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**A pilot study using entropy as a non-invasive assessment of running**

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1 **Title:** A pilot study using entropy as a non-invasive assessment of running

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39 **Abstract**

40 **Purpose:** Running performance is influenced by the interaction of biomechanical and  
41 physiological factors. Miniaturised accelerometers worn by the athlete can be used to  
42 quantify mechanical aspects of running and be used as a non-invasive tool to assess training  
43 status and progression. The aim of this study was to define and validate a method to assess  
44 running regularity and allow the estimation of an individual's  $\dot{V}O_2$  and/or blood lactate  
45  $[La]_b$  based on data collected with accelerometers and heart rate (HR).

46  
47 **Methods:** Male adolescent endurance athletes completed an incremental submaximal  
48 aerobic stage test where  $\dot{V}O_2$  and  $[La]_b$  were measured. The test was terminated when  
49  $[La]_b$  concentration at the end of the stage exceeded 4 mmol/L. Two wireless tri-axial  
50 accelerometers were placed on the right shank and lower back throughout the test. The  
51 Root Mean Square (RMS) and the Sample Entropy (SampEn) were calculated for the  
52 vertical (VT), medial-lateral (ML) and anterior-posterior (AP) components of acceleration.

53  
54 **Results:** There were significant positive correlations of acceleration and entropy variables  
55 with  $[La]_b$  and  $\dot{V}O_2$ , with moderate to high coefficients ( $r = 0.43 - 0.87$ ). RMS of the  
56 shank acceleration was the most highly related with both physiological variables. When the  
57 accelerometer was attached on the trunk, SampEn of the VT acceleration had the strongest  
58 relationship with  $\dot{V}O_2$  ( $r = 0.76, P < 0.01$ ).

59

60 **Conclusions:** The described method of analysis of running complexity may allow an  
61 assessment of gait variability which tracks non-invasively  $\dot{V}O_2$  and/or  $[La]_t$  allowing  
62 monitoring of fatigue or training readiness for trained adolescent individuals.

63

64 **Keywords:** Accelerometry, Regularity, Lactate, Aerobic, Gait

65

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## 66 **Introduction**

67 Running economy has been the subject of many studies indicating that this parameter  
68 increases from childhood <sup>1,2</sup>. While the metabolic aspects are well studied,<sup>2</sup> little research  
69 has investigated the relationship between kinematic and kinetic parameters and running  
70 economy.

71

72 In recent years, various approaches have been implemented to study human gait using  
73 accelerometry, with reference to the detection of gait events and spatiotemporal  
74 characteristics <sup>3,4</sup>. Conventional approaches to the analysis of gait parameters have evolved  
75 to consider regularity statistics (measurements conducted to assess the variability of a  
76 measure) as a possible alternative to the detection of gait events and spatiotemporal  
77 characteristics that may improve our understanding of the regularity and complexity of  
78 running <sup>5,6</sup>.

79

80 Entropy has been recently suggested as an analytical technique that provides information  
81 regarding the degree of complexity of the system's behaviour by indexing the regularity of  
82 patterns present in the dynamics of running movements <sup>7</sup>. In adolescents, where  
83 maturational changes in stride length and frequency accompany ongoing limb growth,<sup>8</sup> the  
84 variability in movement oscillations can be evaluated by complexity analysis  
85 techniques, which would allow the identification of variability in a spatio-temporal  
86 perspective. Recent work from McGregor and colleagues (2009) reported for the first time

87 the regularity values of well-trained runners suggesting this approach as a valid way to  
88 ascertain the control constraints during running in such a population.

89

90 The aim of this study was to determine a method that allows quantification of adolescent's  
91 running quality in conjunction with their metabolic characteristics (oxygen uptake ( $\dot{V}O_2$ )  
92 and/or blood lactate concentration ( $[La]_b$ )) with a combination of kinematic, entropy and  
93 traditional accelerometry measures. It was hypothesised that running complexity is affected  
94 by speed and related to lactate accumulation and could be used as an explanatory variable  
95 for lactate threshold and maximal aerobic power.

