Application

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Integrated Solution for Physical Activity Monitoring Based on Mobile Phone and PC

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Objectives: This study is part of the ongoing development of treatment methods for metabolic syndrome (MS) project, which involves monitoring daily physical activity. In this study, we have focused on detecting walking activity from subjects which includes many other physical activities such as standing, sitting, lying, walking, running, and falling. Specially, we implemented an integrated solution for various physical activities monitoring using a mobile phone and PC. **Methods:** We put the iPod touch has built in a tri-axial accelerometer on the waist of the subjects, and measured change in acceleration signal according to change in ambulatory movement and physical activities. First, we developed of programs that are aware of step counts, velocity of walking, energy consumptions, and metabolic equivalents based on iPod. Second, we have developed the activity recognition program based on PC. iPod synchronization with PC to transmit measured data using iPhoneBrowser program. Using the implemented system, we analyzed change in acceleration signal according to the change of six activity patterns. **Results:** We compared results of the step counting algorithm with different positions. The mean accuracy across these tests was 99.6 ± 0.61%, 99.1 ± 0.87% (right waist location, right pants pocket). Moreover, six activities recognition was performed using Fuzzy c means classification algorithm recognized over 98% accuracy. In addition we developed of programs that synchronization of data between PC and iPod for long-term physical activity monitoring. **Conclusions:** This study will provide evidence on using mobile phone and PC for monitoring various activities in everyday life. The next step in our system will be addition of a standard value of various physical activities in everyday life such as household duties and a health guideline how to select and plan exercise considering one's physical characteristics and condition.

Keywords: Walking, Ambulatory Monitoring, Cellular Phone

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I. Introduction

Over the past two decades, a striking increase in the number of people with the metabolic syndrome worldwide has taken place. This increase is associated with the global epidemic of obesity and diabetes. With the elevated risk not only of diabetes but also of cardiovascular disease from the metabolic syndrome, there is urgent need for strategies to prevent the emerging global epidemic [1,2]. Although the metabolic syndrome appears to be more common in people who are genetically susceptible, acquired underlying risk factors-being overweight or obese, physical inactivity, and an atherogenic diet-commonly elicit clinical manifestations [3].

Current guidelines recommend practical, regular, and moderate regimens of physical activity (eq, 30 minutes moderate-intensity exercise daily) [4]. Regular and sustained physical activity will improve all risk factors of the metabolic syndrome. Sedentary activities in leisure time should be replaced by more active behavior such as brisk walking, jogging, swimming, biking, golfing, and team sports. Combination of weight loss and exercise to reduce the incidence of type 2 diabetes in patients with glucose intolerance should not be dismissed [5,6].

A variety of methods exist to quantify levels of habitual physical activity during daily life, including objective measures such as heart rate, one-and three dimensional accelerometer, and pedometer, as well as subjective recall questionnaires like the International Physical Activity Questionnaire and physical activity logbooks [7,8]. Yet all possess some important limitations. Heart rate monitors have been widely used to quantify physiological stress, but their efficacy at low intensities has been questioned due to the potential interference of environmental conditions and emotional stress [9]. A wide range of self-report activity questionnaires exist that are well suited to large surveillance studies but are limited due to their reliance on subjective recall. Pedometers are an inexpensive form of body motion sensor, yet many fail to measure slow walking speeds or upper body movements, and most are unable to log data to determine changes in exercise intensity [10]. The most common accelerometers used in human activity research measure accelerations either in a vertical plane (uni-axial), or in three planes (tri-axial), with excellent data-logging abilities [1,10,11].

In recent years, mobile consumer devices on the market have undergone a substantial increase in both processing power and features. Apart from ever-increasing CPU speed and memory, the evolution of portables has seen the addition of capabilities such as GPS receivers and accelerometers, which has lead to the emergence of a platform for a whole new rage of context-aware applications [12].

The mobile phone is a relatively well accepted device, which makes it potentially a non-discriminating service media. Some earlier studies have successfully used mobile phone applications to wellness management [13]. The accelerometer, in particular, now among the standard features in most mobile phones and entertainment devices, can be used as a source of information about its owner's activity and motion. The accelerometer can also be used for characterization of higher-level physical activities, which is a rich source of context information for a mobile application. One kind of such context information is the step count during walking or running. Step counting has been a central feature for a lot of mobile applications in the sport and wellness field [14-16]. However, almost the whole mobile application for monitoring of the user's steps, estimates the energy consumption, distance, and intensity. Installed software tools on the mobile phone have limitations of analyzing daily physical activity patterns. Most are unable to determine movement change in daily life by use of a mobile phone alone.

Therefore this paper will describe the methods, synchronization of data between PC and iPod for long-term physical activity monitoring. First, we have developed the solution using iPod to creating activity-informed applications. The iPod can be used to create application with real-time activity classification using the iPod's three-axis accelerometer. The iPod is an attractive device for these applications because of its rich multi-touch user interface, location sensing framework, fast processor, and highly available network connection [17]. We developed of programs that are aware of step counts, velocity of walking, energy consumptions and metabolic equivalents (METs). Second, we have developed the activity recognition program based on PC using visual studio. NET 2008 tools. iPod synchronization with PC to transmit measured body acceleration data using iPhoneBrowser (ver.1.9.3.0, Apple Inc., Cupertino, CA, USA) program. Using the implemented system, we analyzed change in acceleration signal according to the change of six activity patterns such as standing, sitting, lying, walking, running, and falling.

