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Capturing and Analyzing Wheelchair Maneuvering Patterns with Mobile Cloud Computing

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Abstract— **Power wheelchairs have been widely used to provide independent mobility to people with disabilities. Despite great advancements in power wheelchair technology, research shows that wheelchair related accidents occur frequently. To ensure safe maneuverability, capturing wheelchair maneuvering patterns is fundamental to enable other research, such as safe robotic assistance for wheelchair users. In this study, we propose to record, store, and analyze wheelchair maneuvering data by means of mobile cloud computing. Specifically, the accelerometer and gyroscope sensors in smart phones are used to record wheelchair maneuvering data in real-time. Then, the recorded data are periodically transmitted to the cloud for storage and analysis. The analyzed results are then made available to various types of users, such as mobile phone users, traditional desktop users, etc. The combination of mobile computing and cloud computing leverages the advantages of both techniques and extends the smart phone's capabilities of computing and data storage via the Internet. We performed a case study to implement the mobile cloud computing framework using Android smart phones and Google App Engine, a popular cloud computing platform. Experimental results demonstrated the feasibility of the proposed mobile cloud computing framework.**

I. Introduction

Independent mobility is important to people of all ages. For example, mobility is an essential indicator for adults with disabilities to evaluate their quality of life and levels of participation in social activities. For young children, independent mobility, such as rolling, crawling, or walking, is associated with their social, cognitive, perceptual, and motor development [1]. Young children with severe motor impairments are at risk for secondary impairments in the aforementioned areas due to locomotor limitations [2]. To acquire independent mobility, power wheelchairs are widely used. It is estimated that more than 200,000 people in the United States use power wheelchairs as their primary means of mobility [3].

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However, wheelchair maneuvering typically requires hand-eye coordination and precise motion control, which is very challenging for people with disabilities, especially for aged or young wheelchair users. Accidents related to wheelchair maneuvering occur frequently and may be accompanied by serious results [4, 5]. To provide safe and improved wheelchair maneuvering, intelligent robotic assistance for wheelchair maneuvering is necessary [6]. Intelligent robotic assistance consists of various assistance algorithms to intelligently assist different maneuvers (e.g., driving straight forward or backward). Foremost, wheelchair maneuvering data should be captured and analyzed to extract maneuvering patterns and enable accurate and safe intelligent robotic assistance.

This study aims to capture wheelchair maneuvering data, which are used to (1) quantify wheelchair maneuvering patterns for use by assistance algorithms; (2) recover wheelchair movement trajectories to quantify wheelchair users' daily activities; and (3) gauge activity and participation levels since mobility is essential to ensure regular social activities and improve the quality of life for people with disabilities.

Traditionally, professional accelerometers, e.g., ActiGraph monitors [7], are regularly used to quantify wheelchair maneuvering activities. The accelerometers are installed on the wheelchairs to continuously record maneuvering data for a certain period of time (e.g., one week). The disadvantages of such a data collection scheme are threefold. First, only offline analysis is possible because analysis can only be performed after the data collection process is finished. Second, it is hard to manage massive data files. With a sampling duration of one week and frequency of 30 Hz, 18 million data points would be generated. This amount of data can be difficult to export into portable and manageable files. For example, the management software of ActiGraph supports the export of recorded data into an Excel file. However, older versions of Excel imposed a 65,536 row limit, and although newer versions (2007 and later) have raised this limit to 1,048,576 rows, one week's data will still exceed this size limitation. Third, such a data collection scheme is expensive. Dedicated personnel are required to travel back and forth between the research lab and research participants' homes to install accelerometers on research participants' wheelchairs and periodically fetch maneuvering data. The cost incurred by dedicated personnel and travel is high. In addition, accelerometer sensors are expensive. For example, an ActiGraph package, including software, USB cables, and one monitor, is more than $1,200.

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To overcome the aforementioned issues associated with using accelerometers to monitor wheelchair maneuverability, we propose to use mobile cloud computing techniques to capture, store, and analyze wheelchair maneuvering data. Accelerometers and gyroscopes are typically equipped in smart phones, such as iPhones and Android phones, and such smart phones have become extremely pervasive in the modern world. Therefore, it is practical and convenient to use smart phones to capture wheelchair maneuvering data. The use of smart phones potentially enables more wheelchair users to participate in the research and alleviates costly travel expenses. More importantly, the cloud can extend smart phones' computational and storage capabilities through the Internet. The combination of these two techniques yields the so-called mobile cloud computing, which leverages the benefits of both techniques.

