Physical Activity Group Classification Algorithm using Triaxial Acceleration and Heart Rate

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***Abstract*— As described in this paper, a physical activity classification algorithm is proposed for energy expenditure estimation. The proposed algorithm can improve the classification accuracy using both the triaxial acceleration and heart rate. The optimal classification also contributes to improvement of the accuracy of the energy expenditures estimation. The proposed algorithm employs three indices: the heart rate reserve (%HRreserve), the filtered triaxial acceleration, and the ratio of filtered and unfiltered acceleration. The percentage HRreserve is calculated using the heart rate at rest condition and the maximum heart rate, which is calculated using Karvonen Formula. Using these three indices, a decision tree is constructed to classify physical activities into five classes: sedentary, household, moderate (excluding locomotive), locomotive, and vigorous. Evaluation results show that the average classification accuracy for 21 activities is 91%.**

I. Introduction

The increasing number of patients with lifestyle-related diseases presents an important social issue. The major cause of the increase is that the modern lifestyles predispose people, who have a scant amount of a high-level physical activity (PA) and excess dietary intake over daily energy expenditure (EE). To prevent diseases, a lifestyle habit improvement is important. The effective method to support the lifestyle improvement is recording daily PA information such as type, intensity, and duration. This information is useful to obtain advice from a specialist of an appropriate exercise. In our previous studies [1, 2], metabolic equivalents (METs) estimation method from a PA classification using the triaxial acceleration was proposed. The METs are useful as EE.

In this paper, we propose an advanced PA classification algorithm to improve the METs estimation accuracy by increasing the number of PA classifications, which include ascending and descending stairs, and riding a bicycle. To increase the number of classifications, a sensor fusion approach using both the triaxial acceleration and heart rate is introduced. The heart rate has a linear relation with the EE of light or more intensity of physical activity [3, 4].

EE prediction equations have been proposed in the previous study [5]. This method uses personal characteristics of user (e.g., weight, age, and height) and the heart rate. However, the heart rate is influenced by mental condition especially with low-level physical activity intensity (PAI), such as at rest or at sedentary activity. The EE is overestimated in a very nervous situation with low-level PAI. However, the EE estimation using the acceleration has benefits for accuracy with low-level PAI. In other words, the EE estimation using the heart rate presents benefits with high-level PAI.

Previous studies [6, 7] have demonstrated that a combination of the heart rate monitor and the movement sensor can improve the EE estimation accuracy. However, these studies do not consider the PA classification. The classification of PAI is significant to reduce the lifestyle related diseases. Therefore, the purpose of this study is to develop a new algorithm that has a potential of PA classification by combining the heart rate and the acceleration. Furthermore, previous works require an individual calibration with the heart rate at stepping and sleeping state. In this work, we try to reduce the complicated individual calibration to the greatest extent possible.

II. Subjects and Experimental Methods

To develop and to evaluate the proposed PA classification algorithm, we measured the accurate METs, the triaxial acceleration, and the R–R interval (RRI) of volunteered subjects with several activities.

A. Subjects

This study of 42 volunteer participants was conducted at the National Institute of Health and Nutrition in Tokyo, Japan, according to the guidelines laid down in the Declaration of Helsinki. All procedures involving human subjects were

TABLE 1. Distribution of age and gender of subjects

	Age (Average±SD)	Male [N]	Female [N]
20-29	24.7±3.1	6	5
30-39	34.0±3.5	4	6
40-49	43.1±3.8	6	5
50-59	52.5±1.5	5	5
Total	38.4±10.9	21	21

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TABLE 2. MEASURED METABOLIC EQUIVALENTS (METS) WITH EACH ACTIVITY IN THE VALIDATION GROUP

