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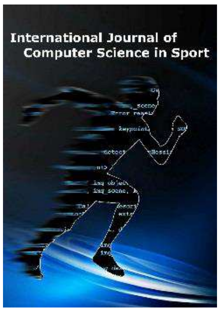

A Pilot Study in Sensor Instrumented Training (SIT) - Ground Contact Time for Monitoring Fatigue and Curve Running Technique

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Abstract

This study examines the possibilities of sensor-instrumented training (SIT) in mid-distance running training sessions. Within this framework, variations of ground contact time (GCT) between straight and curved running, as well as GCT as a fatigue indicator, are explored. Seven experienced runners, with two elite female athletes, participated in two training protocols: 15 sets of 400 m with 1-minute rest and five sets of 300 m with 3-minute rest. GCT was calculated using two inertial measurement units (IMU) attached to the athletes' feet. The running speed of all athletes was measured with wearable GPS devices. GCT showed variations between inner and outer feet, notably during curve running (300m: 2.56%; 400m: 2.35%). However, for the 300m runs, statistically insignificant GCT differences were more pronounced in straight runs (3.54%) than in curve runs (2.56%), contrasting with the typical assumption of higher differences in curve running. A fatigue-indicating pattern is visible in GCT, as well as speed curves. Other data of this study are consistent with prior research that has observed differences between the inner and outer foot during curve running, while our understanding of the development throughout the training session is enhanced. Using SIT can be a valuable tool for refining curve running technique. By incorporating novel sensing technology, the possibilities enhance our understanding of running kinematics and offer an excellent application of SIT in sports.

KEYWORDS: PERFORMANCE ANALYSIS, TRAINING CONTROL, SENSORS, CURVE RUNNING, GROUND CONTACT TIME

Introduction

Sports disciplines like mid-distance running, characterized by demanding speed and endurance, are predominantly staged on oval tracks with varying distances. Achieving peak performance in these disciplines necessitates athletes to undergo specialized training regimens, including a spectrum of different training protocols. Different running parameters can be measured throughout these training sessions and come under assessment.

For instance, ground contact time (GCT) is one important factor affecting a runner's performance and running economy (Joubert, Guerra, Jones, Knowles, & Piper, 2020; Mooses et al., 2021). GCT is the time a runner's foot spends in contact with the ground during each stride. A shorter ground contact time (GCT) is linked to swifter acceleration and exerts a positive impact on running economy, whereas a longer GCT can result in delayed finishing times and reduced force production (Lockie, Murphy, Schultz, Jeffriess, & Callaghan, 2013; Weyand, Sternlight, Bellizzi, & Wright, 2000). Research on mid-distance running has primarily focused on competition or race conditions (Renfree, Mytton, Skorski, & St Clair Gibson, 2014), with little attention given to GCT, especially during training. Inertial measurement units (IMU) application and appropriate data processing can monitor entire training sessions (Falbriard, Mohr, & Aminian, 2020; Schmidt et al., 2016). Understanding GCT during training is essential, as it can provide insight into a runner's technique. Generally, implementing feedback from measurements is essential within training control (Hohmann, Lames, Letzelter, & Pfeiffer, 2020). Furthermore, the effects of running on different track sections, such as straight and curved passages, on GCT during training have not been thoroughly investigated. Running on curved surfaces requires greater changes in direction and may lead to differences in GCT between feet compared to straight running (Alt, Heinrich, Funken, & Potthast, 2015; Churchill, Salo, & Trewartha, 2015).

Another aspect of training control is fatigue. It represents a multi-factorial phenomenon that impacts an athlete's performance capacity (Halson, 2014). Assessment of fatigue is crucial for optimizing training regimens and preventing injuries. One approach to assessing fatigue involves the study of stretch-shortening cycles within muscle contractions. Here, the muscle undergoes rapid transitions between eccentric and concentric phases, like, for example, within a ground contact in running, sprinting or jumping (Hennessy & Kilty, 2001). GCT has been proven a valuable parameter in this context for controlling fatigue in running, although mostly in lab settings (Apte et al., 2021). By monitoring GCT, coaches and sports scientists might gain insights into an athlete's fatigue status and make informed in-training decisions regarding training intensity, ultimately improving athletic performance and reducing the risk of injuries.

This example highlights that different variables need to be monitored to support training control (Fernandes, Garganta, & Anguera, 2012). The concept of ubiquitous computing in sports brings the integration of small, interconnected, and intelligent tools, particularly sensor technologies like IMUs and GPS sensors, within the pervasive computing paradigm (Baca, Dabnichki, Hu, Kornfeind, & Exel, 2022). These sensors, usually integrated into wearable devices, facilitate real-time data acquisition and analysis, enabling athletes and practitioners to integrate objective information. Especially over the past years, this field saw remarkable advancements driven by the convergence of wearable technology, cloud computing, and artificial intelligence.

