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Cow Behavior Monitoring Using a Multidimensional Acceleration Sensor and Multiclass SVM

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Abstract

The daily behavior of dairy cows reflects the health status and well being. An automated monitoring system is needed for suitable management. It helps farmers to have a comprehensive view of the cattle healthy and manage large of cows. Acceleration sensors can be found in various kinds of applications. In this paper, we detect the cow's activities by using a multidimensional acceleration sensor and multiclass support vector machine (SVM). The acceleration sensor is attached to the cow's neck-collar in order to sense the movements in X, Y, and Z axes. The data is brought to a microprocessor for pre-processing, and join in a wireless sensor network (WSN) through a Zigbee module. After that, the data are transferred to the server. At the server, a suitable SVM algorithm is chosen and applied to classify four main behaviors: standing, lying, feeding and walking. A well know kernels, Radius Basic Function (RBF), is chosen. After that, a cross validation (k-fold) is used to measure the error and select the best fit model. The sensor is used to acquire experimental data from Vietnam Yellow cows in the cattle farm. The promising results with the average sensitivity of 87.51% and the average precision of 90.24% confirm the reliability of our solution. The classification results can be automatically uploaded to the cloud internet and the farmer can easily access to check the status of his cows.

Keywords

Classification,

SVM,

Monitoring,

Cow,

Acceleration,

Sensor,

3-DoF

1. Introduction

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Viet Nam is the Agriculture country and has a tropical monsoon climate so the cattle industry is very developed especially is cow farming. The cattle industry in our country has a great potential for development as the demand for meat and milk of people is increasing, natural conditions, customs, habits have advantages for development cow farming. Cattle are raised in all regions of our country. Cattle raise for meat and traction in our country have developed for a long time. Dairy farming has appeared in the 20th century, but by the beginning of the 21st century, it has become an important economic sector [2]. At present, the trend of using beef and cow products is increasing in our country so it motivates cow farming. In the limit of economic integration, large companies have continuously expanded their activities in beef and milk dairy farming, such as: TH True Milk, Vinamilk etc. Beside of the extend scale breed, they opposite with some difficulties as climate, economic etc. To develop the cattle industry, become a major livestock industry, we should apply the modern technique, some of the difficulties have been solved and the management of cattle gets much easier and easier [3]. In addition, they save the labor and the price of the product is also reduced. Some companies apply the technique to manage the cattle, for example they set up the camera on the farm to observe a herd of cattle through display. But it has some disadvantage as they only view in daytime in the night if they turn on light they do not observe the cattle.

An automated monitoring system is needed for suitable management [1]. There are many different types of sensors and methods which are used to classify the animal behavior. In [14], the authors applied a K-means classifier to classify the data of location of cows. Linear classification methods and decision tree were applied for the sheep behavior by using the pitch and roll tilt sensor data [15]. Fuzzy logic and neural network classifiers are also applied to classify the behavior of sheep [16]. This paper constructs an automatic system for classification behavior of animals typically on the cow. We developed the system based on the touch 3-axis accelerometer and 3-axis angle sensor (MPU-6050 sensor) help determine status more accurately. This system is designed to set on the collar of the cow and the data received from the sensor will process and classify behavior by using multi-support vector machine as: standing, feeding, lying, and walking. The work found that support vector machine classifiers can be classified with the highest classification success rate [17].

In the next section, we describe the working principles of the proposed system in section 2. In section 3, 4 we focus to cow's behavior classification and the data acquisition. Our experimental results are presented in section 5. Finally, the conclusion is given in section 6.

2. Working Principles

The system includes three main components: IMU6050 sensor [4], PIC18F45K20 [5], and Zigbee module (see Figure 1). Due to the strong growth of MEMS (Microelectromechanical systems) technology, the MEMS based sensors can be found in various kinds of applications [11] [13]. IMU6050 sensor is attached to the cow's neck-collar in order to sense the movements in X, Y, and Z axes. The sensor can be also attached to the cow's leg in some previous works. It can be seen that both positions are sensitive to the cow's movements. The working range of the acceleration sensor can be chosen among ± 2, 4, 8, or 16 g (1g =9.8 m/s2). In this paper, we choose the range of ± 4 g which is suitable for cows' movements. The acceleration in each axis is computed as

$$A_i = \frac{raw\_data_i}{scaling\_factor} \tag{1}$$

where i= X, Y, Z; and the scaling factor is 8192 LSB/g.