96

## 97 **Methods**

98 Six national level youth middle-distance athletes ( $15.6 \pm 1.2$  years,  $51 \pm 5.8$  kg,  $169.2 \pm 9.2$   
99 cm,  $\dot{V}O_{2max}$   $62.01 \pm 3.37$  ml.kg<sup>-1</sup>.min<sup>-1</sup>,  $v\dot{V}O_2$   $16.92 \pm 1.54$  km.h<sup>-1</sup>,  $14.68 \pm 1.22$  km/h at 4  
100 mmol/L) participated in the study. The study design consisted of performing an incremental  
101 running test. The local ethics committee approved the procedures.

102

103 During the assessment, the participants wore a Polar RS800 heart rate monitor (Polar  
104 Electro, Kempele, Finland). Oxygen uptake was measured breath-by-breath with a Jaeger  
105 Oxycon (Oxycon, Germany) throughout. The gas analysis system was calibrated before  
106 each test in line with the manufacturer's instructions.

107

108 Two wireless tri-axial accelerometers ( $37 \times 26 \times 15$  mm, 14.7g; Trigno, Delsys, Boston,  
109 MA) were securely attached on the proximal anterior-medial side of right shank and on the  
110 proximal posterior-medial side of the trunk on a level with the sacrum in order to  
111 approximate the whole body centre of mass position. The vertical axis of the accelerometer  
112 was aligned with the longitudinal axis of the body segment. The accelerometer was attached  
113 directly on the skin by double-sided adhesive tape and wrapped with elastic tape to hold it securely  
114 in place throughout the test and prevent any excessive movement due to the weight of the  
115 accelerometer itself. Three-dimensional (3-D) accelerations were sampled at 148.15 Hz over  
116 each of the 3 minute stages of the treadmill protocol.

117

118 The running test consisted of an incremental and discontinuous protocol characterised by 3  
119 minute stages separated by 30 s periods. The starting speed was chosen based on previous  
120 tests to determine a blood La concentration of 4 mmol/L after 5 -7 stages. Each stage was  
121 run at 1% gradient on the motorized treadmill (ELG-70, Woodway, Germany). After each  
122 stage, the speed was increased by 1 km/h. At the end of each stage the subjects straddled  
123 the treadmill and blood lactate concentration ( $[La]_b$ ) was measured with an automated  
124 analyser (Biosen C-line, EKF Diagnostics, Germany). The average values of  $\dot{V}O_2$  and heart  
125 rate in the last 30 s of each stage were used for analysis. The subjects continued to the next  
126 stage until their La concentration exceeded 4 mmol/L. Across subjects this occurred at  
127 stage  $6 \pm 1$  (mean  $\pm$  SD).

128

129 A custom written code written in Matlab (Version 8.4, Mathworks, Inc., Natick, MA) was  
130 used to process the signals from the three acceleration axes. To ensure the analysed data



131 corresponded to a steady state of running, only the last two minutes epochs of each stage  
132 were analysed. The Root Mean Square (RMS) and Sample Entropy (SampEn) for the  
133 vertical (VT), medial-lateral (ML) and anterior-posterior (AP) components of acceleration  
134 were calculated. The degree of regularity of the shank and trunk movement patterns was  
135 assessed using the SampEn. SampEn estimation was performed based on the description  
136 provided by Richman and Moorman (2000) as indicated by the expression below:

137

$$138 \text{SampEn}(m, r, N) = -\ln\left(\frac{A}{B}\right)$$

139

140 Where A and B are the counts of vectors of length  $m+1$  and  $m$  that matches the template  
141 vector within the predetermined tolerance  $r$  in the times series respectively. The output  
142 value from SampEn is unitless, typically ranging from 0 to 2 in physiological systems.  
143 Highly regular and repeatable behaviour approaches 0, while a higher SampEn indicates a  
144 more irregular and complex behaviour. The template pattern length and matching criterion  
145 of similarity were set as previously described<sup>10</sup> ( $m=2, r=0.2$ ). Each of the acceleration  
146 time-series was normalized to unit variance.

