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Abstract

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

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

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

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

Keywords: Accelerometry, Regularity, Lactate, Aerobic, Gait

Introduction

Running economy has been the subject of many studies indicating that this parameter increases from childhood [1,2]. While the metabolic aspects are well studied,[2] little research has investigated the relationship between kinematic and kinetic parameters and running economy.

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

Entropy has been recently suggested as an analytical technique that provides information regarding the degree of complexity of the system's behaviour by indexing the regularity of patterns present in the dynamics of running movements [7]. In adolescents, where maturational changes in stride length and frequency accompany ongoing limb growth,[8] the variability in movement oscillations can be evaluated by complexity analysis techniques, which would allow the identification of variability in a spatio-temporal perspective. Recent work from McGregor and colleagues (2009) reported for the first time the regularity values of well-trained runners suggesting this approach as a valid way to ascertain the control constraints during running in such a population.

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

Methods

Six national level youth middle-distance athletes (15.6 ± 1.2 years, 51 ± 5.8 kg, 169.2 ± 9.2 cm, $\dot{V}O_2max$ 62.01 ± 3.37 ml.kg^{-1}.min^{-1}, $v\dot{V}O_2$ 16.92 ± 1.54 km.h^{-1}, 14.68 ± 1.22 km/h at 4 mmol/L) participated in the study. The study design consisted of performing an incremental running test. The local ethics committee approved the procedures.

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

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

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

A custom written code written in Matlab (Version 8.4, Mathworks, Inc., Natick, MA) was used to process the signals from the three acceleration axes. To ensure the analysed data corresponded to a steady state of running, only the last two minutes epochs of each stage were analysed. The Root Mean Square (RMS) and Sample Entropy (SampEn) for the vertical (VT), medial-lateral (ML) and anterior-posterior (AP) components of acceleration were calculated. The degree of regularity of the shank and trunk movement patterns was assessed using the SampEn. SampEn estimation was performed based on the description provided by Richman and Moorman (2000) as indicated by the expression below:

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

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

Pearson correlation coefficients between HR, RMS, and SampEn of the acceleration versus La and $\dot{V}O_2$ across the test stages and the corresponding *p*-values were determined to assess the relationship between the variables. Significance was set at an alpha level of $p < 0.05$. In an attempt to understand factors that are most related to $[La]_b$ and $\dot{V}O_2$, a multiple linear regression analysis was performed incorporating the independent variables of location of accelerometer and quantificational algorithm of the acceleration. HR was included as a covariate within the model to explain its effects on $[La]_b$ and $\dot{V}O_2$.

Results

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

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

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

Discussion

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

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

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

Conclusion

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

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

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

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

[a] Correlation is significant at the 0.01 level.
[b] Correlation is significant at the 0.05 level.

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

	Participants	Constant	Variable	B	Beta	Adjusted r^2
$[\mathrm{La}]_b$	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

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