Cross-Platform and Cross-Device Pedometer System Designed for Healthcare Services

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***Abstract*—Physical activity is closely related to one's health status. Especially the intensity of physical activity is more important than other features for health benefits, which can be computed by the number of steps. With the advent of mobile devices, pedometer system can be implemented on mobile devices with their built-in sensors. However, due to the variety of types of platforms and devices, it is hard to ensure the consistency of step counting. In this paper, we propose a robust pedometer system for healthcare services, which ensures the consistent results of step counting upon heterogeneous platforms and multiple mobile devices. Based on the proposed system, we present the actual implementation of pedometer applications for different platforms and devices. We examine our implementation to verify that it is useful in real life with respect to the accuracy of step counting and battery consumption.**

Keywords—pedometer architecture; step counting; healthcare serices; cross-platform; cross-device

I. Introduction

It is well known that regular physical activity is directly related to a healthy lifestyle. Physical activity leads to a number of health improvements in medical factors including coronary heart disease (CHD) risk factors, blood liquid profile, hypertension, ischemic stroke, type 2 diabetes, bone density, depression, and fall injuries [1-2].

For the medical and healthcare purposes, it is important to estimate how often or how long physical activity is done. However, to measure the amount of physical activity is not an easy task. Self-reporting, such as using health screening form, is a naive yet popular way of measuring physical activity. However, self-reporting has some drawbacks, such as it is difficult to capture daily activity patterns [3], and it may be inaccurate due to an overestimation of physical activity [4]. Thus self-reporting is not a suitable method to measure the objective physical activity.

In particular, it is beneficial to measure the intensity of physical activity because it is more important for health benefits [5]. Although the intensity is difficult to measure by smartphones, we can indirectly compute one of the intensity measures, the Metabolic Equivalent of Task (MET), by using the results of step counting. The average METs per an hour can be estimated by the following equation [6]:

$$MET = (1.4 \times d) + (4 - 1.4) \times (c / 7200) \times d \qquad (1)$$

where c is the number of steps per hour and d is the duration in hours. According to (1), MET is proportional to the number of steps. Therefore, computing accurate METs is relying on measuring the exact number of steps. However, since there are a number of types of platforms and devices, it would be difficult to ensure the consistent results of step counting.

One of the most effective methods for step counting is by using pedometers. Pedometer is a small, portable device that keeps a counter on the total number of steps by detecting the motion of the user. Pedometers can be used to obtain accurate and objective amounts of physical activity [7]. In addition, using pedometers may promote physical activity to users [8-9]. Pedometers, however, should be worn by the users, which may cause discomforts or inconvenience.

Instead of wearing a pedometer, individuals may use their own smartphone that has built-in sensors, such as accelerometers and gyroscopes. Since a large number of people almost always carries around a smartphone, physical activity can be conveniently assessed by motion sensors in the smartphone without wearing additional devices. With this advantage, a number of developers and vendors have produced pedometer applications, such as Argus [10], Runtastic [11], Footsteps [12], Moves [13], and so on. Although these pedometer applications have received a lot of attention, they are limited to computing the number of steps and engaging people in physical activity. To use the step count data for practitioners or healthcare services, we should take into account the integration of step counting with medical records.

In this paper, we propose a robust pedometer system for healthcare services, which guarantees that the number of steps is reliably computable on different mobile platforms. We explain the details of our architecture to show how pedometer applications can be built on various mobile platforms with the same pedometer system and how pedometer applications are integrated with medical records for medical and healthcare services. We also introduce the actual implementation of pedometer applications for different platforms and devices based on the same architecture. With experiments, we examine our implementation with respect to two aspects: consistency of step counting and battery consumption. The experiment results veri-

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fy that pedometer devices are replaceable by our pedometer applications, especially with the latest devices, although our applications can still be used in older devices for a short period of time.

The rest of this paper is organized as follows. In Section II, we summarize previous studies on benefits of physical activity measured by pedometers and on pedometer algorithms using smartphone sensors. Section III presents the system architecture of a pedometer application for heterogeneous platforms and multiple devices. Section IV describes the implementation details and usability issues of pedometer applications. Finally Section V provides some concluding remarks regarding this study.

