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Automatic Classification of Sheep Behavior sing 3-Axis Accelerometer Data

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***Abstract*—** Monitoring animal behavior can prove challenging when working in inaccessible environments. This problem can be addressed by using animal attached accelerometers and automatic classifiers. This study considers the feasibility of using specially designed hardware to capture three-dimensional accelerometer data from sheep and subsequently automatically classify their behavior based on these measurements. Five common behaviors have been identified: Lying, standing, walking, running, and grazing. Linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) classifiers were trained based on 10 features. A greedy selection procedure was used to determine which features provide the highest classification accuracy. It is shown that both classifiers can automatically identify the five behaviors with high accuracy when all the features are used for training. The LDA and QDA classifiers achieved an overall accuracy of 87.1% and 89.7% respectively. Grazing was misclassified the most in both classifiers because it was confused with lying. This result was expected considering the high similarity between the raw accelerometer data associated with grazing and lying. The QDA classifier showed larger improvements when using a smaller number of features. identifying and classifying feeding behavior in free-ranging ruminants will help improve the efficiency of animal production. Another potential benefit would be in understanding the role behavior has in determining the heritability of methane measurement. This study aimed to determine the accuracy, sensitivity, specificity, and precision with which tri-axial accelerometers can identify sheep behavior at pasture. The animals were located in either a semi-improved pasture (0.3 ha) or in a small (30 m^2) area with access to water to observe five mutually exclusive behaviors, grazing, lying, running, standing, and walking. A tri-axial accelerometer was attached to a halter on the under-jaw of each animal. Three epochs (3 s, 5 s, and 10 s) with forty-four features calculated from acceleration signals were used to classify behaviors. The five most important features for each epoch were determined using random forest and the five behaviors were classified using a decision-tree algorithm to determine model accuracy, sensitivity, specificity, and precision. The decision-tree algorithm correctly classified 90.5, 92.5, and 91.3% of the evaluation data set for grazing behavior for the 3, 5, and 10 s epochs, respectively. There was no difference in the accuracy between the evaluation and validation data sets for grazing behavior at each epoch. The model predicted grazing and running behavior highly accurately and with the highest precision, sensitivity, and specificity for the validation data set for the 10 s epoch. The 5 s epoch for both the evaluation and validation data sets were selected as the most suitable epoch based on the Kappa values. We successfully identified from the distribution of component populations that the natural log-transformation of the mean of X-axis accelerations for each epoch could identify grazing and non-grazing states. Therefore, this methodology will be useful in identifying sheep activity for research applications such as before methane measurement using portable accumulation chambers or other applications addressing temporal grazing patterns.

***Keywords*—** Sheep; Behavior; Lameness; Activity; Accelerometer; on-animal sensor.

I. INTRODUCTION

The study of animal behavior provides us with a better understanding and insight into their health, which is a priority in conservation attempts. While monitoring animals in a supervised environment is relatively simple, this is not true for unsupervised animals in their natural environment. In this latter case, monitoring can be achieved by attaching sensors to the animal. Depending on the type of sensor, information concerning the animals energy expenditure, location, speed, heart rate, temperature, and behavior can be monitored. This provides researchers with information on the behavior of animals in environments that are inaccessible for human observation. An accelerometer is often used in animal monitoring systems. It can be embedded in a lightweight tag that can be attached to the animal with minimal obstruction or interference with the natural movement of an animal. Mono- and bi-axial accelerometers are available but have a few disadvantages compared to a tri-axial accelerometer. Measuring the acceleration in all three axes provides a more complete picture of animal movement patterns and could reveal information that would have otherwise been missed. Several studies have considered the classification of animal behavior with the aid of accelerometers. Goat grazing behavior has been automatically classified with a high success rate using tri-axial accelerometers. In this work moving averages were used in conjunction with selected threshold values to distinguish between resting, eating, and walking.

A recent study extended this work by using the k-nearest neighbor classifier. It found that the classification accuracy was comparable to what was achievable using more complex techniques. In different works, the recognition of cow behavior was investigated by applying support vector machines to 3-axis accelerometer data. This study attempted to distinguish between eight behaviors and achieved an accuracy of over 80% for all the classified behaviors. Another study combined a support vector machine and hidden-Markov models to classify the behavior of cheetahs. In this way, it was possible to classify five minute segments into three behavior classes (feeding, mobile and stationary). Finally, the behavior of vultures was classified using classification and regression trees, random forests, support vector machines and artificial neural networks with linear discriminant analysis (LDA). Although the LDA classifier was intended as a baseline, it was found that all the algorithms had an accuracy of 80% or higher, with the non-linear algorithms outperforming LDA. This study considers the feasibility of using specially designed hardware to capture three-dimensional accelerometer data and subsequently automatically classify the behavior of sheep using LDA as well as quadratic discriminant analysis (QDA). LDA was chosen for this preliminary study because it was used as a baseline classifier in a previous study. The QDA classifier was subsequently investigated and compared to LDA since it is a simple extension of the LDA classifier. The classifiers were used to distinguish between five common behaviors types.

