Physical Activity Recognition based on Rotated Acceleration Data using Quaternion in Sedentary Behavior : A Preliminary study

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Abstract — **This paper suggests a physical activity assessment method based on quaternion. To reduce user inconvenience, we measured the activity using a mobile device which is not put on fixed position. Recognized results were verified with various machine learning algorithms, such as neural network (multilayer perceptron), decision tree (J48), SVM (support vector machine) and naive bayes classifier. All algorithms have shown over 97% accuracy including decision tree (J48), which recognized the activity with 98.35% accuracy. As a result, physical activity assessment method based on rotated acceleration using quaternion can classify sedentary behavior with more accuracy without considering devices' position and orientation.**

I. INTRODUCTION

Sedentary people spend less time on physical activity than others. Because metabolic syndrome is closely associated with lifestyle factors, including low physical activity level, people who spend most of their time in sedentary behavior have an increased risk of metabolic syndrome, such as diabetes, obesity and hypertension [1]. On the other hand, regular and moderate physical activity reduces the risk factor of metabolic syndrome [2]. For this reason, sedentary people need a physical activity encouraging system that will emphasize the importance of physical activity. And the system has to correctly recognize user's activities, record the elapsed time of each activity and provide overall data to the user.

To assess physical activity, many researches adopt self-report method and external devices like an accelerometer or a heart rate monitor [3 - 4]. Self-report method is an easy and fast way to recognize the activity. But, the method is inconvenient for the user because the user has to record the activity personally. Also it has low accuracy because the activity recognition only depends on user's records. To resolve these problems, there are many external devices based systems that consistently measure and recognize user's physical activity, such as activPAL, acti-graph and acti-heart [5]. However, these systems are also uncomfortable for the user because they have to wear unaccustomed devices all day. And these systems measure acceleration with fixed orientation and recognize activity with the algorithm using signal patterns or simple parameters [6 - 7]. So, if the device is fixed differently from supposed circumstance in the algorithm, such as fixed on different position of the body, it is hard to recognize the activity accurately.

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In order to improve performance and accuracy on recognizing user's activity, physical activity assessment researches, based on quaternion, are being conducted recently [3, 5]. A quaternion is a four-dimensional complex number that can be used to represent the orientation of coordinate frame in three-dimensional space [3]. Acceleration data can be rotated by quaternion from the device coordinate frame to the world fixed coordinate frame. Rotated acceleration signals always represent the same coordinate frame data regardless of the device's orientation.

This paper suggests the quaternion based physical activity assessment method in sedentary as preliminary study and analyzes the recognition accuracy with various machine learning algorithms in WEKA. Also, mobile application system is developed to recognize activity using only user's mobile device.

II. METHOD & MATERIAL

A. Quaternion

A quaternion is a four-dimensional complex number that can be used to represent the orientation of coordinate frame in three-dimensional space [3]. The equation of quaternion can be found in (1).

$$\begin{aligned} q &= [q_1\ q_2\ q_3\ q_4] = [s, \vec{v}] \\ &= \left[\cos\frac{\theta}{2}, \sin\frac{\theta}{2}\vec{n}\right] \\ &= \left[\cos\frac{\theta}{2}\ \ \sin\frac{\theta}{2}\vec{n}_x\ \ \sin\frac{\theta}{2}\vec{n}_y\ \ \sin\frac{\theta}{2}\vec{n}_z\right] \end{aligned} \tag{1}$$

Where q_1 : the scalar part of quaternion

and q_2, q_3, q_4 : the vector part of quaternion

An arbitrary orientation of frame ***B*** can be achieved through a rotation of angle $\boldsymbol{\theta}$ around an axis ***n*** defined in frame ***A*** [3, 5]. This is represented graphically in Fig. 1. A three dimensional vector $\mathbf{v_A}$ in frame ***A*** can be rotated by a quaternion to frame ***B*** using the relationship described in (2). $\boldsymbol{v_A}$ and $\boldsymbol{v_B}$ are same vector described in frame ***A*** and frame ***B*** respectively [3, 5].

$$v_B = q \otimes v_A \otimes q^* \tag{2}$$

Where q^* : conjugate of q

When acceleration data is rotated by quaternion, it can be described in world fixed coordinate frame. Rotated acceleration data always represents same coordinate frame acceleration data regardless of device's orientation.