IMUs, for instance, enable precise motion tracking, while GPS sensors provide geospatial data critical for performance assessment. This study mainly focuses on implementing IMU-measured data while additionally consulting GPS-measured data at specific sections and not analyzing it holistically. These innovations have impacted the landscape of sports analysis, offering the potential to capture data under field conditions. Numerous applications of these sensor-driven measurements can be found across a wide range of sports. In the following, we refer to this as sensor instrumented training (SIT). The current limitations in data acquisition, processing practices, and sensor functionalities, which hinder data-driven decision-making in the present technological and scientific context, must be acknowledged.

This study aims to explore the potential of conducting SIT in sports. Exemplary looking at GCT in curve running and indicators of fatigue within intensive and extensive running training sessions. While developing an entirely sophisticated solution is not the immediate goal, the feasibility and practicality of training control with SIT are shown.

Methods

Sample and protocol

The sample consists of seven experienced runners (age: 25.0 ± 3.2 years; weight: 61.7 ± 7.0 kg; height: 175.3 ± 10.1 cm; gender: 4f/3m). The data comprises five training sessions, with one participant completing both training protocols on different days. In order to cover a broad spectrum of practical training methods, one protocol each for the intensive and the extensive interval method (Hohmann et al., 2020) was included. During the different training protocols (extensive: 15*400 m, 1 min rest; n=4; intensive: 5*300 m, 3 min rest; n=4), GCT was measured using two sets of two IMUs (Physilog5 & Physilog6, Gait Up SA. Lausanne, Switzerland; Physilog5, size: 47.5 mm x 26.5 mm x 10 mm, weight: 11 g & Physilog6, size: 42.2 mm x 31.6 mm x 15.0 mm, weight: 15 g; Figure 1) each at the athletes' feet (Blauberger, Horsch, & Lames, 2021). The coach set the threshold based on individual training experiences regarding the intended running speed. The training protocol can be overviewed in Table 1. One athlete had to skip the final run within the intensive training protocol. The analysis included two female athletes who competed at the highest international level (WC/EC; official 800 m best times of 1:59.41 min and 2:00.36 min). Additionally, all athletes were equipped with GPS sensors (transponder (GPSports Sports Performance Indicator (SPI) Pro X, Canberra, Australia); Figure 1).

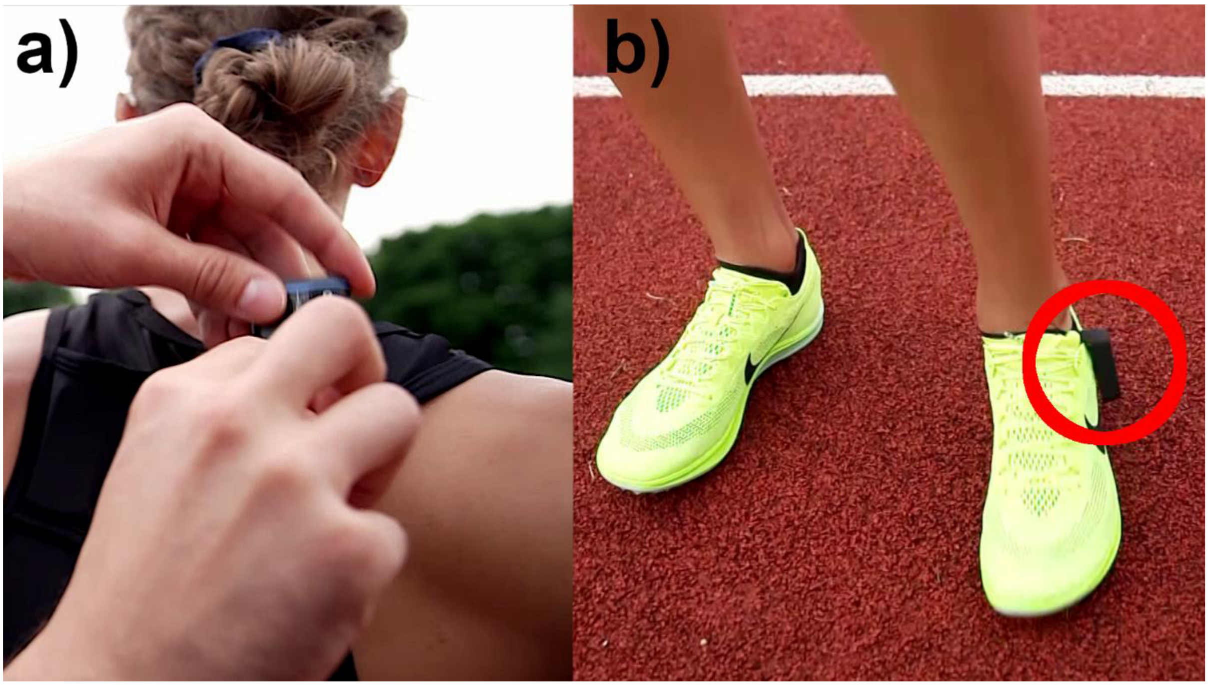

Figure 1: GPS receiver attachment location (a) and IMU sensor attachment location at both shoes (b).

