Estimation of Oxygen Uptake during Fast Running Using Accelerometry and Heart Rate

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\textsuperscript{1}International Centre for East African Running Science and \textsuperscript{2}Institute of Biomedical & Life Sciences, University of Glasgow, Glasgow, UNITED KINGDOM; and \textsuperscript{3}School of Physical Education and Sports, Institute of Movement Sciences and Sports Medicine, Faculty of Medicine, University of Geneva, SWITZERLAND

\textbf{ABSTRACT}

FUDGE, B. W., J. WILSON, C. EASTON, L. IRWIN, J. CLARK, O. HADDOW, B. KAYSER, and Y. P. PITSILADIS. Estimation of Oxygen Uptake during Fast Running Using Accelerometry and Heart Rate. \textit{Med. Sci. Sports Exerc.}, Vol. 39, No. 1, pp. 192–198, 2007. Previous investigations have reported that accelerometer counts plateau during running at increasingly faster speeds. \textbf{Purpose:} To assess whether biomechanical and/or device limitations cause this phenomenon and the feasibility of generating oxygen uptake (\(\dot{V}_O_2\)) prediction equations from the combined use of accelerometry and heart rate during walking and running. \textbf{Methods:} Sixteen endurance-trained subjects completed two exercise tests on a treadmill. The first was a continuous incremental test to volitional exhaustion to determine ventilatory threshold and peak \(\dot{V}_O_2\). The second was a discontinuous incremental exercise test while walking (3, 5, and 7 km h\(^{-1}\)) and running (8, 10, 12, 14, 16, 18, and 20 km h\(^{-1}\), or until volitional exhaustion). Subjects completed 3 min of exercise at each speed, followed by 3–5 min of recovery. Activity counts from uni- and triaxial accelerometers, heart rate, and gas exchange were measured throughout exercise. \textbf{Results:} All accelerometer outputs rose linearly with speed during walking. During running, uniaxial accelerometer outputs plateaued, whereas triaxial output rose linearly with speed up to and including 20 km h\(^{-1}\). Prediction of \(\dot{V}_O_2\) during walking and running using heart rate (\(R^2 = 0.42\) and 0.59, respectively), accelerometer counts (\(R^2 = 0.48–0.83\) and 0.76, respectively), the combined methodologies (\(R^2 = 0.54–0.85\) and 0.80, respectively), and the combined methodologies calibrated with individual data (\(R^2 = 0.99–1.00\) and 0.99, respectively) was completed by linear regression. \textbf{Conclusions:} Uni- and triaxial accelerometer outputs have a linear relationship with speed during walking. During running, uniaxial accelerometer outputs plateau because of the biomechanics of running, whereas triaxial accelerometer output has a linear relationship. The combined methodologies predict \(\dot{V}_O_2\) better than either predictor alone; a subject’s individually calibrated data further improves \(\dot{V}_O_2\) estimation. \textbf{Key Words:} UNIAXIAL, TRIAXIAL, ACCELEROMETER, TREADMILL EXERCISE, PREDICTION EQUATIONS

Accelerometry and heart rate monitoring are two commonly used methods for measuring physical activity (1.5–7,10,11,19,20,30). However, the precise quantification of physical activity and energy expenditure at the population level using accelerometry or heart rate is difficult and prone to errors (18,19,29). For example, heart rate can be affected by factors other than physical activity (e.g., age, gender, training status, emotional state), especially at low intensities (18,19). On the other hand, a major limitation of accelerometry is the failure to quantify net external work such as uphill walking, cycling, swimming, or load-bearing activities (29). However, combining methodologies may, to a large extent, overcome some of these limitations and, in doing so, improve the assessment accuracy of physical activity and energy expenditure (6,24,29–31).

