Dynamic Time Warping for classifying cattle behaviors and reducing acceleration data size

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Abstract: This paper proposed a method for classifying the cattle behaviors. An embedded accelerometer system has been attached to the cow's neck. Dynamic Time Warping (DTW) was applied to measure the similarity between acceleration data corresponding to the cow movements and the templates collected from the acceleration data corresponding to the cow behaviors. The results of these processes are the sets of accumulated distances whose minimum value is used to select a behavioral model. Two cows used in the experiment, and the accuracy of classification was measured. The results showed that the accuracy of the proposed system is more than 90% for all behavioral models. Moreover, the three-axis acceleration data combined before sending through the wireless network to the computer base resulted in the power consumption of wireless network reduced.

Keywords: cattle behaviors, embedded accelerometer system, Dynamic Time Warping

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1 Introduction

The cows spend the time periods in each day for standing, walking-grazing and lying. Therefore, monitoring the behavioral time periods of the cows can help us to know their health. This leads to remedy in time before it becomes a serious problem. However, in the case of a large herd, monitoring cow behaviors require more labors that are unable to monitor all the time. Thus, automated monitoring system for the cow behaviors is necessary for that requirement because it can reduce labor, increase the frequency of observation and reduce bias and observer influence. In automated monitoring system, an embedded sensor device is attached to the cow's body for measuring the data of the cow's movement and sends these data to a central base station through wireless for classifying cow behaviors.

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Different types of sensors have been used in the automated monitoring system such as Global positioning system (GPS) and accelerometer. GPS are deployed in outdoor environments to estimate the temporal and spatial distribution of animal herds (Butler et al., 2004; Oudshoorn et al., 2008; Schwager et al., 2007). However, it needs high energy consumption and is the frequent loss of connection with the satellites in the areas of a field covered with obstacles (e.g., trees). Thus, GPS are less practical and less reliable in terms of long-term behavior registration than other monitoring systems in some environments.

The most popular sensor is the three-axis accelerometer which is attached to the cow's leg for measuring its orientation. The acceleration data of X, Y, and Z axes corresponding to the cow's movements are easily classified into the behavioral models based on; the amplitude of Y-axis by using two level thresholds for classifying lying behavior (Darr and Epperson, 2009), the amplitude average of each axis, vector magnitude average and vector magnitude maximum by using the classification tree for classifying walking, standing and lying (Robert et al. 2009) and the amplitude average of each axis and variance of Y-axis by using the classification tree for classifying walking-grazing, standing and lying (Aurasopon et al. 2015).

Another way, the accelerometer is easily attached to the cow's neck, but it is difficult to classify the cow behaviors because the acceleration data of each behavior are similar. To perform data processing, different methods such as k-means classifier, multiple model adaptive estimation approaches, support vector machines, hidden Markov models and supervised machine learning algorithms have been suggested by Schwager et al. (2007), Nadimi et al. (2008a, b) and Nadimi and Søgaard (2009), Martiskainen et al. (2009), Langrock et al. (2012), and Ritaban et al. (2015).

Although these methods show the high percentages of successful classification, they need more complex mathematics and the algorithms are difficult to implement in the embedded sensor system for saving battery life. Jorge et al. (2015) have concerned this limitation, therefore, the decision-tree was used based on the simple structure and low computational cost, making it feasible to be implemented directly in the embedded sensor device. However, the parameter choices used within the algorithm, behavioral variation across individual cows could have an effect on the classification performance. Each cow would have different values for the threshold.

This paper proposes a simple behavioral classifier method by using DTW where the behaviors are classified in three models: standing, walking-grazing and lying. DTW is applied to measure the similarity between the acceleration data of cow movements and the templates of each behavioral model resulting in three sets of accumulated distances. The minimum accumulated distance of these sets is used to select a behavioral model. The paper is organized as follows: Section II and III give the material for accelerometer data collection and the method for classifying the cow behaviors, respectively. Section IV shows the experimental results for the classification success rates. Finally, Section V concludes the work.

