MACHINE-LEARNING ESTIMATION OF BODY POSTURE AND PHYSICAL ACTIVITY BY WEARABLE ACCELERATION AND HEARTBEAT SENSORS

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ABSTRACT

We aimed to develop the method for estimating body posture and physical activity by acceleration signals from a Holter electrocardiographic (ECG) recorder with built-in accelerometer. In healthy young subjects, triaxial-acceleration and ECG signal were recorded with the Holter ECG recorder attached on their chest wall. During the recording, they randomly took eight postures, including supine, prone, left and right recumbent, standing, sitting in a reclining chair, sitting in chairs with and without backrest, and performed slow walking and fast walking. Machine learning (Random Forest) was performed on acceleration and ECG variables. The best discrimination model was obtained when the maximum values and standard deviations of accelerations in three axes and mean R-R interval were used as feature values. The overall discrimination accuracy was 79.2% (62.6-90.9%). Supine, prone, left recumbent, and slow and fast walk were discriminated with >80% accuracy, although sitting and standing positions were not discriminated by this method.

KEYWORDS

Accelerometer, Holter ECG, Posture, Activity, Machine learning, Random Forest, R-R interval

1. INTRODUCTION

The importance of physical activity for health maintenance and promotion is gathering increasing attention. Sedentary behaviour is known to be associated with the incidence of malignant arrhythmias, and there is accumulating evidence to support that the maintenance and increase of physical activity decrease the risk of sudden cardiac death [1]. Increased physical activity by exercise can be expected to be effective in lowering the functional level of daily life and in preventing life-style related diseases including diabetes, dyslipidaemias, metabolic syndrome, heart diseases, and malignancies [2]. The World Health Organization's Global Recommendation for Physical Activity [1] states an increase in total step counts in daily life as a goal in the field of daily physical activity and exercise. It says that an increase of 1500 steps a day accounts for 2% reduction in the incidence and mortality by non-communicable diseases and 1.5-mm Hg reduction in blood pressure.

Even though these required physical activity criteria have been proposed based on scientific evidence, the information used to assess physical activity is often depends on that obtained by conventional methods such as a pedometer, in which information such as the type and frequency of postural changes and the speed of action and movement is ignored. As a result, the adjustment for the effects of age, gender, weight, and height on the assessment of physical activity, if implemented, become less rigorous.

To overcome this problem, several studies proposed acceleration and other sensors [3-10] and algorithms including machine learning for the precise estimation of body posture and the type and level of physical activity [6,7,10]. The reported performance, however, differed with the type, number, and placement of sensors, signal sampling frequency, analysis window size, machine learning technique, and measurement setting, i.e., laboratory or free-living conditions [11]. In this study, we investigated the posture and activity estimation performance of a built-in accelerometer of a chest-mounted Holter electrocardiographic (ECG) recorder widely used for clinical purposes in combination with the Random Forest machine learning technique.

2. EXPERIMENT METHODS

2.1. Subjects

We studied 11 healthy subjects (2 men, 9 women, 22 ± 1 yr) who gave a written informed consent to participate this study. The protocol of the present study was approved by the Institutional Review Board of Nagoya City University Graduate School of Medical Sciences and Nagoya City University Hospital (approval number, 60-18-0211).

2.2. Measurement device

Holter ECG recorders with a built-in 3-axis acceleration sensor (Cardy 303 pico+, Suzuken Co., Ltd; size, W28×D42×H9 mm, weight, 13 g) were used for measuring acceleration and ECG signals. The sampling frequency of the ECG was 128 Hz. The accelerometer recorded acceleration from left to right, cranio-caudal, and postero-anterior directions as the X, Y, and Z values, respectively, at a frequency of 31.25 Hz.

2.3. Experimental protocol

Experiments were conducted in an air-conditioned laboratory at 24 ± 2 ºC. The Holter ECG recorder and electrodes were attached on subjects' chest wall at 09:30. Subjects were instructed to take supine, prone, right and left recumbent, and standing positions, to sit in three different chairs (a recliner and chairs with and without a backrest), and to walk slowly and walk fast, in a randomized order. Subjects maintained each posture and activity for 110 s, and then moved to the next posture or activity within 10 s.

2.4. Data analysis

2.4.1. Analysis of 3-axis acceleration time series and RRI time series

The acceleration signals in X, Y, and Z axes at 31.25 Hz were under-sampled at 2 Hz per axis, and average, median, maximum, minimum, and standard deviation (SD) were calculated for every 10 s for each axis. Because the acceleration data were unstable during the beginning of each posture and activity, the first 20 s of each posture was removed, resulting in nine 10-s segments per posture/activity.

