ENERGETIC COST OF RUNNNING STABILITY EVALUATED WITH WIRELESS TRUNK ACCELEROMETRY

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The purpose of this study was to determine inter-individual variance in the energetic cost of running (Ec) using dynamic stability measures derived from a single tri-axial trunk accelerometer. These measures were extracted from fifteen male recreational runners at their fastest steady-state treadmill running speed. A select group of dynamic stability measures were entered in a hierarchical regression to explain Ec (kcal.km^{-1}) after reducing dimensionality with factor analysis. Two dynamic stability parameters could explain an additional 9.9% of inter-individual variance in Ec over and above body mass, attributed to anteroposterior (AP) stride regularity (6.5%) and mediolateral (ML) sample entropy (3.4%). Our results suggest that recreational male runners with better stability in terms of greater AP stride consistency and greater ML trunk movement complexity have an energetic advantage at running speeds approximating race pace.

KEY WORDS: 3D accelerometer, running economy, wearable technology

INTRODUCTION: Establishing a biomechanical basis to the energetic cost (Ec) of running has long been of interest to researchers and coaches. Recently, the 2016 ISBS congress devoted an applied session to this topic, titled *"Economy of running: Biomechanical research for running economy"* (Enomoto, Kyrolainen, Arellano, & Heise, 2016). The session concluded that more research is needed to clarify key biomechanical determinants of running Ec. Some of the current limitations identified in the literature were: the ability to evaluate mechanical parameters over significantly more strides as well as the ability to transfer biomechanical analysis to *in situ* training environments. The advent of wearable inertial measurement sensors (IMU's) offers a novel approach to potentially overcome these limitations and determine a "real-world" biomechanical basis for the Ec of running.

Tri-axial accelerations extracted from trunk IMU's have become a popular approach to approximate center of mass (CoM) motions with the potential to assess running gait from both a stability and loading perspective. Evolutionary theory suggests that structural adaptations have allowed human running to be more dynamically stable and energy sparing (Bramble & Lieberman, 2004), with most (~80%) energy being used for body weight support and forward propulsion (Arellano & Kram, 2014). Although, it has also been suggested that surplus accelerations and dynamic instabilities of the CoM during human locomotion can be energetically "wasteful" and thus performance hampering (LeBris et al., 2006; Schütte, Maas, Exadaktylos, Berckmans, & Vanwanseele, 2015). However, to the best of our knowledge this link remains untested.

In this study, we test a *cost of stability hypothes*is that proposes a link between a runner's stability and running Ec, and that this link can be assessed using wearable trunk accelerometry. Specifically, we hypothesize that runners running with less deviations in CoM motion such as 1) less variability; 2) more consistency; and 3) more regularity have a running gait that is energetically advantageous. To evaluate these hypotheses, we used simple and non-linear metrics including 1) the root mean square (RMS) of each acceleration axis (vertical, ML, AP); 2) inter-step and inter-stride regularity, and 3) the sample entropy of waveforms, each of which express unique aspects of dynamic stability during running.

METHODS: Fifteen male recreational runners were recruited for this study, with a mean (SD) age (21±1.88 years); height (1.78±0.08 m); weight 74.11 kg (10.43) and VO_2 max (52.77±5.2 ml.kg^{-1}.min^{-1}). To be included in the study runners had to be running recreationally (> 10 km per week) and have prior experience with treadmill running. All participants were screened to have no history of lower extremity injury within the past three months and no known metabolic, neurological, or cardiovascular disease. Written informed consent was received from all runners prior to participation in accordance with the Declaration of Helsinki. The local ethics committee approved the study (# SU-HSD-002032).

After a warm-up of ~ 4 minutes starting at 9 km•hr^{-1} on a motorized treadmill (Saturn h/p/cosmos, Nussdorf-Traunstein, Germany), speed was increased discontinuously in increments of 1.5 km•hr^{-1} every four minutes interspersed by a one minute rest until onset of blood lactate (OBLA), defined as > 4mmol.L^{-1} using a portable lactate analyzer (Lactate Pro 2 LT-1730, Japan). Treadmill gradient was maintained at 1% throughout to reflect the energetic cost of outdoor running (Jones & Doust, 1996). All tests were performed under similar laboratory conditions (20 – 25 ° C, 50 – 60% relative humidity at 130m of altitude).