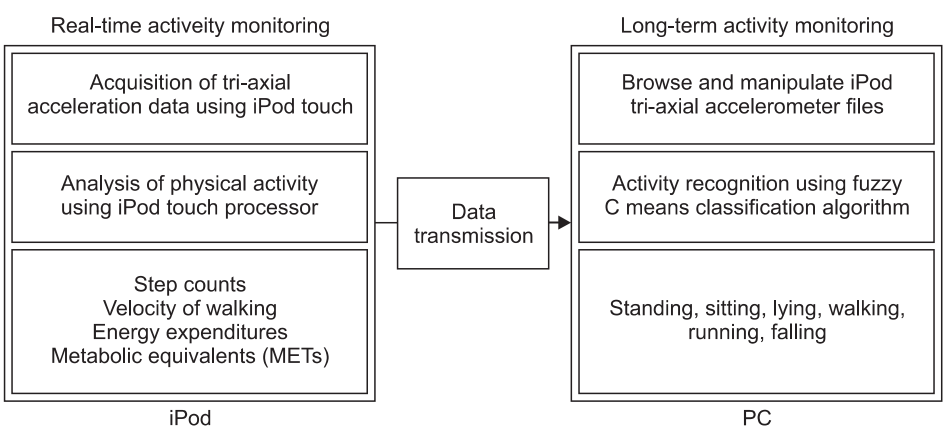

Figure 1. Overall system architecture of real-time monitoring and long-term activity monitoring.

Figure 1 is the overall system architecture of real-time and long-term activity monitoring.

This study is part of the ongoing development of treatment methods for metabolic syndrome (MS) project, which involves monitoring daily physical activity. In this study, we have focused on detecting walking activity from subjects which includes many other physical activities such as standing, sitting, lying, walking, running, and falling. Specially, we implemented an integrated solution to convenient monitoring of daily physical activity using a mobile phone platform.

1. iPod Sensors

In Apples iPod touch has built in a tri-axial accelerometer which can be used to physical activity recognition. Below we discuss the sensors used in our developed application.

1) Accelerometer

The iPod has tri-axial accelerometer, one working along each of the three primary axes of the device. Actually it's the LIS302DL from STM which can be sample up to 100x per second. The x-axis measures along the short side, the y-axis measures along the long side and the z-axis is a line perpendicular to the iPod through its center. Values are given in terms of "g," where 2 g is the force of gravity. With these specification it's not the most impressive accelerometer but it can do a whole range of human motion testing.

2) Three types of filtering

None, low-pass filtering and high-pass filtering a available for the accelerometer data as shown in Figure 2. High-pass filtering helps to get rid of the gravitational effects and find out the instantaneous movement of the device. Low-pass filtering that you can use to isolate the effects of gravity. Previous works normalized with reference to the frequency range of maximal sensitivity of the body (4-8 Hz and 1-2 Hz for the vertical and horizontal components of the vibration, respectively). This means that the relevant weighting factors were for these frequencies all of value unity. Therefore, we have used low-pass filtering on the accelerometer's raw data [18,19].

II. Case Description

First, six healthy adults (5 males: 27.4 ± 3.5 years, BMI 23.2 ± 3.6 kg/m^2; 1 female: 34 years, BMI 21.1 kg/m^2) participated in this study. All subjects were free of musculoskeletal pathology or symptoms that may have influenced movement. Tri-axial acceleration data were acquired at 60 Hz using custom software and accelerometer-based mobile device (iPod touch, Apple Inc.). iPod was worn on different position at the right waist, over the right anterior superior iliac spine (ASIS) using a waist belt and user's right pants pocket. Data were acquired during the walking in semi natural condition. The subjects walked along a 100-foot walkway and returned.

Second, subjects performed a variety of activities in the three times on outdoor conditions. We put the iPod touch has built in a tri-axial accelerometer on the right waist of the subjects, and measured change in acceleration signal according to change in ambulatory movement and physical activities. In the experiment performed in this research, the change of acceleration was measured while the subject was repeating postures such as standing, sitting, lying, walking, running, and falling. While the movements and postures contained within the routine are by no means a complete set of all possible activities that a given person might perform, they do form a basic set of simple activities which form an underlying structure to a person's daily life, and are likely to provide a great deal of information in terms of the person's balance, gait and activity levels if they can be accurately identified.

