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Tri-axial high-resolution acceleration for oxygen consumption estimation: Validation of a multi-sensor device and a novel analysis method

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Abstract: We validated a multi-sensor chest-strap against indirect calorimetry and further introduced the total-acceleration-variability (TAV) method for analyzing high-resolution accelerometer data. Linear regression models were developed to predict oxygen uptake from the TAV-processed multi-sensor data. Individual correlations between observed and TAV-predicted oxygen uptake ($\dot{V}O_2$) were strong (mean r = 0.94) and bias-low (1.5 mL·min^{-1}·kg^{-1}, $p < 0.01$; 95% confidence interval: 8.7 mL·min^{-1}·kg^{-1}; –5.8 mL·min^{-1}·kg^{-1}); however, caution should be taken when a single-model value is used as a surrogate for $\dot{V}O_2$.

Key words: energy expenditure, exercise physiology, chest-strap, ambulatory assessment, accelerometer.

Résumé : Dans cette étude, on valide l'utilisation d'une sangle thoracique à capteurs multiples par rapport à la calorimétrie indirecte et on approfondit la méthode total-accélération-variabilité (TAV) pour l'analyse des données accélérométriques à résolution élevée. On élabore des modèles de régression linéaire pour estimer la consommation d'oxygène à partir des données provenant de multiples capteurs. Les corrélations individuelles entre les valeurs du consommation d'oxygène ($\dot{V}O_2$) mesuré et celles prédites par la méthode TAV sont élevées (r moyen = 0,94) et le biais est faible (1,5 mL·min^{-1}·kg^{-1}, $p < 0,01$; IC 95 %: 8,7 mL·min^{-1}·kg^{-1}; –5,8 mL·min^{-1}·kg^{-1}); néanmoins, il faut être prudent quand on utilise un seul modèle pour estimer le $\dot{V}O_2$.

Mots-clés : dépense d'énergie, physiologie de l'exercice, sangle thoracique, évaluation ambulatoire, accéléromètre.

Introduction

The relationships among physical activity, fitness, and positive health effects have been well established on a population level (Holtermann et al. 2010; Kujala et al. 1998; Lee and Paffenbarger 2000; Paffenbarger et al. 1994; Sandvik et al. 1993; Savela et al. 2010). Consequently, technology that enables a precise unobtrusive assessment of physical activity and exercise intensity in the ambulatory setting is essential for detailed investigations of dose–response relationships between physical activity and health, the evaluation of interventions, and the monitoring of compliance.

Oxygen uptake ($\dot{V}O_2$) is the most accurate measure for energy expenditure (EE) and — related to, for example, the maximal oxygen uptake ($\dot{V}O_{2max}$), ventilatory, or lactate thresholds — ~~is~~ also a measure of exercise intensity. Unfortunately, the direct assessment by analyzing respiratory gas concentrations and volumes is limited almost exclusively to the laboratory, using metabolic measuring carts. Although there are mobile metabolic measuring systems, these systems are expensive, need time consuming preparation, are relatively obtrusive, and do not provide continuous long-term measurements (>12 h). Thus, many researchers evaluated more time- and cost-efficient methods for ambulatory EE-estimation, e.g., self-reports, pedometry, heart-rate measurements, and accelerometry, against indirect calorimetry (IC) as a gold standard method (e.g., (Corder et al. 2005; Eisenmann et al. 2004; Eston et al. 1998; Welk et al. 2000)).

Accelerometers, in particular tri-axial devices (Bouten et al. 1994; Fudge et al. 2007), have proven their potential to give good estimates of EE and were often used as a reference method under ambulatory conditions (Aadahl and Jorgensen 2003; Bharathi et al. 2010; Boon et al. 2010; Hagstromer et al. 2007; Johansen et al. 2001).

