Development of a human movement monitoring system based on wearable devices

Xiaochen Zheng, Joaquín Ordieres-Meré

Abstract**—**It is essential to remotely and continuously monitor the movements of individuals in many social areas, for example, taking care of aging people, physical therapy, athletic training etc. Many methods have been used, such as video record, motion analysis or sensor-based methods. Due to the limitations in remote communication, power consumption, portability and so on, most of them are not able to fulfill the requirements. The development of wearable technology and cloud computing provides a new efficient way to achieve this goal. This paper presents an intelligent human movement monitoring system based on a smartwatch, an Android smartphone and a distributed data management engine. This system includes advantages of wide adaptability, remote and long-term monitoring capacity, high portability and flexibility. The structure of the system and its principle are introduced. Four experiments are designed to prove the feasibility of the system. The results of the experiments demonstrate the system is able to detect different actions of individuals with adequate accuracy.

Keywords**—**accelerometer, movement monitoring, smartwatch, smartphone, wearable device.

I. Introduction

THE body movements of a human being can reflect their behavioral habits and functional activities. The ability to record and analysis these movements is essential in many areas, for example, taking care of aging people, physical therapy, athletic training, sports monitoring etc.

Several methodologies have been used to monitor the human movements, from questionnaires in early days [1] to video records [2] and motion analysis [3] later on. With the development of wireless communication and sensor technology, inertial sensors have been widely applied for this purpose [4]-[8], since they have good performance with high accuracy, good repeatability, and relatively low price [9]. Among different kinds of sensors, the tri-axial accelerometer is one of the most popular ones. Its high accuracy has been proved by many researches [10]-[14]. However, there still remain some drawbacks of these methods in practical applications. For example, the accelerometers send data directly to a computer through wireless communication with a distance limitation; some sensors are specially-made under the laboratory environment and they are inconvenient for the user to carry around. Attempts also have been made to use the accelerometers inside smartphones [15], [16]. The imperfection of such solutions also lies in the inconvenience of attaching the smartphone onto the user's body.

In recent years, the fast growth of wearable technologies provides a new option for monitoring the movements of individuals without the limitations described above. Wearable devices may be worn under, over, or in clothing, or may also be clothes themselves [17]. The improvement of various technologies creates the best environment ever for the application of wearable devices: more efficient and smaller high capacity batteries provide enough power; sensors become smaller and processors become faster without overheating or requiring active cooling systems [18]. As good examples, smart glasses, smartwatches, smart bands, smart shirts and so on are already influencing the lives of thousands of users.

The objective of this paper is to develop a human movement monitoring system that (1) can continuously collect a user's movements data and send it to a remote server in an accurate and efficient manner; (2) has wide adaptability, like waterproof capability, without distance limitation; (3) has the ability to process and analyze a large amount of data; (4) is easy to carry without causing any inconvenience to the user. The system is based on a three layer model composed by a Pebble watch (a smartwatch containing a tri-axis accelerometer), an Android smartphone and Elasticsearch (a distributed data management engine) on a remote server.

The rest of this paper is organized as follows: an overview of the method is presented in section 2. Experiments and results are described in section 3. Section 4 discusses the advantages and limitations of the system. Conclusions and future works are given in section 5.

II. Method Overview

The proposed movement monitoring system contains three parts: (1) a Pebble smartwatch for recording the user's arm movement data; (2) an Android smartphone receives data from Pebble and sends it to remote server together with data collected from its GPS sensor and accelerometer; (3) a data search and analytic engine on remote server for data storage and analysis. The overall architecture of the system is shown in Fig. 1.

This work is partially supported by the China Scholarship Council.

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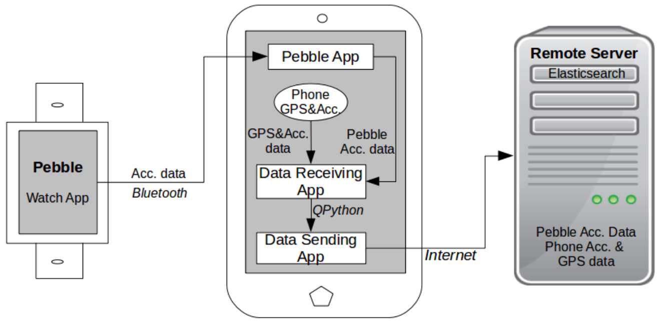

Fig.1 three-layer architecture of human movement monitoring system

A. Data Collection with Pebble

Pebble is a smartwatch released in early 2013, which contains a tri-axis accelerometer and Bluetooth 4.0. The accelerometer can measure acceleration caused by gravity or some type of physical movements as simple as the twist of a wrist or the flick of a finger. It is calibrated to measure a maximum acceleration from -4G to +4G, measured in milli-Gs (mG). Therefore, the range of possible values for each axis is -4000 to +4000 mG, which is enough for monitoring the normal human movements.