Pulmonary gas exchange was recorded through-out the test using a breath-by-breath metabolic analyser (Cosmed Quark CPET, Rome, Italy). Gas analysers were calibrated before each session to 16% O_2, 4% CO_2 balance N_2 and the turbine flow meter is calibrated with a 3L calibration syringe before each test. VO_2 data collected from the last two minutes of each speed stage were checked for steady-state i.e. no additional rise in the slow component of VO_2 was to be detected. Updated nonprotein respiratory equations were used to estimate substrate use (g.min^{-1}) and the relative energy derived from fat and carbohydrate was calculated by multiplying by 9.75 and 4.07 respectively (Jeukendrup & Wallis, 2005). Ec was defined as gross absolute (expressed as kilocalories per kilometre), quantified as the sum of these values to reflect the mean energy content of the metabolized substrates during moderate to high-intensity exercise (Jeukendrup & Wallis, 2005).

Tri-axial trunk accelerometry (Shimmer3 wireless accelerometer, ±16 g range, 1024 Hz, 16-bit resolution, 23.6 g weight, Shimmer Sensing, Dublin, Ireland) was acquired during the entire running test. The accelerometer was securely positioned over L3 spinous process of the trunk and directly mounted to the skin using double sided tape, with additional self-adhesive bandage wrapped around the waist to individual comfort. All signal processing of acceleration curves expressed as g's was performed using customized software in MATLAB version 8.3 (The Mathworks Inc., Natick, MA, USA). Dynamic 3D trunk accelerations were trigonometrically tilt-corrected (Moe-Nilssen & Helbostad, 2004) and filtered using a zero-lag 4th order low-pass Butterworth filter (cut-off frequency 50 Hz) prior to parameter extraction. Accelerometry parameters were computed from the final twenty consecutive steps of acceleration signals at each runner's highest speed prior to OBLA which allowed cross-study comparison.

A total of 15 *dynamic stability parameters* were extracted using each acceleration axis (vertical, ML, AP) and were quantified: firstly using of each linear acceleration axis root mean square (RMS) absolute and ratio relative to the resultant vector RMS to capture movement loading variability; secondly using step regularity and stride regularity (unbiased autocorrelation procedure) to capture consistency of motions; and thirdly using the sample entropy statistic to capture complexity of unfiltered waveforms, with higher values indicating less periodicity. Detailed procedures and algorithm inputs for the computation and extraction of these dynamic stability parameters are the same as previously explained (Schütte et al., 2015).

All *statistical analyses* were performed using SPSS (version 20.0; SPSS Inc, Chicago, IL). A factor analysis was performed to reduce the dimensionality of the 15 respective accelerometry outcome measures and to prevent overfitting of subsequent regression analysis. A scree-plot determined the number of extracted factors (eigenvalues > 1.0) with VariMax rotation to optimize loadings of variables onto factors. The most representative (highest loading) accelerometry measures were entered in an *a priori* hierarchical multiple regression analysis (MRA) to explain inter-individual variance in Ec. Specifically, body mass was entered first as block 1 into the MRA model. Thereafter, block 2 was entered containing the most representative accelerometry measures, assessing the adjusted R^2 change to determine the proportion of additional variance explained and significance from 0. This sequential order was based on an a priori hypothesis that additional variance in Ec could be explained by dynamic parameters, after accounting for body mass that is a well-known primary determinant of running Ec (Bergh, Sjödin, Forsberg, & Svedenhag, 1991).

RESULTS: All runners successfully completed the treadmill running test, with a mean (SD) highest steady-state running speed in absolute (11.19±1.12 km/h) and relative (79.85±5.15 %VO_2 max); respiratory quotient (0.95±0.02 au); and Ec (81.69±12.61 kcal.km^{-1}).

Factor analysis showed four components that could explain 88.4% of total variance in accelerometry measures (eigen values > 1). The variables with the highest loading on each factor were AP stride regularity (factor one loading = 0.96), ML RMS (factor two loading = 0.92), AP RMS (factor three loading = 0.79), and ML sample entropy (factor four loading = 0.63). Therefore, only these four accelerometry measures were entered in a stepwise fashion to the regression model after body mass to the regression model.