Also, a combination of heart rate and accelerometric (ACC) data can improve accuracy of EE-estimates (Brage et al. 2004; Corder et al. 2007; Zakeri et al. 2010), which might be of importance especially under static muscular load. Nevertheless, there are some limitations when using heart rate for EE estimation, since heart rate is affected by factors such as fitness, emotional and environmental conditions, the intensity and kind of physical exercise, and genetic disposition. Thus, mobile sensors that are capable of measuring additional physiological indicators, such as heart rate variability or respiration rate, might improve models for EE estimation under conditions of nonmetabolic heart rate changes (Smolander et al. 2008; Wilhelm et al. 2006; Wilhelm and Roth 1998). Crouter et al. (2006) introduced a simple but effective methodology for distinguishing locomotor activities (walking and running) from other activities. They improved EE-calculation algorithms by classifying the type of activity based on the calculation of the coefficients of variation of Actigraph accelerometer outputs (Crouter et al. 2006). Another innovative approach is the application of heart rate and ACC for an ambulatory prediction of cardiorespiratory fitness (Plasqui and Westerterp 2006; Weyand et al. 2001), which is based on the inverse relationship between $\dot{V}O_{2max}$ and heart rate at a given exercise level (Astrand and Ryhming 1954; Margaria et al. 1965).

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There is 1 commercially available compact multi-sensor device (Actiheart, Cambridge Neurotechnology, UK) capable of synchronously sensing body acceleration and heart rate that has been validated against IC (Brage et al. 2005; Corder et al. 2007; Spierer et al. 2011). To the authors' best knowledge, no IC-validated device exists that is capable of sensing acceleration and heart and respiratory activity.

The aim of the study was to (*i*) validate a new multisensory device for the unobtrusive estimation of $\dot{V}O_2$ and (*ii*) develop a new method for analyzing high-resolution accelerometer output that was validated against measured $\dot{V}O_2$ and compared with established methods. As heart rate and especially respiration rate correlate well with $\dot{V}O_2$, we further evaluated whether a combination of accelerometer output and these physiological measures would provide a stronger estimation of instantaneous $\dot{V}O_2$.

Material and methods

Subjects

Twenty-three healthy subjects (8 female, 15 male) were recruited by personal invitation and gave their informed written consent to take part in this study. Approval of the local ethics committee at the University of Rostock was obtained. Based on the order of appearance, subjects were either assigned to the developmental (N = 12) or the cross-validation sample (N = 11).

Protocol

All subjects performed the following activities for 5 min each: supine rest, seated resting, mental arithmetic at the desktop, writing at the desktop, sorting books at the desktop, walking (4 and 6 km·h^{-1}), and running (8 km·h^{-1}) on a treadmill (H/P cosmos pulsar, Germany; Fig. 1) with a 1-min break between adjacent activities.

Multi-sensor device

The multi-sensor chest-strap Equivital (Hidalgo Ltd., GB; Fig. 1) contained 3 dry electrocardiogram (ECG) electrodes and provided a 2-channel ECG (sampling frequency: 256 Hz, resolution: 10 bits, heart rate range: 0–300 beats·min^{-1}, heart rate accuracy: <±5 beats·min^{-1}/10%) by using belt. Respiration rate was measured with a resistive strain-gauge sensor implemented in the anteromedial part of the belt (sampling frequency: 25.6 Hz, resolution: 10 bits, breathing rate range: 0–60 beats·min^{-1}, breathing rate accuracy: ±2 beats·min^{-1} static use, ±3 beats·min^{-1} moderate activity, ±6 beats·min^{-1} high activity) (Hidalgo 2009). Average heart rate (HR_{EQ}) and average respiration rate (RR_{EQ}) were reported every 15 s. Accuracy of the Equivital heartbeat measurementwas recently validated against an ECG system (Weippert et al. 2011). Beyond these and additional physiological parameters, the Equivital also registered mediolateral (ACC_x), vertical (ACC_y) and anteroposterior (ACC_z) movement changes of the trunk, using an internal ADXL-330-sensor (Analog Devices, USA). ACC data were provided as raw and mG values, respectively (1 G = 9.81 m·s^{-2}), with a resolution of 25.6 values per second (25.6 Hz). Because initial signal input was bidirectional (acceleration or deceleration), ACC data assumed positive or negative values. All measured data were stored on a micro-SD memory card within the belt-logger and provided in text formats for further analysis. Importantly, all data could be derived in real time from the device via Bluetooth, thus enabling a real-time monitoring of a person's physiological strain and physical activity.

Three methods for the processing of body acceleration data were applied.