The data is brought to a microprocessor for pre-processing. In this work, we use the microcontroller (MCU) PIC 18F45K20 from Microchip INC [6] [7]. It is a strong processing unit to build any electronics projects. It is small, thin and high performance RISC CPU. It incorporates a range of features that can significantly reduce power consumption during operation as: alternate run modes, multiple idle modes, on-the-fly mode switching, and low consumption in key modules. Furthermore, it has the self-programmability as it can write to their own program memory spaces under internal software control, an Analog-to-Digital Converter (ADC) module with 10-bit resolution and 13 external channels.

After that, the electronic board joins in a wireless sensor network (WSN) through a Zigbee module. We use Zigbee module DRF1605 which is simple and stable for using, and it offers a large distance for transmitting and receiving data. This module can be also configured as a coordinator or a router. Other characteristics of this module can be listed: operation voltage of DC 3.7V; the data rate of 9600bps, 19200bps, 38400bps; the working frequency of 2.4GHz, and the transmission distance of 400m. Consequently, the data are transferred to the server. At the server, a suitable SVM algorithm is chosen and applied to classify four main behaviors: standing, lying, feeding and walking. The sensor measure movement of a neck's cow in X, Y, Z axes, the MCU will receive the data, then process and send it to the server through a Zigbee module. The power source for these components is from a 3.7V-4000mAh rechargeable battery. The lifetime of the device is about one week. The photo of a real device is shown in Figure 2.

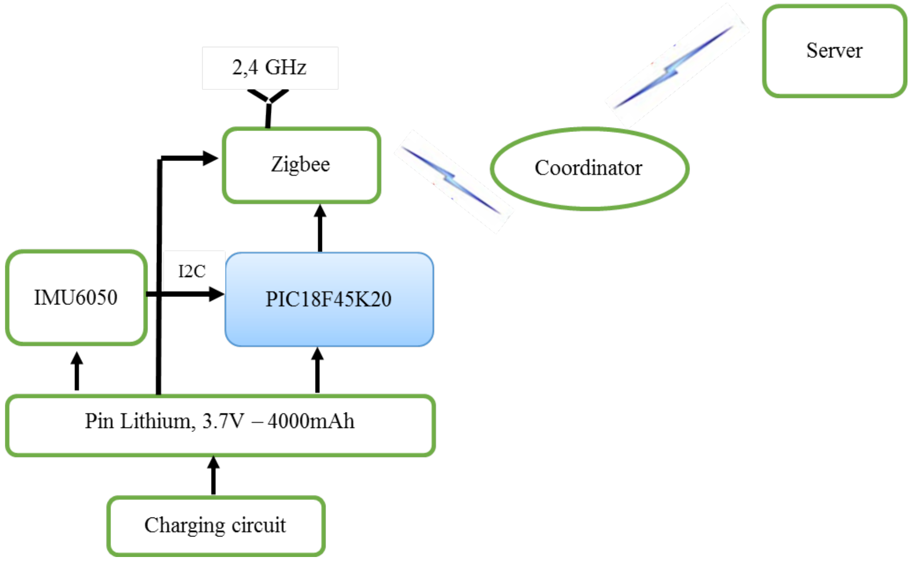

Figure 1. Block diagram of our proposed system

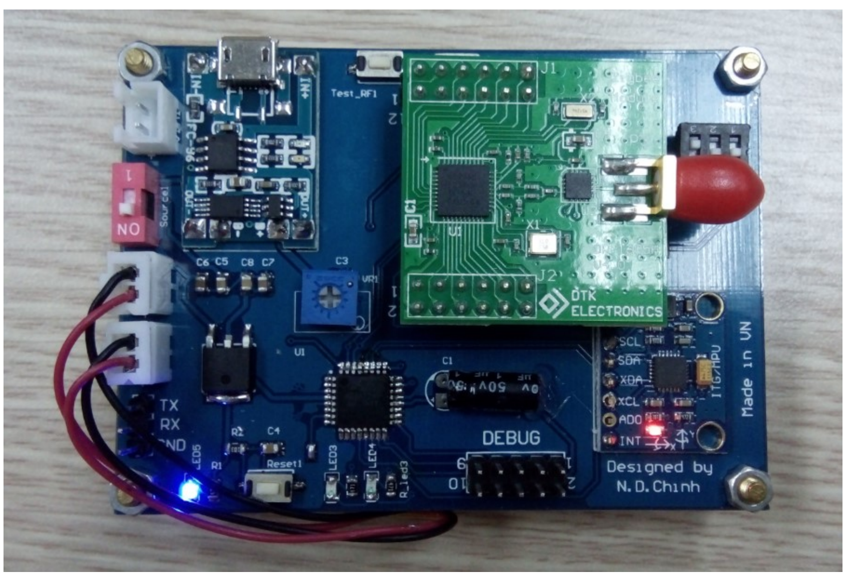

Figure 2. The photo of real device

3. Cow's Behavious Classification

The classification problem divides a data object to give classes owning to the model which is constructed based on a training set [9],[19]. The process of data classification includes two steps: 1) construct the model and 2) use the model for classifying the data.

