Paper

Comparison of Wristband Type Activity Monitor and Accelerometer during Locomotive and Non-locomotive Activity

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The purpose of this study was to compare estimation accuracy of an accelerometer (Lifecorder Ex: LC) and a wristband type accelerometer (ViM sports memory: ViM) during non-locomotive activities. We chose fifteen activities. Fourteen young adults (7 males and 7 females) participated into 8 activities at least. An indirect calorimeter (MetaMax 3B) measured metabolic equivalent (MET) throughout all activities. Participants wore the LC on their hip and the ViM on non-dominate their wrist to estimate MET. To estimate MET, LC derivations (LC1 and LC2) were used and ViM derivations (ViM1 and ViM2) were used. Differences between MET and each estimates were analyzed by 2-way repeated ANOVA model in mixed model. Both of the LC1 and the LC2 significantly underestimated MET during most of activities ($p \leq 0.008$). The ViM1 was significantly different from MET for all activities ($p < 0.001$), while the ViM2 showed not significant differences to MET during Dynamic stretch, Darts, Active video game (boxing), and Walking ($p \geq 0.162$). These results show that the ViM can assess MET during non-locomotive activities more accurate than the LC and the LC consistently underestimates MET during all of non-locomotive activities.

Key words : MET, estimation equations, sports and leisure activities

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1. Introduction

Accelerometers are well known as an objective and useful method to assess physical activity during daily living. Today, there are accelerometers of many types (Brage et al., 2003; Campbell et al., 2002; Eston et al., 1998; Freedson et al., 1998; King et al., 2004; Kumahara et al., 2004a; Ohkawara et al., 2011; Rowlands et al., 2004). Each device has different features (number of axes, dynamic range, epoch, sampling frequency, frequency response). Although the accuracies of accelerometers differ according to the features of each device, the accuracy of accelerometers commonly deteriorates during activities except walking and running (non-locomotive activity). Accelerometers are unable to measure metabolic equivalents (MET) during non-locomotive activities, such as arm activity, standing posture, vertical work (i.e., stair climbing or uphill walking), or non-weight-bearing activity (e.g. bicycling) (Chen and Bassett, 2005). The main cause of the deterioration is that accelerometers cannot detect the change of relationship between MET and accelerometer outputs for walking and running (locomotive activity) and non-locomotive activity and several methods have been investigated to improve their accuracy (Brage et al., 2005; Brage et al., 2004; Crouter et al., 2006; Crouter et al., 2010; Fruin and Rankin, 2004; Ohkawara et al., 2011).

The ViM sports memory wristband (ViM; Microstone, Saku, Japan) that includes a uniaxial accelerometer and a gyro-sensor is a relatively new device. The device is designed to distinguish walking, running, and non-locomotive activities using these exercises' respective angular velocity and vertical acceleration of arm movements and their periodicity. In a previous study, Takahashi et al. (2009) reported that during non-locomotive activities, the ViM can estimate physical activity with smaller errors than the Lifecorder EX (LC; Suzuken Co. Ltd., Nagoya, Japan), which is known as a valid and accurate accelerometer (Abel et al., 2008; Crouter et al., 2003; Kumahara et al., 2004a; Takahashi et al., 2012). However, this device significantly overestimates energy expenditure by 24–74% during moderate walking. The cause of the problem was the estimation model in the manufacturer's software (Takahashi et al., 2009). Subsequently, the accuracy of the ViM was improved during walking by recalibrating the relationship between energy expenditure (Takahashi et al., 2010). The recalibrated model showed errors of less than 13.0% during locomotive activity.

Given the features of the ViM and results reported by previous studies, the ViM appears to be a good device for non-locomotive activities. However, the evidence that the ViM is better than a conventional accelerometer during non-locomotive activity is limited in only activities of two types: static stretch and hop-scotch (Takahashi et al., 2009). Therefore, the accuracy of the ViM was examined by comparing it with the LC during locomotive and non-locomotive activities.

2. Material and Methods

2.1. Participants

Seven Japanese men (age 20.9±0.3 years, height 169.0±5.0 cm, weight 63.5±8.9 kg, BMI 22.2±2.5 kg·m^{-2}) and 7 women (age 20.7±0.6 years, height 163.7±7.7 cm, weight 56.5±5.6 kg, BMI 21.1±2.0 kg·m^{-2}) with no regular training experience voluntarily participated in this study. The participants were asked to refrain from alcohol use or strenuous physical activity for 24 h before exercise tests, and from food or caffeine during the 2 h preceding the study. Written informed consent was obtained from all participants before exercise tests. The study protocol was approved by the Human Subjects Committee of Tohoku Gakuin University.