The rest of the paper is organized as follows. Section II presents a general mobile cloud computing framework for data collection, storage, and analysis. Correspondingly, we discuss how to use mobile phones to collect data and how to store, smooth, and process data in the cloud. Then, we evaluate the framework with a case study in Section III and present our conclusions in Section IV.

II. A General Mobile Cloud Computing Framework

In this section, we present a general mobile cloud computing framework designed to overcome the disadvantages of traditional accelerometers and gyroscopes, namely, offline-only analysis, massive data files, and high cost.

A. *Objectives*

Mobile cloud computing makes it possible to conveniently record wheelchair maneuvering data in real-time at low cost. Figure 1 illustrates the major elements in the framework, including wheelchairs, smart mobile devices, and information recipients, such as mobile users with smart phones, tablets, laptops, etc., and traditional users with desktop PCs.

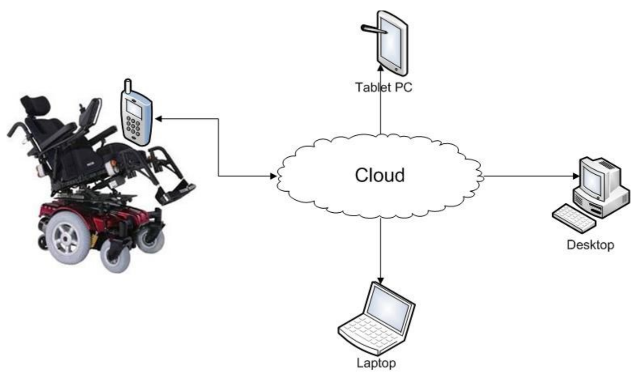


Figure 1. The mobile cloud computing framework

Smart mobile devices are physically bound to wheelchairs and serve as the information provider; the cloud is responsible for storing and analyzing the maneuvering data; and the information recipients retrieve from the cloud the analysis results, which will be shown in different formats (e.g., table, charts, etc.) to facilitate understanding.

B. *Mobile Computing*

The use of smart mobile devices in biomedical research has started to emerge. For example, Georgia Tech Research Institute (GTRI) proposed to use iPhones to enable patients with Parkinson's disease or people in some other neurological conditions to record data on hand and arm tremors and deliver recorded data to medical personnel [8].

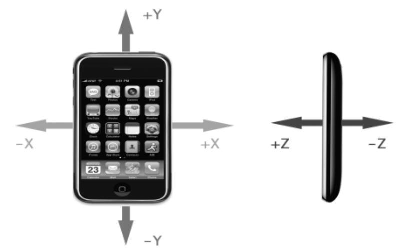


Figure 2. Illustration of 3-D accelerations and orientation

In our study, we utilize the accelerometers and gyroscopes equipped in smart phones to record wheelchair maneuvering data. These sensors can record data in three dimensions (3-D) as shown in Figure 2. The advantages of smart phones are their ubiquitous nature and easy-to-carry characteristics. However, smart phones have relatively limited computing power and small storage capacity. It is impractical to require smart phones to perform extensive online data analysis and store all the recorded data locally.

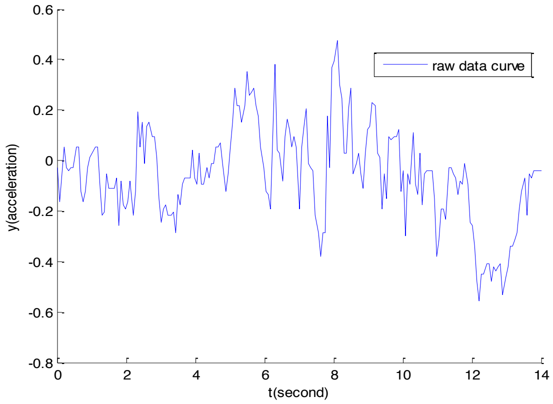
Fortunately, cloud computing provides a natural extension to mobile computing, i.e., moving data storage and analysis from smart phones into the cloud. Instead of sending the recorded data to the cloud instantly, our application stores the data temporarily in the memory of the phones. Then, the cumulated data are periodically (e.g., every 10 minutes) uploaded into the cloud for storage. Such a batch processing approach brings two additional benefits: (1) it can avoid overloading smart phones from frequent network connections; and (2) it can consequently save power consumption because WIFI or 3G connections consume significant energy [9].

