CONCURRENT ASSESSMENT OF SYMMETRY, VARIABILITY, AND COMPLEXITY OF STRIDE DURING PROLONGED OUTDOOR RUNNING

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The aim of this study was to analyse the influence of acute fatigue on the asymmetry, variability, and complexity of the running pattern. We equipped 11 half-marathon participants with an inertial measurement unit (IMU) on each foot and a global navigation satellite system (GNSS)-IMU sensor on chest. Every 10 minutes of the race, the participant pronounced their perceived rating-of-fatigue (ROF) on a scale of 1 to 10. We divided the race into 8 equal segments, with one ROF score per segment, and included only the flat running parts. Temporal gait parameters were extracted using validated algorithms, followed by the computation of their asymmetry, and the variability and complexity of the cycle time (CT). Gait asymmetry increased significantly toward the end of the race and at higher perceived fatigue; faster runners showed a greater increase in asymmetry. CT variability increased significantly at the beginning of the race and then remained stable for all participants, but faster runners showed up to 20% less variability. No significant change was observed in CT complexity. This study highlights the increase in asymmetry and variability due to acute fatigue, with differences between fast/slow runners, and the importance of simultaneously measuring perceived fatigue and gait parameters under real-world conditions.

KEYWORDS: FATIGUE, BIOMECHANICS, PERFORMANCE, WEARABLE SENSORS

INTRODUCTION: Measurement of symmetry during running can help evaluate the risk of overuse injury for a particular limb and test the athlete’s readiness to resume training after rehabilitation (Zifchock et al., 2008). 10% increase in the asymmetry in step time and contact time can lead to increased metabolic costs of running, up to 3.5% and 7.8%, respectively (Beck et al., 2018). Similarly, cycle time variability and its long-range correlations (complexity) are an indicator of running technique, and a potential predictor of running related injuries (RRIs) (Gruber et al., 2021; Meardon et al., 2011), with trained runners showing lower variability and higher complexity (Nakayama et al., 2010). Therefore, measuring symmetry, variability, and complexity of stride cycles during prolonged running may allow athletes to better understand their technique and optimize their pacing strategies, as well as their training plan. Acute fatigue, which is the onset of fatigue occurring concurrently with the activity (Apte et al., 2021), led to an increase in the asymmetry of kinetic and kinematic variables during running (Radzak et al., 2017; Tabor et al., 2021), but these findings were limited to treadmill running and 50 m sprints. Variability and complexity of stride time varied non-linearly for amateur and experienced runners, during prolonged running on track (Meardon et al., 2011) and treadmill (Mo & Chow, 2018), due to acute fatigue. However, these results were not considered in relation to the progression of perceived fatigue, which can enable a more in-depth understanding of exercise-induced acute fatigue. This work aims to complement existing research by providing a synchronous analysis of the symmetry, variability, and complexity of gait cycles and the evolution of perceived fatigue during a half-marathon. These results should lead to a better understanding of the effects of fatigue on gait quality and thus play a role in improving performance and reducing risk of RRI.

METHODS: The dataset used for this study is from (Prigent et al., 2022) and included 11 healthy half-marathon participants, equipped with a GNSS-IMU sensor (*Fieldwiz, ASI, Switzerland, IMU: 200 Hz, GNSS: 10 Hz*) on the chest, an IMU sensor (*Physilog 5, Gaitup SA, Switzerland, acc: 512 Hz, gyro: 512 Hz*) on each foot. Every 10 minutes during the race, the participants verbally reported their perceived rate of fatigue (ROF) on a scale of 1 to 10, which were recorded by the smartphone. For each participant, gait velocity (v) was estimated from the GNSS receiver and gait parameters were extracted from foot IMU signals – contact time (t_c) swing time (t_s), cycle time (t_g), peak swing velocity (p_s), and duty factor (d_F). To address the change in speed at the start/end of the race, we removed first and last 50 strides and made sure the step number corresponding to both legs was identical. The five fastest and slowest participants were selected as the fast and the slow groups, respectively.

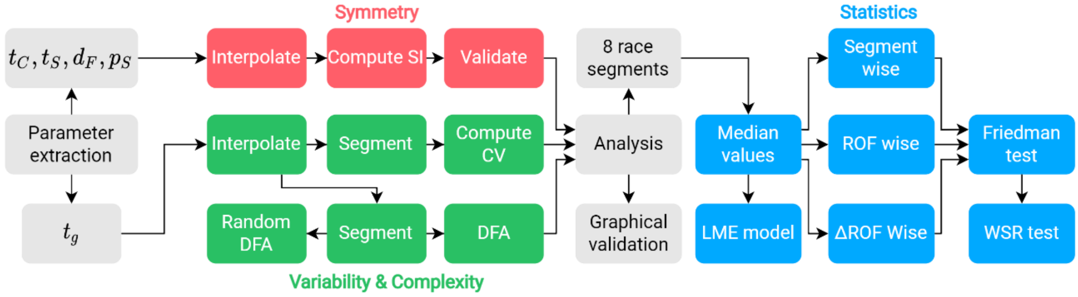

Figure 1: Flowchart of the stride quality study, with the steps for calculating the symmetry, variability, and complexity of the extracted gait parameters and statistical analysis shown in red, green, and blue, respectively.