2 Material and method

2.1 Measuring cow movements

Figure 1 shows the neck collar mounted the embedded sensor device on the cow's neck. The acceleration directions of X, Y, and Z axes are accorded to the illustration while the cow stands. The changes in the accelerations in the X and Y axes measure the cow's bob and the changes in the accelerations in the Y and Z axes measure the rotation of the cow's neck. To collect the raw data, the three-dimensional analog accelerometer (ADXL335) with a measurement range of ±3 g was used.

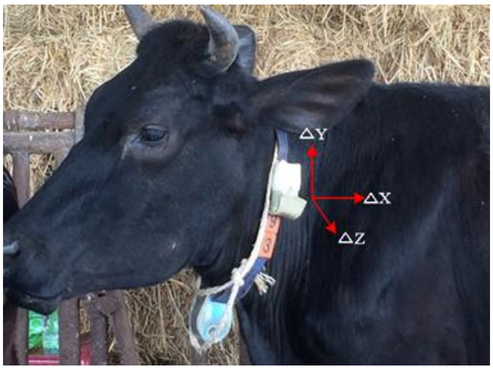


Figure 1 Embedded accelerometer device attached around the cow's neck.

2.2 Acceleration data size reduction

The acceleration data correspond to the cow movements sent through a wireless network to the computer base for classifying the behaviors. Generally, these data consist of the cow's personal code and the acceleration data of X, Y, and Z axes. In the case of the acceleration data with one decimal point, the data size is equal to 10 bytes resulting in high power consumption. To reduce the data size, the square root of the square of the sum of 3-axis acceleration data is calculated as

$$S_r = \sqrt{x^2 + y^2 + z^2} \qquad (1)$$

The Equation (1) implemented by the microcontroller results in a vector of three-axis acceleration data sent through the wireless network to the computer base. Therefore, the data size remains 4 bytes.

2.3 Dynamic Time Warping for classifying the cow behaviors

The goal of this paper is to classify the cow behaviors into three models: standing, walking and looking for grass or walking-grazing, and lying. From our algorithm, we collected the acceleration data templates corresponding to the cow behaviors. These templates are used to measure the similarity with the acceleration data of the cow movements. To measure the similarity between two-time series, Euclidian distance is simply the sum of the squared distances from each *n*-th point on one-time series with the *n*-th point on the other. However, its results produce a poor similarity score. If two- time series is identical, but one is shifted slightly along the time axis. DTW has been introduced to overcome this limitation and give intuitive distance measurements between time series by ignoring both global and local shifts in the time dimension.

For the basic algorithm of DTW, let us start with two-time series X and Y of lengths N and M (Giorgino, 2009).

$$X = x_1, x_2, \dots, x_i \dots x_N$$
$$Y = y_1, y_2, \dots, y_j \dots y_M \qquad (1)$$

The local cost matrix, *d*, is a matrix which stores all pairwise distances between X and Y is created. The cost in each cell of the local cost matrix is calculated by using the Equation (2):

$$d(i,j) = \sqrt{(x_i - y_j)^2} \qquad (2)$$

After calculating the local cost matrix, the next process is to calculate the accumulated cost matrix, *D*, which is a matrix storing the accumulated least cost required to arrive at any location in the matrix by following a specified search pattern from (1, 1) to (*N, M*). The most common search pattern allows the algorithm to check costs in the next cell vertically, horizontally, or diagonally away from the current cell in the matrix. The accumulated least cost in each cell of the matrix can be found by Equation (3).

$$D(i,j) = d(i,j) + \min\{D(i-1,j-1), D(i,j-1), D(i-1,j)\}$$
$$i \in N, i \in M \qquad (3)$$

For the last step, we find the optimal alignment by calculating the warp path through the accumulated cost matrix. The warp path is the shortest path from (*N, M*) to (1, 1) through the accumulated cost matrix, following a specific search pattern. Similar to the process for constructing the accumulated cost matrix, the warp path search pattern typically allows searching the next cell vertically, horizontally, and diagonally away from the current cell in the warp path. Figure 2 shows the accumulated cost matrix, D and the optimal warping path where the vertical axis is a time series of the template and the horizontal axis is a time series of the measured acceleration data for testing. The cost of the matrix, $D(N,M)$,an accumulated distance, is a minimum error between two time series that is our interest.

