Remote Monitoring Using Smartphone Based Plantar Pressure Sensors: Unimodal and Multimodal Activity Detection

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Abstract. Automatic activity detection is important for remote monitoring of elderly people or patients, for context-aware applications, or simply to measure one's activity level. Recent studies have started to use accelerometers of smart phones. Such systems require users to carry smart phones with them which limit the practical usability of these systems as people place their phones in various locations depending on situation, activity, location, culture and gender. We developed a prototype for shoe based activity detection system that uses pressure data of shoe and showed how this can be used for remote monitoring. We also developed a multimodal system where we used pressure sensor data from shoes along with accelerometers and gyroscope data from smart phones to make a robust system. We present the details of our novel activity detection system, its architecture, algorithm and evaluation.

Keywords: Algorithm, Measurement, Performance, Design, Remote Monitoring.

1 Introduction

Physical activity (PA) is bodily movement produced by skeletal muscles that results in energy expenditure [1]. Automatic detection and measurement of physical activity has applications in context sensitive systems [5], for remote monitoring the activity of patients and to track one's own activity level. It also has application in the area of monitoring elderly people while maintaining their independence. For people with impairments, due to disease or injury, an estimation of activity level reflects his/her wellbeing. Such system provides a tool to doctors by enabling them to remotely monitor activity level of patients.

The automatic physical activity detection systems mostly use accelerometer data collected from accelerometers placed on different locations in the body [2], [3], [4]. For example, Bao [2] used 5 accelerometers and placed them in five different parts of the body. Some of the systems use other sensor data along with accelerometer data [3]. Such systems suffer from some limitations. First, many of these studies primarily focused on the task of activity detection and ignored the usability part resulting in an obtrusive system. Second, some of the systems [4] perform well in a controlled laboratory environment but not so well in naturalistic environment.

We present a system that is wireless, requires no extra devices to wear and was designed to accommodate human phone behavior patterns. Recent activity detection systems are smart phone-based as they are unobtrusive, have built-in accelerometers and people carry them everywhere. The problem with such system is that it is based on the assumption that the smart phone will be 'worn' by the users (usually in the pocket) all the time. Such assumptions are not necessarily realistic as we have observed that people often put their phone on the table while working on desk. It is found that people's phone carrying habits varies a lot depending on gender, country, culture, the type of activity she/he is engaged in and some other factors. Cui et al. studied the phone carrying behavior of people in 11 cities in Europe, America, Africa, the Middle East, India and East Asia extensively and showed in their paper [12] that generally women used bags (61% of women versus 10% of men) and men use trouser pockets as the primary way to carry a phone. A significant percentage of men (~14%) used belt cases to carry phones whereas the percentage of women using belt cases is insignificant. Culture also matters as 80% women in Helsinki carry phones in their handbags while only 50% do so in Delhi.

Consequently, people's behavior patterns limit the applicability of such systems although a smart phone based system is unobtrusive. Here, we present and discuss our novel activity detection system which overcomes this limitation. Also, at the same time as our system uses accelerometer and gyroscope data from smart phones and pressure data from pressure sensors placed in shoes, users will not be required to carry or wear any more devices they are not already carrying or wearing.

Our Contributions are manifold. First, we proposed a novel architecture for the unobtrusive detection of human physical activity using accelerometer and gyroscope data from smart phones as well as pressure data from shoes. Second, our architecture was designed to address unobtrusiveness as well as to ensure robustness against various human behavior patterns. Third, we built a prototype of the activity detection system using smart phones and plantar pressure sensors based on our proposed architecture that uses pressure data. Fourth, we developed the system so that activity can be monitored by someone remotely. Fifth, we analyzed data from 4 activities and based on our analysis we developed a fusion algorithm which uses accelerometer and gyroscope data from phone and pressure data from both shoes. We evaluated the performance of our fusion algorithm and observed very good accuracy.

The rest of the paper is organized as follows: section 2 discusses related works, section 3 describes the system architecture, section 4 discusses the prototype system we built, section 5 describes our multimodal system, and section 6 is discussion, conclusion and future works.

