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Accuracy of Posture Estimation by ActiGraph and Development of Posture Prediction Model from Raw Acceleration Data

Kazuhiro Sugawara, and Kosuke Shimizu, *Member, IEEE*

***Abstract*— Full body motion tracking system was used to obtain accurate posture information under free-living condition and the accuracy of posture prediction by ActiGraph was verified. ActiGraph tends to detect people as standing when they are actually sitting. By combining a prediction model that detects posture change, lying posture, and walking from raw acceleration data obtained by ActiGraph, we were able to predict posture information with higher accuracy.**

***Clinical Relevance*— By combining model for predicting posture changes, lying posture, and walking from raw acceleration data obtained by ActiGraph, it is possible to obtain more accurate posture information.**

I. Introduction

For daily health management, it is important to know the physical activities in daily life. In particular, avoiding a sedentary lifestyle is an important factor in preventing chronic diseases [1]. Sedentary behavior is defined as any waking behavior with an energy expenditure below 1.5 metabolic equivalents, while in a sitting, reclining or lying posture [2]. To avoid a sedentary lifestyle, it is essential to be able to record the amount of time spent in a sitting position in daily life.

ActiGraph GT3X+ accelerometer (AG3) is a widely used wearable device in research field that can easily record the changes in posture and the amount of activity. AG3 identifies four different states (standing, sitting, lying, and with the device removed) based on the activity counts and the inclinometer function of the device attached to a desired location [3]. In a previous study using the AG3 to examine sitting time in daily life, it was reported that people with obesity tend to spend more time in a sitting position during the day than people with normal BMI. [4]. However, until now, the accuracy of posture information obtained from AG3 has been mostly evaluated for specific behavioral patterns in an experimental environment [5], and verification under free-living condition has not been sufficiently examined due to the difficulty of obtaining correct data.

A typical method for verifying the validity of posture information is to use a camera to visually check and record the posture information [5]. However, this method has a limitation in that the behavior is limited to the range that can be captured by the camera, and it is limited to the behavior in a specific space. Therefore, in this study, we used a full-body motion tracking system using inertial sensors called Xsens MTw Awinda (XS) as a method to obtain accurate posture information under free-living condition. Using the XS, accurate posture information can be obtained from the skeletal model of the whole body, and accurate training data such as posture changes and walking timing can be obtained from the whole body movements and the acceleration of each body part.

The purpose of this study is to verify the accuracy of the posture information of AG3 under free-living condition and to investigate methods to obtain more accurate posture information using prediction model by the raw acceleration data recorded by AG3.

II. Methods

A. Participants

Five adults volunteers (percentage male 60%, 35.6±8.2 years) participated in this study. Individuals had no significant physical limitations and medical conditions. The study was conducted in the spirit of the Declaration of Helsinki (revised in October 2013) and in accordance with the Ethical Guidelines for Medical Research Involving Human Subjects (partially revised on February 28, 2009 by the Japanese Ministry of Education, Culture, Sports, Science and Technology and the Japanese Ministry of Health, Labor and Welfare).

B. Data collection

To obtain posture information, ActiGraph GT3X+ (ActiGraph LLC, Pensacola, FL) and Xsens MTw Awinda from Xsens Technologies B.V. (Enschede, Netherlands) were used in this study.

The AG3 can be worn at the waist or on the wrist to easily estimate the amount of activity and posture information. It has been reported that the optimal wearing position of the accelerometer to obtain posture information is at the waist [6]. Therefore, in this study, we attached the AG3 at the waist. The wearing position was the lateral side of the right anterior superior iliac spine. AG3 can detect standing, lying, sitting, and device-off based on the activity counts and the inclinometer function. The sampling frequency of the measurement was set at 50 Hz.

The XS has 17 inertial sensors to be attached to the head, the back of the shoulders, breastbone, pelvis, thighs, lower

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Kazuhiro Sugawara is with the Arblet Inc., Shibuya-ku, Tokyo, 150-0021, Japan (e-mail: kazuhiro.sugawara@arblet.com)

Kosuke Shimizu is with the Arblet Inc., Shibuya-ku, Tokyo, 150-0021 Japan (e-mail : kosuke.shimizu@arblet.com.

legs, feet, upper arms, forearms, and hands to accurately measure whole body motion. The position and the velocity of -each segment with the sensor attached, as well as the acceleration, tilt, and angular velocity of each sensor can be calculated. The sampling frequency was set to 60 Hz.

