Examination of a Foot Mounted IMU-based Methodology for Running Gait Assessment

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Abstract

Gait assessment is essential to understand injury prevention mechanisms during running where high impact-forces can lead to a range of injuries in the lower extremities. Informing running style to increase efficiency and/or selection of the correct running equipment such as shoe type can minimize risk of injury through e.g., matching a runner's gait to a particular set of cushioning technologies found in modern shoes (neutral/support cushioning). Informing training or selection of the correct equipment requires understanding of a runner's biomechanics such as determining foot orientation when it strikes the ground. Previous work involved a low-cost approach with a foot mounted inertial measurement unit (IMU) and associated zero-crossing (ZC) based methodology to objectively understand a runner's biomechanics (in any setting) to inform shoe selection. Here, an investigation of the previously presented ZC-based methodology is presented only to determine general validity for running gait assessment in a range of running abilities from novice (8km/h) to experienced (16km/h+). In comparison to Vicon 3D motion tracking data, the presented approach can extract pronation, foot strike location and ground contact time with good ($ICC_{(2,1)} > 0.750$) to excellent ($ICC_{(2,1)} > 0.900$) agreement between 8-12km/h runs. However, at higher speeds (14km/h+) the ZC-based approach begins to deteriorate in performance, suggesting other features and approaches may be more suitable for faster running and sprinting tasks.

1 Introduction

Running has become one of the most prevalent sports, promoting health benefits through increased physical activity whilst remaining readily-accessible for all (Shipway and Holloway, 2010). With the increased uptake of running and running-based exercise, the incidence of lower-extremity injuries associated with running e.g., Achilles' tendinopathy and Plantar Fasciitis has risen (Dempster et al., 2021). Injury can be exacerbated in beginner and novice runners (Linton and Valentin, 2018), with a higher injury rate linked with self-devised, informal training plans compared to well informed approaches i.e., novice runners may not access/are unaware of information leading to efficient, safe running practices to minimize injury. Prominently, it has been shown that a high-incidence of injuries are due to impact-load management issues where a better understanding of the biomechanical properties within each running style plays a key role to understand type of injury. For example, rear-foot (heel) strikers are significantly more likely to incur an injury over those who run fore-foot (Daoud et al., 2012). More specifically, over-pronation during running can lead to medial tibial stress and Plantar Fasciitis (Rolf, 1995, Hintermann and Nigg, 1998).

Selection of the correct running equipment such as shoe type has shown to minimize injury risk through various cushioning technologies influencing load-management. For example, a support shoe will include anti-pronation cushioning to minimize roll of the foot on impact (Jafarnezhadgero et al., 2019). However, challenges arise when selecting the correct running shoe. Typically, a runner is manually assessed by an individual who (i) visually assesses the fall of the foot during walking or running overground or on a treadmill and/or, (ii) observes the wear pattern of previous running shoes to understand pronation severity and foot strike location (Higginson, 2009). However, visual assessments are intrinsically flawed through a lack of subjectivity and reliability (Higginson, 2009). Particularly, it has been shown that while the visual assessment of foot strike pattern is highly accurate, visually assessing pronation is unreliable between assessors, with agreements between 42% and 56% (Meyer et al., 2018). As such, the use of technology is essential for accurate instrumentation of running gait.

Three-dimensional (3D) motion capture video-based systems are generally considered the reference/gold-standard in gait assessment, consistently demonstrating validity and reproducibility in a range of applications (Baskwill et al., 2017, Albert et al., 2020, Jakob et al., 2021). However, use of a 3D motion tracking system demonstrates obvious pragmatic issues through high costs, an intrusive nature (i.e., users must be fitted with a range of anatomical markers) as well as need for technical expertise (Schlagenhauf et al., 2018, Sharma et al., 2019); limiting the technology's use in low-resource, real-world settings. As such, wearable inertial measurement unit's (IMU) have seen a recent usage uptake in running gait assessment through providing a low-cost apparatus capable of detecting intricate running gait outcomes (Benson et al., 2022, Young et al., 2020). Typically, IMUs contain a combination of inertial accelerometer and gyroscope sensors to provide an understanding of acceleration and rotation, respectively (Ahmad et al., 2013). IMUs can measure a wide range of running biomechanics including gait phase estimation (Young et al., 2021, Sui et al., 2020), impact analysis (Tan et al., 2020), flexion angles (Nagahara et al., 2020, Cooper et al., 2009), foot orientation (Falbriard et al., 2020) and asymmetry measures (Ueberschär et al., 2019, Benson et al., 2022). Crucially, their use enables reproduceable, objective gait outcomes that can enable standardization within the domain, especially in opposition to traditional visual assessments (Benson et al., 2022, Chew et al., 2018, Higginson, 2009). Furthermore, with a small form factor and relatively low cost, IMUs can measure beyond the lab(Strohrmann et al., 2011, Benson et al., 2022), which can help to understand running gait in a variety of environments and of varying lengths, from short capture sessions under observation in low-resource settings to prolonged periods over ground e.g., marathons (Meyer et al., 2021).

IMUs are typically reliant on algorithms to extract useful gait features from inertial signals. Algorithms can be generally described as the software-based methodology, translating from raw (sample level) data into meaningful and quantifiable gait outcomes. To date there have been a plethora of IMU-based algorithm developed for running gait assessment (Mason et al., 2022). Typically, algorithms rely upon the identification of initial contact events from the inertial data to segment the gait cycle for specific phases of analysis (Young et al., 2021, Gujarathi and Bhole, 2019). One common approach is the zero-crossing (ZC) technique (Mason et al., 2022) which is particularly useful when used in conjunction with other inertial feature extraction methods such as gradient maxima (i.e., peak detection), often used to extract peaks in corresponding inertial signals (Norris et al., 2014, Alahakone et al., 2010). Particularly, bouts of running gait naturally exhibit higher acceleration during impact, and as such create easily identifiable peaks within acceleration signals, justifying the use of a ZC gradient maxima algorithm to segment gait. Consequently, use of an accelerometer can inform gyroscope-based outcomes (e.g., roll of the foot, impact location). This benefit of that multi-modal sensing strategy is particularly evident when IMU devices are placed on the lower extremities (e.g., foot), increasing the sensitivity to ground-impact biomechanical related inertial signal features (Panebianco et al., 2018), of which has been demonstrated in running gait (Alahakone et al., 2010, Young et al., 2020).

Furthermore, ZC has pragmatic utility in comparison to recent approaches such as artificial intelligence and machine learning within the wider gait assessment field, which, despite their ability to provide comprehensive gait outcomes (Xu et al., 2022, Zhang et al., 2019) are both computationally intensive (Khera and Kumar, 2020), and require complex logistics such as setup, training and hosting. Conversely, ZC methods require low computational power for more immediate deployment for running gait assessment tasks (Hölzke et al., 2020) as the technique is more readily deployable (i.e., do not require building of datasets and complex implementation), indicating a suitability for low-resource deployment e.g., on a tablet or smartphone without Cloud connectivity. Previous work (Young et al., 2020, Young et al., 2021) developed a low-power IMU ZC methodology with a foot mounted IMU to assess biomechanical properties such as foot strike location, pronation, and ground contact time to recommend shoe type while participants ran at a single set pace (8km/h). Yet, the validity of the ZC approach has not been comprehensively investigated for general use in running analysis. Here, we conduct a thorough investigation of the fundamental ZC methodology for foot strike identification, and pronation ground contact time at varying speeds, cross-referenced with 3D-motion capture system and slow-motion video reference streams. We hypothesize that the ZC is a useful approach for examining running gait outcomes across a range of speeds.

