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Highly accurate classification of postures and activities by a shoe-based monitor through classification with rejection*

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Abstract— **Monitoring human beings' major daily activities is important for many biomedical studies. Some monitoring applications may require highly reliable identification of certain postures and activities with desired accuracies well above 99% mark. This paper suggests a method for performing highly accurate classification of postures and activities from data collected by a wearable shoe monitor (SmartShoe) through classification with rejection. The classifier used in this study is support vector machines that uses posterior probability based on the distance of an observation to the separating hyperplane to reject unreliable observations. The results show that a significant improvement (from 95.2% ± 3.5% to 99% ± 1%) of the classification accuracy has been reached after the rejection, as compared to the accuracy reported previously. Such an approach will be especially beneficial in application where high accuracy of recognition is desired while not all observations need to be assigned a class label.**

I. Introduction

Monitoring of posture allocations and physical activity is used in many areas of biomedical research [1]. For instance, it has been shown that prostate cancer is directly related to extensive sitting [2]. Obesity may be caused by insufficient physical activity (e.g. walking, standing) and prolonged car driving [3]. Osteoporosis is reported to be related to daily physical activity. Higher physical activity was associated with lower bone loss [4]. Moreover, abnormal patterns of daily activities are symptoms of many diseases. It is reported that the kids with autism have weak muscles and may result fewer daily activities than healthy kids [5]. The same situation exists in the post stoke patients [6] and patients with Amyotrophic Lateral Sclerosis [7]. Thus, monitoring physical daily activities can assist clinical diagnosis of the diseases, and most importantly, can help people to have a healthy life style.

Many methods and devices exist for monitoring of physical activity in research, clinical and consumer applications. However, most of these devices have difficulty in recognition of basic weight-bearing and non-weight bearing activities (such as recognition of sitting vs. standing, walking vs. cycling). Our group has developed a shoe-based activity monitoring system (SmartShoe) that resolves the issues common to other monitors by incorporating pressure and acceleration sensors in footwear. SmartShoe has been applied to the accurate prediction of energy expenditure [8], monitoring of posture allocations and activities in healthy [1], automatic detection of temporal gait parameters in post stroke individuals [6], and prediction of body weight [9].

While the accuracy of recognition of basic postures and activities by SmartShoe has been high and varied between 95% and 98% in various subject populations, some research and clinical applications may require very high reliability of classification, well in excess of 99%. For example, such activity as walking may need to be recognized to provide biofeedback specific to walking. In such an application, quite often it is not necessary to recognize all instances of walking during the day, but those instances that are recognized should be classified with high reliability.

Classification of postures and activities from SmartShoe sensors can be performed by one of the many classifiers available, such as decision trees, k-nearest-neighbors, and regression methods etc. In this study, we used Support Vector Machines (SVM) to classify different postures. SVM is widely used to pattern classification in the data mining field [10], and it was developed from the theory of Structural Risk Minimization (SRM) [11]. However, for some data sets, a good classifier may not provide satisfactory classification results since there are always outliers in the data sets. An approach, called classification with rejection, has been developed to solve the problem [12]. The approach rejects the data points that are closed to the decision boundary. For example, if there are 1000 data points to be classified, we reject 200 data points that are relatively close to the decision boundary. However, we are 99% sure that the remaining 800 data points are classified correctly. Thus, it can improve the accuracy of the classification significantly, especially for big sample size classifications. This technique has a sound theoretical justification [13] and has been successfully used by us in sleep state classification [14]. This paper will focus on highly accurate detection of the postures and activities by using the classification with rejection approach.

II. Methods and Materials

A. Description of the shoe-based monitor system

The shoe-based monitor system contains six sensors total in each shoe as shown in Fig. 1, including five pressure sensors on the insole and one three dimensional accelerometer on the heel of the shoe. The detail description can be found in [1]. A single sample of data from a shoe is represented by vector $S = \{A_{AP}, A_{ML}, A_{SI}, P_H, P_{5M}, P_{3M}, P_{1M}, P_{HX}\}$, where

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A_{AP} is anterior–posterior acceleration, A_{ML} is medial–lateral acceleration, A_{SI} is superior–inferior acceleration, P_H is heel pressure, P_{5M}, P_{3M}, P_{1M} are pressures from fifth, third, and first metatarsal head sensors, respectively, and P_{HX} is pressure from the hallux sensor.