2.2. Experimental design

Participants performed various leisure and sporting activities divided into four routines. When choosing activities, we considered the following points: 1) activities for exercise training, 2) activities as a leisure activity that are performed frequently, and 3) activities that have not been described in reports of previous studies. We chose "sports and leisure activities" as a non-locomotive activity rather than "free-living activities" because there are few studies that reported Japanese MET during "sports and leisure activities". Because features of "free-living activity" and "sports and leisure activities" measured by an accelerometer are almost equivalent (Crouter et al., 2006; Crouter et al., 2010; Freedson et al., 2011), our data appear to be able to be applied to the whole of non-locomotive activities although we chose "sports and leisure activities". Finally, the following 16 activities were chosen.

1) Routine 1: Kendama, Active video game (Nintendo Wii Sports, tennis; Nintendo Co. Ltd., Kyoto, Japan), Dynamic stretch (radio calisthenics first and second), and Jump rope
2) Routine 2: Static stretch, Active video game (Nintendo Wii Sports, baseball), Harvard step test, and Table tennis
3) Routine 3: Darts, Ball juggling, Active video game (Nintendo Wii Sports, boxing), and Bicycle pedaling at a work rate of 100 W.
4) Routine 4: Balance ball exercise, Putter golf, Walking at 6.0 km·h^{-1} on a motor-driven treadmill, and Resistance exercise with two dumbbells (a dumbbell was 3.0 kg for men, 1.0 kg for women).

Six participants (3 women) performed all four routines, five participants (2 women) performed three routines, and three participants (2 women) performed two routines. Oxygen uptake ($\dot{V}O_2$) was measured continuously throughout the routine by an indirect calorimeter (IC; MetaMax-3B; Cortex, Leipzig, Germany). Participants wore the LC and the ViM on the non-dominant side hip and wrist for the duration of the routine. All routines were performed in a physiology laboratory. Bicycle pedaling was performed to verify the accuracy of the IC, the measurements of bicycle pedaling were not used for statistical analyses. $\dot{V}O_2$ at bicycle pedaling (21.3±3.7 ml·kg^{-1} ·min^{-1}) showed close agreement with the predicted value (21.5 ml·kg^{-1}·min^{-1}) from the formula of the American College of Sports Medicine (2000). Participants performed one routine in one day. The duration of each activity in a routine was 10 min, except the Dynamic stretch and Harvard step test, which were each approximately 3 min. First, each participant was seated on a comfortable chair for 15 min. Then each performed each activity with 5 min intervening rests. The participants were required to establish their own pace and maintain it throughout each 10 or 3 min. The order of routines was randomized.

2.3. Equipment

ViM. The ViM sports memory wristband Version 2.1.0 (Microstone, Saku, Japan) is 6.5 cm wide, 7.5 cm high, 1.5 cm thick, and 100 g. The ten motion patterns of the ViM are as follows: Very Slow Walking, Slow Walking, Normal Walking, Brisk Walking, Jogging, Running, Light Irregular Activity, Moderate Irregular Activity, Heavy Irregular Activity, and Rest. Details of the algorithm are shown in Table 1. However, cut off-points of each category are not disclosed. According to technical details provided by the manufacturer, this device samples vertical acceleration and the angular velocity of the arm every 50 ms. Dynamic ranges of the acceleration and the angular velocity are, respectively, 0.05–2.00 G and 0–300 deg·s^{-1}. The frequency response is 0.25–20 Hz. The time period is 2 s. The ViM analyzes 10 patterns of physical activity, and records the sum of frequencies of each activity pattern every 30 or 180 s. In this study, 30 s mode was selected.

Lifecorder EX. The Lifecorder EX (Suzuken Co. Ltd., Nagoya, Japan), which weighs 60 g, is 7.25 cm wide × 4.15 cm high × 2.75 cm long. During recording, the LC samples vertical acceleration with sampling frequency of 32 Hz using a ceramic piezoelectric uniaxial accelerometer. The dynamic range of the accelerometer is 0.06–1.94 G. The accelerometer signal proceeds through an analogue band pass filter. It is then digitized. Maximum acceleration greater than 4 s is recorded as activity intensity. Activities are categorized into 11 activity levels (arbitrary unit).

