Identification of the Best Accelerometer Features and Time-scale to Detect Disturbances in Calves

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Abstract. While human activity has received much attention in time-series analysis research, animal activity has received much less attention. The monitoring of cattle in Precision Livestock Farming is a promising application area as it is reasonable to expect that cattle will be equipped with low-cost sensors for animal welfare reasons. In this paper, we present work on feature selection to detect disturbance in calves such as diseases or stressful events from accelerometer sensors attached to a neck-collar. While the long-term objective is to generate an alert when a disturbance is detected, the work presented here focuses on identifying the most discriminating accelerometer features to detect activity changes associated with a calf stressful event. For that purpose, we used accelerometer data from 47 calves who were dehorned at 16 days +/- 10 days, a routine procedure known to be painful and stressful for calves. We calculated 7 primary features that could change after an occurrence of a disturbance, within a 24 hours period before and after dehorning for each calf, falling under the areas of energy expenditure and the structure of the calf activity. These features were explored under 17 time-scales from 1 second to 24 hours to find the best time-scale associated with each feature. First filtering with Mutual Information (MI) and Gini index was applied to reduce the candidate set of features for the second features selection with Random Forest Features Importance (RFFI). Performance were evaluated with Random Forest, k-Nearest Neighbor and Gaussian Naive Bayes models on test-sets to assess the relevancy of the selected features. Performance of all classifiers is improved or maintained when features from MI and Gini selection are used but decreased when further feature reduction with RFFI is applied. Therefore, based on MI and Gini selection, the most discriminating features are linked to activity peaks (maximum), amount of dynamic behaviors (standard-deviation) and activity structure (spectral entropy, Hurst exponent) with time-scales ranging from 1 second to 24 hours depending on the features, which is consistent with animal welfare literature.

Keywords: Feature Selection · Accelerometer time-series data · Animal Welfare · Calves · Disturbance detection

1 Introduction

New decision tools are emerging in the context of Precision Livestock Farming (PLF) to improve the efficiency of livestock management [1] and the monitoring of health and welfare [2]. Especially, PLF greatly encourages the development of tools to detect any disease or stressful events in livestock [3]. Early detection would improve animal health and welfare as requested by consumers [4], but would also reduce the costs of treatment for the farmer when it is necessary.

In dairy cattle, several tools are already available to automatically obtain the behaviour over time, such as the time spent grazing, ruminating, resting, and detect heat events (oestrus) [5, 6] but no proper tools are available to detect disturbances such as stressful events or diseases in cattle. It is also worth mentioning that no disturbance detection tools exist for calves even though they are prone to a lot of different stressful events during the first few months (separation from the mother, weaning, dehorning, transport, etc) and vulnerable to certain diseases (neonatal diarrhoea, bovine respiratory disease, etc.) [7]. Thus, improving the welfare and health status of calves through early detection of stressful events or disease would be a major contribution to the field.

Calf activity changes when a disease or distress is experienced [7]. More resting behaviours are usually observed around the time of the diagnosis of diseases [8] while fewer dynamic behaviours such as running or playing are observed after dehorning and after separation from their dams [9, 10]. Accelerometer sensors attached to a neck-collar are now used abundantly in livestock management to automatically obtain the behaviour of animals in their daily routines from raw accelerometer time-series data [11–13]. Accelerometers have the advantages of (1) being small enough not to alter the behaviour of the cattle, and (2) collecting accelerometer data over time without interruption over a long period (> 1 month) as they have low battery consumption [14]. Accelerometer data collected from a neck collar seems therefore relevant for detecting a disturbance based on a sudden change in calf activity and should be able to support the development of a stress or health event detection model.

Energy expenditure and activity structure are both likely to change after a disturbance in calves [15, 16]. Accelerometer features can thus be computed from the raw accelerometer data to account for these two components. Indeed, features like mean, median, standard deviation, motion variation and maximum are related to the energy expenditure levels while features like entropy and fractal patterns are informative about the structure of activity. Such features could thus be used as inputs to a Machine Learning (ML) model to detect disturbances. To develop such a ML model, it is first required to identify the accelerometer features that are altered after a disturbance and that are therefore the most promising for discriminating a normal situation from a disturbed one in calves.

