Improving energy expenditure estimation by using a triaxial accelerometer

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Chen, Kong Y., and Ming Sun. Improving energy expenditure estimation by using a triaxial accelerometer. *J. Appl. Physiol.* 83(6): 2112–2122, 1997.—In our study of 125 subjects (53 men and 72 women) for two 24-h periods, we validated energy expenditure (EE), estimated by a triaxial accelerometer (Tritrac-R3D), by using a whole-room indirect calorimeter under close-to-normal living conditions. The estimated EE was correlated with the measured total EE for the 2 days ($r = 0.925$ and $r = 0.855$; $P < 0.001$) and in minute-by-minute EE ($P < 0.01$). Resting EE formulated by the Tritrac was found to be similar to the measured values [standard errors of estimation (SEE) $= 0.112$ W/kg; $P = 0.822$]. The Tritrac significantly underestimated total EE, EE for physical activities, EE of sedentary and light-intensity activities, and EE for exercise such as stepping (all $P < 0.001$). We developed a linear and a nonlinear model to predict EE by using the acceleration components from the Tritrac. Predicted EE was significantly improved with both models in estimating total EE, total EE for physical activities, EE in low-intensity activities, minute-by-minute averaged relative difference, and minute-by-minute SEE (all $P < 0.05$). Furthermore, with our generalized models and by using subjects' physical characteristics and body acceleration, EE can be estimated with higher accuracy (averaged SEE $= 0.418$ W/kg) than with the Tritrac model.

physical activity; metabolism; modeling; validation; whole-room indirect calorimeter

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WITH THE ESTABLISHMENT of a negative correlation between energy costs of physical activities and incidence of morbidity/mortality for some chronic diseases, such as coronary heart disease, hypertension, and diabetes (2, 20), the quantification of energy expenditure (EE) and daily physical activities has gained considerable interest. Several methods and automated devices have been adopted, including doubly labeled water (9, 27), indirect calorimeter (27, 28), pencil and paper methods (30), heart-rate monitors (26, 27), pedometers (6), and motion sensors (12, 16, 21). Researchers as well as the general public use these methods to facilitate assessment of EE, activity levels, and general fitness profiles (18). Each method has strengths and limitations. The indirect calorimeter can measure EE accurately under laboratory conditions and is regarded as the accepted standard in validating energy costs of various physical activities (15), but accurate minute-by-minute activity monitoring and EE predictions in free-living conditions are needed as a more practical alternative for the measurement of EE.

In recent years, a growing number of portable devices has become available for daily physical activity monitoring, such as the Polar heart-rate recorder (Polar Electro, Kempele, Finland) and the Caltrac and the Tritrac-R3D accelerometers (both by Hemokinetics, Madison, WI). Heart-rate monitors have been studied extensively in terms of technical reliability and methodological usefulness in measuring physical activities and predicting EE (27). Accelerometers have become more attractive to the researchers because they have a longer recording time period, a rugged nature, and are capable of providing an indication of reliability and objectiveness (1, 14, 19). These devices use piezoelectric accelerometers and advanced microcomputers to register body motion (specifically, acceleration and deceleration during activities that involve energy cost). A linear relationship has been reported between EE and the body acceleration in walking (4, 5, 32). However, the uniaxial accelerometer, such as the Caltrac, was found to be inaccurate in measuring certain activities, including some sedentary activities (13, 19, 23) and running (7).

A triaxial accelerometer, the Tritrac-R3D, is a monitor developed to correct some of the limitations of the Caltrac. This device, which combines three independent sensors in orthogonal axes to detect acceleration in the three-dimensional space, may improve accuracy, especially during sedentary activities. The Tritrac monitor provides minute-by-minute data in acceleration counts by which EE of physical activity (EEact) is estimated. Moreover, with one-time programming, it allows a recording period of up to 14 days, and this information can be downloaded to a computer. These advances simplify the data-retrieval process, can reduce some possible risks of subject tampering, and may increase the reliability of this triaxial accelerometer in measuring daily physical activity and the associated EE. A linear relationship ($r > 0.77$, $P < 0.05$) has been reported between triaxial accelerometer output and EE for some physical activities (4, 14). These investigators have also suggested that a triaxial accelerometer, such as the Tritrac, could be a good method for correlating acceleration of physical activities with EE.

However, the validity of the Tritrac is under considerable investigation. It still cannot adequately detect slow or subtle changes in EE, such as during sleeping, the thermic effect of food, or EE caused by some physical activities or exercises. Furthermore, theoretical questions have been raised about the linearity of the relationship between body acceleration and EE (4). It has been reported that the Tritrac overestimated time accumulated in sedentary activities but underestimated active time components; thus it significantly underestimated total EE under free-living conditions (14). Limited studies using the Tritrac have been reported that correlated with heart rate, the Caltrac, and self-reports in children (31) and adults (14) under

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free-living conditions. But to our knowledge, no one has studied the accuracy of EE estimation by using the Tritrac, compared with a whole-room indirect calorimeter, in a minute-by-minute basis over 24-h periods. Furthermore, no modified models have demonstrated more accurate estimations of EE from the body accelerations. With an accurate and fast-responding whole-room indirect calorimetry chamber, we can accomplish these goals by using simultaneously measured EE and body acceleration.

The primary purpose of this investigation was to use a whole-room indirect calorimeter to evaluate the validity and accuracy of the Tritrac for the normal adult population under conditions close to free living and with different physical activities and exercises of various intensities. We also compared the resting EE (REE) formulated by the Tritrac to the values measured by the indirect calorimeter in two separate 24-h periods. Mathematical models were established to predict EE on a minute-by-minute and on a daily basis for each subject by using the acceleration output from the monitor. Furthermore, we evaluated the significance of these model parameters with respect to the subject's characteristics, and we simplified the models from individual to general forms that can be useful for the estimation of EE in large populations in free-living conditions.

METHODS

Subjects

One hundred twenty-five individuals (53 men and 72 women) completed the study. All subjects were healthy, with no evidence of past or present thyroid disorders or diabetes mellitus. They did not use drugs known to affect energy metabolism, were consuming a balanced diet, and were nonsmokers. Women participants were studied during the follicular phase of a menstrual cycle. All participants were encouraged to maintain their normal pattern of activity and diet. The characteristics of these subjects are shown in Table 1.