The application on Pebble watch is supposed to collect the raw data from the accelerometer hardware and relay it to the smartphone. To accomplish this goal, several Pebble Application Program Interfaces (APIs) are used in our application, for instance, accelerometer, data logging, UI framework and event services. The application is developed on Cloud Pebble, which is a cloud development platform provided by Pebble Technology. The interface of the watch application is shown in Fig.2.

Fig. 2 User interface of the Pebble watch application

Five values are recorded by the application: a timestamp value to identify the time when the action happens, acceleration values on the three axes and an angle value to show the angle between wearer's arm and the horizontal plane. The first 4 values are produced by the accelerometer itself and the angle is calculated from the three acceleration values according to equation 1. Fig. 3 illustrates the calculating method. The value of the angle ranges from -270° to 90°.

$$Angle = \operatorname{atan}2(acc.z, acc.a) \cdot 360° / (2\pi) - 270° \quad (1)$$

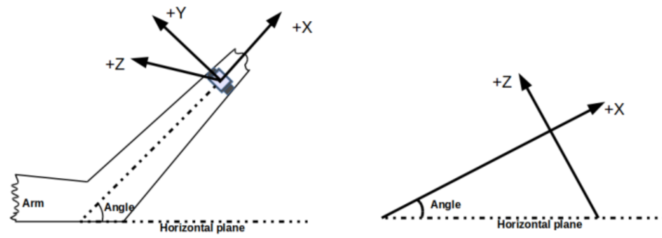

Fig. 3 Angle of the wearer's arm

These 5 values are recorded every 300 milliseconds (3.33 Hz), thus 200 records are produced in 1 minute. This frequency can be set to as high as 1000 Hz according to different scenarios. The data is stored in data logs created by the application. A new data log is created every one minute after the end of the previous one. If the Pebble watch is connected to a smartphone via Bluetooth, the data logs will be sent to the smartphone immediately, and if the smartphone is not available, the data logs will be saved in the memory of the smartwatch until the smartphone is connected. This character makes the system more flexible in real life scenario, since the users do not have to carry the smartphone with them all the time. This is especially important when doing sports like running or swimming. Fig.4 shows the data stream in the Pebble watch.

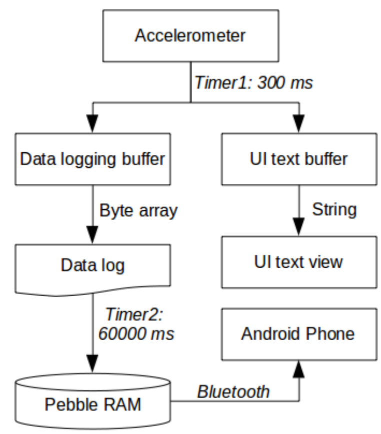

Fig. 4 Data flow inside Pebble watch

B. Data Integration and Transfer with Android

The smartphone in our system is responsible for collecting body posture information and transferring data to the server. It contains three components:

(1) Data reception from Pebble

The task of receiving data from Pebble watch is completed by the Pebble App on Android, which is an application provided by Pebble Technology Company. The received data logs will be saved into the App buffer space in the format of byte array. They can be exported to other Android applications for further utilization through Pebble APIs.

(2) Data extraction and integration

Every Pebble watch application possesses a Universally Unique Identifier (UUID). The Pebble API object *PebbleKit.PebbleDataLogReceiver* is able to identify a certain watch application through this UUID and extract the data logs produced by it from the Pebble App buffer space mentioned above. Based on this API, another Android application is developed to extract watch data and combine it with that collected from smartphone sensors.

The integrated data is then saved into a local text file every 200 records (the amount of data produced in 1 minute). The format of the data is changed from byte array to string before being saved. The text files are named with the data log timestamp to make them easier recognized. A sample record of data is presented in Fig. 5. The value of the timestamp is the number of milliseconds since the epoch time.

