Performance Evaluation of a Multi-stage Classification for Cow Behavior

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***Abstract*— Decision tree (DT) algorithm is a simple and effective method for classification of cow behavior. In order to evaluate the performance of this classifier, Receiver-Operating Characteristic (ROC) curve is used. However, this classification often consists of multiple stages of simpler classifiers with multi-level decision thresholds. This paper proposes to use a parallel of multiple thresholds in order to maximize one of statistical measures of performance (i.e. sensitivity, specificity, and precision), after the evaluation of the performance of the multi-stage system using a series of ROC and thresholds is done. The proposed method is then applied to the existing experimental data provided in literature in order to highlight its advantages.**

Keywords—cow behavior, multi-stage, decision tree, accelerometer)

I. INTRODUCTION

Cow monitoring has become easier thanked to the strong developments of sensor, electronics, and communication techniques. An efficient monitoring system would improve the quality of milk and the productivity. However, for the developing country such as VietNam where dairy cows are mostly raised in small farms [1], low-cost solution of monitoring system in cow farming is an important issue which needs to be concerned.

The parameter which is normally used for the classification of cow behavior is the acceleration. Each cow is attached with a three-dimensional acceleration sensor to the neck, leg, or both of them in order to track movements during its daily activities [2-4], [7], [13], [16], [18]. The procedure of classification can then be executed using different kinds of algorithms and methods such as Decision Tree (DT) [2-4], k-means [5], hidden Markov model [6], Support Vector Machine [7], and Neural Network model [8], [17]. Among the known methods, DT offers a simple solution with good accuracy and it is easy to be embedded in micro-controllers. For the DT algorithms which have been performed in the previous research studies, the performance's indexes are optimized at each stage using the corresponding ROCs. However, the performance's indexes of the whole system are not guaranteed to be maximized by using these thresholds. In this paper, we aim to develop a DT algorithm to achieve the maximization of one of the statiscal measures of performance (sensitivity, specificity, and precision). The proposed DT algorithm uses a parallel of multiple thresholds. With this developed algorithm, the monitoring system can be low cost and effective. The proposed method is then verified by applying it to an existing set of experimental data given in literature [2].

II. METHOD PROPOSAL

A. Data acquisition

The configuration of monitoring system is shown in Fig 1. It has three main parts:

1. Sensor node (worn on the neck of the considering cows): each sensor node includes a three-axis accelerometer, a micro-controller, and a wireless module;

2. A Gateway;

3. A Mobile Device

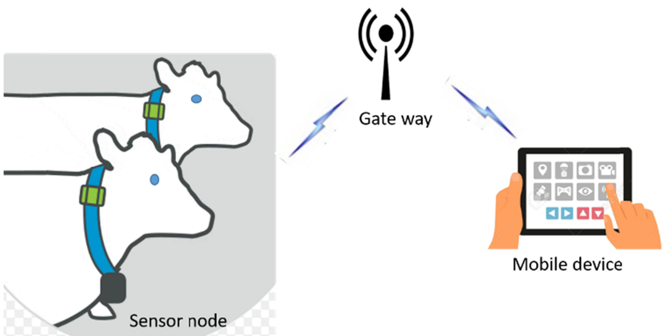


Fig 1. Monitoring System

For each sensor node, three-axis accelerometer tracks the movements, or *accelerations*, of the cow in three directions X, Y, and Z. The acceleration signals are then brought to the Micro Controller Unit (MCU). In order to save the power of each node, the MCU does not send a batch of the raw data directly to the gateway. MCU will pre-process the acceleration signals and classify the cow behavior by using DT algorithm. The most advantage of the use of DT algorithm given in [10,11] in this scenario is the easy implementation in MCU because of its simplicity. Results of the classification are sent to the Gateway and then forwarded directly to the Mobile Device (without cloud/server). After that, a complicated process utilizing HMMs, k-means, Neural Network Model, or SVM will apply to classify the cow behavior. Because the cloud or the server is not used, the cost is reduced. As a result, we can offer a cheaper system.