Experimental Procedures

Male and female adult volunteers were recruited from the Nashville, TN, area by means of posters, the Vanderbilt University periodical, and personal contact. Before participation, all subjects signed an informed consent form approved by the Vanderbilt University Committee for the Protection of Human Subjects. For each subject, two 24-h stays in the room calorimeter were scheduled within 8 consecutive days; these stays were separated by at least 1 day. Tritrac monitoring was recorded on a minute-by-minute basis with the same device during the 2 days. During one 24-h stay, the subjects were

asked to structure their activity patterns as closely as possible to their normal daily activity routine (normal day). For the other day, the subject was asked to engage in a defined physical activity-exercise protocol (exercise day). The protocol consisted of three 10-min walking bouts (with average speeds of 0.6, 0.9, and 1.2 m/s) and four 10-min simple step up-and-step down movements (with an average speed of 12, 18, 24, and 30 steps/min), with each activity separated by a 10-min resting period. The same pattern of exercises was performed at two defined time periods in the morning and the afternoon. The order of participation in the normal and the exercise modes was randomized among subjects. During both the normal day and the exercise day, the subjects were also provided with free access to a step-exercise bench and a stationary bike for additional exercise needs. Meals were provided at exact times during the days. The REE measurement was obtained in a 30-min awake and quiet resting period preceded by overnight sleeping and fasting for all subjects on both days in the chamber. The subjects were also instructed to maintain a diary of physical activity during the entire study period to be used for verification purposes.

Instrumentation

Accelerometer. The Tritrac activity monitors were used to measure minute-by-minute acceleration in three dimensions (*x* or anteroposterior axis, *y* or medial-lateral axis, and *z* or vertical axis). The monitor (weighing 170 g and measuring $11.1 \times 6.7 \times 3.2$ cm) was worn on the right hip, in a nylon pouch secured to a belt at the waistline, during all activities throughout the study days except during sleeping. Part of the output of the Tritrac is expressed as integrated acceleration over each minute in the three axes. The subject's physical characteristics are entered (gender, age, height, and weight) on initializing the monitor. This information is used to calculate an individual's REE, in kilocalories per minute (4.19 kJ/min), based on established predictive equations (shown in *Eqs. 1* and *2*) used by the Tritrac (8)

$$\text{Men: } \frac{\begin{array}{c}[473 \times \text{weight (lb)}] + [971 \times \text{height (in.)}] \\ - [513 \times \text{age (yr)}] + 4{,}687\end{array}}{100{,}000} \quad (1)$$

$$\text{Women: } \frac{\begin{array}{c}[331 \times \text{weight (lb)}] + (352 \times \text{height (in.)}] \\ - [353 \times \text{age (yr)}] + 49{,}854\end{array}}{100{,}000} \quad (2)$$

The prediction of EEact is calculated internally by an unpublished regression equation with the use of the vector magnitude of the acceleration registrations from the *x*-, *y*-, and *z*-axes.

Activity-energy measurement system. The activity-energy measurement system at Vanderbilt University combines a whole-room indirect calorimeter with a large force platform inside as the floor (see Fig. 1). The unit is housed in the Clinical Research Center at Vanderbilt and represents a highly accurate system in EE and physical activity measurements (25, 28, 29). The room calorimeter is an airtight environmental room measuring $2.5 \times 3.4 \times 2.4$ m. Equipped with a desk, chair, toilet, sink, telephone, television (TV)/videocassette recorder, audio system, stationary bike, step bench, and a bed, it bridges the difference between laboratory and free-living conditions. O_2 consumption and CO_2 production are measured at 1-min intervals and used along with urinary nitrogen excretion to calculate minute-by-minute EE

Table 1. *Subject physical characteristics*

Characteristics	Women (*n* = 72)		Men (*n* = 53)	
	Mean ± SD	Range	Mean ± SD	Range
Body mass, kg	76.9 ± 24.0	46.0–154.4	89.1 ± 21.4	55.5–143.5
Height, cm	163.5 ± 6.1	150.5–184.0	177.3 ± 6.7	162.0–189.0
Age, yr	37.1 ± 9.8	20.0–62.0	35.7 ± 10.0	19.0–56.0
BMI, kg/m²	28.6 ± 8.1	17.8–53.4	26.5 ± 6.6	18.8–45.5
Body fat, %	34.6 ± 10.5	5.4–58.9	24.1 ± 9.9	8.3–44.9

Values are means ± SD and ranges (minimum to maximum); *n* = no. of subjects. BMI, body mass index.

Fig. 1. Activity-energy measurement system at Vanderbilt University. EE, energy expenditure; REE, resting EE; RQ, respiratory quotient: rate of CO_2 production/rate of O_2 consumption.
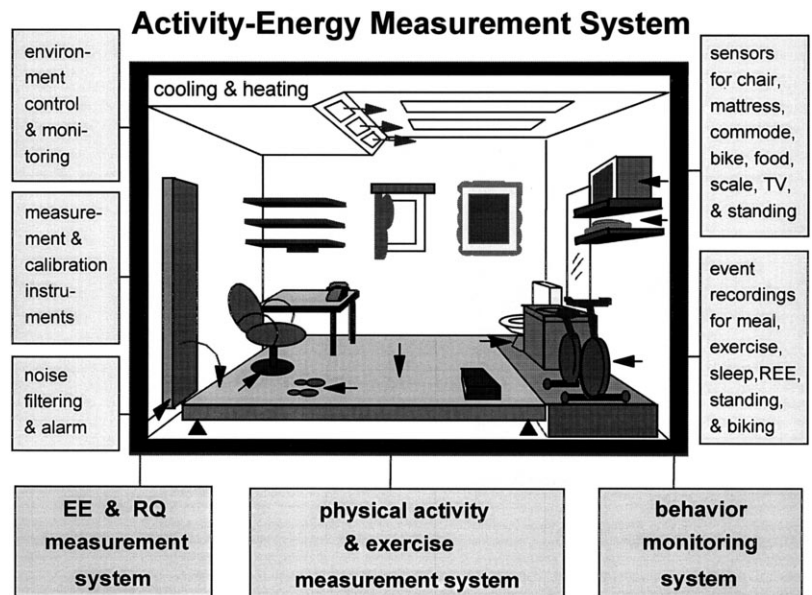
with a system error of <1% (29). This accuracy is critical for validation and model development of EE. The force platform, measuring 2.5×2.5 m, covers the entire living area inside the whole-room indirect calorimeter and is supported by multiple precision force transducers. During a subject's stay, the platform allows computer-aided measurement (60 times/s) of body position, displacement, and mechanical forces with an accuracy of 97% or higher (28). The electronic monitoring/sensing system in the calorimetric chamber consists of sensors and switches installed inside the TV/videocassette recorder, underneath the mattress used for sleeping, inside the chair, and at the airlock door where the subject receives food. Eight additional event buttons were used by the individual to signal for sleeping, mealtime, exercising, and watching TV. Therefore, the combination of the force platform, sensors, and event buttons provides precise determination of the nature, duration, and frequency of physical activities while simultaneously obtaining EE and Tritrac readings. This unique measurement facility provides us with an ideal system for validation and development of portable physical activity monitors. The details of the calorimeter have previously been reported (28, 29).

Other physical measurements. Body mass was measured to the nearest 0.05 kg with the use of a digital scale. Height was measured to the nearest 0.5 cm. Body fat and fat-free mass were determined by hydrodensitometry (underwater weighing). The subjects were weighed underwater while their residual lung volume was measured by the nitrogen-dilution technique (10). Body fat percent was calculated from body density by using Siri's equation (24), whereas fat mass and fat-free mass were calculated from body mass.