	Activity	N	METs	
			Average	SD
At rest position	Supine	42	--	--
	Sitting	42	--	--
Group1 Sedentary	Standing	39	1.079	0.066
	Calling mobilephone	38	1.138	0.097
	Operating PC	38	1.133	0.080
Group2 House hold	Sorting Documents while sitting	39	1.508	0.270
	Washing dishes	38	2.118	0.382
	Laundry	37	2.452	0.446
	Changing body position	37	2.408	0.303
	Sorting Documents while standing	39	2.702	0.363
	Cleaning desks	38	2.584	0.551
	Stretching	32	2.076	0.326
	Vacuuming	35	2.994	0.659

	Activity	N	METs	
			Average	SD
Group3 Moderate	Moving Load	38	2.435	0.340
	Radio exercise*	32	3.171	0.476
Group4 Locomotive	Stair descent	39	2.722	0.381
	Slow walking (55m/min)	32	3.101	0.797
	Normal walking (70m/min)	31	3.684	0.493
	Brisk walking (100m/min)	34	5.007	0.832
	Normal walking with Load(3kg)	30	4.079	0.456
	Slow walking with Load(5kg)	36	4.101	0.672
Group5 Vigorous	Stair Ascent	38	7..349	0.875
	Jogging (130m/min)	34	9.162	1.297

*Radio exercise is a famous warm-up exercise in Japan, it is a mixture of exercise and stretching.

approved by the Ethical Committee of the National Institute of Health and Nutrition. Subjects were excluded from the study if they had any contraindications to exercise, or if they were physically unable to complete the activities, because we need to monitor the triaxial acceleration, the RRI and the EE of various PA at the same duration to develop and to validate the algorithm. Distribution of age and gender of the subjects are presented in Table 1. The purpose and procedure of this study were explained to subjects in detail before measurement. Written informed consent was obtained by all subjects.

B. Experimental Methods

Weights and heights of all subjects were measured. The BMI was calculated from these values. The subjects performed 23 distinct activities including a rest position. During each activity, the triaxial acceleration, the heart rate and the estimated EE were recorded. The triaxial acceleration and the RRI were recorded using Health Patch MD (Vital Connect Inc., USA), which has been developed for 24-hour monitoring. Its clinical validation as reported in Ref. [8]. It was pasted to the bottom of the thorax. After measurements, the recorded acceleration and RRI were analyzed using MATLAB 2013b (the MathWorks Inc., USA).

EE is estimated from VO_2 and VCO_2 using Weir's equation [9]. The METs value, which is used as a reference value, is calculated from the EE divided by the measured relative metabolic rate (RMR). The present study classified 21 activities excluding the at rest position, into five classes based on the type of activity. Group 1 is a sedentary group. Group 2 includes household activities in daily life. Group 3 is a moderate excluding locomotive activities. Group 4 is locomotive activities except Jogging. Group 5 is a vigorous PAI. Table 2 shows means and standard deviations (SD) of METs and the numbers of subjects, with each activity.

III. STATISTICAL ANALYSIS

A. Triaxial Acceleration

The measured triaxial acceleration is processed according to the same manner as that in our previous study [1]. First, each signal from the triaxial accelerometer is passed through a high-pass filter with 0.7 Hz cut-off frequency to remove the gravitational acceleration component. Next, the synthetic acceleration of three axes (vector magnitude $\sqrt[2]{X^2+Y^2+Z^2}$) is calculated using the raw (unfiltered) acceleration signals and the filtered acceleration signals with the high-pass filter. Then, the ratio of filtered signals to unfiltered signals (RFU) is calculated. Here, ACC_{fil} is defined as the mean value of the synthetic acceleration from the filtered signal during each activity. ACC_{fil} is calculated by averaging the mean values of the synthetic acceleration in each 10 s.