Indirect calorimeter. The MetaMax-3B measurements (Volger et al., 2010), described in MET, were used as the validity criteria. The IC measures breath-by-breath ventilation ($\dot{V}_E$), concentration of expired oxygen (F_EO_2), and carbon dioxide (F_ECO_2). The IC was calibrated before each test. The turbine flow meter (range: 0.05–2.00 L·s^{-1}) was calibrated with a 3.0-L calibration syringe, and the O_2 and CO_2 analyzers were calibrated with room air and a calibration gas of known O_2 (15.94%) and CO_2 (3.97%) composition.

2.4. Data Treatment

Internal clocks of the IC, LC and ViM were initialized and set to the standard time before each test. After downloading data as CSV format from each software, all measurements were converted to synchronize the unit time as 1 min: The ViM outputs, recorded every 30 s, were summed for 1 min. The LC activity levels, recorded every 4 s, were averaged for 1 min. The IC breath-by-breath data were averaged every 60 s except the Dynamic stretch and Harvard step test. During both of Dynamic stretch and Harvard step test, the breath-by-breath data were averaged every 30 s. To compare the respective devices, all measurements were converted to MET. Oxygen uptake was converted to MET using the following equations:

Table 1. The algorithm of the ViM sports memory.

Category	Acceleration	Angular velocity	Periodicity
Very Slow Walking	Low	Very low	Present
Slow Walking	Low	Low	Present
Normal Walking	Low	Moderate	Present
Brisk Walking	Low	High	Present
Jogging	Moderate	Moderate	Present
Running	High	Moderate	Present
Light Irregular Activity	Low	Irregular	None
Moderate Irregular Activity	Moderate	Irregular	None
Heavy Irregular Activity	High	Irregular	None
Rest	Very low	Irregular	None

This material is provided by the manufacturer (Microstone Co., Saku, Japan).

$MET = \dot{V}O_2\ (ml \cdot kg^{-1} \cdot min^{-1}) \div 3.5$ (Eq. 1)

Table 2 presents details of each equation to estimate MET of the LC and ViM. The estimated MET of the LC was calculated using methods described by Kumahara et al. (2004a) (LC1) and by Takahashi et al. (LC2). Estimated MET of the ViM was calculated using the manufacturer's software (ViM1) and the method described by Takahashi et al. (ViM2). For calculation estimates of the ViM1, the energy expenditure (kcal) estimated using the manufacturer's software was converted to MET. However, details of the equation were not disclosed. To ensure the steady state of each MET, all measured and estimated MET were averaged for the last 7 min of each activity, except Dynamic stretch and Harvard step test. MET at Dynamic stretch and Harvard step test were selected for last 30 s.

2.5. Statistical Analysis

Statistical analyses were conducted using software (IBM SPSS 19.0; SPSS Inc., Chicago, IL, USA). From the experimental design of this study, the dataset included some missing data because all of participants did not perform all activities. When there are missing data in a longitudinal dataset, normal repeated ANOVA, which uses the least squares method for calculation of parameters, omits missing data from the analysis procedure, and the result of repeated ANOVA is biased. It is known that mixed model, which uses the restricted maximal likelihood for calculation of parameters, is a better method than repeated ANOVA when analyzing a longitudinal dataset including missing data (Twisk, 2004). Therefore, each estimate and MET were compared using a two-way repeated ANOVA model in mixed model, in which the response variable was MET and the explanatory variables were methods (5 levels: IC, LC1, LC2, ViM1, and ViM2), types of activity (15 levels), the interaction of methods and types of activity, and the random intercept for each participant. If the interaction was significant, then we examined the differences of methods for each activity using a one-way repeated ANOVA model in mixed model with the random intercept for each participant. Mean differences between estimates and MET at each activity were assessed using regression coefficients (IC MET was set as a reference value) yielded by one-way repeated ANOVA models. The significance levels for the two-way and one-way repeated ANOVA models were $p = 0.05$.

We also considered the root mean squared error (RMSE) as well as mean differences between estimates and MET. In fact, RMSE is similar to the mean of the absolute differences whereas the mean difference is the aggregation of negative and positive differences. When both negative and positive errors exist for an activity, the mean difference is smaller than the actual magnitude of errors because of offset. RMSE shows the mean magnitude of errors.

3. Results

Figure 1 shows the relationships between the measurements by the IC and four estimates by each method. Table 3

Table 2. Estimation equations of MET by the Lifecorder EX and the ViM sports memory.