The training was performed on an official running track (World Athletics, 2019) in five training sessions. Before each training session, the participating athletes were informed about the purpose of the study and the collected data. The study accorded to the ethical standards of the Technical University of Munich, and all subjects gave informed written consent. Additionally, all personal data were anonymized to ensure privacy. The study design corresponded to the recommendations of the Declaration of Helsinki.

Table 1: Description of running protocol and analyzed steps per athlete and run.

	300m	400m
Number of runs	5	15
Rest [min]	3	1
Number of athletes	4	4
Steps in curve per athlete per run	5	5
Steps on straight per athlete per run	5	5
Total steps in curve per run	20	75
Total steps on straight per run	20	75

Measurement systems

The IMUs were securely attached to the side of each running shoe. This methodology was chosen for its ease of application, lightweight design, and minimal impact on athletes' performance. The positioning of the IMUs on the ankle was also used in a previous validation study (Blauberger et al., 2021) to ensure data comparability. Athletes who participated in the study reported no issues with the sensor attachment. Each IMU includes a 3D accelerometer and a 3D gyroscope, both operating at a sampling frequency of 512 Hz. The accelerometer has a range of ±16 g, while the gyroscope has a range of ±2000°/s.

Additionally, the athletes were equipped with a GPS. The transponder was positioned on the upper thoracic spine, between the scapulae. All GPS transponders were activated 15 minutes before data collection for proper satellite signal acquisition. Only GPS signals that met the manufacturer's internal quality standards were recorded (Shergill, Twist, & Highton, 2021).

Data processing and analysis

The raw signals of the IMUs' accelerometer and gyroscope were used to find the step event of initial contact and toe-off. Therefore, data was filtered and analyzed using a previously developed and validated methodology (Blauberger et al., 2021). Each resulting ground contact can be associated with the precise event time relative to the start of the run. GCT was assessed using the average GCT of the five steps closest to the middle of the first curve and one linear running corridor. The total step counts per curve and straight section can be seen in Table 1. All total run values comprise all steps of the whole run. Additionally, GPS data enabled continuous measurement of speed and covered distance.

All values, tables, and graphs were developed using Matlab (R2022a, The MathWorks Inc., Natick, MA, USA). For the figures, data was filtered using a 4th-order Butterworth low-pass filter with a cut-off frequency of 1 Hz. Percentage differences were calculated as the percentage deviation of the former value. To compare GCT between the left and right foot during entire runs, we first assessed the normality of the data using the Shapiro-Wilk test. Depending on these results, a paired t-test (for normally distributed data) or Wilcoxon signed-rank test (for nonnormally distributed data) was employed to display statistical differences in GCT values. The level of significance was set to p<0.05. Cohen's d effect sizes (ES) were classified as trivial (0-0.19), small (0.20-0.49), medium (0.50-0.79) and large (>0.80) (Cohen, 1992).

Results

The first result section includes GCT results on all 300 m and 400 m runs, emphasizing curve running. In the second part, results are shown for indications of fatigue with exemplary looking into the data of an elite athlete's training session. This athlete's runs are particularly interesting, as the coach signalled the athlete after the first run that the intensity was slightly too high to complete the planned training. This feedback arose only from the coach's "gut feeling" and the measurement of the final time.

Results on curve running

For the 300 m runs, a total difference of 1.44% between the inner and outer foot was found. This difference is not significant (p = 0.35) and shows a trivial ES (0.19). The mean contact time during straight sections (143.87 ms) was lower than in curve sections without statistical signifance (149.78 ms; p = 0.18; ES = 0.32). Also, the percentual disbalance was higher in straight sections than in curve sections. The overall mean GCT increased insignificantly but with a high ES (p = 0.25; ES = 4.74) from 140.57 ms (run 1) to 156.00 ms (run 5). Although the absolute GCT was longer, the difference between the feet did not show an increase. The progress within the training can be seen by showing run 1, run 3, and run 5 (Table 2). It needs to be emphasized, that none of the differences in Table 2 showed statistical significance.