II. MATERIAL AND METHODS

A. Site and animals

Data collection was performed on a farm (Choir) in Mongolia, in December 2018. The owner of the farm provided access to the livestock for the experiment. Five sheep were randomly chosen on each of 3 separate days. The sample size was constrained by what was practically feasible at the time of the study. The sheep were held in a camp large enough to allow for unrestricted movement throughout the day.

B. Hardware

The hardware (referred to as the tag hereafter) consisted of a 3-axis accelerometer, USB and battery. The tag was designed to allow the accelerometer to be constantly sampled at a frequency of 100Hz and to subsequently store the measurements. The tag was enclosed in a durable casing and fitted around the necks of the sheep.

Table 1. Five Observable Behaviors of the Sheep

Behavior	Description
Lying	The sheep are lying down with its head on the ground.
Standin	The sheep is standing with its head up.
Walking	The sheep is walking at a slow pace.
Running	The sheep running at a fast pace.
Grazing	The sheep is grazing with its head down while standing still or walking slowly.

using collars as seen in Figure 1a. The hardware was placed in approximately the same orientation on all the tested animals. Figure 1b shows the orientation of the accelerometer's axes when the tag is attached to the sheep's necks. In the same figure, it can be seen that movement in the x-axis is associated with the left-right movement of the sheep. The y axis is associated with the up-down movement of the sheep and the z-axis is associated with the forward-backward movement of the sheep.

C. Data collection

Data was gathered on three separate days. The sheep were collected in the mornings and the tags were fitted around their necks. The sheep were led to the camp and left undisturbed for the day. The hardware logged the acceleration of the sheep at a rate of 100 samples per second throughout the day. Five common behaviors (Table I) were identified: lying, standing, walking, running, and grazing. The sheep were monitored from a distance on the three testing days and the behavior of the herd and corresponding time-stamps were manually logged. The sheep were also chased on various occasions to collect "run" data because there was little reason for them to run without provocation. At the end of the day, the sheep were collected, the collars were removed, the data was downloaded from the sensor saved to a file. Each data file included the following information of interest: an ID of the current logging session, timestamps in milliseconds and the acceleration along the three axes. Each data file was manually segmented and labeled with the corresponding behavior by reconciling the logged data with the manual

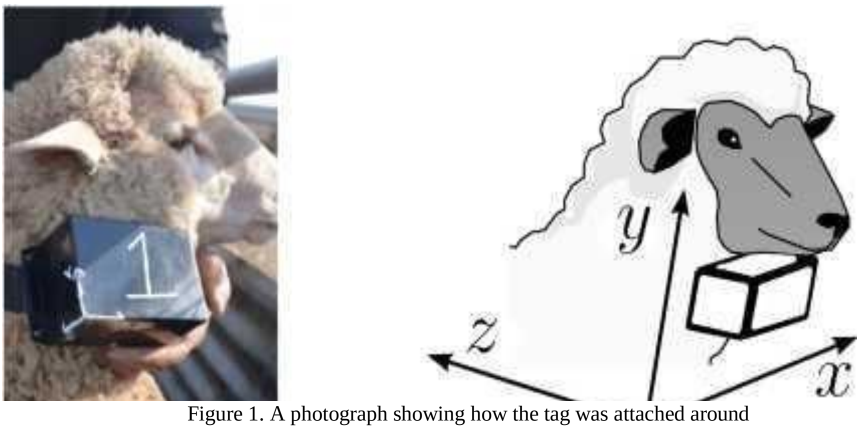

Figure 1. A photograph showing how the tag was attached around

annotations. A summary of the data collected for each behavior and sheep is displayed in Table 2

Table 2 Distribution of Data Collected for Each Behavior Class and Sheep (HH:MM:SS)

Sheep	Lying	Standing	Walking	Running	Grazing	Total
1_tag1	0:00:00	0:03:43	0:09:27	0:04:14	0:13:37	0:31:01
1_tag2	0:00:00	0:02:46	0:08:55	0:04:16	0:17:32	0:33:29
1_tag3	0:00:00	0:01:32	0:10:45	0:05:24	0:19:26	0:37:07
1_tag4	0:00:00	0:04:13	0:07:36	0:05:02	0:09:20	0:26:11
1_tag5	0:00:00	0:04:03	0:08:04	0:05:31	0:08:01	0:25:39
2_tag1	5:08:43	0:13:28	0:55:27	0:05:45	1:11:45	7:35:08
2_tag2	5:52:14	0:04:37	1:07:50	0:05:45	1:43:18	8:53:44
2_tag3	1:17:24	0:01:09	0:28:48	0:04:20	0:21:28	2:13:09
2_tag4	1:23:32	0:04:06	0:20:51	0:04:52	0:11:17	2:04:38
2_tag5	0:21:12	0:00:34	0:04:58	0:04:22	0:03:09	0:34:15
3_tag1	0:29:59	0:03:44	0:24:16	0:04:18	0:15:50	1:18:07
3_tag2	0:39:33	0:00:44	0:25:29	0:04:19	0:23:00	1:33:05
3_tag3	0:30:24	0:06:49	0:31:22	0:04:16	0:27:02	1:39:53
3_tag4	0:54:56	0:02:33	0:33:13	0:04:16	0:22:15	1:57:13
3_tag5	0:40:05	0:00:53	0:31:14	0:04:50	0:20:17	1:37:19
Total	17:18:02	0:54:54	6:08:15	1:11:30	6:27:17	1d 7:59:58