2 Methods

2.1 Participants

Ethical approval was granted by the Northumbria University Research Ethics Committee (Reference: 21603). All participants were supplied with informed consent and gave verbal and written consent before performing treadmill-based testing in Northumbria University's Gait and Biomechanics Laboratory. Thirty-one healthy participants (34.5 ± 9.67 years; 1.75m ± 0.3m; 76.2 ± 4.1 kg; 20M:11F) were recruited from running clubs in the Northeast of England. Participants exhibited a range of running abilities from ≈30minute (amateur) to ≤20-minute (experienced) for a 5Km pace. Inclusion criteria required participants could run unassisted for short periods and must be under the age of 60 years. Participants were screened for running-related injury history, as well as any gait/mobility-affecting conditions (e.g., orthopedic, cardiovascular) that would adversely impact running ability. No participants reported any current running gait affecting injuries or pre-existing conditions to warrant exclusion. Participants were provided with a standardized, neutral cushioning running shoe (Saucony Guide Runner) for use during testing in an effort to minimize impact at higher speeds.

2.2 Instrumentation: IMU

All participants were fitted with two wearable IMUs (AX6, Axivity, UK, https://axivity.com/, tri-axial accelerometer and tri-axial gyroscope, 23.0mm × 32.5mm × 8.9mm, 11g) on the talus joint of each foot with medical tape, *Figure 1*. IMUs were programmed in Axivity's omGUI software suite, configured with ±16g accelerometer range, 2000dps gyroscope range polling at 60Hz. The location of the IMU on the talus is essential to reproduce ZC methodology under investigation. Specifically, tracking the orientation of the talus provides an optimal representation of foot rotation throughout the running gait cycle (Hontas et al., 1986) to determine foot strike pattern, pronation and ground contact time.

2.3 Instrumentation: Reference

For standard reference, a 3-dimensional (3D) 14 camera motion tracking system (Vertex, Vicon, UK, www.vicon.com) was used. The 14 Vicon Vertex motion tracking cameras were distributed around a space of 9.8 × 7.9 × 3.2m^3, polling at 200Hz to provide a high-resolution observation of the participant's running gait. Participants were fitted with 16 neo-reflective markers for use with the Vicon 3D motion tracking system in the following locations: (1) calcaneal tuberosity (heel), (2) lateral malleoli (ankle), (3) base of the second metatarsal (front-foot/toe), (4) lateral mid-shank, (5) lateral knee joint line (6) mid-lateral thigh, (7) anterior superior iliac spine (8) posterior superior iliac spine, *Figure 1*.

2.4 Data Capture

Participants initially performed a static pose (arms to the side, feet shoulder-width apart) to calibrate the 3D motion tracking system. Subsequently, participants were prompted to walk for short periods within the 3D tracking environment, providing synchronized data between 3D tracking, video and IMU data streams. To ensure synchronization between Vicon and IMU data streams, digital timestamps were consistently created in-software for both systems based upon the operating system clock in "milliseconds since epoch" format. Upon successful configuration, participants stood still on the treadmill to provide a baseline reading from IMU devices and to account for any local inclination error or misalignment during fitting. Participants were then asked to perform short, 1-minute bouts of treadmill running at four set speeds (8, 10, 12 and 14 km/h) in line with guidelines in previous work (Young et al., 2020) and to ensure participants could successfully complete the tests despite their running ability. A period of 1-minute was chosen as it generally aligns with other similar studies in the field with data capture periods ranging from 20s (McGrath et al., 2012) to 90s (Tan et al., 2020, Bailey and Harle, 2014). Additionally, participants also ran at a speed that was comparable to their most recent outdoor 5km pace (15.1 ± 0.8 km/h). If their self-selected pace was below or equal to pre-defined speeds, no self-selected pace was captured. All runs captured inertial, 3D-motion and video data (240FPS side and rear perspectives). Tests were conducted twice after a short break (≈1 minute) to provide multiple running bouts for participants at each pace. As such, a total of 148 running bouts were assessed during this study.

2.5 Data labelling

Foot strike location, pronation severity and ground contact time were manually labelled by-hand through observation of 3D motion tracking data and slow motion video reference streams in accordance with labels of the previous studies (Young et al., 2020, Young et al., 2021) by a team of trained researchers (sports science, biomechanics) such that each foot may exhibit: neutral, slight or pronated roll of the foot; or heel, mid or fore foot strike location, *Figure 2.* Labels are generated by observing skeletal output generated by the Vicon system in cross reference with slow-motion video streams such that: pronation is the angle between heel, ankle and leg angle (*Figure 2B)* and foot strike location denotes the impact location of the foot (*Figure 2C)*. A runner is considered pronated should they exhibit 5° or greater of foot roll during initial contact, in line with previously outset guidelines (Young et al., 2020). Due to different sampling resolutions between 3D motion capture (200Hz) and IMU signals (60Hz), ground contact time is measured and labelled with respect to milliseconds to standardize the measurements. For example, ground contact time from 3D motion capture could output 38Hz, whereas the IMU could output 11Hz. Consequently, each method is resampled to 190ms and 183ms for 3D motion tracking and IMU data respectively. Ground contact time is measured as the time elapsed (ms) between initial contact (foot first makes contact with the ground) and final/terminal contact (foot last leaves the ground). Of the 148 running bouts observed, a total of 9327 strides (mean steps per test = 57.2 ± 4.09) were extracted, labelled and assessed as part of the study.

2.6 Data processing and algorithm

Data handling and processing have been described previously (Young et al., 2020, Young et al., 2021). In brief, acceleration and rotation data are extracted and analyzed in a Jupyter notebook Python 3.7

environment for execution of the algorithm. Data were prepared/filtered by a Butterworth band-pass filter performing at 60Hz with a sampling frequency of 3Hz and a cut-off frequency of 5Hz is applied to the vertical acceleration plane and vertical/horizontal rotational velocity to account for signal noise.

2.7 IMU algorithm methodology

The method analyses tri-axial accelerometer and tri-axial gyroscope signals in tandem during running to quantify foot strike location, pronation severity and ground contact time. The method relies on the identification of initial contact from ZC to inform gait feature extraction surrounding impact. A short breakdown of the algorithm is presented below:

(a) Initial contact identification, *Figure 3A*: A ZC gradient maxima algorithm is deployed for detection of peaks in the vertical acceleration plane is deployed for initial contact identification through observing significant changes in gradient. Operating within a dynamic threshold based upon the signal maxima, the ZC gradient maxima algorithm is effective in identifying initial contact peaks in vertical acceleration.