	Source	Modeling method	Equations	R^2 and SEE
LC1	Kumahara et al. (2004a)	Linear regression	$MET = 0.043 \cdot x_{LC}^2 + 0.379 \cdot x + 1.361$	$R^2 = 0.93$, SEE = 0.46 MET
LC2	Takahashi et al. (2012)	Mixed model	$MET = 0.048 \cdot x_{LC}^2 + 0.508 \cdot x + 1.007$	$R^2 = 0.86$, SEE = 0.99 MET
ViM1	Manufacture's software	Undisclosed	$MET = \dfrac{200 \cdot estimated\ EE}{3.5 \cdot body\ weight}$	Undisclosed
ViM2	Takahashi et al. (2010)	Mixed model	Male: $MET = 0.07 \cdot x_{ViM1} + 0.13 \cdot x_{ViM2} + 0.22 \cdot x_{ViM3} + 0.32 \cdot x_{ViM4} + 1.22$	Male: $R^2 = 0.74$, SEE = 1.51 MET
			Female: $MET = 0.08 \cdot x_{ViM1} + 0.13 \cdot x_{ViM2} + 0.19 \cdot x_{ViM3} + 0.31 \cdot x_{ViM4} + 1.30$	Female: $R^2 = 0.84$, SEE = 1.16 MET

LC, Lifecorder EX; R^2, coefficient of determination; SEE, standard error of estimate; x_{LC}, outputs of Lifecorder EX (activity levels); estimated EE, estimated energy expenditure (kcal·min^{-1}) by manufacture's software that does not disclosed details of the equation; x_{ViM1}, sum of outputs of Very Slow Walking, Slow Walking, Normal Walking, and Light Irregular Activity in the ViM (frequencies·min^{-1}); x_{ViM2}, outputs of Brisk Walking in the ViM; x_{ViM3}, sum of outputs of Jogging and Moderate Irregular Activity in the ViM; x_{ViM4}, sum of outputs of Running and Heavy Irregular Activity in the ViM (frequencies·min^{-1}).

presents means and standard deviations of MET and each estimate for each activity. The five methods were compared by two-way ANOVA model in mixed model. Significant interaction was found (F (56.0, 751.9) = 11.6, p < 0.001). The results of one-way repeated ANOVA models revealed that main effects of the methods were significant for all activities (F (4, 44) ≥ 7.8, p < 0.001 at N = 12; F (4, 40) ≥ 13.9, p < 0.001 at N = 11; F (4, 36) ≥ 11.7, p < 0.001 at N = 10).

Table 4 shows the mean differences (estimates minus MET) for each activity. The LC1 significantly underestimated MET for all activities (p ≤ 0.008). The difference between MET and the LC2 was not significant at Walking (p = 0.505), but the LC2 significantly underestimated MET during other activities (p < 0.001). The ViM1 significantly underestimated MET for all activities (p < 0.001) except Walking, the ViM1 significantly overestimated MET (p < 0.001) during Walking. For ViM2, no significant difference was found for Dynamic stretch, Darts, Active video game (boxing), and Walking (p ≥ 0.162), although ViM2 underestimated measurements for other activities significantly (p ≤ 0.002).

Table 4 also presents the RMSE. When investigating activities for which there were no significant differences between MET and estimates, the RMSE of the LC2 at Walking was 0.24 MET. For ViM2, RMSEs were, respectively, 0.71 MET at Dynamic stretch, 1.21 MET at Darts, 0.84 MET at Active video game (boxing), and 0.60 MET at Walking.

4. Discussion

Major Findings. In this study, we compared the ViM with the LC during activities of various types. Our results show that the ViM2 can assess MET during Dynamic stretch, Darts, Active video game (boxing) and Walking accurately. Moreover, given the 95% confidence interval (95%CI) of errors in Table 3, errors of ViM2 during Jump-rope, Dumbbell exercise, and Static stretch are significantly smaller than those of the LC1 and the LC2. These results show the ViM can assess MET during non-locomotive activities more accurate than the LC. The wrist, as a location for placement of a typical uniaxial accelerometer, is known to be inferior to the hip (Kumahara, et al., 2004b; Swartz et al., 2000). Swartz et al. reported that addition of the wrist uniaxial accelerometer (Actigraph) outputs improved the accuracy of the hip accelerometer outputs estimate by only about 3.0%. Kumahara et al. (2004b) also reported that it improved only 2.6% of the accuracy to add the wrist