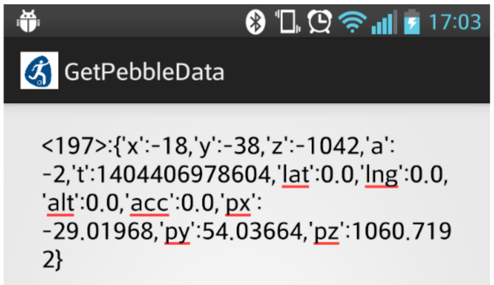

Fig. 5 Data receiving UI

Besides the 5 values collected by the Pebble watch, 7 more parameters are added to the records which represent the information collected from smartphone sensors, as shown in Fig. 5. The first 4 parameters, *'lat'*, *'lng'*, *'alt'* and *'acc'*, indicate the location information collected from GPS sensor, referring to latitude, longitude, altitude and accuracy respectively. The last 3 parameters, *'px'*, *'py'* and *'pz'*, indicate the acceleration values on the three axes of the accelerometer inside the smartphone.

Since the smartwatch can only measure the movements of the arm, the data collected from the smartphone sensors can help analyze the location of the users and their body postures.

(3) Data uploading to remote server

A mechanism composed by Scripting Layer for Android (SL4A) [19], QPython [20] and a Python script is built to upload the data from the smartphone to the remote server. SL4A brings scripting languages to Android by allowing users to edit and execute scripts and interactive interpreters directly on the Android device [19]. QPython is a script engine running on Android devices. It embeds the python interpreter, console, SL4A library for android, which can make the android device run python script or project [20].

After the above processes, the data collected from the Pebble watch and smartphone sensors is saved into text files in a local folder. A Python script file is created for sending this data to the server. When this script is running supported by QPython and SL4A, it will check if there is any .txt file in the above folder. If any text file is found, it will send the data to the remote server through Internet and delete the file after all the data inside has been sent. This process is repeated until all the text files are uploaded and deleted. Fig. 6 illustrates the working process.

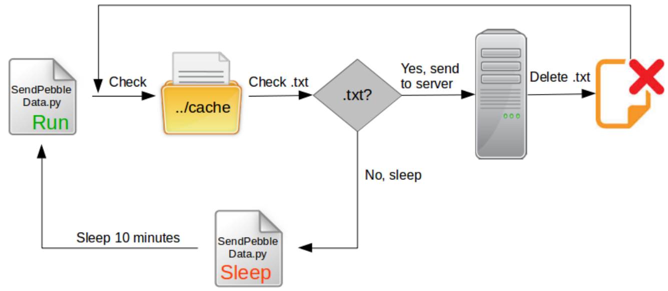

Fig. 6 Upload data from phone to remote server

C. *Data Storage with Elasticsearch*

On the remote server, Elasticsearch is used to manage the data received from the smartphone. Elasticsearch is a flexible and powerful open source, distributed, real-time search and analytic engine [21]. Each record received from smartphone is saved as a doc in Elasticsearch.

Search conditions of Elasticsearch can be defined very flexibly. We can either use the combinations offered by it or define more complicated conditions by programming. The search result can be presented in three different formats: table, JavaScript Object Notation (JSON) and Comma-Separated Values (CSV). It is convenient to export the data to different software for further studies.

III. Experiments and Results

Four experiments are designed to test the ability of the system to: (1) distinguish different actions of the user; (2) separate different movement habits of different individuals; (3) continuously monitor the movements of the user for a long time; (4) collect information from different sensors of both the smartwatch and smartphone.

A. *Experiment 1*

In the first experiment, the participant wears a Pebble watch on his left wrist and performs 4 actions sequentially: sitting and inputting on the keyboard, standing and talking with a cup in the left hand, normally walking and jogging, as shown in Fig. 7. Each action lasts for about 30 seconds.

Fig. 7 Actions of first experiment

ISBN: 978-1-61804-254-5

The collected data is exported from Elasticsearch as CSV format and the analysis is finished with R, which is a language and environment for statistical computing and graphics [22]. As mentioned before, the collected data includes the acceleration values on the three axes and the angle of wearer's arm. All these parameters change with the movement of the wearer's arm. The result is plotted in Fig. 8.

