Smartphone-Based Activity Recognition Model (SBARM)

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Abstract - *This research aims to use context awareness data from Android mobile devices in activity recognition. This paper presents about a smart phone-based activity recognition model which can automatically record people's daily activities. The capability to recognize human activities is useful in different sectors such as healthcare, eldercare, target advertising and in many research platforms. Great deal of researches has been carried out in activity recognition using wearable sensors and mobile devices. But wearing sensors on human body can bring inconvenience and discomfort to the user. To avoid this mobile device can be used as an unobtrusive device in activity recognition. Even there has been several researches done using mobile devices, relatively little practical work has been in the area of applications. With this motivation, this project investigates the ability to recognize activities of a smart phone user such as Idling or phone-not-on-person, walking, running, jogging, climbing up stairs, climbing down stairs, travelling or driving and shopping through a smart phone. The data collection of this research has been carried out using the smart phone sensors over a period of 4s time window. Due to the limited memory availability of the smart phone, the collected data was sent to the server which provides the storage and processing. Then it has been pre-processed in order to eliminate noise and redundancy of data and the time domain features Mean, Variance and Standard deviation were extracted. Then the data is split into training set and test set. The training set is used to train the activity recognition algorithm and the test set is used to evaluate the recognition algorithm after training. The extracted features are the input data needed for the Hidden Markov Models (HMM) which is used in order to construct the activity recognition model.*
The recognized activities can be viewed in android dashboard application integrated with any applications.

Keywords: *Activity Recognition Model (ARM), Hidden Markov Model (HMM), smart phone, sensors*

1 INTRODUCTION

User context awareness is one of the emerging properties used in mobile applications and services in the area of ubiquitous computing. Human activity recognition is an important area of machine learning research because of the requirement of real-world applications. Getting to know the daily activities will be very useful for healthcare, eldercare, research platforms and target advertising.

There have been several researches done in activity recognition using mobile devices instead of wearable sensors which are obtrusive and uncomfortable to the user. But relatively little practical work has been in the area of applications. With this motivation, SBARM is proposed and designed to recognize daily activities through a smart phone.

2 LITERATURE SURVEY

Activities can be divided into two categories namely complex high-level activities such as cleaning, cooking or simple low-level physical activities, such as walking and running (Dernbach *et. al.*, 2012) Some existing works have explored user activity inference methods with accelerometer sensors. They can be divided into two major approaches: sensor-worn lab experiment approach and sensor-enabled mobile phone approach.

Some of the earliest work on wearable sensor based activity recognition used multiple accelerometers placed on different parts of the body and demonstrated that the use of dedicated accelerometers can provide good results in activity recognition (Bao and Intille, 2004), (Ravi *et. al.*, 2005), (Krishnan, *et. al.*, 2008). Then the idea was expanded with the inclusion of additional sensor information. For example, Lee and Mase proposed a system for recognizing activities using information about the user's location and inertial sensors such as accelerometers and gyroscopes (Lee and Mase, 2002). The collected data from five accelerometers placed on various body locations along with a heart rate monitor for implementing a real-time system to recognize thirty gymnasium activities (Tapia *et. al.*, 2007). It uses small sensors attached to a user's body or clothing. But using body sensors require daily effort from the user to wear and maintain them or else they are useless for collecting data (Lara and Labrador, 2013).

There have been few studies similar to the one proposed in this report, instead of placing different sensors on person's body that use commercially available mobile devices to collect data for activity recognition. Current generation smart phones are equipped with a variety of sensors such as GPS sensors, microphones, camera, light sensors, proximity sensors, temperature sensors, accelerometers, gyroscopes and compasses. These devices have become a part of our daily lives. Thus, the ubiquity and unobtrusiveness of the phones and the availability of different wireless interfaces, such as Wi-Fi, 3G, and Bluetooth, make them an attractive alternative platform for multisensory based HAR (Ustev *et. al.*, 2013).

For example, researchers have considered six activities to recognize user activities which are walking, jogging, ascending stairs, descending stairs, sitting, and standing using cell-phone accelerometer sensors (Kwapisz *et. al.*, 2010), (Yang, 2009), (Kwapisz *et. al.*, 2011). Some studies use the Smartphone GPS sensor to recognize transportation related activities (NA, 2005). It has used multiple sensors such as accelerometer, microphone, and pressure sensor for activity recognition (Khan, *et. al.*, 2014).

