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On the use of ensemble of classifiers for accelerometer-based activity recognition

Cagatay Catal*, Selin Tufekci, Elif Pirmit, Guner Kocabag

Istanbul Kultur University, Department of Computer Engineering, 34156 Bakirkoy, Istanbul, Turkey

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A B S T R A C T

Activity recognition aims to detect the physical activities such as walking, sitting, and jogging performed by humans. With the widespread adoption and usage of mobile devices in daily life, several advanced applications of activity recognition were implemented and distributed all over the world. In this study, we explored the power of ensemble of classifiers approach for accelerometer-based activity recognition and built a novel activity prediction model based on machine learning classifiers. Our approach utilizes from J48 decision tree, Multi-Layer Perceptrons (MLP) and Logistic Regression techniques and combines these classifiers with the average of probabilities combination rule. Publicly available activity recognition dataset known as WISDM (Wireless Sensor Data Mining) which includes information from thirty six users was used during the experiments. According to the experimental results, our model provides better performance than MLP-based recognition approach suggested in previous study. These results strongly suggest researchers applying ensemble of classifiers approach for activity recognition problem.

1. Introduction

Activity recognition (AR) is a research topic under Human Computer Interaction (HCI) research area. Some of the researchers first focused on activity recognition from videos and images, but later when daily life was considered, researchers started to apply sensors such as accelerometers for activity recognition [1]. Although there are common research challenges between activity recognition and pattern recognition, several unique challenges which are explained in detail in Bulling et al.'s [1] study exist for AR.

Many machine learning approaches such as Hidden Markov Models (HMMs) [2], Decision Trees (DT) [3], Support Vector Machines (SVM) [4], Conditional Random Fields (CRFs) [5], k-nearest Neighbor (KNN) Ayu et al. [6] were successfully used in AR studies. There are many sensors which can be used for AR problem, and some of them which were used previously are given as follows: accelerometers, gyroscopes, magnetometer, GPS, RFID, light sensor, Inertial measurement units, skin temperature, ECG, EEG, and camera [1]. Recent studies showed that mobile phones can be effectively used for activity recognition and there is no need to use an extra sensor on the body [7]. In a mobile phone, several sensors such as gyroscope, camera, microphone, light, compass, accelerometer, proximity, and GPS can be used in conjunction with the wireless interfaces such as Bluetooth, Wi-Fi, or 3G/4G. In smartphones, accelerometers are generally used to show landscape or portrait views of the phone. For example, when you rotate your smartphone, accelerometer can detect changes in orientation, and the user interface can be updated appropriately. Also, there are different applications of accelerometers such as pedometers and games. A mobile application, which can be used as a pedometer, is used to count the steps a person takes and it uses the accelerometer of the smartphone. Accelerometer-based games are more fun compared to the other games because player only tilts the smartphone instead of using keys. As explained in these examples, accelerometers have a wide application area in smartphones.

Despite of these benefits of mobile phones, there are many limitations regarding to the hardware [8]. For example, battery limitation and resource consumption of classifiers must be taken into account when designing an activity recognition system.

In this study, we used the accelerometer sensor of a mobile phone and recognized specific activities which are walking, jogging, upstairs, downstairs, sitting, and standing. These activities were chosen because we perform them everyday in our daily life. Jogging means running at a slow pace, and running is a faster activity compared to jogging. Also, calorie burn and activation of muscles will be very different in these two activities. Downstairs and upstairs activities mean descending stairs and ascending stairs, respectively. For each activity, acceleration is recorded in three axes (*z*-axis: forward

* Corresponding author. Tel.: +90 5370621312; fax: +90 5370621312.
E-mail address: c.catal@iku.edu.tr (C. Catal).

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acceleration, y-axis: upward/downward motion, x-axis: horizontal movement of the leg). Kwapisz et al. reported that while walking, jogging, upstairs, and downstairs activities show periodic behavior, sitting and standing do not have such a property. During descending stairs, small peaks were reported for y-axis and during ascending stairs, peaks were reported for z-axis and y-axis. Sitting and standing do not have such a periodic behavior but the main difference between these activities is each axis's relative magnitude values [7].

We used a publicly available dataset which is known as WISDM (Wireless Sensor Data Mining) and it can be accessed from the following link: http://www.cis.fordham.edu/wisdm/dataset.php. There are activity information of thirty six users in this dataset. Therefore, this dataset is very appropriate for benchmarking studies.