From the ECG signal, all R waves (sharp deflections corresponding to the ventricular electrical excitation) were detected and an R-R interval time series were obtained. R-R intervals consisting of consecutive sinus rhythms were extracted, resampled at 2 Hz using a step function, and averaged over every 10 s.

2.4.2. Feature Selection

As the feature datasets of acceleration variables for machine learning, we examined (1) the averages and SDs of 3 axes, (2) the medians and SDs of 3 axes, (3) the maximums and SDs of 3 axes, (4) the minimums and SDs, and (5) all indices of 3 axes. In addition, the average of the R-R interval was added to each of the acceleration datasets, yielding 10 feature datasets. The number of data for one posture was nine (90 seconds) per variable. The data for sitting positions in different chairs were put together and nine time points were randomly selected from the pooled dataset.

2.4.3. Machine learning of classification and verification

We used Random Forest for the machine learning classifier. To reduce the bias of the learning data, learning and verification were performed using k-fold cross validation method (k = 11). There was no overlap between the training and the test data. These processes were performed with Python (3.6) obtained from the open data science platform Anaconda (ANACONDA, https://www.anaconda.com/).

Verification of discrimination was performed by calculating the true positive (TP) and false negative (FN) for each posture from each subject, and then adding the TP and the FN from all subjects. The recall rate defined as equation (i) was calculated for each posture. For example, in the discrimination of the supine position, the TP was the number of successful discriminations of supine and FN was the number of unsuccessful discriminations of supine.

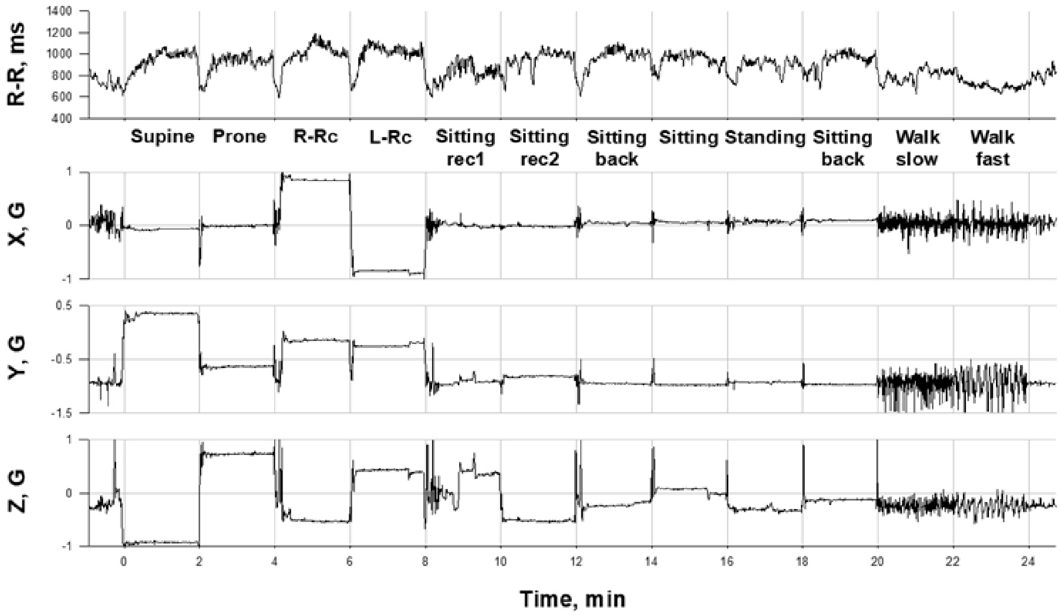

Fig. 1. Time series of R-R interval and 3-axis acceleration during experiment.

R-Rc = Right recumbent, L-Rc = Left recumbent, Sitting rec1 = sitting in a recliner with knee extending, Sitting rec2 = sitting in a recliner with knee bending, Sitting back = sitting in a chair with a backrest.