Method A (ODBA)

The mean accelerometer output of each axis was calculated for each activity. Subsequently, the mean of each axis was subtracted from the corresponding raw accelerometer output to remove baseline shifts that were due to different body posture and the static components of the accelerometer output. Integrals of the absolute (rectified) values of the x, y, and z axes were integrated over a 30-s time window. Then the sum of the integrals was calculated. A comparable procedure for the handling of accelerometric data has been described elsewhere (Bouten et al. 1994; Gleiss et al. 2011; Qasem et al. 2012; Wilson et al. 2006) and is sometimes referred to as overall dynamic body acceleration (ODBA).

Fig. 1. Subject wearing a face mask and the chest-strap multisensor Equivital (Hidalgo Ltd., UK) (under the shirt) while exercising on the treadmill. Small picture shows the sensor system and its correct positioning.

$$\mathrm{ODBA} = \int_{t_0}^{t_0+T} |\mathrm{ACC}_x(t) - \overline{\mathrm{ACC}_x}|\mathrm{d}t + \int_{t_0}^{t_0+T} |\mathrm{ACC}_y(t) - \overline{\mathrm{ACC}_y}|\mathrm{d}t + \int_{t_0}^{t_0+T} |\mathrm{ACC}_z(t) - \overline{\mathrm{ACC}_z}|\mathrm{d}t$$

where t_0 is the starting time of the window and T = 30 s.

Method B (total acceleration variability (TAV))

Instantaneous acceleration variability

A measure of the instantaneous variability in the acceleration data has been defined for the analysis. Let ACC(t) be the acceleration vector at time t defined as follows:

$$\mathrm{ACC}(t) = \begin{bmatrix} \mathrm{ACC}_x(t) \\ \mathrm{ACC}_y(t) \\ \mathrm{ACC}_z(t) \end{bmatrix}$$

Now, an instantaneous measure of the acceleration variability is defined as

$$AV(kT_s) = \|ACC(kT_s) - ACC[(k-1)T_s]\|$$

where $k = 0, 1, 2, \ldots$ is an integer, $T_s > 0$ is the sampling period, and $\|\cdot\|$ denotes Euclidean norm.

TAV

The acceleration variability data within a finite interval of time can be summed to calculate total acceleration variability as follows:

$$TAV = \sum_{t \in T} AV(t)$$

where T is the considered time duration that was taken equal to 30 s.

Method C (VeDBA)

The raw acceleration values were used to calculate the magnitude (i.e., Euclidean norm) of acceleration vector at any time:

$$\|ACC(t)\| = \sqrt{|ACC_x(t)|^2 + |ACC_y(t)|^2 + |ACC_z(t)|^2}$$

Let $\overline{\|ACC\|}$ denote the average of acceleration vector norm over 30 s. Then total variability in data are calculated as

$$VeDBA = \sum_{t \in T} (\|ACC(t)\| - \overline{\|ACC\|})$$

where T = 30 s.

Similar methods have been studied in the literature (McGregor et al. 2009; Qasem et al. 2012), and are typically referred to as the vector-based dynamic body acceleration (VeDBA).

Respiratory gas analysis

$\dot{V}O_2$ was measured by indirect calorimetry by using an automated open-circuit breath-by-breath respiratory gas analyzing system (OxyconPro, Viasys Healthcare, Germany). It consists of a transducer holder with a turbine connected to a face mask. Ventilation is measured by an optoelectrical segment that measures turbine rotation. Expired air is sampled via a tube (attached to the transducer holder) and analyzed by a differential-paramagnetic sensor (oxygen) and an infrared absorption sensor (carbon dioxide), both located in a sensor box. Concentrations of oxygen and carbon dioxide were measured under standard temperature, pressure, and dry conditions with the help of the installed LabManager 4.6 software program (Viasys Healthcare). Before the tests, oxygen and carbon dioxide sensors as well as the respiratory flow sensor were calibrated according to manufacturer's instructions.