Establishment of Models

The output of the integrated minute-by-minute body acceleration from the Tritrac and the subject's physical characteristics were used to estimate EEact (EEact = EE − REE). For each subject, a linear and a nonlinear model were used. We first established individual models for each subject with independent parameters for optimal estimation, as shown in Fig. 2. These parameters were then generalized so that only body mass, height, gender, and age were needed from a subject to predict his or her EE by using the acceleration output. Data from the *exercise day* were used to generate the

models because of the rich signal information in acceleration and EE recordings. Each model (individual or generalized) was then used to predict EE of the *normal day* and compared with the measured EE from the room calorimeter. Before modeling, vertical (V) and horizontal (H) acceleration components were synchronized to EE measured by the indirect calorimeter and were low-pass filtered by a three-point moving-average filter to reduce artifacts, such as the monitor's sudden movements caused by the subject's adjustment of the pouch.

Linear model. The Tritrac calculates the EEact on the basis of the combined acceleration of all three axes (the vector magnitude $\sqrt{x^2 + y^2 + z^2}$). In our models, the acceleration in the z axis was isolated from the x- and y-axes as the V component, as shown in Fig. 2. The H component was defined as the square root of the sum of squared signals of the x- and y-axes ($\sqrt{x^2 + y^2}$). The rationale for separating z from x and y signals is that acceleration in the V component differs from the rest of dimensions because of gravity.

The linear model estimates EEact (in kJ/min) with the acceleration signals from the Tritrac

$$\hat{EE}act(k) = a_L \times H(k) + b_L \times V(k) \tag{3}$$

where a_L and b_L represent the regression parameters in the linear equation.

Nonlinear model. In the second model, the V and H signals were applied by two power parameters ($p1$ and $p2$) for the modeling of nonlinear relationship between EEact and body acceleration

$$\hat{EE}act(k) = a_N \times H(k)^{p1} + b_N \times V(k)^{p2} \tag{4}$$

where a_N and b_N represent the regression parameters in the nonlinear equation. $\hat{EE}act(k)$ represents the estimated EEact at the kth minute. In each model, parameters such as a, b, $p1$, and $p2$ were first chosen according to our experience, and $\hat{EE}act$ was calculated. By comparing it with the measured EEact, errors were determined and used as the optimization factor. Computer programs were utilized to repeat the calculation by changing parameters until the minimal error was reached. These error values were defined as a fitted error that represented the validity of the model. From *Eqs. 3* and *4*,
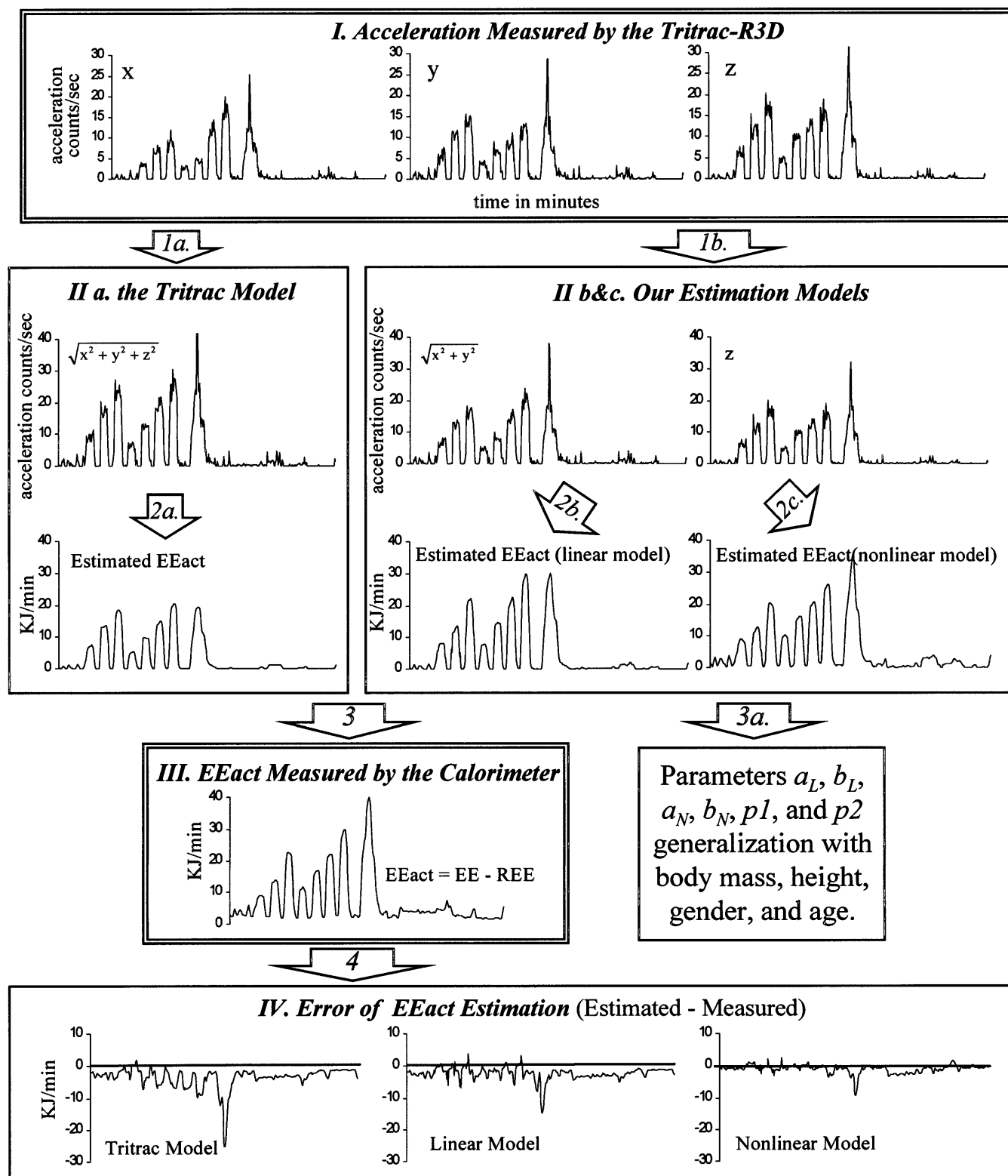
Fig. 2. Schematic diagram of model development and processing steps. *Process arrows 1a* and *2a*: Tritrac model, using $\sqrt{x^2 + y^2 + z^2}$ to estimate EE for physical activity (EEact). *Process arrows 1b, 2b,* and *2c*: linear and nonlinear models, using horizontal ($\sqrt{x^2 + y^2}$) and vertical (z) to estimate EEact. *Process arrow 3a*: generalization of model parameters by using stepwise linear-regression analysis. *Process arrows 3* and *4*: EEact estimated by each model were compared with actual EEact measured. $p1$ and $p2$, Power parameters; a_L, b_L: regression parameters in linear model (see *Eq. 3*); a_N, b_N: regression parameters in nonlinear model (see *Eq. 4*).

the *a*, *b*, *p*1, and *p*2 values with minimal error were kept as the optimal parameters for that individual.