Asymmetry: Our dataset is based on single values of gait parameters per gait cycle, and thus we used discrete symmetry coefficients, though they are less sensitive than the continuous coefficients (Błażkiewicz et al., 2014; Tabor et al., 2021),. To quantify symmetry for spatio-temporal parameters, four metrics (Błażkiewicz et al., 2014) have been previously used: Ratio Index (RI), Symmetry Index (SI), Symmetry Angle (SA), and Gait Asymmetry Index (GAI). However, for RI, SA and GAI, the calculation considers the ratio between the right and left limb values, and thus remains susceptible to influence of the dominant leg. Furthermore, results from (Błażkiewicz et al., 2014) suggested a high similarity between RI and SI, and their advantage over SA. Based on these conclusions, SI ($SI = 2|X_L - X_R|(X_L + X_R)^{-1} \text{ x } 100\%$), where X_R and X_L are parameters for the right and left limbs) was selected as the metric for assessing symmetry. We thus used SI (Figure 1) for four gait parameters– contact time (SIt_c), swing time (SIt_s), duty factor (SId_f) and peak swing velocity (SIp_s), based on their evolution with acute fatigue during running (Apte et al., 2021; Prigent et al., 2022). SI was also computed for the gait cycle time to check its validity, as the cycle time should present a SI close to zero.

Variability and Complexity: To characterize the variability and complexity of stride, we used the gait cycle time as a parameter of interest. This choice allowed comparison with results from previous studies (Meardon et al., 2011; Mo & Chow, 2018) on prolonged running. To assess the stride-to-stride variability and quality of strides over a given time, coefficient of variation (*CV*) is an efficient metric (Meardon et al., 2011). The race was therefore divided into 25 segments of equal duration and CV of gait cycle time was computed for each of these segments. However, two distinct signals can show the same variance in the form of CV and thus we need to study them further. In order to fully capture the nature of the evolution of the cycle time over the race, we analysed the complexity of the stride (Mo & Chow, 2018). Complexity can be defined as the amount of nonlinear information that a time series conveys over time. A reliable metric to assess the complexity of gait is the *α-DFA* coefficient (Damouras et al., 2010), that can be computed with Detrended Fluctuation Analysis (DFA). We performed the DFA analysis over a sliding window of size 500 strides, with an increment of 100 strides. A random DFA analysis was also performed to validate the procedure by shuffling the input values and check that obtained vector showed no memory (alpha around 0.5).

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 metrics and gait velocity (*v*) was computed for each segment (Figure 1). To reduce inter-subject variance, we normalized the values by dividing each median value by the median value of the segment with the highest running velocity. 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. To consider the perceived fatigue, we compared segments with the highest (H), medium (M), and lowest (L) ROF values. Fatigue levels of each participant were pooled into three different groups, which were compared with the F test and WSR tests (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 three states, by combining ΔROF 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 (FG/SG 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). All computations were performed using MATLAB 2020.

RESULTS AND DISCUSSION: The overall asymmetry increased for all participants along the race; Figure 2A shows the trend for SIt_c and similar trends were observed for SIt_s, SId_f, and SIp_s. While the range of increase (~10%) is in accordance with the results from literature (Radzak et al., 2017), we have presented a full race profile for asymmetry, which complements the existing pre-post results. Except for SIp_s, all SI metrics showed a significant increase at the end of the race and at high perceived fatigue levels (Table 1). The increase of asymmetry is higher for the fast runner halfway through the race; they typically have a lower t_c and d_f, which can accentuate the dominant leg effect. Only fast runners showed an increase in SIt_c for change in perceived fatigue (Figure 2D). This trend was also observable for other parameters, with SIt_s increasing significantly (Table 1) for all three ΔROF levels. Since *v* did not show any significant changes, we can conclude that acute fatigue led to the observed increase in asymmetry.

