Classification of the cattle behaviors by using magnitude and variance of accelerometer signal

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Abstract: Time periods of walking-grazing, standing and lyingof cattle's life can be used to predict their health. However, famer cannot observe those in all the time. Therefore, this paper proposes a simple technique to classify the cattle behaviors by using the magnitude and the variance of accelerometer output signal. There are two steps of algorithm detection, the first step employed the magnitude of each axis for classifying the cattle behaviors into two groups: 1) walking-grazing and standing and 2) lying. After that, the second step used the variance of Y-axis to notify between walking-grazing and standing behaviors. The classification results were inform time periods of each behavior and tested with two cattle. The measured precise times of each behavior were compared with human observation. As a result, we found that the detection testing can identify the cattlebehaviors with a high success rates, the system has the errors as follows walking-grazing maximum errors 2% standing maximum errors 13% and lying maximum errors 7%.

Keywords: cattle behaviors, accelerometer, variance, decision tree and activity monitoring.

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1 Introduction

The time periods of cattle behaviors such as walking-grazing, standing and lying can be used as the data for predicting their health. Analyzing the cattle behaviors to identify health problems is significant impact on practical farming and also be useful in alleviating economic costs associated with illness (Nadimi, et al., 2008a; Robert, et al., 2009)

The automatic systems for recording the cattle behavior data have been needed because the farmer cannot monitor those all the time. In literatures, various sensors systems have been reported for automatic measuring of animal behaviors such as GPS, accelerometers, etc. However, most researchers stated that the accelerometer is a suitable sensor for using in animal behavior classification system (Pastell, et al., 2009; Valenza, et al., 2012; Yin, et al., 2013).

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Munksgaard et al. (2006) used accelerometer as a data logger by attaching the sensor to the leg of cattle and registering the status of the leg, they demonstrated reliable results.

However, this sensor is applied based on offline monitoring system that cannot work with real-time monitoring. As for Matthew Darra and William Epperson (Darr and Epperson, 2009), they designed embedded sensor device for classifying and monitoring the lying behavior by using 3-axis accelerometer. This work found to be sufficient in determining lying behavior.

Guo, et al. (2006) were employed a K-means classifier to classify the data of location and pitch angle of a neck of cattle's herd into two categories, stationary and travelling states. The stationary state consists of sitting and standing activities where the travelling state comprises of running and walking activities. In similarly case, Nadimi's thesis (Nadimi, 2008b) classified structure of dairy cow behaviors by a hierarchical classification. The classification is started from the highest layer activities. Activity and inactivity can then be divided into different sub-modes such as eating, ruminating, lying down and drinking.

Nadimi et al. (2012) studied the behavior classifying techniques by comparing the performance of neural network with other techniques (Nadimi and Søgaard, 2009; Sallvik and Oostra, 2005; Nadimi et al., 2008a and Szewczyk et al., 2004) such as the Kalman filter with a multiple model adaptive estimation, discriminant analysis classification, classification tree and threshold (Classification tree with two nodes). The work found that neural network classifiers can be classified with a highest classification success rate.

Despite most of these techniques provide a high classification success rate, they still needed to construct with an excessive amount of mathematical operations and used highly-resources requirements. Therefore, such techniques may be unsuitable applying when implementing with a low-cost processor or resource-constrained embedded devices.

Objective of this paper, we propose a simple technique to classify the cattle behaviors using acceleration data. The classification technique based on a decision tree method by using the magnitude of X Y and Z axis and the variance of Y axis for classifying the cattle behaviors into three groups such as walking-grazing, standing and lying, respectively.

This paper is organized as follows: Section II gives the material for accelerometer data collection and the method for classifying the cattle behaviors. Section III shows the experimental results for the classification success rate. Finally, Section IV concludes the use of classification method.

2 Material and method

2.1 Accelerometer data collection

With regards the automated classifyingsystem, such systems comprises of an embedded device and server based, as shown in Figure 1. The embedded device consists of three main elements: 1) 3-axis accelerometer (X, Y, and Z) for measuring the cattle activity. 2) Microcontroller for acceleration data processing and 3) Wireless transceiver (ZigBee-based RF modules) for transmitting data to the server based. As for the server based, it has function for classifying the behaviors and showing the result by time series plotting.

