Activity Recognition by Smartphone Accelerometer Data Using Ensemble Learning Methods

Eu Tteum Ha, Kwang Ryel Ryu

Abstract—As smartphones are equipped with various sensors, there have been many studies focused on using these sensors to create valuable applications. Human activity recognition is one such application motivated by various welfare applications, such as the support for the elderly, measurement of calorie consumption, lifestyle and exercise patterns analyses, and so on. One of the challenges one faces when using smartphone sensors for activity recognition is that the number of sensors should be minimized to save battery power. In this paper, we show that a fairly accurate classifier can be built that can distinguish ten different activities by using only a single sensor data, i.e., the smartphone accelerometer data. The approach that we adopt to deal with this twelve-class problem uses various methods. The features used for classifying these activities include not only the magnitude of acceleration vector at each time point, but also the maximum, the minimum, and the standard deviation of vector magnitude within a time window. The experiments compared the performance of four kinds of basic multi-class classifiers and the performance of four kinds of ensemble learning methods based on three kinds of basic multi-class classifiers. The results show that while the method with the highest accuracy is ECOC based on Random forest.

Keywords—Ensemble learning, activity recognition, smartphone accelerometer.

I. INTRODUCTION

SCIENCE and technology development is marked by the elaboration of various sensors, and their technical capabilities are also greatly improved. Numerous studies using sensors have been carried out, and, especially in recent years, research proposals for sensors built into smartphones have been made. One trend in this research has focused on the use of sensors, such as the acceleration sensor, phone, gravity sensors, and GPS sensors, for activity recognition. Activity recognition is defined as prediction of user behavior carried out through data collection and analysis from any sensor. This activity recognition can be utilized in various fields, such as measurement of the momentum, the elderly welfare assistance, as well as the analyses of life and movement patterns.

However, one of the characteristics of smart-phones is their limited battery capacity. Therefore, minimizing the number of sensors used while increasing the efficiency of operation of the battery to increase the recognition accuracy becomes an important issue. In the past studies, reducing the number of sensors to increase battery efficiency has however lowered the accuracy of recognition of various activities.

This paper proposes the method to recognize 12 types of activities using a single sensor in order to increase the efficiency of the battery. There is a problem because, when a single sensor is used, the number of classes increases, which lowers the recognition accuracy. Therefore, in order to boost recognition accuracy across the 12 types of activities, ensemble learning methods have been used. Ensemble learning methods are typical learning techniques that can be acquired the numerous classifiers to solve more efficiently the multi-class problems. In order to carry out activity recognition by using the ensemble learning methods, data were collected using the 3-axial accelerometer built into a smartphone, and the total of 12 types of activities was divided into specific activities, such as standing, sitting, walking, running, and so on. Afterwards, features were generated by analyzing statistical geometric characteristics of the acceleration sensor data that help to identify each activity. The experiments compared the performance of four kinds of basic multi-class classifiers and the performance of four kinds of ensemble learning methods based on three kinds of basic multi-class classifiers [1].

II. RELATED WORK

According to the number of sensors, activity recognition is conventionally divided into activity recognition using single sensor and multiple sensors.

A. Activity Recognition Using Single Sensor

First, in a recent study by Kose et al. (2012), activity recognition in real time was performed using the clustered k-Nearest Neighbors classifier method. In this method, clusters are formed using k-Nearest Neighbors. This increases the efficiency of the battery, because the amount of calculation is reduced. However, the recognizable number of activities is limited to four, and the accuracy rate in the study was 92.13% [2].

Another study by Ataya and Jallon (2012) used a Markov Chain and Support Vector Machine. In this research, Support Vector Machine for recognizing activity was used, followed by the use of Markov Chain to improve accuracy. Activities were classified into lying down, sitting, bent sitting, standing, walking, running, and the reported accuracy rate was 92% [3].

In other relevant studies using single sensor the efficiency of the battery increased, but the accuracy of recognition of various activities decreased, compared to the studies using multiple sensors.

B. Activity Recognition Using Multiple Sensors

Firstly, a recent study by Cho et al. (2012) proposed to use multiple sensors such as an acceleration sensor, gravity sensor,

Eu Tteum Ha and Kwang Ryel Ryu are with the Department of Electrical and Computer Engineering, Pusan National University (phone: +82-51-510-3645, +82-51-510-2453; e-mail: gkdmema@naver.com).

a magnetic sensor, and the SVM classifier. In this case, battery efficiency decreased through the use of multiple sensors, but several types of activities—such as a floating posture, walking, running, ascending the stairs and the descending stairs—were highly recognizable. In this study, the recognition accuracy rate reached 98.26% [4].

Secondly, a recent study by Anguita et al. (2012) used the acceleration and the gravity sensors, as well as Hardware Friendly-SVM classifier. In total, 17 features were generated. The use of Hardware Friendly-SVM reduced the battery load, and the recognizable activities included sitting, standing, lying down, running, as well as ascending and descending the stairs. However, in this study the accuracy of recognition was reduced to 89% [5].