Tri-axial acceleration data were used to compute a resultant acceleration vector. The resultant was low-pass filtering, cut off frequency of 5 Hz. The adaptive peak detection algorithm was used to identify steps using filtered resultant acceleration data. The number of peaks identified during the walking trial was used to define number of steps. To develop iPod touch applications, we use iPhone OS ver. 4.0 and Xcode 3.2.1, Apple's Integrated Development Environment. Xcode provides tools to design the application's user interface and write the code that makes it work. Interface builder is another Apple graphical editor for designing user interface components for plot graphic library. Moreover, we use Objective C programming language for associate data and operation and building applications with the iPhone 4.0 SDK (A software development kit). SDK is a software tool from Apple, used to implement and develop an application for iPhone. The SDK consist of four layers. Each layer includes a certain number of frameworks. These layer's frameworks correspond to libraries that we can include in our code. The purpose of these frameworks is to reduce the amount of code lines and make the coding more effective.

1. IPod Touch: Step Counting Algorithms

Human walking is cyclic. We put forward our left or right foot first and then put the right or left foot. This event occurs repeatedly. This observation is the motivation behind looking for cyclic pattern in the accelerometer data. While analyzing the accelerometer data we found out that the part

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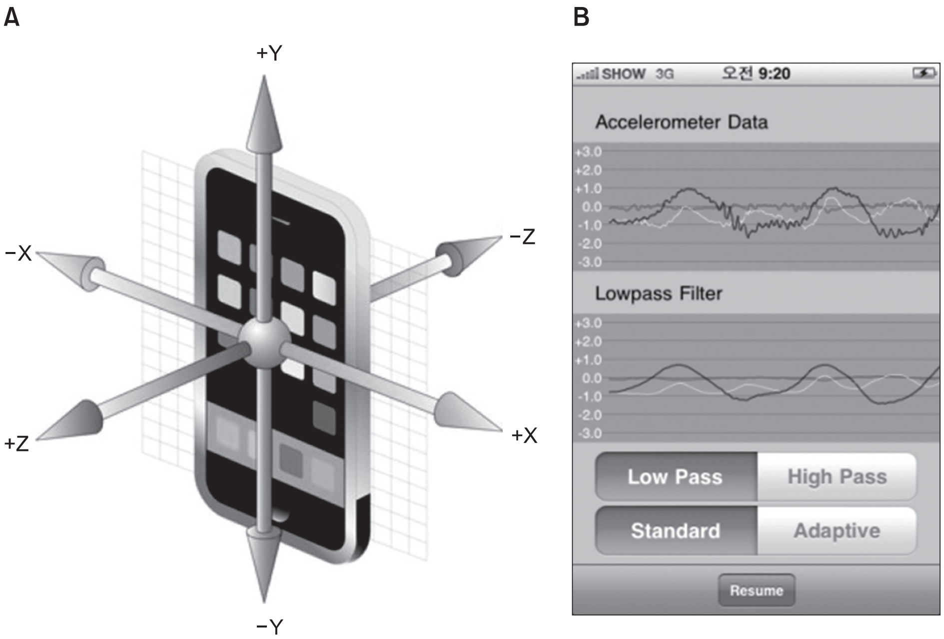

Figure 2. (A) Axes on iPod Touch. (B) Accelerometer graph sample application graphs the motion of the device.

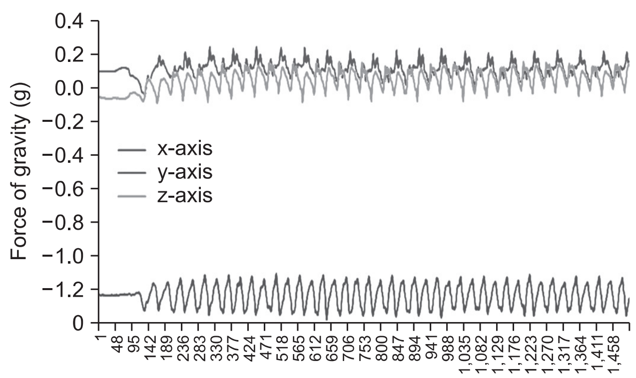

Figure 3. Acceleration signal measured from the waist during walking. The three dimensions of the sensor are shown separately (X shows acceleration ting the left-right direction, Y in the vertical direction, and Z in the back-forth direction). The gravitational force is visible in Y as a negative DC component in the signal. The vertical axes are arbitrary units. The horizontal axis is time in seconds. The sampling frequency of the signal is 60 Hz.

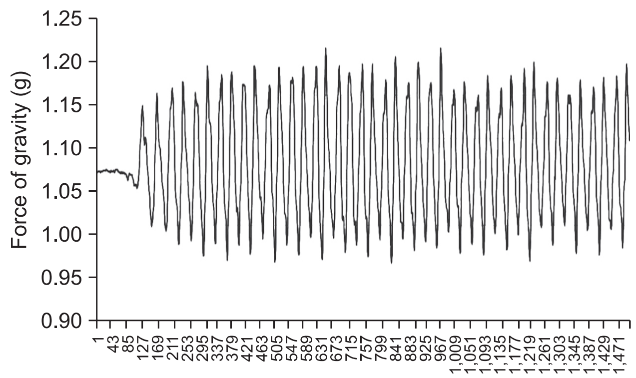

Figure 4. Vector magnitude of tri-axis accelerometer. iPod touch was worn on the right waist, over the right anterior superior iliac spine using a waist belt.

of data between two consecutive peaks repeats. It has been found out that output of any of the three axes is more erratic than the combined output of all the three axes. For this reason we shall use the combined signal to extract the representative gait cycle. An example of acceleration signal measured from the attached to the waist in a belt-like fashion during walking is shown in Figure 3.