147

148 Pearson correlation coefficients between HR, RMS, and SampEn of the acceleration versus  
149 La and  $\dot{V}O_2$  across the test stages and the corresponding  $p$ -values were determined to assess  
150 the relationship between the variables. Significance was set at an alpha level of  $p < 0.05$ . In  
151 an attempt to understand factors that are most related to  $[La]_b$  and  $\dot{V}O_2$ , a multiple linear  
152 regression analysis was performed incorporating the independent variables of location of

153 accelerometer and quantificational algorithm of the acceleration. HR was included as a  
154 covariate within the model to explain its effects on  $[La]_b$  and  $\dot{V}O_2$ .

155

## 156 **Results**

157 All variables except SampEn of the VT shank and AP waist acceleration were significantly  
158 correlated with  $[La]_b$ , with moderate to high coefficients ( $r = 0.43 - 0.87$ ) and with positive  
159 direction for all variables (Table 1). Overall, RMS of the shank acceleration was the most  
160 highly related with  $[La]_b$ , and the best related variable was the RMS of the VT shank  
161 acceleration ( $r = 0.87, P < 0.01$ ). However, when the accelerometer was attached on the  
162 waist, SampEn of the VT acceleration had the strongest relationship with  $[La]_b$  ( $r = 0.73, P$   
163  $< 0.01$ ).

164

165 RMS of the shank acceleration in all directions, RMS of the VT, ML waist acceleration,  
166 and SampEn of the VT waist acceleration were significantly correlated with  $\dot{V}O_2$ , with  
167 moderate to high coefficients ( $r = 0.49 - 0.85$ ) and with positive direction for all variables  
168 (Table 1). Similar as the relationship between acceleration variables and  $[La]_b$ , RMS of the  
169 shank acceleration was the most highly related with  $[La]_b$ , and the strongest relationship  
170 was with the RMS of the ML shank acceleration ( $r = 0.85, P < 0.01$ ). However, when the  
171 accelerometer was attached on the trunk, SampEn of the VT acceleration had the strongest  
172 relationship with  $\dot{V}O_2$  ( $r = 0.76, P < 0.01$ ).

173

174 The multiple linear regression models for HR and accelerometer outputs to explain  $[La]_v$   
175 and  $\dot{V}O_2$  were also examined for each individual within the study (table 2).

176

## 177 Discussion

178 It was hypothesised that running complexity was affected by speed and lactate  
179 accumulation and could be used as an explanatory variable of lactate threshold and  
180 maximal aerobic power. In this study we showed that this relationship holds and we  
181 established models based on these variables that may be applicable for future studies with  
182 larger sample sizes. We also showed how these models differed across individuals.

183

184 Previous work has reported strong relationships (0.95) for anterior-posterior and resultant  
185 vectors for speed and acceleration over a range of paces<sup>9</sup> and for predications of  $\dot{V}O_2$  from  
186 accelerometry in adults<sup>11</sup>. Only one paper to date has used regularity statistics to ascertain  
187 the quality of running mechanics<sup>12</sup>. Schütte and colleagues reported that fatigue from  
188 running on a treadmill may result in a greater variability of horizontal trunk accelerations.  
189 Sample entropy values for the trunk were higher and thus less predictable in all three axes  
190 without a change in step or stride regularity. This higher sample entropy potentially reveals  
191 protective neuromuscular centre of mass control to preserve musculoskeletal structures. As  
192 a potential predictor of fatigue, entropy has value as any physiological change acute across  
193 stages in this case or chronic as in non-functional overreaching<sup>13</sup>, can alter the magnitude  
194 and/or structure of a movement through changes in the acceleration pattern and hence alter  
195 the entropy.

196

197 To the authors' knowledge no measure of SampEn relative to the metabolic parameters of  
198  $[La]_b$  or  $\dot{V}O_2$  has been previously published and certainly not in a well-trained youth  
199 population. The use of accelerometers in the same sense as a heart rate monitor for the  
200 quantification of global training load is appealing. Similarly, with further work entropy may  
201 play a role in assessing recovery or training readiness with a standardised submaximal  
202 intervention. Running outside on variable surfaces may represent a technical challenge,  
203 though recent studies have shown proof of concept in measuring the foot strike pattern over  
204 variable terrain <sup>14</sup>.

205

## 206 **Conclusion**

207 It is proposed that the described method of analysis of running complexity may allow an  
208 assessment of gait variability which non-invasively tracks  $\dot{V}O_2$  and/or  $[La]_b$  potentially  
209 allowing monitoring of fatigue or training readiness for trained adolescent individuals.