II. Related Work

A. Studies on Effects of Physical Activity Using Pedometers

Many researchers have been interested in the relationship between physical activity and health status. Although physical activity is highly relevant to health disorder [14], 31.1% of the adults in the world are physically inactive [15], and only 25% of the adults in the United States do the recommended amounts of physical activity [2]. As a way of encouraging physical activity, walking is recommended for less active people because walking is a costless, unskilled, and riskless activity [16]. Marshall et al. suggested that walking 3000 steps in 30 minutes a day for five days a week is recommended in order to meet physical activity guidelines, as a result of experiments with 97 Latino adults with a mean BMI of 28.8 [17].

A large number of studies exploited pedometers to find the relationships between step counts and certain diseases. Vincent et al. evaluated the amount of physical activity, measured by pedometers, and body mass index (BMI) levels of 1954 children in the United States, Sweden, and Australia [18]. The authors revealed that American children were likely to be the least active and heaviest while Swedish and Australian children were the more active and had lower BMI, although there were few significant relationships between step counts and BMI. Mark et al. paid attention to the effects of physical activity bouts [19]. The authors found that bouts of moderate-to-vigorous physical activity (MVPA) can be beneficial to adiposity status beyond the total volume of MVPA. Tudor-Locke et al. investigated the association between BMI and steps per day among 160 free-living individuals with type 2 diabetes [8]. The authors found that BMI and steps per day are inversely correlated. Manjoo et al. conducted an experiment to reveal the relationship between walking and blood pressure [20]. The authors concluded that a 1,000 steps per day increment led to blood pressure reductions among women with type 2 diabetes. Moy et al. concentrated on patients with chronic obstructive pulmonary disease (COPD) [21]. The authors uncovered an inverse correlation between daily step count and acute exacerbation risk and COPD-related hospitalizations.

B. Pedometer Algorithms

There are a number of pedometer algorithms that detect steps and count the number of steps via smartphone sensors, especially using accelerometers and gyroscopes. Shin et al. introduced a movement detection algorithm that exploited a triaxial accelerometer to find peak points that satisfied given conditions [22]. Oner et al. adopted a similar idea that step detection depended on peaks generated by an accelerometer [23]. Tran et al. presented an acceleration-based step detection algorithm that used two noise reduction filters [24]. After filtering, their algorithm simply counted pairs of increasing and decreasing signals. Jayalath et al. presented a gyroscope-based step detection algorithm that exploits a zero-crossing detector and a threshold detection mechanism, assuming that the smartphone is located in a pocket of the trouser [25]. The authors claimed that their algorithm showed high step detection accuracy regardless of activity types or stepping speeds. The step detection algorithms in these studies could be used for the implementation of the step counting module in our system.

III. Cross-Platform and Cross-Device Pedometer System Architecture

In this section, we present an overview of the system architecture of a pedometer application for heterogeneous platforms and multiple devices. Since the same architecture is used for any kind of platforms and devices, the architecture is helpful when one needs to develop a pedometer application for various target devices.

The system has four significant layers: data collection layer, data conversion layer, data storage layer, and data provision layer. Note that depending on the type of device or the purpose of the application, the components of each layer may vary. Fig. 1 describes the architecture of the pedometer application.

A. Data Collection Layer

The data collection layer plays a fundamental role in collecting step-related data, which are generated by a step counting module or a device-inherited step counter. The step counting module leverages some of the built-in sensors to detect the