Table 2: Mean IMU measured ground contact time (GCT) ± standard deviation in milliseconds and the percentage difference between inner and outer foot in 300 m runs. The total run aggregates the GCT of all steps. P-values are presented as $^{-}$ (p > 0.05) and * (p < 0.05). Cohen's d effect sizes were classified as ^{t} = trivial (0-0.19), ^{s} = small (0.20-0.49), ^{m} = medium (0.50-0.79) and ^{l} = large (>0.80). Both indicators are superscripted after the percentage difference value. No statistical significant differences were found.

		All runs	Run 1	Run 3	Run 5
Total run	Inner foot [ms]	146.46±7.97	139.04±7.39	146.83±6.28	152.21±9.97
	Outer foot [ms]	148.57±13.12	142.10±12.90	147.57±15.23	159.78±8.16
	Difference [%]	1.44^{-t}	2.20^{-s}	0.51^{-t}	4.97^{-l}
Curve section	Inner foot [ms]	151.72±9.69	141.70±7.02	155.08±10.46	158.33±11.59
	Outer foot [ms]	147.84±12.08	141.11±14.09	146.09±11.12	155.47±5.83
	Difference [%]	2.56^{-s}	0.41^{-t}	5.79^{-m}	1.81^{-s}
Straight section	Inner foot [ms]	141.37±9.14	134.77±9.74	144.43±7.39	146.52±9.43
	Outer foot [ms]	146.37±12.35	141.36±11.95	148.14±15.76	156.38±7.82
	Difference [%]	3.54^{-s}	4.89^{-s}	2.57^{-t}	6.73^{-l}

Overall, the GCT for 400 m runs revealed a deviation of 1.31% (p = 0.01; ES = 0.36) between the inner and outer foot. By separating the 15 runs into three equal groups, development within the training session can be tracked. The discrepancy of GCT between feet is smaller in the straight part of the runs than in the respective curved section. While the deviation between the inner and outer foot in curve running rose, the absolute GCT remained at the same level (Table

3). Out of 12 reported deviations in Table 3, four showed statistical significance.

Table 3: Mean IMU measured ground contact time (GCT) ± standard deviation in milliseconds and percentage deviation between inner and outer foot in 400 m runs. The total run aggregates the GCT of all steps. P-values are presented as $^{-}$ ($p > 0.05$) and * ($p < 0.05$). Cohen's d effect sizes were classified as ^{t} = trivial (0-0.19), ^{s} = small (0.20-0.49), ^{m} = medium (0.50-0.79) and ^{l} = large (>0.80). Both indicators are superscripted after the percentage difference value.

		All runs	**Run 1-5**	**Run 6-10**	**Run 11-15**
Total run	Inner foot [ms]	190.79±15.39	189.50±17.98	193.62±14.48	189.12±14.17
	Outer foot [ms]	188.30±12.85	186.59±16.71	192.28±6.72	185.84±13.26
	Difference [%]	1.31^{*s}	1.53^{-m}	0.69^{-t}	1.73^{*m}
Curve section	Inner foot [ms]	192.48±16.25	189.06±19.86	195.79±15.14	192.06±14.06
	Outer foot [ms]	187.95±14.76	184.88±19.92	192.95±7.06	185.54±14.84
	Difference [%]	2.35^{*s}	2.21^{-s}	1.45^{-s}	3.39^{*s}
Straight section	Inner foot [ms]	189.71±15.70	187.47±19.45	193.02±13.78	188.06±14.73
	Outer foot [ms]	188.37±14.85	186.73±17.67	192.47±8.11	185.44±17.29
	Difference [%]	0.71^{-s}	0.40^{-s}	0.29^{-t}	1.39^{-s}

Figure 2 illustrates the GCT of the inner and outer feet in 300 m and 400 m runs during straight and curve running. The inner foot's GCT was always more prolonged in the curve than during straight running. However, the outer foot's contact time did not differ substantially during straight and curve running.

