

1 **Portable High Resolution Accelerometers (HRA) for the Estimation of VO<sub>2</sub> in**  
2 **Highly Trained Inter-collegiate Distance Runners.**

3

4 **Abstract**

5 **Background:** Accurate quantification of training load is important to optimize training in  
6 any sporting discipline. In running this is problematic, but high resolution  
7 accelerometers (HRA) may be of value. Since workload is proportional to VO<sub>2</sub> in  
8 running, the objective of this study was to determine the relationship of HRA and VO<sub>2</sub> in  
9 highly trained inter-collegiate runners. **Methodology:** Runners performed 2 incremental  
10 VO<sub>2</sub>max trials while wearing HRA affixed to the lower back. RMS of high frequency  
11 unfiltered signal from three axes (VERT, LAT, A/P) and the Euclidean resultant (RES)  
12 were compared to VO<sub>2</sub>. Also, test-rest correlations were determined for each axis and  
13 RES to determine reliability of this approach. **Principal Findings:** RMS of acceleration  
14 in g's for each axis were significantly correlated to VO<sub>2</sub> (0.868-0.945). Importantly, a  
15 single linear regression best described the strong VO<sub>2</sub> to RES relationship (R = 0.95)  
16 across the speed spectrum including both walking and high speed running. This single  
17 regression did not require correction for individual characteristics such as heart rate.  
18 High reliability was also observed with RES (ICC = 0.99; CV = 5.1).  
19 **Conclusions/Significance:** Results of this study indicate that HRA can accurately and  
20 reliably predict VO<sub>2</sub> during treadmill locomotion in highly trained runners.

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**Introduction**

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Standardized quantification of mechanical (e.g. cycle ergometry) or metabolic  
(indirect calorimetry; VO<sub>2</sub>) work has been performed in the laboratory setting for over a  
century (3). Often athletes and/or coaches may take principles determined from  
laboratory testing (e.g. lactate threshold) and apply them in the field. Historically  
though, in disciplines such as cycling and running, there has been no way to quantify  
work performed in the field as accurately and reliably as in the laboratory. Heart rate  
monitors have been used extensively in an effort to estimate metabolic work from  
estimates of oxygen consumption, but these devices have numerous limitations

31 (reviewed in (1)). Recently, there has been a revolution in the discipline of cycling with  
32 the advent of portable on-board power meters (4, 15, 19, 39, 40). These devices  
33 provide laboratory quality data, and enable coaches and athletes to more effectively  
34 quantify training loads and evaluate training/racing efforts than with heart rate monitors.  
35 Also, portable power meters provide objective criteria (e.g. watts or Kj) for rational  
36 progressive training overload based on specific effort based criteria obtained from  
37 competition (39, 40).

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39 In the discipline of running, there is currently no device that serves the same role  
40 as the power meter in cycling. It has been demonstrated that power can be derived  
41 from running on a track (6, 11), but due to changes in grade and difficulty in accurately  
42 quantifying distance, this cannot be extended to running on open, varied terrain. Efforts  
43 have been made to utilize global positioning system (GPS) devices to account for  
44 changes in grade and the resulting change in energy expenditure relative to speed (26),  
45 but these devices have lower resolution than true power meters, and some problems  
46 inherent to the technology have yet to be resolved (e.g. altitude errors, errors on curved  
47 courses) (10, 35). A possible candidate that might serve as a “power meter” for  
48 running, is the accelerometer. The use of accelerometers to measure human  
49 movement has increased greatly in recent years (9, 36, 41), but, from a physiological  
50 perspective, they have commonly been used as “activity monitors” for the course-  
51 grained measurement of gross movements. In many cases, the goal of using these low  
52 resolution accelerometers has been in attempt to objectively determine energy  
53 expenditure during free living non-formal activities (37). Due to the discretized nature of

54 the data obtained from activity monitor accelerometers, numerous studies have been  
55 performed in attempts at developing regression equations to fit activity counts obtained  
56 from these devices to other measures of metabolic work (e.g.  $VO_2$  and/or doubly  
57 labeled water) (38, 41, 42) . Although clinical/epidemiological studies are numerous,  
58 there have been few attempts to use this approach in athletic populations in order to  
59 objectively quantify external work of a dynamic activity such as running. Fudge et al.  
60 (14) did investigate the relationship between activity monitor accelerometers and  $VO_2$  in  
61 trained runners, but determined that a correction for HR was necessary to obtain strong  
62 correlations. Further, some of the accelerometers tested would not show a strong  
63 correlation with  $VO_2$  during running even with a correction for HR (14). So, although the  
64 utility of accelerometer based activity monitors for the measurement of “work” in running  
65 has been investigated with some success, it might be expected that resolution could be  
66 improved relative to this approach (i.e. higher resolution, greater accuracy), and in turn,  
67 with higher resolution, greater accuracy relative to other measures such as  $VO_2$  might  
68 be obtained. Further, in an activity such as running, portable accelerometers might not  
69 only serve as ergometers to measure work, but some insight might be gained by using  
70 the high frequency signal from such a device to examine running mechanics collected  
71 during “real world” activities such as racing and training. Low resolution “activity  
72 monitors” do not provide this capability.