A number of studies have reported improved accuracy to predict physical activity and energy expenditure when combining accelerometry and heart rate compared with their respective individual methods (1,10,11,19,20). For example, Haskell et al. (11) reported an \(R^2\) value improved from 0.69 to 0.82 when arm motion, as assessed by accelerometry, was combined with heart rate monitoring during arm ergometer exercise. Subsequent studies have explored various calibration methods using the combined methodologies (6,7,25,27,28,32). Combining methodologies seems promising, but it remains to be determined whether laboratory-defined relationships between heart rate, accelerometer counts, and oxygen uptake (\(\dot{V}_O_2\)) will also apply in free-living situations (29). Indeed, studies have reported that despite increased energy demands from increasingly faster running speeds, output from some motion sensors plateau (7,12,21). For instance, Brage et al. (7) investigated whether a commonly used accelerometer (6,7,21,27,28), the Computer Science Applications (CSA) Model 7164 (now also known as the MTI accelerometer; Manufacturing Technology Inc., Fort Walton beach, FL), could predict \(\dot{V}_O_2\) during walking (3–6 km h\(^{-1}\)) and running (8–20 km h\(^{-1}\)) on a motorized treadmill.

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treadmill and in the field. It was found that CSA output rose linearly ($R^2 = 0.92$, $P < 0.001$) with increasing speed up to 9 km h$^{-1}$ but leveled off at approximately 10,000 counts per minute during running (8–20 km h$^{-1}$). This phenomenon will render it impossible for regression models to accurately predict VO$_2$ during vigorous exercise, and the full benefits of combining these methodologies might not be exploited. Brage et al. (7) hypothesized that this limitation may be attributable to biomechanical factors such as a reduced vertical component with increasing speed. However, device dynamics may also be a limiting factor, to a certain degree. The Nyquist–Shannon sampling theorem (22,26), also known as the Whittaker–Shannon theorem (14), states that the sampling frequency (of the device) must be greater than twice the frequency of the input signal to allow reconstruction of the original signal from the sampled version. Once data have been sampled using a standard accelerometer, the output is filtered to eliminate external artifacts such as electrical noise and vibrations; this is generally termed band pass filtering. Hence, the frequency range of band pass filtering must include the maximum frequency elicited during running, and the sampling frequency must be twice this frequency. In considering the requirements for mechanical properties of accelerometers for measuring activity during running, it is noteworthy that vertical frequencies can be as high as 10 Hz but are generally lower at the center of mass (15). A further consideration for the mechanical properties of accelerometers is the amplitude of accelerations that can be sampled. For example, Bhattacharya et al. (3) reported vertical peak accelerations ranging from 0.9g to 5.0g measured at the lower back during running (8.1–11.3 km h$^{-1}$). Considering that the CSA accelerometer has a sampling frequency of 10 Hz, band pass filtering of 0.21–2.28 Hz, and can measure $\pm$ 2.13g, the device may not be adequate for fast running. Bouten et al. (4) have suggested that accelerometers should be able to measure up to $\pm$ 6g at the waist and between 0 and 20 Hz. However, to date, no study has investigated the outputs from a number of different accelerometers with various sampling frequencies, band pass filtering ranges, and peak acceleration amplitudes during fast running.

The main aim of the present investigation was to assess whether biomechanical and/or device limitations cause the observed leveling off of accelerometer counts during running. This was achieved by investigating the outputs from a number of accelerometers, uni- and triaxial, with various sampling frequencies, band pass filtering ranges, and peak acceleration amplitudes. It was hypothesized that accelerometers with device dynamics that more closely satisfied the sampling frequency, band pass filtering, and peak acceleration amplitude required for fast running would yield the greatest relationship between running speed and accelerometer output. A secondary aim of this investigation was to assess the feasibility of generating VO$_2$ prediction equations from the combined use of accelerometry and heart rate that could be employed during fast running up to world-record marathon-running pace.

### METHODS

#### Subjects.
Sixteen endurance-trained males (Table 1) gave their written informed consent to take part in the present study, which was approved by the local ethics committee and was performed according to the code of ethics of the World Medical Association (Declaration of Helsinki).