3 METHODOLOGY

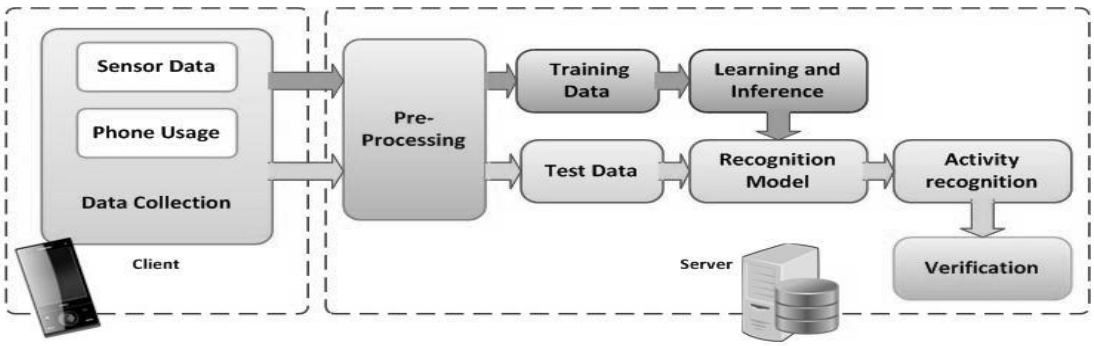

Figure1: Block diagram of SBARM

The block diagram of the system is shown above in Figure 1. The system comprise with two phases which are training phase and the testing phase.

- The recognition process starts with collecting data from the smart phone sensors and user performed activities on the phone
- Then the available sensor data is preprocessed to produce training and test data
- In training phase, Hidden Markov Modelis used to generate an activity recognition model from the dataset of extracted features
- In testing phase, the test data is sent to the activity recognition model to produce the recognized activity
- Finally the verification is done manually

Sensors

The smart phone sensors investigated in this project are shown in the Table 1.

Table 1: Inertial Sensors

Sensors	Description	Common Use
GPS Sensor	Longitude & Latitude Tolerance: 30% of measurements within 50m	Track location
Acceleration Sensor	Measures the acceleration force in m/s2 that is applied to a device on all three physical axes (x, y, and z), including the force of gravity. Range: 0…19.613	Motion detection (shake, tilt, etc.)
Gyroscope Sensor	Measures a device's rate of rotation in rad/s around each of the three physical axes (x, y, and z). x-axis(roll), y-axis(yaw) & z-axis(pitch) Range: 0…8.727	Rotation detection (spin, turn, etc.)
Proximity Sensor	Measures the proximity of an object in cm relative to the view screen of a device. This sensor is typically used to determine whether a handset is being held up to a person's ear. Range: 0…5	Phone position during a call
Magnetic field Sensor	Measures the ambient geomagnetic field for all three physical axes (x, y, z) in µT. Range: 0...2000	Creating a compass
Orientation Sensor	Measures degrees of rotation that a device makes around all three physical axes (x, y, and z). x-axis(-180<=pitch<=180) y-axis(-90<=roll<=90) & z-axis(0<=azimuth<360)	Determining device position

Activities

Proposed activities for this model are listed below,

- Idling/ Phone-not-on person (Sitting, Standing and etc.)
- Walking
- Running
- Jogging
- Climbingup stairs
- Climbing down stairs
- Travelling/Driving
- Shopping