B. Data description

This study utilizes data collected in an experiment preformed at Clarkson University [1]. Nine subjects were recruited to participate in the study (anthropometric characteristics are shown in Table I).

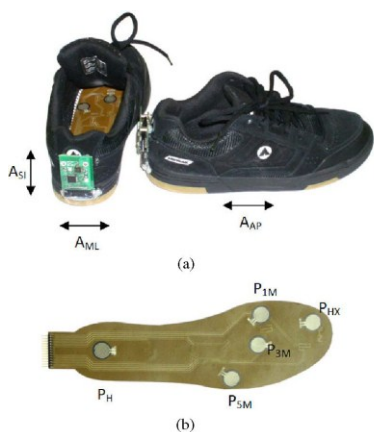

Figure 1. (a) A pair of shoes with wearable sensors, wireless transmitter, and batteries. Arrows show anterior–posterior (A_{AP}), medial–lateral (A_{ML}), and superior–inferior (A_{SI}) axes of the accelerometer equiped. (b) A pressure sensitive insole. P_H is heel pressure sensor, P_{MO}, P_{MM}, and P_{MI} are the fifth, third, and first metatarsal head sensors, respectively, and P_{HX} is the hallux sensor.

TABLE I. THE ANTHROPOMETRIC CHARACTERISTICS OF THE 9 SUBJECTS

Description / Subject	*Gender*	*Weight (kg)*	*Height (inches)*	*BMI[a]*	*Age*	*Shoe size*
1	F	55	64.25	20.7	24	7.5
2	F	55.6	62.25	22.2	18	7
3	M	83	67.75	28.0	31	10.5
4	F	70	61	29.2	26	8.5
5	F	100.9	63	39.4	29	7.5
6	M	84	71	25.8	20	10.5
7	M	59	69.5	18.9	22	9.5
8	F	59.2	70	18.7	20	9
9	F	67.6	66	24.1	23	8.5

a. Body Mass Index (BMI)

All the subjects were required to perform a variety of activities while wearing SmartShoe on both feet. All subjects were healthy and informed written consent was obtained from each participant. The research protocol was approved by the Institutional Review Board (IRB) at Clarkson University, Potsdam, NY where the study was conducted.

TABLE II. SAMPLE SIZE FOR THE SIX POSTURES IN THE STUDY

	Sit	*Stand*	*Walk/ Jog*	*Ascend stairs*	*Descend stairs*	*Cycle*
N.o. of epochs	3218	3207	10721	550	506	2688

C. Signal processing

Minimal signal preprocessing was applied to the sensor data collected, including feature vector forming and normalization. No statistical features were calculated from sensor signals and no cleaning or artifact rejection was applied. Feature vectors were constructed to represent a time period (epoch) of two seconds in duration. Table II shows counts of all the epochs recorded for six classes of postures and activities, including sitting, standing, walking at different speeds and jogging, ascending stairs, descending stairs and cycling. The time series of data from both shoes were combined as $f_i = \{S_L, S_R\}_i$, $i = \{1, \ldots, M\}$, where S_L, S_R were the data samples from the left and right shoe, respectively, and M was the length of time series. The sampling frequency was 25 Hz.

Since different sensors may generate signals in different scales, a normalization procedure was performed to the raw data as following,

$$x_{ij} = \frac{X_{ij} - min(\boldsymbol{F})}{max(\boldsymbol{F}) - min(\boldsymbol{F})},$$

where X_{ij} is the element of the raw signal in the *i-th* row and the *j-th* column of the dataset, x_{ij} is the scaled value of X_{ij}. $\boldsymbol{F}$ is the entire matrix of the raw signal. After the normalization, all the elements follow $x_{ij} \in [0,1]$.