#### Experimental design.
All subjects completed two incremental exercise tests on a motorized treadmill (Woodway PPS55 Med, Weil am Rhein, Germany) at standard room temperature (20–21°C) with at least 1 wk separating each test. The first test was a continuous incremental test to volitional exhaustion to determine the ventilatory threshold (V(TH)) and peak oxygen uptake (VO$_2$peak). The second assessment involved a discontinuous incremental exercise test to volitional exhaustion to assess the relationships between accelerometry counts and walking and running speeds, accelerometer counts and heart rate, and accelerometer counts and VO$_2$.

#### Experimental Procedures.
Subjects reported to the laboratory on the day of testing after a 3-h fast and having refrained from alcohol, caffeine, and strenuous exercise the day before. On arrival at the laboratory, body mass (Avery Berkel 33/448, W&T Ltd, UK) and height (Leicester height measure, Invicta Plastics Ltd, UK) were measured before each test.

#### Heart rate and gas exchange measurements.
Heart rate and gas exchange measurements were obtained in the same manner for both tests. A heart rate transmitter belt (Suunto t6, Suunto Oy, Vantaa, Finland) was attached to the chest to record heart rate continuously. Subjects were equipped with a headset, which supported the mouthpiece, and a nose clip. Gas exchange variables were determined breath-by-breath using algorithms developed by Beaver et al. (2). Respired volumes were measured with a bidirectional turbine transducer (VMM; Alpha Technologies, Laguna Niguel, CA) calibrated with a 3-L syringe using a range of different flow profiles (Hans Rudolph, Kansas City, MO). Respired gas concentrations were measured every 20 ms by a quadruple mass spectrometer (QP9000S; Morgan Medical, Gillingham, Kent, UK), which was calibrated against precision-analyzed gas mixtures. Barometric pressure was measured using a standard mercury barometer.

#### Accelerometry.
The four accelerometer devices used for the present study were 1) a uniaxial CSA 7164 model (now also known as the MTI accelerometer; Manufacturing Technology Inc., Fort Walton beach, FL) sensitive to body accelerations in the vertical direction (6,7,21,27,28); 2) a

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**Table 1.** Physical characteristics of the subjects ($N = 16$) who participated in the present study.

<table>
<thead>
<tr>
<th>Age (yr)</th>
<th>Mean</th>
<th>SD</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>23</td>
<td>3</td>
<td>19–31</td>
<td></td>
</tr>
<tr>
<td>Height (cm)</td>
<td>182.9</td>
<td>5.7</td>
<td>170.5–192.0</td>
</tr>
<tr>
<td>BM (kg)</td>
<td>76.3</td>
<td>8.0</td>
<td>68.5–100.0</td>
</tr>
<tr>
<td>BM (kg m$^{-2}$)</td>
<td>23</td>
<td>2</td>
<td>20–28</td>
</tr>
<tr>
<td>V(TH) (mL kg$^{-1}$ min$^{-1}$)</td>
<td>38.1</td>
<td>4.0</td>
<td>30.1–43.4</td>
</tr>
<tr>
<td>VO$_2$peak (mL kg$^{-1}$ min$^{-1}$)</td>
<td>60.3</td>
<td>4.2</td>
<td>55.0–67.8</td>
</tr>
</tbody>
</table>

Values are mean ± SD and range. BM, body mass; BMI, body mass index; V(TH), ventilatory threshold; VO$_2$peak, peak oxygen uptake.
uniaxial ActiGraph GT1M model (Manufacturing Technology Inc., Fort Walton Beach, FL) sensitive to body accelerations in the vertical direction; 3) a triaxial 3dNX model (BioTel Ltd., Bristol, UK) sensitive to body accelerations in the vertical, anterior–posterior, and medial–lateral directions; and 4) a uniaxial ActiHeart model (Cambridge Neurotechnology Ltd., Papworth, UK) sensitive to body accelerations in the vertical direction (5). The CSA, ActiGraph GT1M, and 3dNX devices were secured to the subject’s waist by means of an elastic belt. The CSA and ActiGraph GT1M devices were placed on the right hip, and the 3dNX device was placed on the left hip. The ActiHeart device was placed on the subject’s upper left chest. Placement of the ActiHeart device required light preparation of the skin to apply two standard ECG electrodes (Blue Sensor, Medicotest, Ølstykke, Denmark) to the chest, onto which the unit was clipped. The medial electrode was placed at the level of the third intercostals space on the sternum, and the lateral electrode was placed on the same horizontal level and as laterally as possible on the major pectoral muscle. The technical specifications of each accelerometer are listed in Table 2.