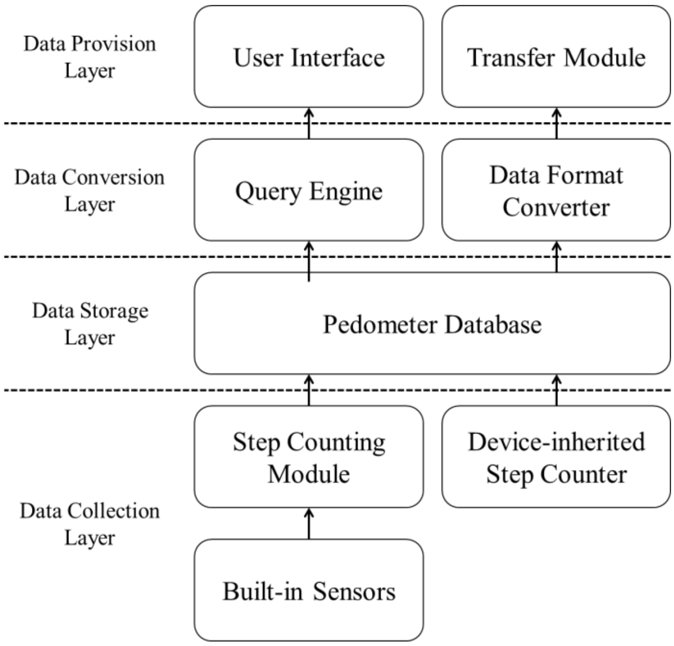

Fig. 1. SYSTEM ARCHITECTURE OF PEDOMETER APPLICATION

moment that step occurs and to count the number of steps. For a few number of the latest devices, there are device-inherited step counters that support built-in step counting modules in a low power mode. For those devices, it is beneficial to use the inherited step counters instead of implementing the step counting module. Fig. 2 describes how the data collection layer is working.

1) Device-inherited Step Counter

If the device can use the inherited step counter, it first tries to take a permission to handle the step counting API. In general, the permission is granted by the user in a way that an approval prompt is displayed and waited until the user makes a decision. If the user approves, then it is possible to leverage the device-inherited step counter. Otherwise, the step counting is performed by the step counting module.

For instance, the latest iOS devices now have an M7 motion processor after the iPhone 5S was launched. Since the M7 chip gathers step information in the background and in the low power mode, the latest iOS devices can be supported with the aid of the M7 processor with a CMStepCounter class [26]. For the latest Android devices the step counting and step detecting APIs are introduced from Android 4.4 KitKat [27]. Thus, the latest Android devices can the inherited step detector by calling *getDefaultSensor()* with the parameter *Sensor.TYPE_STEP_DETECTOR*.

2) Step Counting Module with Built-in Sensors

Most of smartphones cannot exploit the device-inherited step counter. Thus it is required to develop their own step counting module. A number of smartphones, including older devices, usually have quite a few sensors, like an accelerometer,

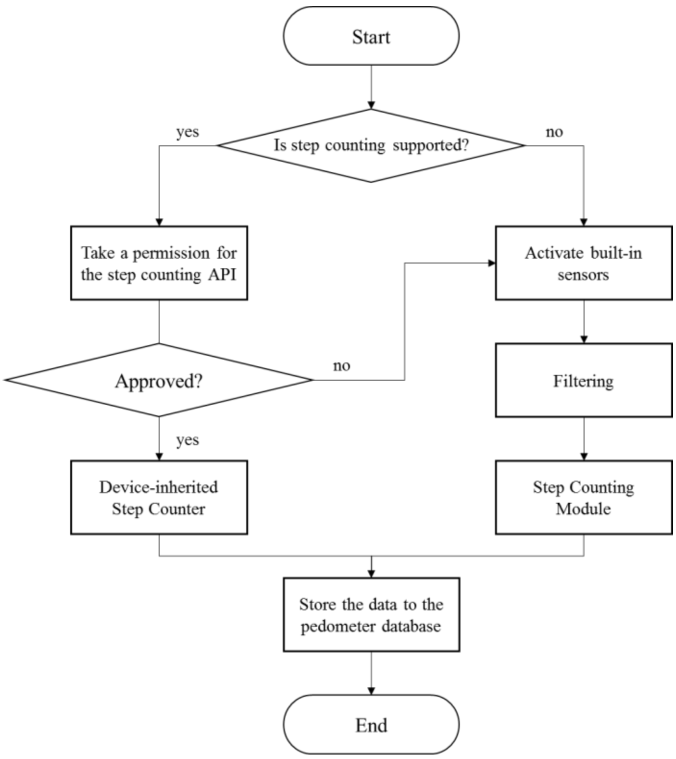

Fig. 2. FLOW CHART OF DATA COLLECTION LAYER

a gyroscope, etc. Since these sensors are useful for measuring the user's activities, we can leverage them to detect the user's steps. Among a number of pedometer algorithms, we choose a gyroscope-based algorithm in [25] because it is claimed that the algorithm is a robust step detector to the user's speed.