sheep ID consists of the testing session (day 1, 2, or 3) and the tag's number. "Lying" behavior was not observed during the first testing session.

D. Data preprocessing and feature extraction

The accelerometer data were preprocessed using Python's Scipy library (version 0.14.0)

[10] as shown in Figure 2. Each segment file was loaded and examined to make sure the segment contains at least 512 samples in order to have an epoch length of 5.12 seconds. An epoch length of 5.12 seconds was selected to window the segments as it was found in [11] that a 3-5 second epoch was optimal. The three acceleration values were then low-pass filtered using an 8th-order Butterworth filter with a cut-off frequency of 10Hz before applying a Hamming window. Consecutive features were obtained by allowing a 50% overlap in this data window. The features extracted were based on those recommended in [4] and [12] and included the following 10 features that consisted of 31 variables:

Mean

Standard deviation (STD)

Variance

Skewness (Skew)

Kurtosis

The maximum and minimum value (MaxMin)

Energy

Frequency-domain entropy (FreqEntropy)

Pairwise correlation between the axes (Corr)

Average signal magnitude vector (ASMV)

The skewness and kurtosis were calculated for each axis. The skewness provides insight into the symmetry of a frame while the kurtosis serves as an indication of peakedness relative to the normal distribution. The aforementioned was accomplished by calculating the third and fourth standardized moment of each axis per frame. The "MaxMin" feature contains the maximum and minimum values for each axis in a frame. This results in a vector with 6 values which represents the dynamic range. The energy was calculated as the sum of the squared FFT magnitudes with the DC component excluded. The sum was then normalized by the window length. The frequency-domain entropy was calculated by normalizing the FFT and then treating the FFT magnitudes as discrete probabilities. The frequency entropy has been found useful to discriminate between behaviors with similar energy values [12]. The cross-correlation between each axis pair was calculated as the ratio between the cross-covariance and the product of the standard deviations. The average signal magnitude vector (ASMV) for each frame was

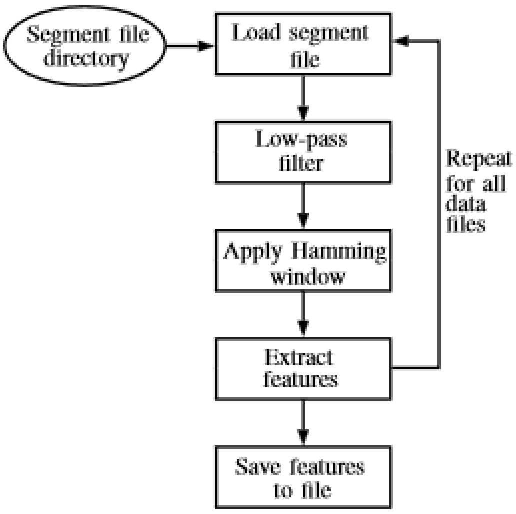

Figure 2. Flow chart of the feature extraction process

calculated by summing the vector length over the frame and normalizing the result with the frame's length.

The distribution of each feature was visualized in a 1dimensional histogram to visually inspect the underlying distribution. It was found that the "Skew" and "MaxMin" features resemble da Gaussian distribution, while the rest of the features had a closer resemblance to a Rayleigh distribution.

Table 3. Number of Usable Frames Extracted for Each Sheep and Behavior

Sheep	Lying	Standing	Walking	Running	Grazing	Total
1_tag1	0	59	145	65	229	498
1_tag2	0	46	141	72	330	589
1_tag3	0	27	198	88	359	672
1_tag4	0	73	123	82	157	435
1_tag5	0	58	121	84	125	388
2_tag1	7202	248	1003	94	1214	9761
2_tag2	8237	75	1291	101	1803	11507
2_tag3	1807	23	560	76	392	2858
2_tag4	1954	82	357	88	201	2682
2_tag5	494	11	84	74	53	716
3_tag1	697	64	447	69	260	1537
3_tag2	913	12	464	69	402	1860
3_tag3	707	130	610	71	508	2026
3_tag4	1281	46	608	63	390	2388
3_tag5	934	14	559	73	340	1920
Total	24226	968	6711	1169	6763	39837