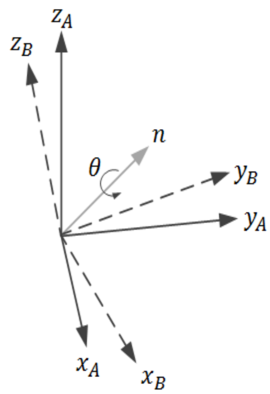

Figure 1. Graphical representation of quaternion

B. Android mobile application system

Android based mobile application was developed, in Fig.2, to measure acceleration signal by only using user's mobile device without any extra measurement devices. The user's acceleration and quaternion data are saved in the device as a text file and the sampling rate of the system is 50Hz.

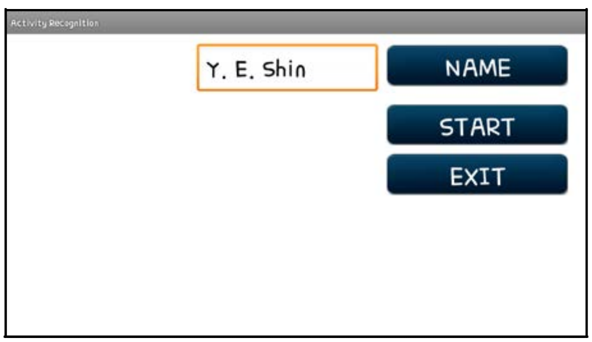

Figure 2. User interface of android mobile application

C. Experiment

Since sedentary people spend more time for sitting than other activities during their daily lives [1, 2], when it comes to assess of physical activity, their main concern is the assessment of activities performed while sitting.

Five healthy subjects have participated in the experiment in Table 1. Subjects performed sedentary activities for 30 minutes. For the experiment, mobile device (Galaxy Note II, Samsung Inc.) was put in the subjects' trouser pocket to acquire accelerometer and quaternion data in Fig. 3. Subjects were arranged to perform sitting activities as Fig. 3(a), such as computer work and reading, for most of the time and also performed other types of activities as Fig. 3(b), e.g., standing and walking, for less time. Activities were divided into two separate states, sitting and other activities, because the amount of time for sitting is important to sedentary people.

TABLE I. SUBJECTS' FEATURES

N(Gender)		Age	Height(cm)	Weight(kg)
5	Mean	23.5	175.17	73
(Male)	SD	±1.76	±5.27	±9.03

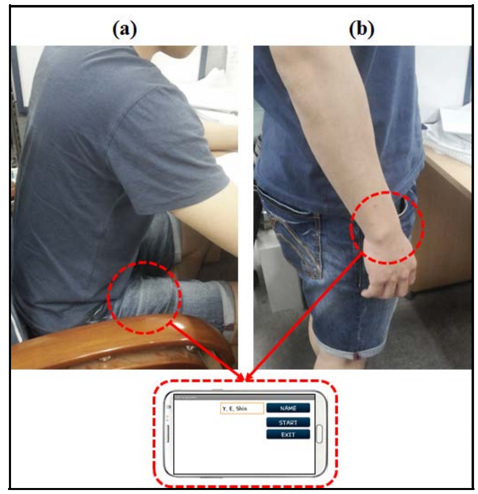

Figure 3. Subject putting mobile device in trouser pocket (a) Sitting activity, (b) Standing activity

D. Data pre-processing

For the activity recognition, data pre-processing was performed as Fig. 4. First, accelerometer and quaternion data were collected by the mobile device as Fig. 5(a). Second, sets of acceleration data were rotated to world fixed coordinate frame by (2) as Fig. 5(b). Third, the magnitude of rotated z-axis acceleration data was selected as a parameter to divide into two separated states, sitting and others. Because it presents the vertical line activity in Fig. 5(c). Finally, applying the window to the magnitude of rotated z-axis acceleration data with 66% overlap was performed every second and average of windowed data was calculated in Fig. 5(d).