In this context, the objective of this study is to identify the best accelerometer features and the relevant time-scales to detect a disturbance in calves. Especially, we focused on the disturbance related to dehorning, a procedure carried out routinely in farming to comply with Regulations under the Diseases of Animals Act (1966) which prohibits the sale or export of horned animals [17]. Dehorning is known to be stressful and painful in calves [18, 16] and is therefore used as a disturbance model to select features in our study.

2 Background Research

2.1 Animal Welfare

2.1.1 Energy expenditure

A decrease of the energy expended by calves can be expected when experiencing a disease. For example, calves with a respiratory disease lay for longer and tended to have longer lying bouts a few days before the diagnosis and during the peak of the disease [8]. Similarly, Hixson *et al.* [15] applied an experimental disease challenge model with *Mannheimia haemolytica (MH)* in group-housed Holstein bull calves and observed less activity following inoculation with MH.

A drop in overall activity level may also be observed after stressful events. An increase in the time spent lying, combined with a decrease of the time spent running, jumping [19] and playing [10] is for example observed in the following days after the separation of the calves from their dams. In the same way, calves may spend more time lying down in hours following dehorning [20, 21] and less time playing [9], running or walking [19]. Such a change in the amount of time spent expressing these behaviours may lead to an overall decrease in the energy expended by the calves after these stressful events.

2.1.2 Structure of the activity

An alteration of the activity structure in calves experiencing disease is also expected. Indeed, Hixson *et al.* [15] observed a decrease in grooming, feeding and social interactions in the MH-infected calves. This reduction in the range of expressed behaviours may lead to a loss of complexity in calf activity, as observed in other livestock species experiencing parasitic infection [22].

An alteration of the activity structure in calves after certain stressful events is also expected. Dehorned calves are highly restless in the hours following the procedure and expressed a higher frequency of abnormal behaviors such as tail flicking, head shaking and ear flicking [16, 18]. Similarly, the agitation manifested by vocalisation and searching for the dam is observed in calves after separation from the mother [10, 23]. These repetitive, unvarying behaviors without apparent biological function may also lead to a loss of activity complexity [22].

2.2 Feature Selection

Model development to classify livestock behavior from raw accelerometer data has been explored elsewhere [11] but only a few studies have focused on disturbance detection in livestock. Calf disturbance detection has been recently investigated from behavioral metrics (e.g., number of daily lying bouts, daily lying time) obtained either from a commercial system [24] or from a behavior classification model applied on raw-time series data [25]. However, relevancy of accelerometer features indicative of the energy expended level and the structure of the activity has never been explored. Furthermore, the focus in these studies is on disease detection and the detection of a stressful event has never been investigated. Features selection would therefore be relevant to gain knowledge about the accelerometer features that would help to address the research question. This requires to identify (i) potential accelerometer features-candidates to feed the model and (ii) a suitable pipeline to select the accelerometer features.

Several accelerometer features have already been investigated to address a similar issue in related communities. For example, the average of acceleration has already been used to classify human motion quality for knee osteoarthritis in humans [26]. Similarly, spectral entropy displayed a good ability to characterize the Parkinson posture at an early stage [27]. Stress detection in humans has also been explored with accelerometer features including statistical features and energy expenditure features with a considerable accuracy [28].

There are several ways to select features in the ML context proposed in the literature, such as filter, wrapper, embedded, hybrid, etc. Filter methods basically use statistic measures to select the best features in the pre-processing step rather than relying on the learning algorithm. This method include techniques such as Information Gain, Gini and the Chi-square metric. Advantages of using filter methods are the low computation time and they usually do not overfit the data. Wrapper methods basically consider the feature selection as a search problem. It creates different combinations of the features and evaluate the outcome in terms of classifier performance to compare it with other combinations. Forward selection, exhaustive feature selection are some of the wrapper methods. Embedded methods combine the advantages of both the filter and wrapper methods. These methods are faster and more accurate than wrappers. Regularization and regression methods such as lasso or ridge regression are some of the techniques of the embedded methods [29–31]. It is worth noting that a common limitation in model development in livestock science is the few animals available to train and validate the model, which usually leads to a drop in performance when the model is applied on new animals [32]. Consequently, features selection with Gini index or Mutual Information (MI) combined with Random Forest Feature Importance (RFFI) sounds promising mainly as we are dealing with a high amount of features and few individuals to train and validate the model [33, 34].

