34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Classification of Posture and Activities by Using Decision Trees

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Abstract—**Obesity prevention and treatment as well as healthy life style recommendation requires the estimation of everyday physical activity. Monitoring posture allocations and activities with sensor systems is an effective method to achieve the goal. However, at present, most devices available rely on multiple sensors distributed on the body, which might be too obtrusive for everyday use. In this study, data was collected from a wearable shoe sensor system (SmartShoe) and a decision tree algorithm was applied for classification with high computational accuracy. The dataset was collected from 9 individual subjects performing 6 different activities—sitting, standing, walking, cycling, and stairs ascent/descent. Statistical features were calculated and the classification with decision tree classifier was performed, after which, advanced boosting algorithm was applied. The computational accuracy is as high as 98.85% without boosting, and 98.90% after boosting. Additionally, the simple tree structure provides a direct approach to simplify the feature set.**

I. Introduction

The World Health Organization (WHO) predicts that overweight and obesity may soon become the most significant cause of poor health replacing more traditional public health concerns, such as under-nutrition and infectious diseases [1]. Obesity may have a significant effect on health, leading to reduced life expectancy and increased health problems including heart disease, type 2 diabetes, obstructive sleep apnea, osteoarthritis and certain types of cancers [2]. In addition to these health impacts, obesity may cause many social stigmatization problems. Obesity is due to a sustained positive energy balance and is typically coupled with low level of physical activity [4] [5]. In other words, obesity may be caused by excessive food energy intake and lack of physical activity. A sedentary lifestyle plays a significant role in obesity. The amount of work that is not physically demanding is increasing worldwide. Moreover, there appear to be declines in levels of physical activity in walking due to mechanized transportation, and declines in energy expenditure in housework due to laborsaving technology at home. Studies show that there is an association between television viewing time and the risk of obesity [6]. Therefore, an accurate monitoring of physical activity directly helps in the research of obesity. Monitoring of everyday life activities may also provide detailed recommendations to people who are seeking a healthy lifestyle.

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For monitoring physical activities and allocations of human beings, various devices and systems were proposed by different research groups. For example, Bao and Intille [7] mounted accelerometers on the wrist, upper arm, hip, ankle and thigh, with the evaluation of a single best sensor location. They achieved an accuracy of 84% in the activity recognition for 20 different activities. Pirttikangas et al. [8] attached accelerometers to left and right wrists, right thigh and a necklace, with a recognition accuracy of 93% for 17 different activities. However, those devices rely on sensors distributed on the body might be too obtrusive for everyday use. To develop the systems to be more convenient for real-life usage, Zhang et al. [9] proposed a single tri-axial accelerometer placed on the waist and achieved a classification accuracy of 80%. Long et al. [10] proposed a 3D-accelerometer in a smart phone and achieved a recognition accuracy of 82.8%. A wearable non-obtrusive device to reach high classification accuracy in detecting posture activities still remains a desire and challenge.

Various algorithms have been applied in physics activity classification, such as Support Vector Machines [11] [12], Artificial Neural Network (ANN) [13], Hidden Markov Model (HMM) [14], Continuous Activity Recognition (CAR) algorithm [10]. Researchers are still seeking for an optimal solution that combines a computational effective algorithm and an advanced sensor system.

In this study, data was acquired from a wearable shoe sensor system (SmartShoe) developed previously by our group [15]. After statistical feature computation from sensor signals, decision tree algorithm with boosting [17] was used for classification. This approach reached high classification accuracy. The simple tree structure provided a direct approach to simplify the feature set and this can help improving computational efficiency.

II. Methods

A. Wearable shoe sensors and data collection

The sensor system embedded into the shoes contains sensors to collect plantar pressure data and heel acceleration data. For each shoe, there are five force-sensitive registers integrated in a flexible insole, positioned under heel, heads of metatarsal bones, and the hallux. With this configuration, differentiation of the most critical parts of the gait cycle, such as heel strike, stance phase and toe-off can be performed. The motion information is provided by a 3-D accelerometer positioned on the back of each shoe. This wireless sensor system is lightweight, minimally obtrusive and with advanced power saving strategies [15].