The optimized parameters of each model were then applied to the acceleration components recorded on the other 24-h stay in the room calorimeter, i.e. the *normal day. Equations 3* and *4* were used to obtain the predicted EÊact. The predictive validity of each model was reflected by the errors of estimation when comparing EÊact to that measured by the indirect calorimeter. In each model, the final step involved superimposing EÊact and REE to derive total EE, which was then validated by EE measured by the indirect calorimeter.

The model parameters derived from these 125 subjects were then generalized to a set of parameters that would suffice for any adult subjects, as long as his or her body mass, height, and age are given. This was done using multiple linear-regression analysis.

Statistics

The accuracy of a particular model was evaluated by the difference between predicted and actual EE under various conditions over the 24-h period. The periods during the stays inside the room calorimeter were also segmented according to the intensity of EE. Sleeping periods were identified and isolated as the lowest intensity category. The other four categories (sedentary, light, moderate, and high intensities) were designated to represent 1–2.5, 2.6–4.0, 4.1–6, and >6.0 times the REE (MET = EE/REE). Correlation coefficient (Pearson's *r*), averaged relative differences (ARD), and standard errors of estimation (SEE) were used as the evaluation criteria, as shown in *Eqs. 5* and *6*

$$ARD = mean \left(\frac{|EEestimated - EEmeasured|}{EEmeasured} \right) \quad (5)$$

$$SEE = SD (EEestimated - EEmeasured) \quad (6)$$

EEestimated represents the estimated EE value, by the Tritrac model, by the fitted equations (linear or nonlinear), or by the generalized equations. EEmeasured represents the EE measured by the indirect calorimeter. All values for ARD and SEE were calculated from the minute-by-minute data, as in EEmeasured and EEestimated. They were calculated by using the MATLAB software package (MathWorks, Natick, MA) both in the optimization during the model development and in the evaluation of final predictions. Optimization was performed using the least-square simplex algorithm for the universal minimum errors in the SEE. Multiple linear regression analysis was used for the generalizations of the prediction equations. Differences were compared by analysis of variance (Tukey's test) or by *t*-test, all with the use of SPSS for Windows (SPSS, Chicago, IL).

RESULTS

From the study of 125 adults, we found a significant intra-individual correlation between the two separate 24-h stays of total EE measured by the indirect calorimeter (*r* = 0.914, *P* < 0.001) as well as of total EE estimated by the Tritrac (*r* = 0.959, *P* < 0.001). For EEact, the correlation between the days was lower in measured values (*r* = 0.534, *P* < 0.01) and in estimated values (*r* = 0.429, *P* < 0.01). REE measured in the two stays in the calorimeter were not significantly different (*t* value = 0.802, *P* = 0.424) by paired *t*-test. The Tritrac also predicted the REE accurately (SEE = 0.112 W/kg; *P* = 0.822) compared with the measurement from the calorimeter, as shown in Fig. 3. Thus the REE formu-
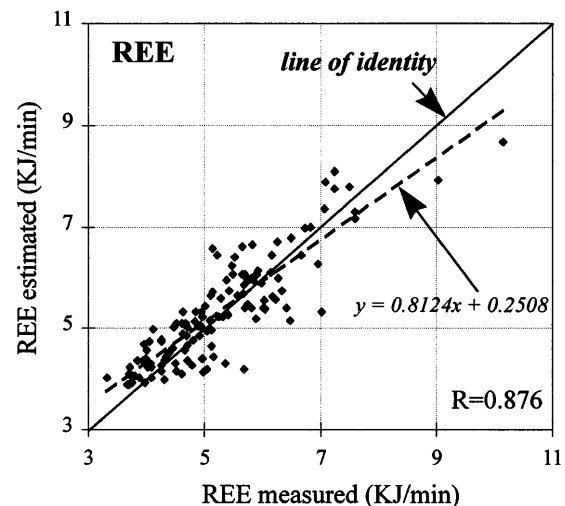

Fig. 3. REE estimated by Tritrac from subjects' physical characteristics vs. average values from 2 separate days of measurements by whole-room indirect calorimeter. Line of identity (solid line) signifies perfect match between estimated and the measured values (dashed line).

lated by the Tritrac was also used in our estimation models. Within each of the 24-h periods, total EE estimated by the Tritrac was significantly correlated (*P* < 0.001) with that measured by the whole-room indirect calorimeter (Fig. 4). Correlations between the measured and the estimated EEact were lower than the total EE for the exercise and the normal days (*r* = 0.737 and 0.539 respectively; *P* < 0.01). On a minute-by-minute basis, the Tritrac-estimated EE values were strongly correlated with measured values for the *exercise day* (*P* < 0.001) and the *normal day* (*P* < 0.01), as illustrated in Tables 2 and 3.

Despite these significant correlations, the Tritrac significantly underestimated total EE for both the *exercise day* and the *normal day* (SEE = 0.523 and 0.468 W/kg, respectively; *P* < 0.001) compared with the calorimeter. There also existed a consistent underestimation of EEact by the Tritrac for both days combined (*P* < 0.001). This underestimation occurred in all the intensity categories except sleeping, in which a significant overestimation (*P* < 0.001) by the Tritrac was observed, as shown in Tables 4 and 5.