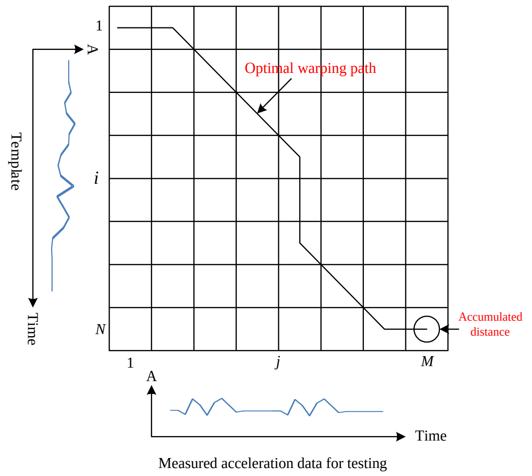


Figure 2 Accumulated cost matrix and optimal warping path.

3 Classifying processes

In this session, the important parameters using in the classifying processes such as the templates and the accumulated distance are explained.

3.1 Templates

The acceleration data collected from all patterns of the cow movements were used as the templates. In each behavior, the cow has several movement patterns. For the examples, while the cow is standing, it may stand still or ruminate or bob or shake one's head. While the cow is grazing, it may feed or stop feeding to look up for chewing. While the cow is lying, it may lie still or ruminate or bob or shake one's head.

To correctly classify processes, the acceleration data of the templates should cover all the cow movement patterns. We carefully selected the templates for standing, walking-grazing and lying behaviors as the graphics shown in Figure 3. These templates were recorded by observing the cow movement patterns in one minute, 60 data. Figure 3(a)-(c) shows the templates for the different standing patterns. For examples, the cow may stand still or also swing the head or change the movements from lying to standing still or standing still to lying or grazing to standing still, and standing to grazing. Figure 3(d)-(f) shows the templates used for classifying the walking-grazing model. They were recorded while the cow was grazing. It may sometimes bob up or down or stand still. The templates for using in classifying the lying model shown as in Figure 3(g)-(i), the cow may sometimes lie still or change the movements from standing still to lying or lying to standing still or grazing to lying or lying to grazing.

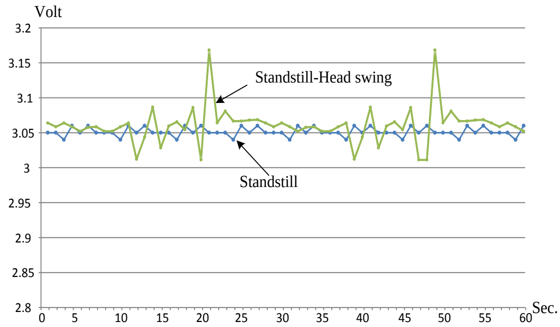
3.2 Measuring the accumulated distance

Figure 4 shows the classifying processes of the proposed system. The first step the acceleration data of a cow sampled at 1 s were collected every 60 samples. These data are calculated by Equation (1) measured the similarity with all templates of the behavioral models by DTW. The processing results are the accumulated distances that indicate the similarity between the acceleration data for testing and the templates. Therefore, the minimum accumulated distance can be used for selecting a behavioral model.