3 Materials and Methods

3.1 Time-Series data collection around dehorning in calves

The experiment was conducted at Teagasc Moorepark Research Farm (Fermoy, Co. Cork, Ireland; $50°07'N$; $8°16'W$) from January 21 to April 5, 2022. Ethical approval for this study was provided by the Teagasc Animal Ethics Committee (TAEC; TAEC2021-319). All experimental procedures were performed in accordance with European Union (Protection of Animals Used for Scientific Purpose) Regulations 2012 (S.I. No. 543 of 2012).

Forty-seven Holstein Friesian and Jersey calves were used for the trial. All calves were dehorned at the age of 16 +/- 10 days using cauterisation and were administrated a local anaesthetic on each side of the head in the corneal nerve (Lidobel ; 2 cc/side) 15 minutes before the procedure. AX3 dataloggers[5] were used for this trial. Activity AX3 are MEMS 3-axis accelerometers and have a flash based on-board memory (512 MB), measuring 23 × 32.5 × 7.6mm and weighting 11g. The accelerometers were configured at 25 Hz during the experiment. The 47 calves under study were equipped with a AX3 data logger attached to a neck-collar. Accelerometer data were collected from 1-4 weeks before dehorning, during the dehorning procedure, and 4-9 weeks after dehorning.

3.2 Methodology applied to calculate and select features

The pipeline of the methodology is described in Figure 1.

3.2.1 Calculate features from Time-Series

Two periods of 24 hours of data were selected for the feature selection process:

- The 24 hours period immediately preceding the dehorning procedure. No disruption occurred during these 24 hours. This period is therefore considered as the baseline period and labeled D-1.
- The 24 hours period immediately following dehorning. The disruption has just occurred and the main change in activity due to dehorning is expected at this time [21]. This period is therefore considered as the period after disturbance and labeled D+1.

In each D-1 and D+1 period, the magnitude (see equation 1) was first calculated from the 3 axis-accelerometer readings to get a time-series independent of the sensor orientation. A unit value was reduced from the magnitude time-series to remove the gravitational acceleration component.

$$magnitude = |\sqrt{x^2 + y^2 + z^2} - 1| \tag{1}$$

The magnitude scalar of the activities got in pre-dehorning (D-1) and post-dehorning (D+1) phases is shown for two calves in Figure 2.