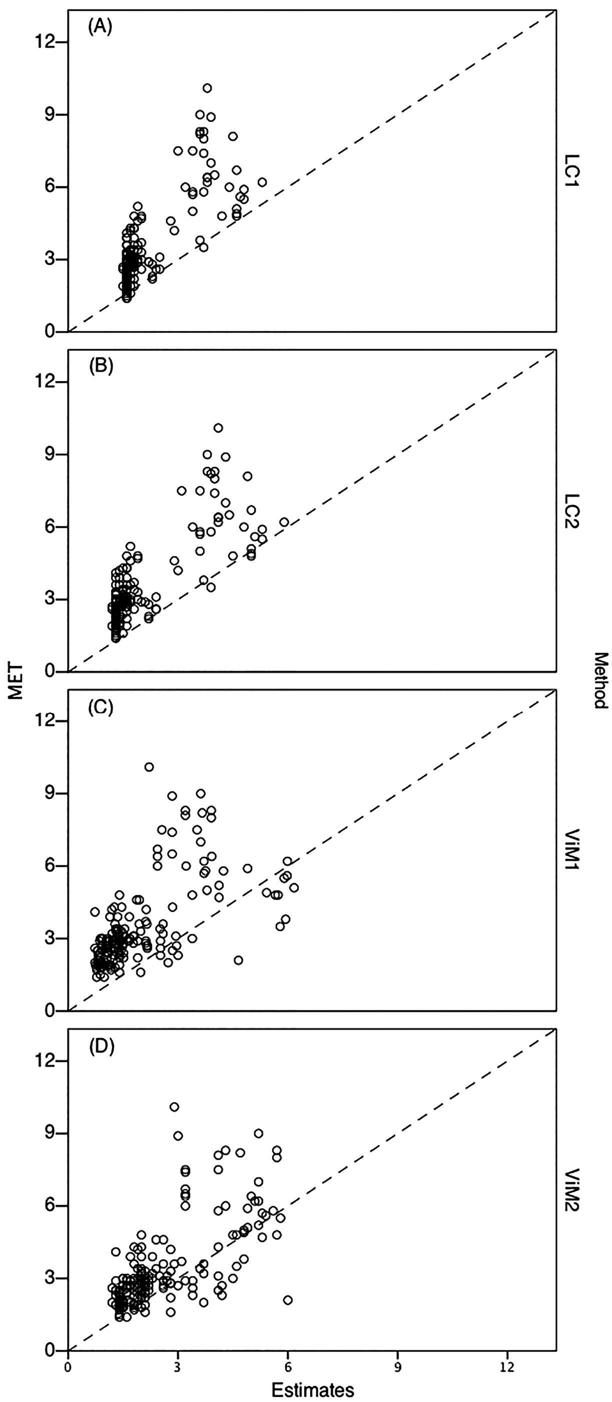

Figure 1. Two plots show the relationships between measurements by the IC (Y axis) and four estimates (X axis): (A) LC1, (B) LC2, (C) ViM1, and (D) ViM2. For each plot, dash line is identity line (y = x).

Table 3. Means (SD) for metabolic equivalent (MET) and estimates; results are shown for each activity.

Activity	MET	LC1 (MET)	LC2 (MET)	ViM1 (MET)	ViM2 (MET)
Kendama (*N* = 12)	2.10(0.38)	1.59(0.03)	1.29(0.03)	0.94(0.09)	1.54(0.14)
Active video game (tennis) (*N* = 12)	2.21(0.43)	1.58(0.04)	1.28(0.04)	1.15(0.50)	1.74(0.44)
Dynamic stretch (*N* = 12)	3.01(0.65)	1.77(0.09)	1.54(0.12)	2.33(0.47)	3.27(0.70)
Jump-rope (*N* = 12)	6.78(1.28)	3.60(0.21)	3.86(0.26)	3.75(0.24)	5.07(0.52)
Static stretch (*N* = 11)	2.33(0.50)	1.61(0.03)	1.31(0.03)	1.10(0.17)	1.78(0.26)
Active video game (baseball) (*N* = 11)	2.30(0.8)	1.60(0.00)	1.30(0.00)	1.13(0.32)	1.75(0.37)
Harvard step test (*N*= 11)	7.58(1.21)	3.88(0.48)	4.19(0.58)	2.78(0.41)	3.42(0.49)
Table tennis (*N* = 11)	3.76(0.82)	1.77(0.13)	1.57(0.16)	1.89(1.11)	2.60(1.32)
Darts (*N* = 12)	2.64(0.52)	1.63(0.07)	1.38(0.09)	1.96(1.15)	2.79(1.43)
Ball juggling (*N* = 12)	3.12(0.85)	1.80(0.09)	1.59(0.14)	1.50(0.24)	2.14(0.26)
Active video game (boxing) (*N* = 12)	3.18(0.93)	2.16(0.42)	2.03(0.55)	2.18(0.76)	3.04(0.89)
Balance ball exercise (*N* = 10)	3.15(0.59)	2.05(0.30)	1.90(0.34)	1.51(0.30)	2.25(0.45)
Golf putting (*N* = 10)	2.42(0.38)	1.60(0.00)	1.30(0.00)	0.83(0.07)	1.35(0.11)
Walking (*N* = 10)	5.01(0.86)	4.51(0.54)	4.87(0.67)	5.75(0.36)	5.06(0.43)
Dumbbell exercise (*N* = 10)	3.03(0.29)	1.65(0.05)	1.41(0.09)	1.34(0.22)	2.03(0.34)