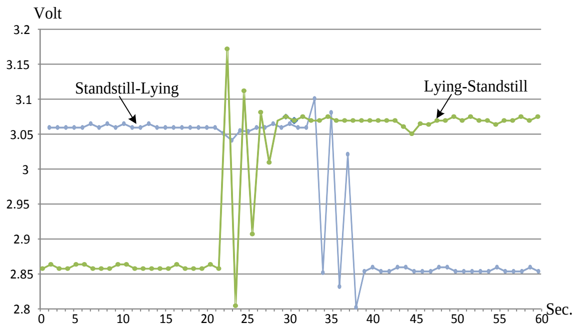
4 Experimental results

To find the success rate of the classification, the experiments used two cows. The cows were released from the barn for looking for grass in the field during 8.30 AM and 4.30 PM. This period is suitable for testing the system because the cows perform all activities that are standing, walking-grazing and lying.

During the test, the embedded sensor device was mounted around the cow's neck as shown in Figure 1. We collected the acceleration data for the templates by observing the cow movements corresponding to its behaviors. Each template consists of 60 data at sampling frequency 1 Hz. These templates used for classifying the behavior models for the both cows.



(a)



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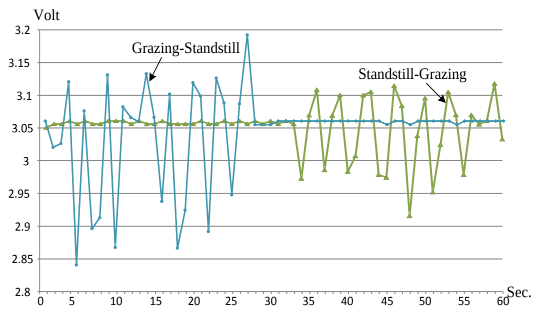

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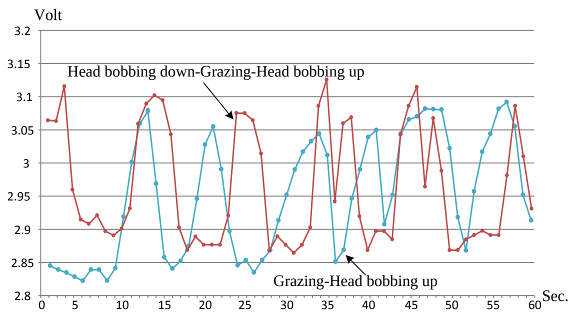

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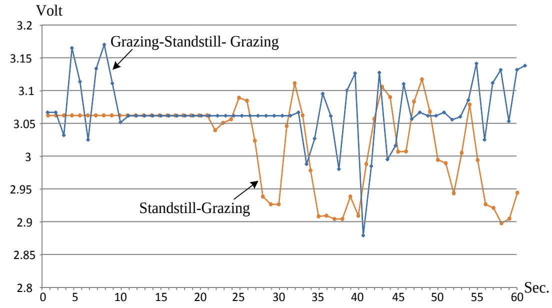

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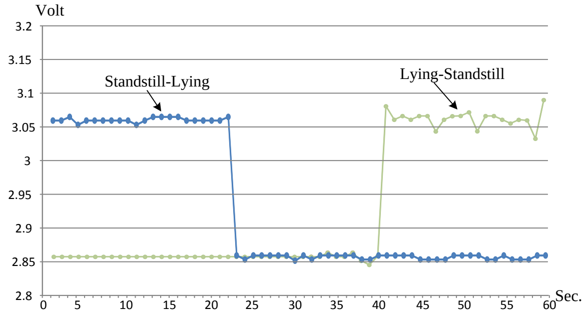

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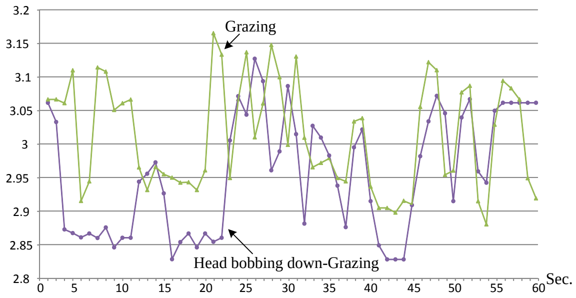

