TRUNK MOTION DURING A HALF-MARATHON: THE IMPACT OF PERCEIVED FATIGUE ON MOTION STABILITY AND SMOOTHNESS

Salil Apte[1], Nathan Laroche[1], Vincent Gremeaux[2], Kamiar Aminian[1]
[1]Laboratory of Movement Analysis and Measurement, EPFL, Lausanne, Switzerland
[2]Institute of Sport Sciences, University of Lausanne, Lausanne, Switzerland

Our objective was to investigate the effects of acute fatigue on stability and smoothness of trunk motion during a half marathon. 13 recreational runners were fitted with a GNSS-IMU sensor on their chest. Every 10 minutes of the race, the participant pronounced their perceived fatigue, recorded by a smartphone attached to the arm. We divided the race into 8 equal segments, corresponding to one fatigue score per segment, and considered only level running. Based on mediolateral acceleration and running velocity (*v*), stability was characterized by spectral entropy, RMS of acceleration (*RMSA*), and autocorrelation between successive steps and strides; smoothness by jerk cost (*JC*), spectral arc length (SPARC), and inverse number of peaks (IPV) of *v*. Both RMSA and JC increased significantly shortly after race onset. RMSA increased significantly at a lower perceived fatigue level, while JC increased at a higher level. Whereas other measures did not change substantially, RMSA and JC showed a clear change with acute fatigue and also differentiated well between the five fastest and five slowest runners. With increasing perceived fatigue, both parameters showed a higher change for 'slow' group. This study highlights the loss of stability and smoothness in running due to acute fatigue and the importance of simultaneously measuring perceived fatigue and trunk biomechanics under real-world conditions.

KEYWORDS: running, wearable sensors, biomechanics, performance

INTRODUCTION: A decrease in trunk stability along the mediolateral axis induces an energy loss during running, thus entailing higher energetic cost (or loss of efficiency) (Schütte et al., 2015, 2018). Trunk motion can also be characterized by its smoothness, which indicates the proficiency of coordinated movements during running (Kiely et al., 2019). Assessing trunk motion through the lens of stability and smoothness during running events and training may provide a deeper understanding of the biomechanics of running and their development with acute fatigue. Current research shows that stability (Schütte et al., 2018) and smoothness (Kiely et al., 2019) tend to decrease with increased duration of running, likely due to acute fatigue. Acute fatigue also affects the trunk flexion during prolonged running (Apte et al., 2021), resulting in an increase in knee loading (Teng & Powers, 2015), which may lead to a higher injury risk. However, these results have not been considered in relation to the progression of perceived fatigue. Perceived fatigue can provide a holistic idea about the feelings of exercise induced acute fatigue. Recent work (Prigent et al., 2022) on the concurrent assessment of running biomechanics and perceived fatigue during a half marathon has mainly focused on spatiotemporal parameters rather than specifically on the trunk motion. This work aims to complement existing research by providing a synchronous analysis of the stability and smoothness of trunk motion and the development of perceived fatigue.

Methods: The dataset used for this study is the same as that in (Prigent et al., 2022). In this protocol, 13 participants ran a half marathon while fitted with a GNSS-IMU sensor (Fieldwiz, ASI, Switzerland) on the chest, a IMU sensor (*Physilog 5, Gaitup SA, Switzerland*) on each foot, and an Android smartphone on the upper arm for audio recording. Fieldwiz was used with a sampling frequency of 200 Hz for the IMU, and 10 Hz for the GNSS receiver. Every 10 minutes during the race, the participants pronounced their rate of fatigue (ROF) on a scale of 1 to 10 and this sound was recorded with a timestamp by the smartphone. The first and last 50 strides of gait data were removed as transients due to the start and end of the race. We selected the acceleration along the mediolateral axis (a_{ML}) for the computation of stability and smoothness metrics, since the acceleration along this axis presents a clear and substantial change with fatigue (Apte et al., 2021; Provot et al., 2021). Furthermore, gait velocity (*v*) was extracted from the GNNS for the estimation of smoothness. We split the race into windows of