[5] Axivity Ltd ; https://axivity.com/product/ax3

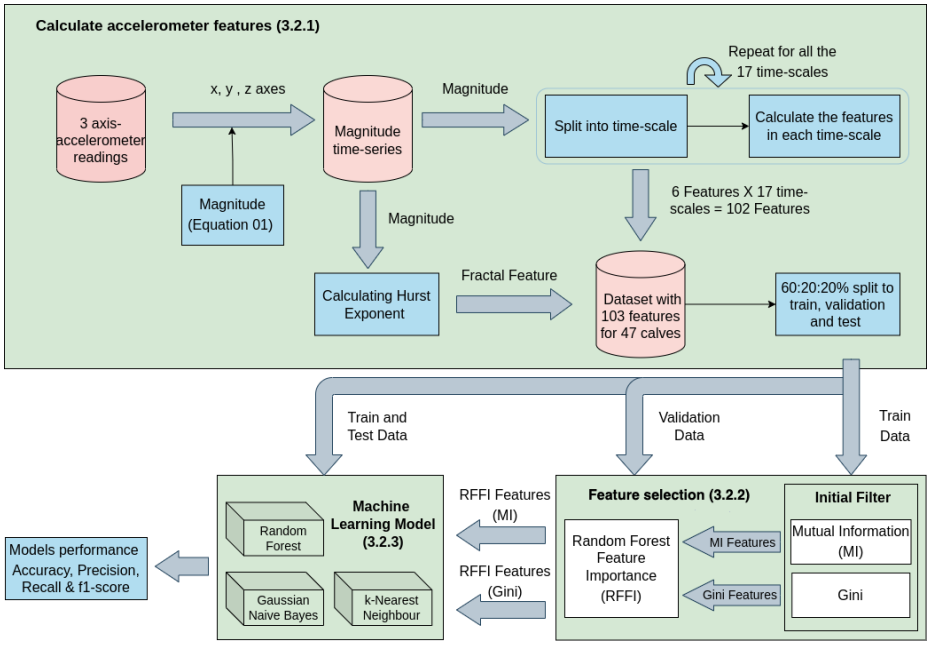

Fig. 1. Pipeline of the methodology followed.

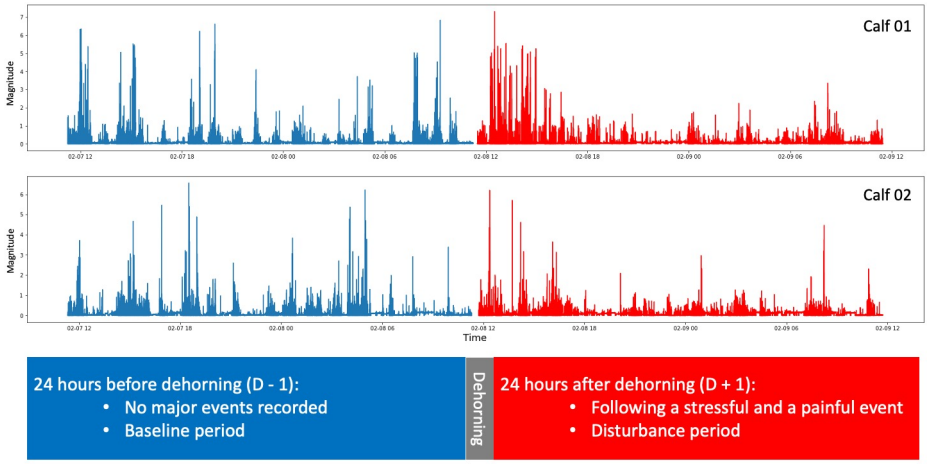

Fig. 2. Behavior of the raw magnitude time-series data in pre-dehorning (D-1) and post-dehorning (D+1) phases.

Magnitude time-series were then split into 17 time-scales ranging from 1 second to 24 hours. Six features indicative of energy expenditure and activity structure were then calculated in each time-scale in the D-1 and D+1 periods resulting in 102 different features. The Hurst exponent fractal feature was calculated considering a 24-hour time-scale only, as proposed in Burgunder *et al.* [22]. Thus the final feature dataset consists of 103 features. The details of the features calculated are listed in Table 1.

Table 1. Main Feature Details

Category	Name	Meaning and Calculation
Energy level/ Activity rate	Mean	Mean of the values present within the time-scale. This feature is indicative of the overall activity level. $A = \frac{1}{n}\sum_{i=1}^{n} a_i = \frac{a_1 + a_2 + \cdots + a_n}{n}$
	Median	Median of the values present within the time-scale. This feature is indicative of the overall activity level. $m(x) = \begin{cases} x_{\frac{n+1}{2}} & n \text{ odd} \\ \frac{1}{2}\left(x_{\frac{n}{2}} + x_{\frac{n}{2}+1}\right) & n \text{ even} \end{cases}$
	Standard Deviation	Standard Deviation of the values present within the time-scale. This feature is indicative of the amount of dynamic activities of the animal. $s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2}$
	Maximum	Maximum value out of the values present within the considered time-scale. This feature is indicative of the scale of the activity peaks for the period.
	Motion Variation	A measure of the variation between the values present within the considered time-scale. This feature is indicative of the amount of dynamic activities of the animal. MV = mean(abs(1st order discrete difference of the signal window))
Structure of the Activity	Spectral Entropy	A measure of disorder or uncertainty. This feature is indicative of the predictability of the time-series (predictable using a few frequencies *versus* hardly predictable with many frequencies, close to a random process [35, 36]. $SE(F) = \frac{1}{logN_u \sum_u (P_u(F) log_e P_u(F))}$ [36]
	Hurst Exponent	Hurst exponent is used to classify the series as mean-reverting, random walk or as trending [37, 38]. The Hurst exponent features used here is the average of the Hurst exponent obtained with Linear Detrended Fluctuation Analysis and Bridge Detrended Fluctuation Analysis. We refer to [22, 39, 40] for more details about the Hurst exponent calculations. Fathon python package [41] was used to calculate the Hurst exponent.