The subjects were first attached with 17 XS sensors on various parts of the body and then were calibrated. After the calibration, the AG3 was attached to the right waist. After starting the measurement of AG3, the measurement of XS was started. To synchronize the time of both devices, we created a synchronization point by tapping AG3 from above with the right hand.

The area of free-living condition was set within 10m from the XS inertial sensor receiver so that inertial sensor information could be received. The subject was asked to move freely within the area of free-living condition. The subjects were also instructed to change their posture about once every 15 minutes in order to detect the changes in posture. The measurement locations were in the office or at home. Each subject was measured five times for one hour, for a total of 25 hours of data under free-living condition.

The data measured by AG3 was divided into 5-second epochs to output posture information (0:Device off, 1:Standing, 2:Sitting, 3:Lying), as well as its raw acceleration data was also obtained. The raw acceleration data between start and the end synchronization points was also divided into 5-second epochs.

On the XS analysis software, a skeletal model of the whole body composed of the information from each sensor was used to label the standing, lying, sitting and walking. Acceleration data from the sensors attached to both feet were also used for walking detection. These labeled posture data was synchronized with the AG3 measurements and created a time series of training data.

C. Feature extraction

Features were extracted from raw acceleration data using a window size of 250 samples(5 seconds). Features in the time-domain include median, mean, max, min, min-max difference, signal vector magnitude, vector angle(VA) and zero-crossing number of the raw acceleration data. Signal vector magnitude and VA were calculated using equation (1) and (2). The zero-crossing number was defined as the number of times the acceleration signal crossed the zero level during a data window.

$$Signal\ Vector\ Magnitude = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (1)$$

$$VA_{xy} = \arctan(\frac{median(a_x)}{median(a_y)}) \quad (2)$$

Additionally, we used linear regression for the acceleration data and the slope value was used for the features. We also used binned data, which divided a 250 samples into 5 section (50 samples each), and the features at the beginning and the end of the frame was used.

Features in the frequency-domain include maximum peak frequency which is the frequency at which the amplitude is

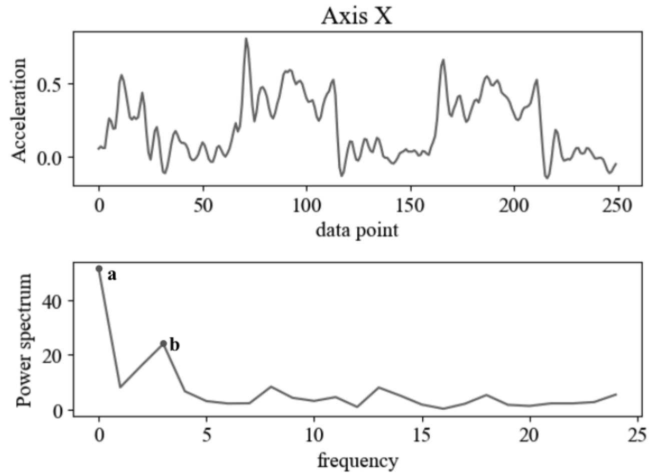

Figure 1. A 5-second (1 epoch) sample of raw acceleration data. a: DC component of acceleration. b: maximum peak frequency which is the frequency at which the amplitude is maximum. The ratio of the maximum amplitude to the DC component was defined as the value of b divided by a.

TABLE I. TIMEAND FREQUENCY DOMAIN FEATURES

Type of features	Features
Time domain	*Min, Max, Mean, Median, Min-max difference, Signal Vector Magnitude, Vector angle, Linear regression value, zero-crossing number,*
Frequency domain	*Maximum peak frequency, ratio of the maximum amplitude at maximum peak frequency to the DC component*

maximum in the power spectrum obtained by Fourier transforming the acceleration data. The ratio of the maximum amplitude at the maximum peak frequency to the DC component was also included in features (Fig.1).