30 seconds and computed all the stability and smoothness metrics on each window. The five fastest and slowest participants were selected as the fast and the slow groups, respectively.
Stability: Out of the variety of metrics used to quantify stability present in literature (Bruijn et al., 2013), we selected three different methods (Figure 1). First method was the computation of the root mean squared of the acceleration (*RMSA*) on a window of 1 stride (Schütte et al., 2015)**.** Next, we used spectral entropy (*SE*) to quantify the regularity of fluctuations within the acceleration profile (Schütte et al., 2015). Finally, we estimated the autocorrelation of the acceleration signal with a lag of one step (R_P) and one stride (R_D). Autocorrelation quantifies the similarity of each step (or stride) compared to the others (Cushman, 2010). Loss of stability is indicated by an increase in *RMSA* and *SE*, and a decrease in that of R_P and R_D.

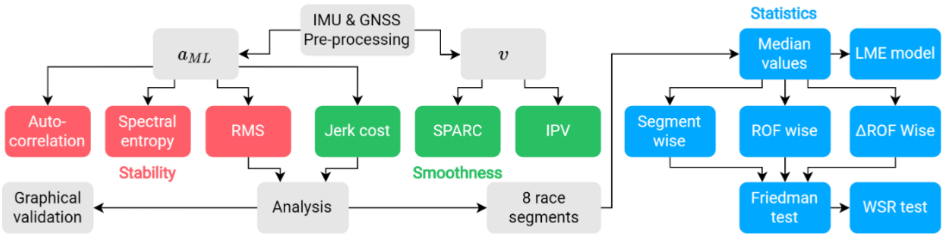

Figure 1 Flowchart of the trunk movement study, with the steps for stability and smoothness computation, and statistical analysis indicated in red, green, and blue respectively.

Smoothness: The smoothness was also evaluated with three different metrics (Figure 1). First, jerk cost (*JC*), which quantifies the change in the jerk profile and thus loss of smoothness due to rapid changes in acceleration (Kiely et al., 2019). Additionally, the spectral arc length (*SPARC*) (Balasubramanian et al., 2015) on the velocity profile was computed, which is arc length of the Fourier magnitude spectrum within an adaptive frequency range. Smoother movements tend to have less intermittencies and thus a higher SPARC measure. Lastly, smoothness was quantified using the inversed number of peaks (*IPV*) (Brooks et al., 1973) on the velocity profile, where smooth motion tends to have less peaks.
Statistical analysis: The race was divided into 8 equal segments, such that one ROF value could be assigned to each segment. The median value of the stability and smoothness metrics was computed for each segment (Figure 1). To analyse the effect of race progression on the metrics (‘Segment wise’), we compared the segments 1, 5, and 8 using the Friedman (F) test and the pairwise Wilcoxon Signed-Rank (WSR) test. In order to consider the perceived fatigue, we compared segments with the highest (H), medium (M), and lowest (L) ROF values. Fatigue levels were considered individually and pooled into three different groups. F test and WSR test were also used to compare these three groups (ROF wise). To overcome inter-subject variability in ROF baseline values, ΔROF was computed as the difference between each ROF value and the one at the first segment (baseline). We created 3 states, by combining ΔROF of value 1 and 2, 3 and 4, and all values ≥ 5, and compared them to baseline (ΔROF = 0) using WSR and F tests (ΔROF wise). Finally, we designed a 3-levels Linear Mixed Effects (LME) model with the performance (fast/slow groups), the ΔROF, and the interaction between performance and ΔROF as the fixed effects. Then, a random effect (slope and intercept) was defined on the participants and the MATLAB function “fitlme” function was used for implementation. Further details of the statistical analysis can be found in (Prigent et al., 2022).