(b) The rotational velocity of the foot in vertical and horizontal planes is observed around identified points of initial contact, *Figure 3B*. An average is taken of each feature, providing a final output of pronation severity and foot strike location.

(c) Final contact identification and ground contact time estimation: The same ZC gradient maxima algorithm is used to identify an inverse peak in the acceleration signal within a 500ms region of interest proceeding an identified initial contact event. Ground contact time is consequently calculated as the time between an initial contact event and proceeding final contact event.

2.8 Statistical analysis

Examining the performance of the proposed algorithms and their respective videos was conducted in SPSS v27. Shapiro-Wilks tests indicated a normal distribution of all data ($p<0.05$). Consequently, intra-class correlation ($ICC_{(2,1)}$) models examined absolute agreement between IMU algorithm and 3D reference/slow motion video streams. A predefined ICC performance scale was deployed (Koo and Li, 2016), defined as poor (<0.500), moderate (0.500-0.750), good (0.750-0.900) or excellent (>0.900). Mean error were calculated between algorithm and 3D motion data for descriptive purposes and are observed as an accuracy metric in ground contact time. Furthermore, Bland Altman (Bland and Altman, 1986) and box plot were used to visually assess the agreement between ground truth and algorithm outcomes for ground contact time.

3 Results

Of the 31 participants, no data loss or dropout was experienced during treadmill running sessions. Upon preliminary observation of the quantified algorithm outcomes, no significant outliers were identified. A total of 148 running bouts containing 9327 strides were analyzed as part of the study.

3.1 Initial contact

Intraclass correlation performance degrade at higher speeds in identifying points of initial contact, demonstrating excellent agreement between 8-10km/h ($ICC_{(2,1)}$ >0.900), and good agreement ($ICC_{(2,1)}$ >0.750) at 14km/h and higher self-selected paces, *Table 1*. The ZC gradient approach to initial contact identification tends to over-estimate number of initial contact events, especially at higher speeds.

3.2 Foot strike location and pronation severity

Intraclass correlations demonstrate an excellent agreement between algorithm and reference streams for foot strike identification ($ICC_{(2,1)}$ >0.900), particularly, demonstrating robustness at the full range of speeds, with low error rates throughout, *Table 2*. Between 8-12km/h, the pronation identification algorithm demonstrates good agreement ($ICC_{(2,1)}$ >0.750), but begins to depreciate at 14km/h+ with moderate ($ICC_{(2,1)}$ >0.500) agreement.

3.3 Ground contact time

The ground contact time identification approach demonstrates low mean error at 8, 10 and 12km/h (9ms – 17ms) when compared to 3D motion tracking labels, *Table 3*. Equally, at the lower speeds, observing the median and upper/lower range demonstrates an ability to estimate ground contact time of varying length, *Figure 4*. Conversely, mean error rate is slightly higher (21ms – 27ms) at the higher speeds (14km/h +), while additionally demonstrating a wider deviance from median and upper/lower range in comparison to labelled data, *Figure 4*.

4 Discussion

Understanding running gait is crucial in injury prevention; particularly, quantifying pragmatic biomechanical properties. That can reduce impact-related or strain injuries commonly associated with e.g., over pronation (Daoud et al., 2012). The proposed work investigates and evaluates the performance of a ZC methodology at different running speeds to assess suitability to quantify foot strike location, pronation and ground contact time. It was found that the ZC method had reduced agreement when compared to a standard reference at higher running speeds suggesting that use for running analysis may be suitable for amateur runners only (i.e., those with 5Km time >20minutes) compared to elite athletes and their gait assessment at higher speeds.

4.1 Performance of zero-crossing methodology

In line with studies utilizing a ZC gradient approach for gait cycle segmentation (Han et al., 2019, Bastas et al., 2018), our IC identification algorithm demonstrated excellent absolute agreement across the lower range of speeds ($ICC_{(2,1)} > 0.9$) and good agreement ($ICC_{(2,1)} > 0.75$) at higher speeds through identifying peaks in vertical acceleration above a dynamic threshold. The ZC approach to initial contact identification demonstrates a mean error between 9 and 27ms between algorithm and labelled output dependent upon speed, *Table 3.*

Through observing Bland Altman plots of the initial contact identification approach at higher speeds, *Figure 5,* (14km/h+), it is evident the approach successfully identifies labelled initial contact events, likely due to higher impact forces exerting significant vertical acceleration that gradient analysis can easily identify. However, false positives are occasionally encountered at higher speeds where extraneous noise is often present (supplementary material, signal-to-noise analysis) following a large impact*, Figure 6*. The evaluated methodology attempts to remove false positives based upon a dynamic threshold, estimated through observation of the average quantified stride length (Young et al., 2020); however, the process is not consistently performant to warrant use in higher speeds. Recently, the use of deep learning has demonstrated utility in identifying temporal gait outcomes in both normal (Gadaleta et al., 2019) and running gait (Gholami et al., 2020, Johnson et al., 2020) from wearable inertial sensors; but require further investigation and validation (i.e., in range of speeds) before adoption. Should such approaches exhibit a ranged validity within the domain, their use could be warranted to inform impact-related gait feature extraction outcomes.

In opposition to gyroscope-only based methods, e.g., (Falbriard et al., 2018) that perform gait cycle segmentation through estimating the rotation of the foot for mid-swing analysis, the use of a ZC approach in vertical acceleration (accelerometer) for initial contact identification can inform a wider understanding of running gait outcomes at the point of impact due to their sensitivity to ground forces. Crucially, by using initial contact as a marker from an accelerometer, we are able to search for rotation-based outcomes surrounding initial contact (e.g., pronation, foot strike location).

4.2 Ground Contact Time

Ground contact time is essential to understand due to the implications on running economy (Di Michele and Merni, 2014). The evaluated approach performs amicably when observing mean error from labelled data, demonstrating efficacy between 8-12km/h (mean error 0.32 – 2.65%), with a degradation at 14km/h+ (3.94% mean error at 14km/h; 10+% mean error at self-selected), *Table 3*. However, observing box and Bland Altman plots, *Figure 4, Figure 5,* one can observe that despite low deviation from average labels at higher speeds (14km/h+), there is a significantly wider range of estimated values. These findings are comparative to similar work within the field. For example, (Falbriard et al., 2018) assessed a range of signal features (e.g., min/max, ZC) for identification of temporal gait outcomes including ground contact time. Similar to the evaluated algorithm, utilizing optimally selected features the approach presented a degradation in accuracy with respect to speed. However, the observed work also provides discussion of alternate, lesser-performant features (i.e., minimum of pitch angular velocity within IC zone and the maximum of vertical acceleration in TC zone) that are not greatly affected by speed, which may warrant further investigation for use in high-speed running.

4.3 Gait Feature Extraction

The gait feature extraction layer of the algorithm relies upon observing horizontal and vertical angular velocity of the foot at impact for pronation and foot strike location respectively. *Table 1* illustrates the performance of the gait feature extraction layer, demonstrating consistently excellent performance across multiple speeds for foot strike location identification; but showing degrading performance in pronation identification at higher speeds.