Data processing

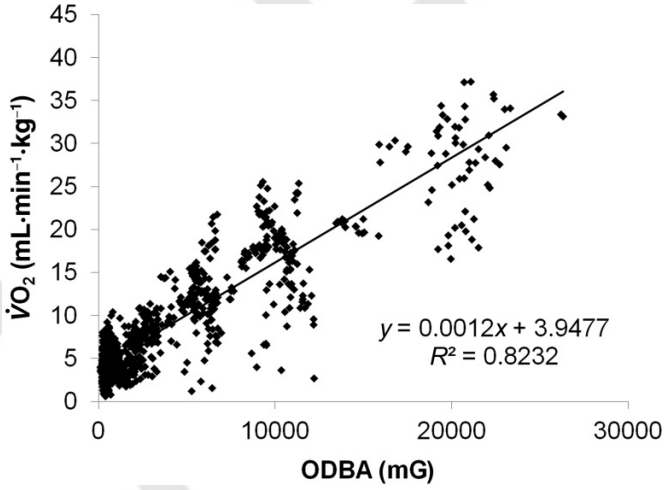
Only the last 3 min of each activity were analyzed to cover steady-state conditions. The TAV data values were calculated for a 30-s period, and synchronous HR_{EQ}- and RR_{EQ}-data were averaged over the corresponding 30-s periods. The same was done for respiration rate and $\dot{V}O_2$ measured by the OxyconPro. Thus, 6 data sets per subject and activity were generated.

Graphical presentations and Pearson's correlation coefficient r were used to test the association between the processed accelerometer data and measured $\dot{V}O_2$. Then multiple stepwise linear regression analyses were applied to the developmental data to derive linear models for ambulatory $\dot{V}O_2$ prediction. Measured $\dot{V}O_2$ served as the dependent criterion. ODBA, TAV, or VeDBA, respectively, as well as HR_{EQ}- and RR_{EQ}-data where used as explanatory variables in the regression models. The multiple correlation coefficient squared (R^2) and its change were calculated. In principle, the interpretation of R^2 is similar to the interpretation of r^2, namely the proportion of variance of the observed variable (measured $\dot{V}O_2$) that may be predicted by the explanatory variables (acceleration, heart rate and respiration rate). The change in R^2 gives information about the increase in predictive power of the particular explanatory variables, given the variables already in the model. Agreement between the measured and the predicted $\dot{V}O_2$ in the cross-validation sample was determined by the method of Bland–Altman (Bland and Altman 2007). This method allows the calculation of agreement between the different models and the measured $\dot{V}O_2$, even if there are multiple measurements per individual. When this method was applied, we designated the 95% confidence interval (CI) as limits of agreement. The significance of differences between measured and modeled $\dot{V}O_2$ was evaluated using Student's t test for paired observations. Intra-class correlation coefficient (ICC) was calculated to assess the agreement between respiration rate measured by the OxyconPro and the Equvital, respectively. All analyses were carried out using the Statistical Package for Social Sciences (SPSS, version 15.0; SPSS Inc., Chicago, Ill., USA) or MicroSoft Office Excel 2007.

Table 1. Characteristics of the developmental and cross-validation sample.

	Developmental sample, N = 12		Cross-validation sample, N = 11	
	Mean (SD)	Range	Mean (SD)	Range
Age, y	24.6 (2.9)	21–32	30.1 (9.5)	25–54
Weight, kg	71.4 (14.7)	54–99	84.3 (16.6)	64–125
Height, m	176.8 (9.2)	1.63–1.93	185.6 (6.3)	1.75–1.96
BMI, kg·m^{-2}	22.6 (3.3)	19.1–30.6	24.4 (4.2)	20.2–34.6
Resting heart rate, beats·min^{-1}	68.7 (10.5)	52.1–86.7	60.1 (9.6)	49.4–75.2

Fig. 2. Correlation between overall dynamic body acceleration (ODBA) and measured oxygen uptake ($\dot{V}O_2$) in the developmental sample.



Results

Table 1 shows the selected characteristics of the participants in the developmental and cross-validation sample. Samples were statistically different regarding age (Mann–Whitney U test, $p = 0.016$), body height ($p = 0.032$), and resting heart rate ($p = 0.034$). T1

Correlation between ODBA, VeDBA, and TAV with $\dot{V}O_2$ was high (Fig. 2, 3, 4). F2-F4

Fig. 3. Correlation between total acceleration variability (TAV) and measured oxygen uptake ($\dot{V}O_2$) in the developmental sample.