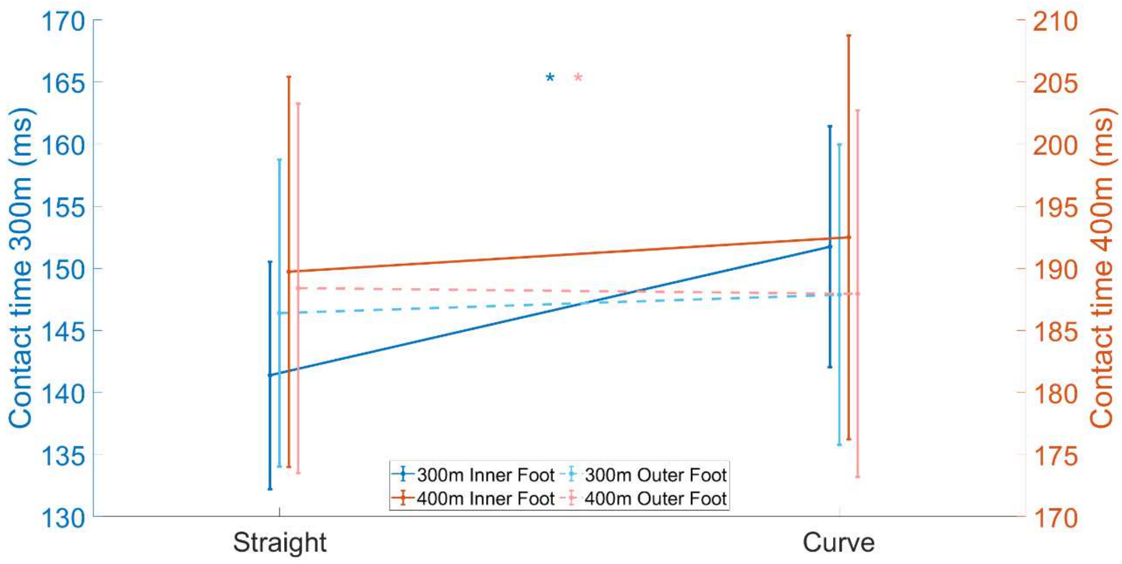

Figure 2: Mean IMU measured ground contact time (GCT) in milliseconds between straight and curve running for the inner and outer foot in 300 m and 400 m runs with standard deviations. Statistical significance ($p > 0.05$) is indicated with * in the respective colour.

Figure 3 displays the continuous development of the GCT in 300 m runs. The first part (a) presents the smoothed average GCT of both feet, while section (b) illustrates the GCT of the left and right foot individually. This exemplary figure indicates the influence of curve running on GCT. The running times are normalized, and display all runs' average times.

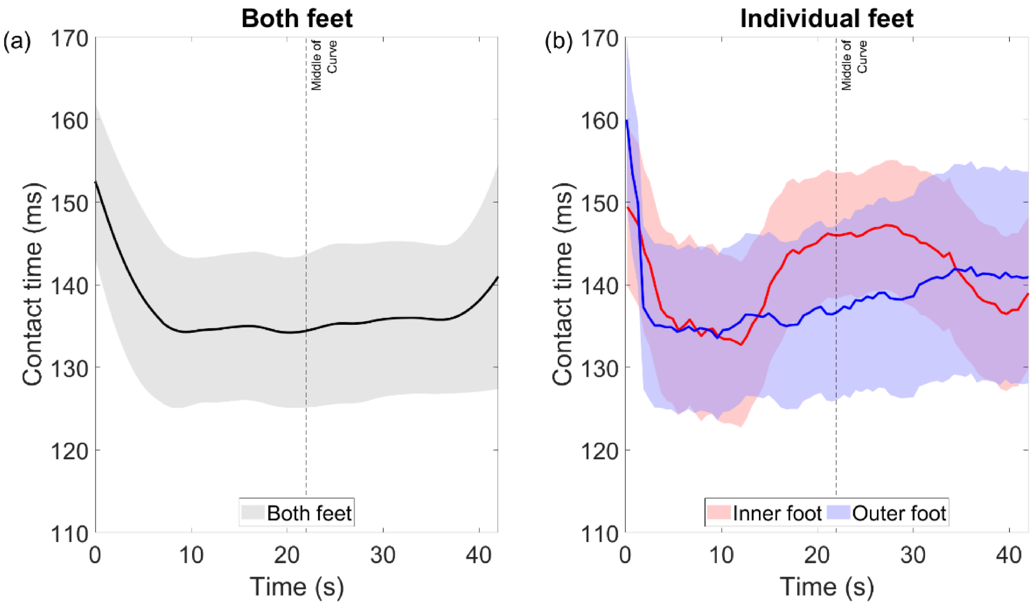

Figure 3: Illustration of ground contact time (GCT) across a 300 m distance run within an intensive training session. Plot (a) displays the smoothed average of the GCT for both feet, while the subsequent plot (b) presents the GCT of each foot separately. Both plots show the respective continuous standard deviations in transparent colour. A pattern concerning the laterality of the foot can be linked to running on the curved sections of the track.

Results on fatigue

To visualize results regarding fatigue during training, the data of one elite athlete is shown in detail. Figure 4 illustrates the GPS-recorded continuous speed during five 300 m runs within the same training. The blue and red lines are highlighted to underline the development between the first and second runs. The “too fast first run” found by the coach can be seen in the GPS data.