3.2.2 Two stages feature selection strategy

The data was split into train, test and validation data in a ratio of 60 : 20 : 20%. It was ensured that the labels D+1 and D-1 for each calf are both in one of the training set, test set or in the validation set.

Features selection was applied with a two stages pipeline (see Figure 1). A first filter stage was applied with Gini filter and MI filter [33, 34] in order to remove the least informative features thereafter. The tree-based structure of the Random Forest model is naturally ranked by how well they improve the purity of the node thus giving an idea itself about the importance of the features considered. In that way, the least informative features can be identified easily based on the features ranking. The training data was first fed into Gini and MI filters separately and the feature importance scores were calculated for each feature.

Next, the bottom 60% of features from the MI and Gini rankings were respectively removed for the rest of the features selection process. Thus, 40 features from MI and Gini filters were fed separately into the RFFI procedure with the validation dataset to obtain the RFFI ranking. This process was carried out in 10 iterations and the features that were outputted in each iteration were recorded. Next, a count of occurrence for each feature was taken and the presence value for each feature was calculated by taking the percentage of occurrences to the number of iterations.

3.2.3 Classification performance with selected features

To get a better knowledge of the features selected, five subsets of features were used:

- All the features: As a baseline, the 103 features were used in the training and testing data.
- Initial filtering features from MI (noted *MI* features) and from Gini (noted *Gini* features): Features leading to non-zero MI and Gini scores were used to filter out the training data and the testing data.
- RFFI features from MI (noted *MI+RFFI*) and from Gini (noted *Gini+RFFI* features): Features obtained after the first filtering with a presence value greater than the mean presence value in the RFFI process were used to filter out the training data and the testing data.

For each subset of features, Random forest (RF), K-Nearest Neighbour(k-NN) and Gaussian Naive Bayes (GNB) models were trained with the training data and the model accuracies were assessed.

4 Results

4.1 Model performance obtained with each subset of features

Accuracy with the 103 features is above 75% for each model, with the highest achieved with the RF model (87.35%) (Figure 3).

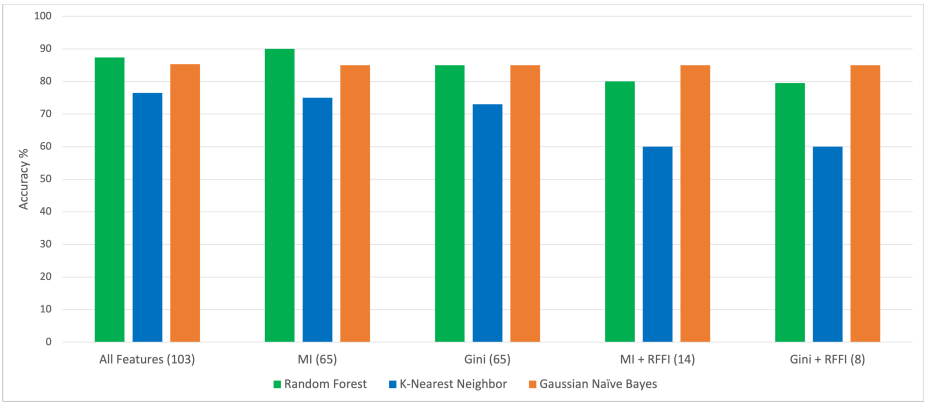

Fig. 3. Model accuracies obtained for all the features, 65 non-zero MI features, 65 best Gini features, best 14 MI + RFFI features and best 8 Gini + RFFI features.