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E. *Classification*

The Python LDA en QDA implementations in Scikit Learn (version 0.14.0) was used to determine the best features to use for sheep behavior classification. A greedy feature selection procedure, as illustrated in Figure 3, was used to determine the best combination of features. For each iteration of the procedure, a balanced subset (an equal number of frames for each class) was selected for classification. The procedure tested each feature's classification accuracy and then retained the feature with the highest score. The accuracy was defined as the overall correctly classified

Table 4. Confusion Matrix Result When using the QDA Classifier with All the Features for Classification

Observed behavior	Predicted behavior					Tota
	Lying	Standing	Walking	Running	Grazing	
Lying	898	26	0	0	36	960
Standing	10	914	34	0	2	960
Walking	0	18	900	12	30	960
Running	0	0	4	946	0	950
Grazing	270	7	45	0	638	960
Total	1178965		983	958	706	479

feature vectors as a proportion of the total classified feature vectors [3]:

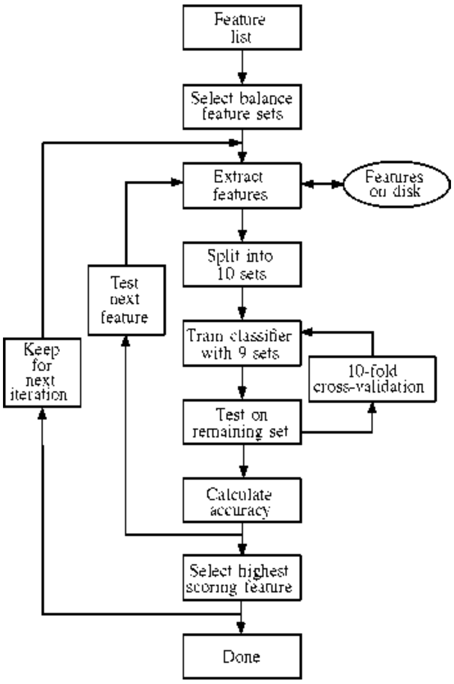


Figure 3. The greedy feature selection procedure.

A breakdown of the number of usable frames extracted for each sheep and class is presented in Table 3

$$\text{Accuracy} = \frac{TP + T}{\text{TP + TN + FP + F}} \text{..........} \quad (9)$$

Where TP, TN, FP and FN are the true positive, true negative, false positive and false negative counts respectively. The procedure iterated until all the features were used in classification. 90% of the balanced subset was used for training the classification algorithm and the remaining 10% was used as a testing set. 10-fold cross-validation ensured the best utilization of the limited data. The total accuracy for each cross-validation iteration was the average over the 10 cross-validation iterations. Both LDA and QDA classification were evaluated using this procedure.

F. SELF-TEST

The ADXL345 incorporates a self-test feature that effectively tests its mechanical and electronic systems simultaneously. When the self-test function is enabled (via the SELF_TEST bit in the DATA_FORMAT register, Address 0x31), an electrostatic force is exerted on the mechanical sensor. This electrostatic force moves the mechanical sensing element in the same manner as acceleration, and it is additive to the acceleration experienced by the device. This added electrostatic force results in an output change in the x-, y-, and z-axes. Because the electrostatic force is proportional to VS2, the output change varies with VS. This effect is shown in Figure 4. The scale factors shown in Table 14 can be used to adjust the expected self-test output limits for different supply voltages, VS. The self-test feature of the ADXL345 also exhibits a bimodal behavior. Use of the self-test feature at data rates less than 100 Hz or 1600 Hz may yield values outside these limits. Therefore, the part must be in normal power operation (LOW_POWER bit = 0 in BW_RATE register, Address 0x2C) and be placed into a data rate of 100 Hz through 800 Hz or 3200 Hz for the self-test function to operate correctly as shown the Figure 4.

III. RESULTS AND DISCUSSION

The LDA and QDA classifiers were both tested using the greedy feature selection procedure described in Section II-F. The results are presented in Figure 5.

Figure 5 shows the winning feature at each iteration of the greedy feature selection procedure. The accuracy of the LDA classifier was lower than the QDA classifier at each iteration of the procedure. From Figure 5. it can be concluded that the most important feature in classifying the sheep's behavior was the "MaxMin" feature. By just using the first feature the LDA and QDA classifiers achieved a classification accuracy of 73.8% and 84.5%, respectively. On the other hand, the LDA classifier achieved a final accuracy of 87.1% when all of the features were used for classification, compared to an accuracy of 89.7% for the QDA classifier. Even though the LDA and QDA classifiers only had a 2.6% accuracy difference when all of the features were used, the QDA classifier showed larger improvements when using a smaller number of features.