C. *Cloud Computing*

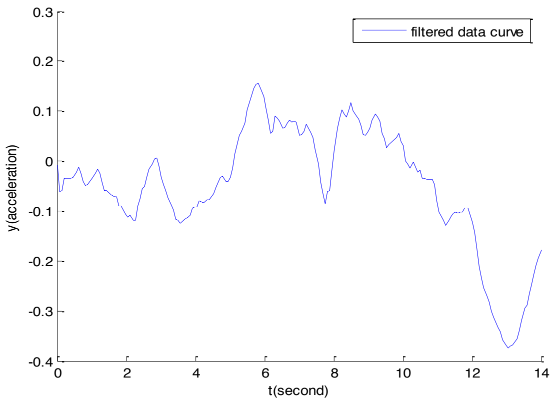
The cloud provides virtually unlimited storage and processing power. Therefore, the cloud in our study assumes two responsibilities, namely, data storage and data processing.

1) Data storage. Periodically, smart phones upload wheelchair maneuvering data to the cloud. These data are subsequently appended to an existing database table, which corresponds to a particular smart phone client. The one-to-one mapping between a smart phone device and its database table in the cloud should be established before data collection begins.

2) Data Smoothing. Data collected from a smart phone's accelerometer could be very noisy. The data often appear jagged in places, where it should be obvious that acceleration is continuously increasing or decreasing over a given time interval. For this reason, we utilize the well-known Kalman filter [10] approach to mitigate the impact of noise. Figure 3 (a) shows an example of a piece of raw data and Figure 3 (b) shows the smoothed data by using the Kalman filter, which obviously generated smoother and more precise curves.



(a)



(b)

Figure 3: Raw and smoothed data

3) Maneuvers Classification. In order to recognize activities from maneuvering data, such as left and right turns, forward and backward movements, etc., we choose the K-Nearest Neighbors (KNN) machine learning algorithm. The KNN algorithm classifies a set of data points by calculating the Euclidian distance between the target data (i.e., testing data) and multiple sets of sample data (i.e., training data). These sample data sets are pre-classified into categories of left, right, forward, and backward motions and are used as the algorithm's training data. The target data are divided into pieces, each having the same size as the training samples in terms of the number of data points. Formula (1) shows how the Euclidian distance is calculated.

$$\sqrt{\sum_{k=1}^{p}({S^i}_k - {T^j}_k)^2} \qquad (1)$$

where S^i_k (i = 1, 2, … m) denotes the k-th data point in the i-th sample S^i with m being the number of samples; T^j_k (j = 1, 2, …, n) denotes the k-th data point in the j-th target data with n being the total number of pieces in the entire target data; and p is the number of data points in the sample data S^i (or equally in the target data T^j).

For each piece of target data T^j, its distance to each of the sample data is calculated as shown in formula (1). KNN classifies T^j based on the majority of the K closest sample data. Despite its simplicity, our experimental results show that KNN is a very effective approach to accurately classify maneuvering data.

In addition, the combination of accelerometer and gyroscope data can give us a comprehensive view of the wheelchair motions. Specifically, acceleration data are used to determine the linear movements, such as forward and backward motions of the wheelchair. Orientation data from the gyroscope are used to determine whether the wheelchair is turning left or right.

4) 3-D Trajectory Estimation. With Simpson's rule (as shown in Formula (2)), we can roughly estimate the trajectory of wheelchair movements.

$$\int_a^b f(t)dt \approx \frac{1}{3}\Delta t[f(t_0) + f(t_n) + 4(f(t_1) + f(t_3) + \cdots + f(t_{n-1})) + 2(f(t_2) + f(t_4) + \cdots + f(t_{n-2}))] \qquad (2)$$

where $\Delta t = (b - a) / n$, $t_0 = a$ and $t_n = b$, and n is an even number.

Specifically, we can apply Simpon's rule twice to calculate the moving distance during the time period [a, b] in a particular dimension w (w = x, y, or z). Speed $v_w(t)$ during the time period [t_1, t_2] is calculated as $v_w(t) = \int_{t_1}^{t_2}(v_{w0} + \alpha_w(t)dt)$, where v_{w0} is the initial velocity in the dimension w; and $\alpha_w(t)$ is the acceleration in dimension w. Then, the distance moved can be calculated as $\int v_w(t)dt$. Hence, we can calculate the total distance traversed in a particular dimension during a short time period δ_t (e.g., δ_t = 2 seconds). Combining the calculated results from all three dimensions can roughly reveal the physical displacement in a 3-D space. Therefore, putting all such time points together, we will be able to draw a 3-D wheelchair movement trajectory for the time period [a, b].

