Mobile Online Activity Recognition System- Based on Smartphone Sensors

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ABSTRACT: *In this paper, we propose an efficient and flexible framework for activity recognition based on smartphone sensors. We develop a mobile application that integrates data collection, training and recognition, feedback monitoring. This system allows user smartphones are randomly placed in any position and at any direction. In the proposed framework, Fast Fourier Transform (FFT) is used to extract a set of features from sensor data. Then, we deploy Random Forest, Naïve Bayes, K-Nearest Neighbor (KNN), Support Vector Machine (SVM) classification algorithms for recognizing a set of user activities. Our framework dynamically takes into account real-time user feedbacks to increase prediction accuracy. Our framework will be able to apply for intelligent mobile applications. A number of experiments were carried out to show the high accuracy of the proposed framework for detecting user activity when walking or driving a motorbike.*

Keywords: Activity Recognition, Mobile Sensor, Online Training Model, Motorbike

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1. Introduction

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Activity recognition plays an importance role in context-aware applications such as security, healthcare, transportation, social networking, etc. In early time, most of researches focused on analyzing data collected from wearable sensors [1]. Nowadays, due to the emerging of smartphones, activity recognition studies concentrate on inferring user activity by analyzing smartphone sensor data. In an activity recognition framework, user smartphone data is first collected, and then analyzed based on

algorithms. There are two approaches to deal with this problem that are external approach and the internal approach. In the external approach, the sensor data is collected on smartphones then these data are sent to a server or a cloud database for further processing. The main classification process is performed on a server and the results are sent to the corresponding smartphone. This approach is adapted in order to run functions requiring heavy computations on server. It is meaningful because computational capacity of smartphone devices is limited. Besides, it requires internet connection at all times for sending sensor data to a server or a cloud database. On the other hand, in the internal approach, the activity recognition procedure, including data collection, preprocessing and classification, is performed on smartphones in real time. In this approach, information about classifier and raw data is also sent to server for further analysis. Moreover, the training data is preprocessed and analyzed in advance on a local machine. Then, the computed features of these data is integrated in the activity recognition application installed on smartphones. In the internal approach, smartphones do not need any internet connection to send and receive data. This advantage allows saving not only power consumption but also processing time. However, it requires smartphones to have high computational capacity that are often expensive. Hence, this approach is applied to limited models of smartphones.

In this paper, we propose the Mobile Online Activity Recognition System (MOARS) to automatically recognize several activities of smartphone users, for example stopping and moving activity while users are travelling by a vehicle or walking. MOARS is composed of three modules: First, the labeled data collector module periodically collects and preprocesses smartphone sensor data. Secondly, the training module is responsible for building a training model for each smartphone user because each user has different habits when carrying his smartphone during a trip. Thirdly, the Monitoring module processes and classifies sensor data online. Our system is deployed on an Android framework version 4.2 to 5.0. A number of experiments are carried out for various types of transportations that are very popular in Viet Nam such as walking, motor-biking that achieve considerable high accuracy. The system also maintains high accuracy in predicting user status in real time.

The main contributions of this work: proposing a set of suitable features; suggesting a strategy that detecting user activity in the dynamic mode which utilizing real-time user feedbacks to increase accuracy; proposing an activity recognition framework that can be performed solely on smartphones, it thus allows preserving user privacy; carrying out experiments on primitive vehicles i.e. motorbike.

2. Mobile Online Activity Recognition System (Moars)

2.1 Related work

Due to the increase in usage of smartphones, activity recognition based on smartphone sensor data has become a focused research area. Gomes et al. [1] proposed a general prototype for activity recognition in real time. In the proposed framework, no detailed data preprocessing and types of extracted features were specified. It is thus impossible to evaluating the activity recognition accuracy of this framework. Tran and Phan [2] suggested a method using support vector machine (SVM) algorithm for the feature extraction and training model. However, this method requires a connection to server for activity recognition. Chetty et al. [3] proposed to use information theory to rank extracted features and tested various classification algorithms. They showed that lazy learning (e.g. IBk), random forests and ensemble learning based approaches (e.g. random committee) classifiers allow to achieve promising accuracy. However, data used in their experiments were collected when smartphones were placed at a fixed position. Researches have studied various methods for optimizing data collection, noise data reduction, and the best feature selection. Moreover, the computational capacity and the activity recognition model using on smartphones are limited. In this paper, we demonstrate an efficient framework for data collection, feature extraction and real-time training model building for the classification process. Recognized activities are immediately displayed to users.