As we want to detect steps from the different person's gate patterns and the different measurement location conditions the same person. The easiest way to produce useful data out of the three components of the sensor is to take magnitude of the acceleration vector. The next is to filter out any irrelevant data from the resulting magnitude signal. It is known that human muscle reaction and movement information lies below a frequency of 16 Hz. However, according to our experiment, if the data is reduced to 5 Hz, walking and running steps can still be detected [12].

The iPod extracts the gait cycle pattern from the accelerometer data. As shown in Figure 2. In addition, the time domain signal features of step count from body acceleration typically include: signal magnitude (area under the 3D acceleration magnitude curve) is shown Figure 4.

The pattern of the acceleration signal in time t has a given acceleration profile which repeats at each step. In detail, the acceleration profile comprises in succession: a positive phase, in which a positive –acceleration peak occurs, due to contact and consequent impact of the foot with the ground; and a negative phase in which a negative acceleration peak occurs due to rebound, having an absolute value smaller than that of the positive-acceleration peak.

As shown Figures 5 and 6, different measurement location conditions and each individual user have given characteristics and peculiarities that affect the gait, differentiating it form that of others. Therefore, the algorithm starts with initialization of the values of the positive and negative reference thresholds S+ and S-, respectively, at a positive minimum value S_1 and at a negative minimum value S_2, the latter being smaller, in absolute value, than the positive minimum value S_1. As will be clarified, said minimum values represent limit values below which the reference thresholds are not allowed to drop. In addition, the values of a positive envelope Env+ and of a negative envelop Env- of the acceleration signal's vector magnitude are initialized, respectively, at the positive minimum value S1 and at the negative minimum value S_2.

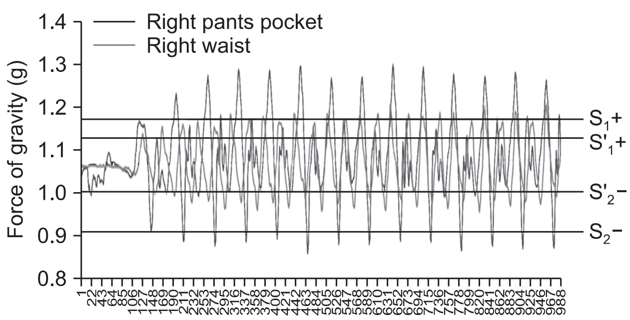

Figure 5. The different value of the positive and negative thresholds in the different measurement location conditions the same person.

There will now be described in Figure 7, first acceleration data CalAcc, and consequently modifies the values of the reference thresholds. The algorithm search for the positive phase of the step, by comparing the value of the acceleration data CalAcc with the positive reference threshold S+, to detect a positive acceleration peak of the acceleration signal. Until a positive phase of the step is found, the algorithm proceeds with acquisition of a new acceleration data, and with the comparison of said new acceleration data with the positive reference threshold S+. The positive phase is detected when the acceleration data exceeds the positive reference threshold S+ and then drops below the positive reference threshold, the instant of detection of the positive phase corresponding to the instant in which the acceleration data drops again below the positive reference threshold S+. At this instant, the processing unit stores the value assumed