Individual Models

Linear model. By separating the V component (*z*-axis) from the other components, the linear model significantly reduced the prediction error of the total EE in the *exercise day* (*P* < 0.001), the *normal day* (*P* = 0.014), and the total EEact for both days (*P* < 0.001 and *P* = 0.003) compared with the Tritrac model. Such improvement existed in all of the four nonsleeping activity categories for the 2 days (*P* < 0.01) except in the sedentary activities (1.0–2.5 MET) during the *normal day*, as shown in Tables 4 and 5. The ARD also showed significant improvements (*P* ≤ 0.001) for the two stays, and the SEE was significantly improved for the *exercise day* (*P* = 0.002), as seen in Fig. 5. However, the total EE and EEact estimated by the linear model were still significantly lower than that measured by the
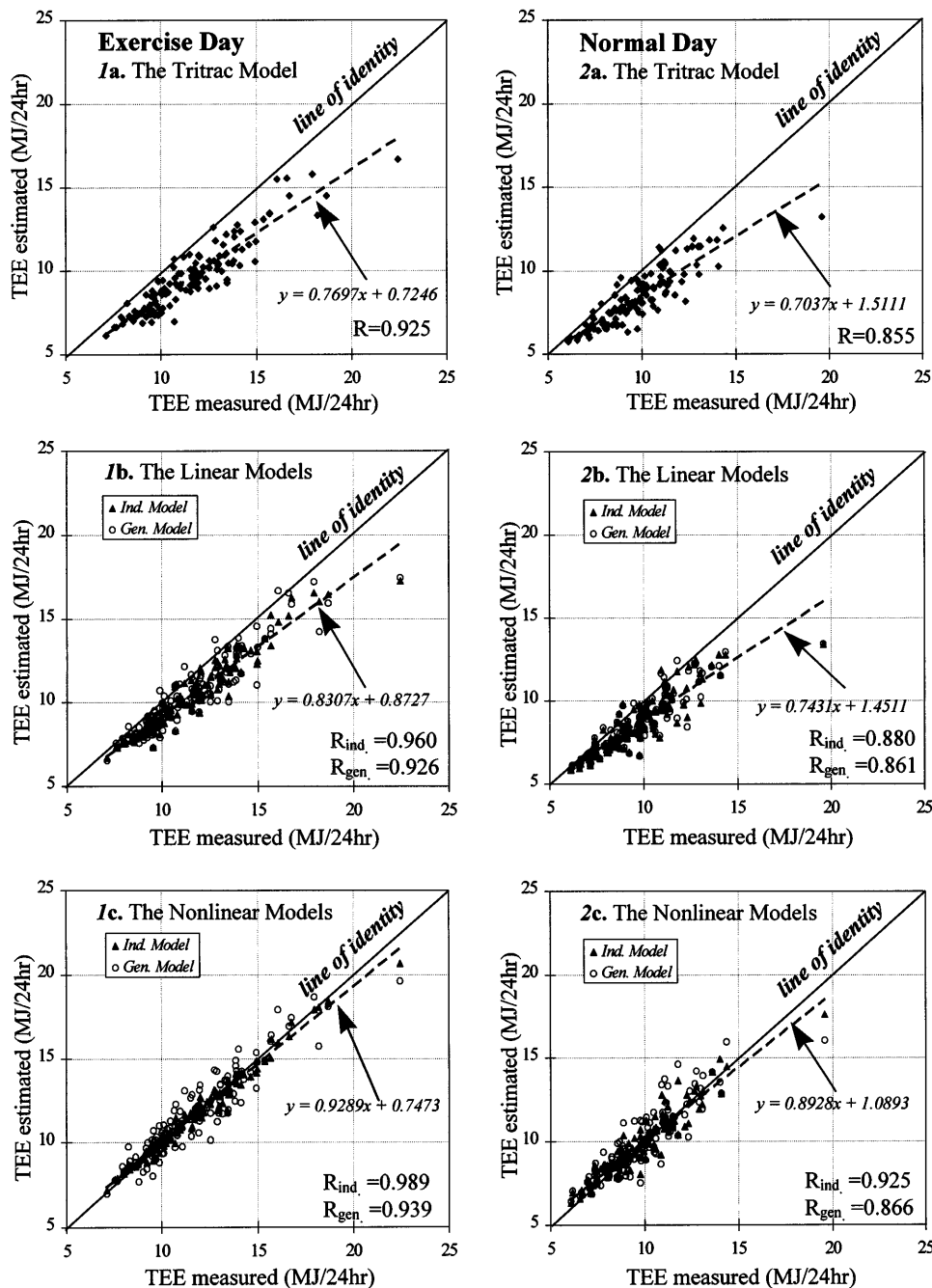
Fig. 4. Total daily energy expenditure (TEE) estimated by Tritrac (*a*), linear models (*b*), and nonlinear models (*c*) vs. TEE measured by calorimeter in *exercise day* (*1*) and *normal day* (*2*). Line of identity (solid line) signifies a perfect match between estimated and measured values (dashed line). ind, Individual; gen, General; *R*, correlation coefficient.

calorimeter for both days ($P < 0.01$). Significant ($P < 0.01$) difference in EE during activities of lower intensities in the *exercise day* and during all activities on the *normal day* contributed to the underestimation of the daily totals.

Nonlinear model. After introducing power parameters to the H and V components of the body acceleration, total EE estimated by the nonlinear power model was comparable to the measured values by the calorimeter for the two 24-h stays ($P > 0.05$). The differences between the measured and estimated total EE and EEact were also significantly decreased over the Tritrac model and the linear model ($P < 0.001$ and < 0.01, respectively), as seen in Fig. 4. This improved accuracy was a result of the significant ($P < 0.001$) improvement

in estimation of the sedentary and light-intensity activities for both days (Tables 4 and 5). As shown in Fig. 5, the ARD and SEE were also significantly lower for both days ($P < 0.001$), whereas the minute-by-minute correlation between the measured and estimated EE in the *exercise day* was higher ($P < 0.01$), as shown in Tables 2 and 3. However, because the Tritrac cannot distinguish sleeping from other activities for which the acceleration registration is zero, and we utilized the same REE formulated by the Tritrac for our models, an overestimation (8–10%) exists for sleeping. Such overestimation slightly affects the overall performance of the estimation models.

Furthermore, when focusing on the walking and stepping protocol on the *exercise day*, the Tritrac signifi-

Table 2. *Total EE, EEact, and minute-by-minute correlation coefficient measured by indirect calorimeter and estimated by models for exercise day*

Measurement	Total EE, MJ/24 h		Total EEact, MJ/24 h		R, Estimated vs. Measured EE	
	Mean ± SD	Range	Mean ± SD	Range	Mean ± SD	Range
Measured by calorimeter	11.59 ± 2.57	7.11–22.46	4.02 ± 1.23	1.48–7.76		
Estimated by Tritrac	9.65 ± 2.14*	6.14–16.66	1.97 ± 0.75*	0.53–4.99	0.912 ± 0.038	0.665–0.969
Individual linear model	10.50 ± 2.22*†	6.70–17.26	2.83 ± 0.85*†	1.09–5.05	0.917 ± 0.037	0.675–0.971
General linear model	10.55 ± 2.26*†	6.59–17.43	2.88 ± 0.93*†	0.98–6.18	0.914 ± 0.037	0.670–0.969
Individual nonlinear model	11.52 ± 2.41†‡	7.19–20.64	3.84 ± 1.11†‡	1.59–8.16	0.941 ± 0.025†‡	0.812–0.979
General nonlinear model	11.61 ± 2.51†‡	6.99–19.60	3.93 ± 1.16†‡	1.32–7.41	0.934 ± 0.024†‡	0.779–0.975

Values are means ± SD and ranges (minimum to maximum); $n = 125$ subjects. EE, energy expenditure; EEact, EE for physical activity; R, correlation coefficient. *Significantly different from measured by indirect calorimeter; $P < 0.05$. †Significantly different from estimate by Tritrac; $P < 0.05$. ‡Significantly different from linear model (individual or general); $P < 0.05$.

cantly underestimated the total EE during stepping exercises (EEstep) ($P < 0.001$) but not during walking exercises (EEwalk) ($P > 0.05$). The linear model significantly reduced ($P < 0.01$) the estimation error of EEstep but not for EEwalk ($P > 0.05$). However, total EEstep estimated by using this model was still significantly lower ($P < 0.05$) than measured values. The nonlinear model did not significantly ($P = 0.232$) improve the prediction over the linear model in EEstep or EEwalk (Table 6).