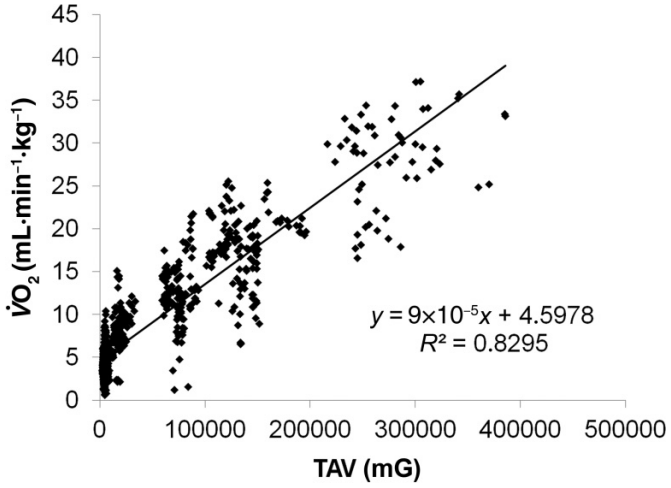


Fig. 4. Correlation between the vector-based dynamic body acceleration (VeDBA) and measured oxygen uptake ($\dot{V}O_2$) in the developmental sample.

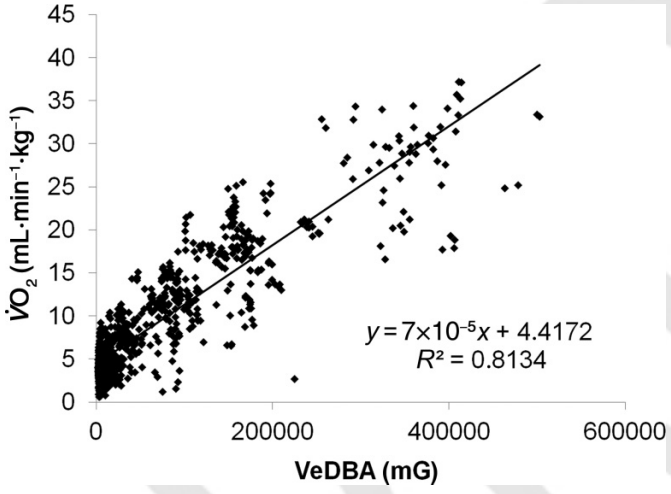


Fig. 5. Total acceleration variability (TAV) cut-off value for distinguishing walking and running from all other activities.

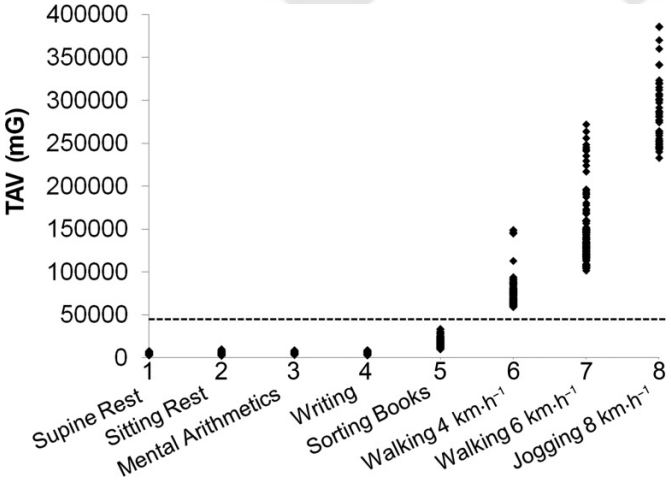


Fig. 6. Overall dynamic body acceleration (ODBA) across all activities.

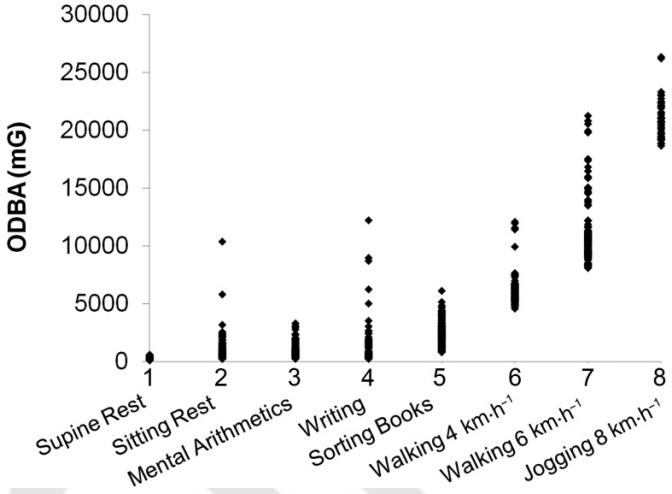


Fig. 7. Vector-based dynamic body acceleration (VeDBA) across all activities.