The confusion matrix in Table IV was obtained using the QDA classifier and all the features. Most of the behaviors could be identified with high accuracy except grazing, which was misclassified as lying in 33.5% of cases. This outcome can be understood by viewing the raw accelerometer segments associated with lying and grazing, illustrated in Figure 6. The y-axis indicates the sheep's head position. A typical grazing segment consisted of the sheep moving his head down to the ground to graze then either standing still or walking. Finally, the sheep lifts his head up again. A lying segment usually corresponded to the sheep lying on its stomach, with its head

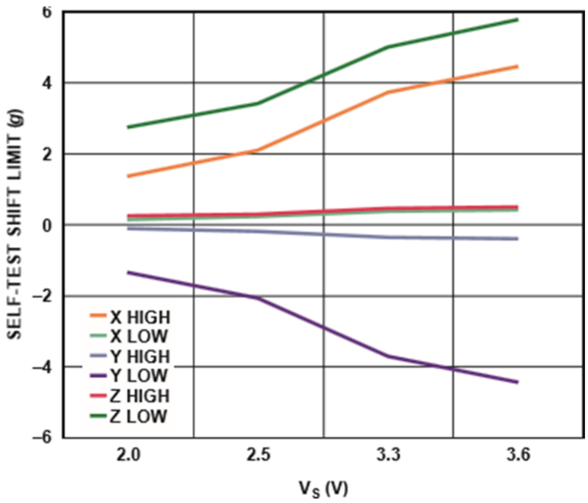


Figure 4. Self test

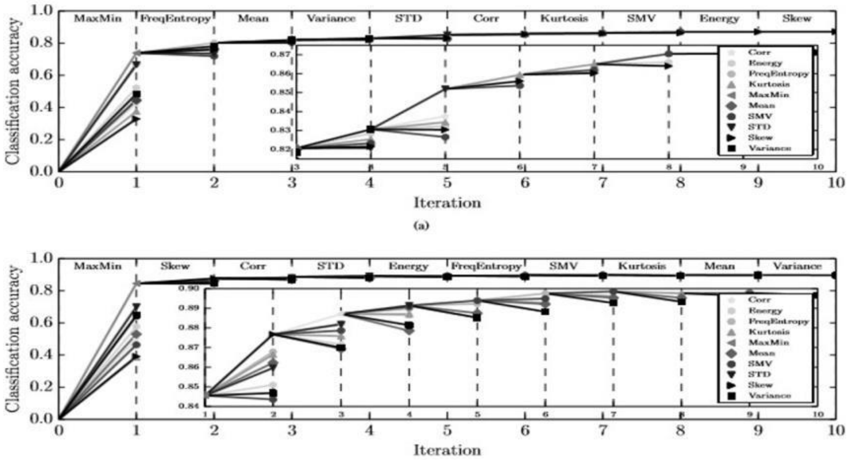


Figure 5. The accuracy of the LDA (a) and QDA (b) classifiers at each iteration of the greedy feature selection procedure. The winning features at each iteration are indicated at the top of each plot. The inset shows a magnified view of the top segment of the plot

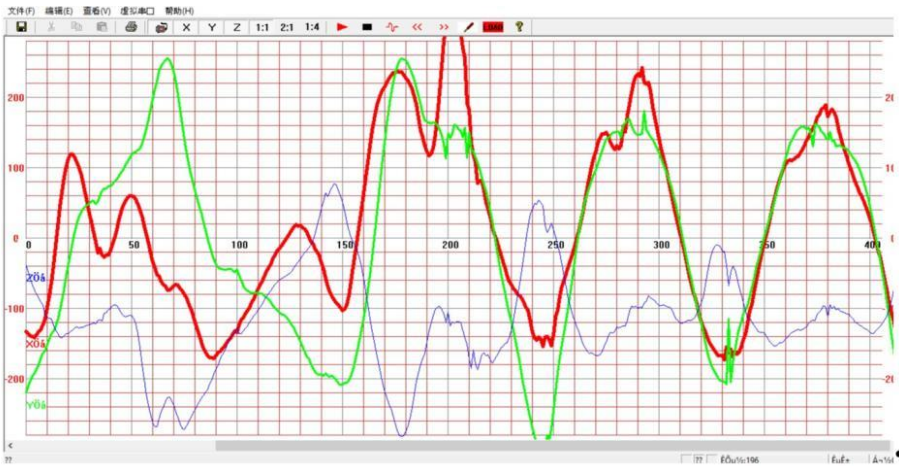


Figure 6. Real-time process

A. Observations

Down on the ground. Since the accelerometer data is limited to the placement around the neck, it is difficult to distinguish between these two behaviors. Standing, walking, and running were correctly classified in 95.2%, 93.7% and 99.5% of cases respectively. The high classification

accuracy for "running" is important if we aim to determine when animals are being pursued, as may be the case for stock theft.