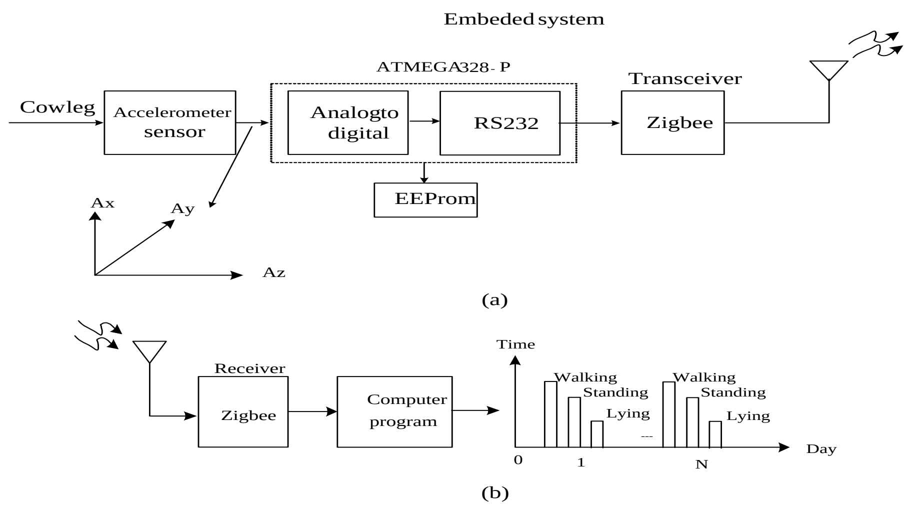

Figure 1 Block diagram of automatic system for classifying the animal behaviors (a) embedded devices and (b) server based system.

In practical terms, when measuring the cattle behaviors, embedded system was fitted around a leg of cattle. Figure 2 shows the relationship between the acceleration and the angle of each axis. Please note that, when the animal is standing, the Y and Z-axis is perpendicular to a leg while the X-axis is perpendicular to the ground.

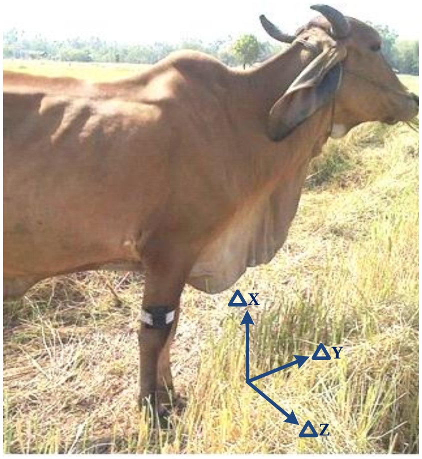

Figure 2 Accelerometer sensor attached around a leg of cattle.

To collect the raw data of such animal, acceleration data from three-dimensional analog accelerometer (ADXL335) was measured every 1 s (Sample rate 1 Hz). An example of time series of acceleration data can be shown in Figure 3.

The graphic represents the 3-axis acceleration data that show different voltage level of each activity. It can be seen that each activity displays the distinct acceleration data pattern. To classify the cattle behaviors, Robert, et al. (2009) and Nadimi et al. (2012) used a vector of 3-axis acceleration data for using in decision tree and neural network classifiers. However, classification accuracy of these techniques is still low. Because, voltage level of the vector of 3-axis acceleration data of walking-grazing activity is very close to that of standing activity.

2.2 Classification of cattle behaviors using magnitude and Y-axes variance

The main purpose of this paper has interested to classify the cattle behaviors in an outdoor environment. Therefore, this work classified the cattle behaviors in three behavior types that are: standing, walking and looking for the grass or walking-grazing and lying.

Considering Figure 3, the voltage levels of 3-axis of lying activity are different from other activities. Therefore, lying activity can be classified from the others by using reference voltage levels.

Figure 3 An example of time series plotting of acceleration signal of each cattle behavior

While the voltage levels of the standing activity is very similar to the walking-grazing activity. This makes it difficult to use the voltage levels for classify these activities. Therefore, this paper proposes the classification of standing and walking-grazing activities using a variance of Y axis.

Therefore, to simplify the classified approach, the mean and variance reference voltage values of each axis is calculated by using 300 data and compared with a set of the present data. For a proposed algorithm, there are two steps as follows:

1) The first step, the cattle behaviors are classified into two groups are: 1) the standing and walking-grazing

activities and 2) the lying activity. Before starting the classification, the reference voltage values of each axis can be found as follows:

The average of each axis of the standing and walking-grazing activities is found by Equation (1):