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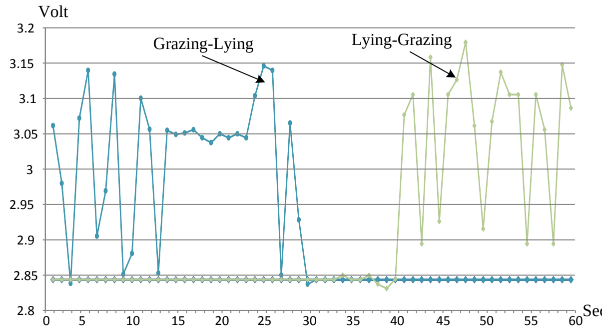
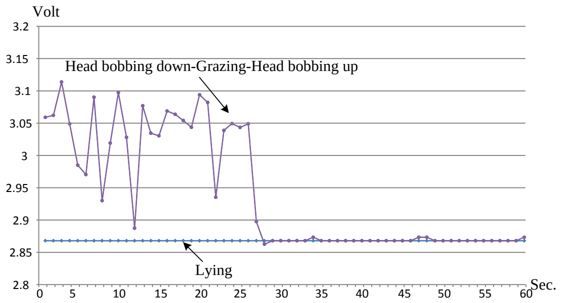


(i)



(g)

Figure 3 Templates of each behavioral model: Different movement patterns for (a)-(c) standing, (d)-(f) walking-grazing and (g)-(i) lying.

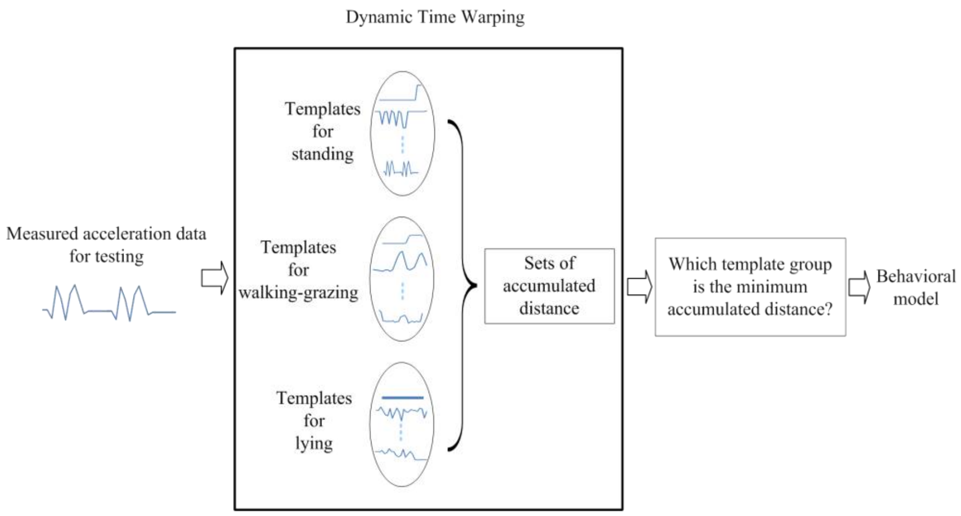
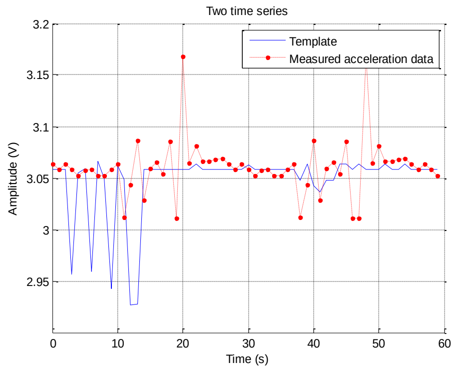