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74           Accelerometers have been used in the field of biomechanics for decades (8, 29)  
75 for the purposes of gait analysis. In contrast to “activity monitors” used for  
76 metabolic/activity studies, these devices generally collect data at higher frequencies in

77 continuous, as opposed to discretized fashion and as such, provide higher resolution.  
78 The high resolution accelerometers (HRA) provide some advantages over traditional  
79 approaches (e.g. force plate analysis or inverse dynamics), in particular, HRAs are  
80 portable, light, and generally can be used to either stream data at high frequency in real  
81 time, or datalog similarly high frequency signals collected during “real world” activities of  
82 locomotion that would not be possible using other means. Although HRA used for gait  
83 analysis have previously been limited by data storage capacity and portability, with the  
84 recent innovation of microelectromechanical system (MEMS) accelerometers, the  
85 aforementioned advantages may be exploited to a greater extent.

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87         Since the current technology exists to measure acceleration in a high frequency,  
88 high resolution manner using portable devices, it would seem that this might be an  
89 interesting way to determine work/energy expenditure in running, while at the same time  
90 collecting data with regard to the gait characteristics of the individual. As a first step,  
91 the validity of such high resolution accelerometers (HRA) should be compared to an  
92 objective physiological measure such as  $VO_2$  and/or running speed. Therefore, it was  
93 the objective of this study to examine the potential utility of HRA to quantify workload in  
94 trained intercollegiate cross country runners by determining 1) the relationship of the  
95 HRA signal with  $VO_2$  and speed and 2) the test – retest reliability of HRA across a wide  
96 range of walking/running speeds. It was anticipated that since course-grained activity  
97 monitor based accelerometers have demonstrated reasonable correlations with  $VO_2$ ,  
98 and high frequency accelerometers have demonstrated validity and reliability against  
99 force plates, HRA units should provide good correlations with  $VO_2$  and be indicative of

100 the mechanical work in treadmill locomotion in trained runners. Further, examples are  
101 provided where raw signal from HRA can provide insight into the mechanics of running  
102 on an individual basis.

103

## 104 **METHODS**

105

### 106 *Subjects*

107 Nine male NCAA Intercollegiate Division 1 runners (Table 1) gave written  
108 informed consent to take part in this study, which was approved by the local Human  
109 Subject Review Board.

### 110 *Experimental Design*

111 Subjects completed two continuous, incremental exercise tests on a motorized  
112 treadmill (True ZX-9, St. Louis, MO) with at least 6 days separating each trial. Exercise  
113 tests were performed to volitional exhaustion while high resolution triaxial accelerometry  
114 (HRA) and metabolic gasses were collected to determine relationships between, HRA,  
115  $VO_2$ , walking and running speed. In addition, validity and reliability of the unfiltered,  
116 HRA was determined. After the first trial, two subjects could not complete a second  
117 trial due to injury. Data for these subjects was therefore not included in the reliability  
118 analysis, but was used for correlations and regression curve fits.

### 119 *Procedure*

120 Subjects reported to the laboratory on the day of examination after a 3 hr fast  
121 and having refrained from strenuous exercise, alcohol, and caffeine for 24 hours prior to

122 the day of testing. Height and body mass were measure upon arrival at the laboratory  
123 (Mettler-Toledo, OH).

#### 124 *Incremental exercise test to volitional exhaustion*

125 In each of the two tests, subjects began walking at 2km/h and speed was  
126 increased 2km/h every two minutes until volitional exhaustion. The treadmill grade was  
127 held constant at 1% to simulate normal over-ground walking/running. During tests,  
128 metabolic data was collected on a breath-by-breath basis using portable open circuit  
129 spirometry (Jaeger Oxycon Mobile, CA).  $VO_{2max}$  was determined as the highest 30s  
130 average of the test.