III. ACTIVITY RECOGNITION

A. Data Collection

Three-axis accelerometer sensor is detecting a change in the speed, such as the acceleration device, vibration, shock, etc., per unit of time to sense the dynamic forces. This accelerometer sensor uses inertial force, electrical modifications, and the principle of the gyro. Fig. 1 shows the direction of each axis of the accelerometer sensor in a smartphone. To collect data using a smartphone, the front of its screen was placed in the front pocket of the pants bottom, and the data were collected during each activity. In our study, accelerometer sensor data were collected at intervals of 0.1 of a second, and the total of five volunteers for each activity carried them out for 2 to 10 minutes. Therefore, the number of samples of each activity is 6000 (60×10×0.1), and the total of the collected data for all types of activities amounts to 72,000 samples.

Fig. 1 Directions of each axis

B. Activity Classes

To recognize human activity, a classification of activities is needed. In this paper, human activities were divided into two kinds of risk activity and 10 types of most frequent human behaviors.

A1. Sitting
A2. Standing
A3. Walking on a flat road
A4. Running on a flat road
A5. Walking uphill

A6. Walking downhill
A7. Running uphill
A8. Running downhill
A9. Falling
A10. Hobbling
A11. Ascending the stairs
A12. Descending the stairs

C. Feature Generation

Each activity of the acceleration sensor signal because it has a similar waveform to the raw data collected using only a high degree of accuracy is impossible to recognize the activity. Therefore, in the data analysis for each activity of the acceleration sensor there is a need to extract a useful feature for the activity recognition. In this paper, 18 kinds of features within the time window were generated.

When creating the feature, the present time including the past two seconds of the data were used. The first two seconds of the time window in the past were included because there were not enough data to generate the features. Thus, the first two seconds of data for each activity, except for 5900 (= 5 × (60×2-2)/0.1) were generated for each of the features. 4700 data samples for each activity were used for training, and the remaining 1200 samples were used for the performance evaluation.

We generated 18 kinds of features, such as maximum and minimum acceleration, maximum and minimum tilt angle of each axis, magnitudes of acceleration vector, maximum and minimum magnitude of acceleration vector, mean of magnitude of acceleration vector, difference between the maximum and the minimum magnitude of acceleration vector, and standard deviation of the magnitudes of acceleration vector. Magnitudes of acceleration vector were generated at each time point, and the remaining feature was generated in the time window of the last two seconds.

$$TiltAngle(x) = \operatorname{atan}(\frac{x}{\sqrt{y^2+z^2}}) \qquad (1)$$

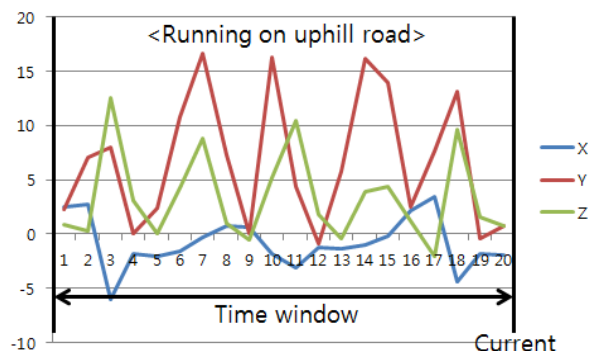$$Magnitude(AccData) = \sqrt{x^2 + y^2 + z^2} \qquad (2)$$

Fig. 2 Time window in data streams

Equation (1) is the equation for measuring Tilt angle value that tilted around the *x*-axis; (2) is the equation for measuring

the size of the vector. In this equation, *x, y, z* stand for each axis of the data of the acceleration sensor. Fig. 2 shows the data window. In order to remove unnecessary features, we applied Feature subset selection scheme, but the more features were removed, the more accuracy decreased. Therefore, we used all 18 generated features [1].

D. Classifiers

The accuracy of activity is greatly influenced by the choice of the classifier. In particular, because activity recognition is a multi-class problem, using a binary classifier should not be classified with high accuracy. In this paper, we used four kinds of basic multi-class classifiers (Decision Tree, *k*-NN, 1-vs-rest SVM, and Random Forest), and carried out the comparative analysis of their performance. Furthermore, to improve the performance, we used four kinds of ensemble learning methods (Ensemble of Nested Dichotomy, Bagging, Boosting, and Error-Correcting Output Codes) using three kinds of basic multi-class classifiers (Decision Tree, *k*-NN, and Random Forest), and conducted a comparative analysis of their performance. The ensemble of Nested Dichotomy (END) that is based on Nested Dichotomy (ND) is solving the multi-class problem by generating different n ND. Fig. 3 shows two different versions of nested dichotomies, and Table I shows error-correcting code table [6]-[8].
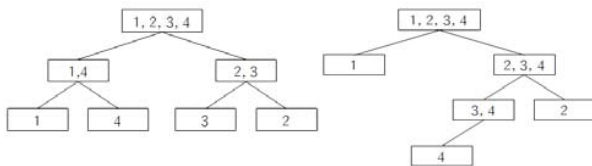