2.2 Mobile Online Activity Recognition System

The activity recognition systems were used in many application areas. Most previous researches use classifiers that are trained offline [4]. As a result, the training process is static. These systems may be not adapted to new users. Example, some users walk quite slower than others do. It is possible to mistake from one activity to another similar pattern activity, for example stopping and slow driving. One of the most important aspects in every online system is to monitor the activity recognition relying on real-time assistant feedbacks. Therefore, we propose an online system that is able to perform data preprocessing, automatically set up a suitable training model and monitor activity recognition with real time assistant feedbacks (Fig. 1). This system is composed of three main modules: The Labeled data collector module is responsible for collecting smartphone sensor data for each type of activity of each volunteer. Such data is then preprocessed, and extracted into a set of representative features that serve as inputs for the Training module. In the Training module, the selected classification algorithm is trained by using the features of

each activity. Based on the trained knowledge, the current activity of user is detected in real-time by Monitoring module.

Figure 1. Mobile Online Activity Recognition System Framework

In this Framework, Labeled Activity Collector module collected Labeled activity data by accelerometer, gyroscope, magnetic sensor then reoriented Smartphone coordinate to the Earth coordinate systems. Some technical such as low-pass, hi-pass filter was used for reduce noise. The windowing technic also use for cutting segment of sensor signal. We transform this data to the set of suitable features. The training model will be built by them. When framework setup on smartphone, user can recognize activity from their sensor data, data stream transform to features and labeled activity is received by training model real time able.

2.3 Data Collection and Feature Extraction

In the present day, smartphones are pervasively used in the world; many applications are incorporated on it. So user information achieved from smartphone sensors, especially accelerometer, is very useful for activity recognition. However, users might put their smartphones on their pocket, handbag, or in their hands, etc. while moving. As a result, the orientation of smartphones will be frequently changed. Consequently, smartphone sensor data is noisy. An approach to solve this issue is to transform accelerometer data from the smartphone coordinate system (Fig. 2a) to the Earth coordinate system (Fig. 2b) by relying on the additional data collected from magnetometer, and gyroscope sensors [5].

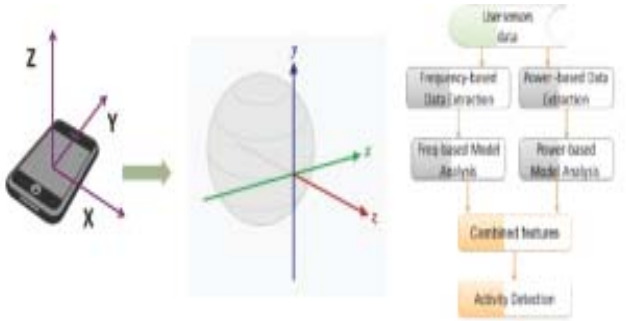

Figure 2. (a) The smartphone coordinate (b) the Earth coordinate (c) The proposed activity recognition framework

Indeed, the amount of raw data collected from smartphone sensors is huge. Hence, directly analyzing such data would require a lot of either time or memory space. A popular approach to deal with this issue is extracting certain important features from such data. Several types of features have been proposed, for instance time-domain feature, frequency-domain feature, wavelet, etc. Selecting suitable features would lead to increase the accuracy of activity recognition. In the proposed framework, we use Short-Time Fourier Transform (STFT) and Hjorth parameter to extract seven features from reoriented accelerometer data, that are accelerometer energy (vertical and horizontal accelerometer energy), Hjorth mobility (vertical and horizontal mobility), Hjorth complexity (vertical and horizontal complexity). The Hjorth parameter is one of the ways of indicating statistical property of a signal in time domain. Activity parameter, the variance of the time function, can indicate the surface of power spectrum in frequency domain. That is, the value of Activity returns a large or small value if the high frequency components of the signal

exist many or few. Mobility parameter is defined as the square root of the ratio of the variance of the first derivative of the signal and that of the signal. This parameter has a proportion of standard deviation of power spectrum. Complexity parameter indicates how the shape of a signal is similar to a pure sine wave. Three kind of parameter as Table 1.

Parameter	Notation
Activity	var(y(t))
Mobility	$\sqrt{\frac{var(y'(t))}{var(y(t))}}$
Complexity	$\frac{mobility(y'(t))}{mobility(y(t))}$

Table 1. Three Hjorth parameters

The Fourier transform is used for analyzing a signal in entire frequency domain and shows the relative power of each frequency. The Short-Time Fourier Transform (STFT) is one of the most conventional feature extraction methods. We use function for STFT as

$$X(k) = \sum_{m=0}^{N-1} x[m].w[m].\exp(-j(2\pi/N)k.m)$$

Where $w[m]$ is a window function, then we compute four features of STFT for our framework.