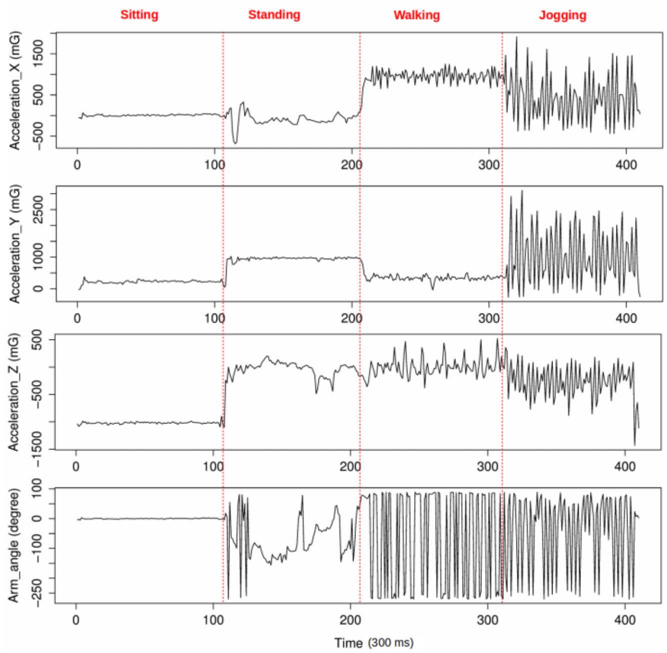

Fig. 8 Data collected during the 4 actions of first experiment

It is obvious in the figures that all the values are divided into 4 different periods and each period covers about 100 records. This experiment indicates how the system can be used to distinguish different actions of the same person at different times. We can also use it to compare the same action taken by different individuals. In other words, the system is able to figure out if the same person is wearing the Pebble watch all the time.

B. *Experiment 2*

In the second experiment, another participant (marked as Person B) is invited to perform the same actions as the one (marked as Person A) did in the first experiment. To make the result clear, we selected the acceleration values on the X axis of the walking action and plotted them together (Fig. 9).

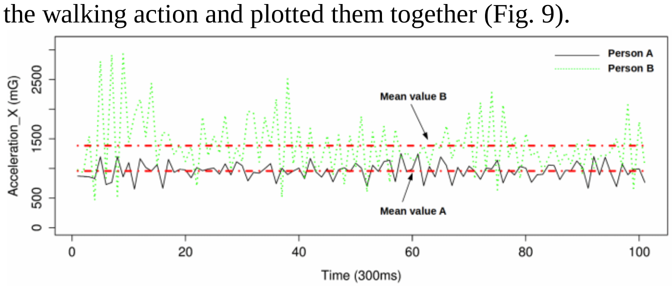

Fig. 9 Comparison results of two individuals

The difference is clear, since an obvious gap exists between the mean values of the two individuals, although their frequencies are similar. This result demonstrates that people's walking habits are not all the same. A possible application of this principle is to develop anti-theft applications for smart devices.

C. *Experiment 3*

In the third experiment, the movement data of a whole day was collected to test the system's ability to monitor the wearer's movements consistently. Part of the result is shown in Fig. 10, including the data of sleep at night and some actions in the morning.

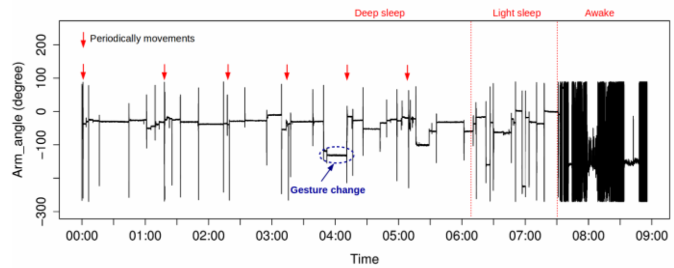

Fig. 10 Long term monitoring result

The participant begins to sleep at 00:00 and wakes up at 07:30. A sharp distinction between sleeping and waking appears in the result. The result also shows the difference between deep sleep and light sleep. During the first 6 hours, a few movements appear regularly, approximately every one hour. After 06:00, the frequency of movement increases evidently, indicating the beginning of light sleep. More details about the morning actions can be found in the following zoom-in chart (Fig. 11).

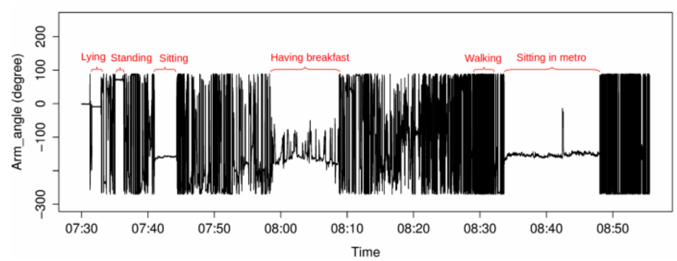

Fig. 11 Analysis of actions in the morning

A series of actions are reflected in Fig. 11: the individual wakes up at 07:30 in the morning and stays lying in bed for a few minutes after turning off the alarm, then gets up and goes to the bathroom, sits and reads news on his smartphone, sits and has breakfast, walks in the street and sits in the metro etc.

D. *Experiment 4*

A limitation of using a smartwatch to monitor human action is that it can only measure the movements of the arms. The accuracy decreases when it is necessary to identify body postures, such as monitoring sleep habits or detecting falls among aging people. Considering people usually carry smartphones in their pockets, the data produced by the sensors inside the smartphone is also collected by the system to help identify users' postures.

