Classification of Cow Behavior using 3-DOF Accelerometer and Decision Tree Algorithm

Phung Cong Phi Khanh,
Department of Technology Education
Hanoi National University of Education
Ha Noi, Viet Nam
phungcongphikhanh@gmail.com

Nguyen Dinh Chinh, Trinh Thi Cham,
Pham Thi Vui, Tran Duc Tan
VNU University of Engineering and Technology
Ha Noi, Viet Nam
{chinhnd,tantd}@vnu.edu.vn

***Abstract*—Monitoring cattle motion is essential, since it helps farmers to take a comprehensive view of the cattle's health and estrus time. However, the issue is not able to supervise the cattle in a long time and raising many cattle especially. Therefore, this paper aim to build a device which can sense the states of behavior actives and researches a method to prognosticate the cattle's health by using a cattle monitoring device that can record the 3-axis acceleration to analyze. This sensor is used to measure three-axis accelerometer data on the natural behavior of Vietnamese Yellow cows that live in a cage. The data of the accelerometer output signal are used to modify a simple behavioral classification such as: lying, standing and feeding. Therefore, we can identify some of cattle health events like lameness and estrus cycle. The classification results were tested with the model of the cow.**

Keywords: cow behavior, decision tree, accelerometer.

I. INTRODUCTION

Vietnam is located in the region of tropical monsoon climate, where is endowed with cow farming. In fact, 95% dairy cows in the country have been scattered raised by small [14]. Thanks to applying modern techniques, the management of cattle gets easier and easier. In additions, the prices of production are also reduced and saving labor. Some milk processing companies in Vietnam, where implements advanced technology in order to increase their livestock numbers and improve productivity and quality of fresh milk. Such as: TH true milk, applying Israel's technology (AFIMILK) one of the biggest industrial dairy farms in the world; VINAMILK using electronic chip wear on the neck with the modern system ALPRO provided by DELAVAL. As [1], they measured the pitch angle of the neck of the animal and categorized the behavior of animal in active (grazing or looking for the grass) and inactive mode (lying down or ruminating) [2]. This literature has used accelerometers to classify behavior, activities in dairy cows, but this approach can just discriminate three basic status such as feeding, lying and standing. Methods recently proposed for automatic behavior classification in animals are mainly based on different machine learning algorithms such as decision-trees [3, 4], k-means [5], SVM [7], and HMMs [6].

In this study, we develop a decision-tree that uses tri-axial accelerometer data from a neck. In particular, the advanced cow monitoring systems collect and analyze data points on every individual cow, to forecast some activities in the long time.

It will provide farmers with all of the information that they need and therefore they could be defined health problems or a risk of animals for disease, moreover predicting estrus status. Actually, dairy cows must calve on intervals of 12-14 months to maximize average daily milk production on their lifetime. A deficient detection of heat is one of the main factors that negatively affects calving intervals and reproductive management. Timely insemination is crucial for reproduction and heat detection is the key to the successful use of artificial insemination [8]. When heat excited, the activity levels of cows increase significantly. When cows are sick or lame, their activity will clearly reduce. The study tested a 3D-accelerometer (ADXL345) without transceiver device, here we record the acceleration data into the memory card. Furthermore, the decision tree algorithm has detected 4 states of cow behaviors: lying, standing, feeding.

II. WORKING PRINCIPLES

2.1. Monitoring and classification using three-dimensional accelerometers

The system includes three main components: Kit Arduino Uno, Sensor ADXL345 and SD Card Module. We using this Kit to processing data receive from the sensor and write the data after calibration to the SD Card during each period of time. And, we set two LED to notify the activity of the system. The green LED on when Kit reading data from sensor and write to SD Card. If there is any trouble happening in this system, the red LED will be on continuously.