$$\mu_{swrj} = \frac{1}{N}\sum_{i=1}^{N} R_i \qquad (1)$$

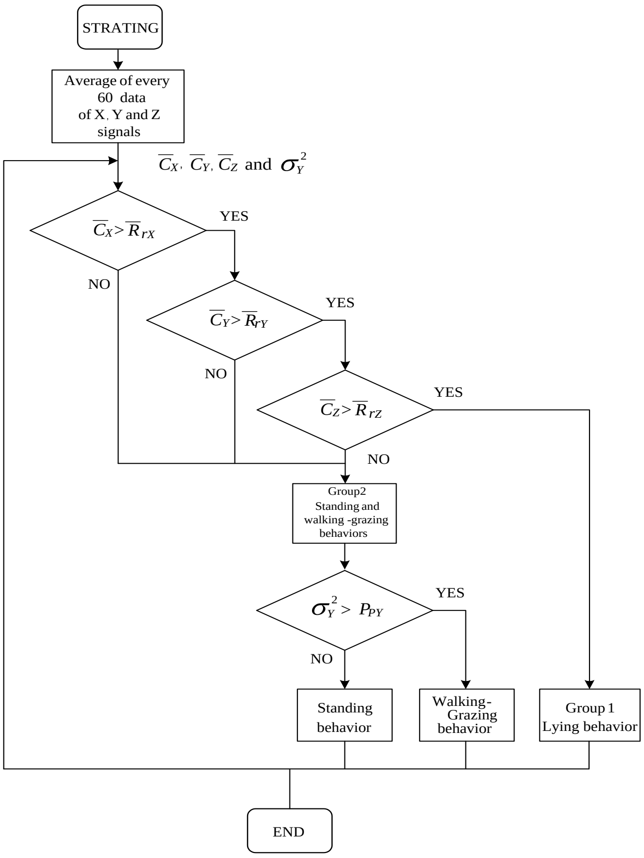

Figure 4 Classification flowchart of cattle behaviors.

And, the average of each axis of the lying activity is found by Equation (2):

$$\mu_{lrj} = \frac{1}{N}\sum_{i=1}^{N} R_i \qquad (2)$$

Therefore, the reference voltage levels of each axis for classifying the cattle behaviors into two groupsare found by Equation (3):

$$\bar{R}_{rj} = \frac{\mu_{swrj}+\mu_{lrj}}{2} \qquad (3)$$

Where $R_i$is the signal data for $i = 1, 2 \dots N$.

$N$is the data number, 1, 2…300.

$j$is the axis for X, Y and Z.

While the voltage average of the present data of each axis is as Equation (4):

$$\bar{C_j} = \frac{1}{60}\sum_{i=1}^{60} R_i \qquad (4)$$

As shown a flowchart in Fig. 4, the results from Equation (3) are used to classify the cattle behaviors by using decision tree. The present data of each axis, R_i is received in every second where $i = 1, 2 \dots 60$. Then, these data are averaged to be $\overline{C_X}$, $\overline{C_Y}$ and $\overline{C_Z}$ compared with the reference voltage values of each axis $\bar{R}_{rX}$, $\bar{R}_{rY}$ and $\bar{R}_{rZ}$, respectively. Thus, the results of these processes, the cattle behaviors are classified into two groups: 1) standing and walking-grazing activities and 2) lying activity.

2) The second step is to classify the standing and walking-grazing activities using variance of Y axis. The average of variance of Y axis while the cattle is standing found by Equation (5):

$$\sigma_{srY}^2 = \frac{\sum_{i=1}^{N}(R_i-\mu_{srY})^2}{N} \qquad (5)$$

And, while the cattle is walking-grazing is as Equation (6):

$$\sigma_{wrY}^2 = \frac{\sum_{i=1}^{N}(R_i-\mu_{wrY})^2}{N} \qquad (6)$$

Where μ_{srY} and $\mu_{wrY}$are the average of Y axis while cattle are standing and walking-grazing, respectively. Therefore, the reference variance value for classifying these activities can be found by Equation (7):

$$P_{PY} = \frac{\sigma_{srY}^2+\sigma_{wrY}^2}{2} \qquad (7)$$

For the variance of the present data of Y axis is as Equation (8):

$$\sigma_Y^2 = \frac{\sum_{i=1}^{60}(R_i-\overline{C_Y})^2}{60} \qquad (8)$$

Where, $\overline{C_Y}$ is the present average value of Y axis. As shown the flowchart in Figure 4, the result of variance value of Y axis (Equation(8)) will be compared with the reference value (Equation(7)). If the condition is true, this means that the cattle behavior is walking-grazing. On the other hand, the cattle is standing.

3 Experimental results

3.1 Measurement approach and methodology

To find the success rate of classification, the experiment was tested at Mahasarakarm University in Thailand over 5 days with two cattle. The cattle were released from the corral for looking for grass in the field during 8.00 AM and 4.00 PM. This period is suitable for testing the proposed system because the cattle can perform all activities for observation that are standing, walking-grazing and lying.

During the test, each cattle was installed wireless sensor node attachment around a leg of cattle. The acceleration data was measured with a sampling rate at 1 Hz. In the first step, the reference voltage averages of each axis for classifying the standing and walking-grazing activities from the lying activity were found by using Equation (3); $\bar{R}_{rX} = 1.82$, $\bar{R}_{rXY} = 1.52$ and $\bar{R}_{rZ} = 1.57$. While the reference variance value of Y axis for classifying the standing and the walking-grazing activities using Equation (7) was found as$P_{PY} = 0.0031$.