Flowchart

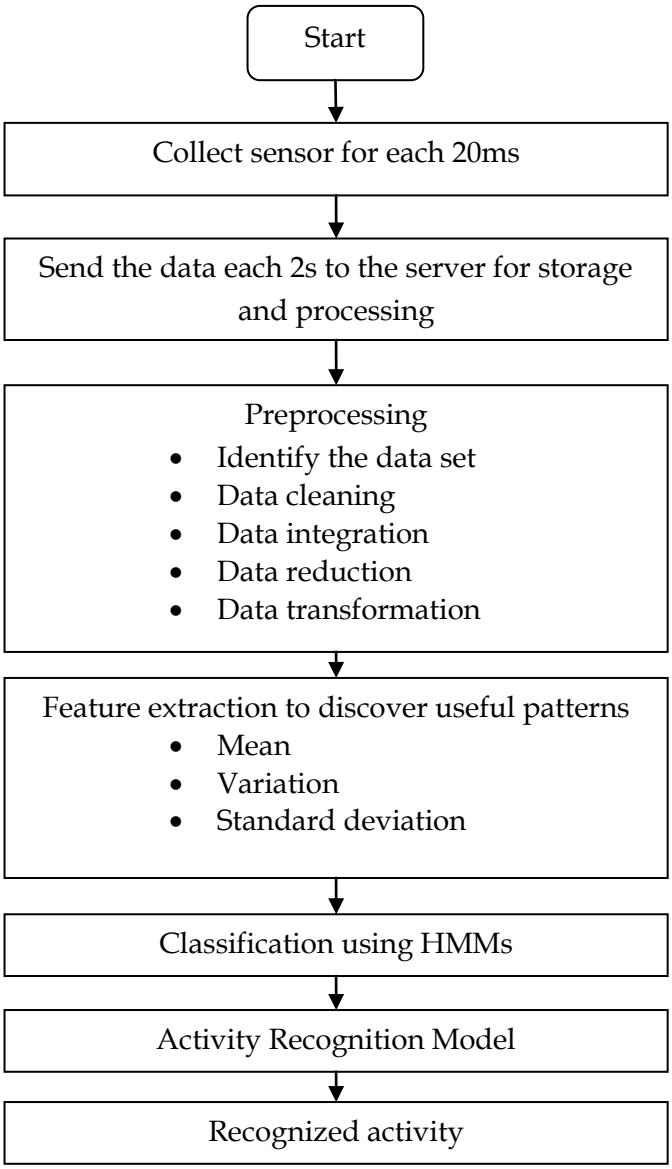

Figure 2: Flowchart of the system

4 IMPLEMENTATION

Android smart phone application has been developed to collect data and to send data to server for storage. Then Weka tool (V 3.7.11) has been used for further pre-processing and implementation of the activity recognition model.

Samsung Galaxy S2 smart phone is being used for data collection. Using this smart phone, data collected for different physical activities. They are walking, travelling and idle/phone-not-on-person. Only one participant used to perform these activities for a few minutes. As these are repetitive activities, so the amount of time for each activity was kept between 3-5 minutes, which gave enough examples for the evaluations.

Table 2: Activity performed by user

Activity	Smartphone on Body Position	Duration
Walking	Right Hand	3-5 minutes
Idle/Phone-not-on-person	Phone on the table while sitting	3-5 minutes
Traveling (By Bus)	Right Hand	10-15 minutes

Below fig. 3 shows the attribute patterns of all 3 activities; walking (dark blue), traveling/driving (red) and idling/phone-not-on-person (light blue).