For further analysis, LDA was used to reduce the feature space to the two most important dimensions. These are shown in Figure 7. The figure illustrates the difference between the LDA and QDA classifier's decision boundaries. The quadratic boundary is more flexible compared to a straight line leading to a higher classification accuracy. Clusters of data points corresponding to each behavior can also be observed. Again, the ambiguity between lying and grazing is indicated by the overlapping clusters. Even though walking and standing are

Figure 8 shows the normalized confusion matrices for the QDA classification. The first matrix indicates only the first three features selected by the greedy feature selection procedure. The second matrix shows all ten features for classification. A classification accuracy of 88.7% was achieved by using only the first three features, while a 89.7% accuracy was achieved when all the features were used. Hence, by retaining only the first three features, less than 1% in classification accuracy is sacrificed also closely grouped, it was still possible to separate them with a high degree of accuracy.

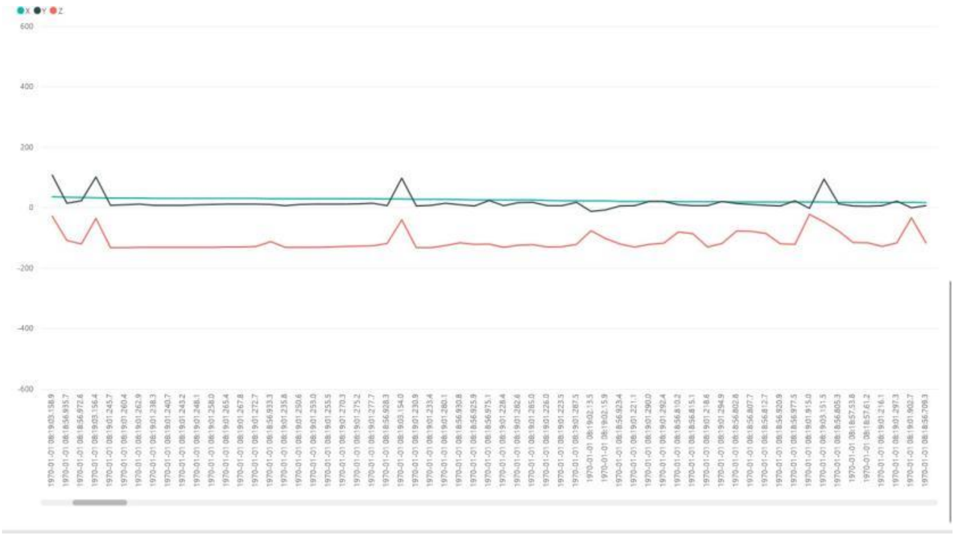


