**HUMAN ACTIVITY RECOGNITION**

**ABSTRACT**

Human activity recognition, or HAR for short, is a broad field of study concerned with identifying the specific movement or action of a person based on sensor data.

The sensor data may be remotely recorded, such as video, radar, or other wireless methods. It contains data generated from accelerometer, gyroscope and other sensors of Smart phone to train supervised predictive models using machine learning techniques like SVM , Random forest and decision tree to generate a model. Which can be used to predict the kind of movement being carried out by the person, which is divided into six categories walking, walking upstairs, walking down-stairs, sitting, standing and laying?

MLM and SVM achieved accuracy of more than 99.2% in the original data set and 98.1% using new feature selection method. Results show that the proposed feature selection approach is a promising alternative to activity recognition on smart phones.

**INTRODUCTION**

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This data can be used to design and con-

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Physical activity is well-known by the general public to be crucial for leading a healthy life. Thus, researchers are seeking a better understanding of the relationship between physical activity and health. Precise recording of the conducted activities is an essential requirement of their research. (Bauman et al., 2006) This data can be used to design and construct activity recognition systems. These systems allow physicians to check the recovery development of their patients automatically and constantly (da Costa Cachucho et al., 2011). Another rising concern is the sedentary life many people live, due to the shift in lifestyle occurring in the modern world, where work and leisure tend to be less physically demanding (Gyllensten, 2010). Several reports have already found links between common diseases and physical inactivity (Preece et al., 2009). Thus, activity recognition can be used by recommender systems to help the users track their daily physical activity and promote them to increase their activity level. With the recent progress in wearable technology, unobtrusive and mobile activity recognition has become reasonable. With this technology, devices like smartphones and smartwatches are widely available, hosting a wide range of built-in sensors, at the same time, providing a large amount of computation power. Overall, the technological tools exist to develop a mobile, unobtrusive and accurate physical activity recognition system. Therefore, the realization of recognizing the individuals’ physical activities while performing their daily routine has become feasible. So far, no-one has investigated the usage of light-weight devices for recognizing human activities. An activity recognition system poses several main requirements. First, it should recognize activities in real-time. This demands that the features used for classification are computable in real-time. Moreover, short window durations must be employed to avoid delayed response. Finally, the classification schemes should be simple, light-weight and computationally inexpensive to be able to run on hand-held devices.

**MODULES**

The activity recognition process is described, containing four main stages.

1. **Data Collection:** The first step is to collect multivariate time series data from the phone’s and the watch’s sensors. The sensors are sampled with a constant frequency of 30 Hz. After that, the sliding window approach is utilized for segmentation, where the time series is divided into subsequent windows of fixed duration without interwindow gaps (Banos et al., 2014). The sliding window approach does not require preprocessing of the time series, and is therefore ideally suited to real-time applications.
2. **Preprocessing:** Filtering is performed afterwards to remove noisy values and outliers from the accelerometer time series data, so that it will be appropriate for the feature extraction stage. There are two basic types of filters that are usually used in this step: average filter (Sharma et al., 2008) or median filter (Thiemjarus, 2010). Since the type of noise dealt with here is similar to the salt and pepper noise found in images, that is, extreme acceleration values that occur in single snapshots scattered throughout the time series. Therefore, a median filter of order 3 (window size) is applied to remove this kind of noise.
3. **Feature Extraction:** Here, each resulting segment will be summarized by a fixed number of features, i.e., one feature vector per segment. The used features are extracted from both time and frequency domains. Since, many activities have a repetitive nature, i.e., they consist of a set of movements that are done periodically like walking and running. This frequency of repetition, also known as dominant frequency, is a descriptive feature and thus, it has been taken into consideration.
4. **Standardization:** Since, the time domain features are measured in (m/s 2 ), while the frequency ones in (Hz), therefore, all features should have the same scale for a fair comparison between them, as some classification algorithms use distance metrics. In this step, Z-Score standardization is used, which will transform the attributes to have zero mean and unit variance, and is defined as

xnew = (x−µ)/ σ

where µ and σ are the attribute’s mean and standard deviation respectively (Gyllensten, 2010).

**EXISTING SYSTEM**

Several investigations have considered the use of widely available mobile devices. Ravi et. al. collected data from only two users wearing a single accelerometer-based device and then transmitted this data to the phone carried by the user (Ravi et al.,2005). Lester et. al. used accelerometer data from a small set of users along with audio and barometric sensor data to recognize eight daily activities (Lesteret al., 2006). However, the data was generated using distinct accelerometer-based devices worn by the user and then sent to the phone for storage.

Some studies took advantage of the sensors incorporated into the phones themselves. Yang developed an activity recognition system using a smart-phone to distinguish between various activities (Yang, 2009). However, stair climbing was not considered and their system was trained and tested using data from only four users. Brezmes et. al. developed a real-time system for recognizing six user activities (Brezmeset al., 2009). In their system, an activity recognition model is trained for each user, i.e., there is no universal model that can be applied to new users for whom no training data exists. Bayat et al. gathered acceleration data from only four participants, performing six activities. (Bayat et al., 2014) Shoaib et al. evaluated different classiﬁers by collecting data of smart-phone accelerometer, gyroscope, and magnetometer for four subjects, performing six activities. (Shoaib et al., 2013).

**PROPOSED SYSTEM**

The purpose of being able to classify what activity a person is undergoing at a given time is to allow computers to provide assistance and guidance to a person prior to or while undertaking a task.

The difficulty lies in how diverse our movements are as we perform our day-to-day tasks.

There have been many attempts to use the various machine learning algorithms to accurately classify a person’s activity, so much so that Google have created an Activity Recognition API for developers to embed into their creation of mobile applications.

**CONCLUSION**

In this paper, a platform to combine sensors of smartphones and smartwatches to classify various human activities was proposed. It recognizes activities in real-time Moreover, this approach is light-weight, computationally inexpensive, and able to run on handheld devices. The results showed that there is no clear winner, but naive Bayes performs best in our experiment in both the classification accuracy and efficiency. The overall accuracy lies between 84.6% and 89.4%, at which the differences are negligible. Thus, this platform is able to recognize various human activities. However, all of the tested classifiers confused walking and using the stairs activities. The second conclusion is that adding the smartwatch’s sensor data to the recognition system improves it’s accuracy with at least six percentage point. Finally, it is computations that the best sampling frequency is in the field of 10 Hz. Some questions still require to be answered. Most important is the conducting of larger experiments with more people in order to perform more robust evaluation to clearify if indeed one method is better than the other, or whether, any off-the-shelf method can do well in this classification task. This work could be furhter extended by incorporating more sensors (e.g. heart rate sensor), recognizing high-level activities (e.g. shopping or eating dinner) or extrapolating these trained classifiers to other people.

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