B. Data Storage Layer

In the data storage layer, the outputs from the data collection layer are stored in the pedometer database. Note that although the data collection layer can be implemented in different ways, the outputs should be stored in the same form because the upper layers should be working regardless of the type of platform and device. In our implementation, the pedometer database consecutively stores the moment at which a step is detected. However, the pedometer database can store in a more dedicated form, for instance, of the number of steps for a given period with start time and end time, with respect to the applications. In addition, the pedometer database may store augmented columns, such as energy expenditure. Since the size of step-related data is small enough, smartphones can keep the pedometer database without suffering from storage capacity. Table I shows an example of data in the pedometer database.

TABLE I. STEP COUNTING DATA IN THE PEDOMETER DATABASE

Start Time	End Time	Number of Steps	Energy Expenditure
1403668800	1403672400	1382	123.44 kcal
1403672400	1403676000	2693	154.21 kcal
1403676000	1403679600	1105	116.93 kcal
1403679600	1403683200	1919	136.04 kcal
1403683200	1403686800	2040	138.88 kcal

C. Data Conversion Layer

The data conversion layer transforms the data in the pedometer database into an appropriate form for each purpose. Since the schema of the pedometer database is independent of platforms and devices, the data conversion area can be equally implemented on any platform and device.

As a user application, the query engine receives the user's request to convert the data into the form that the user wants. For instance, if the user give a request to summarize by day, the step-related data are aggregated per day. For healthcare services, the data format converter transforms the data into a medical or health record description format. For instance, the data format converter may change the format to a health record standard format, such as Continuity of Care Record (CCR) [28]. In our implementation, however, this layer for healthcare services is not implemented yet, but we have a plan for integrating our system with the Health Avatar Platform [29] in the near future.

D. Data Provision Layer

The data provision layer prepares the data to be uncovered for each purpose. As a user application, the data are prepared with a graceful user interface so that the user can easily look

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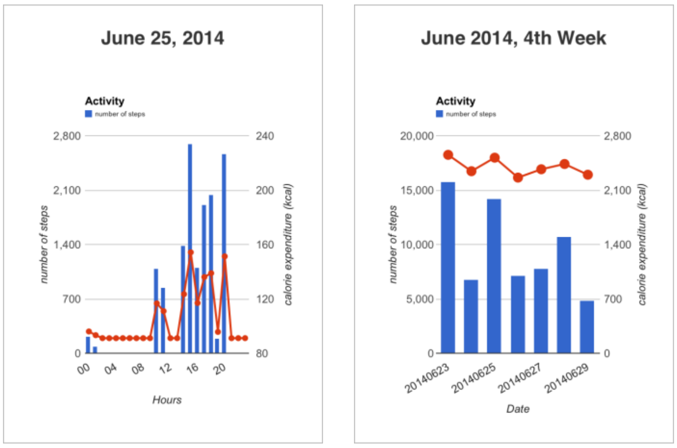

Fig. 3. SCREENSHOTS OF PEDOMETER APPLICATION

over the data. For healthcare services, the data are transferred into other medical or healthcare systems. It should be ensured that the data are transferred securely and reliably because of the sensitivity of the data [30].

IV. IMPLEMENTATION OF PEDOMETER APPLICATIONS

In this section, we present brief experiments to examine the usability of our pedometer applications (Fig. 3). We examined two aspects of our system: consistency of step counting and battery consumption. For the following experiments, we used four different devices: iPhone 4S (with step counting module), iPhone 5S (with device-inherited step counter), Galaxy Nexus (with step counting module), and Nexus 5 (with device-inherited step counter).