Generalized Models

Linear model. When the linear model parameters of all subjects were generalized, body mass was a significant ($P < 0.05$) contributing factor for both a_L and b_L (*Eq. 3*) by stepwise multiple-linear regression. Parameter a_L also showed a significant correlation with height and age of the 125 subjects studied ($P < 0.05$). Thus a simple linear model estimated EEact by using the H and V acceleration components from the Tritrac; the parameters a_L and b_L were generalized

$$a_L = \frac{[5.78 \times \text{mass (kg)} + 11.95 \times \text{height (cm)} + 6.89 \times \text{age (yr)} - 2{,}001]}{1{,}000} \quad (7)$$

$$b_L = \frac{[5.96 \times \text{mass (kg)} + 349.5]}{1{,}000} \quad (8)$$

Nonlinear model. Similarly, the nonlinear model parameters from *Eq. 4* were analyzed by stepwise

multiple regression analysis. Body mass significantly contributed in all parameters ($P < 0.05$)

$$p1 = \frac{[2.66 \times \text{mass (kg)} + 146.72]}{1{,}000} \quad (9)$$

$$p2 = \frac{[-3.85 \times \text{mass (kg)} + 968.28]}{1{,}000} \quad (10)$$

$$a_N = \frac{[12.81 \times \text{mass (kg)} + 843.22]}{1{,}000} \quad (11)$$

$$b_N = \frac{[38.90 \times \text{mass (kg)} - 682.44 \times \text{gender} + 692.50]}{1{,}000} \quad (12)$$

The factor of gender in *Eq. 12* was defined as 1 for men and 2 for women. Thus model parameters in *Eq. 4* could be expressed in *Eqs. 9–12* with only subjects' physical characteristic parameters such as body mass and gender known.

The comparisons between the EE measured by the indirect calorimeter and those estimated by the generalized models are shown in Figs. 4 and 5 and in Tables 2–6. Both models significantly reduced ($P < 0.001$) the estimation error over the Tritrac model and were not significantly different ($P > 0.05$) from their respective individual models. They utilized the subject characteristic parameters, the same as the Tritrac, to estimate EEact. Together with REE, which is formulated by *Eqs.*

Table 3. *Total EE, EEact, and minute-by-minute correlation coefficient measured by indirect calorimeter and estimated by models for normal day*

Measurement	Total EE, MJ/24 h		Total EEact, MJ/24 h		R, Estimated vs. Measured EE	
	Mean ± SD	Range	Mean ± SD	Range	Mean ± SD	Range
Measured by calorimeter	9.74 ± 2.03	6.10–19.58	2.16 ± 1.03	0.13–5.20		
Estimated by Tritrac	8.39 ± 1.70*	5.74–14.69	0.72 ± 0.50*	0.13–3.35	0.663 ± 0.302	0.252–0.970
Individual linear model	8.71 ± 1.74*†	5.87–14.44	1.03 ± 0.64*†	0.24–3.46	0.668 ± 0.289	0.285–0.971
General linear model	8.72 ± 1.75*†	5.88–15.57	1.04 ± 0.65*†	0.24–4.69	0.670 ± 0.300	0.281–0.968
Individual nonlinear model	9.81 ± 1.99†‡	6.32–17.62	2.13 ± 0.91†‡	0.31–5.40	0.715 ± 0.274	0.301–0.978
General nonlinear model	9.88 ± 2.11†‡	6.42–17.98	2.21 ± 0.91†‡	0.40–5.81	0.719 ± 0.279	0.295–0.977

Values are means ± SD and ranges; $n = 125$ subjects. *Significantly different from measured by the indirect calorimeter; $P < 0.05$. †Significantly different from estimate by the Tritrac; $P < 0.05$. ‡Significantly different from linear model (individual or general); $P < 0.05$.

Table 4. *Total EE estimated by models in specific intensity categories for exercise day*

Measurement	Sleeping		Sedentary (1–2.5 MET)		Light (2.6–4 MET)		Moderate (4.1–6 MET)		High (>6.1 MET)	
	Mean±SD	Range	Mean±SD	Range	Mean±SD	Range	Mean±SD	Range	Mean±SD	Range
Measured by calorimeter	2.15±0.57	0.93–4.17	6.08±1.39	3.62–12.76	1.70±0.46	0.59–4.28	1.24±0.45	0.04–2.52	0.63±0.51	0.07–2.61
Estimated by Tritrac	2.34±0.56*	1.14–4.02	4.84±1.05*	2.94–8.82	1.26±0.39*	0.36–3.01	0.91±0.38*	0.02–2.22	0.42±0.34*	0.05–1.52
Individual linear model	2.34±0.56*	1.14–4.02	5.02±1.07*†	3.09–9.04	1.56±0.42*†	0.54–4.07	1.19±0.44†	0.04–2.30	0.57±0.49†	0.07–2.40
General linear model	2.34±0.56*	1.14–4.02	5.04±1.07*†	3.12–9.09	1.59±0.46*†	0.50–3.76	1.21±0.47†	0.04–2.66	0.57±0.44†	0.07–2.23
Individual non-linear model	2.34±0.56*	1.14–4.02	5.93±1.29†‡	3.63–11.77	1.71±0.46†‡	0.60–4.29	1.16±0.44†	0.04–2.37	0.54±0.46†	0.06–2.31
General non-linear model	2.34±0.56*	1.14–4.02	6.02±1.37†‡	3.57–11.09	1.77±0.50†‡	0.52–4.04	1.13±0.44†‡	0.04–2.27	0.48±0.37*†‡	0.03–1.93

Values are means ± SD and ranges (in MJ). MET = EE/resting EE. All models used same baseline (resting EE) for sleeping; $n = 125$ subjects except for moderate and high activity where $n = 124$ and 88 subjects, respectively. *Significantly different from measurement by indirect calorimeter; $P < 0.05$. †Significantly different from estimate by Tritrac; $P < 0.05$. ‡Significantly different from linear model (individual or general); $P < 0.05$.

1 and *2*, EE can be estimated on a minute-by-minute basis in general applications.

DISCUSSION

In this study, accuracy of EE estimation by the Tritrac monitor on a minute-by-minute basis and on a daily basis was evaluated by using a whole-room calorimeter. We found the intraindividual variation of the Tritrac in estimating total EE was small between 2 separate days, and the estimated total EE was correlated to measured EE. The REE, the major component of the total EE, was estimated accurately with subjects' characteristics by the Tritrac compared with the REE measured in the calorimeter in our study. We found a significant underestimation of total EEact by the Tritrac in the whole-room indirect calorimeter under conditions close to free living. The Tritrac explained ~50% of the EEact during the *exercise day* and 30% for the *normal day*. Underestimation by the Tritrac was significant in all waking activities, especially for sedentary and light intensities. Total EE was partially compen-

sated for during sleeping because the formulated REE (*Eqs. 1* and *2*) was higher than actual sleeping EE. A similar result was also found with the Caltrac (3). The total EE, expressed as the superimposed EEact and REE, was underestimated by the Tritrac compared with the measured values as a net result.