Upon investigation of the horizontal (pronation) and vertical (foot strike location) rotational velocity planes, extraneous noise became apparent surrounding an initial contact event within the vertical rotational velocity plane at higher speeds, *Figure 6*. *Supplementary Table 1* shows the average noise-to-signal ratio across the range of speeds in both vertical and horizontal rotational velocity within a 167ms (10Hz) window of an initial contact event. The experiment demonstrates an obvious and significant increase in noise (+10.1%) in horizontal roll between slow and high speeds, offering an explanation as to the degradation in pronation accuracy. Conversely, the vertical rotation plane demonstrates far lower noise, consistent across all speeds, concurrent with consistently excellent results in testing. The use of a continuous wavelet transform (CWT) may be warranted in future iterations, due to high performance in single-sensor applications through noise suppression by removal of extraneous signal fluctuations leading to clearer gait feature extractions (McCamley et al., 2012).

The proposed approach performs comparably with similar work within the field. For example, (Murai et al., 2018) utilized a single, foot-mounted IMU to observe the angular velocity of the foot during impact to assess pronation at a correlation of $r = 0.800$, coinciding with our $ICC_{(2,1)}$ score of 0.779 – 0.867 between 8-12km/h. However, our evaluated approach provides a significantly higher number of participants (31 runners of varying demographic: evaluated approach, 10 male runners: observed study) and insight into the speed of the runners and how it affects performance, providing a more generalizable assessment of IMU-based pronation assessment.

4.4 Implications on free-living running gait assessment

Through development and evaluation of an IMU-based algorithm with promising results, the approach provides scope for implementation in low-cost commercial technologies, reducing reliance on expert analysis and/or gold-standard, high-cost technologies (Young et al., 2020). The methodology investigated here primarily focuses on gait feature extraction during treadmill running for use in habitual or low resource environments. However, there is some debate as to the efficacy of treadmill-based gait assessment due to gait kinematics differing in overground, outdoor running scenarios (Lafferty et al., 2021, Benson et al., 2022), potentially inhibiting the utility of the evaluated ZC method. Consequently, the approach should be validated in outdoor scenarios to assess the performance in uncontrolled settings. In performing outdoor validation, the use of IMU-based methods could contribute to a full-scale running gait analysis, providing relatively sparce, long-term observations such as gait monitoring across 10km or marathon running (Benson et al., 2018, Meyer et al., 2021).

4.5 Limitations

Due to the potential of high impact force at greater speeds, the use of a running shoe during testing was warranted in order to minimize the risk of impact-related injuries (Sun et al., 2020). The deployed running shoes in this study (Saucony Guide Runner) exhibit a 'neutral' cushioning shoe, thus, do not provide pronation-minimizing support. However, running shoes are widely accepted to influence and change aspects of a runner's gait in opposition to barefoot running (Stacoff et al., 1991, Aguinaldo and Mahar, 2003). Consequently, although the evaluated algorithms can extract pronation, foot strike location and ground contact time in comparison to labelled data, the outcomes may not be indicative of the runner's 'true' gait, i.e., when running barefoot. Additionally, running shoes reduce impact force upon the lower extremities (Aguinaldo and Mahar, 2003), potentially minimizing acceleration at impact observed by the IMU in comparison to previous work (Young et al., 2020). As such, although the evaluated ZC approach to IC identification performs well within the constraints of the study, it should be noted that the ZC approach may not scale between different running shoes i.e., that exhibit larger levels of support.

IMUs are susceptible to drift error in due to high-frequency noise within micro electro mechanical systems (Narasimhappa et al., 2019), and the potential of local misalignment. Although the evaluated algorithm takes into account local alignment error and uses a Butterworth filter in an attempt to account for noise, the approach may not be drift-free among different running patterns, and as such, may impact gait outcomes. As such, to ensure the approach is note hindered by drift, it may be necessary to implement a drift-minimizing algorithm e.g., (Falbriard et al., 2020). This could be especially useful in analysis at higher speeds, where sensors may be more susceptible to drift due to extensive exposure to high impact forces.

5 Future Work

Currently, the evaluated algorithm degrades in performance at higher speeds (14km/h+) due to extraneous noise encountered at higher impact speeds and misidentification of initial contact events. Some shortcomings have been identified for future iterations of the algorithm, namely requiring the use of CWT processing and potential implementation of artificial intelligence for identification of IC events in anomalous signals. Future work will validate the approach in overground (i.e., off-treadmill), outdoor running to assess IMU-based running gait assessment over extended running bouts.

6 Conclusion

The proposed work investigates and evaluates a ZC methodology for the extraction of a range of biomechanical properties from a single foot mounted IMU that could be useful for general running gait analysis. The evaluated method has demonstrated utility in quantifying foot strike location, pronation severity and ground contact time during treadmill running at speeds up to 12km/h; exhibiting good and excellent agreements with 3D motion capture. Through conducting this investigation on the ZC methodology running gait assessment, we contribute to understanding the efficacy and utility of wearable IMUs during running gait. Particularly, providing approaches to understanding running with low-cost apparatus to promote personalized and objective running gait assessment and reduces reliance on traditional, subjective approaches.

7 References

AGUINALDO, A. & MAHAR, A. 2003. Impact loading in running shoes with cushioning column systems. *Journal of applied biomechanics,* 19**,** 353-360.

AHMAD, N., GHAZILLA, R. A. R., KHAIRI, N. M. & KASI, V. 2013. Reviews on various inertial measurement unit (IMU) sensor applications. *International Journal of Signal Processing Systems,* 1**,** 256-262.

ALAHAKONE, A. U., SENANAYAKE, S. A. & SENANAYAKE, C. M. Smart wearable device for real time gait event detection during running. 2010 IEEE Asia Pacific conference on circuits and systems, 2010. IEEE, 612-615.

ALBERT, J. A., OWOLABI, V., GEBEL, A., BRAHMS, C. M., GRANACHER, U. & ARNRICH, B. 2020. Evaluation of the pose tracking performance of the azure kinect and kinect v2 for gait analysis in comparison with a gold standard: A pilot study. *Sensors,* 20**,** 5104.

BAILEY, G. P. & HARLE, R. 2014. Assessment of Foot Kinematics During Steady State Running Using a Foot-mounted IMU. *Procedia Engineering,* 72**,** 32-37.

BASKWILL, A. J., BELLI, P. & KELLEHER, L. 2017. Evaluation of a gait assessment module using 3D motion capture technology. *International Journal of Therapeutic Massage & Bodywork,* 10**,** 3.

BASTAS, G., FLECK, J. J., PETERS, R. A. & ZELIK, K. E. 2018. IMU-based gait analysis in lower limb prosthesis users: Comparison of step demarcation algorithms. *Gait & posture,* 64**,** 30-37.

BENSON, L. C., CLERMONT, C. A., BOŠNJAK, E. & FERBER, R. 2018. The use of wearable devices for walking and running gait analysis outside of the lab: A systematic review. *Gait & posture,* 63**,** 124-138.