2 Related Works

Phone-based accelerometers were used to perform human physical activity recognition by different researchers. Kwapisz and et al. [6] used labeled accelerometer data from Android phones where as Yang [7] used Nokia N95. Miluzzo et al. developed CenceMe [8], using off-the-shelf, sensor-enabled mobile phones (Nokia N95) and exploited various sensors (such as a microphone, accelerometer, GPS, and camera) that are available for activity recognition. Sun Lin et al [14] used accelerometer embedded cell phones to detect physical activities where the phone location is varying. In all of the above cases, the solution is phone based and the assumption is that the phone will be carried by the users all the time in their pockets.

Some studies tried using multiple sensors. Subramanya et al. in [9] built a model using data from a tri-axial accelerometer, two microphones, phototransistors, temperature and barometric pressure sensors, and GPS. Choudhury in [3] used multiple sensor devices consisting of seven different types of sensors to recognize activities. Cho et al. used a single tri-axial accelerometer, along with an embedded image sensor worn at the user's waist to identify nine activities [10]. Gyo¨rb´ıro´ et al. [11] used "MotionBands" attached to the dominant wrist, hip, and ankle of each subject to distinguish between six different motion patterns. Each MotionBand contained a tri-axial accelerometer, magnetometer, and gyroscope and transmits the collected data wirelessly to a smart phone. The average recognition rate was 79.76%.

3 Architecture

We propose an architecture where pressure sensors will be placed on the shoes and pressure data will be transmitted over Bluetooth to smart phone carried by the user. It does not matter where the phone is being carried as long as the phone is within the Bluetooth range of from the shoes. Our system works in two phases: Learning Phase and Activity Recognition Phase. In the learning phase, after the sensor data is collected and processed, the data is analyzed to develop an algorithm. In the activity recognition phase, the algorithm is implemented and the incoming sensor data is used by the algorithm to detect activities. Figure 1 shows this.

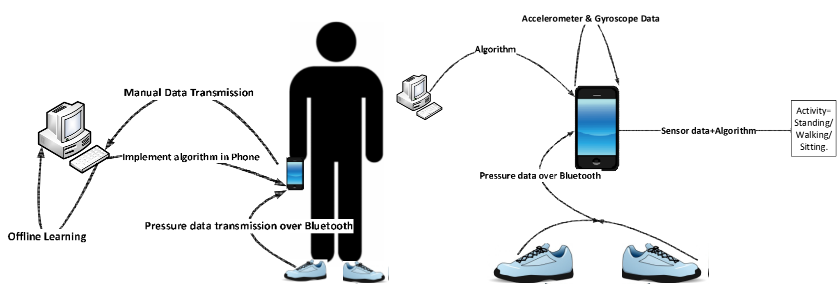

Fig 1. (a) Architecture (Learning Stage) **(b)** Architecture (Activity Recognition Stage)

Our system has two principal components: the Data Collection System and the Activity Recognition System (AR). The Data Collection (DC) System is responsible for collecting sensor data. In our case, we are collecting pressure data from pressure sensors placed on the sole of both shoes, and accelerometer and gyroscope data from the cell phone and store them in four files. We used DC in two stages. First, the DC is used to collect the data and the collected data was later used to learn a classification algorithm. Second, the learnt algorithm detects activities from the incoming sensor data collected by DC during the activity recognition phase. The activity recognition system mainly consists of implementing the algorithm that was learnt in the learning phase. AR takes the sensor data as input continuously and detects the activities real-time and outputs the activity.

4 Prototype Remote Monitoring System

Based on the proposed architecture, we developed a prototype of activity recognition system. To reduce complexity, we only intended to detect sitting, standing, and walking. Also, instead of using data from all sensor systems, we only used pressure data from the left shoe. Development of the system consisted of five stages: data collection, data processing, learning algorithm, implementing recognition system and remote monitoring.

We decided to use an in-shoe plantar pressure sensor system based on a fabric sensor array. This system was developed by Lin Shu and others [13]. It has 8 pressure sensors in each shoe. There is also a Bluetooth interface to transfer the pressure data to an android phone.