2.4 The Online Training Model

Classification is an important step in the activity recognition process. The most commonly used classifiers are decision tree, support vector machine (SVM), K-nearest neighbor (KNN) and Naïve Bayes. In fact, a classifier first needs to be trained by using labeled activity database (training data). There are two training approaches: offline and online mode. In the online mode, the training is performed on smartphones. On the other hand, the offline training is done in advance, usually on a local machine. The most of existing studies use the offline training method [6]. One of reason is to reduce computational cost on smartphones. Nonetheless, the modern smartphones have much better computational capacity. This improvement of smartphones allows us to implement the online training in our MOARS. In addition, the accuracy of activity prediction can be empirically increased with the help of assistant feedback provided from users in real time.

2.5 Real time feedback activity recognition

In the monitoring module, sensor data of smartphone users are collected, then preprocessed by a number of steps such as reorienting, low pass filtering, high pass filtering, sampling, etc. Next, a set of features is extracted from the transformed data, which will be input for the classification process. In traditional activity recognition framework, real-time feedbacks from users are not taken into account. In our framework, MOARS, we eliminate this drawback in order to increase the accuracy in activity prediction. However, the challenge is to process such additional feedback information in short time. In the current version of MOARS, some activities are recognized from 2 to 4 seconds

3. Experiments And Results

3.1 Testing environment

We implemented our mobile online activity recognition system on the Android from 4.0 to 5.0 platform. The labeled activity database is collected by 20 subjects when walking or driving a motorbike. They freely carry a Samsung galaxy S4, Quad-core 1.6 GHz Cortex-A15 processor, 2 GB of Ram, 2600 mAh battery, Android 4.2.2 Jelly Bean. The set of activities for recognition is {stopping, walking, driving}.

3.2 Data collection

In our scenario, data is collected from 3 types of sensors: acceleration sensor, gyroscope sensor and magnetic sensor. Each sensor returns three values corresponding to x, y, and z coordinates. The raw data stream is first cut out 2 seconds at the beginning, and 4 seconds at the end as these time periods are usually redundant. Then, it is split into a number of windows of 6 seconds. We collected 100 examples for each subject.

Figure 3. The interfaces of Data collector and Monitoring modules

3.3 The accuracy of activity detection

We used four classification algorithms employed in the WEKA tool to predict the travelers 'status: Random Forest, KNN, Naive Bayes, SVM. In each case, the default setting was used. For evaluating the accuracy of each classification algorithm, we used 10-fold cross validation.

	Random Forest	**KNN**	**Naïve Bayes**	**SVM**
Stopping	94.64%	85.20%	80.00%	68.00%
Driving	86.00%	80.15%	72.00%	69.50%
Walking	90.30%	86.00%	85.00%	73.15%
Average	90.31%	83.78%	79.00%	70.22%

Table 2. The accuracy of activity recognition by MOARS

Table 2 shows the accuracy for detecting the current activity of smartphone users by MOARS can be up to 94.64% when Random Forest classifier is used. In fact, the accuracy for detecting Driving activity is lower than that of others. The reason is due to misinterpreting some similar patterns such as slowly driving and stopping.

Moreover, the results also indicate that Random Forest is more suitable for our MOARS framework since it always leads to higher accuracy as comparing with the other classifiers, i.e. KNN, Naïve Bayes, and SVM. Note that, our MOARS framework allows detecting the current user activity in the condition that their smartphones can be put at any position and in any direction. In a previous study, Berchtold et al. [7] could achieve 97% accuracy when smartphones are fixed, but only 63% accuracy when smartphones are randomly placed.

3.4 The processing time

Taking into account the real time feedback from users allows increasing the accuracy. However, it usually requires additional time for processing such information. Table 3 shows the average time to detect each type of activity by MOARS. As we can see,

Random Forest also spend least time for detecting user activity as comparing to KNN, Naïve Bayes, and SVM.

	Random Forest	**KNN**	**Naïve Bayes**	**SVM**
Stopping	2	2	3	4
Driving	1	3	2	2
Walking	3	3	3	4
Average	2.0	2.7	2.7	3.3

Table 3. The average detecting time required by MOARS (seconds)

4. Conclusion

In this paper, we proposed a flexible framework, called MOARS, for detecting current user activity when smartphones are randomly placed in any position and at any direction. In addition, our proposed framework also utilizes real-time feedbacks from users to increase the prediction accuracy. In the experiments, MOARS can achieve on average 90.3% accuracy for detecting all activities. In addition, Random Forest classifier is a promising one for our framework. In future, we are planning to further improve the current framework to either increase the activity prediction accuracy or reduce the processing time.

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