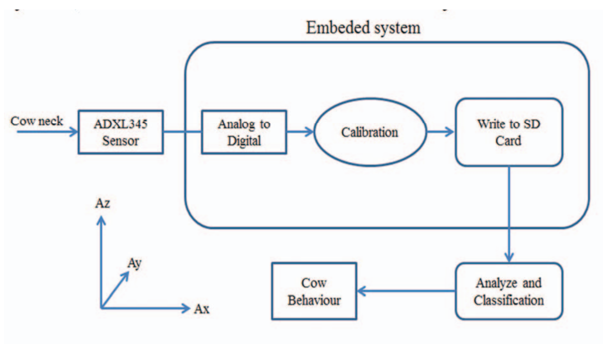

Fig. 1. Block diagram of the system

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2.1.1 Sensor ADXL345

The ADXL345 is a complete 3-axis acceleration measurement system with a selectable measurement range of ±2 g, ±4 g, ±8 g, or ±16 g with g=9.81(m/s^2). It measures both dynamic acceleration resulting from motion or shock and static acceleration, such as gravity, which allows the device to be used as a tilt sensor. The sensor is a polysilicon surface-micro machined structure built on top of a silicon wafer. Polysilicon springs suspend the structure over the surface of the wafer and provide a resistance against acceleration forces. Deflection of the structure is measured using differential capacitors that consist of independent fixed plates and plates attached to the moving mass. Acceleration deflects the beam and unbalances the differential capacitor, resulting in a sensor output whose amplitude is proportional to acceleration. Phase-sensitive demodulation is used to determine the magnitude and polarity of the acceleration.

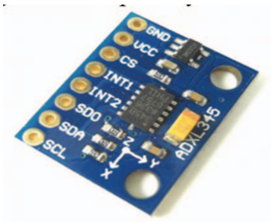


Fig. 2. Sensor ADXL345

2.1.2. Kit Arduino Uno

The Uno is a microcontroller board based on the ATmega328P. It has 14 digital input/output pins (of which 6 can be used as PWM outputs), 6 analog inputs, a 16 MHz quartz crystal, a USB connection, a power jack, an ICSP header and a reset button.

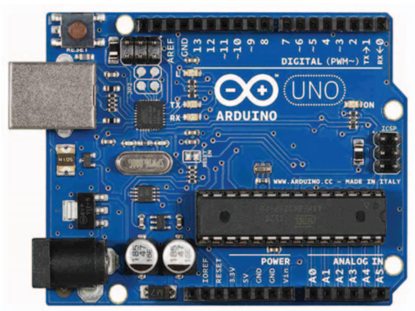


Fig. 3. Kit Arduino Uno

2.1.3. SD Card Module

The Arduino SD Card Shield is a solution for transferring data to and from a standard SD card

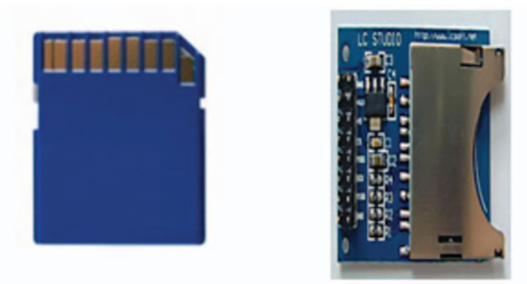


Fig. 4. SD Card Module

2.1.4 Connection and operating principle

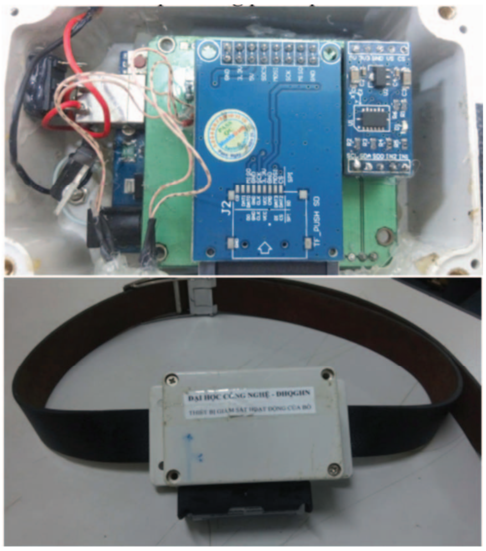


Fig. 5. A real cow behavior's system

We are setting up the connection between devices. First of all, that is sensor ADXL345 which is a small, thin, low power, 3-axis accelerometer with high resolution (13-bit) measurement at up to ±16 g. Digital output data is formatted as 16-bit twos complement and is accessible through either an SPI (3-wire or 4-wire) or I2C digital interface. The communication between the microcontroller and the SD card use SPI.

2.2. Proposed method

2.2.1. Algorithm

Machine learning is a solution to categorize the data set. Because it is regarded as the art of giving a computer data, and will it learn trends from that data and then make predictions based on new data. Fig. 6 presents generally the implementation of any machine learning algorithm.