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Data collection was performed on nine human subjects, including three males and six females. Based on self-report, subjects were weight stable and healthy nonsmokers. The summary of subjects' characteristics is shown in Table I. In the data collection process, each individual wore the sensor-equipped shoes with size (US) ranged from 9.5-11 for men and from 7-9 for women for a duration of 2.5-3h visit. A total of 11h 36min of data were recorded for six major posture/activity classes. The description of the six major posture/activity classes is shown in Table II.

TABLE I. THE CHARACTERISTICS OF THE NINE RECRUITED HUMAN SUBJECTS

Physical features	Range	Mean	Standard deviation
Age (years)	18-31	27.3	4.3
Body weight (kg)	55.6-100.9	70.5	15.8
Body mass index (kg/m^2)	18.1-39.4	25.2	6.5

TABLE II. DESCRIPTION OF THE SIX POSTURE/ACTIVITIES CLASSES

Activities	Description (Total duration)
Sitting	Including sitting motionless and with fidgeting (1 h 47 min)
Standing	Including standing motionless and with fidgeting (1 h 47 min)
Walking/Jogging	Includes several speeds, slopes, and load conditions (5 h 57 min)
Ascending stairs	(18 min)
Descending stairs	(17 min)
Cycling	Includes two load conditions: 50rpm and 75rpm (1h 30min)

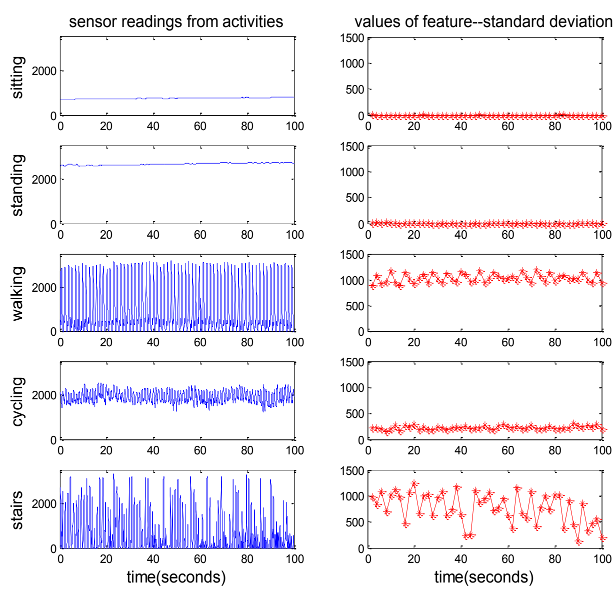

Figure 1. Plots of raw dataset from pressure sensor I and the computed standard deviation from the raw data.

B. Data processing—feature computation

Pressure and acceleration data were sampled at 25 Hz by a 12-bit A/D converter and sent over a wireless communication to the base computer. In two seconds, number of samples N was 50, and data collected followed: 50 samples * (5 pressure sensor readings / sample + 3 accelerometer sensor readings / sample) = 400 sensor readings for each shoe. Feature computation was performed on continuous two seconds data readings. The features are, mean, standard deviation, entropy, variance, maximum value, number of mean crossings (NMC), mean absolute deviation (MAD). Number of mean crossings, is the count of times that the curve composed by the sample values crosses the mean value. Mean absolute deviation, is the mean of the absolute deviations of a set of data about the data's mean [16]. Thus, the feature number is 7, the number of computed features in 2 seconds will be as the followings: 7 features / sensor * 8 sensors = 56 features. Fig. 1 shows raw dataset from pressure sensor I and the computed standard deviation.

C. The classifier—C5.0 decision tree

Decision Tree [17] is a hierarchical model that recursively separates the input space into class regions. The final decision making model is a tree-like structure which composes of decision nodes and leafs. Each node has a test function. Given a node, a test function determines which branch is taken. This process is repeated until one of the leaves is reached.

In decision tree learning, Quinlan [17] invented Iterative Dichotomiser 3 (ID3) algorithm. Entropy and information gain are calculated in the process of generating a decision tree. The algorithm can be summarized as following:

- Take all unused attributes and count their entropy concerning test samples
- Select attribute for which entropy is minimum (This means the information gain is maximum)
- Make node containing that attribute in the tree

ID3 is a decision tree classifier, which can deal with discrete input values. C4.5 [18] is an extension of ID3. C4.5 can handle both continuous and discrete attributes. It creates a threshold and then splits the list into two groups, higher attribute values and lower attribute values. Quinlan went on to create C5.0, which offers a number of improvements than C4.5. Other than speed improvement and more memory efficiency, C5.0 can generate significant smaller decision trees and supports boosting which improves the trees and delivers higher accuracy.