Table 1. Recall ratio for posture with feature dataset of acceleration

Posture/activity	Acceleration				
	Average SD	Median SD	Max SD	Min SD	All indices
Spine	0.869	0.859	0.859	0.859	0.869
Prone	0.798	0.788	0.717	0.778	0.657
R-recumbent	0.727	0.707	0.747	0.747	0.727
L-recumbent	0.909	0.909	0.909	0.919	0.909
Sitting	0.636	0.646	0.616	0.586	0.747
Standing	0.626	0.576	0.616	0.606	0.535
Slow walk	0.677	0.677	0.768	0.727	0.687
Fast walk	0.697	0.747	0.758	0.677	0.758
Accuracy	0.742	0.739	0.749	0.737	0.736
SD	0.106	0.111	0.103	0.116	0.118

Accuracy was calculated as the mean value of recalls for all postures.
SD = standard deviation

Table 2. Recall ratio for posture with feature dataset of acceleration and R-R interval

Posture/activity	Acceleration				
	Average SD	Median SD	Max SD	Min SD	All indices
Spine	0.869	0.838	0.899	0.879	0.859
Prone	0.818	0.859	0.859	0.859	0.636
R-recumbent	0.747	0.727	0.737	0.737	0.747
L-recumbent	0.909	0.859	0.909	0.919	0.909
Sitting	0.758	0.667	0.717	0.667	0.768
Standing	0.525	0.586	0.626	0.535	0.434
Slow walk	0.657	0.606	0.818	0.687	0.828
Fast walk	0.717	0.737	0.768	0.758	0.737
Accuracy	0.750	0.735	0.792	0.755	0.740
SD	0.122	0.110	0.098	0.128	0.149

Accuracy was calculated as the mean value of recalls for all postures.

$$\text{Recall} = \text{TP} / (\text{TP}+\text{FN}) \quad \cdots \tag{i}$$

The number of the decision tree and the maximum depth of the tree of the Random Forest were 3 and 20, respectively, and the maximum value of the recall was calculated by the grid search function in this range.

3. RESULTS

Fig. 1 shows the examples of R-R interval and 3-axis acceleration time series during the experiment. The acceleration signals changed according to the changes in the relative direction of gravitation vector with postures. In addition, the acceleration signals, particularly in Y-axis reflecting cranio-caudal direction, showed fluctuations during walking and its amplitude was greater for fast walk than slow walk.

Table 3. Confusion matrix of feature dataset with the best classification performance

Posture/activity		Estimated posture/activity								Segment	Recall
		Su	Pr	Rr	Lr	Si	St	Sw	Fw		
Actual	Su	89	0	7	0	0	0	1	2	99	0.899
	Pr	1	85	4	7	1	0	1	0	99	0.859
	Rr	7	15	73	1	3	0	0	0	99	0.737
	Lr	0	2	7	90	0	0	0	0	99	0.909
	Si	2	0	0	0	71	26	0	0	99	0.717
	St	0	0	0	0	34	62	3	0	99	0.626
	Sw	0	0	0	0	0	1	81	17	99	0.818
	Fw	0	0	0	0	0	0	23	76	99	0.768

Su = supine, Pr = prone, Rr = right recumbent, Lr = left recumbent, Si = sitting, St = standing, Sw = slow walk, Fw fast walk.

Table 4. Gross confusion matrix for coarse-grained posture/activity

Posture/activity		Estimated				Segment	Recall
		Lying	Sitting	Standing	Walking		
Actual	Lying	388	4	0	4	396	0.980
	Sitting	2	71	26	0	99	0.717
	Standing	0	34	62	3	99	0.626
	Walking	0	0	1	197	198	0.999
Segment		390	109	89	204	792	
Specificity		0.995	0.945	0.961	0.986	Accuracy	
Positive predictive value		0.995	0.651	0.697	0.966	0.907	

Data are classification results by feature dataset with the maximum and SD of acceleration and mean R-R interval.

Tables 1 and 2 shows the recall rate for the posture/activity by each feature dataset. The feature dataset with the highest mean recall rate was a combination of the maximum and SD of acceleration and mean R-R interval (mean recall rate ± SD, 0.792 ± 0.098). Supine, prone, left recumbent, and slow walk were discriminated by recall rates >0.80, while the recall rate for standing was 0.626.

Tables 3 and 4 shows the confusion matrix for the feature dataset with the best performance (maximum and SD of acceleration and mean R-R interval). When the postures and activities were coarse-grained into lying, sitting, standing, and walking, the overall accuracy of classification was 0.907. The recall ratio, specificity, and positive predictive value for classifications of lying and walking were >0.95.