Figure 4 Behavioral classifying processes by using Dynamic Time Warping

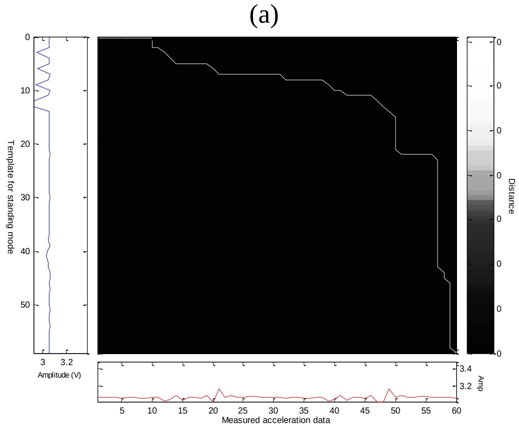
For testing the classification system, we measured the acceleration data of cow#1 and cow#2 while they were standing. The acceleration data of cow#1 measured the similarity with each template as shown some examples in Figures 5-7. From the experiments, the minimum accumulated distance resulted from a template of the standing model. Therefore the classifying system predicted that the cow#1 was standing. In the case of cow#2, we used the same setup and found that the accumulated distances in walking-grazing and lying models are 0.75 and

1.24 respectively. While the lowest accumulated distance resulted from a template of the standing model, 0.21. This implies the cow#2 was standing.

In the case of walking-grazing, the cow#1 was grazing in the field. The measured acceleration data correspond to its movement were measured the similarity with all the templates. Figure 8 shows the results of DTW processes in the case of a template of the walking-grazing model. The accumulated distance is equal to 0.15. This value is lower than the accumulated distances resulted from the other template models. Therefore, the classifying result, the cow#1 was walking-grazing.

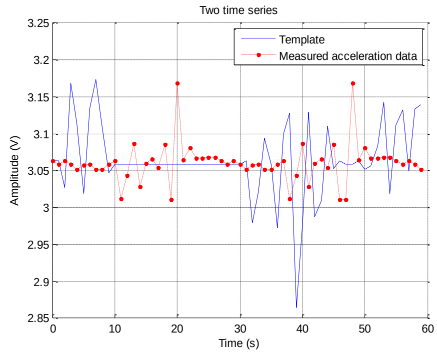


(a)

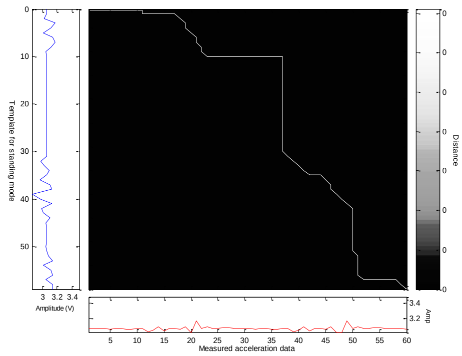


(b)

Figure 5 (a) Template for standing and measured acceleration data (b) Accumulated cost matrix and optimal warping path.

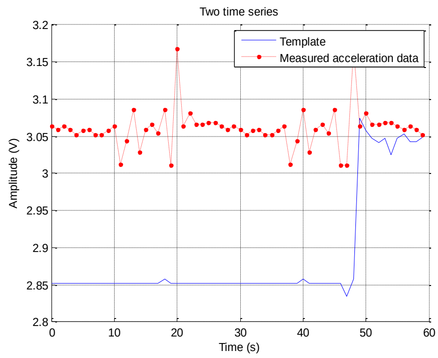


(a)

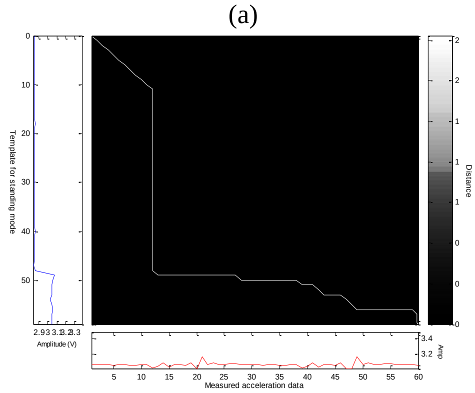


(b)

Figure 6 (a) Template for walking-grazing and measured acceleration data (b) Accumulated cost matrix and optimal warping path.