In this study, C5.0 was applied on the computed features. First, the dataset was split into training and validation subsets. The training and validation subsets were produced by repeated random sub-sampling. We randomly selected 50% of the dataset for training and the remaining 50% for validation. The results were generated from the validation data. Each posture/activity was represented in the same proportion in both training and validation sets.

Then the tree structure was composed. The training and validation sets each contained 56 * (n / 2) values, where 56 is the number of features calculated from 2 second data collection from the 8 sensors and n is the total monitoring time. The leaves (attributes) of the decision tree are defined as the six posture activity classes—"sit", "stand", "walk", "cycle", "stairs-up" and "stairs-down". The class labels were kept in the dataset files at the end of each feature vector. The decision nodes of the decision tree were the thressholds obtained from the feature values.

Six-class individual models were built in the study. Individual model performs training and validation on the same experimental subject. The individual models are the best fit to the individual traits and thus represent the baseline of accuracy for comparison.

D. Advanced boosting option—to increase classification accuracy

Advanced boosting option was applied in C5.0 classification tool for increased accuracy. The tool generated ten different decision trees as simple classifiers, then integrated them and increased the performance through boosting.

III. RESULTS

Fig. 2 shows an decision tree structure obtained from the classification process. It is obtained from dataset from subject 2. The tree leaves are the posture activities and the connecting nodes are values which are the thresholds from the computed features from data collected by eight sensors.

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Decision tree:

mean absolute deviation_pre2 <= 635:
: . . . entropy_acc1 > 28050: cycle (158)
:       entropy_acc1<= 28050:
:       : . . . mean_pre4 <= 1057: sit (180)
:               mean_pre4 > 1057:
:               : . . . max_pre4 <= 1562: sit (3)
:                       max_pre4 > 1562: stand (167)
mean absolute deviation_pre2 > 635:
: . . . max_acc3 > 3686: stairs_down (28)
        max_acc3 <= 3686:
        : . . . mean_acc1 >1225:
                : . . . entropy acc1 <= 36264: walk (3)
                :       entropy acc1 >36264: stairs_up (16)
                mean acc1 <= 1225:
                : . . . mean_acc2 <= 2038:
                        : . . . num of mean crossing acc1 <= 14: stairs_up (6)
                        :       num of mean crossing acc1 > 14: walk (5)
                        mean_acc2 > 2038:
                        : . . .mean acc1 <= 1185: walk (586)
                              mean acc1 > 1185:
                              : . . . num of mean crossing_pre2 <= 3: walk (40)
                                      num of mean crossing_pre2 >3: stairs_up (3)
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Figure 2. Decision tree generated for classification from subject 2.

In this decision tree figure, the connection nodes are displayed as feature names followed by sensor names. For example, "pre 2" means pressure sensor 2, and "acc1" means accelerometer dimension 1, There are feature names prior of the sensor names. Accelerometer sensor demension 1 to 3 means anterior–posterior, medial–lateral, and superior–inferior axes of accelerometer. Pressure sensor 1 to 5 means heel pressure sensor, the fifth, third, and first metatarsal head sensors, and the hallux sensor, respectively [15]. "Max" means maximum value, and "num of mean crossings" means number of mean crossings. The first two lines of the decision tree can be read as: if the mean absolute deviation from pressure sensor 2 is not greater than 635, and entropy from accelerometer dimension 1 is greater than 28050, then the posture activity is classified as "cycle". Among all the feature vectors, there are 158 of them being classified as "cycle".

Table III shows the attribute usages in percentage in the decision tree above. It is obvious that not all features are involved nor all sensors are used.

This table shows that among all the feature vectors mean absolute deviation from pressure sensor 2 is used for all the vectors, while maximum value from accelerometer 3 is used with a rate of 57%. All other features that are not listed in Table III are not used during the classification.