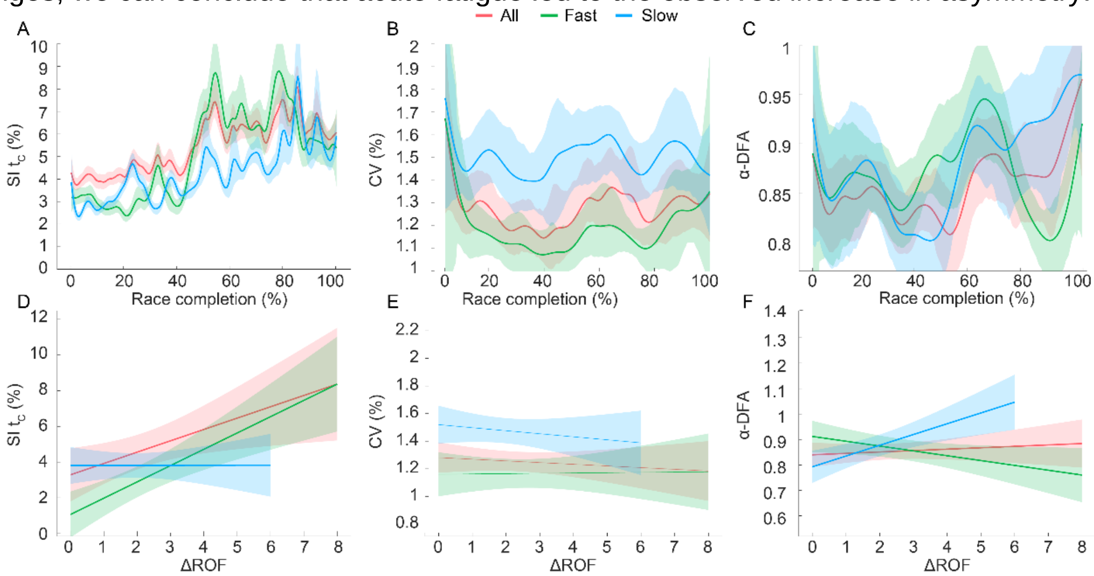

Figure 2: Evolution of the stride quality. Figures A, B, and C show the actual change with race progression for symmetry index of contact time (SItc), coefficient of variation (CV), and the index of detrended fluctuation analysis (α-DFA) for gait cycle time. Figures D, E, and F show the linear change with perceived fatigue. FG (green): group with fastest five runners and SG (blue) the slowest five. 'All' (red) shows trends for 13 participants together.

Unlike symmetry, the variability of the gait changed non-linearly throughout the race after an initial reduction in *CV* (Figure 2B), and the values are consistent with literature (Meardon et al., 2011). Fast group showed a consistently lower CV than slow group (up to 20%) throughout the race and with ΔROF (Figure 2E) but presented an increase in *CV* at the end of the race. This profile for fast runners is similar to the one observed in the lab (Mo & Chow, 2018). This is likely because fast runners are more experienced with managing the regularity of the gait and adjusting their pacing strategy accordingly (Prigent et al., 2022). Though *CV* did not show any significant changes with the race (Table 1), it showed a significant change at low perceived fatigue, despite no significant change in speed. The difference in results for race progression and ΔROF highlights the relevance of the measurement of perceived fatigue during outdoor running protocols. This observation is consistent with (Prigent et al., 2022), where the authors noted significant changes for spatiotemporal parameters at low ΔROF levels. We did not observe a clear distinction between groups for the evolution of α-*DFA* with the race progression (Figure 2C). The obtained values for *α-DFA* are in the similar range as those previously observed in a lab protocol (Mo & Chow, 2018). *α-DFA* decreased for fast and slow groups till around 40% of the race, followed by a sudden increase for slow group and a cyclic change for fast group. This change in complexity could be due to the differences in respective pacing strategies adopted by the fast and slow runners (Mo & Chow, 2018). This is also reflected in the linear trend for ΔROF, where *α-DFA* is increasing for slow runners, and decreasing for fast runners. However, the complexity did not show any significant change during the statistical analysis.

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.

	Race-Wise				ROF-Wise				ΔROF-Wise			
	Friedman	WSR Test (ES)			Friedman	WSR Test (ES)			Friedman	WSR Test (ES)		
Parameter	Test (ES)	S1: S5	S5-S8	S1-S8	Test (ES)	L:M	M:H	L:H	Test (ES)	0-1,2	0-3,4	0-+5
SIt_c	0,11	0,28	0,11	**0,42***	**0,32***	0,08	**0,49***	**0,46***	0,17	0,21	0,25	**0,38***
SIt_s	**0,31***		0,17	**0,46***	**0,28***	0,23	0,40	**0,49***	**0,31***	**0,51***	**0,42***	**0,47***
SId_f	0,11	0,34	0,15	**0,46***	0,17	0,12	**0,45***	**0,44***	0,11	0,30	0,25	**0,38***
SIp_s	0,03	0,36	0,13	0,30	0,08	**0,46***	0,01	0,32	0,23	**0,47***	**0,47***	0,34
CV	0,06	0,40	0,25	0,17	**0,29***	**0,45***	0,38	0,06	0,14	**0,49***	0,28	0,04
α-DFA	0,07	0,10	0,11	0,11	0,04	0,16	0,11	0,13	0,02	0,17	0,12	0,12
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 that fatigue leads to an increase in asymmetry of gait and influences variability and complexity of gait cycle time. Faster runners showed a lower variability than slower runners, but a higher increase in asymmetry with fatigue. Assessment with respect to perceived fatigue provided different results than that with race progression for gait variability. However, further studies with a larger number of runners are recommended. Utilization of such wearable sensor setups may further allow a more personalized approach to fatigue analysis and aid runners to optimize their pacing strategies by understanding their running technique better.

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