LC1, the Lifecorder EX derivations by Kumahara et al (2004a)'s method; LC2, the Lifecorder EX derivations by Takahashi et al (2012)'s method; ViM1, the ViM derivations by the manufacture's software; ViM2, the ViM derivations by Takahashi et al (2010)'s method.

Table 4. Mean differences (95%CI) and RSEM for each estimation method; results are shown for each activity.

Activity	LC1		LC2		ViM1		ViM2	
	Difference	RMSE	Difference	RMSE	Difference	RMSE	Difference	RMSE
Kendama (*N* = 12)	-0.53 (-0.69, -0.38)	0.56	-0.82 (-0.97, -0.67)	0.82	-1.16 (-1.32, -1.01)	1.16	-0.58 (-0.73, -0.43)	0.61
Active video game (tennis) (*N* = 12)	-0.65 (-0.90, -0.40)	0.65	-0.93 (-1.18, -0.69)	0.93	-1.06 (-1.31, -0.81)	1.06	-0.49 (-0.74, -0.24)	0.50
Dynamic stretch (*N* = 12)	-1.26 (-1.61, -0.92)	1.27	-1.49 (-1.84, -1.14)	1.49	-0.69 (-1.03, -0.34)	0.85	0.24 (-0.10, 0.59)*	0.71
Jump-rope (*N* = 12)	-3.19 (-3.67, -2.70)	3.19	-2.94 (-3.42, -2.46)	2.93	-3.03 (-3.51, -2.54)	3.03	-1.71 (-2.20, -1.23)	1.71
Static stretch (*N* = 11)	-0.76 (-0.97, -0.55)	0.76	-1.04 (-1.25, -0.83)	1.04	-1.25 (-1.46, -1.03)	1.25	-0.58 (-0.79, -0.37)	0.62
Active video game (baseball) (*N* = 11)	-0.74 (-1.09, -0.39)	0.77	-1.02 (-1.37, -0.67)	1.02	-1.17 (-1.52, -0.82)	1.16	-0.56 (-0.91, -0.21)	0.68
Harvard step test (*N* = 11)	-3.70 (-4.30, -3.11)	3.70	-3.39 (-3.99, -2.79)	3.39	-4.81 (-5.41, -4.21)	4.81	-4.18 (-4.78, -3.58)	4.18
Table tennis (*N* = 11)	-1.96 (-2.50, -1.42)	1.96	-2.18 (-2.72, -1.64)	2.18	-1.85 (-2.39, -1.31)	1.85	-1.16 (-1.70, -0.62)	1.26
Darts (*N* = 12)	-1.02 (-1.66, -0.38)	1.02	-1.29 (-1.92, -0.65)	1.29	-0.69 (-1.33, -0.05)	1.35	0.14 (-0.50, 0.78)*	1.21
Ball juggling (*N* = 12)	-1.32 (-1.63, -1.01)	1.32	-1.53 (-1.84, -1.23)	1.53	-1.62 (-1.93, -1.31)	1.62	-0.98 (-1.28, -0.67)	0.98
Active video game (boxing) (*N* = 12)	-1.04 (-1.56, -0.51)	1.04	-1.16 (-1.68, -0.63)	1.16	-1.00 (-1.53, -0.48)	1.10	-0.13 (-0.65, 0.40)*	0.84
Balance ball exercise (*N* = 10)	-1.11 (-1.47, -0.75)	1.13	-1.26 (-1.62, -0.89)	1.26	-1.64 (-2.00, -1.27)	1.64	-0.89 (-1.25, -0.52)	1.01
Golf putting (*N* = 10)	-0.86 (-1.01, -0.72)	0.86	-1.15 (-1.29, -1.00)	1.14	-1.60 (-1.74, -1.46)	1.60	-1.07 (-1.22, -0.93)	1.07
Walking (*N* = 10)	-0.53 (-0.90, -0.12)	0.61	-0.12 (-0.51, 0.26)*	0.24	0.74 (0.35, 1.13)	0.98	0.04 (-0.35, 0.43)*	0.60
Dumbbell exercise (*N* = 10)	-1.38 (-1.55, -1.21)	1.38	-1.63 (-1.80, -1.46)	1.63	-1.69 (-1.86, -1.52)	1.69	-1.00 (-1.17, -0.83)	1.00
Total [pooled data] (*N* = 168)	-1.33 (-1.51, -1.15)	-	-1.46 (-1.63, -1.30)	-	-1.50 (-1.71, -1.28)	-	-0.84 (-1.05, -0.63)	-