Results and discussion: *RMSA* showed an increasing trend with race progression for both fast and slow groups (Figure 2A, B), which is consistent with the findings from Schütte et al. (Schütte et al., 2015). Despite the similar slope, the intercepts for both the groups were distinct, with *RMSA* showing a good ability to differentiate between experience and amateur runners. For ΔROF (Figure 2C), it showed difference in slopes for the slow and fast groups, with fast runners showing a moderate increase and slow runners showing a decline. Participants in slow group likely have a lower experience in managing the level of fatigue compared to those in the fast group. Thus, they might adopt a strategy of lowering their overall acceleration at higher ΔROF to manage their dynamic stability (Provot et al., 2021), leading to a decline in the *RMSA*. *RMSA* presented significant change (Table 1) for at the start of the race but did not change significantly as the race continued, also visible in Figure 2A, B. It also increased significantly at low ΔROF values but not for ΔROF ≥ 5, which can also be attributed to the reduction in *RMSA* for the slow group. This change at the beginning of the race coincides with results from Prigent et al. (Prigent et al., 2022), where significant biomechanical changes were observed soon after the beginning of the race. Similar results were seen for R_P, R_D, and *SE* (Table 1), with significant reduction in stability from low to medium ROF values. However, this reduction was not sustained further and these metrics did not differentiate well between fast and slow runners. In comparison to other metrics, *SE* has previously shown low construct validity (Bruijn et al., 2013) and our results do not contradict this assertion. Thus, we observed differing trends for stability based on the choice of metric, with *RMSA* presenting the most consistent trends. *RMSA* depends on the running velocity, with fast runners showing a higher RMSA than slow runners at the beginning of the race. However, we did not observe any intra-participant significant changes in velocity (Table 1). Thus, *RMSA* provides a clear indication that stability of the trunk decreases with perceived fatigue, more so for amateur runners.

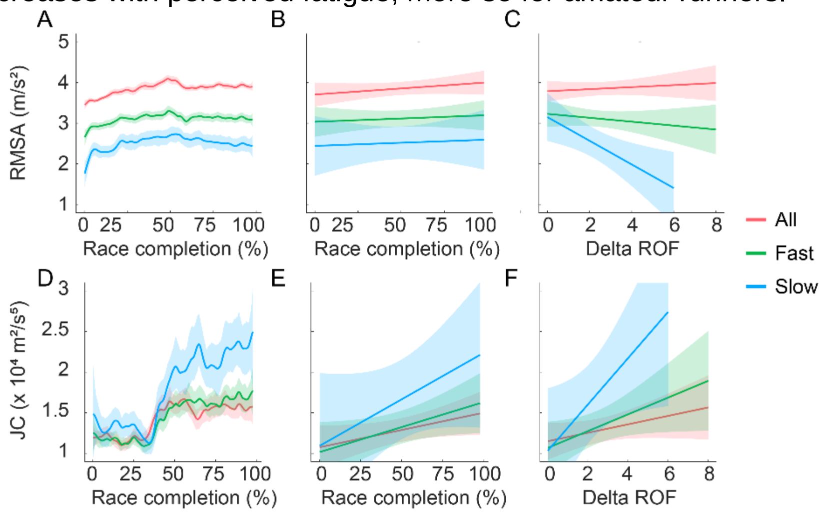

Figure 2 Evolution of the selected metrics for stability and smoothness. Figures A, B, and C show the actual change and linear change with race progression, and linear change with ΔROF for RMSA (RMS acceleration), respectively. Figures D, E, and F show the same information for JC (jerk cost). FG (green) designates the group with fastest five runners and SG (blue) the slowest five. 'All' (red) shows trends for 13 participants together.