#### 131 *Metabolic Measurements*

132 Indirect calorimetry was used to collect breath-by-breath measurements of  $VO_2$   
133 and  $VCO_2$  using electrochemical oxygen measuring cell (SBx) in an Oxycon Mobile  
134 (Cardinal Health, OH) and averaged over 5 sec. Heart rate was collected continuously  
135 via telemetry using a Polar coded transmitter belt (Polar t-31, Polar Electro, Oulu,  
136 Finland). The oxygen and carbon dioxide sensors were calibrated prior to each test for:  
137 ambient conditions (temperature and barometric pressure), volume and gas content  
138 against precision analyzed gas mixtures.

#### 139 *Accelerometry*

140 The HRA device, a triaxial MEMS accelerometer model ADXL210 (G-link  
141 Wireless Accelerometer Node  $\pm 10g$  Microstrain, Inc., Williston, VT) was placed  
142 anatomically at the intersection of the sagittal and axial planes on the posterior side of  
143 the body in line with the top of the iliac crest in order to approximate the center of mass  
144 (28). The accelerometer was mounted to a semi-rigid strap and additionally secured

145 with elastic tape in order to any extraneous movement not associated with locomotion.  
146 Acceleration in g's was streamed in real time using telemetry to a base station at a  
147 frequency of 625 Hz.

#### 148 *Data Analysis*

149 Raw accelerometry signal (in g's) was saved in Agilelink software (Microstrain,  
150 VT) and exported to Signal Express software (Labview, TX) in ASCII format. Full length  
151 files were parsed into 1 min segments, and the last one minute of each treadmill stage  
152 was used to calculate Root Mean Square (RMS) value using Signal Express for each  
153 axis, vertical (VERT), lateral (LAT), anterior/posterior (A/P), and Resultant (RES). The  
154 RES value was calculated according to the equation

155

$$156 \quad \text{RES}_{xyz}^2 = (ix)^2 + (jy)^2 + (kz)^2 \quad (\text{Equation 1})$$

157

158 Where x, y and z equal the Vertical, Lateral and Anterior/Posterior axes, respectively.

159

160 The 1 minute RMS of acceleration were generated using Signal Express and  
161 compared to the 1 minute average of VO<sub>2</sub> for the last minute of each corresponding  
162 stage. Comparisons were made using Pearson's product correlation, RMS of raw  
163 signal were also compared to VO<sub>2</sub> using a linear regression curve fit. Validity and  
164 reliability of the HRA were determined by calculation of coefficient of variation (CV),  
165 test-retest reliability (R) and Interclass Correlations (ICC) (SPSS, IL; α=0.05).

166

$$167 \quad x_{\text{rms}} = \sqrt{\langle x_1^2 + x_2^2 + x_3^2 + \dots + x_N^2 \rangle / N} \quad (\text{Equation 2})$$

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169

## Results

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### 171 Correlations

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173 Significant correlations were observed between RMS of raw acceleration of each  
174 of the axes, as well as  $VO_2$  (Table 2). Although all correlations were highly significant,  
175 the strength of the correlations varied with A/P and RES most highly correlated to  $VO_2$ ,  
176 and to a similar extent (Table 2).

177

### 178 Regressions

179

180 Results of regression curve fits of accelerometry vs.  $VO_2$  can be seen in Table 3  
181 and Figure 1 (a-d). Linear, quadratic and cubic regressions were attempted for  $VO_2$   
182 against each axis, and in all cases, quadratic and cubic regressions were not more  
183 significant than linear. It is readily apparent that the prediction of  $VO_2$  when regressed  
184 to the VERT axis exhibited the weakest relationship across the entire range of speeds  
185 tested. When  $VO_2$  was regressed against A/P and RES, similarly strong R values were  
186 observed, although the RES was much more significant as evidenced by the F values  
187 (Table 3). The strong linear relationship between  $VO_2$  and RES can be seen when  
188 comparing the plot of RES vs speed in Figure 2 d and  $VO_2$  vs speed in Figure 3. Both  
189 plots show a clear change in  $VO_2$  and RES at the walk to run transition occurring  
190 between 6 and 8 km/h. Above and below this transition, both variables exhibit a similar



191 relationship to speed. This bimodal response to speed has been well established with  
192 regard to  $VO_2$  (24), and confirms the observation in the current study.