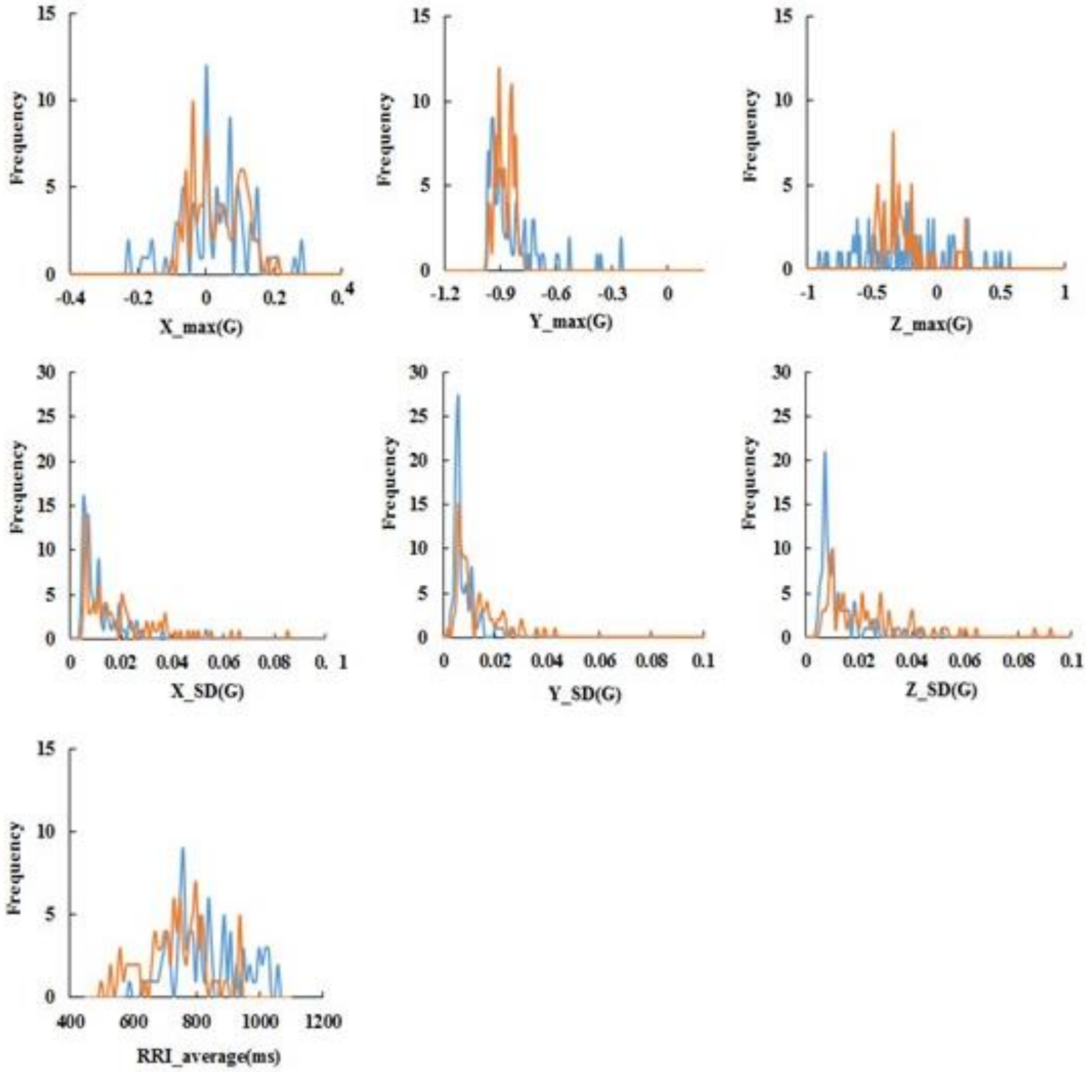

Fig. 2. Histogram of the maximum and SD of acceleration and R-R interval for sitting and standing positions.
Blue: sitting, Orange: standing.

However, the discrimination between sitting and standing were less accurate. Although out of 99 segments in sitting 71 segments were correctly discriminated as sitting, 26 segments were classified as standing, and 2 as prone position, indicating that 26% of sitting was estimated as standing. Similarly, out of 99 segments in standing 62 segments were correctly discriminated as standing, but 34 segments were classified as sitting and 3 as slow walking, indicating that standing was estimated as sitting at 34% probability. Fig. 3 is a histogram of the maximum and SD of acceleration and RRI in the sitting and standing postures. Both show the similar patterns of distribution.