B. Propsal of Multi-stage Classification Algorithm

Decision Tree is a type of the supervised learning methods which works well with large datasets (i.e. *sequential data from real-time acquisition*). Among many methods, the ROC curve has been chosen to apply to multistage classification system of cow behavior [15]. In this paper, ROC curve is used to investigate the cow behaviour through three biologically important activities: feeding (A), lying (B), and standing (C). These activities are the three important activities which can provide necessary information for the health observation of a cow.

ROC curve is normally used for binary classification. Therefore, at least two stages of classification which correspond to two ROC curves have to be considered. We can select two threshold values *th_A* and *th_BC* for the classification procedure.

Some previous work have applied DT algorithms to classify the cow behavior [2]. However, there are not existing results which analyze the effect of ROC curves of the multi-stages to the system performance. Thus, some fundamental formulas are presented in this paper for that purpose.

Let a_x, a_y and a_z be the acceleration components in X, Y, and Z axes which we acquire after every T seconds; α_x, α_y, and α_z be the static acceleration components. The dynamic body acceleration (*DBA*) is supposed to be given as [13].

Define

$$D_x = a_x - \alpha_x$$
$$D_y = a_y - \alpha_y \tag{1}$$
$$D_z = a_z - \alpha_z$$

The vector of the dynamic body acceleration (*VeDBA*) is then computed [13] by

$$VED = \sqrt{D_x^2 + D_y^2 + D_z^2} \tag{2}$$

To classify three different kinds of behaviors, we need to use two thresholds *th_A* and *th_BC* corresponding to *VeD* and α_y in the DT algorithm [2].

In this paper, we propose a flow chart which is shown in Fig 2 for the evaluation of the system's performance

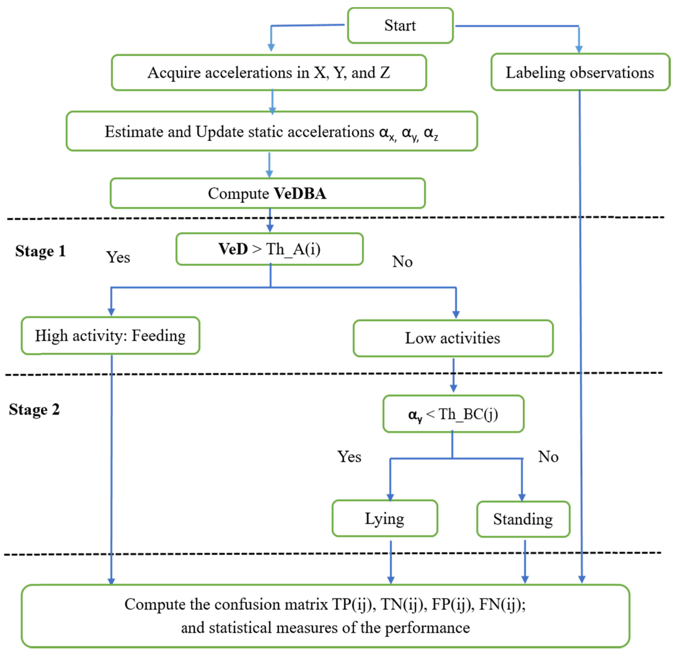


Fig 2. Flowchart for evaluating the system's performance consists of two-stage classification

Remark 1: In Fig 2, TP is True Positive, FN is False Negative, FP is False Positive, and TN is True Negative. The meaning of these parameters have been mentioned in [2].

Both the acceleration and labelling observations are acquired when the procedure starts. By using sampled acceleration signals, we can estimate values of *VeD* and α_y, and forward them to the first stage of the classification. At this stage, the estimated value of *VeD* is compared to *th_A*(i), which is one value of a set *th_A*, $i = 1{:}N$. The outputs of the first stage consist of two states: high and low dynamic activities. Low dynamic activities (if any) will be brought to the second stage. At this stage, the estimated α_y is compared to *th_BC*(j), which is one value of a set *th_BC*, $j = 1{:}M$. The outputs of two stages are combined with the labelling observations to evaluate the confusion matrix, and then, sets of *TPR* and *FPR*, which are the formed ROC curves [15]. For example, the feeding behavior (event A) is evaluated by

$$TPR_A(ij) = \frac{TP_A(ij)}{TP_A(ij) + FN_A(ij)} \tag{3}$$

$$FPR_A(ij) = \frac{FP_A(ij)}{FP_A(ij) + TN_A(ij)} \tag{4}$$

where TP_A is True Positive of event A (feeding state correctly identified as feeding); FP_A is False Positive of event A (lying/standing incorrectly identified as feeding); TN_A is True Negative of event A (lying/standing correctly identified as lying/standing); and FN_A is False Negative of event A (feeding incorrectly identified as lying/standing).