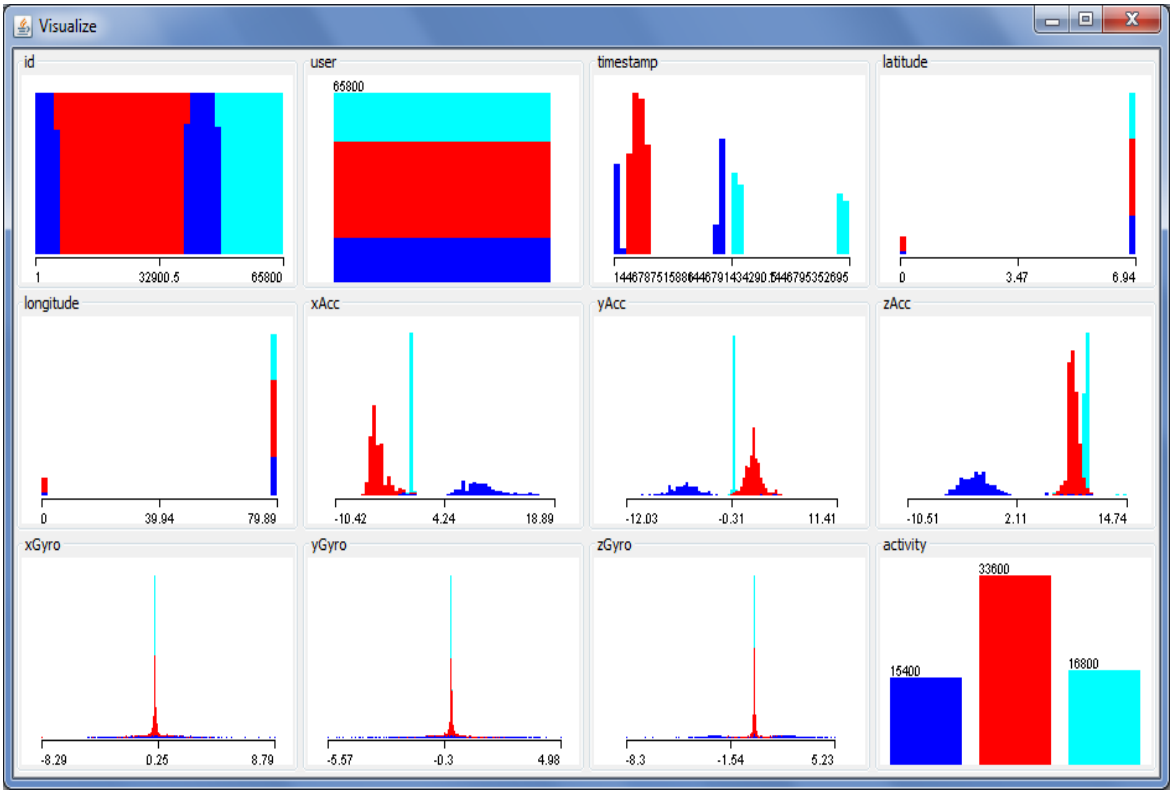

Figure 3: Attribute patterns for all activities

WEKA machine learning tool (Waikato Environment for Knowledge Analysis) was used for preprocessing and classification. Dataset were converted as csv (comma separated values) file format in order to use in Weka.

Selected Attributes:

- Timestamp
- Latitude
- Longitude
- xAcc (Accelerometer X-axis)
- yAcc (Accelerometer Y-axis)
- zAcc (Accelerometer Z-axis)
- xGyro (Gyroscope X-axis)
- yGyro (Gyroscope Y-axis)
- zGyro (Gyroscope Z-axis)
- Activity Label (Class)

Extracted Features: Maximum, Minimum, Mean & Standard deviation

Features were normalized and bounded within [-1, 1]

5 TEST EVALUATIONS

10-fold cross validation used for the evaluation. In 10-fold cross-validation, the data set is divided into 10 bins. Out of these ten bins, nine (90%) are used for training and one (10%) for testing. This process is repeated ten times, each time with a different bin for testing, thereby using all data, both for training and testing.

HMM classifier and Naïve Bayes classifier were used for classification.

Below Table 3 shows the classifier output for both HMM and Naïve Bayes.

Table 3: Classifier output

	HMM	Naïve Bayes
Correctly Classified Instances	23.4%	98.6%

Test dataset of activity walking and idle/phone-not-on-person has sent to the model built using HMM and Naïve Bayes, and the results shows in the Table 4.

Table 4: Test cases

Activity Performed	Expected Output	HMM Recognition Probability	Naïve Bayes Recognition Probability
Walking	Walking	100 %	100 %
Sitting	Idle/Phone-not-on-person	0 %	0 %

6 CONCLUSION

This project is focused on automatically recording physical activities of a user and views it in dashboard application on Android phone.

The three main contributions of this research are identification of the need to apply unobtrusive devices and applications of context awareness, the investigation for the use of classification algorithms for activity recognition, as well as the design of prototype application for the proposed model.

Many of the proposed solutions so far have investigated the use of sensor devices that are regarded as obtrusive and inconvenience for users to adopt their daily activities. This model is a solution for the above challenge in the way of using mobile phone sensors.

As per the results, it is hard to conclude that the HMM method always provide better results. Also the size of the dataset is small, since it is only collected from only one person and collected during a small time period. So if HMM can be trained with more data, the model can be improved.

Future works will be focused on improve the model with more recognition accuracy and to recognize more activities such as sitting, standing, sleeping and etc.

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