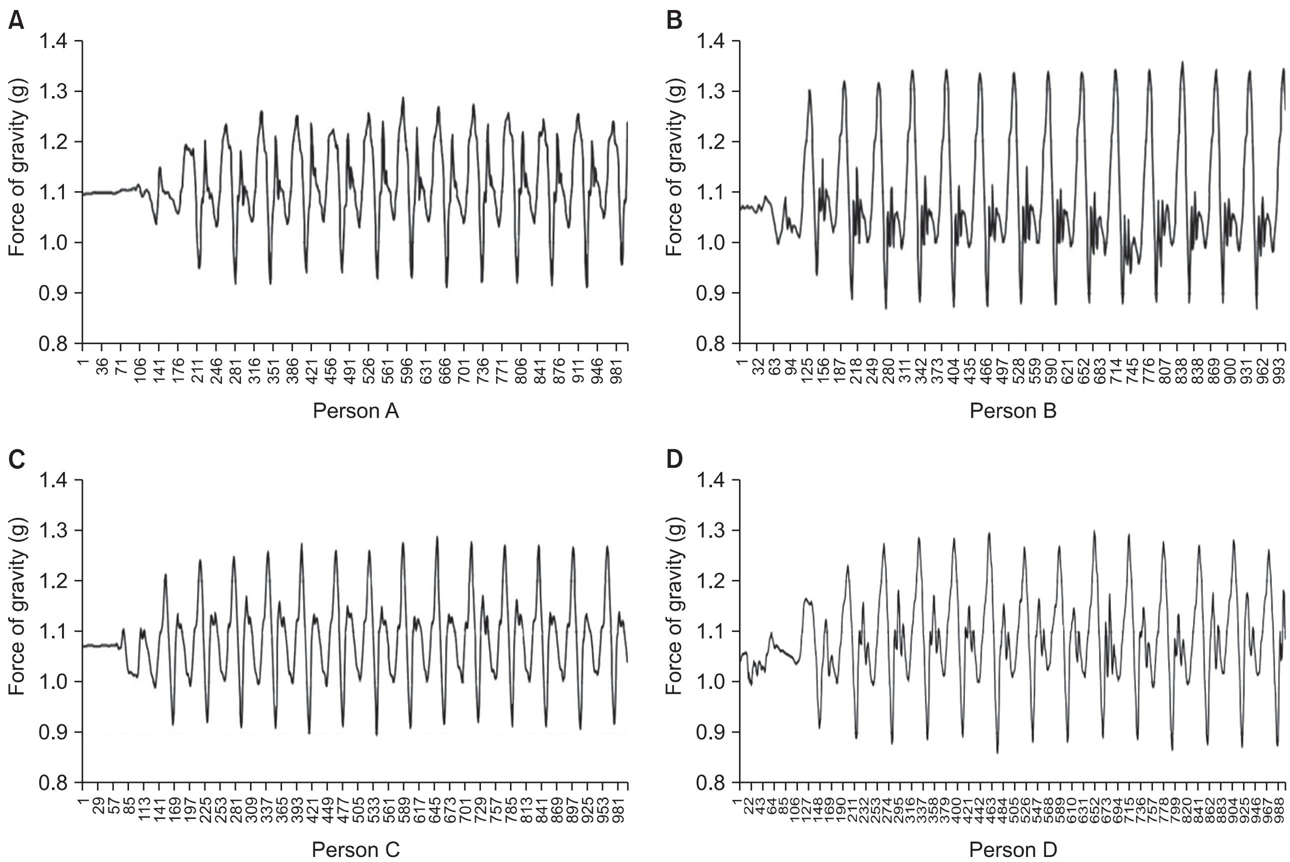

Figure 6. The different values f the positive and negative thresholds of multiple users. iPod touch was wore user's right pants pocket.

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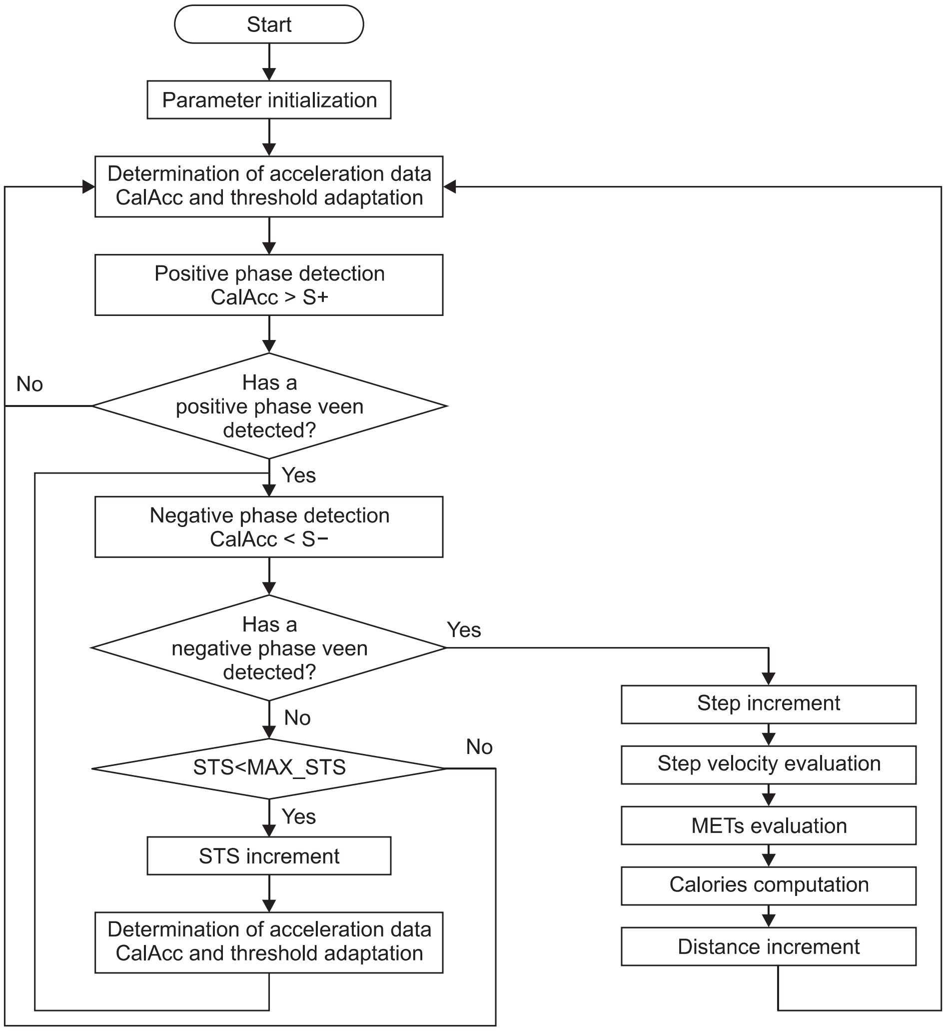

Figure 7. The flowchart corresponding to operations of detection and counting of steps, executed by a processing unit of an algorithm. CalAcc: acceleration data, STS: step to step.

by the positive reference threshold S+, which is a maximum value $S+_{max}$.