TABLE III. ATTRIBUTE USAGE FROM THE DECISION TREE

Attribute name	Attribute usage
mean absolute deviation_pre 2	100%
max_acc 3	57%
mean_acc 1	55%
mean_acc 2	54%
entropy acc 1	44%
mean_pre 4	29%
max_pre 4	14%
Num of mean crossing_pre 2	4%

Table IV shows the number of features and number of sensors that are used for each subject, after which averages are calculated and shown. For the features, there are a total of 56 of them. Obviously, the number of features that involved in classification is much less than the total. For the sensors, there are a total of 5 sensors of them (3D accelerometer sensor is viewed as a single sensor here). The experimental results provide potential suggestions for sensor reduction and optimization.

TABLE IV. NUMBER OF FEATURES AND SENSORS USED IN THE CLASSIFICATION

Subject	1	2	3	4	5	6	7	8	9	Average
N(feature)	8	9	7	10	8	8	11	8	11	10
N(sensors)	4	3	4	5	3	4	5	3	4	4

The above table shows that the usage of the features and the sensors are only a subset of what we have . As there are 56 features in total, the ratio of number of features that are involved is 10/56=17.9%. The ratio of number of sensors that are involved is 4/6=66.7%.

Fig. 3 is a confusion matrix obtained from the classification process. It is from suject 2. The test data contains 1195 cases. Overall the classification accuracy is high, with an error of 1.2%. However, there are still some misclassifications. For example, 4 cases of "stairs up" are misclassified as "cycle".

Evaluation on test data (1195 cases):

Decision Tree:	Size	Errors
	12	14 (1.2%)

Confusion matrix:

(a)	(b)	(c)	(d)	(e)	(f)	← classified as
176	1					(a): class sit
4	185	1				(b): class stand
		639	1			(c): class walk
			141			(d): class cycle
		4		26		(e): class stairs_up
		3			14	(f): class stairs_down

Figure 3. Confusion matrix from classification for subject 2.

TABLE V. COMPUTATIONAL ACCURACY OF THE CLASSIFIER

Subject	1	2	3	4	5	6	7	8	9	Average
Accuracy (%) Without boosting	98.5	98.8	98.2	99.0	99.6	98.8	99.0	99.1	98.1	98.85
Accuracy (%) With boosting	98.8	98.7	98.4	99.0	99.7	99.2	99.0	99.5	98.1	98.90

Table V shows the information about the computational accuracy. The second row shows the computational accuracy in classifying posture activities for the nine experimental subjects. The average accuracy is also calculated and shown. The third row shows the computational accuracy after boosting. It can be seen that advanced boosting algorithm does not substantially increase classification accuracy. Thus, classification by a simple decision tree may be sufficient.

IV. CONCLUSION AND DISCUSSION

In this study, decision tree classification was applied to the problem of recognition of postures and activities in the data captured by SmartShoe. The proposed sensor system should be convenient for everyday real-life usage with very high posture activity classification accuracy. The result of decision tree algorithm can suggest direct and effective way to simplify the feature set and reduce the total computational time. Also, the approach provides simplification suggestions for the shoe sensor system.

The classification accuracy by decision tree classifier is 98.85% by itself and 98.90% after boosting. There is still space for improvement. The confusion matrix shows that there are still cases of misclassifications. There can be multiple reasons that cause this problem. Firstly, feature extraction chooses features which may largely represent the information in the dataset, however it still causes the loss of information. This indicates that a more advanced feature sets may be able to increase the classification accuracy.

After the boosting, the classification accuracy is slightly increased, however is not significantly improved. Also, boosting is not practical in real usage because it obviously increases the computational time. Comparing to SVM (support vector machine) algorithm [15], decision tree needs much less computational cost, thus is significantly faster than SVM classification. Considering real-system implementation, decision tree algorithm is easier to achieve real-time performance.

The model that is experimented in this study is individual model, while a group model may be more valuable. Since individual subjects' physical and activities are different from each other, group model may potentially have lower classification accuracy. However, the accuracy should not be dramatically reduced. The classification method proposed in this study provides a very direct and effective approach to simplify the feature computation stage. As shown in the result, the features that needed to be computed for the classification can be less than 20% of the total features. Moreover, the approach shown in this study creates a simple method to simplify the shoe sensor system. The number of sensors that is involved in each classification is around 4, which is smaller than the proposed sensor number 6. This means that when the shoe sensor system is made into production, 2 sensors out of 6 sensors could be saved in each shoe.

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