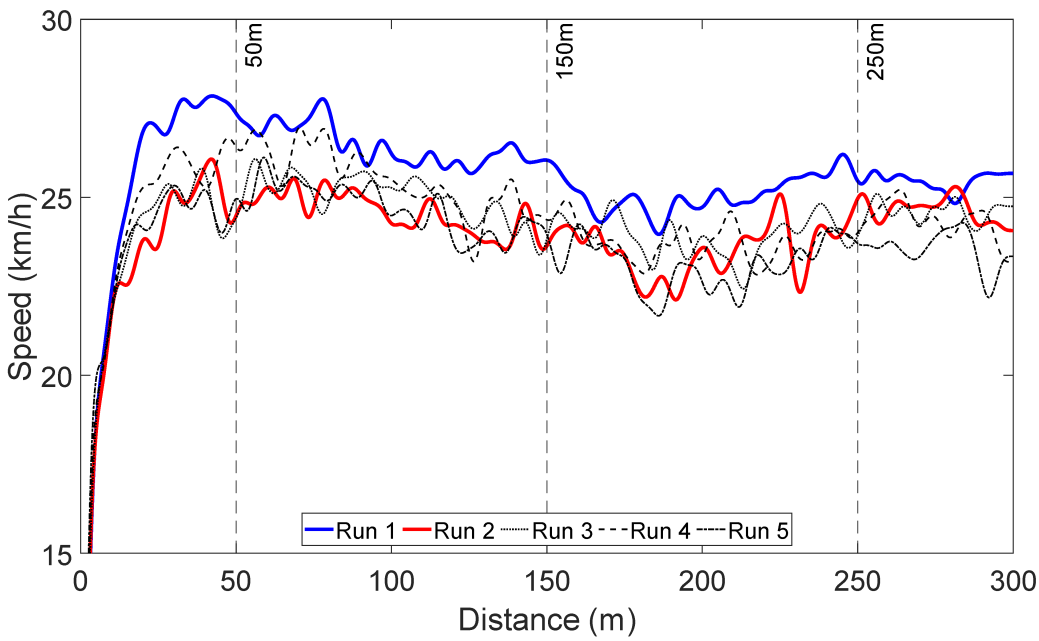

Figure 4: GPS-tracked speed, plotted over the distance of 300 m. The two bold lines (Run 1 & Run 2) show the athlete’s fast start, leading to higher exhaustion than intended and needing to be controlled by the coach. After this intervention, the speed stayed at a comparable level.

In Figure 5, we revisit the training runs of the same athlete, this time focusing on the evolution of GCT. Notably, a major increase in GCT from the first to the second run indicates a change in running mechanics. This growth suggests that the athlete, likely prompted by the coach's intervention regarding their pacing strategy (as observed in Figure 4), adjusted their technique during the subsequent runs. Complementary to the GPS data, it can be distinguished between different step numbers. The first five steps are skipped in the graph to avoid the error-proneness of the methodology close to the start (Blauberger et al., 2021).

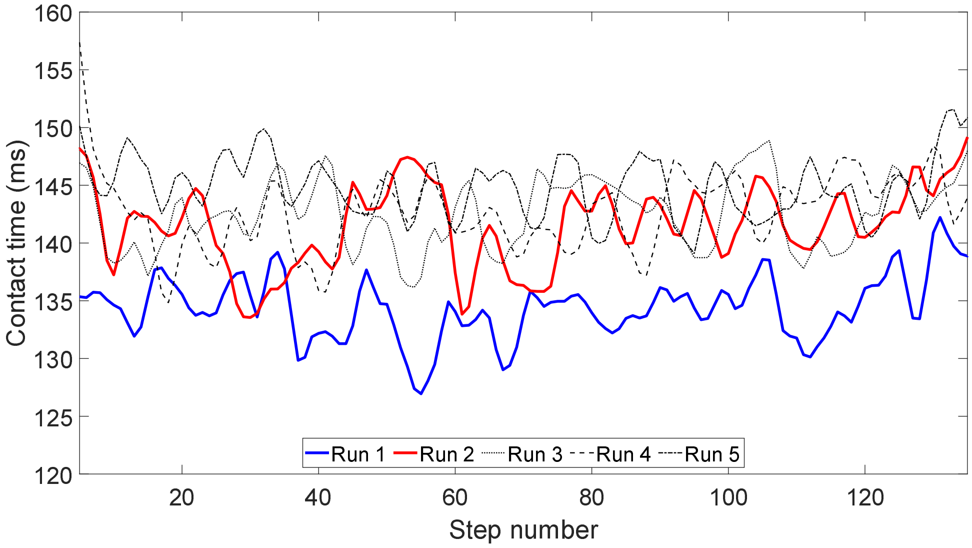

Figure 5: Mean ground contact time (GCT) of the same athlete within five 300 m runs. This data suggests a too-high intensity in the first run, which led to an intervention by the coach.