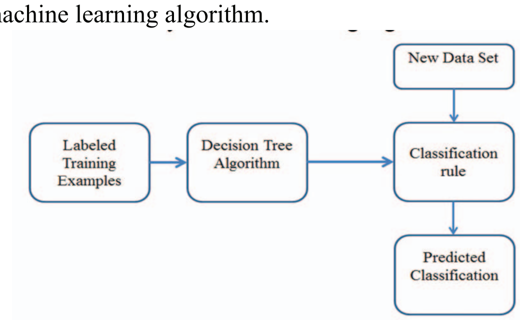


Fig. 6. Classify examples into giving set of categories

A decision tree is a tree in which each branch node represents a choice between a number of alternatives, and each leaf node represents a decision. Decision tree starts with a root node on which it is for users to take actions. From this node, users can split each node recursively according to a decision tree learning algorithm. The final result is a decision tree in which each branch represents a possible scenario of the decision and its outcome. Decision tree learning is a method for approximating discrete-valued target functions, in which the learned function is represented by a decision tree. Decision tree learning is one of the most widely used and practical methods for inductive inference [10].

Decision tree has various advantages such as: able to handle both categorical and numerical data; performs well with large datasets [11]. However, it has some limitations like: problem in an optimal decision tree, don't generalize well with over-complex trees [11]. There are many specific decision-tree algorithms as ID3, C4.5, CART and CHAID. But, in this study, we use ROC to define threshold with the desire to improve the quality of the decision tree algorithm. Because of ROC analysis is increasingly being recognized as an important tool for evaluation and comparison of classifiers when the operating characteristics (i.e. class distribution and cost parameters) are not known at training time [14].

2.2.2. Algorithm flow chart - Feature characteristics

In order to classify cow's activities, we used two different components of the raw acceleration data: a static and a dynamic component. The static component of the acceleration is caused by the orientation of the sensor relative to the gravity field of the earth and can be calculated as a running mean, to determine the body posture [2]. The dynamic component of the acceleration is caused directly by the movement of the animal [13]. Overall dynamic body acceleration (ODBA) and its vectorial variation (VeDBA) represent an aggregated acceleration measure for the subject [13]. Therefore, the dynamic body acceleration is a good candidate to discriminate between behaviors with high dynamic movement (such as feeding) from behaviors with low dynamic movement (such as standing or lying) [2]. After that, the resulting static acceleration is subtracted from the corresponding raw accelerometer data.

$$DBA_i = A_{it} = |A_{it}^* - \mu_{it}^*| \quad (1)$$

Then, we obtained values which presented as follows:

$$ODBA = A_x + A_y + A_z \quad (2)$$

and

$$VeDBA = VeDBA = \sqrt{A_x^2 + A_y^2 + A_z^2} \quad (3)$$

The component in the Y- axis of the gravitation acceleration varies according to

$$SCAY : \overrightarrow{g_y} = g * \cos(180 - \beta) \quad (4)$$

where β is the angle in degrees of the sensor relative to the horizontal. To classify data, there are two thresholds that used in the decision tree algorithm are calculated as the mean of the static component of the accelerometer in Y-axis (SCAY) and the mean of VeDBA, respectively. Both means are taking over the duration of the window selected [2].

To recognize the cow behaviors, cow behavioral activities were recorded by observers performing a visual focal tracking on each individual cow that was wearing a sensor collar according to the following criteria for each behavioral activity:

+ Feeding: cows located in the feeding zone, ingesting food. It will lightly shake and bow its head.

+ Lying: cows located in a cage in a lying down position.

+ Standing: cows standing on their four legs.

+ Estrus: cows usually increase restlessness as well as activity; try to mount other cows; walking to and fro.

+ Lameness: reduce significant activity, too much lying, eat less.

