Journal of Exercise Science & Fitness 17 (2019) 62–66

Contents lists available at ScienceDirect

Journal of Exercise Science & Fitness

journal homepage: www.elsevier.com/locate/jesf

Accuracy of the energy expenditure during uphill exercise measured by the Waist-worn ActiGraph

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ARTICLE INFO

Article history:
Received 9 August 2018
Received in revised form
10 December 2018
Accepted 23 January 2019
Available online 23 January 2019

Keywords:
Accelerometer
Heart rate
Oxygen uptake
Physical activity
Uphill exercise

ABSTRACT

Background/objective: The application of Micro-Electro-Mechanical Sensors (MEMS) as measurements of energy expenditure (EE) has certain disadvantages. For example, the inertial sensors cannot easily distinguish changes in ground slope during walking/running conditions, so the accuracy of EE calculation is biased. To resolve this issue, heart rate (HR) and heart rate reserve (HRR) were used as compensatory factors respectively to correct the classical empirical formula of the accelerometer analyzer for EE in this study.
Methods: To explore the improvement of the accuracy of EE during uphill exercise and compare the correction levels between HR and HRR, oxygen uptake was used as a criterion measure (CM). Thirty healthy adult males wore an ActiGraph GT3X with the Polar HR monitor and Vmax indirect calorimeter during twelve treadmill activities (3 gradients and 4 speeds).
Results: When the slopes were increased by 0%, 3%, and 6%, the measurement accuracy of the accelerometers, calculated by intraclass correlation coefficient (ICC), decreased by 0.877, 0.755, and 0.504, respectively ($p < 0.05$). The HR and HRR parameters of linear regression were used to correct the classical formula. The results showed that HR had higher coefficients of determination (R2) (0.801, 0.700, and 0.642 respectively) and ICCs (0.887, 0.825, and 0.785 respectively) than did the accelerometer outputs. HRR showed the highest coefficients of determination (R2) (0.821, 0.728, and 0.656 respectively) and ICCs (0.901, 0.844, and 0.795 respectively).
Conclusions: Through adding HRR parameters, the accuracy of the classical prediction formula EE was significantly improved during walking/running on sloping ground.

Introduction

It is known that engaging in regular physical activity has many health benefits. A higher level of physical activity is closely related to a lower risk of chronic disease and a lower general mortality rate.[1–3] It was suggested by the American Heart Association (AHA) in 2016[4] that for adults, moderate exercise for at least 150 min per week or vigorous exercise for at least 75 min per week (or the combination of moderate and vigorous exercise) could improve cardiovascular health. In addition, periodic physical activity assessment is recommended for inclusion in treatment plans and healthcare services.[5]

Running or hiking is a whole body physical activity that is increasingly popular. It provides many health benefits for the lowest cost.[6] For busy people, running or hiking may be the easiest form of exercise and a high priority activity chosen by beginners in exercises. In Taiwan, with the advantage of mountainous terrain, it is suitable for running or hiking of various intensities. To increase the energy expenditure (EE), the intensity of exercise for people can be changed by varying the running speed and the slope.[7] In fact, sports scientists have paid much attention to the accuracy of measuring EE. Through using oxygen uptake (VO_2 or METs) or doubly-labelled water as a gold standard, EE and the intensity of physical activity can be quantified accurately in different research designs.[8,9] This approach is unfeasible for the public to use in daily life, however, because metabolic carts are expensive and has many usage limitations. In its stead, a growing number of effective

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https://doi.org/10.1016/j.jesf.2019.01.003

techniques are now available to measure physical activity. One example is the inertial sensor, which has received considerable attention in recent years. The inertial sensor is user-friendly and affordable, and it can be used to measure physical activity accurately and continuously over days or weeks.[10,11]

Inertial sensors are also known as activity monitors. For instance, accelerometers and pedometers are used to monitor and quantize physical activities in daily life, exercise, and research. The accelerations of movements in one or three vertical axes across time are quantized by accelerometers, allowing physical activity to be monitored continuously for a controlled period of time. The values measured by the accelerations can be outputted as steps, activity counts, intensity counts, vector magnitudes (VM), and calories.[12–14] The activity monitors most widely used in research are ActiGraph activity monitors.[15] Also, through group calibration equations, the data output (counts per time unit) can be transformed into EE (VO_2) and the intensity of physical activity.[16,17]