III. CASE STUDY

We performed a case study to evaluate the feasibility of the proposed mobile cloud framework as shown in Figure 4. Specifically, we used a Samsung Galaxy SII (GT-I9100) with Android OS 4.0.3 to collect wheelchair maneuvering data. We used Google App Engine (GAE) as the cloud computing platform. GAE enables software platforms to move from their traditional development environments into the cloud. GAE offers Platform-as-a-Service (PAAS), providing an ideal foundation to build robust and scalable Web applications. The combination of an Android smart phone and GAE provides strong compatibility because they are both developed by Google. Abundant APIs are available to developers to make the mobile devices work seamlessly with GAE. Figure 4 shows the data flow in the sequence of data recording, storage, analysis, and results notification.

Android APIs provide four frequency options, namely, SENSOR DELAY FASTEST, SENSOR DELAY GAME, SENSOR DELAY NORMAL, and SENSOR DELAY UI, which correspond to 46 ~ 48 Hz, 22 ~ 23 Hz, 12 ~ 13 Hz, and 4 ~ 5 Hz, respectively [11]. To record data, we set the frequency to "SENSOR DELAY UI" to prevent overwhelmingly large amount of data collection. Android OS 4.0.3 includes a high-pass filter in its accelerometer APIs, allowing the noise caused by gravity to be filtered out from the recorded data.

Figure 4: Data flow in the experiment

Two types of sensor data were collected: gyroscope and accelerometer data. Accelerometer data were used to identify forward and backward accelerations while gyroscope data were used to identify left and right turns on the wheelchair. Hence, there are 4 types of maneuvers for which we collected data, namely, straight forward, straight backward, and left and right turns around a sharp corner. The data collection was conducted in the corridor of the University of Central Oklahoma's Mathematics and Computer Science (MCS) building. During data collection, we performed each of the maneuvers 5 times in order to have adequate sample data for our KNN algorithm. We drove an Invacare® adult power wheelchair while collecting data with the Samsung Galaxy SII smart phone. Video was taken for the duration of the data collection in order to facilitate the identification of pattern data. Once 10,000 data points were collected, our smart phone app would save the recorded data in a file on the mobile device and then upload the file to the cloud. This is done by sending an upload request to the server operating on the GAE platform through HTTP requests. The server then replied with the upload URL in the header of the reply. This is the link generated by the server, which is the ID of the file being uploaded to the Blobstore. Blobstore is a service offered by GAE allowing applications in the cloud to accept and serve data objects through traditional HTTP connections.

After the raw maneuvering data were collected, the Kalman filter (see Section II.C.2) was used to filter out noise involved in raw data. By watching video, we identified a set of sample data for each of the maneuvers. Afterwards, another set of raw data was collected by following the same process as above to serve as testing data. The sample data as well as the new set of testing data were fed to the KNN algorithm, which helped identify wheelchair maneuvering activities. Our experimental results show that by using the acceleration data to match forward and reverse motions and using the gyroscope data to match left and right turns, KNN could accurately identify the wheelchair motions. And we could obtain a comprehensive view of wheelchair maneuvering activities. Currently, KNN and Kalman filter are running on desktop PCs. We are migrating these programs to the GAE cloud.

IV. Conclusion

In this paper, we propose a general mobile cloud computing framework, consisting of wheelchairs, smart mobile devices, cloud services, and information recipients. The smart mobile devices are attached to the wheelchairs. Wheelchair maneuvering data are continuously recorded and periodically transmitted to the cloud for storage and analysis. Then, the results are made available to various types of information recipients. To effectively filter out the noise, we applied the well-known Kalman filter to smooth the noisy data. We also conducted a case study to evaluate the feasibility of the proposed mobile cloud computing framework by using Android smart phones and Google App Engine (GAE). Experimental results demonstrate that this approach is feasible for conveniently collecting data and performing analysis.

In the next step, we plan to use the Google Cloud Messaging (GCM) service to enable asynchronous communications between an Android smart phone and GAE. With such a new feature, our Android application will not be required to periodically check GAE, thereby substantially reducing the number of requests to GAE to reduce power consumption.

Acknowledgment

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