After the positive phase detection, the algorithm proceeds with the search for the negative phase of the step, of a negative acceleration peak, by comparing the value of the acceleration data CalAcc with the negative reference threshold S-. In particular, the search for the negative phase of the step is executed within a certain time interval step to step (STS), the value of which must be lower than a maximum interval Max_STS from detection of the positive phase (corresponding to a certain number of samples, the value of which is determined also as a function of the sampling rate of the acceleration data).

Until a negative acceleration peak is detected, and as long as the time interval STS is shorter than the maximum interval Max_STS, an algorithm proceed with the search for the negative phase of the step. In detail, the time interval STS is incremented, a new acceleration data is acquired, and the algorithm returns. If no negative phase of the step has been identified after expiry of the maximum interval STS, the algorithm returns to look for a new potential positive phase of the step. On the contrary, if the negative phase is identified within the maximum interval STS, determines the occurrence of the step, increment the count of the detected steps. Furthermore, the estimate of the step velocity, METs, Calorie consumption and the distance traveled is updated.

There will now be described in Figure 8, with reference to the algorithm implemented by the processing unit for determination of a new acceleration data CalAcc and consequent updating of the values of the positive and negative reference thresholds S+ and S-, in such a manner that the aforesaid values will follow approximately the positive and negative envelope of the acceleration signal. In brief, said algorithm envisages calculation, for each new acceleration data CalAcc, of the values of the positive envelope Env+ and negative envelop Env-, and modification of the value of the positive and negative reference thresholds S+ and S- as a function of the positive envelope Env+ and negative envelope Env-, respec-

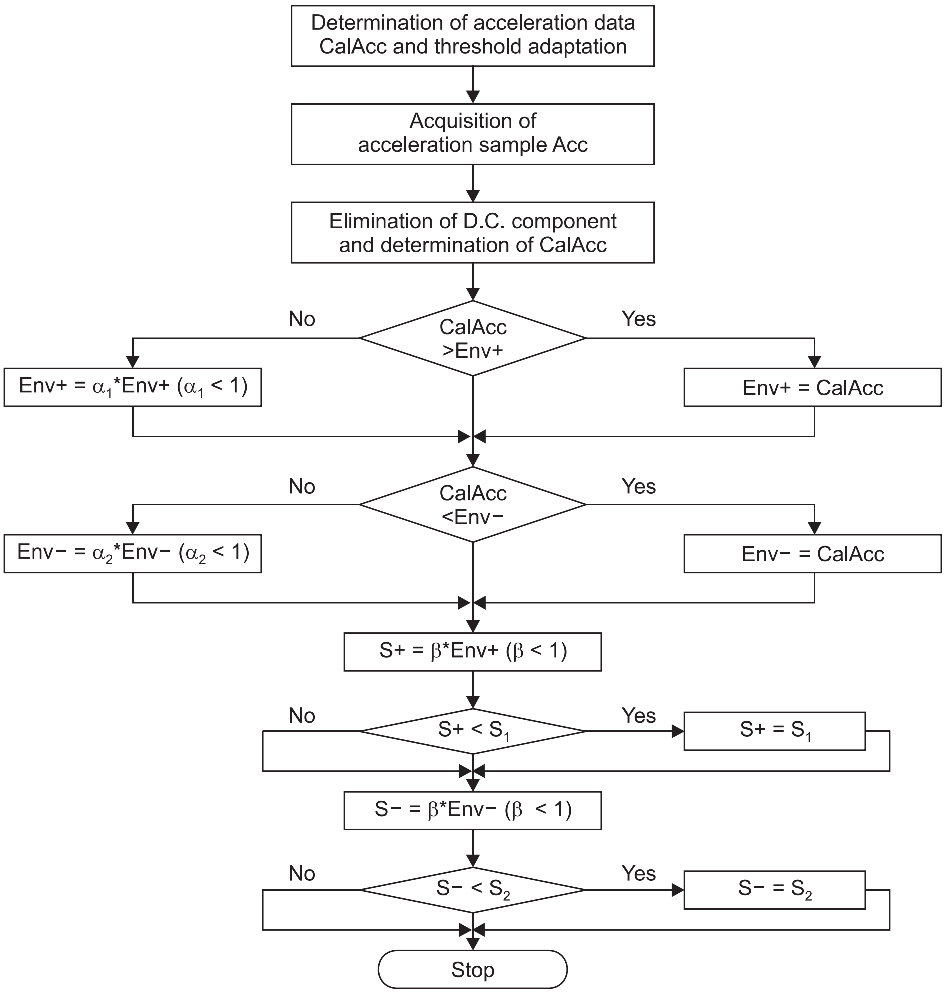

Figure 8. The flowchart corresponding to operations of self-adaptive modification of acceleration thresholds, executed by a processing unit of an algorithm. CalAcc: acceleration data.