B. R–R Interval

For this study, we use a %HRreserve to improve the classification accuracy. It is defined as

$$\%HRreserve = \frac{HR_{act} - HR_{rest}}{HR_{\max} - HR_{rest}} \quad (1)$$

The heart rate [bpm] is converted from the recorded RRI. Heart rate during activity (HR_{act}) denotes the mean value of averaged heart rate in every 10 s during activities. The heart rate at rest (HR_{rest}) is also defined as the mean value of the averaged heart rate in a supine condition during 10 min. The maximum heart rate (HR_{max}) is calculated based on the Karvonen Formula: $HR_{max} = 220 - Age$.

C. Classification algorithm

We hypothesize a decision tree that can classify five activity groups shown in Table 2. The decision tree is presented in Fig. 1. Here, RFU_{th}, and HR_{th} respectively denote the decision threshold of the RFU and %HRreserve. According to a previous study [1], the activity is classifiable into locomotive activities or other activity depending on RFU_{th}. Locomotive group contains two types of activities, which is classifiable using HR_{th}. Three other groups (sedentary, household, and moderate) are classifiable depending on ACC_{fil}. In Fig. 1, $ACC_{th1\text{-}2}$ and $ACC_{th2\text{-}3}$ are thresholds of ACC_{fil}. Methods used to determine RFU_{th}, HR_{th}, $ACC_{th1\text{-}2}$, and $ACC_{th2\text{-}3}$ according to the measurement results are described in Section IV.

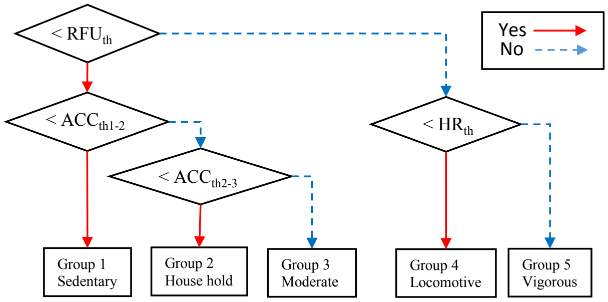

Figure 1. Decision tree to classificate physical activity groups.

IV. Evaluation Results

The measurement results are presented in Fig. 2. Fig. 2(a) describes the relation between RFU and %HRreserve. The locomotive group (group 4) and the vigorous group (group 5) localizes around RFU = 1.0. Mean (SD) of groups 4 and 5 are, respectively, 1.012 (0.042) and 0.998 (0.036). The synthesis of group 4 and group 5 is 1.008 (0.041). The RFU of the sedentary group (group 1), household group (group 2), and moderate group (group 3) are distributed from 1.240 to 18.904. Groups 1, 2, and 3 are not overlapped with groups 4 and 5. Therefore, they are separable from others groups using only RFU. We choose a Mean +3SD of synthesis groups 4 and 5 as RFU$_{th}$, which equals 1.130. However, classification into each group is difficult using only the relation between RFU and %HRreserve because groups 1, 2 and 3 overlap considerably. Therefore, ACC$_{fil}$ is introduced in the next step.

Fig. 2(b) shows the relation between METs and ACC$_{fil}$ of groups 1, 2, and 3. ACC$_{fil}$ of group 1 distributes under 10.69 [mG] [mean + 2SD]. Group 2 is mostly distributed between 3.62 [mG] and 73.35 [mG] [mean ± 2SD]. Group 3 is mostly distributed between 56.61 [mG] and 115.62 [mG] [mean ± 2SD]. Although some data in each group are overlapped with other groups, the overlapped data are limited. Consequently, they are classifiable using ACC$_{fil}$. The means ± 2SD of each group as thresholds ACC$_{th1-2}$ and ACC$_{th2-3}$, respectively 10.69 [mG] and 73.35 [mG], are chosen.

It is difficult to classify groups 1, 2, and 3 using %HRreserve. Fig. 2(c) shows the relation between METs and %HRreserve of groups 1, 2, and 3. As presented in Fig. 2(c), three groups overlap extensively and the correlation (value of R^2) of METs and %HRreserve is lower than ACC$_{fil}$.