First we look at the consistency of step counting. It is important, especially for physical activity studies, that the results of step counting should be consistent [31]. In particular, the accuracy of METs is highly dependent on that of step counting, as described in Section I. In this experiment, we measured the error rate of the pedometer application on each device to verify that our implementation on any device returns the number of steps within a narrow confidence interval. We first began the pedometer application on all devices at the same time, and kept them in trouser pockets. During a one-hour walking, the steps were counted in each device, while a pedometer was worn for ground-truth. Table II shows the experiment results of step counting.

TABLE II. STEP COUNTING RESULTS OF FOUR DEVICES

	Number of Steps	**Error Rate (%)**
iPhone 4S	5959	0.81%
iPhone 5S	6045	2.27%
Galaxy Nexus	5963	0.88%
Nexus 5	5965	0.91%
Pedometer	5911	

The experiment results show that the four smartphones return similar numbers of steps. Although iPhone 5S overestimated a little, the errors of step counting results are within <3%, which are acceptable in practice. Therefore, it is concluded that our architecture assures the accurate and consistent results of step counting even on heterogeneous platforms and multiple devices.

Each device shows small errors of step counting because of the two factors: walking speed and device orientation. We empirically found that device-inherited step counters failed to detect steps during slow walking, while they often overestimated the number of steps during fast walking. Step counting modules, which are implemented based on [25], are robust to the walking speed, but they assumed that the device orientation is fixed. Thus a small vibration of the device, even though it is located in the pocket, may affect the overall accuracy.

With the viewpoint of battery consumption, the application should be run in a low-power mode as the pedometer system is built upon smartphones. In particular, the application must be run for at least 24 hours without charging to record the amount of daily physical activity. In this experiment, we measured the amount of battery consumption on each device. We first turned off and fully charged the devices. After charging, we turned on the devices and began the pedometer application to count the number of steps. Note that we do not begin any other applications. To ignore other factors of battery consumption, we turned the screen off and used airplane mode during the experiment. Table III shows the experiment results of battery consumption after four and eight hours.

TABLE III. REMAINING BATTERY CAPACITY OF FOUR DEVICES

	Battery Status	
	After 4 hours	***After 8 hours***
iPhone 4S	88%	80%
iPhone 5S	100%	100%
Galaxy Nexus	85%	83%
Nexus 5	99%	97%

The experiment results show that the batteries in both iPhone 5S and Nexus 5 drain very slowly, while the ones in iPhone 4S and Galaxy Nexus have drained by 12% and 15% after four hours, and 20% and 17% after eight hours. In iPhone 5S, the battery does not seem to be drained because the M7 processor is working with very low power consumption. The reason for the differences in battery status is that recent devices like the iPhone 5S and Nexus 5 support a device-inherited step counter that can be run in a low power mode. In contrast, step counting modules for older devices like iPhone 4S and Galaxy Nexus continuously use the built-in sensors, which causes the battery to drain quickly. Therefore, the latest devices are able to be exploited for a long-time step counting, while the older devices are still capable of executing pedometer applications for a short period of time, for instance, during exercising.

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V. Conclusion

In this paper, we presented a system architecture of a pedometer application on heterogeneous platforms and multiple mobile devices for healthcare services, to assure the consistent results of step counting regardless of platforms and devices. We also presented the implementation of pedometer applications for different platforms and devices based on the same architecture. Our implementation is examined with respect to two aspects: consistency of step counting and battery consumption. The experiment results show that recent devices can replace pedometers with respect to battery consumption and accuracy, while older devices are still usable for a short period of time, for instance, only during exercising.

As a future work, we plan to integrate our system with the Health Avatar Platform [29]. While our architecture of pedometer applications is considering the integration with healthcare services, the current version does not support any healthcare services. Therefore we will extend our architecture for the Health Avatar Platform to help healthcare services, similarly to [32].

Acknowledgment

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIP) (No. 2010-0028631).

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