BENSON, L. C., RÄISÄNEN, A. M., CLERMONT, C. A. & FERBER, R. 2022. Is This the Real Life, or Is This Just Laboratory? A Scoping Review of IMU-Based Running Gait Analysis. *Sensors,* 22**,** 1722.

BLAND, J. M. & ALTMAN, D. 1986. Statistical methods for assessing agreement between two methods of clinical measurement. *The lancet,* 327**,** 307-310.

CHEW, D.-K., NGOH, K. J.-H. & GOUWANDA, D. 2018. Estimating running spatial and temporal parameters using an inertial sensor. *Sports Engineering,* 21**,** 115-122.

COOPER, G., SHERET, I., MCMILLIAN, L., SILIVERDIS, K., SHA, N., HODGINS, D., KENNEY, L. & HOWARD, D. 2009. Inertial sensor-based knee flexion/extension angle estimation. *Journal of biomechanics,* 42**,** 2678-2685.

DAOUD, A. I., GEISSLER, G. J., WANG, F., SARETSKY, J., DAOUD, Y. A. & LIEBERMAN, D. E. 2012. Foot strike and injury rates in endurance runners: a retrospective study. *Med Sci Sports Exerc,* 44**,** 1325-1334.

DEMPSTER, J., DUTHEIL, F. & UGBOLUE, U. C. 2021. The prevalence of lower extremity injuries in running and associated risk factors: a systematic review. *Physical Activity and Health,* 5.

DI MICHELE, R. & MERNI, F. 2014. The concurrent effects of strike pattern and ground-contact time on running economy. *Journal of science and medicine in sport,* 17**,** 414-418.

FALBRIARD, M., MEYER, F., MARIANI, B., MILLET, G. P. & AMINIAN, K. 2018. Accurate estimation of running temporal parameters using foot-worn inertial sensors. *Frontiers in physiology***,** 610.

FALBRIARD, M., MEYER, F., MARIANI, B., MILLET, G. P. & AMINIAN, K. 2020. Drift-free foot orientation estimation in running using wearable IMU. *Frontiers in Bioengineering and Biotechnology,* 8**,** 65.

GADALETA, M., CISOTTO, G., ROSSI, M., REHMAN, R. Z. U., ROCHESTER, L. & DEL DIN, S. Deep learning techniques for improving digital gait segmentation. 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2019. IEEE, 1834-1837.

GHOLAMI, M., NAPIER, C. & MENON, C. 2020. Estimating lower extremity running gait kinematics with a single accelerometer: a deep learning approach. *Sensors,* 20**,** 2939.

GUJARATHI, T. & BHOLE, K. Gait analysis using imu sensor. 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), 2019. IEEE, 1-5.
HAN, Y. C., WONG, K. I. & MURRAY, I. 2019. Gait phase detection for normal and abnormal gaits using IMU. *IEEE Sensors Journal,* 19**,** 3439-3448.
HIGGINSON, B. K. 2009. Methods of running gait analysis. *Current sports medicine reports,* 8**,** 136-141.
HINTERMANN, B. & NIGG, B. M. 1998. Pronation in runners. *Sports medicine,* 26**,** 169-176.
HÖLZKE, F., HELLER, J., DEATCU, S. A., GOLATOWSKI, F. & TIMMERMANN, D. Step Detection through Ultra-Low Complexity Zero Crossing Analysis. 2020 15th IEEE International Conference on Signal Processing (ICSP), 2020. IEEE, 626-631.
HONTAS, M. J., HADDAD, R. J. & SCHLESINGER, L. C. 1986. Conditions of the talus in the runner. *The American journal of sports medicine,* 14**,** 486-490.
JAFARNEZHADGERO, A., ALAVI-MEHR, S. M. & GRANACHER, U. 2019. Effects of anti-pronation shoes on lower limb kinematics and kinetics in female runners with pronated feet: The role of physical fatigue. *PloS one,* 14**,** e0216818.
JAKOB, V., KÜDERLE, A., KLUGE, F., KLUCKEN, J., ESKOFIER, B. M., WINKLER, J., WINTERHOLLER, M. & GASSNER, H. 2021. Validation of a Sensor-Based Gait Analysis System with a Gold-Standard Motion Capture System in Patients with Parkinson's Disease. *Sensors,* 21**,** 7680.
JANDOVÁ, S., VOLF, P. & VAVERKA, F. 2018. The influence of minimalist and conventional sports shoes and lower limbs dominance on running gait. *Acta of bioengineering and biomechanics,* 20.
JOHNSON, W. R., MIAN, A., ROBINSON, M. A., VERHEUL, J., LLOYD, D. G. & ALDERSON, J. A. 2020. Multidimensional ground reaction forces and moments from wearable sensor accelerations via deep learning. *IEEE Transactions on Biomedical Engineering,* 68**,** 289-297.
KHERA, P. & KUMAR, N. 2020. Role of machine learning in gait analysis: a review. *Journal of Medical Engineering & Technology,* 44**,** 441-467.
KOO, T. K. & LI, M. Y. 2016. A guideline of selecting and reporting intraclass correlation coefficients for reliability research. *Journal of chiropractic medicine,* 15**,** 155-163.
LAFFERTY, L., WAWRZYNIAK, J., CHAMBERS, M., PAGLIARULO, T., BERG, A., HAWILA, N. & SILVIS, M. 2021. Clinical Indoor Running Gait Analysis May Not Approximate Outdoor Running Gait Based on Novel Drone Technology. *Sports Health***,** 19417381211050931.
LINTON, L. & VALENTIN, S. 2018. Running with injury: A study of UK novice and recreational runners and factors associated with running related injury. *Journal of science and medicine in sport,* 21**,** 1221-1225.
MASON, R., PEARSON, L., BARRY, G., YOUNG, F., LENNON, O., GODFREY, A. & STUART, S. 2022. Wearables for Running Gait Analysis: A Systematic Review. *Sports Medicine,* In press.
MCCAMLEY, J., DONATI, M., GRIMPAMPI, E. & MAZZA, C. 2012. An enhanced estimate of initial contact and final contact instants of time using lower trunk inertial sensor data. *Gait & posture,* 36**,** 316-318.
MCGRATH, D., GREENE, B. R., O'DONOVAN, K. J. & CAULFIELD, B. 2012. Gyroscope-based assessment of temporal gait parameters during treadmill walking and running. *Sports Engineering,* 15**,** 207-213.
MEYER, F., FALBRIARD, M., AMINIAN, K. & MILLET, G. P. 2018. How accurate is visual determination of foot strike pattern and pronation assessment. *Gait & posture,* 60**,** 200-202.

MEYER, F., FALBRIARD, M., MARIANI, B., AMINIAN, K. & MILLET, G. P. 2021. Continuous Analysis of Marathon Running Using Inertial Sensors: Hitting Two Walls? *International Journal of Sports Medicine,* 42**,** 1182-1190.

MURAI, A., SHIOGAMA, C., MING, D., TAKAMATSU, J., TADA, M. & OGASAWARA, T. 2018. Estimation of running injury risks using wearable sensors. *ISBS Proceedings Archive,* 36**,** 240.