Finally, we try to separate groups 4 and 5. Fig. 2(d) shows the relation between METs and ACC$_{fil}$ of groups 4 and 5. In group 4, the mean -2SD of ACC$_{fil}$ is 94.29 [mG] and +2SD is 385.24 [mG]. Group 5 has two sets in this relation. The lower ACC$_{fil}$ set indicates the stair ascent activity. The other set is jogging (130 m/min) activity. This result shows that it is difficult to separate the stair ascent activity from group 4 using ACC$_{fil}$, although the METs of stair ascent activity is higher than group 4. Therefore, we choose %HRreserve to classify groups 4 and 5. Fig. 2(e) shows the relation between METs and %HRreserve of groups 4 and 5. Then, the mean +2SD

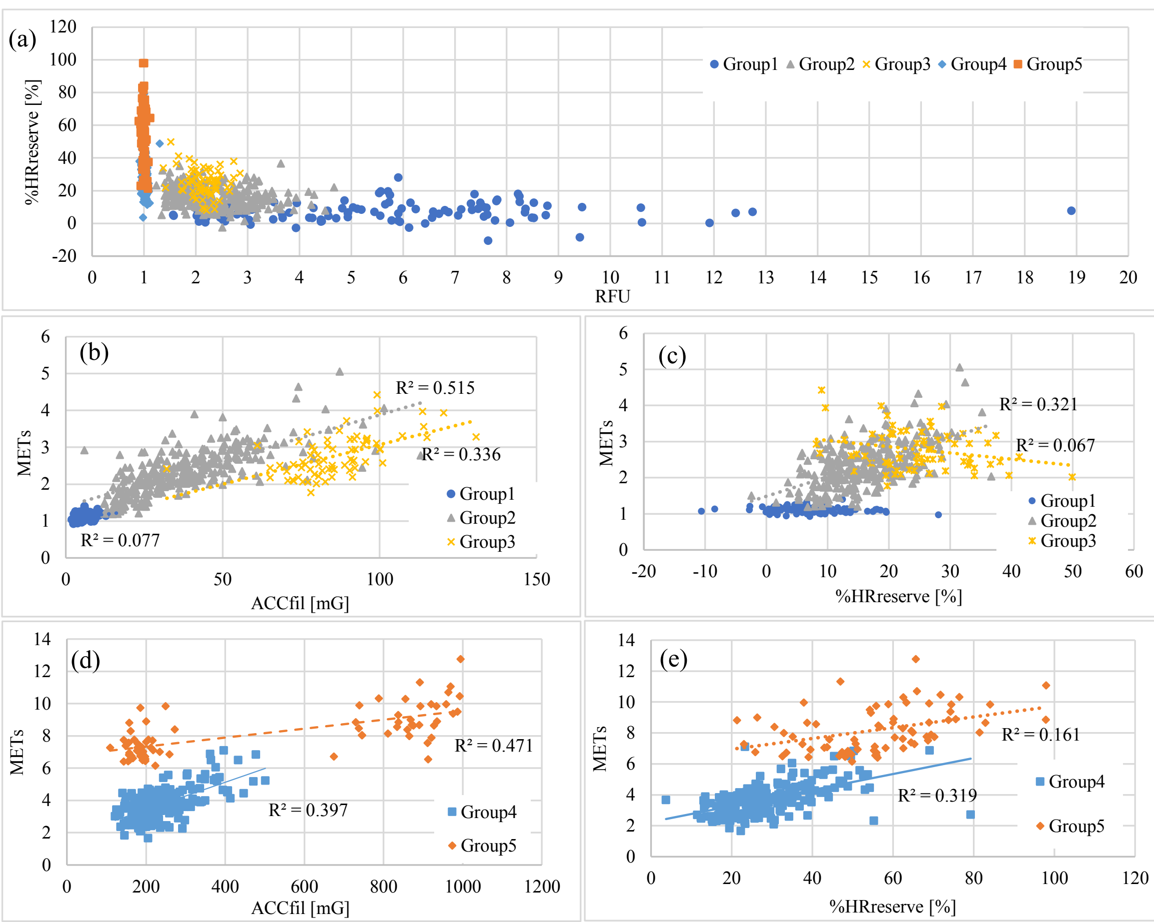

Figure 2. Measurement results of relation between METs, ACC$_{fil}$, and %HRreserve.