Continuous incremental exercise test to volitional exhaustion. During this test, the subjects were asked to complete a 5-min warm-up at 8 km·h⁻¹ that was immediately followed by the incremental test. Initially, the speed was continually increased by 1 km·h⁻¹ every minute until the V(TH) had been passed. The V(TH) was determined as the VO₂ at which a) the breakpoint in the relationship between VO₂ and VCO₂ occurred (V-slope technique; 2) and b) the ventilatory equivalent for O₂ (VE/VO₂) started to increase systematically without a concomitant increase in the ventilatory equivalent for CO₂ (VE/VCO₂) (33). The treadmill gradient was subsequently elevated at a rate of 1% every minute (while speed was maintained at the supra-V(TH) pace) to ensure a work rate that would elicit exhaustion (17). VO₂peak was defined as the highest VO₂ value achieved during the last 30 s of the test. After this point, the treadmill speed was reduced to 4 km·h⁻¹, and the gradient was returned to 0% to allow the subject to actively recover for at least 5 min.

Incremental exercise test to volitional exhaustion.

The second test was an incremental exercise test to volitional exhaustion that involved a continuous walking phase (3, 5, and 7 km·h⁻¹) and a discontinuous running phase (8–20 km·h⁻¹ or until voluntary exhaustion) with 3-min bouts (3–5 min of rest between bouts). All movement data from the accelerometers are expressed in counts per minute and are the mean of 3 min at each speed, disregarding the periods corresponding to changes in speed (±1 min). Once volitional exhaustion was reached, the treadmill speed was reduced to 4 km·h⁻¹ to allow the subject to actively recover for at least 5 min.

**Data Analysis**

Data are expressed as the mean ± SD or median (range) as appropriate after a test for the normality of distribution. The Pearson product–moment correlation coefficient (r) was used to assess the relationship between accelerometer counts from each device and speed, speed and VO₂, speed and heart rate, accelerometer counts and VO₂, and accelerometer counts and heart rate. Prediction of VO₂ from accelerometer counts and heart rate was completed by linear regression. Similarly, prediction of VO₂ from a combination of accelerometer counts and heart rate was completed by multiple linear regression (7). Multiple linear regression was also completed with each subject’s individual data to generate individually calibrated equations to predict VO₂. Normality of regression residuals was explored by agreement of their frequency distributions with the superimposed normality curve. Statistical significance was set at P < 0.05. All statistical analysis was completed using the software package SPSS, version 11.0 (SPSS, Inc., Chicago, IL).

**RESULTS**

**Relationships between accelerometer counts, speed, heart rate, and VO₂.** The relationships between accelerometer counts and speed are reported up to and including 20 km·h⁻¹, and the relationships between accelerometer counts, VO₂, and heart rate are reported up
to and including 18 km·h⁻¹ because most subjects did not complete the full 3 min at 20 km·h⁻¹.

Accelerometry outputs from the ActiGraph GT1M, 3dNX, ActiHeart, and CSA increased linearly with walking speed \((r = 0.954, P < 0.001; r = 0.968, P < 0.001; r = 0.960, P < 0.001; \text{ and } r = 0.956, P < 0.001, \text{ respectively})\). Triaxial 3dNX output during running rose in a linear manner with speed up to and including 20 km·h⁻¹ \((r = 0.892, P < 0.001)\). However, ActiGraph GT1M and ActiHeart output plateaued at a running speed corresponding to approximately 14–16 km·h⁻¹. CSA output also leveled off, but at a running speed corresponding to approximately 10–12 km·h⁻¹. These relationships are illustrated in Figure 2.