D. Posture prediction model

From the raw acceleration data measured by AG3, three models were created to predict postural changes, presence of lying posture, and presence of walking within a 5-second frame.

For the prediction of posture change, a model was created using the XS skeletal model as the training data to classify the 5-second frames into three categories: no posture change, posture change in the upward direction, and posture change in the downward direction. The posture change in the upward direction included three types of movements: lying to sitting, lying to standing, and sitting to standing. Posture changes in the downward direction included three movements: standing to sitting, standing to lying, and sitting to lying. Prediction was performed using multiclass classification model.

For the prediction of the presence of a lying posture, we defined lying to include any of the following five states: lying, standing to lying, sitting to lying, lying to standing, lying to sitting. Prediction was performed using binary classification model.

For the prediction of the presence of walking, walking was defined as the presence of at least one gait cycle within 5-seconds frame. The start and the end of walking were labeled based on the skeletal model and the acceleration of the foot sensor of XS. Prediction was performed using binary classification model.

Machine learning with gradient boosting trees were used for all prediction models. Prediction models were trained and tested using a 5-fold cross validation methods on the set of extracted features. Because of the large number of data for the sitting posture in this study, the data for the standing and supine postures were upsampled before analysis.

After creating the three models, we combined them to predict the posture. We first predicted the following nine states for each 5-seconds frame. (1) Standing (2) Sitting (3) Standing to sitting (4) Standing to lying (5) Sitting to standing (6) Sitting to standing (7) Sitting to lying (8) Lying to standing (9) Lying to sitting. Next, the postures at the beginning and the end of each frame were labeled as (1) standing, (2) sitting, and (3) lying, based on the information of the nine states. The degree of agreement between these results and the postures at the beginning and the end of each frame labeled by XS was investigated.

E. Statistical Analysis

The degree of agreement between AG3 and XS was evaluated using the Kappa coefficient and expressed by confusion matrix.

Each prediction models were evaluated using accuracy, precision, recall, and fscore.

After evaluating the accuracy of each model, we combined the three models and estimated posture and evaluated the accuracy against training data by XS.

III. Results

A. Accuracy of posture estimation by AG3

Accuracy of the posture estimate of AG3 was 0.67. The Kappa coefficient between the posture information estimated by AG3 and XS was 0.301. The confusion matrix between the posture information estimated by AG3 and the XS is shown in Table.2.

The most common error was that the person was judged to be standing while sitting, accounting for 86.3% of all errors. The second most common error was when a person was detected as sitting while standing, accounting for 9.4% of all errors. In this study, there was no situation in which the AG3 was removed, but there were cases in which the AG3 estimated that the device was removed.

TABLE II. CONFUSION MATRIX: ACTIGRAPH VS XSENS

		ActiGraphGT3X+			
		Standing	***Sitting***	***Lying***	***Device off***
XSens MTw Awinda	***Standing***	1626	513	9	0
	Sitting	4698	9479	4	80
	Lying	88	15	460	36
Accuracy		0.253	0.947	0.972	0

TABLE III. EVALUATION OF PREDICTION MODELS

	Posture change detection	***Lying detection***	***Gait detection***
Accuracy	0.996	0.998	0.9880
Precision	0.999	0.997	0.9786
Recall	0.989	0.999	0.9979
F_score	0.994	0.998	0.9881

B. Posture prediction from raw acceleration data

The estimation results of each of the models that predicted posture change, presence of lying posture, and presence of walking for each 5-second frame are shown in Table 3.

Posture prediction accuracy by combining three models was 0.909. To predict the posture, we first used the model which predict a change in posture in the target frame. The detection of posture change determines whether the direction of movement is upward or downward. If there is no posture change in the target data frame, we apply the model to determine that the subject is lying down, and if not, we detect if there is walking in the frame. If there is walking, it determines that the posture is standing, and if there is no walking, it refers to the posture information before detecting the posture change. If a posture change is detected in the target data frame, the direction of the posture change is evaluated, followed by a determination of whether the subject is lying down or not, and if not lying down, the posture is predicted by applying a model that detects whether there is walking or not. The flowchart of the prediction is shown in Fig. 2.