Figure 7. Lying

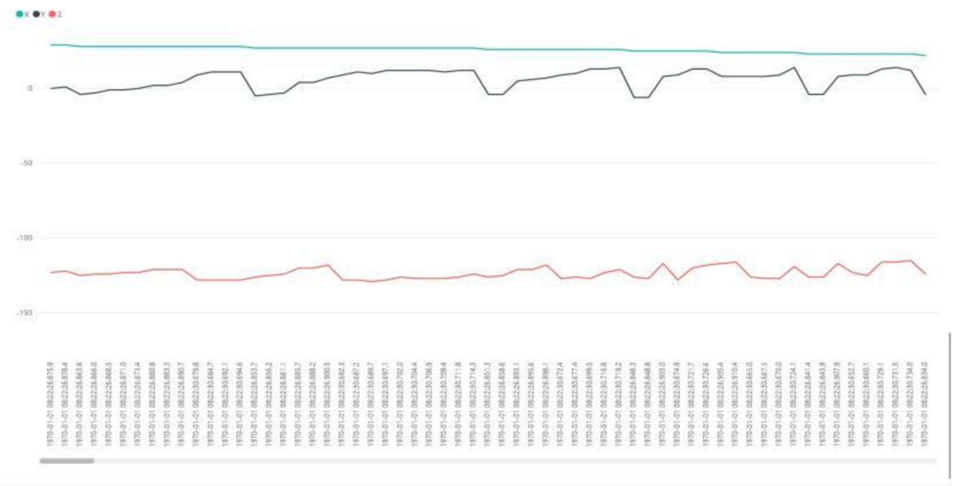


Figure. Standing

Figure 7. Walking

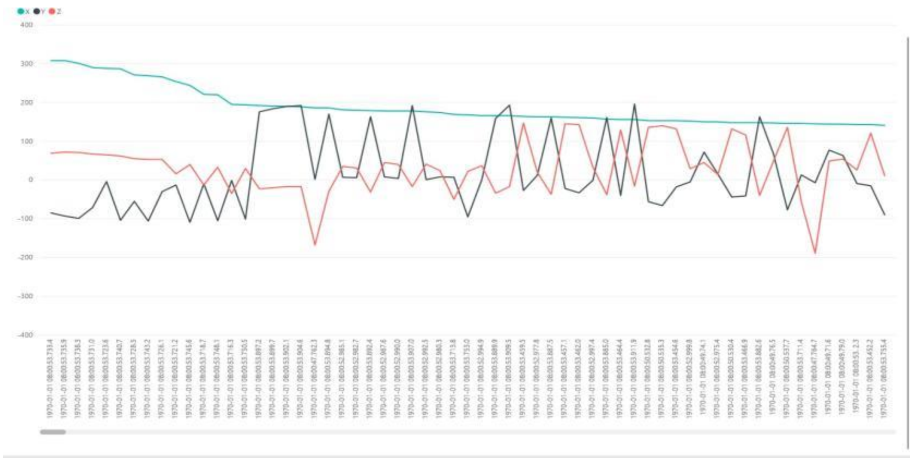


Figure 8. Running

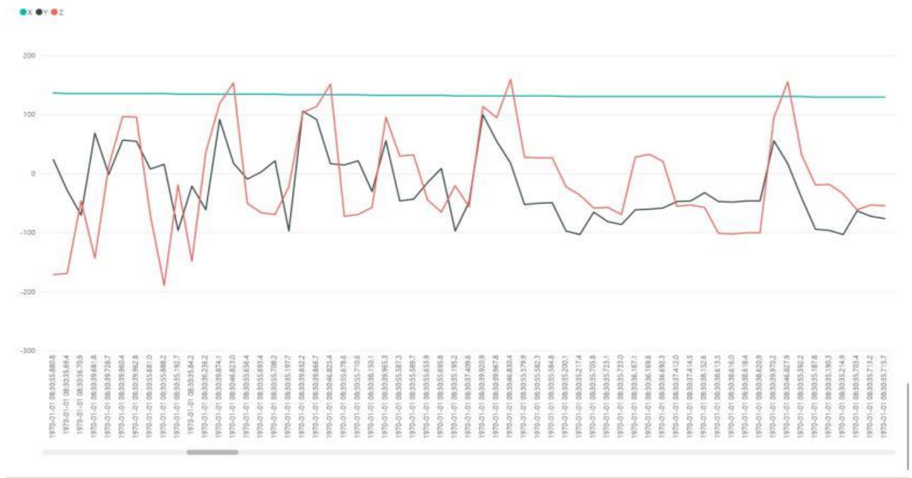
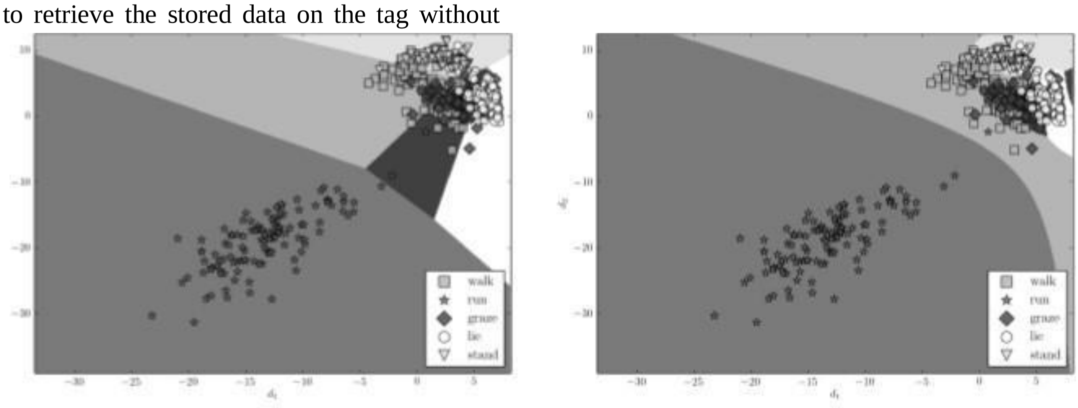


Figure 9. Grazing

Each behavior Graphic observation was obtained for about 5 minutes period.

B. Future Work

The hardware will be further developed in order to improve the practicality of the tag. This includes using radio communication to retrieve the stored data on the tag without disturbing the animal. Future work is needed to increase the overall classification accuracy. The hardware could be improved in order to increase the quality of the accelerometer data. Smarter positioning of the accelerometer should also be attempted to remove or reduce ambiguity between behaviors such as grazing and lying. Additionally, different



(a) (b)

Figure 11 (a) Linear decision boundaries. (b) Quadratic decision boundaries

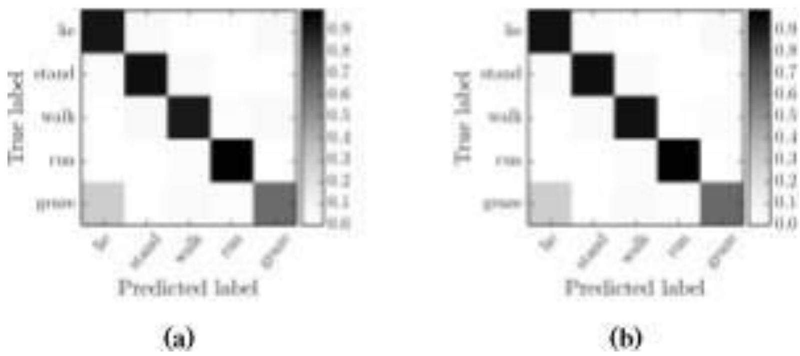


Figure 12. Confusion matrices of the QDA classifier (a) trained with only the first three features selected by the greedy feature test and (b) trained with using all 10 features.