Discussion

Discussion of results

The results of this study, while indicative of specific trends, notably underscore the individuality in performance and response to training. Each athlete's data presents a unique profile, reflecting the interplay of physiological, biomechanical, and environmental factors. Although this individual variability limits the generalizability of our findings, it is crucial in demonstrating the potential and applicability of SIT. Especially, the statistical non-significance of many findings needs to be highlighted. Consequently, while the results may not provide an universal blueprint applicable to all athletes, they are showcasing the role of SIT for the application tailored training interventions. When customized to the individualities of each athlete, these interventions can enhance training outcomes. Thus, although our results are not broadly generalizable, they offer compelling evidence of the efficacy of SIT in a high-performance sports context, underscoring its utility in optimizing training strategies on an individual level.

The statistical results observed in our study should be interpreted with care. Table 2 shows no significant differences at all, while only 4 out of 12 comparisons in Table 3 show significant deviations. Therefore, also effect sizes are reported alongside p-values. Effect sizes offer a deeper insight into the substantive significance of our findings, revealing the magnitude of observed differences or relationships that do not state statistical significance, which might be harder to achieve in this study with a small sample size (Sullivan & Feinn, 2012). While interpreting the statistical outcomes of our study, it is crucial to note that even large effect sizes may not result in statistical significance, underscoring the importance of cautious interpretation, especially in the context of a small sample size.The results show that continuous step-by-step monitoring of the GCT of both feet provides valuable insights into the technique of curve running. Differences between the inner and outer foot in curve running (Figure 2) confirm previous findings in the literature based on an 8 m running corridor in the curve (Alt et al., 2015). To the best of the authors' knowledge, the increasing percentage differences throughout interval training were not reported before.

Moreover, the results show that continuous step-by-step monitoring of the GCT of both feet provides valuable insights into the technique of curve running. This study's training protocols are used commonly in practice (Fernandes et al., 2012) and, therefore, for training and competition analysis at the highest level. The 300 m runs of elite athletes show the necessity of assessing GCT continuously and for both feet separately. It is illustrated that inner and outer feet should be treated individually, showing different patterns (Figure 3).

However, an interesting finding emerged in our analysis of the 300m runs that diverged from common assumptions regarding GCT differences between legs in curved versus straight sections. Table 2 indicates that the observed differences in GCT were more pronounced during the straight sections (mean difference = 3.5%) compared to the curve sections (mean difference = 2.6%). This suggests that factors other than mere directional changes might contribute to GCT variations. This data thus highlights the complexity of GCT dynamics and underscores the importance of considering individual training developments.

In the scope of the discussion of the observed pattern, it is essential to note that while the data presented in Figure 3, 4 & 5 belongs to one elite athlete, similar trends were noticed among the other participants, including both elite and non-elite athletes. This underlines the value of SIT in capturing individual data. It also aligns with our emphasis on the individuality of results, illustrating that while our findings are demonstrative of the effectiveness of SIT, they also highlight the need for personalized training approaches for each athlete. This individual perspective remains central to our discussion and the broader applicability of our study.

The data shown in Figure 4 provides an in-depth look at the speed patterns of one elite athlete during a series of 300-meter runs, offering valuable information about their performance and how they manage fatigue. This figure highlights a notable trend, specifically a "too fast start," which occurs when the athlete begins their training session at a pace that is too quick to maintain throughout the exercise. Essentially, the athlete starts much faster than they can sustain, leading to potential early exhaustion. This pattern is crucial for coaches to observe. It demonstrates the athlete's tendency to exert too much effort too quickly, which can be counterproductive in training and competitive environments. By identifying this development, coaches can provide immediate feedback to the athlete, advising them to adjust their pacing. This might involve starting at a more controlled, sustainable speed, allowing the athlete to conserve energy and maintain a steadier pace throughout the run.

In Figure 5, we revisit the running performance of the same elite athlete, looking into the progression of GCT during the training session. Notably, this athlete's GCT data provides insights into the impact of training intensity and fatigue. The graph shows a visible increase in GCT when transitioning from the first run to the second run. This shift indicates a substantial alteration in running mechanics, potentially driven by the initial high-intensity effort in the first run. It is worth noting that this abrupt change in GCT could result from both the athlete's conscious adjustments and the body's natural adaptation to the running demands. Complementary to the GPS data (Figure 4), it can be distinguished between different step numbers. In combination, exact distances within the run can be associated with ground contacts. Observing such nuanced alterations in GCT underscores its value as a parameter for assessing fatigue and real-time technique modifications during training, emphasizing the crucial role of GCT monitoring in optimizing athletic performance.

Discussion of methodology

The methodology used in this study employed a combination of data collection techniques, including GCT measurements using inertial sensors and GPS data analysis. In other studies, these methods were already utilized to investigate the running characteristics of mid-distance runners during training.

