Activity Recognition using Smartphone low level sensor data

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Abstract

Smartphones with built-in sensors promise a convenient, objective way to evaluate everyday movements and recognize those movements into activities. Using accelerometer as a low level sensor data we estimate the following daily activities performed by the user: walking, jogging, walking up stairs, walking down stairs, sitting and standing. Among five common machines learning algorithms: Decision Tree (J48), Naïve Bayes (NB), Support Vector Machines (SVM), Neural Network (NN), and Logistic Regression. NN classifier was found to be the best choice with classification accuracy of more than 95%. It is shown that this method is appropriate and that the phone's orientation information is not needed.

Index Terms: Activity recognition, Smartphone, Accelerometer, Classification models

I. INTRODUCTION

Human activity recognition (HAR) refers to collecting physiological data from wireless body area networks which can be used to determine the activity and context of an individual independent of external infrastructure. HAR plays an important role in various applications such as health care and elderly monitoring with the aim to improve the quality of life, safety and freedom [1]. Vast numbers of previous works have integrated accelerometer into wearable systems in order to recognize and classify various daily activities. Most of the research done in wireless body area network for activity recognition has dealt with recognizing daily tasks such as performing ambulation activities which include walking, jogging, running, sitting and using stairs [2, 3]. Data from accelerometers have been used for human activity recognition in a large amount of existing works [4, 5]. Previous studies have shown that accelerometers are suitable for identifying high energy actions such as running, jogging, etc which have distinctive patterns. However, many of these approaches in HAR have relied on data gathered from multiple accelerometers which were attached at different locations on the user's body. Although, this provides ample activity and contextual information, using multiple body worn sensors are often obtrusive and can cause inconvenience and discomfort to the users. Therefore, there is a need to investigate new approaches that are unobtrusive and highly to be accepted by the intended users without altering his or her normal habits and lifestyle. For these reasons, in this study, we have investigated the use of a single accelerometer embedded in the Smartphone for recognizing human activities.

II. DEVICE AND DATA COLLECTION

In this study six activities were considered: walking, jogging, walking upstairs stairs, walking downstairs, sitting and standing. We selected these activities because they are performed regularly by many people in their daily routines. Activity data were collected from 36 healthy subjects (20 males and 16 females) between the ages of 21 and 35 years old, with an average height of 172cm and average weight of 62 kg. Subjects were students and staffs of Mokpo National University, Department of Electronics Engineering. These subjects carried the Android phone in their front pants leg pocket and were asked to walk, jog, ascend stairs, descend stairs, and stand for specific periods of time.

The data collection process was controlled by a smartphone application. This application, through a simple graphical user interface, permitted to record the user's ID, start and stops the data collection, and label the activity being performed. The acceleration signals were sampled at 20 Hz and stored on a Secure Digital (SD) card in the Smartphone. Each activity had approximately 6,000 samples with a total number of 1,200,000 samples. For this study, we have used this raw data for feature extraction and building classification model using WEKA. The activities were performed in a naturalistic setting. For recognition purposes is it only required that the user attaches the phone always at the same position. Orientation of the phone is not important for recognition purposes.

A. Data Processing and Classification

Standard classification algorithms cannot be directly applied to raw time-series accelerometer data. Instead features must be extracted from the raw time series data. Total of forty three summary features were generated, although these are all variants of just five basic features: difference between previous acceleration and current acceleration, average acceleration, standard deviation, time between successive peaks and magnitude. The extracted features were stored as a feature vector and written to a features file. These features were then used as input for WEKA data mining software provided by University of Waikato, to build the classifiers. WEKA is a machine learning software environment which offers a collection of visualization tools and algorithms for data analysis and predictive modeling [6].

III. RESULTS AND DISCUSSION

In order to identify which machine learning algorithm provided the most accurate activity detection, the Decision tree (J48), Naïve Bayes (NB), Neural Network (NN) (Multilayer Perceptron) and Support Vector Machine (SVM) where applied to the data. The default parameters for each classification method were used. To further identify which machine learning achieved the best accuracy, a 10-fold cross validation with 10 iterations was performed using the WEKA explorer. The summary results for our activity recognition for classification algorithms using 10-fold cross validation are presented in Table 1. Table 1 demonstrates that in most cases high levels of accuracy was achieved. For the two most common activities, walking and jogging, we generally achieve accuracies above 90%. Jogging appears easier to identify than walking, which seems to make sense, since jogging involves more extreme changes in acceleration. It appears much more difficult to identify the two stair climbing activity that is because those two similar activities are often confused with one another. It also demonstrates that the NN and J48 provided significantly better accuracy than Logistic Regression, NB and SVM for 10 fold cross validation method. NN provided a small, however, significantly greater accuracy of 88.81%.

Table 1. Percentage of correctly classified instances for each activity using each of the five machine learning algorithms. Results show the average percentage correctly classified instances for the 10-fold 10 iteration test. The average percentage accuracy for all the activities is also presented.

Activity	NB	SVM	J48	Logistic	NN
	%Correct	%Correct	%Correct	%Correct	%Correct
Walk	89.72	98.08	95.53	95.15	97.41
Jog	93.35	99.45	96.18	98.65	99.02
Up	17.56	48.58	67.56	50.16	82.28
Down	21.40	25.00	63.26	35.98	64.39
Sit	94.44	96.41	96.41	94.11	95.42
Stand	82.11	93.90	97.56	91.06	94.31
Average	**66.43**	**76.90**	**86.08**	**77.52**	**88.81**

The F-measure was used as a performance index to evaluate the different classifiers ability to classify each of the activities. The F-measure is a combination of precision and *recall* where *TP*, *FP* and *FN* are the numbers of true positive, false positive and false negatives for the considered class respectively.

Table 2. Balanced F-measure for each classifier, detailed by class when using 10-fold cross validation. A weighted average value was added to the Table to represent the average of the F-measure values for each classifier.

Activity	NB	SVM	J48	Logistic	NN
Walk	0.799	0.908	0.946	0.902	0.976
Jog	0.923	0.994	0.958	0.988	0.994
Up	0.242	0.506	0.68	0.519	0.77
Down	0.283	0.337	0.657	0.428	0.685
Sit	0.925	0.977	0.975	0.94	0.962
Stand	0.754	0.947	0.972	0.931	0.943
Average	**0.726**	**0.837**	**0.893**	**0.841**	**0.926**

A higher value of F-measure indicates improved detection of the investigated activity. Table 2 presents the balanced F-measure calculated for each activity for different classification algorithms. Again a 10-fold cross validation was applied. A weighted average value was added to the table to represent the average of the F-measure values for each classification algorithms. Results show activity detection using NN provided the highest F-measure with an average of 0.926, while NB provided the lowest F-measure average of 0.726. In addition to the weighted average value of F-measure, it is possible to identify the accuracy of detecting each activity separately. For example, ascending and descending stairs activities were detected worse when using any of the five classification algorithms, the values are 0.242 and 0.283 respectively. This indicates some confusion of detecting those activities because the patterns in acceleration data between ascending stairs and descending stairs are somewhat similar.

IV. CONCLUSIONS

This work presented an investigation into the accuracy of daily activity detection from the smartphone accelerometer data for six different daily activities. Results have shown that the NN provided the most accurate classification results of the investigated machine learning algorithms, with most activities being recognized correctly over 95% of the time. This study considered activity classification using only data from accelerometers. Recent studies have shown that introducing data from a variety of sensor types can improve the classification accuracy of everyday activities. Future work should therefore consider the effects on the classification accuracy from sensors such as gyroscopes and magnetometers.

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