- Algorithm flow chart

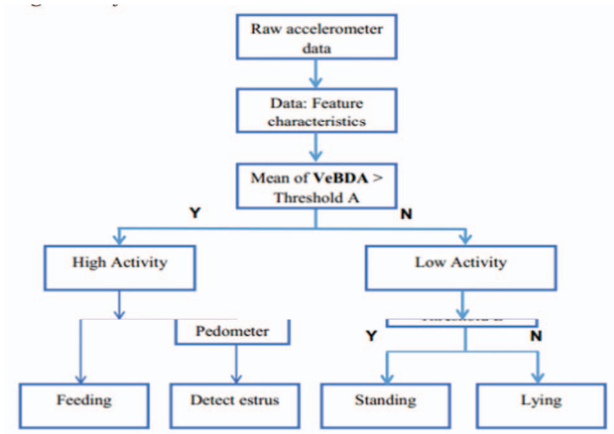


Fig. 7. Algorithm Flow Chart

2.2.4. Moving average filter

The moving average is the most common filter in DSP, because it is the easiest digital filter to understand and use. Besides, it is also a simple Low Pass FIR filter commonly used for smoothing an array of sampled data or signal. Basically, the operation principle of moving average filter like as a low-pass filter that passes signals with a frequency lower than a certain cutoff frequency and attenuates signals with frequencies higher than the cutoff frequency. The window size is optimized for a common task: reducing random and unwanted noise while retaining a sharp step response.

M is the filter length known as the moving window size. As M slides the smoothness of the output increases, whereas the sharp transitions in the data are made increasingly blunt. This implies that this filter has excellent time domain response, but a poor frequency response.

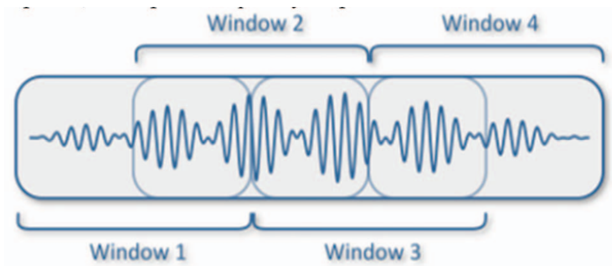


Fig. 8. Sliding window on the data set

2.2.5. Pedometer - Understanding the model

A pedometer is a device that counts step by detecting the motion. The technology for a pedometer includes a mechanical sensor and software to count steps. Today, advanced pedometers rely on micro-electro mechanical system (MEMS) inertial sensors and sophisticated software to detect true steps with high probability.

We also use the Arduino Uno microcontroller board to read the data of ADXL345 3-axis accelerometer in a full-featured pedometer that can recognize and count steps, as well as determine distance and speed. The design principle of pedometers involves using vertical vibration induced by walking to activate the balancing mechanism of the pedometer. Leg motion is the most apparent source of vibration. Some reports pointed out that the numerical curve of the acceleration G value oscillates substantially during walking or running. Thus, the number of vertical motions of the body can be determined by identifying the local peak and valley points of the curve. Different dynamic thresholds can be adjusted according to the users to detect the number of steps.

- Algorithm

A step is defined as happening if there is a negative slope of the acceleration plot (sample new < sample old) when the acceleration curve crosses below the dynamic threshold. Peak Detection: [12] The step counter calculates the steps from the x-axis, y-axis, or z-axis, depending on which axis's acceleration change is the largest one. If the changes in acceleration are too small, the step counter will discard them. The step counter can work well by using this algorithm, but sometimes it seems too sensitive. When the pedometer vibrates very rapidly or very slowly from a cause other than walking or running, the step counter will also take it as a step. Such invalid vibrations must be discarded in order to find the true rhythmic steps. Time window and count regulation are used to solve this problem [8].

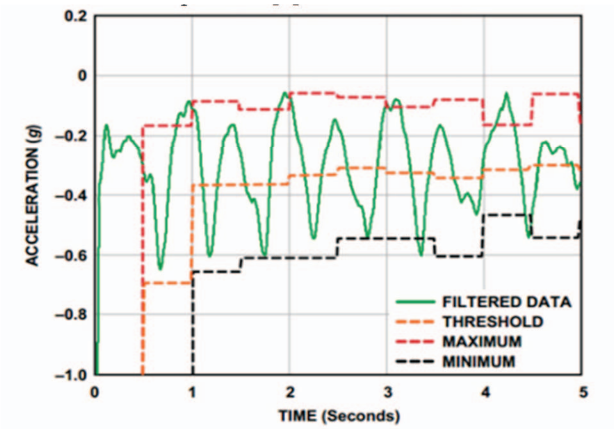


Fig. 9. Filtered data of the most active axis

III. RESULTS AND DISCUSSIONS

3.1. Sensor position and orientation.

In this section, we will discuss the result from two data sets: the data which were published in the work [2] and the data from the experiments with model of cow. The result of behavior classification, were determined by comparing the percent agreement between manual observation and the proposed classification method during the entire experiment. The system can distinguish the three main behavior patterns: lying, standing and feeding.