Accelerometers are limited by the characteristics of biomechanics because of the acceleration–physical activity intensity relationships of different activities. For example, running, stepping, riding bicycles, and loading activities performed on flat surfaces are highly different from the same activities performed on sloped surfaces.[18–21] Changes in ground slope or loading in certain dynamic exercises cannot be easily monitored by accelerometers. This inability is an important disadvantage of the MEMS. In undulating terrain environment, to accurately predict EE, not only the method of topographic maps is applied, but also the use of regression to correct the error. Previous studies have reported overestimation or underestimation of different intensities or exercises types when EE was measured by the accelerometers in ActiGraph activity monitors.[22–24] To ameliorate this issue, methods of reducing the amount of error have been suggested in past research. For example, HR can be measured as the basis for exercise intensity,[25–27] and corrected parameters can be provided for the prediction equation. To date, 3-axis accelerometers and HR have rarely been used together in studies to estimate EE during exercise on slopes. Kuo et al.[28] used the parameters of accelerometers and HR to develop prediction equations that can be applied in EE estimation during walking on slopes. On the other hand, heart rate can be influenced by individual physical fitness or environmental factors, such as fear, excitement, or related emotional stress. Those factors could increase HR and affect the accuracy of estimations of EE.[29] Therefore, the difference between individual physical fitness and resting HR was considered in the concept of HRR, suggested by Karvonen.[30] The difference between maximum HR during exercise and resting HR was used to revise individual standardization and judge exercise intensity.[30,31] Accordingly, the hypothesis of this study was that the personal HRR should be one of the most important parameters to improve more accurate in calculation of energy expenditure. Thus, the purpose of this study was to revise the prediction formula of EE estimation during exercise on slopes. Considering the limitation that accelerometers are unable to distinguish changes in slope (loading) in specific walking/running conditions, HRR was included in the prediction formula as a compensatory factor to explore whether the accuracy of EE estimation during sloped exercise could be improved.

Methods

Participants

A total of 30 healthy adult males (M ± SD; age 24.53 ± 1.55 years; body weight 75.13 ± 10.40 kgw; body height 1.78 ± 0.16 m; body mass index 23.86 ± 2.67 kg/m2) voluntarily participated in this study. Before the start of the study, all participants completed informed consent forms approved by the Landseed Hospital Institutional Review Board. The participants were excluded if they had any contraindications to exercises, were taking drugs that could affect their metabolic rate, or had a diagnosis of cardiovascular disease that might stop them from completing the evaluation procedures safely. After completing the informed consent forms, the subjects were included in this study. The subjects were required to wear research equipment and complete the 1.5-h test in the laboratory environment. The personal information and data would be excluded if a failure in the testing process was found (for example, the speed of the subject was too slow or the subject quit before completing the test).

Indirect calorimeter

VO_2 and VCO_2 were tested by Cardiopulmonary Exercise Testing System (Vmax Encore 29 System, VIASYS Healthcare Inc., Yorba Linda, CA) for the metabolic criterion measure (CM). The subjects wore small-sized masks (Hans-Rudolph) to cover their mouths and noses. The volume of air breath-by-breath and the O_2 and CO_2 compositions were measured by sampling gas lines and digital flow sensors connected to the masks.

Activity monitor

The ActiGraph GT3X (Actigraph Corporation, Pensacola, FL, USA) is a triaxial accelerometer that can collect data from 3-axis activities. This monitor is small (3.8 × 3.7 × 1.8 cm) and light (27 g). Before the test, initialization of the GT3X was completed by the ActiLife6 software (version 6.12.1, Cary, NC, USA). The sampling frequency of this monitor was set at 30 Hz and 10-sec epochs to collect activity counts in this study. According to the ActiGraph user's manual, the GT3X was affixed to the right hip of each subject on the midaxillary line by an adjustable soft elastic belt.

Heart rate monitor

The Polar RS800CX Heart Rate Monitor (Polar, Kempele, Finland) was placed just below the chest, with sampling at 1000 Hz to collect HR (beat-by-beat) during the whole test. HR data were downloaded using Polar Precision Performance Software (Polar).

Experimental protocol

Subjects presented at the laboratory at individually scheduled times to check their height and weight and to calculate individual predicted maximum HR (HRmax = 220 - Age) as the indicator of exercise safety. Before the experiment started, the resting heart rate in the sitting position was first measured. The subject sat in a resting position for 20 min, and the lowest HR recorded during the last 5 min was set as the resting value.[32] The subjects conducted 12 treadmill walking/running trials in a random sequence. The interval between two trials was 4 min. The volumes of VO_2 during the testing process were recorded continuously and synchronously by indirect calorimetry, HR, and accelerometer counts.