D. Classification with rejection and the validation method

After the signal processing, SVM was used to classify the epochs with rejection. The method of classification with rejection is widely used [10, 12] and has been proved to be an effective approach to improve classification accuracy. For the SVM classifier, outputs could be modified to construct a posterior probability from the distance of an observation (in this case an epoch of sensor signals) to the separating hyperplane [15]. The criteria used to decide if a validated epoch was rejected or not in this study was the posterior probability estimates (PPEs) provided by a Matlab package of libSVM [16]. The PPEs are the measurements of how far away the tested epoch is from the decision boundary.

For the classical two-class (binary) formulation of SVM classification, the output of an SVM classifier is in the form

$$y = sign(f(x)),$$

$$f(x) = \sum_{i=1}^{N_{SV}} \alpha_i y_i k(x, x_i) + b,$$

where N_{SV} is the number of support vectors, x_i are the input data points, y_i are the class targets, b is the bias, $k(x, x_i)$ is a kernel function [16], and α_i are the Lagrange multipliers from solving quadratic optimization problem. The output $f(x)$ can be modified to a posterior probability by

$$p(x) = \frac{1}{1+\exp\left(n\times\left(\frac{1-|f(x)|}{\|\omega\|}\right)\right)} = \frac{1}{1+\exp\left(n\times\left(d_{sv}-d_x\right)\right)}$$

where $|f(x)|$ is the absolute value of $f(x)$, n is a scaling factor decided from a validation set, and $\|\omega\|$ is the norm of the weight vector. In terms of distance measures, $(d_{sv}-d_x)$ is the distance between an input epoch and a support vector.

For multi-class classification problem such as the problem at hand libSVM utilizes a one-against-one classification method [17] that trains *k(k-1)/2* binary classifiers (where *k* is the number of classes). During prediction the class with most votes becomes the winner. The posterior probability for the winning class can be obtained by a variety of methods [18]. LibSVM implements an iterative algorithm for performing pairwise coupling and estimating posterior probabilities [18].

The PPEs provided by libSVM package follow $PPEs \in (0,1)$. Posture epochs were rejected if their PPEs are below the desired threshold value *T*. That is, if $PPE_i < T$, the *i-th* epoch was rejected.

The validation method used in this study is 4 fold. All the posture epochs were separated into 4 groups non-intersecting between subjects. Three of the four groups were used to train the SVM model and the other one was used for testing. The procedure was repeated four times until all 4 groups were used for testing.

III. Results

To show the improvement of the posture classification accuracy by the rejection, classification was performed with and without rejection using linear and RBF kernels for comparison.

When different PPEs threshold values are set, different numbers of epochs were rejected. The percentage of the postures epochs left after the rejection with different values of *T* is shown in Fig. 2. According to Fig.2, the higher the threshold value is, the smaller percentage of posture epochs left. With the threshold value of 0.9, the percentage of epochs left is around 80%, which is still a majority of the epochs.

Table III and IV show the confusion matrices without rejection (A) and with rejection (B) when the linear kernel and RBF kernel were used, respectively. The threshold value of the PPEs for the rejection was 0.9. Both specificity and sensitivity have been significantly improved after the rejection for all six postures. The most significant improvement for the linear kernel is the sensitivity of "Ascending stairs"; and for the RBF kernel, the most significant improvement is the specificity of "Descending stairs". Those were increased by 36% and 14%, respectively. The total classification accuracy was increased from 92% to 99% for the linear kernel and 97% to 99% for the RBF kernel.

Moreover, RBF kernel provided a better performance in the classification than the linear kernel. A possible reason was discussed in the work by Keerthi and Lin [19]. In addition, the RBF kernel rejects fewer epochs than the linear kernel according to the confusion matrices shown in Table III and IV, especially in the activities of descending and ascending stairs.