Data Collection. We used the system for collecting pressure sensor data. We used data from only the left shoe. We collected data of sitting, standing and walking. While the data was being collected, the phone was in the user's hand. The collected data has 8 columns for data from 8 pressure sensors along with a time stamp.

Data Processing. We removed corrupted data from the beginning and the end as those data are likely contaminated by data collection process. There are about 37 samples of data for each second (sampling rate 37Hz). First, we created a summery file where each row is a summary of 160 samples of raw data. Summary file for each of the three activities were generated. Each summary file contains 40 columns of data as we estimated mean, median, mode, standard deviation and summation of 160 samples for each of 8 pressure sensors of the left shoe. Then, we merged these three summary files and added another column at the end to indicate the activity class (sit/stand/walk).

Learning and Activity Recognition. We applied a decision tree based machine learning algorithm which generated a decision tree classifier. This classifier algorithm was able to classify correctly with 98.83% accuracy. After we implemented this classifier in our recognition system, we found it took a long time to detect the activity.

According to our previous calculation, 160 samples should take 4.3 seconds at 37Hz sampling rate. But it took much longer than that. To address this issue we reduced sample size to 60 from 160. As a result, the accuracy remained the same but it took less time to detect the activities than the prototype activity detection system. Whenever new data comes, the oldest data from buffer is discarded and features are calculated again. Then the algorithm is used to derive the activity.

Remote Monitoring. Following figure (Fig 2) shows a screen shot from our remote monitoring system. A user can login to view the summary of activities by date. After date column, first column is sitting time, followed by standing time and walking time in seconds.

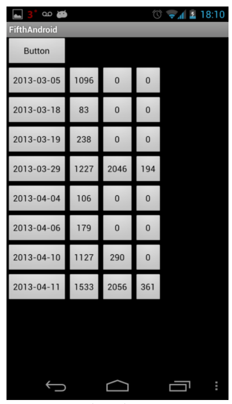

Fig. 2. Remote monitoring system screen shot

5 Multimodal Approach

In the multimodal approach, we combined four classifiers obtained from analyzing data from gyroscope, accelerometer, right and left shoe. Each classifier was obtained following data collection, processing and learning. Four classifiers were combined and in the recognition phase, the combined classifier was used to detect activity.

System Description. We used three services on the android platform: 'TestService', 'GyroService' and 'DataReceiverService'. 'TestService' and GyroService, when started, collect data from the accelerometer and gyroscope in the cell phone respectively and stores it the SD card in two separate files. DataReceiverService' in similarly collects pressure data from the left and right shoes. In all cases, the time stamp is also recorded along with the data. Later during the preprocessing stage, we used the timestamp for synchronization so that data from all four sources start and end at the same time. While collecting data earlier for our prototype system, we only used pressure data from left shoe. Pressure data was transmitted over Bluetooth to the smart phone. As we were not collecting data from cell phones, the location of the phone was not important. But this time, we are collecting data simultaneously from the left shoe, the right shoe, the phone's accelerometer and the phone's gyroscope during different activities. The phone was kept in the right pocket of the trouser.

Data Collection. We collected data for four different activities: standing, sitting, walking and running. As we need to synchronize data from all four systems (gyroscope data collection system, accelerometer data collection system, left shoe data collection system, right shoe data collection system), we needed the timestamp. For each activity, we collected data three times (3 minutes each time).

Data Processing. Data preprocessing is very similar to what we did while developing our prototype. The extra step we did here is some extra preprocessing to ensure the synchronization of data from four different sources. We compile our data so that in each file we have the summary data for running, sitting, standing and walking. There are four such files for each of the four kinds of data: left shoe data, right shoe data, gyroscope data and accelerometer data (total 16files). Next we make a single file for each of the four sensor systems with an additional column indicating the activity.