Treadmill test

In a laboratory setting, the subjects were required to complete treadmill (h/p cosmos mercury 4.0, Nussdorf-Traunstein, Germany) walking/running tests at speeds of 5.61 km h^{-1}, 7.20 km h^{-1} (fast walking), 7.20 km h^{-1} (slow running), and 8.02 km h^{-1} on slopes of 0%, 3%, and 6%. Each test was 7 min, and the interval between two tests was 4 min.[33,34] The speed of 7.2 km/h was used because it is the preferred transition speed (PTS) from walking to running.[34,35]

In any exercise test, if the safe heart rate was exceeded or the subject could not complete the test safely (for example, the speed of the treadmill was too fast), the test was terminated and the data were excluded from the analysis.

Data processing and analysis

All thirty subjects completed the exercise tests safely. The data from the Vmax, Polar, and GT3X were outputted into Excel. The data from the Vmax and Polar were used to calculate the parameter of 10s-by-10s and synchronized with the data from the GT3X. In accordance with the data processing method by Lyden et al.,[33] the first 120 s of each test were excluded to ensure the data were in a steady state, and the last 10 s were excluded to minimize timing synchronization errors between the monitor and metabolic measurements by researchers. The VO_2 and VCO_2 were calculated to determine EE by Weir's formula: EE ($Kcal \cdot min^{-1}$) = 3.491 (VO_2 in L/min) + 1.106 (VCO_2 in L/min).[36] The data from the GT3X were analyzed in ActiLife6. EE was calculated by the Freedson VM3 Combination equation[37] with the following formula: EE ($Kcal \cdot min^{-1}$) = 0.001064 VM + 0.087512 BW (body weight in kgw) - 5.500229. The values of EE were divided by body weight ($kcal \cdot kgw^{-1} \cdot min^{-1}$) as the standardization. The parameter of HHR in each test was calculated by the formula HRmax − HRrest in each stage.

Statistical analysis

All data were summarized as means ± standard deviations. Two-way ANOVA with Bonferroni correction for multiple paired *t*-test was used to analyze the differences between criterion measure EE (CMEE) and Freedson VM3 Combination EE in the 12 treadmill walking/running tests. Linear regression was used to revise the EE prediction models, including Model A: VM activity counts, BW, and HR; and Model B: VM activity counts, BW, and HRR. Pearson's correlation coefficient was applied to evaluate the relationships between CMEE and VM activity counts, HR, and HRR. It was also used to analyze the relationships between CMEE and different prediction formulas (Freedson VM3 Combination, Model A and Model B). In addition, the reliability of EE calculation was further analyzed with the Pearson coefficient of determination and Intraclass correlation coefficient (ICC). The statistical software IBM SPSS Statistics version 20 (IBM Corp., New York, NY, USA) was used for statistical analysis. The significance level was set to $p < 0.05$.

Results

The data collected in the laboratory research are listed in Table 1, including the means and standard deviations of CMEE and GT3X EE and ICCs of CMEE and GT3X EE in treadmill tests with three slope values. During treadmill activities, according to the result of the Two-Way ANOVA test, different measurement methods (CM and GT3X) and the change of the slope (0%, 3%, and 6%) have a significant effect on the calculation of EE ($F = 16.55$, $p < 0.000$). Increasing the exercise intensity (slope and speed) increased the difference between CMEE and GT3X EE ($p < 0.05$, *t*-test with Bonferroni correction). As the slope ratio was increased, the ICC was lowered (0%: 0.877, 3%: 0.755, 6%: 0.504). Significant linear correlations were found between CMEE and VM activity counts ($r = 0.773$), HR ($r = 0.719$), and HRR ($r = 0.776$), with the highest correlation found between CMEE and HRR. To examine the effect of slope, EE values ($kcal \cdot kg^{-1} \cdot min^{-1}$) were predicted by two multifactorial line regression models, including Model A: VM activity counts, body weight, and HR; and Model B: VM activity counts, body weight, and HRR.

The results of two multifactorial line regression models composed of VM activity counts, body weight, HR, and HRR are shown in Table 2. A significantly higher coefficient of determination (R^2) and lower standard error of estimate (*SEE*) were found in Model B than in Model A with different slopes. The correlation coefficient (*r*) and ICC between the measured EE and CMEE in models with different slopes are listed in Table 3. It was found that the *r* and ICC in Model B ($r = 0.810$ to 0.905: strong to high correlation; ICC = 0.795 to 0.901: high ICC) were higher than those in Model A and the Freedson VM3 Combination formula. The *r* and ICC in model B were higher than those in the Freedson VM3 Combination formula. The main differences between Model A and Model B were the HR and HRR factors. Based on the above results, HRR was a precise predictor of the change in slope. HRR could improve the ICC and the validity of predicted values and increase the reliability of the prediction models.