Estimating EE by accelerometers has been studied previously under laboratory and free-living settings. The most commonly used device, the Caltrac, is a single-direction accelerometer that records acceleration counts from which EE is estimated. Some studies in adults and children reported significant correlations between EEact estimated by the Caltrac and by other proven accurate methods (7, 9, 32), but they also found significant underestimation of total EE (3, 11, 17, 19) by the monitor. Pambianco et al. (21) also found that the accuracy of the Caltrac changed with gender, body mass, and walking speed. With a three-dimensional accelerometer, the predicted EE was slightly improved. Ayen and Montoye (1) found that a combination of three uniaxial accelerometers mounted orthogonally could

Table 5. *Total EE estimated by models in specific intensity categories for normal day*

Measurement	Sleeping		Sedentary (1–2.5 MET)		Light (2.6–4 MET)		Moderate (4.1–6 MET)		High (>6.1 MET)	
	Mean±SD	Range	Mean±SD	Range	Mean±SD	Range	Mean±SD	Range	Mean±SD	Range
Measured by calorimeter	2.09±0.54	1.26–4.56	6.67±1.52	4.12–14.60	0.43±0.41	0.02–2.04	0.44±0.39	0.05–2.30	0.74±0.61	0.07–2.93
Estimated by Tritrac	2.29±0.54*	1.38–3.85	5.51±1.29*	3.55–11.20	0.31±0.31*	0.01–1.67	0.26±0.23*	0.02–1.24	0.44±0.37*	0.04–1.38
Individual linear model	2.29±0.54*	1.38–3.85	5.69±1.30*	3.73–10.96	0.38±0.38*†	0.01–2.03	0.33±0.31*†	0.02–1.75	0.58±0.49*†	0.06–1.82
General linear model	2.29±0.54*	1.38–3.85	5.70±1.33*	3.74–12.09	0.38±0.37*†	0.01–1.93	0.33±0.31*†	0.02–1.75	0.58±0.49*†	0.06–1.79
Individual non-linear model	2.29±0.54*	1.38–3.85	6.72±1.59†‡	4.32–13.24	0.43±0.41†‡	0.01–1.95	0.34±0.31*†	0.03–1.74	0.54±0.46*†	0.05–1.65
General non-linear model	2.29±0.54*	1.38–3.85	6.79±1.68†‡	4.23–14.49	0.44±0.42†‡	0.01–1.96	0.34±0.31*†	0.04–1.74	0.52±0.43*†	0.05–1.62

Values are means ± SD and ranges (in MJ). All models used same baseline (resting EE) for sleeping; $n = 125$ subjects except for light, moderate, and high activity where $n = 122$, 72, and 40 subjects, respectively. *Significantly different from measurement by indirect calorimeter; $P < 0.05$. †Significantly different from estimate by Tritrac; $P < 0.05$. ‡Significantly different from linear model (individual or general); $P < 0.05$.
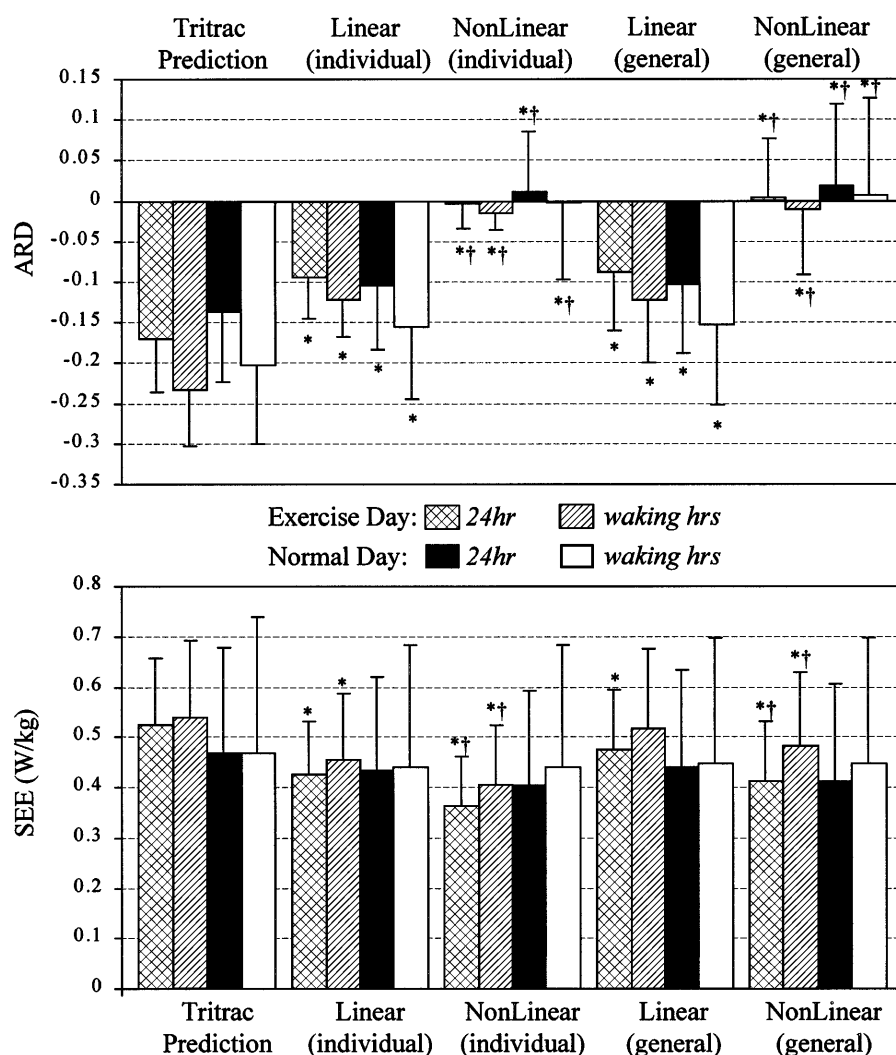
Fig. 5. Averaged relative difference (ARD; *top*) and standard errors of estimation (SEE; *bottom*) factors of Tritrac, linear models, and nonlinear models estimated (general) vs. measured (individual) minute-by-minute EE of the 2 24-h stays in calorimeter. *Significantly different from Tritrac estimate; $P < 0.05$. †Significantly different from linear model (individual or general); $P < 0.05$.

better estimate EE in walking, running, and step exercise than could any of the uniaxial accelerometers. Meijer et al. (16) reported the SEE of 1.32 W/kg for 16 subjects measured under laboratory conditions by using a triaxial portable accelerometer compared with respirometry. Bouten et al. (4) found a correlation value of 0.95 ($P < 0.001$, SEE = 0.70 W/kg) between EEact measured by an indirect calorimeter and estimated by a triaxial accelerometer. Matthews and Freedson (14) reported high correlation values (0.82 and 0.77, both $P < 0.001$) of total EE in free-living conditions as measured by the Tritrac, by 3-day physical activity log and by a 7-day recall. However, they concluded that the Tritrac still significantly underestimated EE in free-living conditions. Our calculations of the SEE (over the 24-h periods) were slightly lower than those found by other investigators (4, 16). We found the errors of estimation in EE during the awake period (Fig. 5) were close to the values previously reported.