Fig. 10. Sensor position and orientation.

3.2. Data from tri-axial accelerometer

When the cow is lying or standing, the both behaviors show little overall movement, therefor the acceleration is changed little. While the cow is feeding, it moves head up and down so we can observe the change of acceleration. There are also differences in the component of y-axis between lying and standing. Fig. 11 shows that different [2].

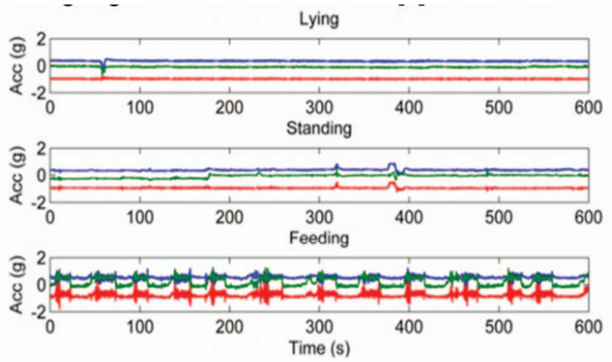


Fig. 11. Raw tri-axial accelerometer for lying, standing, feeding

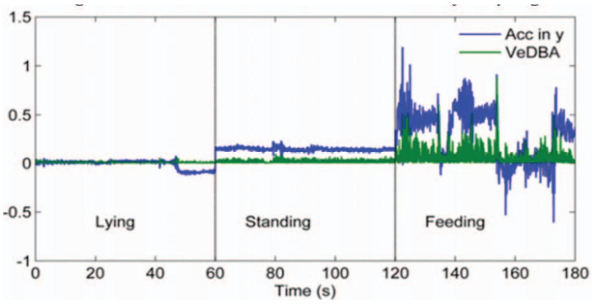


Fig. 12. The running mean of the acceleration in the y-axis (SCAY) and vector dynamic body acceleration (VeDBA) value under the three behaviors.

3.3. Performance of the system

There are many metrics that can be used to measure the performance of classification or predictor; different fields have differences for specific metrics due to different goals [9]. In this paper we consider two performance metrics: sensitivity of classification and precision of classification. Sensitivity and precision are known in statics as classification function:

Sensitivity: $$\mathbf{Sen}=\frac{TP}{TP+FN} \quad (5)$$

Precision: $\quad \textbf{Pre}=\frac{TP}{TP+FP} \quad (6)$

- TP (true positive): the number of instances where the behavioral state of interest that was correctly classified by the algorithm after validation by the visual observer.
- FN (false negative): the number of instances where the behavioral state of interest was visually observed in reality, but was incorrectly classified as some other behavior by the algorithm.
- FP (false positive): the number of times the behavioral state of interest was (incorrecty) classified by the algorithm but not observed in reality.
- TN (true negative): number of instances where the behavioral state of interest was (correctly) classified as not being observed.

3.4 Define the thresholds

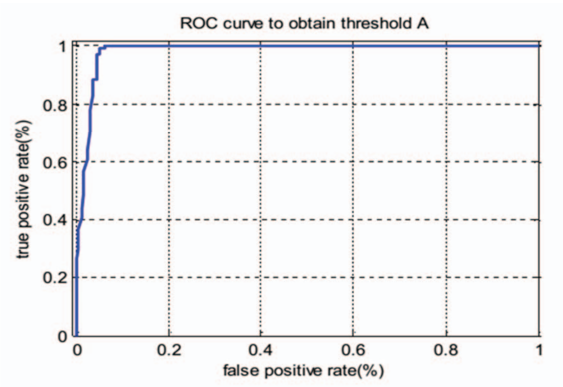
The algorithm contains two thresholds (A and B). Thresholds A were used to discriminate between high activities (feeding) and low activities (lying and standing) through the VeDBA time series. Threshold B was used to discriminate between lying and standing through the SCAY time series. The performance of the system can be affected by the choice of these thresholds. We used two approaches to choice these thresholds.

Approach 1: Using ROC curve to show the true positive rate TPR (known as sensitivity) against the false positive rate and FPR (known as the false alarm rate) when varying the threshold.