Sixty-five features got a MI score greater than 0 over the 10 iterations (see Figure 4). The accuracy obtained with the 65 non-zero *MI* features is similar to that obtained with all features for k-NN and GNB and even higher for RF where 90% was achieved (Figure 3). This suggests that the subset of the 65 non-zero MI features is a relevant one to use in future work. All features got a Gini index greater than 0 over the 10 iterations (see Figure 5). By analogy with the MI ranking, the *Gini* features used to filter out the training and testing data are the 65 best features from the Gini ranking. The top 65 *Gini* features also lead to similar accuracy to that obtained with all features for the three ML models (Figure 3).

After removing the 60% of the least informative features based on MI and Gini ranking, RFFI procedure with 10 repetitions led to 14 *MI+RFFI* features and 8 *Gini+RFFI* features with a presence value greater than the mean presence value of the features of the subset. While the performance was maintained or improved after the first filtering with MI and Gini, a drop of performance is observed when models are trained and tested with *MI+RFFI* and *Gini+RFFI* features, especially for RF and k-NN models (Figure 3), probably due to overfitting.

The accuracy obtained with the different subsets of features suggests that the second stage of feature selection with RFFI does not highlight the most important features and that it is therefore preferable to rely on the first stage of selection with MI and Gini filters to identify the most informative features for the future studies.

4.2 Most informative features based on MI and Gini selection

Ranking features obtained for MI and Gini selection are displayed in Figure 4 and Figure 5, respectively. A visual cut-off to get the most informative features (see highlighted box in Figure 4 and Figure 5) leads to the features selection and associated time-scales proposed in Table 2.

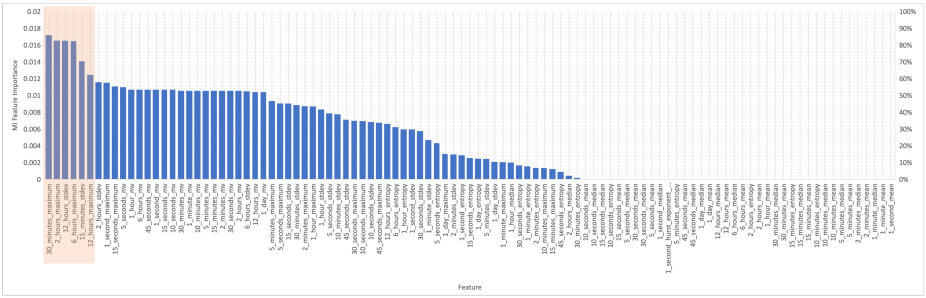

Fig. 4. Mean of MI score for each feature after 10 iterations. 65 features have non-zero MI scores. Highlighted box shows the most important features.

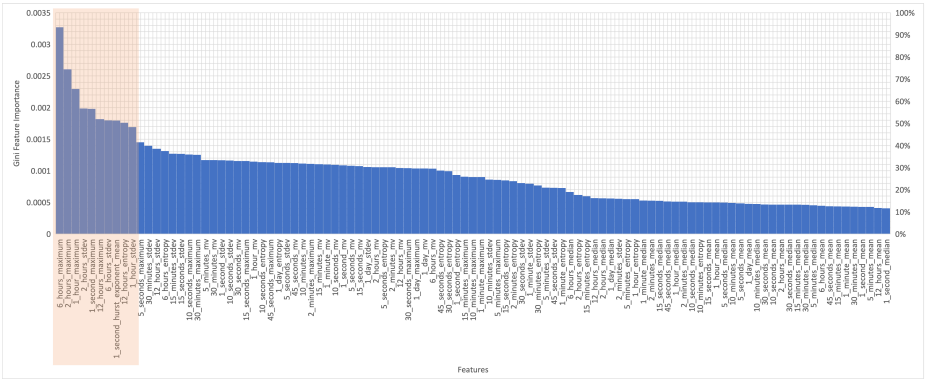

Fig. 5. Mean of Gini score for each feature after 10 iterations. Highlighted box shows the most important features