In our work, we concern to estimate three statistical measures of performance [3][9]. For example, the feeding behavior (event A) is evaluated by

Sensitivity: $$Sen_A = \frac{TP_A}{TP_A+FN_A} \quad (5)$$

Precision: $$Pre_A = \frac{TP_A}{TP_A+FP_A} \quad (6)$$

Specificity: $$Spe_A = \frac{TN_A}{TN_A+FP_A} \quad (7)$$

Similar calculation processes are applied to other cow's behaviors (i.e. lying (B) and standing (C)). After executing M×N iterations of the flow chart on the training sets of data, we can obtain the best couple of thresholds *th_A* and *th_BC* corresponding to the expected statistical performances (i.e. the sensitivity, the precision, or the specificity).

In [2], if one of the statistical measures of performance is maximized, the optimization can be only performed in each stage using the following ROC curves

$$Max(Sen_A) = arg \max_{th_{AC} \in R1} \frac{TP_A(th_A)}{TP_A(th_A) + FN_A(th_A)} \quad (8)$$

and

$$Max(Sen_B) = arg \max_{th_{BC} \in R2} \frac{TP_B(th_A, th_{BC})}{TP_B(th_A, th_{BC}) + FN_B(th_A, th_{BC})} \quad (9)$$

In this paper, we propose the following equation

$$Max(Sen_B) = arg \max_{th_{BC} \in R2, th_A \in R1} \frac{TP_B(th_A, th_{BC})}{TP_B(th_A, th_{BC}) + FN_B(th_A, th_{BC})} \quad (10)$$

where all the stages are combined simultaneously.

III. Results and Discussions

In this section, we will verify our proposed scheme by applying it to an existing published dataset provided in [2]. The datasets which are downloaded from [2] consist of three different sets with T = 1, 5, and 10 minutes, respectively. The obtained results will be then compared to the published performance's indexes with the same datasets.

The estimated values of *VeD* and α_y acquired from the dataset of T=1 minute are shown in Fig. 3. Although we only want to classify the three cow's behaviors of feeding (A), lying (B), and standing (C), there is the involvement of drinking behavior (D) in this dataset. This causes the misclassification in the statically measures of performance. Even if the drinking behavior (D) is not considered, some mixture parts of (A), (B) and (C) can not be ignored. Because of this reason, the statistical measures of the performance are degraded.

The following parameters are also shown in Fig 3:

1. Parameter *th_A* is used in classifying the high dynamic activity (i.e. feeding) and the low dynamic activities (i.e. standing and lying). The value of *VED* in the case of feeding is rather higher than the ones in the cases of standing and lying.
2. Parameter *th_BC* is used in classifying the standing and lying behaviors. If *th_BC* is smaller than the value of α_y, the cow is lying. Meanwhile, if *th_BC* is larger than the value of α_y, the cow is standing. Notice that the value of α_y is maximized when the cow's leg is in parallel to the gravity vector. As shown in Fig 3, there are a lot of mixture sections between standing and lying.