IV. Discussion

The results of this study show that AG3 tends to detect people as standing when they are actually sitting. In a previous study, it was reported that AG3 classified sitting posture with 100% accuracy when measured in an experimental environment using a chair with a seat height of 40cm [5], but in this study, we observed many errors even when sitting in a chair with a seat height of around 50cm.

AG3 estimates the posture based on the tilt and the activity counts of the device, but the results may be affected by a shift in the position of the device. Especially in the sitting posture, if the device is attached to the front of the hip joint, the hip flexion tends to push the device up and make the posture closer to horizontal. On the other hand, if the device is attached to the outside of the hip joint, the device will be in a near upright position This difference in the wearing position of the device can be one of the possible causes of false detection. Therefore, in order to use the information of posture estimation by AG3, it is necessary to specify that the wearing position should always be constant. However, in this study, even though the wearing position was kept constant, many false positives were still observed, suggesting that people may actually be sitting for a lot more time than estimated by the AG3. Furthermore, the many cases detected as standing may also affect the acquisition of step count information.

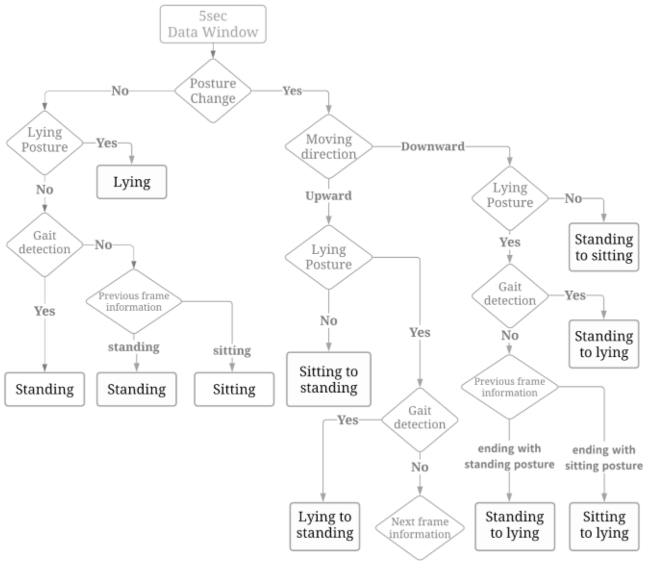

Figure 2. Flow chart of posture estimation.

Although posture information can be used to prevent sedentary lifestyles, it suggests that caution is needed in using the estimated posture results as is.

It was shown that the posture information can be obtained with higher accuracy by combining the model for detecting the posture change in a frame, the model for detecting lying position, and the model for detecting walking. From the results of this study, the most common false positives in posture estimation were judged to be standing while sitting. To reduce this false detection, we thought that detecting the posture change and direction(upward or downward) and adding the information of the posture of the previous frame to estimate the posture would reduce the false detection of judging that the person is standing even though the person has not stood up from a sitting position (no upward posture change has occurred).

In previous research, many studies have been conducted to detect behaviors from the acceleration data of smartphones, and it has been shown that basic behaviors such as walking, standing, and sitting can be predicted with an accuracy of more than 90% [8-11]. In this study, the position of the device is fixed compared to that of a smartphone, so the accuracy of posture prediction is higher than in previous studies. In addition, several features extracted from the acceleration can be cited as the factors that increased the accuracy. First, the 5-second window was further divided and the difference between the feature values at the beginning and the end of the frame was used as the feature value, which contributed to the improvement in accuracy. Second, in the lying posture detection model, the median acceleration in the vertical direction at the start of the frame was one of the effective feature values. In addition, the amplitude of the maximum peak frequency after the Fourier transform expressed as the ratio of the DC component also contributed to the improvement of the accuracy of posture change and gait detection. Thus, in addition to the simple 5-second average value, maximum value, minimum value, the use of features that capture the changes at the beginning and the end of the window and the degree of strength of the amplitude of the peak frequency were suggested to be important for more accurate prediction.

In order to obtain more accurate posture information in daily life, it was suggested that posture prediction with high accuracy is possible by combining a model that detects posture change, lying posture, and walking in a window of several seconds by extracting feature values from the raw acceleration data obtained by AG3.

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