and additional types of sensors could be considered to further remove ambiguity. Classification success can also be influenced by different signal processing parameters, for example, the window length as shown in. Other machine learning classifiers should be investigated. Success has for example been demonstrated when using support vector machines and k-nearest neighbor classifiers.

C. General Discussion

The approach used to categorize lame walking from normal behaviors in the current study is similar to that used by Martiskainen, Järvinen , whereby lame behaviors are added to the classifier as an additional behavior category. Other studies conducted on dairy cattle have used a change in the proportion of behaviors (predominantly lying) to infer a lameness state [16,26,28]. This approach has shown that around 92% of cows which developed clinical lameness also had a decrease in the pedometric activity of at least 15%. Additionally, extreme lying times, observed through increases or decreases in the amount of time spent lying, be predictive of lameness events in cattle. Similar detail on the association between lameness and lying behavior is lacking for sheep; however, a decrease in the activity of lame animals has been previously lying indicated. Further validation to quantify the total lying time to detect lameness in sheep should be investigated. Using a behavioral state proportion approach, lameness could be categorized based on a change in total activity distribution. The novel method used to simulate lameness in this study was extreme and prevented any weight bearing on the restrained limb, creating a more distinct lameness gait than what we would expect naturally. Due to lameness activities being grouped as a different class for classification, this method was preferred to create a distinct difference in the acceleration signals compared to normal behavior. If a difference in the acceleration pattern could not be detected with an extreme gait change as investigated here, there would be little hope of detecting the progression of a mildly lame gait. Additional approaches could be investigated that would also allow for alternate methods of detection such as walking speed, distance traveled, stride length, and stride duration, which have been suggested to be valid indicators of lameness in other species. However, a question that was not explored here, and one that may hold diagnostic value, is "when lame sheep are grazing, do they alter the vertical angle of the 'good' foreleg while grazing to avoid over-balancing?" For example, when the head is lowered so they can eat grass, compared to a normal (non-lame) sheep. Perhaps less tilting of the remaining leg occurs away from the vertical position, although it is unlikely that this adjustment would be detected by an ear-mounted accelerometer sensor. Additionally, lame sheep may tend to kneel while grazing, therefore altering the leg accelerometer orientation, which may hold diagnostic value. Lameness simulations should also investigate the difference between having lame fore and hind limbs as this will affect the acceleration signal obtained, ultimately influencing the classifier's ability to discriminate between sound and lame gaits. There is little information on the ability of sheep farmers to identify lame animals or on the decision when a sheep farmer decides to investigate and treat a lame animal. A study on sheep farmers in England concluded that their estimates of lameness prevalence within flocks were sufficiently accurate. Similar information is lacking for the Australian sheep industry. A valid question is, therefore, "what is the economic and welfare value of detecting lameness earlier and initiating treatment sooner?" Further research is required in this area to quantitatively describe the advantages of an electronic detection system in terms of overall productivity and animal welfare benefits.

Conclusion

The accelerometer was successfully used to classify five behaviors in sheep. The quadratic discriminant analysis classifier proved to be superior compared to the linear discriminant analysis classifier. The quadratic discriminant analysis classifier also proved highly successful even when only a small number of features was used for classification. The feasibility study showed positive results when using specially-built hardware and a basic classification technique.

The identification of animals with abnormal gait patterns could aid in the detection of many diseases which have lameness symptoms. The visual daily monitoring of locomotion or behavior on farms is time-consuming and hence cost-inefficient. The automatic measurement of lameness-related, animal-based characteristics would allow for daily measurements and could, therefore, be a better option. This current study has shown that a tri-axial accelerometer deployed in the ear tag can successfully discriminate lame walking activity from normal grazing, standing, and walking behaviors. The collar and leg deployed accelerometers failed to successfully classify both sound and lame walking activity. This could be a function of sensor place mental the simulation not being a true presentation of lameness. Further research investigating a commercially suitable accelerometer-based, automatic identification system for the onset of lameness is warranted. Additionally, future work should investigate a detection system based on changes in indicators over time, rather than on the deviation from the group mean. Gaitcharacteristicsshouldalsoaccountforvariationsinnormalanda bnormal patterns in terms of animal age, sex, and breed.

ACKNOWLEDGMENT

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CONFLICT OF INTEREST

The Author(s) declare(s) that there is no conflict of interest.

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