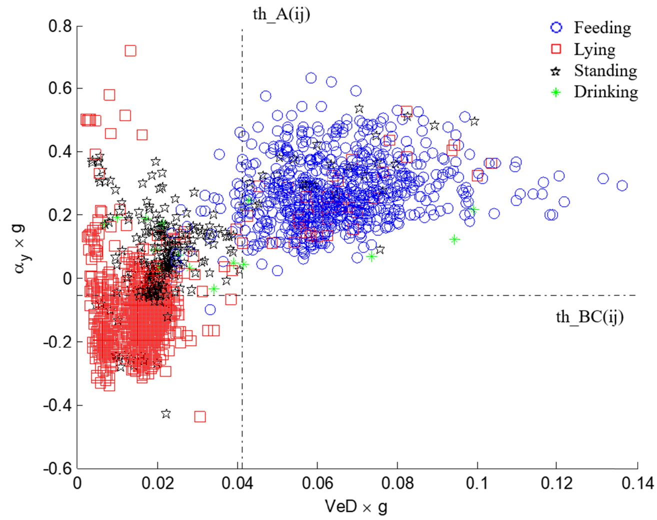
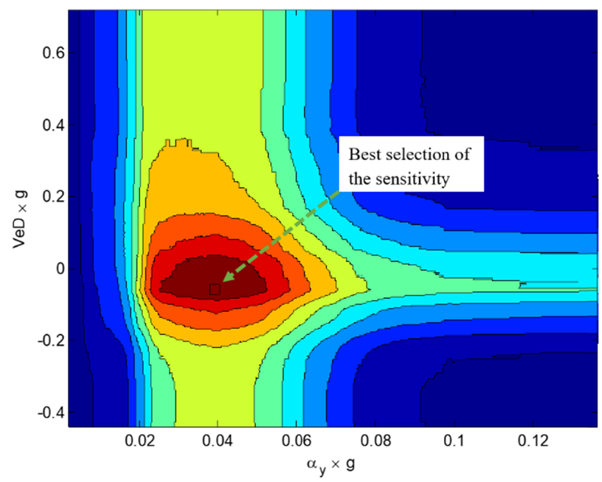
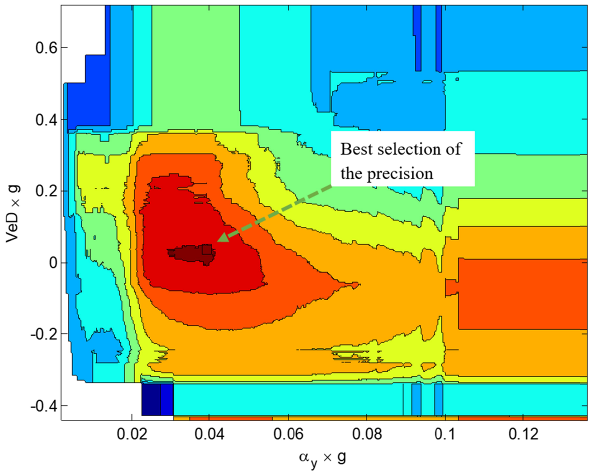


Fig 3. Illustration of *VED* and α_y updated at every one minute.

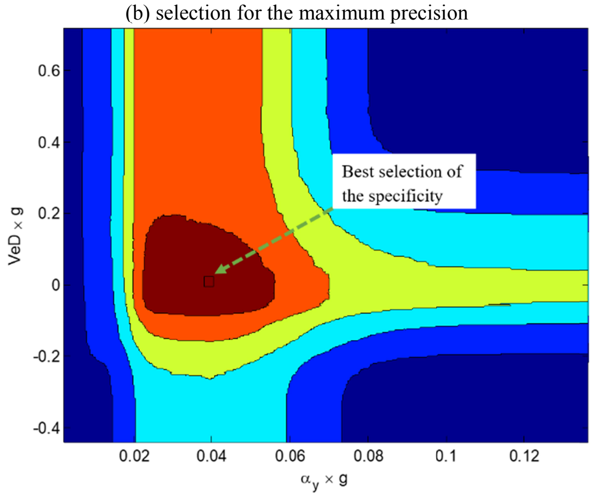
The results of the parallel scanning process are shown in Fig 4 (a)-(c) in order to find out a couple of threshold which can maximize each performance index. The best couple of threshold values of *th_A* and *th_BC* are described in Table 1. It can be recognized that the values of *th_A* are nearly identical among the scenarios while *th_BC* show clear difference in values.