CI, confidence interval; RMSE, root mean squared error; LC1, the Lifecorder EX derivations by Kumahara et al (2004a)'s method ; LC2, the Lifecorder EX derivations by Takahashi et al (2012)'s method; ViM1, the ViM derivations by the manufacture's software; ViM2, the ViM derivations by Takahashi et al (2010)'s method. Asterisks (*) show not significant difference from measured MET ($p > 0.05$).

uniaxial accelerometer (LC) outputs to the outputs of the hip. Uniaxial accelerometers sensitively detect even negligible upper-limb activity that is not related to a main part of physical activity energy expenditure. Therefore, the linear relationship between the wrist accelerometer outputs and energy expenditure deteriorates more than the waist accelerometer outputs.

The ViM2 showed smaller errors than both LC derivations. Although the ViM is a wrist-placed device, the ViM algorithm differs from typical uniaxial accelerometers in that the ViM assesses the intensity of physical activity using a gyro-sensor and an accelerometer. Because the algorithm can distinguish walking, running, and non-locomotive activity, it appears that the deterioration of the linear relationship between the device outputs and MET in the ViM is less than in uniaxial accelerometers.

ViM. Takahashi et al. (2009) reported that ViM1, which uses the manufacturer's software, was able to assess physical activity energy expenditure more accurately than the LC during two non-locomotive activities, static stretch, and hopscotch. As shown in results of this study, during Dynamic stretching with motion resembling hopscotch, errors of the ViM1 were smaller than those of the LC derivations. However, during Static stretch, the mean difference and RMSE of the ViM1 were larger than the two LC derivations. These inconsistent results appear to be attributable to the individuality of Static stretch movements.

The ViM categorizes body motions as ten patterns using angular velocity, vertical acceleration of arm movements, and periodicity of these movements. Takahashi et al. (2009) reported that the ViM algorithm can distinguish changes in arm movements for each, but the ViM cannot distinguish the individuality of arm swinging. Because the individuality of arm swing movements is large, the ViM outputs might be different every individuals even if performing the same type activity. That fact might have influenced the results by which women participated in this study, whereas the participants in the earlier study were men only.

However, ViM2 showed smaller errors than the LC during both of Static stretching and Dynamic stretching. In equations by Takahashi et al. (2010), each ViM output was aggregated based on the magnitude of acceleration to minimize the influence of the large individuality of arm swing movements. The result that the ViM2 was able to estimate MET better than the ViM1 supports the hypothesis that the ViM outputs are strongly influenced by the large individuality of arm movements.

In recent years, various estimation methods have been developed to improve the accuracy of accelerometers during non-locomotive activity (Crouter et al., 2006; Crouter et al., 2010; Ohkawara et al., 2011). Lyden et al. (2011) compared four methods (two methods from Crouter et al., 2006; Freedson et al., 1998; Swartz, 2000) using the Actigraph, which is a typical uniaxial accelerometer. Lyden et al. (2011) reported that the method reported by Crouter et al., the so-called two-regression model, was more accurate than other Actigraph derivations during non-locomotive activity. Before developing the two-regression model by Crouter et al. (2006), estimation models had been developed based on the assumption that the relationship between accelerometer outputs and MET is linear throughout locomotive and non-locomotive activity (Freedson et al., 1998; Hendelman et al., 2000; Swartz et al., 2000), although it had been known that the relationship differs for types of activities and that the relationship is not linear (Hendelman et al., 2000). Crouter et al. (2006) developed the two-regression model by distinguishing activity types from the coefficient of variation of minute-by-minute accelerometer outputs and by applying nonlinear regression (exponential model) for locomotive and non-locomotive activities. Crouter et al. (2006) demonstrated that the approach can improve the accuracy of the Actigraph. Ohkawara et al. (2011) also reported a similar approach, which distinguishes activity types and which uses a nonlinear regression model (exponential model), can enhance the accuracy of a triaxial accelerometer.