Step1: The model will be constructed based on the analysis of pre_label data objects which include standing, lying, feeding, and walking. This data set has also known as the training data set. We define the class labels of training data sets, thus, this method has also known as supervised learning.

Step2: Classify new or unclassified objects and evaluate the accuracy of the model.

The classification can be made by a simple algorithm with a low computation: decision tree. However, it cannot offer good performance compared to other methods. In this work, the multi-class support vector machines (SVM) are used for data classification. The reason is that we have four different kinds of behavior need to classify: standing, lying, feeding and walking. There are four typical types of support vector machines that support the multi-class problems [10]: 1) One-against-all support vector machines; 2) Pair wise support vector machines, 3) Error-correcting output code (ECOC) support vector machines; and 4) All-at-once support vector machines. In this paper, we choose one-against-all support vector machine for the classification. To solve this problem they convert *n*-class into *n(n-1)/2* two-class problems each of them trains data from two classes. For the training data from the ith and jth classed, we solve the following two-class classification problem. We consider data points of the form: $x=\{x_i, i=1,\ldots,N\}$ R^m and x_i belong to one in four classes. If these data are linearly separable, we can determine the decision function:

$$D(x)=w^T x^i + b, \tag{2}$$

where w is an m-dimensional vector and b is a bias term.

$$\min_{w_{ij}, b_{ij}, \xi_{ij}} \quad \frac{1}{2}(w_{ij})^T w_{ij} + C\sum_t \xi_{ij} \qquad \xi_{ij}^t \geq 0 \tag{3}$$

where ξ_i slack variable and C is is the margin parameter that determines the trade-off between the maximization of the margin and the minimization of the classification error.

$$\begin{aligned} &(w_{ij})^T \phi(x_t) + b_{ij} \geq 1 - \xi_{ij}^t && \text{if } x_t \text{ in the i}^{\text{th}} \text{ class} \\ &(w_{ij})^T \phi(x_t) + b_{ij} \leq -1 - \xi_{ij}^t && \text{if } x_t \text{ in the j}^{\text{th}} \text{ class} \end{aligned} \tag{4}$$

where $\phi(x)$ is the function which is used for mapping input vector x from m-dimensional to l-dimensional feature space. We classify x into the class: arg $\max_{t=1,\ldots,n} D_t(x)$ with $D_t(x) = (w_{ij})^T \phi(x_t) + b_{ij}$. After constructing *n(n-1)/2* classifiers, we used a voting strategy: each binary classification is considered to be a voting where votes can be cast for all data point *x*, finally a point is designated to be in a class with the maximum number of votes.

SVM used training data to build a model which is later used to classify the test data. The most important is that we can choose a suitable kernel and its parameters for the model. There are four common kernels, and we select Radius Basic Function (RBF). Cross validation is used to measure the generalization error and selecting the best fit one. There are also four types of cross-validation: k-fold, leave one out, boot trap and hold out. In this study, we use the k-fold to validation and choose the model selection. For k-fold cross-validation, we divide the data initial into k subset have approximately $S_1, S_2,\ldots S_k$ [10]. The learning process and the test are run k times. At the i^{th} time, S_i is the test data set, the remaining are the training data set. The meaning is S_1 is test data and $S_2\ldots, S_k$ are the training data; continue with $S_2, S_3\ldots$. are the test data. From this we find the best cross-validation accuracy and the pairs (C, γ) for the final model. In this method growing sequence of C and γ is a practical method to identify good parameters. Consequently, we use the C and γ to train my data. LIBSVM provides a simple tool to check a grid of parameter [8][12].