Fig. 3 Two different versions of nested dichotomies

TABLE I
ERROR-CORRECTING CODE

Class	Class Vector						
A	1	1	1	1	1	1	1
B	0	0	0	0	1	1	1
C	0	0	1	1	0	0	1
D	0	1	0	1	0	1	0

In this paper, setting of four kinds of multi-class classifiers is that learning algorithm of Decision tree was set C4.5 algorithm, *k* of *k*-NN was set by experiment, the kernel of 1-vs-rest SVM was set Polynomial kernel. Random forest is needed to set *n* for randomly selecting features using the Random subspaces method. Therefore, we were setting *n* by experiment and generated ten different trees. Three kinds of multi-class classifiers were used to inner classifier of the ensemble learning methods. The ensemble of Nested Dichotomy, Bagging, and Boosting were set to generate 10 different classifiers. The number of subcommittees of Boosting was set to 3 for learning the model.

IV. EXPERIMENT AND RESULTS

To evaluate the performance of each learning method, we used Samsung Galaxy Note Ⅱ based on Android 4.1 Version. We compared the accuracy of four kinds of basic multi-class classifiers and the accuracy of four kinds of ensemble learning methods based on three kinds of basic multi-class classifiers. In total, 16 models for experiment were built.

The results of comparing the performance of four multi-class classifiers show that while SVM has the highest accuracy of 97.2%, the *k*-NN is has the lowest accuracy. The results of comparing the performance of four ensemble learning methods based on three basic multi-class classifiers are as follows. First, in case when four ensemble learning methods are learned using Decision tree, END shows the highest accuracy, and ECOC shows the lowest accuracy. Second, in case when four ensemble learning methods are learned using *k*-NN, Boosting shows the highest accuracy and END shows the lowest accuracy. Third, in case when four ensemble learning methods are learned using Random forest, ECOC shows the highest accuracy and Bagging shows the lowest accuracy. Finally, when comparing all models, ECOC based on Random forest shows the highest accuracy.

TABLE II
COMPARING FOUR KINDS OF MULTI-CLASS CLASSIFIERS

Classifier	Accuracy (%)	Setting
Decision tree	96.4	C4.5
k-NN	77.0	K = 10
Random forest	96.2	Random feature subset = 5 Iteration = 10
SVM	97.2	Polynomial kernel

TABLE III
COMPARING THREE KINDS OF ENSEMBLE LEARNING METHODS

Classifier	Accuracy (%)			
	Bagging	Boosting	ECOC	END
Decision tree	96.9	97.5	96.2	97.6
k-NN SVM	21.9	22.4	21.7	17.1
Random forest	97.5	97.5	97.8	97.6

Table II is comparing four kinds of multiclass classifier. Table III is comparing three kinds of ensemble learning methods and Table IV is accuracy of ECOC based on random forest.

V. CONCLUSION

In this paper, we proposed how to improve recognizing 12 kinds of activities using smart phone's built-in accelerometer. To increase the efficiency of the battery use only the accelerometer was used. After collecting the accelerometer data, we generated 18 useful kinds of features for activity recognition. To improve the accuracy of recognition of 12 kinds of activity, we performed the comparative analysis of four kinds of multi-class classifiers and four kinds of ensemble learning methods based on the four kinds of multi-class classifiers. The results show that while the method with the highest accuracy is ECOC based on Random forest, the method with the lowest accuracy is END based on *k*-NN.

TABLE IV
ACCURACY OF ECOC BASED ON RANDOM FOREST

	Activity	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	Accuracy (%)
							Predicted Activity							
Real Activity	A1	1200	0	0	0	0	0	0	0	0	0	0	0	100.0
	A2	0	1189	0	0	11	0	0	0	0	0	0	0	99.1
	A3	0	4	1996	0	0	0	0	0	0	0	0	0	99.7
	A4	0	0	0	1195	5	0	0	0	0	0	0	0	98.7
	A5	0	0	2	0	981	39	7	1	28	56	56	30	81.7
	A6	0	0	15	0	0	1184	0	1	0	0	0	0	99.6
	A7	0	0	0	0	1	4	1194	0	1	0	0	0	99.0
	A8	0	0	0	0	0	0	2	1198	0	0	0	0	99.5
	A9	0	0	1	9	0	1	0	1	1187	0	1	0	99.1
	A10	0	0	0	0	0	0	0	0	12	1188	0	0	99.8
	A11	0	0	0	0	5	0	1	5	5	0	1184	0	98.7
	A12	0	0	0	0	3	0	0	0	0	0	4	1193	99.4
	Average													97.8

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