210

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260 **Table 1:** Mean values and correlation between accelerometer outputs, HR and  $[La]_E$ ,  $\dot{V}O_2$ 

Variable	Mean±SD across stages	$[La]_E$		$\dot{V}O_2$	
		r	P-value	r	P-value
<b>HR</b>	174±17 bpm	0.766 <sup>a</sup>	0.000	0.443 <sup>a</sup>	0.005
<b>Shank VT RMS</b>	2.10±0.24 g	0.865 <sup>a</sup>	0.000	0.843 <sup>a</sup>	0.000
<b>Shank ML RMS</b>	1.43±0.23 g	0.787 <sup>a</sup>	0.000	0.845 <sup>a</sup>	0.000
<b>Shank AP RMS</b>	1.51±0.18 g	0.660 <sup>a</sup>	0.000	0.604 <sup>a</sup>	0.000
<b>Waist VT RMS</b>	1.52±0.05 g	0.430 <sup>a</sup>	0.007	0.715 <sup>a</sup>	0.000
<b>Waist ML RMS</b>	0.50±0.08 g	0.572 <sup>a</sup>	0.000	0.485 <sup>a</sup>	0.002
<b>Waist AP RMS</b>	0.52±0.11 g	0.526 <sup>a</sup>	0.001	0.284	0.084
<b>Shank VT SampEn</b>	0.62±0.08	0.346 <sup>b</sup>	0.034	-0.231	0.162
<b>Shank ML SampEn</b>	0.82±0.13	0.428 <sup>a</sup>	0.007	-0.073	0.662
<b>Shank AP SampEn</b>	0.77±0.09	0.608 <sup>a</sup>	0.000	0.387*	0.016
<b>Waist VT SampEn</b>	0.41±0.08	0.733 <sup>a</sup>	0.000	0.755 <sup>a</sup>	0.000
<b>Waist ML SampEn</b>	0.96±0.09	0.485 <sup>a</sup>	0.002	0.167	0.316
<b>Waist AP SampEn</b>	0.81±0.15	0.247	0.134	0.102	0.542

261

262 VT = Vertical; ML = Medio Lateral; AP = Anterior-Posterior; RMS = Root Mean Squared'  
 263 SampEn = Sample Entropy

264

265 <sup>a</sup> Correlation is significant at the 0.01 level.

266 <sup>b</sup> Correlation is significant at the 0.05 level.

267



268 **Table 2:** Best multiple linear regression models for each individual for both  $[La]_b$  &  $\dot{V}O_2$   
 269

	Participants	Constant	Variable	B	Beta	Adjusted $r^2$
$[La]_b$	1	-23.14	Waist ML RMS	55.14	1.03	0.931
			Shank ML SampEn	-4.46	-0.24	0.992
			Waist VT SampEn	7.26	0.14	1.000
	2	19.30	Waist VT SampEn	16.81	1.25	0.854
			Waist VT RMS	-16.05	-0.46	0.989
	3	-0.44	Waist VT SampEn	5.58	0.90	0.762
4	-6.32	Shank ML SampEn	11.04	0.97	0.920	
5	-1.94	Shank ML RMS	3.32	0.97	0.923	
6	23.09	Shank ML RMS	8.24	1.91	0.920	
		Waist VT RMS	-21.63	-0.97	0.982	
$\dot{V}O_2$	1	0.21	Shank ML SampEn	47.66	0.94	0.857
	2	-7.04	Shank ML SampEn	79.96	0.98	0.964
	3	11.74	Waist AP RMS	70.15	0.92	0.797
	4	40.52	Shank ML RMS	80.33	3.39	0.964
			Waist ML RMS	-136.00	-1.39	0.996
			Waist AP RMS	-93.58	-1.02	1.000
5	83.62	Waist ML SampEn	-43.18	-0.99	0.964	
6	-188.25	Waist VT RMS	152.69	1.00	0.990	

270

271

272

273

VT = Vertical; ML = Medio Lateral; AP = Anterior-Posterior; RMS = Root Mean Squared'  
 SampEn = Sample Entropy