There are some known instances in which EEact is underestimated by the Tritrac. Such activities include weight lifting, stationary bicycling, movements of upper extremities, activities involving extra carried weight, and walking uphill (19). Also, in the case of running, inaccuracy toward overestimation of EE

(+68%) was found by Matthews and Freedson (14). One possible cause may be that the Tritrac predicts EE by a linear equation, which was most likely developed in level walking (14), with the use of the vector magnitude

Table 6. *Total EE for walking and stepping measured by indirect calorimeter and estimated by models*

	EEwalk, MJ		EEstep, MJ	
Measurement	Mean ± SD	Range	Mean ± SD	Range
Measured by calorimeter	1.11 ± 0.39	0.36–3.05	1.60 ± 0.51	0.56–3.37
Estimated by Tritrac	1.02 ± 0.38	0.27–2.89	1.07 ± 0.38*	0.37–2.47
Individual linear model	1.17 ± 0.44†	0.22–3.21	1.38 ± 0.44*†	0.45–2.71
General linear model	1.21 ± 0.44†	0.22–3.12	1.39 ± 0.47*†	0.44–2.93
Individual non-linear model	1.17 ± 0.45†	0.27–3.30	1.42 ± 0.45*†	0.48–2.79
General non-linear model	1.18 ± 0.43†	0.25–3.10	1.42 ± 0.46*†	0.49–2.61

Values are means ± SD and ranges; $n = 125$ subjects. EEwalk, EE in walking; EEstep, EE in stepping. *Significantly different from measurement by indirect calorimeter; $P < 0.05$. †Significantly different from estimate by Tritrac; $P < 0.05$.

of all three axes and the subject's characteristics (mainly body mass).

We believe that the accuracy of equations that estimate EEact by the body acceleration can be improved by using the models developed in this investigation. The reasons are as follows. First, the acceleration recorded in the separate directions can contribute with various strength to enhance EEact prediction. Acceleration and deceleration of the V axis may cause more energy to be expended because of the work against gravity. This effect was shown in the underestimation of EE during the stepping protocol by using the vector magnitude of all three acceleration components (the Tritrac model) vs. the improvement by the linear models when the accelerations in V and H were separated. The V axis of body acceleration is the major component in daily activities such as walking and stepping (7, 32). Earlier studies that involved acceleration and EE had relied solely on this component for estimation, e.g., the Caltrac. But EEact could relate differently to acceleration components in other axes, depending on the type and nature of the activities. For example, Bouten et al. (4) found the best prediction of EE in walking was by using the acceleration in the anterior-posterior (x) direction. Therefore, separating the direction of acceleration components in estimation of EEact may improve the accuracy.

Second, the linear relationship between the acceleration and EEact may not be the best fitting for certain activities. Using a force-platform inside the whole-room calorimeter, we previously found a linear relationship between the EE of some exercises and the mechanical work performed (28). However, Bouten et al. (4) reported that a better estimation of EE was achieved by using the linear prediction than with the quadratic prediction using integrated acceleration for walking and other sedentary activities. We generated two nonlinear variables in the power parameters of an estimation model to optimize the EE estimation.

Third, the room calorimeter enables the subject to perform nearly free-living activities while measuring EE and accelerations accurately on minute-by-minute basis. In addition to walking at various speeds (0.6–1.2 m/s) and stepping (12–30 steps/min), >40 other activities of various intensities were performed by the subjects in the whole-room indirect calorimeter. These activities provided a wide range of daily activity types and patterns for the development of accurate models. With the accurate and quickly responding EE measurement system (28, 29), we were able to validate the Tritrac as well as to develop models on a minute-by-minute basis and in separate intensity categories to best describe the total EE on a daily basis.

The linear model was formulated by reestablishing the H and V components of body acceleration. The general model used the same parameters from the subject characteristics as did the Tritrac model and achieved slightly higher accuracy of estimating EEact over the existing model. As predicted by *Eqs. 3, 7, and 8*, EEact correlated positively with body mass, age, and height. Body mass was a strong determinant of converting acceleration to EE because of the mechanical work needed for motion. Body stature also contributed to the estimation of EEact, possibly because of the additional energy for the movements of upper and lower extremities; the Tritrac cannot measure these. Moreover, with increasing age, EEact for the same amount of physical activity (acceleration over time) in the H direction would also increase. This may suggest a decrease in work efficiency with age for certain activities. This hypothesis is supported by a negative correlation reported between running economy and age (22) and is consistent with the model. Nevertheless, the underestimation of EE still existed with the linear approach. One possible cause is the inherent limitation of recording acceleration and converting it linearly to EEact, especially during the sedentary and light-intensity activities.

The nonlinear model incorporated the variables in the power parameters for the acceleration components. The noted changes in EE estimation for the 2 days (Fig. 4) showed improvements of the nonlinear models over the Tritrac and the linear models in total EE. Furthermore, the nonlinear model estimated ~96 and 98% of the EEact on the *exercise* and the *normal days* for the group. The generalized nonlinear model also proved to have similar accuracy in EEact estimation. The overall reduction in the ARD and SEE suggested that the nonlinear model was a better method. The most important improvement of the nonlinear model was its ability to enhance the acceleration components in sedentary to light-intensity activities (≤4 MET) in comparison with the linear models in which the estimation of EE in moderate- to high-intensity activities (>4 MET) was similar (Tables 4 and 5). In the generalized model (*Eqs. 4 and 9–12*), body mass contributed differently to the power parameters ($p1$ and $p2$) of the H and V components. It suggests that larger body mass tends to push the H component towards a linear relationship ($p1 = 1$ at 320.8 kg) and pull the V component away ($p2 = 0$ at 251.5 kg) from it. Whereas the parameters a_N and b_N were positively correlated with body mass, the slope for b_N was steeper, perhaps to partially compensate for the effect of $p2$. Finally, gender contributed in b_N, showing that women have a smaller parameter in the V component than men in EEact estimation.

In conclusion, this investigation evaluated the Tritrac under close to free-living conditions in a whole-room indirect calorimeter with a large group of healthy adult subjects. We found a significant correlation of the total EE between two 24-h stays as well as between the minute-by-minute EE as estimated by the Tritrac and measured by the calorimeter. We also found that the Tritrac fairly accurately estimated the REE and EE of walking. However, the underestimation of EE by the Tritrac was significant in daily totals and in all intensities except during sleeping. The major underestimation was in the low-intensity activities (EE ≤ 4 MET). We developed two simple models that incorporated each subject's body mass, height, age, and gender to estimate EE by using the body acceleration measured and recorded by the Tritrac. Results showed significant improvements over the Tritrac model (1–2% total EE

difference, compared with a whole-room indirect calorimeter, SEE = 0.349–0.628 W/kg).

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