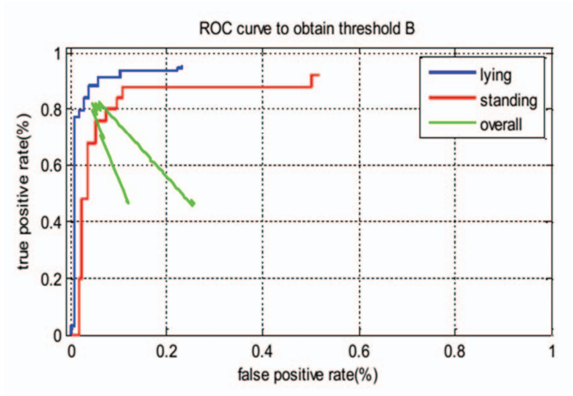
$$TPR = \frac{TP}{TP + FN} \quad (7)$$

$$FPR = \frac{FP}{FP + TN} \quad (8)$$

In this curve, the optimal threshold value is the one that generates the pair of TPR and FPR values closest to the top left corner which represents the value that separates perfectly the positives from the negatives.



(a)



(b)

Fig. 13. ROC curves used to obtain the best threshold values

Fig. 13(a), ROC curve is made by varying threshold A in a range between -0.1 and 0.9g. The optimal threshold was selected by taking the closest point to the top corner, with a value of 0.041g. Fig. 13(b), ROC curve is made by varying threshold B in a range between -0.9 and 0.9g. The overall TPR and overall FPR are defined as mean of their respective rates for lying and standing. The optimal threshold was selected by taking the closest point to the left top corner, with a value of -0.055g.

Approach 2: Selecting both thresholds at the same time by running a comparison of the performance of the algorithm over a 2-dimensional range (threshold A and B). The range of variation was 001 to 0.08g for threshold A and -0.3 to 0.3 for threshold B. Contours illustrate regions with the same sensitivity as the Fig. 14.

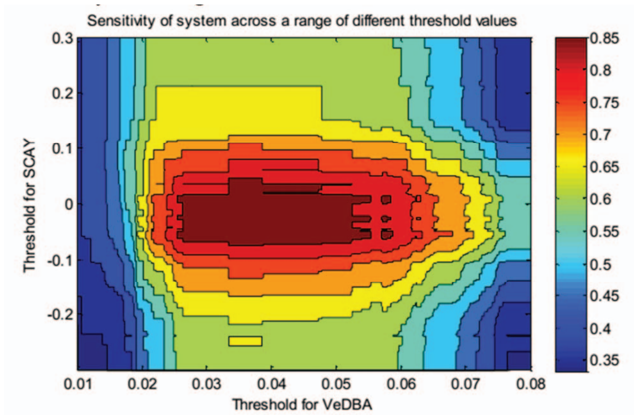


Fig. 14. Sensitivity of the decision-tree algorithm across a range of different threshold values.

Fig. 14 shows that the highest overall sensitivity (~85%) occurs when threshold A is in the range 0.03 to 0.05g and threshold B is in the range -0.08 to 0.1g. The threshold values obtained by using the first approach (0.041g for threshold A and -0.055 for threshold B) are contained in the regions with the highest overall sensitivity obtained by using the second approach. Hence, we used these values for the thresholds in the decision-tree algorithm.

The sensitivity and the precision of the algorithm were obtained in the Table I. Overall sensitivity/precision is calculated as the arithmetic mean sensitivity/precision for the three behaviors.

TABLE I. PERFORMANCE OF THE PROPOSED SYSTEM

	Sensitivity (%)	Precision (%)
Lying	77.42	98.63
Standing	88.00	55.00
Feeding	98.78	93.10
Overall	88.06	82.24

IV. CONCLUSIONS

Our work has shown that accelerometers can be used to recognize some important behavior pattern in cows as: lying, standing and feeding. Simple decision-tree classification algorithm was useful in classification of measured behavior pattern. However, the result of practical experiments is not satisfied due to some reasons. Our cows were not trained to wear the neck-mounted device, although it is not heavy. It need time to get used to wearing something without uncomfortable. With this simple system, it would be feasible to determine the frequency of each behavior. Hence it can automatically detect the health problem in cows even in other similar cattle. It has a good application value. In the future work, we will consider how to enhance the classification performance by combining the decision tree algorithm with SVM algorithm. More behavior will be classified by this. Furthermore, the pedometer is also used to detect cycle of estrus in cow through gathering steps. It becomes easier to prevent cow disease, accurately determine the cow estrus to promote the quality of milk, increase farmers' income.

IV. CONCLUSIONS

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