In this experiment, we compared the data produced by the accelerometer of the smartphone during 4 postures: standing still, sitting on a chair, lying supinely and lying prostrate. The participant carried the smartphone in his trousers pocket close to the thigh. The result is shown in Fig. 12.

ISBN: 978-1-61804-254-5

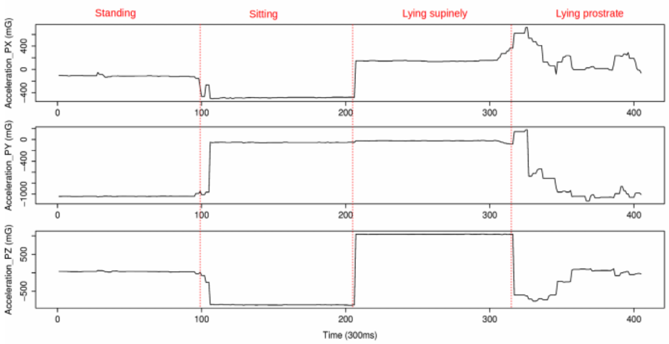

Fig. 12 Smartphone accelerometer monitoring result of different postures

The acceleration values on each axis differ distinctly between different postures. It suggests that the system is able to distinguish user's postures. After integrating both the data from Pebble watch and the smartphone, a more accurate monitoring result of human actions will be available.

The results of these 4 experiments demonstrate that the system is able to monitor the user's movements consistently with adequate accuracy. In practice, this ability is useful in many areas. For example, applications can be developed to analyze and increase the users' sleep quality, remotely monitor the movements of aging people, make better physical therapy plans for patients and so on.

IV. Discussions

The system presented above has several advantages in monitoring movements of individuals compared with similar methods proposed before. However, there are also a few limitations, which are supposed to be solved in the near future with the fast development of wearable technologies. Both the advantages and limitations of the system are discussed as follows:

A. Advantages

Wide adaptability: Instead of sending data directly from the accelerometer to the computer, this system uses a smartphone as a data transfer station. The collected data can be saved in the smartwatch or in the smartphone temporarily and sent to remote server when it is possible. This eliminates the distance limitation. Besides, the waterproof characteristic of the Pebble watch enables it to work in wet environments, like bathing, swimming or even diving.

Remote and continuous monitoring: The monitoring results can be sent to a remote server in almost real-time via the Internet. The users can have access to the result whenever they want to. This is especially useful when taking care of aging people or physically disabled people. Moreover, Pebble smartwatch is able to work for as much as 5 days supported by a battery inside, so the system can continuously monitor the user's movements for a long term.

Data analysis capability: Elasticsearch, which is a distributed, real-time search and analytic engine, is used to manage the collected data. More information can be extracted from the data with the help of machine learning and cloud computing technologies.

Faddish and convenient: Both the smartwatch and smartphone are popular elements in our society. The monitoring function can be accomplished without imposing any extra effort to the user. That makes this system easy to spread in the future.

B. Limitations

In this system, the smartphone works as a second data source to record the location and the body posture of the user in some scenarios. In order to match correctly with the data from Pebble watch, the Android application runs continuously to record the GSP and accelerometer data, which is quite power consuming. Besides, as a data transfer station, the smartphone needs to communicate with Pebble watch and remote server frequently, which also consumes much power. Consequently, the already dissatisfied battery life issue of the smartphone gets worse. This problem can be relieved by adopting other wearable devices, like smart-shirt, to detect the body movements of the user instead of the smartphone.

The immaturity of wearable technologies also creates some limitations to the system. For example, the storage capacity of the Pebble watch is only 640KB, which is not large enough to support long term monitoring without a smartphone. The old data logs will be over written by the new ones after the data pool is full. So the adaptability of the system is weakened currently in real life scenarios. This limitation is supposed to be overcome in the next version of Pebble watch.

V. Conclusions and Future Works

A human movement monitoring system based on a smartwatch, a smartphone and a remote distributed data management engine is developed. Experiment results demonstrate the feasibility of the system in performing the task of remote, long-term and continuous monitoring movements of individuals with adequate accuracy.

The work introduced in this paper focuses on the development of a data collection system. More efforts need to be made in data analysis after enough data is collected with the help of machine learning and cloud computing techniques. Possible directions include: study of movement recognition algorithms; development of practical applications, such as movement monitoring applications on smart devices for aging people; integration of the collected data with information from other sources, like social networks and intelligent household appliances, to better study the behavior of people.

Acknowledgment

Author Xiaochen Zheng thanks the financial support by the China Scholarship Council.

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