NAGAHARA, R., KAMEDA, M., NEVILLE, J. & MORIN, J.-B. 2020. Inertial measurement unit-based hip flexion test as an indicator of sprint performance. *Journal of Sports Sciences,* 38**,** 53-61.

NARASIMHAPPA, M., MAHINDRAKAR, A. D., GUIZILINI, V. C., TERRA, M. H. & SABAT, S. L. 2019. MEMS-based IMU drift minimization: Sage Husa adaptive robust Kalman filtering. *IEEE Sensors Journal,* 20**,** 250-260.

NORRIS, M., ANDERSON, R. & KENNY, I. C. 2014. Method analysis of accelerometers and gyroscopes in running gait: A systematic review. *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology,* 228**,** 3-15.

PANEBIANCO, G. P., BISI, M. C., STAGNI, R. & FANTOZZI, S. 2018. Analysis of the performance of 17 algorithms from a systematic review: Influence of sensor position, analysed variable and computational approach in gait timing estimation from IMU measurements. *Gait & posture,* 66**,** 76-82.

ROLF, C. 1995. Overuse injuries of the lower extremity in runners. *Scandinavian journal of medicine & science in sports,* 5**,** 181-190.

SCHLAGENHAUF, F., SREERAM, S. & SINGHOSE, W. Comparison of kinect and vicon motion capture of upper-body joint angle tracking. 2018 IEEE 14th International Conference on Control and Automation (ICCA), 2018. IEEE, 674-679.

SCHMIDT, M., RHEINLÄNDER, C., NOLTE, K. F., WILLE, S., WEHN, N. & JAITNER, T. 2016. IMU-based determination of stance duration during sprinting. *Procedia engineering,* 147**,** 747-752.

SHARMA, S., VERMA, S., KUMAR, M. & SHARMA, L. Use of motion capture in 3D animation: motion capture systems, challenges, and recent trends. 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), 2019. IEEE, 289-294.

SHIPWAY, R. & HOLLOWAY, I. 2010. Running free: Embracing a healthy lifestyle through distance running. *Perspectives in public health,* 130**,** 270-276.

STACOFF, A., KÄLIN, X. & STÜSSI, E. 1991. The effects of shoes on the torsion and rearfoot motion in running. *Medicine and Science in Sports and Exercise,* 23**,** 482-490.

STROHRMANN, C., HARMS, H., TRÖSTER, G., HENSLER, S. & MÜLLER, R. Out of the lab and into the woods: kinematic analysis in running using wearable sensors. Proceedings of the 13th international conference on Ubiquitous computing, 2011. 119-122.

SUI, J.-D., CHEN, W.-H., SHIANG, T.-Y. & CHANG, T.-S. Real-time wearable gait phase segmentation for running and walking. 2020 IEEE International Symposium on Circuits and Systems (ISCAS), 2020. IEEE, 1-5.

SUN, X., LAM, W.-K., ZHANG, X., WANG, J. & FU, W. 2020. Systematic review of the role of footwear constructions in running biomechanics: implications for running-related injury and performance. *Journal of sports science & medicine,* 19**,** 20.

TAN, T., STROUT, Z. A. & SHULL, P. B. 2020. Accurate impact loading rate estimation during running via a subject-independent convolutional neural network model and optimal IMU placement. *IEEE Journal of Biomedical and Health Informatics,* 25**,** 1215-1222.

UEBERSCHÄR, O., FLECKENSTEIN, D., WARSCHUN, F., KRÄNZLER, S., WALTER, N. & HOPPE, M. W. 2019. Measuring biomechanical loads and asymmetries in junior elite long-

distance runners through triaxial inertial sensors. *Sports Orthopaedics and Traumatology,* 35**,** 296-308.
XU, D., QUAN, W., ZHOU, H., SUN, D., BAKER, J. S. & GU, Y. 2022. Explaining the differences of gait patterns between high and low-mileage runners with machine learning. *Scientific Reports,* 12**,** 1-12.
YOUNG, F., COULBY, G., WATSON, I., DOWNS, C., STUART, S. & GODFREY, A. 2020. Just find it: The Mymo approach to recommend running shoes. *IEEE Access,* 8**,** 109791-109800.
YOUNG, F., STUART, S., MORRIS, R., DOWNS, C., COLEMAN, M. & GODFREY, A. Validation of an inertial-based contact and swing time algorithm for running analysis from a foot mounted IoT enabled wearable. 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), 2021. IEEE, 6818-6821.
ZHANG, H., GUO, Y. & ZANOTTO, D. 2019. Accurate ambulatory gait analysis in walking and running using machine learning models. *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* 28**,** 191-202.

8 Conflict of Interest

All financial, commercial or other relationships that might be perceived by the academic community as representing a potential conflict of interest must be disclosed. If no such relationship exists, authors will be asked to confirm the following statement:
The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

9 Author Contributions

FY and AG conceptualized the question and hypothesis. FY, SS and AG designed the study from which the data originates. FY and RMa contributed to data collection and analysis. FY wrote the first draft. FY, RMa, CW, RMo, SS, and AG contributed to the interpretation, writing and editing of the manuscript.

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12 Data availability statement

Data can be made available based upon reasonable request from the corresponding author.

14 Tables

Table 1: Initial contact identification performance in comparison to reference labels from 3D-tracking data at differing speeds. Average no. of steps denotes the mean steps per participant per foot across the range of datasets.

	Reference	Algorithm Output	
	Average no. of steps	Average no. of steps	ICC(2,1)
8km/h	54	55	0.963
10km/h	56	56	0.981
12km/h	56	57	0.945
14km/h	59	65	0.821
Self-Selected	60	72	0.783

Table 2: Gait feature extraction performance in agreement with reference labels from 3D-tracking data at differing speeds

	8km/h		**10km/h**		**12km/h**		**14km/h**		**Self-Selected**	
	Pronation	Foot Strike	Pronation	Foot Strike	Pronation	Foot Strike	Pronation	Foot Strike	Pronation	Foot Strike
Mean Error	0.184	0.131	0.184	0.105	0.342	0.112	0.382	0.029	0.312	0.025
ICC(2,1)	0.867	0.918	0.833	0.915	0.779	0.915	0.687	0.987	0.712	0.989

Table 3: Performance of ground contact time extraction layer in comparison with labels from 3D tracking data between 8km/h and a self-selected speed (avg=15.1km/h). Results are observed in milliseconds to standardize measurements between reference (Vicon; 200Hz) and IMU (Axivity; 60Hz) output. Mean error is shown in both Hz, seconds and percentage difference for illustrative purposes, and refers to average error between algorithm and labelled data.