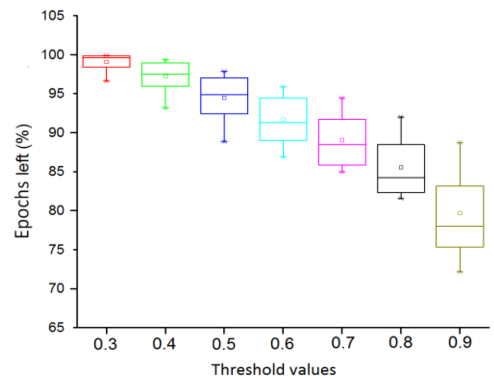

Figure 2. The percentage of epochs left when different probability threshold values are set up. The results are based on the 4 fold validation with linear kernel.

TABLE III. Confusion matrix when linear kernel is used without rejection (A) and with rejection (B), the intersection of the specificity and the sensitivity is the total accuracy.

Predict / Actual	***Sit***	***Stand***	***Walk***	***Ascend stairs***	***Descend stairs***	***Cycle***	***Specificity***
Sit	2937	28	119	43	79	12	0.913
Stand	50	3080	2	41	18	16	0.960
Walk	163	54	10339	52	99	14	0.964
Ascend stairs	109	24	78	237	89	13	0.431
Descend stairs	87	21	63	61	254	20	0.502
Cycle	145	6	75	7	4	2451	0.912
Sensitivity	0.841	0.959	0.968	0.537	0.468	0.970	0.924

Predict / Actual	***Sit***	***Stand***	***Walk***	***Ascend stairs***	***Descend stairs***	***Cycle***	***Specificity***
Sit	2420	2	0	1	0	2	0.998
Stand	1	2893	0	0	0	7	0.997
Walk	4	0	9361	4	29	0	0.996
Ascend stairs	22	2	8	76	14	1	0.618
Descend stairs	11	1	4	3	93	1	0.823
Cycle	9	3	5	0	0	2040	0.992
Sensitivity	0.981	0.997	0.998	0.905	0.684	0.995	0.992

(A)

(B)

TABLE IV. CONFUSION MATRIX WHEN RBF KERNEL IS USED WITHOUT REJECTION (A) AND WITH REJECTION (B), THE INTERSECTION OF THE SPECIFICITY AND THE SENSITIVITY IS THE TOTAL ACCURACY.

Predict / Actual	*Sit*	*Stand*	*Walk*	*Ascend stairs*	*Descend stairs*	*Cycle*	*Specificity*
Sit	3096	3	0	1	0	118	0.962
Stand	44	3131	2	27	3	0	0.973
Walk	2	3	10625	61	30	0	0.991
Ascendstairs	8	6	35	461	37	3	0.838
Descend stairs	0	3	44	88	371	0	0.733
Cycle	115	4	0	0	0	2569	0.956
Sensitivity	0.948	0.994	0.992	0.723	0.841	0.955	0.970

(A)

Predict / Actual	*Sit*	*Stand*	*Walk*	*Ascend stairs*	*Descend stairs*	*Cycle*	*Specificity*
Sit	2533	2	0	0	0	2	0.998
Stand	0	3003	0	0	0	0	1.000
Walk	0	0	9997	42	18	0	0.994
Ascendstairs	0	0	0	304	8	0	0.974
Descend stairs	0	0	3	39	287	0	0.872
Cycle	56	0	0	0	0	2435	0.978
Sensitivity	0.978	0.999	1.000	0.790	0.917	0.999	0.991

(B)

IV. CONCLUSION AND DISCUSSION

Some research and clinical applications may require highly reliable recognition of postures and activities. This paper suggests use of classification with rejection technique based on multi-class classification by Support Vector Machines. The classification performance was compared before and after the rejection, indicating a significant improvement can be achieved by using the classification with rejection.

According to the results of this study, some postures and activities result in lower classification accuracy than others. For example, the average accuracy for "Ascending stairs" is approximately 88% after the rejection. Such accuracy may results from close similarity of this activity to others (such as "Walking/Jogging") or inter-subject variation in performing this activity. A potential strategy to further improve classification accuracy is to incorporate simple individual subject calibration in the future work.

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