Regression results revealed two accelerometry measures that could explain an additional 9.9% inter-individual variance in Ec after controlling for body mass as shown in Table 1. Partial regression plots of the final regression model for the independent contribution of each significant predictor of Ec are shown in Figure 1.

Table 1
Hierarchical multiple regression results of final model explaining inter-individual variance in running Ec

Independent variables	Descriptives (mean±SD)	Unique contribution B	SE B	β	R^2 change
Body mass (kg)	74.72±11.24	0.828	0.10	0.74**	0.817
AP stride regularity (au)	0.75±0.13	-22.59	8.41	-0.24*	0.065
ML sample entropy (au)	0.295 ±0.095	-33.14	14.13	-0.21*	0.034

β = standardized coefficients; */** p < 0.05 / p < 0.001; constant for multiple regression equation = 45.96.

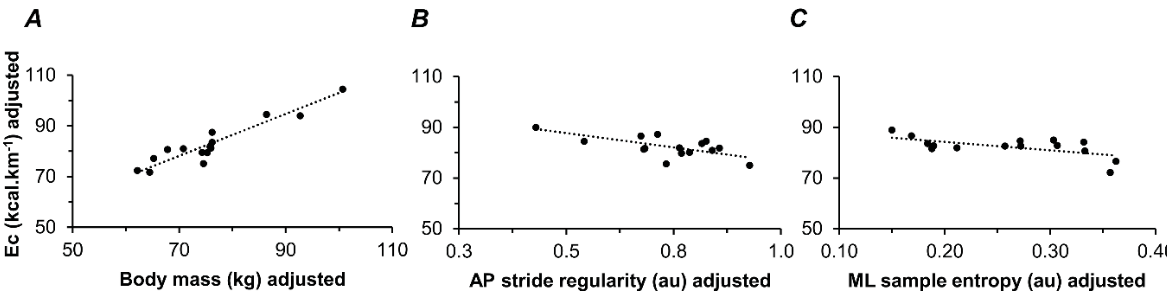

Figure 1. Partial regression plots (n = 15) of three independent variables showing unique contributions to running Ec, scaled by adding regression-residuals to group mean values to enhance interpretation (Moya-Laraño & Corcobado, 2008). Each plot represents the true correlation coefficient for the specific predictor on Ec, while controlling for the other two predictors e.g. in panel B the relationship of AP stride regularity to Ec is shown while controlling for body mass (panel A) and ML sample entropy (panel C).

DISCUSSION: The current study tested a *cost of stability hypothesis* that proposed a link between running stability and running Ec using wearable trunk accelerometry. Our results partially support our hypothesis with two accelerometry stability measures that explained an additional 9.9% variance in running Ec over and above body mass in male recreational runners. The first measure (AP stride regularity) explained 6.5% in running Ec. The direction of the slope in Figure 1 B was as expected, indicating that runners with poor consistency from stride to stride have a more energetically costly gait. From a coaching perspective, this may suggest that for economical purposes runners should give priority to maintaining consistency of their strides in the AP direction of running, aiming for values closer to one (perfect consistency).

A second accelerometry measure (ML sample entropy) explained an additional 3.5% in running Ec. Recently, this non-linear measure (indicating trunk movement complexity) has shown to correlate with blood lactate readings during treadmill running (Murray et al., 2011), showing potential to track endurance markers of running performance non-invasively. Interestingly, the direction of the slope of the regression as seen in Figure 1 C contrasts with what was expected. Based on previous work showing that sample entropy values increase (become more irregular) when runner's become fatigued (Schütte et al., 2015), we hypothesized that higher values would also be associated with higher Ec. The current results suggest otherwise, and we speculate that more degrees of freedom i.e. greater complexity used to regulate mediolateral trunk control is a mechanism used by more economical runners.

Wireless trunk accelerometer could offer some potential for runners to gauge how economical their running stride is relative to other recreational runners, without requiring sophisticated motion analyses equipment or being restricted to indoor environments. Future work is encouraged to evaluate whether this relationship holds for more elite runners and within individuals over a training season.

CONCLUSION: Higher AP stride regularity and ML sample entropy of trunk acceleration waveform signals were found to be energetically advantageous to endurance running performance. A simple non-invasive assessment of dynamic stability using trunk accelerometry could provide additional value to coaches and/or athletes if performed routinely and outside of the laboratory.

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