The individual relationships between speed and 3dNX output for body accelerations in the vertical, anterior–posterior, and medial–lateral directions are presented in Figure 3. \(\dot{V}O_2\) (mL·kg⁻¹·min⁻¹) and heart rate also rose linearly with speed during walking \((r = 0.906, P < 0.001; r = 0.644, P < 0.001, \text{ respectively})\) and running \((r = 0.906, P < 0.001; r = 0.644, P < 0.001, \text{ respectively})\).

ActiGraph GT1M, 3dNX, ActiHeart, and CSA accelerometer counts rose linearly with \(\dot{V}O_2\) during walking \((r = 0.906, P < 0.001; r = 0.913, P < 0.001; r = 0.901, P < 0.001; \text{ and } r = 0.704, P < 0.001, \text{ respectively})\). During running, 3dNX accelerometer output rose linearly with \(\dot{V}O_2\) up to and including 18 km·h⁻¹ \((r = 0.873, P < 0.001)\). Conversely, the relationships between ActiGraph GT1M, ActiHeart, and CSA outputs with \(\dot{V}O_2\) during running increased in a nonlinear manner. These relationships are illustrated in Figure 3. Heart rate rose linearly with \(\dot{V}O_2\) during walking \((r = 0.648, P < 0.001)\) and running \((r = 0.663, P < 0.001)\).

ActiGraph GT1M, 3dNX, ActiHeart, and CSA accelerometer counts rose linearly with heart rate during walking \((r = 0.490, P < 0.001; r = 0.589, P < 0.001; r = 0.568, P < 0.001; \text{ and } r = 0.541, P < 0.001, \text{ respectively})\). During running, 3dNX accelerometer output rose linearly with heart rate \((r = 0.722, P < 0.001)\) during running increased in a nonlinear manner. These relationships are illustrated in Figure 4.

VO₂ prediction models. The linear regression models for heart rate and accelerometer outputs are presented in Table 3. The relationships between ActiGraph GT1M, ActiHeart, and CSA accelerometer outputs and \(\dot{V}O_2\) \((\text{mL·kg}^{-1}·\text{min}^{-1})\) were nonlinear during running. As a result, only walking models are presented for these devices.

FIGURE 2—ActiGraph GT1M (graph A; \(N = 11, \text{ unless otherwise stated})\), 3dNX (graph B; \(N = 16, \text{ unless otherwise stated})\), ActiHeart (graph C; \(N = 12, \text{ unless otherwise stated})\), and CSA (graph D; \(N = 16, \text{ unless otherwise stated})\) outputs plotted against treadmill speed. Values are mean ± SD.

FIGURE 3—The relationships between walking and running speed and 3dNX outputs \((N = 16, \text{ unless otherwise stated})\) for body accelerations in the vertical, anterior–posterior, and medial–lateral directions. The sum of all three directions (tri) and the sum of the anterior–posterior and medial–lateral directions (dual) are also presented. Values are mean ± SD.

FIGURE 4—The relationships between \(\dot{V}O_2\) prediction models. The linear regression models for heart rate and accelerometer outputs are presented in Table 3. The relationships between ActiGraph GT1M, ActiHeart, and CSA accelerometer outputs and \(\dot{V}O_2\) \((\text{mL·kg}^{-1}·\text{min}^{-1})\) were nonlinear during running. As a result, only walking models are presented for these devices.
Regression residuals were normally distributed for all models presented.

**DISCUSSION**

The present investigation was the first to investigate the outputs from a number of accelerometers with various sampling frequencies, band pass filtering ranges, and peak acceleration amplitudes during fast running. It was found that accelerometers with device characteristics that more closely satisfied the sampling frequency, band pass filtering, and peak acceleration amplitude required to track acceleration during fast running yielded a better relationship between running speed and accelerometry output. Furthermore, uniaxial accelerometer output plateaued at fast running speeds because of the biomechanics of running (i.e., vertical acceleration plateaus at high running speeds) in contrast to triaxial 3dNX accelerometer output, which has a linear relationship with speed up to and including world-record marathon pace.