Regarding the results reported by Lyden et al., mean differences of the two-regression model were -4.0 to 0.1 MET, and RMSEs were 0.50 to 4.4 MET. In this study, mean differences (-4.18 to 0.14 MET) and RMSEs (0.5 to 4.18 MET) of ViM2 showed comparable accuracy with that of the two-regression model, although the estimation equations used in the ViM2 were developed using linear regression (see Table 2). These results indicate that the algorithm of the ViM can distinguish activity types correctly. Given these results, the ViM is the more suitable device than the LC for non-locomotive activity. However, the ViM accuracy is equal to that of other accelerometer methods. When considering the usefulness of devices, other methods such as the Actigraph using a two-regression model is more informative than ViM because the algorithm of the ViM is undisclosed and researchers cannot find raw outputs for acceleration and angular velocity.

Lifecorder EX. In fact, LC is the most popular accelerometer in Japan (Ayabe et al., 2012; Ayabe et al., 2013; Ihara et al., 2012). LC devices are often used by international researchers (Abel et al., 2009; Abel et al., 2008; McClain et al., 2007; McClain et al., 2007; Van Remoortel et al., 2012). The LC is known as an accurate device for measuring step counts and energy expenditure during locomotive activity (Abel et al., 2008; Crouter et al., 2003; Kumahara et al., 2004a; Takahashi et al., 2012). However, when using the LC for activity of daily living conditions, it reportedly underestimates physical activity intensity considerably compared with the some Actigraph derivations that were calibrated for non-locomotive activities (Abel et al., 2009; McClain et al., 2007).

This study examined the accuracy of LC and ViM during non-locomotive activities. The LC1 underestimated MET significantly during all 15 activities; mean differences were -3.70 to -0.53 MET. Similarly, LC2 markedly underestimated MET during all activities except Walking; mean differences were -3.39 to -0.12 MET. The estimation equation presented by Takahashi et al. used in LC2 was developed using data of both men and women, whereas the equation reported by Kumahara et al. used in the LC1 was developed using data only of men. Perhaps for that reason, small differences were found between the two LC derivations.

Although small differences existed between the LC1 and the LC2, two LC derivations had common features by which the absolute values of mean differences and RMSEs were approximately equal. The result that mean differences and RMSE were equal for the two LC derivations indicates that LC consistently underestimates MET during non-locomotive activities. The results of Lyden et al. (2011) show that the absolute values of mean differences and RMSEs of methods of the Actigraph using linear regression technique differed more than 0.1 MET during most non-locomotive activities. Although the LC is the uniaxial accelerometer placed on the hip as well as the Actigraph; and while the dynamic ranges of the LC (0.06–1.94 G) and the Actigraph (0.05–2.00 G) are almost identical, differences between absolute mean differences and RMSEs of the LC derivations in this study were less than 0.05 MET. This result demonstrates that the LC has more consistent systematic bias than the common uniaxial accelerometer.

Generally, for accelerometers, acceleration (voltage signal) is digitized (raw outputs) and converted to full-wave rectification. The integration algorithm then sums the converted raw outputs that is called "counts". However, the unit of the LC is not “counts” but the “activity level” (arbitrary unit), and the conversion process to “activity level” is not disclosed. It can be inferred that the LC data processing is the reason that the LC systematically underestimates physical activity energy expenditure during non-locomotive activity.

Limitations. This study has several limitations. A first limitation is on the method. We chose 14 activities as a non-locomotive activity. The types of activities chosen in this study are generally not categorized as “free-living activities” but as “sports and leisure activities”. We think that the results of this study can be applied for “free-living activity”, because when investigating an accuracy of an accelerometer during non-locomotive activity, the difference of “free-living activities” and “sports and leisure activities” measured by an accelerometer appears to be negligible (Crouter et al., 2006; Crouter et al., 2010; Freedson et al., 2011). However, it might be a limitation that we did not measure “free-living activities”.

A second limitation is the accuracy of the indirect calorimeter (MetaMax 3B). Volger et al. (2010) reported that the MetaMax 3B significantly overestimated Douglas bag method around 4.0%. True value of MET might be slightly different form MET measured by the MetaMax 3B.

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