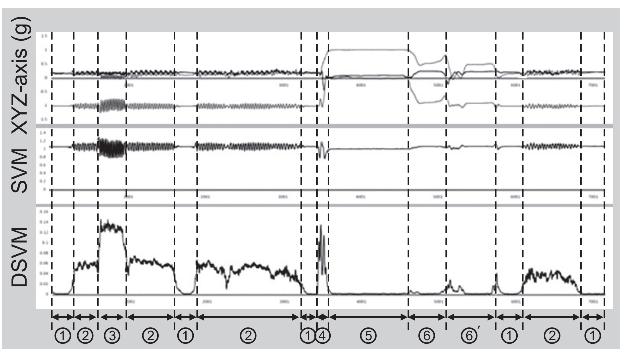

Figure 9. The characteristic of parameter output according to the state of activity. ① standing, ② walking, ③ running, ④ fall, ⑤ lying, ⑥ sitting on the floor, ⑥' sitting on the chair.

tively.

2. PC Program: Daily Physical Activity Monitoring

We have developed the activity recognition program based on PC using visual C# tools. iPod synchronization with PC to transmit measured body acceleration data using iPhoneBrowser program. Using this study implemented system, we analyzed change in acceleration signal according to the change of six activity patterns such as standing, sitting, lying, walking, running, and falling. In order to evaluate the possibility of monitoring activities during daily life, we developed an algorithm that assesses the output characteristic of 3-axisacceleration signal according to various activity patterns and classifies the state of activity based on the characteristic. In order to classify postures and activities from measured 3-axisacceleration information, signal vector magnitude (SVM) was calculated, and then differential signal vector magnitude (DSVM) was calculated by Equation (2) through differentiating SVM and calculating the mean of the absolute values. Figure 9 show the change of 3-axis acceleration, SVM and the pattern of change in DSVM for 1 second according to the change of activity. The figure shows that it is possible to distinguish activity patterns using DSVM.

Features were computed on 512 sample windows of DSVM data with 256 samples overlapping between consecutive windows. At a sampling frequency of 60 Hz, each window represents 8.5 seconds. Maximum acceleration, mean and

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standard deviation of acceleration channels were computed over sliding windows with 50% overlap has demonstrated success in past works. The 512 sample window size enabled fast computation of FFTs used for some of the features. The DC feature for normalization is the mean acceleration value of the signal over the window. Use of mean of maximum acceleration features has been shown to result in accurate recognition of certain postures and activities.

$$\mathrm{SVM} = \sqrt{X_i^2 + Y_i^2 + Z_i^2} \qquad (1)$$

$$\mathrm{DSVM} = \frac{1}{\mathrm{t}}\left(\int_i^{\mathrm{t}+i}(|\textstyle\sum \mathrm{SVM}'|dt)\right) \qquad (2)$$

III. Results

The fact that the acceleration thresholds follow the envelopes of the acceleration signal (analogously to an electronic peak detector) enables said changes to be followed rapidly, without any risk for any loss of steps and counting errors occurring, and at the same time enables a good insensitivity to noise to be achieved. In particular, when the accelerations increase (in absolute value), for example because the walking speed has increased, the reference thresholds increase rapidly, so as to adapt rapidly to the new conditions. When, instead, the accelerations decrease, for example because the user is slowing down, the reference thresholds also decrease, but slowly, and always remaining above a minimum value. In this way, the device is able to follow closely a new increase in the acceleration values as shown in Figure 10.

A summary of step counts obtained from accelerometer-based mobile device, iPod touch is presented in Table 1. iPod touch was worn on different position at the right waist, over the right ASIS using a waist belt and user's right pants pocket. Data were acquired during the walking in semi natural condition. The subject walked along a 100-foot walkway, 3 times. The results of this evaluation can be seen in Table 1. The mean accuracy across these tests was 99.6 ± 0.61%, 99.1 ± 0.87% (right waist location, right pants pocket).

In the pilot test, subjects continuous posture change including standing, walking, running, sitting, lying and falling. In the experiment, each posture was recognized third. Mean and standard deviation of acceleration and correlation features were extracted from acceleration data. Activity recognition on these features was performed using fuzzy c means (FCM) classification algorithm. Fuzzy clustering techniques have been applied effectively in image processing and pattern recognition. The best known approach to fuzzy clustering is the method of FCM, proposed by Bezdek [20] and Dunn

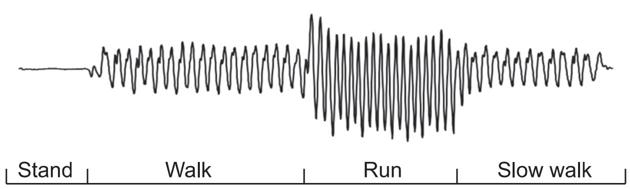

Figure 10. Vector magnitude of tri-acceleration data from iPod. Time line of activities is indicated along the abscissa.