4. Data Acquisition

Acceleration data in X, Y, and Z axes were recorded by using MPU-6050 sensors in the period of time with from Viet Nam Yellow. Figure 3 shows acceleration samples in four activities of cows. The sampling frequency is 50 Hz. It is brought to an average filter in order to smooth the acceleration signals. Some abnormal samples are removed by setting a threshold. After collecting the data, we pre-process the noise and abnormal samples. Then, we stick the label for each status using recorded videos (see Figure 4). When observe the cow we can see that if the cow is lying or standing it less movement so the acceleration is less change and when it is feeding the collar move up and down so the acceleration change significantly. When they are walking the acceleration also changes dramatically because their neck also move as turns left or right. But in lying status, three axis accelerometer change quite strongly. We can see that in figure about lying above, it is quite similar to standing status. Why so? When we observed and received about lying status, we realized that when cow were lying their knelt down and the head was still up. So the head shaking and it affects to the sensor value. There are four main statuses of cows that we concern:

Standing: the cow stands without swinging its head.

Lying: the cow lies without chewing.

Feeding: the cow moves head up and down and chew grass.

Walking: the cow walks straight and the head shaking.

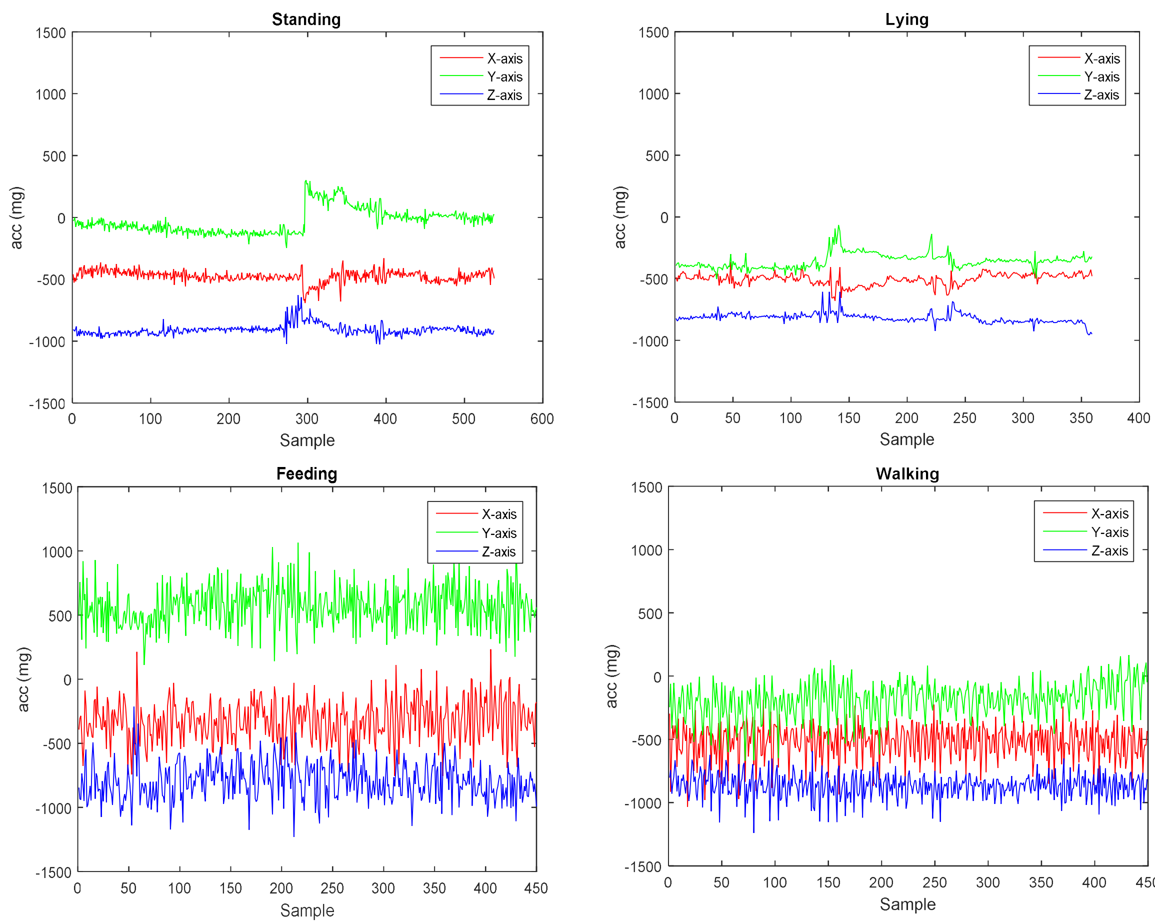

Figure 3. Acceleration samples in four activities of cows

Figure 4. Recording for building the labelled data objects. The videos are synchronized with the acceleration data in order stick labels to the acquired data.