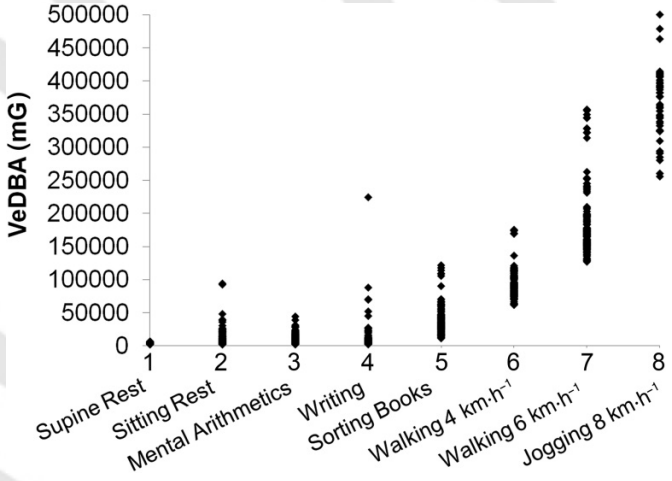


Fig. 8. Average measured and modeled oxygen uptake ($\dot{V}O_2$) across the different activities. ODBA, overall dynamic body acceleration; TAV, total acceleration variability; VeDB, vector-based dynamic body acceleration.

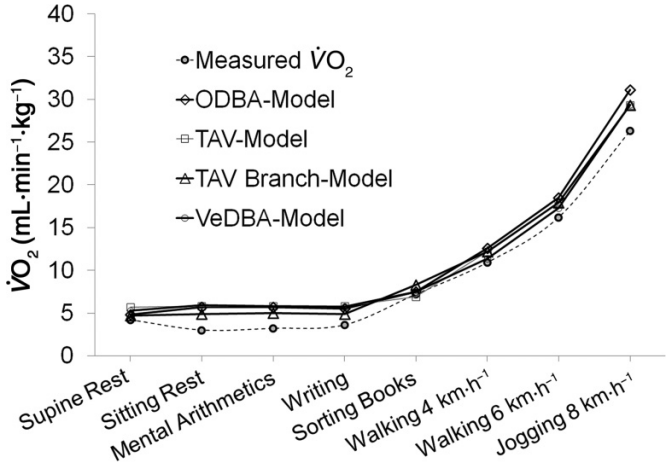


Table 2. Mean (±SD) of measured oxygen consumption ($\dot{V}O_2$) and model bias (mean of individual difference of calculated–measured $\dot{V}O_2$) across the different activities (cross-validation sample).

Activity	*n*	Measured $\dot{V}O_2$ (±SD), mL·min^{-1}·kg^{-1}	Bias ODB model (upper Lo; lower Lo), mL·min^{-1}·kg^{-1}	Bias TAV model (upper Lo; lower Lo), mL·min^{-1}·kg^{-1}	Bias TAV-branch model (upper Lo; lower Lo), mL·min^{-1}·kg^{-1}	Bias VeDB model (upper Lo; lower Lo), mL·min^{-1}·kg^{-1}
All	484	7.8 (6.5)	1.9 (9.5; –5.8)**	1.7 (8.9; –5.4)**	1.5 (8.7; –5.8)**	1.6 (9.3; –6.2)**
Supine rest	66	4.2 (1.8)	0.7 (3.4; –2.0)**	1.5 (4.2; –1.2)**	0.6 (3.2; –2.0)**	1.1 (3.8; –1.6)**
Sitting rest	66	3.0 (1.0)	2.7 (5.2; 0.2)**	2.8 (4.4; 1.2)**	1.9 (3.6; 0.2)**	2.9 (5.2; 0.6)**
Mental arithmetics	66	3.2 (1.3)	2.5 (4.7; 0.3)**	2.6 (4.6; 0.6)**	1.8 (3.9; –0.2)**	2.6 (5.6; –0.4)**
Writing	66	3.6 (1.1)	1.9 (4.1; –0.3)**	2.1 (4.0; 0.2)**	1.3 (3.2; –0.6)**	2.1 (4.2; 0.1)**
Sorting books	66	7.2 (2.2)	0.3 (3.0; –2.4)	0.3 (3.6; –3.0)	1.2 (4.7; –2.3)**	0.3 (3.2; –2.6)
Walking 4 km·h^{-1}	66	10.9 (3.2)	1.7 (8.1; –4.7)**	1.2 (7.6; –5.2)*	1.2 (7.6; –5.2)*	0.5 (6.7; –5.7)
Walking 6 km·h^{-1}	66	16.2 (4.2)	2.3 (10.9; –6.3)**	1.6 (9.5; –6.3)*	1.6 (9.5; –6.3)*	1.1 (9.5; –7.3)
Jogging 8 km·h^{-1}	22	26.3 (5.2)	4.8 (10.0; –0.4)**	3.1 (8.3; –2.1)*	3.1 (8.3; –2.1)*	3.1 (9.8; –3.6)