Speed (km/h)	**8**	**10**	**12**	**14**	**Self-Selected**
Mean Algorithm Output (ms)	335.5±44.78	317.5±31.52	282.5±35.06	272±27.86	272±28.83
Mean Labelled Data (ms)	344.5±46.55	316.5±31.64	279.5±33.06	261.5±28.61	245.5±29.95
Mean Error (Hz)	3.58	2.15	2.93	4.21	5.48
Mean Error (ms)	9	11	15	21	27
Mean Error (%)	2.65	0.32	1.07	3.94	10.24

15 Figures

Figure 1: Example of a participant mounted with the full range of markers and sensors. Figure shows: A) a macro view of a runner during testing, donning B) 16 neo-reflective 3D motion tracking markers and 2 AX6 IMU devices. C) Illustrates a zoomed view of the foot with the markers at heel, ankle and front-foot positions; with the AX6 at the talus joint of the foot.

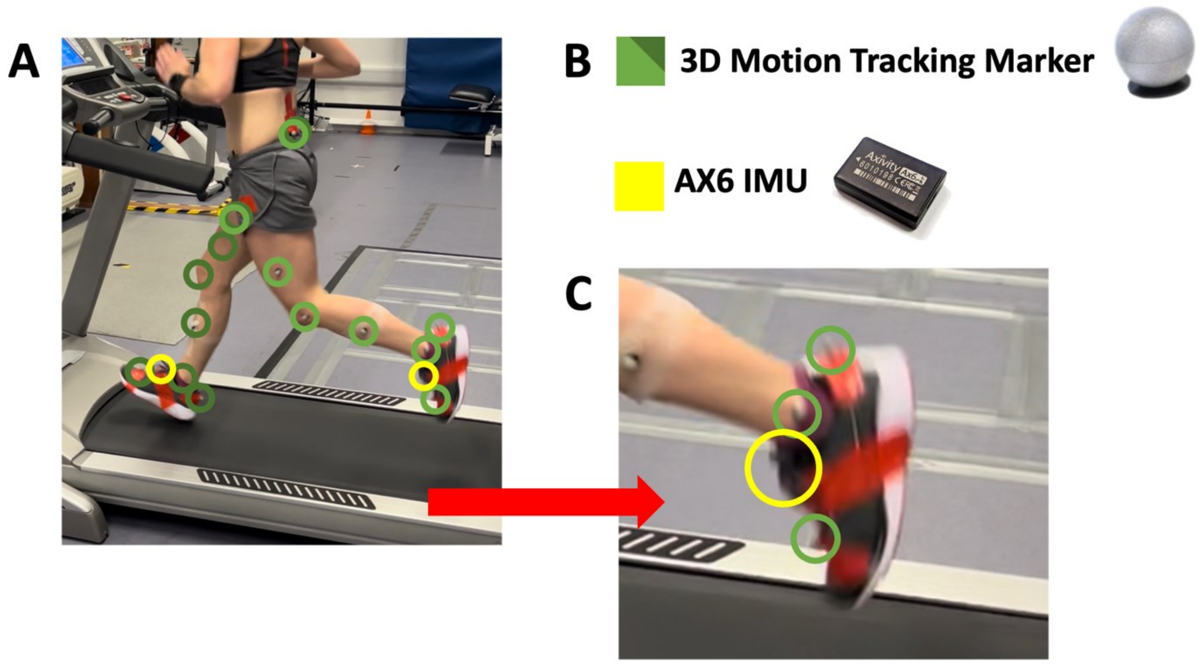

Figure 2: Illustrated view of the labelling process of pronation and foot strike between three neo-reflective markers located at the ankle, heel and front-foot positions. Pronation angle is derived based upon the angle of the leg in comparison to the angle of the foot. Foot strike is determined as the first point that made contact with the ground (red x): heel, mid or fore foot.

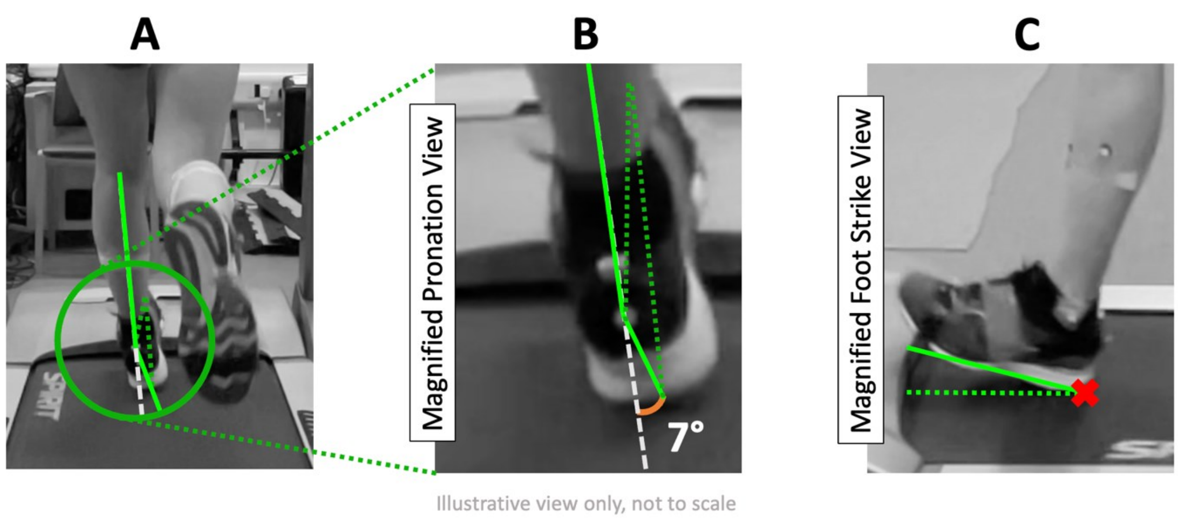

Figure 3: Data illustration of the evaluated algorithm at the key stages of execution: a) initial/final contact identification and b) gait feature extraction at point of contact

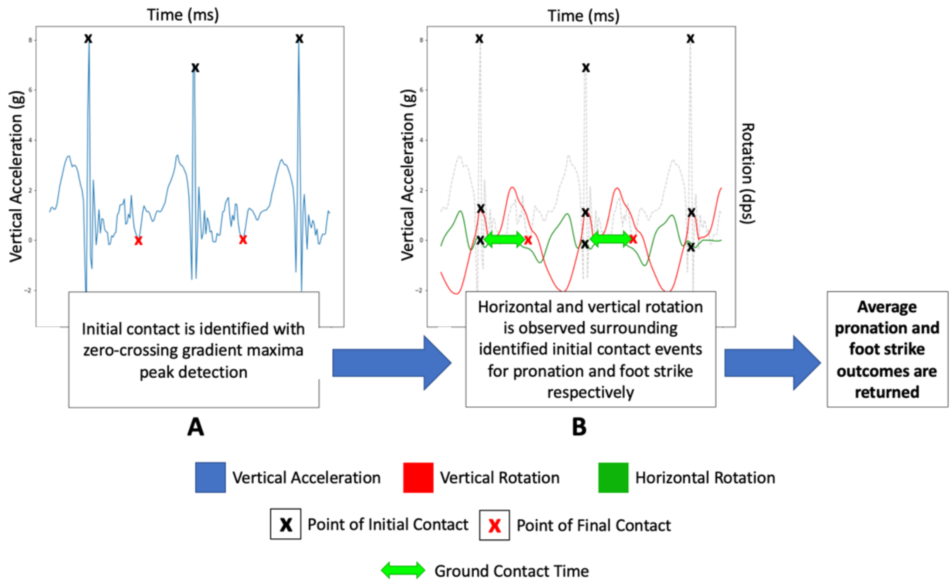

Figure 4: Box plots illustrating the performance of the contact time algorithm at 8,10,12,14km/h and a self-selected pace. **A** refers to actual (labelled) contact time, **P** refers to predicted (ZC algorithm) contact time.