5. Experimental Results

The acceleration values in X, Y, and Z axes are used for the inputs of SVM classifier. After recording the data and sticking the label (using video surveillance) we divide into two datasets: 50% as the training set, and 50% as a test set. The rule of selecting is random. Firstly, in the training data set we conducted the model. By using grid-search with the cross validation method (in LIBSVM) to compute the best CV accuracy with training data set and it equal 93.83% and then shows the optimization of C and γ (in this work C=8 and $\gamma = 2^{-15}$). We use these values of C and γ to train the whole the training data set to create the optimal classifier. Finally, we used it for classification the data set to evaluate the SVM model. Because it is a multi-class problem, we need a confusion matrix where the elements at the main diagonal show correct classifications and all other elements show incorrect classifications. Using this matrix, we can directly see which class is confused with which other class. For example, we have a confusion matrix for standing behavior as shown in Table 1.

Table 1: Confusion matrix for standing behavior

		Observed behavior	
		Standing	Non-standing (Lying/Feeding/Walking)
Predicted behavior pattern	Standing	TP (True positive)	FP (False positive,)
	Non-standing (Lying/Feeding/Walking)	FN (False Negatives)	TN (True Negatives)

We can calculate the sensitivity and precision of the classification using the following formulas:

$$\text{Sensitivity} \quad Sen = \frac{TP}{TP + FN} \tag{5}$$

$$\text{Precision:} \quad Pre = \frac{TP}{TP + FP} \tag{6}$$

Result of confusion matrix is shown in Table 2. We can see the occurred misclassification of each behavior as behavior within each column. Standing and feeding were classified with high accuracy. However, there are some misclassifications, for example the lying status was misclassified as standing status

(27%); walking was misclassified (20%) as standing.; standing was misclassified as walking (8.5%); the remaining was negligible.

Table 2: Results of confusion matrix

		Observed behavior				Total
		Standing	**Lying**	**Feeding**	**Walking**	
Predicted behavior pattern	Standing	**297**	0	0	20	317
	Lying	0	**137**	0	37	174
	Feeding	10	0	**341**	4	355
	Walking	52	2	2	**248**	304

The boldface text is the number of correctly classified samples for each behavior. We compare the reality observation and the classification to evaluate the performance. The classification performance is shown in Table 3. Average sensitivity and precision is computed from four behaviors' ones. Sensitivity of lying is not good as compared to the others. One of the reasons is that the number of observed events in lying is smallest among these behaviors. The highest sensitivity is 96.06% and the highest precision is 99.42% at feeding. It can be seen that, in the classification using SVM, one behavior categories may be confused with one or two other behaviors (e.g. lying and walking). The performance was good for feeding and lying, but the lower precisions are found in standing and walking. It means that these behavior patterns are easily confused with the others. On the other hand, the sensitivities were generally high. It means that not many negative cases were falsely classified as positive. With the similarities between certain behaviors bring to misclassification so we need to collect more data to improve the accuracy and sensitivity.

Table 3: Performance of classification using LIBSVM

Status	Sensitivity (%)	Precision (%)
Standing	93.69	82.73
Lying	78.74	98.56
Feeding	96.06	99.42
Walking	81.57	80.25
Average	87.51	90.24

6. Conclusions

This paper was successful to conduct the system by acquiring the three-dimensional accelerations from the neck's cows, pre-processing and classification of four behaviors using SVM. Four main behaviors of the cows: standing, lying, feeding and walking are detected successfully. Acceleration sensor is used to acquire experimental data from Vietnam Yellow cows in the cattle farm. The experiment results offer the average sensitivity of 87.51%, and the average precision of 90.24%, which can confirm the reliability of our system. The classification results can be automatically uploaded to the cloud internet and the farmer can easily access to check the status of his cows. In the future work, more data will be collected to provide more accurate analysis of each status. The pedometer will be attached to the leg's cow to detect precisely the cycle of estrus in cow by counting the number of steps per day. We will combine two devices to classify more behaviors and obtain the best classification results. It becomes easier to prevent cows from disease, and then improve the quality of milk and beef.

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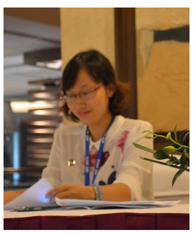

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