**Relationships between accelerometer counts, speed, heart rate, and VO\(_2\).** All devices used in the present investigation (Table 2) had outputs that rose linearly over the walking speed range (i.e., 3–7 km·h\(^{-1}\); Fig. 2). However, three of the four devices had outputs that tended to plateau at fast running speeds (Fig. 2). Our results are consistent with previous studies that used the CSA activity monitor during walking and running (7, 21).

That is, CSA output was linear during walking but not during running, when accelerometer output leveled off at approximately 10,000 counts per minute at a speed corresponding to approximately 10–12 km·h\(^{-1}\). Brage et al. (7) attribute this to biomechanical limitations. In particular, below 4 km·h\(^{-1}\), vertical power predominates during walking; however, at faster running speeds, vertical acceleration becomes constant and horizontal power increases (8). Brage et al. (7) argue that without a concomitant increase in vertical acceleration during increasingly fast running speeds, there will not be an increase in CSA output because it measures only in the vertical plane; hence, the plateau. Our data are consistent with this hypothesis in that outputs from the other uniaxial accelerometers, ActiGraph GT1M and ActiHeart, also plateaued, albeit at higher speeds corresponding to approximately 14–16 km·h\(^{-1}\). A possible explanation may be superior device electronics (Table 2). These devices may, to a greater degree, fulfill the sampling rate and band pass filtering range required for running (the frequency range of band pass filtering must include the maximum frequency observed during running, and the sampling frequency must be twice this frequency to allow reconstruction of the original signal from the sampled

**TABLE 3. VO\(_2\) prediction models with accelerometer outputs and heart rate as predictors during walking and running.**

<table>
<thead>
<tr>
<th>VO(_2) Prediction Models</th>
<th>(R^2)</th>
<th>SEE</th>
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</thead>
<tbody>
<tr>
<td>Walking (3–7 km·h(^{-1}))</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HR</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CSA</td>
<td></td>
<td></td>
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<tr>
<td>CSA + HR</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ActiGraph GT1M</td>
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<td></td>
</tr>
<tr>
<td>ActiGraph GT1M + HR</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3dNX + HR</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ActiGraph GT1M + HR MI</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ActiHeart</td>
<td></td>
<td></td>
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<tr>
<td>ActiHeart + HR</td>
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<tr>
<td>ActiHeart + HR MI</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Running (6–18 km·h(^{-1}))</td>
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</tr>
<tr>
<td>HR</td>
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<td>3dNX</td>
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<tr>
<td>3dNX + HR</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3dNX + HR MI</td>
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</tbody>
</table>

VO\(_2\), oxygen uptake (mL·kg\(^{-1}\)·min\(^{-1}\)); HR, heart rate (bpm); MI, mean of prediction equations calibrated with individual subject data; CPM, accelerometry output (counts per minute); SEE, standard error of the estimate (mL·kg\(^{-1}\)·min\(^{-1}\)).
version). The maximum frequency observed during running is less than 10 Hz (15); therefore, accelerometers intended for measuring physical activity during running must have a sampling frequency of at least 20 Hz and band pass filtering of at least 10 Hz. The electronic properties of both the ActiGraph GT1M and ActiHeart accelerometers fulfill these criteria better than the CSA (Table 2). A further consideration for the electronic properties of accelerometers is the amplitude of accelerations that can be sampled. The ActiGraph GT1M, ActiHeart, and CSA may be limited, as Bhattacharya et al. (3) have reported vertical peak accelerations ranging from 0.9g to 5.0g measured at the lower back during running. However, this is unlikely to be a major factor in the leveling off of accelerometer outputs during fast running, because output from the vertical axis of the 3dNX accelerometer also plateaued (Fig. 3) despite an acceleration range of ±10.0g (Table 2). Regardless of a plateau in the vertical axis, the compound triaxial 3dNX accelerometer output (i.e., the sum of vertical, anterior–posterior, and medial–lateral accelerations) did have a linear relationship between output and running speed up to world-record marathon pace (i.e., up to and including 20 km h⁻¹) (Fig. 2). A previous investigation (8) reported that despite running from 7 to 32 km h⁻¹, vertical power is almost constant, whereas horizontal power increases by a factor of >10. Our data corroborate this; Figure 3 suggests that a reduction in vertical acceleration at approximately 14–16 km h⁻¹ was compensated for by a concomitant increase in accelerations in the anterior–posterior and medial–lateral directions. This likely explains why 3dNX accelerometer output has a linear relationship with speed up to and including 20 km h⁻¹. Thus, for metabolic assessment of walking and slow running/jogging, when using only acceleration counts and not heart rate, the ActiGraph GT1M and ActiHeart devices are adequate and are, therefore, probably sufficient for use in most epidemiological studies for which they are intended. However, for the assessment of fast running (>16 km h⁻¹), a triaxial accelerometer such as the 3dNX device is necessary (23).