Note: $\dot{V}O_2$, oxygen uptake; bias, mean of individual difference between calculated $\dot{V}O_2$ and measured $\dot{V}O_2$; ODBA, overall dynamic body acceleration; TAV, total acceleration variability; VeDB, vector-based dynamic body acceleration; Lo, limits of agreement; *, **, difference between calculated and measured oxygen consumption is significant on a level of $p < 0.05$, $p < 0.01$, respectively.

Table 3. Mean and range of the individual correlation coefficients for the cross-validation sample.

	ODBA model	TAV model	TAV-branch model	VeDB model
Measured $\dot{V}O_2$	0.931 (0.986–0.771)	0.929 (0.991–0.794)	0.94 (0.991–0.803)	0.928 (0.984–0.766)

Note: $\dot{V}O_2$, oxygen uptake; ODBA, overall dynamic body acceleration; TAV, total acceleration variability; VeDB, vector-based dynamic body acceleration.

Furthermore, in contrast to ODBA and VeDBA, TAV enabled a 100% discrimination between walking–running and all other activities in the developmental as well as in the cross-validation sample (Fig. 5, 6, 7). A cut-off value of 46404 mG was defined by calculating the mean of the TAV-maximum for book-sorting (33634 mG) and the TAV-minimum during walking (59175 mG) to distinguish walking and running from all other activities.

Multiple stepwise linear regression analyses of the developmental data revealed that including respiration rate as well as heart rate as predicting variables only marginally improved prediction of $\dot{V}O_2$ compared with the accelerometer-based only models. The increase of the explained variance in the developmental sample was 2.3% for absolute respiration rate, 0.1% for the absolute heart rate values, and 2.2% and 0.6% for the individual increases of breathing rate and heart rate, respectively. Thus, respiration rate and heart rate data were not included in the regression models. Likewise, quadratic regression models only marginally improved prediction accuracy by 2% for each method.

Linear regression analysis resulted in the following equations for $\dot{V}O_2$ prediction:

Model A (ODBA model): $\dot{V}O_2 = 0.0012 \times \text{ODBA} + 3.9477$

Model B1 (TAV model): $\dot{V}O_2 = 0.00009 \times \text{TAV} + 4.5978$

Based on the TAV cut-off, a branched equation model was developed (TAV-branch model).

Model B2 (TAV-branch model): If TAV ≥ 46 404, then $\dot{V}O_2 = 0.00009 \times \text{TAV} + 4.5978$; if TAV < 46404, then $\dot{V}O_2 = 0.000273 \times \text{TAV} + 3.589$

Model C (VeDBA model): $\dot{V}O_2 = 0.00007 \times \text{VeDBA} + 4.4172$

Applied to the cross-validation sample, average $\dot{V}O_2$ of the developed models matched average measured $\dot{V}O_2$ very well (Fig. 8), at which the TAV-branch model was showing marginally higher prediction accuracy and the smallest bias across all data (Table 2). Table 2 shows the bias and limits of agreement for the different activities and models. Average individual correlation coefficients across all activities were high for measured $\dot{V}O_2$ and the regression models (Table 3).

Respiration rates measured by the multisensory device (RR_{EQ}) and respiration rates measured by the OxyconPro were similar. Intra-class correlation coefficient was 0.893 (ICC 95% CI: 0.877–0.907). As per the limits reported by Nunan and colleagues (2008), methods can be considered interchangeable if the lower ICC 95% CI value exceeds 0.75. Thus, respiration rate measured by the Equivital was comparable to the respiratory measuring cart values.