The sample consists of seven experienced runners, focusing on one female athlete who competed at the highest international level (e.g., winning national championships). This selection ensures the inclusion of highly skilled athletes and provides valuable insights into the running characteristics of elite runners. P-values and effect sizes from pilot studies like this can help guiding the design of future studies, particularly in determining the necessary sample sizes to detect meaningful effects . By understanding the magnitude of the effects observed in a pilot study, researchers can more accurately estimate the sample size required for subsequent studies to ensure adequate statistical power.

Specific steps from each run were selected for evaluation. For the 300m runs, 20 steps from each curve and linear section were analyzed, amounting to 100 steps to the final assessment. Similarly, in the 400m runs, 20 steps per curve and linear section were examined, adding to 1125 steps across all runs. For the total run, every detected step was used. This methodological approach allowed for capturing the variations in GCT in different running sections. Another methodological procedure could have ended in slightly different results.

GCT is measured using four IMUs attached to the athletes' feet. This method is relatively new (Falbriard et al., 2020; Schmidt et al., 2016). The accuracy of GCT measurements using IMUs was previously tested and documented in another manuscript. Also, the positioning of the IMUs on the foot ankle follows this study's procedure to ensure consistency and comparability of the collected data (Blauberger et al., 2021).

To complement the GCT analysis, GPS transponders were utilized. These transponders were placed on the upper thoracic spine, between the scapulae, to capture and analyze the athletes' movement and speed during the training sessions. The GPS transponders were activated well before data collection to allow for satellite signal acquisition and ensure the quality of the recorded GPS data. Nevertheless, a margin of error can be found with this kind of tracking device, especially at higher speeds and curve running (Linke, Link, & Lames, 2018).

The collected data, GCT from the IMUs and GPS speed measurements are analyzed using appropriate statistical methods. The mean values and patterns of GCT for the inner and outer foot are examined, mainly focusing on the influence of running on the curved section of the track. The GPS speed measurements provide insights into the athletes' performance and allow for a comprehensive analysis of their running characteristics during different sections of the training runs.

The combination of IMUs and GPS data collection provides a validated methodology for analyzing the running characteristics of mid-distance runners. By incorporating both GCT measurements and GPS speed analysis, this study offers a comprehensive understanding of the athletes' running technique, performance, and the impact of different training conditions on their running characteristics.

Sensor instrumented training

The analysis of GCT dynamics within the training provides information about the athlete's adaptability and highlights the potential of SIT as a valuable tool for enhancing coaching decisions. By continuously monitoring GCT and other relevant metrics, coaches and athletes can adapt current training protocols to optimize performance.

Furthermore, the drop-off in GCT between the two more detailed analyzed runs underscores the importance of coaching intervention. These measurements can be implemented in the cycle of training control (Hohmann et al., 2020). Coaches control athletes' training and make informed decisions to optimize their training regimens. In this context, the observed changes in GCT provide a valuable cue for the coach to assess the athlete's level of fatigue and running efficiency. The coach's before-mentioned "gut feeling" can be supported with objective data.

The integration of real-time feedback mechanisms in sports training is a promising aspect to consider within the discussion of our study. In the context of our research, the continuous monitoring of GCT using sensor technologies like IMUs and GPS sensors presents an opportunity for real-time feedback to athletes and coaches. The data acquired could be directly processed and wirelessly distributed to provide live insights during training sessions (Baca et al., 2022). This real-time feedback empowers coaches to make required interventions, such as adjusting pacing strategies or refining running form, optimizing training regimens, and ultimately enhancing athletic performance. Furthermore, athletes can benefit from immediate feedback, enabling them to adapt even during the training. Thus, incorporating real-time feedback mechanisms based on GCT measurements possesses substantial promise for advancing sensor-instrumented training in sports. This study did not use real-time feedback but emphasized developing appropriate tools. For example, integrating various sensors into a mobile application could be tackled in future works.

Conclusion

This study adds to our current understanding of how running kinematics and training intersect. Commonly used information – like GPS-measured speed – can add information to regular training procedures. It is shown that this data can back up coaches' decisions regarding fatigue. Additionally, the application of sensing technology and specifically developed detection algorithms enable the continuous assessment of further parameters like ground contact time. Using this information, a prolonged GCT was found during curve running, especially in later phases of training.We advocate for further analysis of fatigue and curve run technique on a broader data basis, as their comprehensive understanding could potentially lead to enhanced training methodologies. We conclude that incorporating different sensor measurements showed indicators that could support the coaches' decisions during training and possibly competition.

Additionally, an improved comprehension of running techniques and their monitoring during training can benefit the effectiveness and quality of training in elite-level sports. We suggest that these applications can support sensor-instrumented training. This approach needs to be further investigated and developed to ultimately provide coaches and athletes with real-time feedback, for example, with a mobile application.

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