Table 2. Clustering results of different posture in a continuous motion

Postures	Jaccard score	Purity	Efficiency
Standing	0.98	0.98	0.98
Sitting	0.97	0.97	0.96
Lying	0.98	1.00	1.00
Walking	0.98	0.99	0.98
Running	1.00	1.00	1.00
Falling	0.99	1.00	0.99
Average	0.98	0.99	0.98

Table 1. Accuracy results of step counts obtained from iPod was worn on different position at the right waist and user's right pants pocket

Subject	Right waist				Right pants pocket			
	1st	2nd	3rd	Mean ± SD	1st	2nd	3rd	Mean ± SD
A	99	100	100	99.7 ± 0.58	99	100	99	99.3 ± 0.58
B	100	100	100	100	100	100	99	99.7 ± 0.58
C	100	100	99	99.7 ± 0.58	99	100	99	99.3 ± 0.58
D	99	98	99	98.7 ± 0.58	98	97	99	98.0 ± 1.00
E	100	100	100	100	100	99	100	99.7 ± 0.58
F	99	100	100	99.7 ± 0.58	99	98	98	98.3 ± 0.58
Accuracy (%)		99.6 ± 0.61				99.1 ± 0.87		

Figure 11. Implementation of the physical activity monitoring based on iPod Touch.

[21], and generalized by other authors [22]. Recognition accuracy of over 98% on a six activities such as standing, sitting, lying, walking, running, and falling as shown Table 2.

IV. Discussion

The aim of this study was to present a method, integrated solution to convenient monitoring of daily physical activity using a mobile phone platform. Therefore, we have developed the solution using iPod to creating activity-informed applications. We put the iPod touch has built in a tri-axial accelerometer on the waist of the subjects, and measured change in acceleration signal according to change in ambulatory movement and physical activities. First, we developed of programs that are aware of step counts, velocity of walking, energy consumptions and metabolic equivalents (METs) based on iPod (Figure 11). Second, we have developed the activity recognition program based on PC using visual C# tools. iPod synchronization with PC to transmit measured body acceleration data using iPhoneBrowser program. Using the implemented system, we analyzed change in acceleration signal according to the change of six activity patterns such as standing, sitting, lying, walking, running, and falling such as Figure 12. It shows when and how intense the activity was made, by walking and by lifestyle activity separately, helpful tool to make advice upon each individual's life pattern.

We emphasize the practical applicability of the physical activity monitoring system. By using light weight and comfortable sensors the user's mobile phone. Activities can be monitored and recorded throughout a longer period of time. Our research project aims to record all kinds of information that can be gathered on the phone for later retrieval. Archiving the current physical activity seems to be a useful search key for browsing recorded events. Because mobility among chronic disease patients is mostly reflective of their medical conditions and hence has been strongly emphasized as the most important criteria to determine functional performance, monitor overall treatment effectiveness, and assess the readiness for discharge [23-25].

The next step in our system will be addition of a standard

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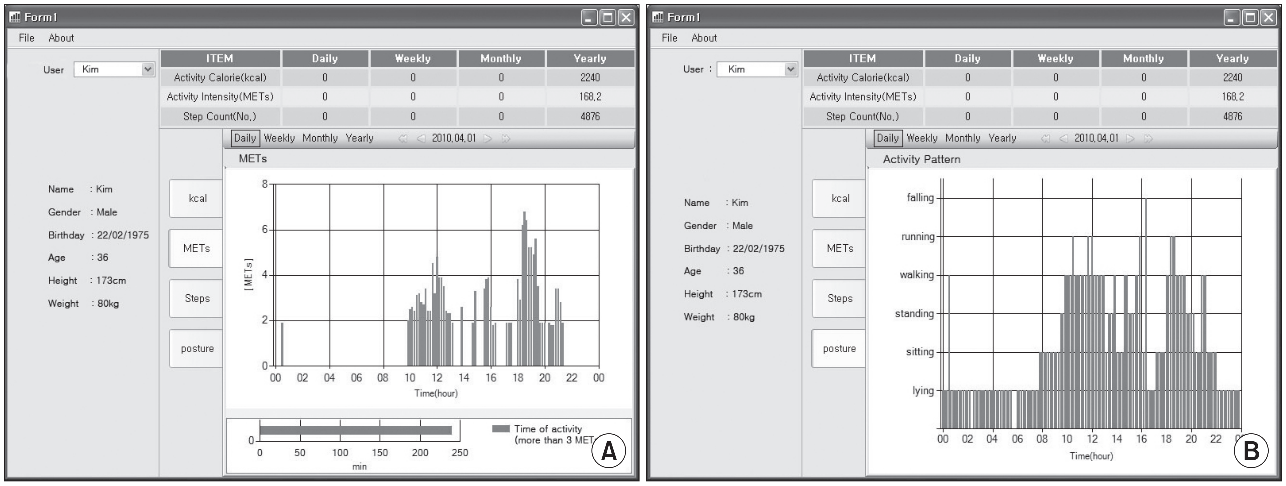

Figure 12. Analysis of the physical activity monitoring based on PC. Graphs out by step count, calorie consumption, metabolic equivalents level and activity pattern. (A) Step counts of the day. (B) An hourly change of activity pattern is shown with a bar chart.

value of various physical activities in every-day life such as household duties and a health guideline how to select and plan exercise considering one's physical characteristics and condition.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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