4. DISCUSSIONS

In the present study, we examined the usefulness of built-in triaxial accelerometer of a chest-mounted Holter ECG recorder in combination with machine learning for estimating body posture and activity. All possible combinations of variables derived from triaxial acceleration signals every 10 s were used as feature dataset and discriminant models were generated by the Random Forest algorithm. The best classification performance was obtained by the feature dataset consisting of the maximum and SD of acceleration. For all feature datasets of acceleration variables, addition of mean R-R interval improved the classification performance. By the model using the maximum and SD of acceleration and mean R-R interval classified lying, sitting, standing, and walking with an overall accuracy of 0.907. The model showed, however, lesser discrimination performances for sitting and standing than those for lying and walking. While the recall ratios for lying and walking were 0.980 and 0.999, the ratios for sitting and standing were 0.717 and 0.626, respectively. Our observations show both the strengths and weaknesses of posture/activity estimation by acceleration signals and seem to suggest hints for improving the estimation.

There are many studies of the sensors and signal processing algorithms to discriminate body postures [3-10]. They reported different performance depending on factors related to sensors, signal processing, data analysis including machine learning techniques, and measurement settings. As expected, using multiple sensors gives better performance than a single sensor. Yeoh et al. [3] used 3 accelerometers at the waist and both thighs and achieved an overall accuracy of 100% for classification of lying, sitting, standing, and walking and an overall mean-square error of 1.76 km/h for walking and running speeds. As to the type of sensor, Godfrey et al. [4] used chest mounted tri-axial accelerometer sensitive to both static and dynamic acceleration and reported sensitivity and specificity of >0.83 to detect activity types and postural transitions between sitting and standing using a sophisticated algorithm of Velocity Estimate and Scalar Product Activity. As to sensor placement, Fulk et al. [5] used acceleration and pressure sensors built into the shoe and successfully distinguished between sitting and standing with an accuracy of 82-100% in patients after stroke. Also, Doulah et al. [7] reported the detection of sit-to-stand posture transitions by orthosis-mounted sensors and Fanchamps et al. [9] used a acceleration sensor attached to the thigh in post-stroke patients. To discriminate activity types and postures, machine learning-based approaches are employed in most of recent studies, such as artificial neural network [7], support vector machines [5], Random Forest [10], Naïve Bayes, and K-nearest neighbours [11]. Finally, as to measurement setting, the reported performance of activity and posture discriminations obtained in free-living settings were generally lower than those obtained in laboratory settings [9,11]. In the present study, we used a simple tri-axial static acceleration sensor built in a chest-mounted Holter ECG recorder, measured data in a laboratory setting, and generated the discriminant model for posture and activity by Random Forest technique. Thus, it is difficult to compare the present results with those of earlier studies, but the discriminant accuracies were comparable to them except that between sitting and standing.

The low discrimination accuracy between sitting and standing may be attributable to the use of chest-mounted accelerometer that was less sensitive to dynamic acceleration and insensitive to the changes in angular velocity. Although the gravity vector is almost vertical in the sitting position, it may shift backward to some extent depending on the type of chair (more precisely, on the angle at which the body leans on the backrest). In contrast, the gravity vector in the standing posture is vertical theoretically; however, since the Holter ECG recorder is worn on the inclination of the chest, some backward inclination occurs. During standing acceleration may fluctuate slightly due to body sway, while it may more stable during sitting. In this experiment, however, the fluctuation of acceleration signal was observed also during sitting (Fig. 3). In addition, the backward movement of the vertical acceleration vector may also occur due to walking and other forward movements, further complicating the determination. To overcome this problem, not only static features of acceleration such as mean, SD but also dynamic features of acceleration such as the pattern of changes seem necessary.

To our knowledge, there was no study to report posture discrimination using both acceleration and R-R interval. Although the discrimination accuracy differed depending on the selection of the feature dataset, the discrimination accuracy was consistently improved by combining 3-axis acceleration and R-R interval. Since R-R interval is expected to shorten with standing [12], mean R-R interval may be useful feature to discriminate sitting and standing. This suggests possibility of using the indices of heart rate variability as the additional feature to discriminate posture/activity. Particularly, low frequency to high frequency power ratio may be useful for the feature to detect standing [13,14].

5. CONCLUSIONS

We examined the posture and activity discrimination performance of signals from a built-in tri-axial acceleration sensor in a chest-mounted Holter ECG recorder using Random Forest machine learning technique. We observed acceptable discriminate accuracy of activities and postures except for that between sitting and standing. Additionally, we found that the inclusion of R-R interval data as a feature improves the discriminatory accuracy. Because Holter ECG recorders with built-in accelerometer are widely used clinically, our findings seem to provide useful insight into the benefits and limitations of the clinical use of the accelerometer signal.

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