3.2. Classification results

To monitor the cattle behaviors, MATLAB® software were conducted to monitor the behaviors in an outdoor environment as shown in Figure 5 where numbers 1 and 2 show real time acceleration data of cattle #1 and #2, respectively, and numbers 3 and 4 show the results of cattle behaviors in form of bar graph while the numbers 5 and 6 show those in form of time, and numbers 7 and 8 show the current behavior status. The cattle were plotted cumulative behavior time for all activities.

Table1 shows the percentages of classification accuracy of the proposed method compared with human observation. According to the table, the proposed technique available to classify the behaviors of cattle with a high classification success rate, it has the errors as follows standing maximum errors 13%, walking-grazing maximum errors 2% and lying maximum errors 7%.

Table1 Percentages of classification accuracy in experimental period

Cattle number	Behavioral mode		
	Walking-grazing (%)	Standing (%)	Lying (%)
Cattle#1	98	88	95
Cattle#2	98	86	91
Mean (μ)	98	87	93

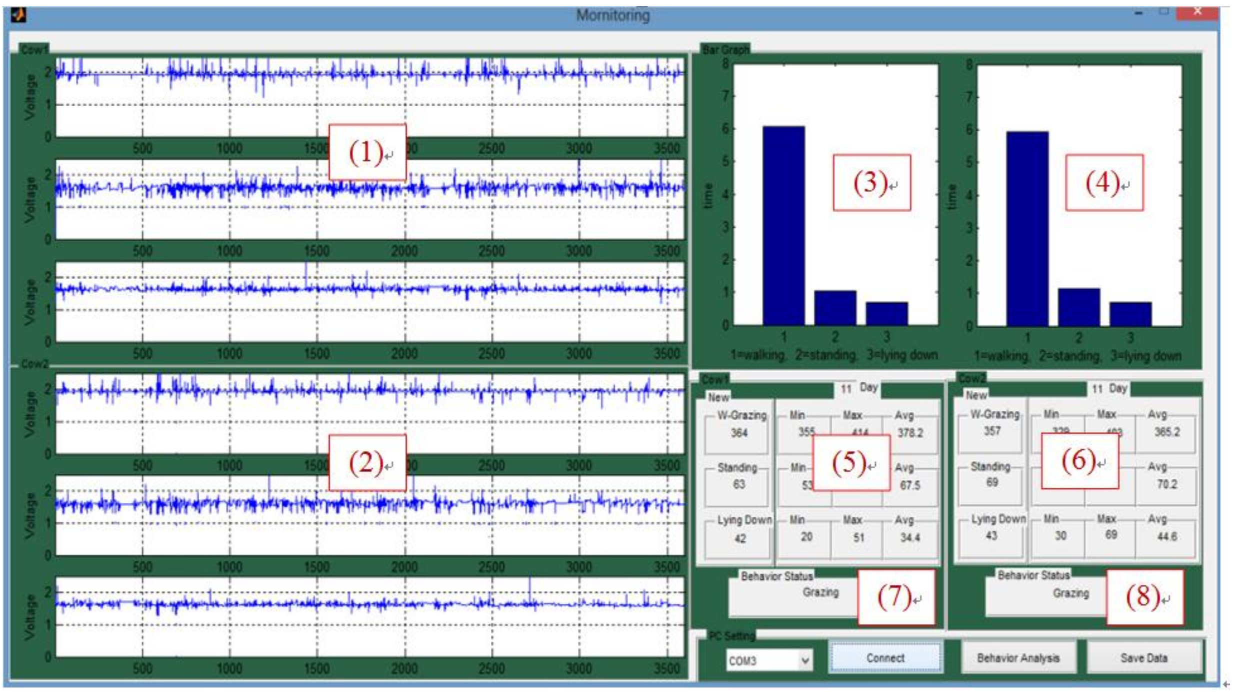

Figure 5 Graphical program for monitoring the cattle behaviors.

From the results, we examine the causes of classified errors as follows: 1) While, the cattle are standing and its leg moves slightly, this resulting may determine the behavior as walking-grazing. 2) When the cattle changed the activity such as from standing to lying or from lying to standing. The system sometimes classifies these stepsto walking-grazing. This is because the variance value of Y axis has been changed.

4 Conclusions

This paper is attended to classify the cattle behaviors in an outdoor environment using acceleration data with a simple behavioral method. This work proposed a simple technique which employed threshold level from magnitude and standard deviation of acceleration data to address an excessive amount of mathematical operations and highly-resources requirements from other different classification methods.

The system performances were focused to determine the classification success rate and monitor of the cattle behaviors. The results of this work show that the percentages of classification accuracy of this empirical experiment was higher compared to related works with found in literatures.

Overall, this paper concludes that the use of proposed method is an efficient classification technique for use with a wide range of animals. This is also a practical way of implementing this technique in outdoor environment with low-cost system.

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