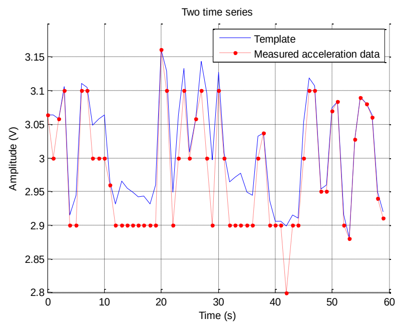


(a)

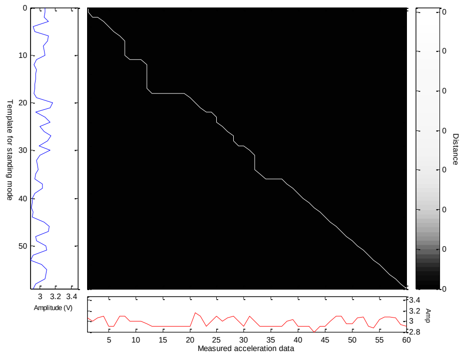


(b)

Figure 7 (a) Template for lying and measured acceleration data (b) Accumulated cost matrix and optimal warping path.

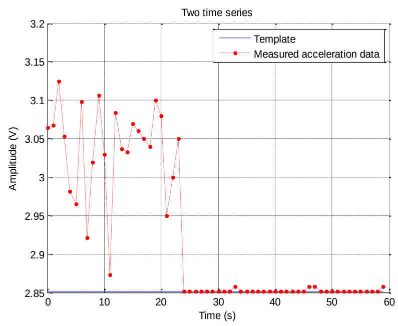


(a)

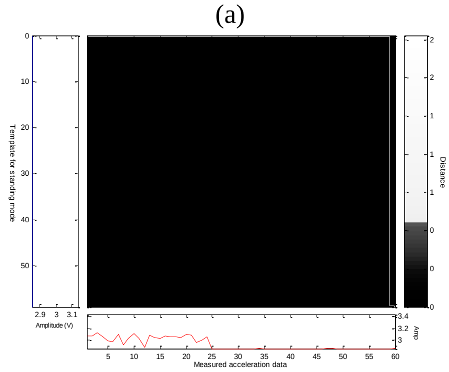


(b)

Figure 8 (a) Template for walking-grazing and measured acceleration data (b) Accumulated cost matrix and optimal warping path.



(a)



(b)

Figure 9 (a) Template for lying and measured acceleration data (b) Accumulated cost matrix and optimal warping path.

It's in a case of lying. The cow#1 spent the time periods for grazing about 20 s and then lying down. The acceleration data of its movements measured the similarity with all the templates. In this example, we show the result in the case of a template of the lying model. The results the accumulated distance is equal to 0.89. This value is high when compared with the accumulated distances resulted from the other templates of lying model. However, it is still low when compared with the accumulated distances resulted from the templates of other template models.

From the experimental results, the average of the classification accuracy of two cows is more than 90 percentages of all the cases. However, there are some errors resulting from the time periods of the behavioral transition and the position of the embedded sensor device shifted. From the results, we recommended that the test could use more adequately templates to increase the classification accuracy.

5 Conclusions

This paper proposed the method for classifying the cattle behaviors. The three-axis accelerometer is attached to the cow's neck. To classify the cow behaviors, the measured acceleration data of the cow movements measured the similarity with the templates by using Dynamic Time Warping where the templates are the acceleration data of the cow corresponding to its behaviors. The process results in the sets of accumulated distance whose minimum value is used to select a behavioral model.

From the experiment results, the classifying accuracy is higher than 90% of all the behavioral classification. However, there are some errors resulting from the behavioral transition periods and the embedded device position shifted. While there is a considerable drop in power consumption (40%) because of the acceleration data size reduced.

Acknowledgments

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