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## 194 **Reliability**

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196 The reliability of the HRA and  $VO_2$  instruments used for this study are presented  
197 in Table 4. It can be seen that the test-retest reliability was quite high for all axes, but  
198 highest for RES, which was comparable to  $VO_2$ . Further evidence of the reliability of  
199 using RES is demonstrated by the CV which was also on par with  $VO_2$ . On the other  
200 hand, CVs were quite high in the LAT and A/P axes. This may be due to the well known  
201 sensitivity of CV as mean values approach zero. In the case of both Lat and A/P,  
202 means were much closer to zero than in VERT and RES, yet, the variance was quite  
203 high for both axes. Therefore, the high CVs in this case may be an artifact associated  
204 with the nature of the data.

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206

## 206 **Discussion**

207

208 The present investigation is the first to report the relationship of HRA to  $VO_2$  at a  
209 range of walking and running speeds, including maximal aerobic speed, in highly trained  
210 runners. It was determined that the RMS of the RES acceleration value calculated from  
211 the three individual axes exhibited a strong correlation with  $VO_2$  (Table 2), strong  
212 internal validity (Table 3) and strong test-retest reliability (Table 3). These data indicate  
213 that HRA may prove of value for monitoring training load in trained runners in similar

214 fashion to portable HR monitors, while providing additional information on gait  
215 characteristics, and changes in speed with high accuracy.

216

## 217 **Correlations**

218

219 Previous work by Fudge et al. (14) examining the utility of accelerometers for the  
220 assessment of running workload relative to  $VO_2$  in trained runners at high running  
221 speeds (8-18 km/h) showed some promise. They reported reasonably strong  
222 predictions of  $VO_2$  in walking and running with a triaxial activity monitor accelerometers,  
223 but these strong relationships required correction using HR. In the current study, no  
224 correction for HR was examined, and yet, stronger relationships were observed than in  
225 the Fudge et al. study when  $VO_2$  was regressed to RMS of accelerometer signal, in  
226 particular, when regressed to RMS of RES (Figure 1d). The stronger relationships  
227 between  $VO_2$  and RES observed in the present investigation are presumably because  
228 of the higher resolution of the HRA devices used. In the case of activity monitor  
229 accelerometers such as those used for the Fudge et al. study, considerations such as  
230 the thresholds for determining activity counts, as well as filtering bands applied are  
231 important (9, 25, 41). In the case of HRA, the continuous signal “captures” all  
232 movement, and more complete information regarding the movement is collected.  
233 Additionally, it should be noted that in the current study, no filtering was applied to the  
234 signal as to avoid losing sensitivity at lower exertion levels (e.g. 2 kph). Therefore, if  
235 used in athletes where sensitivity to low level activity is of little interest, it is plausible  
236 that stronger relationships between HRA and  $VO_2$  could be obtained by the use of

237 different filtering strategies. On the other hand, if this technology were employed for  
238 activity monitoring in other situations, the strong relationship observed in the present  
239 study demonstrates the sensitivity that can be achieved with HRA at low activity levels  
240 with little or no filtering. Therefore, the use of HRAs may be more broadly applicable for  
241 estimation of  $VO_2$  and/or energy expenditure than simply in trained runners, but this will  
242 require further investigation.

243

244         Recently, Halsey et al. (17) used a similar approach to the current investigation  
245 by mounting HRA on the lower back (as well as other sites) of humans and reported  
246 strong relationships with  $VO_2$  (l/min) during walking and running. In contrast to the  
247 current study, they used absolute  $VO_2$  (l/min) as the criterion measure, and as such,  
248 relationships were improved by adding subject weight as a covariate in regression  
249 analysis. In the current investigation, the use of relative  $VO_2$  (ml/kg/min) as the criterion  
250 inherently corrects for bodyweight, and therefore strong correlations were observed and  
251  $VO_2$  was strongly predicted by acceleration when regressions were performed using  
252 only relative  $VO_2$  and RMS of RES. Another interesting contrast between the Halsey et  
253 al. and the present study is the fact that Halsey reported two separate regressions  
254 equations for walking and running, whereas in the current study, it can be seen in  
255 Figure 1d that the same regression of  $VO_2$  to RMS of RES showed a strong relationship  
256 ( $r = 0.95$ ). This is of interest because the use of a single regression equation simplifies  
257 data analysis and interpretation by negating the requirement of distinguishing walking  
258 and running activities.

