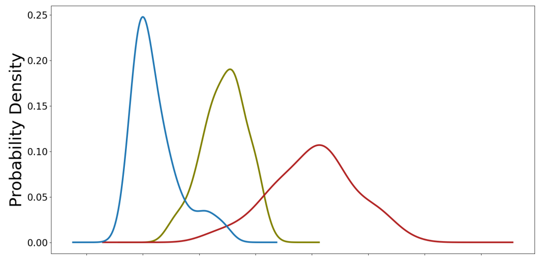


Figure 8: Current and proposed solutions performance comparison. Black curve represents the original CM signal, while the red one is the CS and the green one is the SAX_{15} combination.



(a) X axis.



(b) Y axis.

Figure 9: Probability density functions for error rates in AVG. Red represents the errors for the CS, while green and blue are the combinations of 64 levels and 1 section for equidistant and equiprobable levels, respectively.

As in any Data Science project, the proposed methodology and the obtained results has been presented and explained to the experts of the domain. Digitanimal experts' opinion is that the animal position with a fewer density seen in Figure 10 for the Y axis can be associated to grazing animals. These insights, as others related to different patterns in animal behavior, can be used to new definitions of equiprobable and equidistance levels. Some animal movements could be explained in a more accurate way if these levels are validated by experts considering abnormal behavior situations.

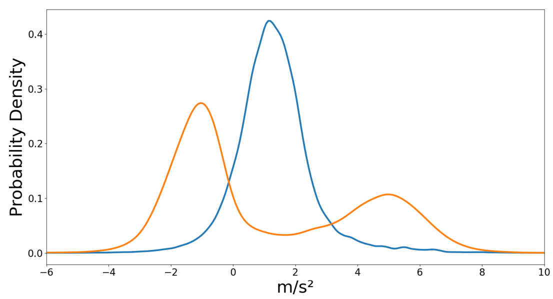


Figure 10: PDF of the X and Y axis, recorded by one of the devices during the 15 days of the experiment.

6 CONCLUSIONS

In this work, a novel strategy based in SAX is proposed to improve the representation of cattle information gathering through WSNs. As the study has been promoted within the Digitanimal project, different insights and requirements from the company has been considered to define the solution.

The proposed approach is based on the SAX representation technique. Different combinations for the parameters of the SAX representation have been evaluated, and compared with the current company solution, through a common procedure for the estimation of the error. Major improvements have been achieved.

Besides, the present study is the first step towards the development of higher quality services for the company. A better accuracy in the representation of animal behavior could improve real-time problem detection such as animal calvings or heats.

Next steps and future work will imply different tasks related to the validation of these results, using more animals and more days, and development of new possible strategies. In order to verify the results achieved in this work, devices programmed with the proposed solution will be used in future studies. This task should be done in collaboration with the company and experimental farms that allow the new stage of information gathering. On the other hand, devise of new strategies can be done expanding the study by introducing different amount of bits per axis and variables, by using different representation techniques or even by using alternative levels definitions. In this way, the Trend Segmentation Algorithm (Siordia et al., 2011), the Trend Feature Symbolic Aggregate approXimation (Yu et al., 2019) or the Fast Low-cost Online Semantic Segmentation (Gharghabi et al., 2019) could be considered.

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APPENDIX

Table 4: SAX Solution (SS) combinations of levels (α) and sections (β) for AVG, SD and EX variables.

Comb.	AVG_α	AVG_β	SD_α	SD_β	EX_α	EX_β
SS_1	4	3	4	3	4	2
SS_2	4	3	4	3	16	1
SS_3	4	3	8	2	4	2
SS_4	4	3	8	2	16	1
SS_5	4	3	64	1	4	2
SS_6	4	3	64	1	16	1
SS_7	8	2	4	3	4	2
SS_8	8	2	4	3	16	1
SS_9	8	2	8	2	4	2
SS_{10}	8	2	8	2	16	1
SS_{11}	8	2	64	1	4	2
SS_{12}	8	2	64	1	16	1
SS_{13}	64	1	4	3	4	2
SS_{14}	64	1	4	3	16	1
SS_{15}	64	1	8	2	4	2
SS_{16}	64	1	8	2	16	1
SS_{17}	64	1	64	1	4	2
SS_{18}	64	1	64	1	16	1

Table 5: Average and standard deviation error rates per axis.

Solution	$\bar{x}_{error}$	$\bar{y}_{error}$	$\bar{z}_{error}$
CS	4.00±0.52	8.72±1.50	3.56±0.41
SS_1	61.34±8.53	4.06±0.37	6.85±2.78
SS_2	61.70±8.52	4.31±0.40	7.13±2.79
SS_3	61.31±8.53	4.01±0.37	6.80±2.78
SS_4	61.67±8.52	4.25±0.41	7.08±2.80
SS_5	61.35±8.53	4.03±0.37	6.82±2.79
SS_6	61.71±8.52	4.27±0.41	7.11±2.81
SS_7	14.55±3.33	4.27±1.12	6.84±2.76
SS_8	14.91±3.34	4.52±1.14	7.12±2.77
SS_9	14.51±3.34	4.22±1.12	6.79±2.76
SS_{10}	14.87±3.34	4.46±1.14	7.07±2.78
SS_{11}	14.55±3.34	4.24±1.13	6.81±2.77
SS_{12}	14.91±3.34	4.48±1.15	7.10±2.78
SS_{13}	2.79±0.27	2.88±0.85	2.51±0.26
SS_{14}	3.15±0.34	3.12±0.92	2.79±0.33
SS_{15}	2.75±0.27	2.82±0.86	2.45±0.27
SS_{16}	3.11±0.34	3.06±0.93	2.74±0.34
SS_{17}	2.79±0.28	2.84±0.86	2.48±0.28
SS_{18}	3.15±0.35	3.09±0.93	2.77±0.36