(a) selection for the maximum sensitivity



(b) selection for the maximum precision



(c) selection for the maximum specificity

Fig 4. Illustration of the best couple of thresholds th_A and th_BC corresponding to expected statical performance

TABLE 1. Selections of thresholds for maximizing the statical performance

	th_A (× g)	th_BC (× g)
For maximum sensitivity	0.0392	-0.0583
For maximum precision	0.0392	0.0379
For maximum specificity	0.0393	0.0102

The performance of the proposed monitoring system in this paper is compared to the results in [2]. The comparison of results is summarized in Table 2. It is recognized that the proposed system in this paper has offered better performances. With the proposed scheme shown in (10), we can optimize in each statistical measure of performance. In practice, if the manager focuses on any of these indexes, he just simply applies the corresponding threshold values, which are shown in Table 1, to obtain the best performance. Note that all the diagrams shown in Fig 2 are used for finding the most suitable threshold values which are corresponding to the statistical measures of performance. After we obtain these thresholds, a simple DT algorithm, depicted in Fig 7, will be embedded to each MCU. Results of classification of each cow's behavior is then sent to the Gateway node, and forwarded to the mobile user. The farmer can access to the information anytime and anywhere as long as the internet is available.

TABLE 2. Performance comparisons between our propose system with previous work using the same datasets

		T = 1 minute		**T = 5 minutes**		**T=10 minutes**	
		Prev	**Ours**	**Prev**	**Ours**	**Prev**	**Ours**
Sensitivity (%)	Feeding	95.65	97.28	97.44	99.40	98.78	100
	Lying	74.09	76.40	74.09	78.40	77.42	80.90
	Standing	82.08	91.70	88.46	93.60	88.00	95.45
	Total	83.94	88.46	86.66	90.40	88.06	92.12
Precision (%)	Feeding	92.03	91.20	93.25	91.20	93.10	91.11
	Lying	96.57	89.10	97.95	89.90	98.63	93.41
	Standing	47.01	63.60	47.92	81.80	55.00	80.00
	Total	78.53	81.30	79.71	87.70	82.24	88.17
Specificity (%)	Feeding	×	94.60	×	95.10	×	94.90
	Lying	×	71.47	×	74.00	×	82.60
	Standing	×	87.87	×	92.60	×	91.10
	Total	×	84.60	×	87.20	×	89.50

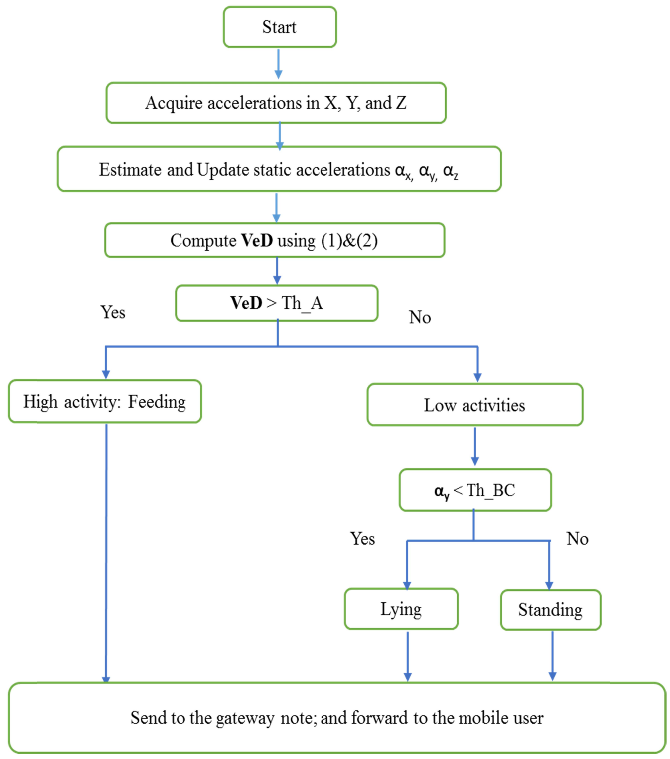


Fig 7. DT algorithm embedded in each MCU

Remark 2: Fig 7 shows the flowchart which we have applied to the proposed monitoring system in this paper.

IV. CONCLUSION

In this paper, we have successfully classified the cow behavior using the proposed DT algorithm. Our work has shown that we can maximize the statistical measures of performance by introducing the parallel scanning technique in order to find out the best thresholds for the series of binary classifications. Obtained results from the proposed method show better performances than the results obtained in the previous work. An advantage of the proposed DT algorithm in this paper is that it can be embedded to MCU. Besides, the classification results can be sent to the gateway and then be forwarded to the mobile device. Because no computing on the cloud or the server is required, we can offer a cheaper solution.

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