259           Neither of the aforementioned studies investigated reliability of the devices used,  
260 and the reproducibility of their measures within subjects. Importantly, we show in the  
261 present investigation that HRA is not only valid relative to  $VO_2$ , but also reliable on re-  
262 test. This is in comparison with a report from Henriksen et al. (18) in which HRA  
263 mounted to the lower back and RMS of vector sum derived values exhibited ICCs of  
264 0.81-0.85. In the current study, the ICCs for the analogous RES were higher (0.99;  
265 Table 4). Although CVs of individual axes A/P and Lat were higher in the present study  
266 (Table 4) than in the Henriksen et al. (18), they were within generally acceptable range  
267 for the VERT, and importantly, the RES. This is a serious consideration if HRA is to be  
268 used as a device to monitor training load across multiple workout sessions, or over  
269 extended periods. Also, from a practical perspective, it seems that if the HRA are not  
270 mounted in the exact same orientation on different occasions, the RES should not be  
271 dependent upon orientation, and therefore, the RES should be robust for determination  
272 of workload over the span of multiple workout sessions.

273

274           Potential applications of this work are significant on several levels. First, the use  
275 of HRA in the same sense as a traditional, downloadable HR monitors for the  
276 quantification of global training load becomes readily apparent, while HRA would not be  
277 susceptible to some of the limitations to HR (e.g. dehydration, psychological motivation  
278 etc) (1). This could be of particular value for the application of performance modeling  
279 approaches such as the training impulse (TRIMPS), with the use of a work output based  
280 metric as opposed to HR. The TRIMPS system have been used extensively in various  
281 sports (2, 12, 31, 34), including running (31). HR has been quite convenient with the

282 advent of downloadable monitors, but poses some limitations with regard to its  
283 dependence on environmental conditions (e.g. cardiac drift), lag with efforts, and the  
284 fact that it cannot account for supramaximal efforts (1). Therefore, a metric that is more  
285 responsive to efforts, particularly at high intensities, and is not influenced by  
286 environmental factors is of interest.

287

288 A second, potentially quite valuable application is that, aside from simple estimation  
289 of training workload, HRA can provide post-hoc information in great detail with regard to  
290 the mechanics of the runner which, in turn, can be informative with regard to overall  
291 performance. For example, in Figure 4, we see a comparison of two different runners  
292 who compete at similarly high levels, and yet have quite different characteristics. In  
293 particular, Athlete A (Green/White) possesses a lower  $VO_{2\text{ max}}$  (65 ml/kg/min) than  
294 Athlete B (Red; 78 ml/kg/min), and yet is on par competitively, and in fact won a  
295 conference championship in front of Athlete B. As can be seen from the figures, on test  
296 day one, the week prior to a conference championship, Athlete A exhibits a strikingly  
297 unique pattern of acceleration spikes in the anterior plane. Athlete B who exhibits a  
298 greater aerobic capacity and maximal running speed in the incremental trial doesn't  
299 display these spikes. The difference in aerobic characteristics between these two  
300 runners is evidenced by the fact that Runner A reached  $VO_{2\text{ max}}$  at 22 km/h, but was  
301 able to start the 24 km/h stage. Runner B reached  $VO_{2\text{ max}}$  during the 24 km/h stage  
302 and also reached exhaustion. Despite the differences in aerobic capacity, Runner A  
303 won the conference 5 km championship in front of Athlete B four days after the Trial 1.  
304 In contrast the week after the conference championship where Athlete A expressed

305 comments about fatigue, the athlete did not exhibit the striking acceleration spikes, and  
306 also became exhausted upon reaching  $VO_{2\text{ max}}$  at 22 km/h (Figure 4 a) White plot). It is  
307 not entirely clear why some runners can outperform others with equal or higher aerobic  
308 capacity, some have proposed anthropomorphic differences (13, 23), while others have  
309 argued for neuromuscular characteristics (32), and HRA may provide insight into this  
310 question. The value in using HRA as opposed to other biomechanical measures to  
311 determine such differences is that in traditional gait mechanics analysis, only a few gait  
312 cycles can be measured, whereas if HRA are worn over the course of entire workout, or  
313 multiple workouts, a more complete picture of running mechanics/dynamics may be  
314 obtained and some characteristics identified that might not be observed in a limited lab  
315 testing scenario.

316

317 Finally, a potential implementation of these devices is for the application of complex  
318 frequency or non-linear dynamical analysis of such data to gain further insight into the  
319 nature of fatigue or the constraints of running. There has been some interest in the field  
320 of biomechanics with regard to high level mathematical (e.g. non-linear dynamical  
321 analysis, spectral analysis etc.) of walking/running gait patterns (7, 16, 20, 21, 27, 30).  
322 There have been a few attempts to extend some of these techniques to theories of  
323 fatigue in competitive running and this area potentially holds promise (5, 22, 33). The  
324 use of HRA signal for these types of analysis may provide additional insight due to the  
325 high accuracy and high frequency sampling of these devices.