Before we explain the features in this dataset, we must address how the dataset was prepared by those researchers. Raw time-series data was divided into 10-s segments and features were identified for 200 readings in each 10-s segment. Researchers reported that they compared the 10-s and 20-s example duration and since 10-s duration was slightly better, they used this example duration for their dataset. They created features based on 200 readings and 43 features, which are mainly variations of six basic features, were identified. Six feature types are: Average-A (3), Standard Deviation-SD (3), Average Absolute Difference-AAD (3), Average Resultant Acceleration-ARA (1), Time Between Peaks-TBP (3), Binned Distribution-BD (30). The numbers which are shown in parenthesis indicate how many features were generated from this feature-type. Therefore, we have 43 features in total. The number three (3) in parenthesis represents different feature values for each axis. Average shows the average acceleration, and SD represents the standard deviation. AAD is the difference between each value in 200 readings and the mean of 200 values. ARA is computed by calculating the average of square root of the sum of the squared values of each axis. TBP represents the time between peaks. BD is calculated by dividing the range of values into 10 bins and recording the fraction of 200 values which fall within each bin [7].

In Fig. 1, we depict the activity recognition problem. After the data from accelerometer sensor of the smart phone is read, this time series data is transformed into 43 features and the class label of this exercise is recorded in the dataset. In our datasets, we have exercises of 36 people and there are different number of exercises for each exercise type. By using a machine learning classifier, it is possible to build some hypothesis and new activity's exercise type can be predicted based on new 43 features' values. There are many benefits of this challenging problem. For example, when user is in running mode, the smart phone may automatically send an SMS to the caller about this issue or when user is in walking mode, ring tone may increase. Also, if he/she is in sitting mode, location must not be updated due to the battery power considerations.

There are many application areas of activity recognition such as targeted advertisement, health monitoring, and ambient assisted living [8]. From this application perspective, we should consider not only recognition of simple activities such as climbing stairs, sitting, and running but also complex ones such as cleaning, cooking, and sweeping. Dernbach et al. [9] reported that although they achieved 93% accuracy by using Multi-Layer Perceptron for simple activities, they only reached to 50% accuracy for complex activities. This shows that a mobile phone can be a part of a system which can recognize complex activities, but we should take into account extra sensor or devices for a better prediction result.

In this study, we made several experiments with J48, Logistic Regression, and Multi-Layer Perceptron algorithms. Our novel recognition model applied Voting algorithm by combining the power of these three methods. We used these classifiers because we aimed to compare the performance we reached with the performance reported in the recent study of Kwapisz et al. [7]. Although many approaches were suggested for activity recognition in literature, there was no clear consensus which approach is the best one for this problem because researchers mostly used proprietary datasets instead of public ones. However, we applied the public dataset released by Kwapisz et al. [7], but we had to repeat the experiments since the dataset was updated after their publication. Our aim was to provide a better model compared to the model suggest in Kwapisz et al.'s study and therefore, we made experiments with the algorithms used in their study. Miluzzo et al. [10] used J48 classifier for activity recognition task by applying various sensors in smart phones. Al-Bin-Ali and Davies [11] showed that simple Logistic Regression can be used for activity recognition. Mantyjarvi et al. [12] applied Multi-Layer Perceptron for this problem and reported that it can provide acceptable performance. We empirically observed that we can achieve better performance with ensemble of classifiers approach. The detail of our approach is explained in Section 3.

The main contribution of this paper is two-fold:

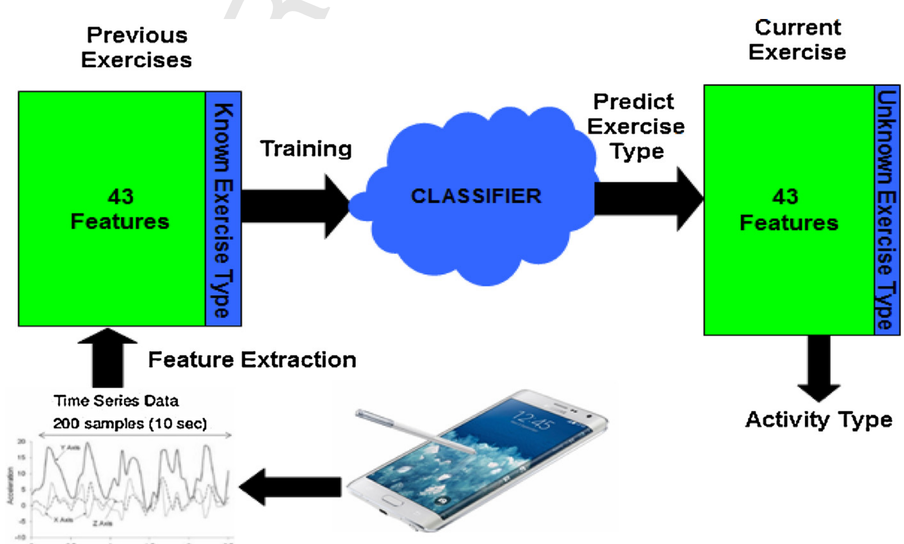

Fig. 1. Activity recognition problem.

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