Learning. Then, we applied decision tree algorithms to each file compiled to find a classifier. In each case, the decision tree algorithms gave us a classifier. Now we have four classifiers for each of four kinds of data from four sensor systems. The classifiers are mentioned below.
*Classifier 1.*This one classifies based on the accelerometer data. The accuracy is 99.5305 %.
*Classifier 2.*This classifier classifies based on the gyroscope data. The accuracy is 94.3662 %.
*Classifier 3.*This one classifies based on the pressure data from the left shoe. The accuracy is 99.061 %.
*Classifier 4.*This one classifies based on the pressure data from the right shoe. The accuracy is 98.8263 %.

Combined Algorithm for Activity Recognition. In this setting, we developed the following algorithm which basically is a fusion of four classifiers. Classifier 1 takes accelerometer data as input and outputs an activity. In the same way, classifier 2, 3, and 4 takes gyroscope data, pressure data from left shoe and pressure data from right respectively. All four classifiers output activity based on the decision tree they have learnt previously in the learning phase. After each classifier gives an activity as output, the algorithm decides the final activity based on the majority vote.

Activity Recognition and Evaluation. In this particular setting, we have 4 files each consisting of 426 rows of summary data. Each of these rows was created using a summary of 60 samples of pressure data (or 80 samples of accelerometer data from phone or 167 samples of gyroscope data from phone). Four separate classifiers were learnt (decision tree, in our case) based on four separate datasets in the learning phase. Now in the recognition phase, for a given input, each decision tree decides an activity using the corresponding classifier. Final activity is decided based on what the majority of classifiers has decided. In the case of a tie, the system fails to classify.

Here we discuss the results of this algorithm. Our results show that though each classifier individually shows errors, their combination results in a zero error system. For example, row 94 is classified as sitting by classifier 1, while classifier 2 decides it to be walking, classifier 3 and 4 both classifies it to be running. So the final activity will be decided as running (voted by majority classifiers). The following table summarizes different combination of sensor systems and corresponding number of errors (misclassification) by the arrangement.

Table 1. Relative performances

Structure	Number of errors
Classifier 1,2,3,4	**0**
Classifier 1,2,3	1
Classifier 1,2,4	1
Classifier 1,3,4	0
Classifier 2,3,4	0
Classifier 1,2	9
Classifier 1,3	1
Classifier 1,4	3
Classifier 2,3	9
Classifier 2,4	12
Classifier 3,4	3

As we can see, combined algorithm uses data from all four sensor system and using this algorithm for our data, there was zero error. Average number of errors in general decreases with the incorporation of more and more sensor system as can be seen in Fig 3.

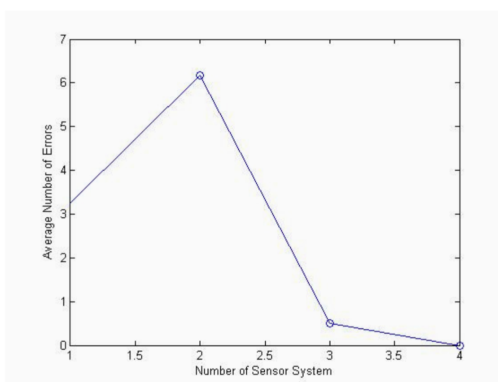

Fig. 3. Number of Sensor Systems vs Average Number of Errors

6 Discussion, Conclusions and Future Works

In Table 1, we want to emphasize the last row where we showed classifier 3 and 4 together made 3 errors. Classifier 3 and 4 were learnt based on pressure data collected from the left shoe and the right shoe. These two classifiers take pressure data as input during the recognition time. This means that classification based on only shoe data is possible with reasonable accuracy. As a result it is possible to detect activities in scenarios where people take their phone out of their pocket assuming they are keeping their shoes on. The advantage is that although people tend to use their phones in various ways, the phone is almost always within the Bluetooth range of them hence in range of their shoes. This shows that our architecture ensures robustness against various human behavior patterns.

Also, we plan to incorporate our fusion algorithm and use all four kinds of data in our future prototype. We are working on to deploy our current prototype to monitor patients remotely and evaluate its performance. We showed that a decision made from the data of multiple sensors is more accurate than decisions made from data of a single sensor system. The goal is to detect more activities, like climbing up and down stairs, driving and biking.

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