Same trends were seen for the *JC*, with its magnitude increasing with the race progression and perceived fatigue (Figure 2 D, E). *JC* presented a sudden increase around 40% of the race and continued to increase throughout race for the SG group. However, for the fast group, it barely increased after halfway point of the race. This is also reflected in the statistical analysis, with significant differences between S1:S5 and S1:S8. The continued increase for slow runners is reflected in the ROF comparison, with significant different for M:H and L:H groups. All groups showed a positive slope for the relation between *JC* and ΔROF (Figure 2F), with slow group presenting a considerably larger slope but a similar intercept as fast group. The increase in *JC* points to a reduction in smoothness of movement and consequently a higher energy cost of running (Kiely et al., 2019; Provot et al., 2021; Schütte et al., 2018). These results suggest that faster runners tend to better manage the energy costs of running and do not experience the cascading effect (Figure 2D) of increased energy costs on running smoothness and decreased running smoothness on increased energy costs. Moreover, unlike stability, slow runner seem unable to recover the smoothness of movement with reduced overall acceleration.
Compared to *JC*, *SPARC* measures and *IPV* did not show any significant change and could not differentiate well between FG and SG. Whereas JC was computed on a_{ML}, these metrics were calculated using *v*, where the velocity profile did not change significantly throughout the race. Furthermore, SPARC value depends on the choice of cut-off frequency (Balasubramanian et al., 2015), which might have affected the results. Thus, we observed that *JC* quantified well the quality of the continuality of movements and remained independent of amplitude of speed (Kiely et al., 2019). Apart from those specific observations, it can be observed, generally, that the variance (on all results) for slow runners is higher than for fast

runners. Finally, these results highlight the utility of assessing perceived fatigue along with the race progression (Prigent et al., 2022).

Table 1 Statistical analysis of all the metrics investigated using Friedman (F) test and pairwise Wilcoxon signed rank (WSR) test for comparison across segments, ROF and ΔROF. S1, S5, and S8 indicate race segments 1, 5, and 8. L, M and H for low, median, and high value of ROF. The significance was set at p<0.05 with * for p ∈ [0.01,0.05) and ** for p ∈ [0.001,0.01). Bolded numbers indicate the effect size (ES) for significant differences.

	Segment wise				ROF wise				ΔROF wise			
	F Test (ES)	WSR test (ES)			F Test (ES)	WSR test (ES)			F Test (ES)	WSR test (ES)		
Parameter		S1:S5	S5:S8	S1:S8		L:M	M:H	L:H		0:1,2	0:3,4	0:≥5
R_P	0,11	0,42*	0,01	0,36	0,18	0,51*	0,08	0,35	0,05	0,34	0,39*	0,35
R_D	0,11	0,35	0,02	0,35	0,10	0,46*	0,06	0,34	0,05	0,35	0,32	0,36
SE	0,08	0,37	0,12	0,24	0,10	0,38*	0,05	0,17	0,05	0,31	0,25	0,18
RMSA	0,45**	0,56**	0,27	0,53**	0,20	0,46*	0,23	0,4*	0,32**	0,56**	0,56**	0,27
JC	0,29*	0,42*	0,25	0,54**	0,36*	0,32	0,4*	0,54**	0,24*	0,25	0,44*	0,53**
SPARC	0,01	0,01	0,12	0,03	0,01	0,11	0,09	0,03	0,01	0,02	0,10	0,02
IPV	0,13	0,30	0,39	0,29	0,24	0,36	0,40	0,24	0,06	0,23	0,00	0,07
v	0.08	0.25	0.32	0.21	0.03	0.08	0.05	0.10	0.06	0.10	0.16	0.10

Conclusion: This study showed a significant decrease for stability and smoothness of trunk movement using a wearable GNSS-IMU sensor during a half-marathon. The metrics led to different trends, with jerk cost and RMS acceleration presenting reliable results for smoothness and stability, respectively. Assessment with respect to perceived fatigue provided different results than that with race progression for some metrics. Less experienced runners were able to slightly recover the stability of their trunk movement but not the smoothness. However, further studies with a larger number of runners are needed. Use of such wearable sensor setups may further allow a more personalized approach to fatigue analysis and help runners to optimize their pacing strategies by understanding their running technique better.

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