As per the table 2, features maximum and standard deviation are both in the top rankings of MI and Gini filtered features. These features are indicative of activity peaks and amount of dynamic behaviors, respectively, which seem to be the most important components of calf activity to discriminate between a 24 hours baseline period and a 24 hours post-stressful event period. This is also consistent with the Figure 2 where less peak activity appears to occur from

6 hours after dehorning. The lower expression of peak activity and dynamic behaviors suggests less social behaviors such as agonistic behaviors and playing, and less maintenance behaviors such as feeding, over the day following dehorning. This finding is consistent with the calf welfare literature [9]. It is worth noting that 3 time-scales for the feature maximum are common for both the MI and Gini filters (2 hours, 6 hours and 12 hours; Table 2), suggesting that these time-scales should be retained for the future model development. For the standard-deviation feature, there is no time-scale in common between MI and Gini. There is thus no specific time-scale to be preferred, but time-scales from 15 minutes to 12 hours may work properly (see Table 2).

Table 2. Top features and associated time-scales obtained from MI and Gini selection based on their ranking score

Legend: *Cell background is in orange if the features and time-scales are included in the top ranking for the corresponding feature selection method.*

Top features	Time-Scale	MI	Gini
Maximum	1 second		
	30 minutes		
	1 hour		
	2 hours		
	6 hours		
	12 hours		
Standard Deviation	15 minutes		
	1 hour		
	2 hours		
	6 hours		
	12 hours		
Hurst Exponent	24 hours		
Spectral Entropy	12 hours		

Hurst exponent with 24-hour time-scale and spectral entropy with 12 hours time-scale are also in the top ranking of Gini filter, suggesting that the structure of the activity is also helpful to discriminate between a 24 hours baseline period and a 24 hours post-stressful event period (see Table 2). It should be noted that the decrease in spectral entropy observed in this study (*data not shown*) suggests a loss of complexity in the calf activity. Similarly, the Hurst exponent increases towards 1 in the post-dehorning period, reflecting a strengthening of the persistent trend after dehorning, and thus less stochasticity, namely less complexity. This can also be seen in the Figure 2, as we observe a peak of activity in the 6 hours after dehorning, probably due to agitation (ear flicking, tail shaking, frequent transitions between standing and lying down), followed by a period without clear activity peaks, reflecting a long and constant state of rest

[9]. It is worth noting that loss of complexity of animal activity associated with pathology or stress is also consistent with the animal welfare literature [22].

Finally, mean and median features are not included in the top ranking of neither MI nor Gini. Overall activity level is thus not helpful to discriminate between a 24 hours baseline period and a 24 hours post-stressful event period.

5 Conclusions

In terms of insights on the problem domain, both features for energy expenditure and structure are included in the most important features with a time scale that is different from one feature to another suggesting that (i) both components of the activity must be considered and (ii) the time scale should be adapted to each feature in the final model.

In terms of the subset to be selected for the development of the model in future work, it seems that the 65 non-zero MI features are the best candidates for the moment as the addition of the second filtering stage with the RFFI procedure decreases the performance of the models. This may be due to the high correlation between features. In future work, we will evaluate correlation-based feature selection [30] and wrappers to address this issue.

Finally, the model that will be developed in the future will also have to take into account the variation of the features animal-wise, which has not been considered in the present study. It is also necessary to consider other sources of disturbances, such as diseases or other stressful procedures (e.g., weaning, transport) to develop a robust model of disturbances detection in calves. This work should contribute to the development of an intelligent model to improve calf welfare by detecting stressful events from accelerometer data, which will be a major addition to the field.

Acknowledgements

This publication has emanated from research conducted with the financial support of SFI and the Department of Agriculture, Food and Marine on behalf of the Government of Ireland to the *VistaMilk SFI Research Centre* under Grant Number 16/RC/3835.

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