Discussion

The subjects in this study wore the ActiGraph GT3X and Polar RS800CX to complete the treadmill tests at three slope ratios. The differences of measured EE accuracy between the regression equations with HR (Model A) and HRR (Model B) parameters were compared. The Freedson VM3 Combination equation[37] was also compared. Based on this equation, the EE, and CMEE of ICC for the three slopes were 0%: 0.877; 3%: 0.755; and 6%: 0.504, respectively.

Table 1
Comparison of measured EE by Vmax (indirect calorimetry) and estimated EE by GT3X EE in 12 treadmill walking/running tests (mean ± SD).

Grade	Treadmill Speed (km/h)	CMEE ($kcal \cdot kgw^{-1} \cdot min^{-1}$)	GT3X EE ($kcal \cdot kgw^{-1} \cdot min^{-1}$)	MPE (%)	*ICC*
0%	5.61	0.080 ± 0.007	0.083 ± 0.010	2.27	.877
	7.20	0.113 ± 0.012	0.110 ± 0.014		
	7.20	0.137 ± 0.012	0.138 ± 0.022		
	8.02	0.153 ± 0.012	0.150 ± 0.021		
3%	5.61	0.097 ± 0.009	0.088 ± 0.009	10.85	.755
	7.20	0.130 ± 0.013	0.112 ± 0.015		
	7.20	0.154 ± 0.012	0.141 ± 0.022		
	8.02	0.169 ± 0.014	0.149 ± 0.020		
6%	5.61	0.111 ± 0.010	0.088 ± 0.013	20.97	.504
	7.20	0.151 ± 0.017	0.112 ± 0.016		
	7.20	0.171 ± 0.012	0.141 ± 0.023		
	8.02	0.187 ± 0.013	0.150 ± 0.021		

Mean values ± standard deviation (SD). CMEE, criterion measure energy expenditure; GT3X, ActiGraph GT3X accelerometer; Mean Percentage Error (MPE) = {[(Predict value-Actual value)/Actual value] * 100}/n; *ICC*, intraclass correlation coefficient.

Table 2
Models to predict EE (kcal·kg^{-1}·min^{-1}) from VM, BW, and HR/HRR.

Model	Grade	Prediction equation	R^2	*SEE*
Model A	0%	0.000010 VM - 0.000195 BW + 0.000286 HR + 0.024446	.801	0.013
	3%	0.000011 VM - 0.000376 BW + 0.000185 HR + 0.058023	.700	0.016
	6%	0.000012 VM - 0.000423 BW + 0.000086 HR + 0.085319	.642	0.019
Model B	0%	0.000009 VM - 0.000166 BW + 0.000493 HRR + 0.044276	.821	0.013
	3%	0.000009 VM - 0.000379 BW + 0.000445 HRR + 0.068036	.728	0.016
	6%	0.000011 VM - 0.000361 BW + 0.000256 HRR + 0.081400	.656	0.018

VM, vector magnitudes; BW, body weight in kgw; HR, heart rate; HRR, heart rate reserve; R^2, coefficient of determination; *SEE*, standard error of estimate.

Table 3
Correlation and reliability analysis of the measured EE and CMEE in models with different slopes.

Grade	Freedson VM3 Combination		Model A		Model B	
	r	ICC	r	ICC	r	ICC
0%	.878	.877	.895	.887	.905	.901
3%	.848	.755	.836	.825	.854	.844
6%	.780	.504	.801	.785	.810	.795

r, Pearson's correlation coefficient.

These results indicated that with a higher slope, the reliability of the accelerometer was reduced. The reliability of EE calculation was improved by revising Model A and Model B. The ICCs between Model A and CMEE were 0%: 0.887; 3%: 0.825; and 6%: 0.785, respectively, and the ICCs between Model B and CM were 0%: 0.901; 3%: 0.844; 6%: 0.795, respectively. Accordingly, better effects of revising the measured EE during sloped exercise were found for Model B.

The results of this study showed that the error rate of the ActiGraph GT3X was increased by increasing the slope of the treadmill, and significantly underestimated EE at all walking. The average underestimation rates were 0%: 2.27%, 3%: 10.85% and 6%: 20.97% (slope: mean percentage error), respectively. The ICC fell from 0.877 to 0.504. The results of this study are consistent with findings in Brage et al.'s[21] study that the variability of exercise intensity in accelerometers is higher during exercise on sloped ground than during exercise on flat ground, and that the greater variability further resulted in imprecise EE results. The results of previous studies on walking/running tests of the ActiGraph indicated that overestimation or underestimation of EE by prediction formula was evident in diverse types of physical activity intensity tests.[22,24] Schneller et al.[23] compared the accuracies of different brands of activity monitors and, for the ActiGraph, found overestimation of EE by 17% in stationary activity-type tests and underestimation of EE by 24% in physical activity-type tests. However, in this study, the main independent variable was the change in slope of a treadmill. As the slope was increased, VM activity counts were non-significantly increased by physical metabolism. Due to the functional limits of the accelerometer, the change in slope could not be distinguished precisely during walking or running. Accordingly, the calculation of EE became less accurate.