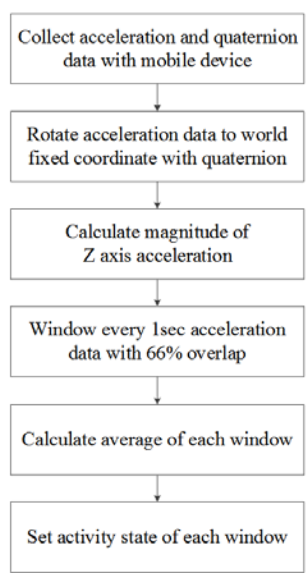

Figure 4. Data pre-processing flow chart

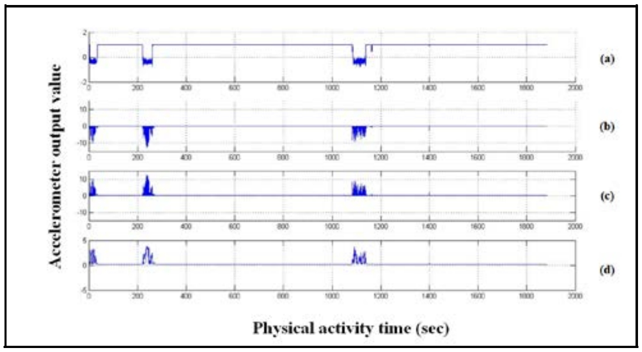

Figure 5. Signal pre-processing of accelerometer signal

(a) Original data of z-axis acceleration, (b) Rotated data of z-axis acceleration using quaternion, (c) Magnitude of rotated z-axis acceleration data, (d) Windowing of the magnitude of rotated z-axis acceleration data with 66% overlap

E. Activity Recognition with WEKA

After data pre-processing and average calculation, we used the WEKA (Waikato Environment for Knowledge Analysis) to assess physical activity using various algorithms, such as neural network (multilayer perceptron), decision tree (J48), naive bayes classifier and SVM (support vector machine).

III. RESULT

Table 2 shows the activity recognition results through various machine learning algorithms in WEKA. All algorithms showed over 97% accuracy and among those algorithms, decision tree (J48) recognizes the activity with 98.35% accuracy. And it takes 0.03s to build a model.

TABLE II. ALGORITHM EVALUATION RESULT

Classifier	Accuracy (%)	Training time (s)
Multilayer Perceptron	98.30	8.69
Naive Bayes	97.99	0.04
J48	98.35	0.03
SVM	97.81	0.45

Confusion matrix in Table 3 shows the activity classification result of J48 which has the highest accuracy. 0.09% of sitting activity data were misclassified as other activity and 13.08% of other activity data were misclassified as sitting activity.

TABLE III. CONFUSION MATRIX OF J48

Activity (state)	Classified as	
	Sitting	Others
Sitting	20969	19
Others	375	2491

IV. CONCLUSION

In this paper, we recognize sedentary activity with the acceleration data rotated by quaternion as preliminary research. We intend to confirm that whether the physical activity assessment method based on quaternion has valid results or not.

Acceleration data was rotated by quaternion and windowed with 66% overlap to get average and then classified as two activity states, sitting and others. Results were verified by various machine learning algorithms. Four well-known machine learning algorithms were used to recognize activity and all algorithms had high accuracy with over 97%. Most of all, decision tree (J48) classifier showed the best result in recognizing the activity with 98.35% accuracy. As a result, physical activity assessment method based on rotated acceleration data using quaternion can classify the sedentary behavior with high accuracy.

From confusion matrix of J48, the error of sitting activity data recognition was very low with 0.09%. It means that algorithm classifies the sitting activity very accurately. On the other hand, the error of other activity data recognition was relatively high with 13.08%. This is because that the standing activity in the other activity state was classified as the sitting activity. Between the sitting and standing activity, there are no differences in acceleration so the algorithm can't distinguish the two activities well. In further study, additional parameters will be used to distinguish the two activities with more accuracy.

Previous systems based on the accelerometer for assessing and recognizing sedentary behaviors are used by putting the device on the fixed position such as arm, wrist, thigh, hip and shank of user's body. These systems can't estimate the physical activity accurately because they don't consider the devices' orientation. For this reason, we suggest the physical activity assessment method based on the rotated acceleration data using quaternion. Using this method, sedentary behaviors can be classified with more accuracy without considering the devices' position and orientation.

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