**VO₂ prediction models.** The relationships between heart rate and accelerometer outputs and VO₂ and accelerometer outputs followed a similar pattern observed in the relationships between accelerometer outputs and speed (Fig. 3). All devices had a linear relationship through the walking speed range, whereas only accelerometer output from the 3dNX device had a linear relationship during running. As expected, heart rate also rose linearly with VO₂ during walking and running. However, the relationship between heart rate and VO₂ yielded the lowest \( R^2 \) value during walking (Table 3), a finding consistent with previous investigations that reported a limitation of heart rate as a predictor of VO₂, especially during low-intensity exercise (18,19). However, including heart rate as a copredictor for VO₂ during both walking and running yielded greater \( R^2 \) values and lower standard errors of estimates than single-measure models that used accelerometer outputs alone (Table 3). The CSA accelerometer yielded the lowest predictive power when combined with heart rate during walking, with little difference between the remaining three devices. However, for an indirect estimation of VO₂ during running, the 3dNX accelerometer, in combination with heart rate, was the most accurate.

The VO₂ prediction models presented here are not intended for use at the population level. Rather, this investigation was designed to 1) explore the leveling-off phenomenon of accelerometer counts with increasing speed during running and 2) examine the feasibility and accuracy of combining heart rate and accelerometer counts to estimate VO₂ during walking and running. Indeed, prediction models calibrated with a subject’s individual data further improve VO₂ estimation compared with population prediction models, as evidenced by greater mean \( R^2 \) values and lower SEE (Table 3). The possible reasons for this may be variations in biomechanical characteristics of locomotion and the different heart rate versus speed relationships between individuals. Differences in movement (e.g., vertical oscillations) between individuals would undoubtedly result in under/overestimation of metabolic cost if measured by accelerometry. With this in mind, and the concept that vertical (13,16) and horizontal (9) forces are major determinants of metabolic cost during running, a further application of accelerometry may be a discriminatory role for differences between individuals in running economy or changes in running economy within individuals. It follows that excessive changes in momentum in the vertical, anterior–posterior, and medial–lateral directions may be wasteful in terms of metabolic energy consumption (13). Indeed, Heise and Martin (13) have reported that less economical runners (i.e., those with a higher VO₂ for a given speed) demonstrated higher total and net vertical impulses. This may be reflected in a larger accelerometer output for a given speed in less economical runners. However, although promising, this is yet to be determined.

**CONCLUSIONS**

In summary, both uni- and triaxial accelerometer outputs have a linear relationship with speed during walking. However, during fast running, uniaxial accelerometer output plateaus because of biomechanical and device limitations. In contrast, the triaxial 3dNX accelerometer output has a linear relationship with speed up to and including world-record marathon pace. The combined methodologies of heart rate and accelerometry predict VO₂ better than either predictor alone. Moreover, prediction models calibrated with a subject’s individual data further improve VO₂ estimation compared with population prediction models.

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REFERENCES