TABLE 3. EVALUATION RESULTS OF CLASSIFICATION ACCURACY

Activity	Accuracy [%]	Activity	Accuracy [%]
Calling mobilephone	97.37	Stair descent	94.87
Operating PC	92.11	Slow walking (55m/min)	100.00
Standing	100.00	Normal walking (70m/min)	100.00
Changing body position	100.00	Brisk walking (100m/min)	76.47
Cleaning desks	81.58	Slow walking with Load(5kg)	91.67
Sorting Documents while sitting	100.00	Normal walking with Load(3kg)	93.33
Sorting Documents while standing	97.44	Stair Ascent	71.05
Laundry	100.00	Jogging (130m/min)	79.41
Stretching	100.00	Group 1	96.49
Vacuuming	80.00	Group 2	94.92
Washing dishes	100.00	Group 3	85.71
Moving Load	78.95	Group 4	92.57
Radio exercise	93.75	Group 5	75.00
		Total	91.77

of %HRreserve in group 4 is 50.9%, and mean -2SD of %HRreserve in group 5 is 23.3%. However, the %HRreserve of group 5 has a large SD (= 16.4), which might cause classification accuracy degradation. Consequently, the mean +1.5SD of group 4 is chosen as HR_{th}, which equals 45.5%. Table 3 presents the classification accuracy for each activity and each group. The average classification accuracy of the 21 activities is 91%, although five activities (vacuuming, moving load, brisk walking, stair ascent and jogging) have lower accuracy of 70–80%.

V. DISCUSSION

Classification results of group 5 and brisk walking have lower accuracy compared with other results because the %HRreserve is distributed in the wide range of 20-50%. Although we use the maximum heart rate without individual calibration in this study, it can be improved using other maximum heart rate calculation methods [10], or using individual information such as exercise experience.

In the previous study [1], the estimated EE of ascending activities shows low accuracy because they are excluded from regression. The main reason underlying this problem is that the relation of METs and ACC_{fil} differs from other locomotive activities. The evaluation results of ACC_{fil} show a similar tendency to that found in the earlier study. In contrast, %HRreserve shows a different trend. The measurement results present the possibility of classification of ascending and other locomotive using %HRreserve. As presented in Fig. 2, a strong correlation exists between METs and %HRreserve (R = 0.77, in synthetic groups 4 and 5). Therefore, the proposed method, which combines the acceleration and the heart rate to improve the accuracy of PA classification, can contribute to improvement of the accuracy of EE estimation when using an optimal estimation equation.

The proposed algorithm uses heuristic parameters, which were derived from the measurements in the present study. However, further investigations are required to validate the algorithm in different populations and to explore better classification algorithms with the optimum thresholds of RFU_{th}, HR_{th}, ACC_{th1-2} and ACC_{th2-3}.

VI. CONCLUSION

In this work, we proposed a PA classification method using both the acceleration and the heart rate. The evaluation results show that the average classification accuracy for 21 activities is 91%. The proposed method presents the possibility of classifying more types of physical activity groups. However, a challenge remains of improving the accuracy and the range of application. For example, we have not evaluated some activities such as riding a bicycle. In a future study, we will address more activities by analyzing RFU, ACC_{fil} and %HRreserve. Then, it is necessary to improve the algorithm, for example by increasing the layers of the decision tree. By considering this point, the accuracy of PA classification to the optimal group can be improved. It will contribute to improvement of the EE estimation accuracy using an optimal equation for each PAI group.

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