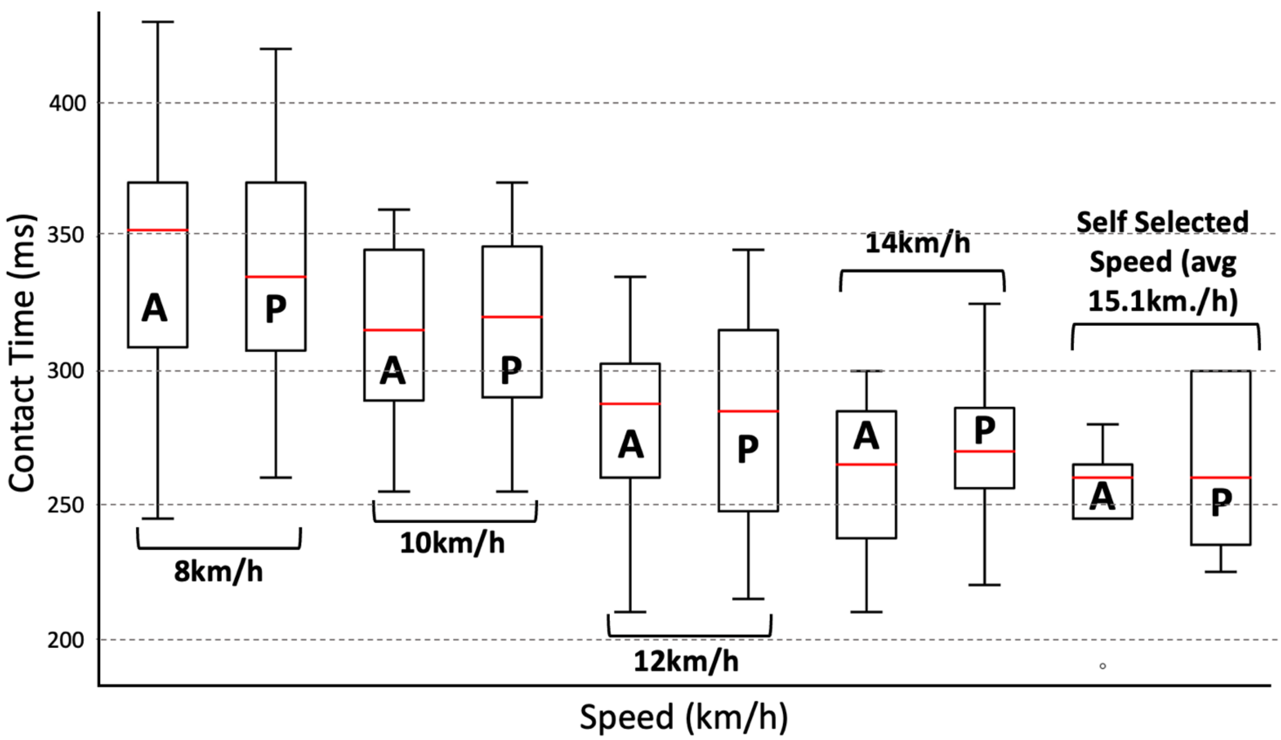

Figure 5: Bland-Altman plots of the ground contact time between ground truth and algorithm output. Blue and orange lines denote mean ± STD of the error.

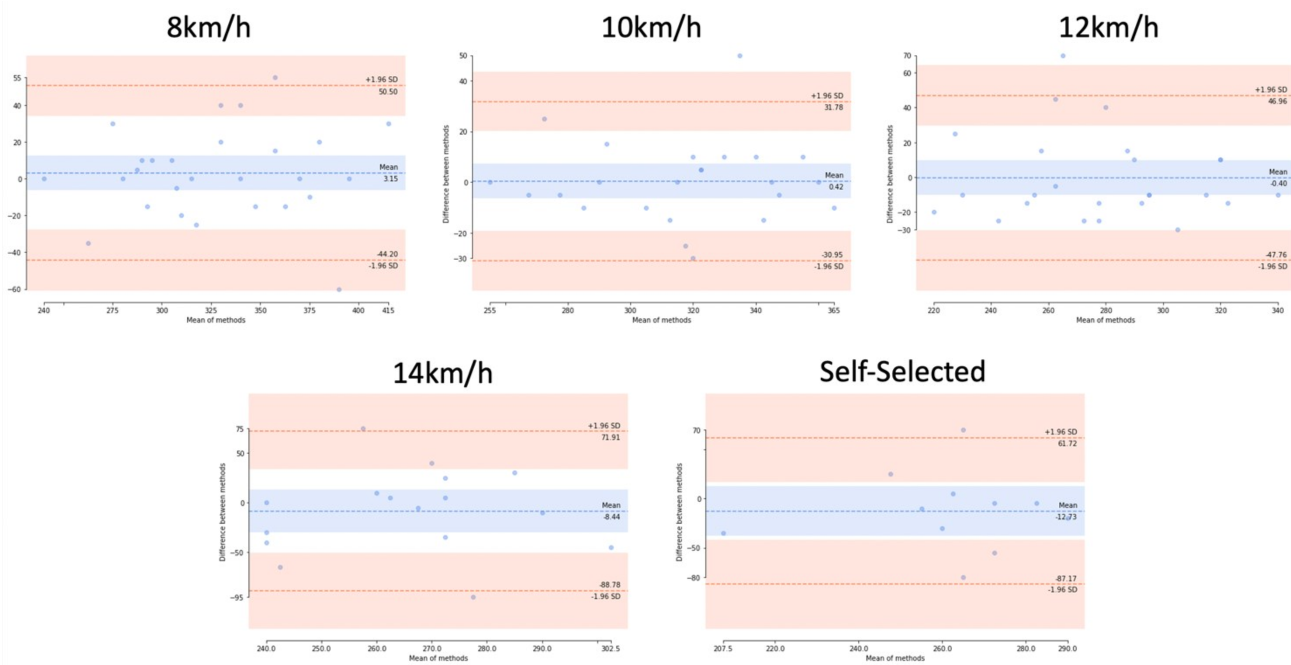

Figure 6: Comparison of a runner's vertical acceleration data at two different speeds, 8kmh and 16kmh. As observed, within higher speeds a considerable increase of noise is experienced after an initial contact event. Additionally, the signals have obvious differences between speeds due to (i) noise and (ii) potential of changing gait with respect to speed (e.g., fore strike at 8km/h and heel strike at 16km/h). Consequently, extracting gait features around a point of impact could be significantly impacted at higher speeds.