Discussion

The aim of this study was to validate a multi-sensor chest-belt that provides physiological and activity data against indirect calorimetry. It was shown that across different activities tri-axial acceleration, measured by the Equivital, is strongly correlated with oxygen consumption, assessed by indirect calorimetry. The introduced method for analyzing high-resolution tri-axial accelerometric data, called total acceleration variability (TAV), automatically handles not only the bidirectional nature of the accelerometer output but also any possible baseline shift during the measurement. Thus, the method ensures a reliable analysis of high-resolution accelerometer data. Moreover, the TAV method is ideally suited for on-line analyses, since no averaging procedure has to be carried out to correct accelerometer output for baseline shifts. In comparison with the established methods of ODBA and VeDBA for analyzing accelerometer outputs to predict energy expenditure, the TAV method was similar or even slightly more accurate. However, although generally accelerometer-based models followed changes in activity and associated $\dot{V}O_2$, the results of the estimated instantaneous $\dot{V}O_2$ should be evaluated cautiously, since there were a relatively strong biases and, more importantly, relatively wide limits of agreement. Especially under terms of light physical activity estimated $\dot{V}O_2$ deviated up to 100% and more from the measured value. Although the OxyconPro is a validated system, it yields a measuring error, which might bea source of variance between the measured and the estimated $\dot{V}O_2$ (Carter and Jeukendrup 2002; Macfarlane and Wong 2012; Rietjens et al. 2001). Furthermore, beyond the well-known between-subject variability of the (basal) metabolic rate (Javed et al. 2010; Johnstone et al. 2005; Larsen et al. 2011; Melville and Mezey 1959), not all of the participants might have achieved a steady state within 2 min of the treadmill or other exercises. Also, emotionally induced breathing and energy consumption patterns might have added variability to the physiological measurements that cannot be de-

tected by accelerometers (Birbaumer and Schmidt 2006; Boiten 1998; Gailliot et al. 2007; Lane et al. 2011).

An advantage of the TAV analysis is its ability to distinguish walking and running from all other activities with 100% accuracy. This exceeds the accuracy of a method proposed by Crouter and colleagues, which used the coefficient of variation of the accelerometer output calculated over a defined time to classify walking and running from other activities (Crouter et al. 2006). Furthermore, when applying the TAV analysis, no additional procedure for removing accelerometer baseline shifts is needed.

In contrast to the expectations, heart rate as well as respiratory rate did not improve accelerometer-based $\dot{V}O_2$-prediction accuracy significantly. On the one hand, this might be due to the strong variability of heart and respiration rates at rest as well as in response to exercise (e.g., caused by the participants' different ages, genetic dispositions, and physical fitnesses). On the other hand, the experimental setup did not include static muscular activities, resistance exercises, or upper-extremity dynamic work. All these activities can elicit increases in $\dot{V}O_2$, respiration and heart rate (Bloomer 2005; Buitrago et al. 2012; Louhevaara et al. 2000), while body acceleration (measured with a trunk-mounted device) is negligible. Further, it is well known that accelerometer-based estimation of energy consumption has drawbacks if applied to activities with limited vertical movements, such as bicycling and in-line skating (Arvidsson et al. 2009; Soric et al. 2012). Thus, under conditions of static muscular load or dynamic activities with limited (vertical) movements of the trunk, the ambulatory $\dot{V}O_2$-estimation might be improved if additional physiological indicators, such as respiration rate or heart rate are available. Future investigations are warranted, and should cover a broader range of activities to test the additional value of RR_{EQ} and HR_{EQ} for ambulatory $\dot{V}O_2$ estimation as well as the discriminative potential of the TAV analysis.

Finally, respiration rate measured by the Equivital agreed well with the respiratory measuring cart values and thus seems to be valid when applied to similar activities.

We conclude that the combination of tri-axial high-resolution accelerometric data (provided by the Equivital and comparable devices) and the TAV analysis enables an accurate distinction between walking and running and all other activities. Further, the TAV-processed accelerometer output can follow average $\dot{V}O_2$ very well across a range of diverse activities. However, caution should be taken when a single model value — in our case representing the average $\dot{V}O_2$ of a 30-s period — is used as a surrogate for $\dot{V}O_2$. Applied to similar activities, heart rate and respiration rate do not improve $\dot{V}O_2$-prediction based on high-resolution tri-axial accelerometer data.

Competing interests

The authors declare that they have no competing interests.

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