326

327 In conclusion, we report here that RMS of unfiltered HRA signals, particularly RES,  
328 provide valid, reliable estimates of  $VO_2$  during walking and running in highly trained  
329 runners. Further work is necessary to determine if these results, obtained in highly  
330 trained runners, are generalizable to a broader population by looking at untrained  
331 individuals. It should also be determined if the same relationship between HRA and  
332  $VO_2$  hold on inclined surface, and in open terrain.

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Table 1: Physical Characteristics of Subjects (N=7)

	<b>Mean</b>	<b>SD</b>	<b>Range</b>
Body Mass (kg)	65.5	5.7	58.2-75
Height (cm)	181.8	4.1	175.3-188.0
Age (yr)	21.4	1.7	19-24
VO <sub>2max</sub> (mL/kg/min)	70.1	6.2	60-79

Values are mean ± SD and range. BM, body mass. VO<sub>2max</sub>, peak oxygen uptake.

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450 Table 2. Correlations between RMS of acceleration in individual axes and VO<sub>2</sub>.

**Correlations**

		Vert	Lat	AntPos	Result	VO <sub>2</sub>
Vert	Pearson Correlation	1.000	.787**	.779**	.953**	.868**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N		148	148	148	148
Lat	Pearson Correlation		1.000	.931**	.929**	.879**
	Sig. (2-tailed)			.000	.000	.000
	N			148	148	148
AntPos	Pearson Correlation			1.000	.919**	.946**
	Sig. (2-tailed)				.000	.000
	N				148	148
Result	Pearson Correlation				1.000	.945**
	Sig. (2-tailed)					.000
	N					148
VO <sub>2</sub>	Pearson Correlation					1.000
	Sig. (2-tailed)					
	N					

\*\* . Correlation is significant at the 0.01 level (2-tailed).

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463 Table 3. Regression parameters of VO<sub>2</sub> vs individual axes.

<b>Axis</b>	<b>Equation</b>	<b>F</b>	<b>R</b>	<b>Adjusted R<sup>2</sup></b>
Vertical	Linear	444.7	.868	.751
	Quadratic	221.0	.868	.750
	Cubic	221.2	.868	.750
Lateral	Linear	496.3	.879	.771
	Quadratic	420.3	.924	.851
	Cubic	280.1	.924	.851
Ant/Pos	Linear	1242.3	.946	.894
	Quadratic	668.3	.950	.900
	Cubic	445.1	.950	.900
Resultant	Linear	1213.5	.945	.892
	Quadratic	602.9	.945	.891
	Cubic	603.4	.945	.891

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466 Table 4. Reliability parameters for test-retest conditions and VO<sub>2</sub>.

<b>Axis</b>	<b>ICC</b>	<b>CV</b>	<b>Pearson's R</b>
Vertical	.980	5.7	.964
Lateral	.972	23.7	.945
Ant/Pos	.968	23.7	.939
Resultant	.990	5.1	.982
VO <sub>2</sub>	.992	5.2	.984

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470 Figure 1. Regressions of  $VO_2$  vs RMS of acceleration of individual axes during walking  
471 and running in highly trained distance runners. Linear regressions are significant in all  
472 cases ( $p < .001$ ). a) Vertical b) Lateral c) Ant/Pos d) Resultant. — = linear, - - -  
473 = quadratic, — · — = cubic.

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476 Figure 2. RMS of accelerations (g) for individual axes vs. speed in highly trained  
477 runners during walking and running in trials 1 and 2. A) Vertical b) Lateral c) Ant/Pos d)  
478 Resultant. Green = Trial 1 and Blue = Trial 2.

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481 Figure 3.  $VO_2$  vs speed in highly trained runners during walking and running for trials 1  
482 and 2. Green = Trial 1, Blue = Trial 2.

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485 Figure 4. Raw acceleration in Ant/Pos axis for two different athletes. Green = athlete A  
486 trial 1, White = Athlete A trial 2, Red = Athlete B, trial 1. A) Acceleration plots for the  
487 entire run portion of the incremental test. B) highlighted segment at 18 km/h which  
488 shows acceleration “spikes” in anterior plane. C) a four stride segment showing  
489 successive acceleration spikes. D-F) three spikes from c) shown individually to  
490 demonstrate they are not aberrant artifacts and appear to be characteristic of the  
491 athletes running mechanics on this test day.

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