HR is controlled by the autonomic nervous system and induced by exercise. This modification process is complex and dynamic. Cardiovascular functions are modified by the autonomic nervous system to meet metabolic requirements during skeletal muscle exercise.[38–40] Previous studies on diverse types of physical activity measures have suggested that the accuracy of EE calculation could be improved by combining an accelerometer with a device capable of monitoring the change in HR. It has been indicated in studies that HR and VO_2 are closely related and have a linear correlation.[25–27,41,42] The results in this study also showed CMEE to have significant linear correlations with VM activity counts ($r = 0.773$), HR ($r = 0.719$), and HRR ($r = 0.776$), with the highest correlation between CMEE and HRR. Thus, linear regression was used to explore the prediction equation, considering these parameters. The results of the regression equations in this study showed that the outcomes of EE calculation and gold standard air analysis had good validity and a lower amplitude of variation when the EE calculation was revised with the HR parameter on diverse loading (slope). Villars et al.[26] found that the ICC between measured EE, calculated by Actiheart with HR, accelerometers, and standard-measured by doubly labelled water was 0.81. Altini et al.[43] pointed out that the EE estimation error of measuring low intensity activities of daily living (ADLs) such as sedentary activities and low-speed walk (3–4 km/h) could be decreased by the HR standardized parameter. Kuo et al.[28] explored the accuracy of activity energy expenditure during walking uphill, measured by 3-axis accelerometers and ECG. The results showed increases in the coefficient of determination (R^2) (>0.842) and reliability (87.9%) when the accelerometers and HR parameter were included in the linear regression formula. The results of this study are consistent with those in previous research. It was further indicated in this research that, after the HR parameter was replaced by HRR in the equation, the accuracy of predicting exercise intensity of model B was elevated from moderate to high (ICC: 0%: 0.901, 3%: 0.844, 6%: 0.795). On the other hand, it is known that unstable initial values of HR can be caused by individual physical fitness and psychological factors, which can affect the accuracy of EE calculation. Therefore, HRR was used to reduce the error rate in our study. HRR is the difference between maximum heart rate and resting heart rate in each stage. Great differences in resting heart rate caused by differences in individual physical fitness could be standardized to serve as the basis for energy expenditure or exercise intensity calculation. The results of this study indicated that HRR had better anticipation of EE calculation.

In this study, HRR was hypothesized to be a crucial factor, as compared with the formula with only VM activity counts, or the formula including VM activity counts and HR both, could be closer to the actual measured value, and the validity of the hypothesis was examined. Including HRR in EE calculation improved the reliability of the predicted value; the error rates of the standard measure were 0%: 1.44%; 3%: 0.30%; and 6%: 1.63%, respectively. From physiological and physical viewpoints, this finding seems reasonable. For future research, if the prediction formula can be further revised, the reliability of predicted results will be increased. In this experiment, only specific slopes were applied, the result may differ from applying in real life. However, as the development of 3D mapping, the accuracy and practicality of EE measurement in this study would be improved. However, it must be noted that all subjects in this study were healthy adult males. If the equation in this study is used in other populations, such as females, children, the elderly, athletes, or populations with specific diseases, the usage of this equation might be limited. During EE calculation, it is essential to consider age, body weight, and height because these factors may cause variance. Overall, future research is necessary to apply the

results of this study to calculating the EEs of more types of activities.

Conclusion

The wearable inertial sensor is a significant product. Vibration signals produced by exercise are processed and calculated as predicted EE values to facilitate the measurement of physical activity for the general population. Practically, an essential issue is the increased loading with changes in energy metabolism during an appropriate sports training plan in athletes or the general public. Thus, having an effective method of EE calculation is critical. The results of this study showed that combining the vector magnitude parameters of the accelerometer with HRR parameters had good compensatory effects and led to more precise prediction of EE during exercise on slopes.

Declarations of interest

None.

Acknowledgment

We thank all participants in this study. The study was supported by a grant from the Ministry of Science and Technology, Taiwan (NSC 102-2410-H-179-013-MY2).

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