Northumbria Research Link

Validation of an inertial-based contact and swing time algorithm for running analysis from a foot mounted IoT enabled wearable

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Abstract: Running gait assessment for shoe type recommendation to avoid injury often takes place within commercial premises. That is not representative of a natural running environment and may influence normal/usual running characteristics. Typically, assessments are costly and performed by an untrained biomechanist or physiotherapist. Thus, use of a low-cost assessment of running gait to recommend shoe type is warranted. Indeed, the recent impact of COVID has heightened the need for a shift toward remote assessment in general due to social-distancing guidelines and restriction of movement to bespoke assessment facilities. Mymo is a Bluetooth-enabled, inertial measurement unit (IMU) wearable worn on the foot. The wearable transmits inertial data via a smartphone application to the Cloud, where algorithms work to recommend a running shoe based upon the users/runner's pronation and foot-strike location/pattern. Here, an additional algorithm is presented to quantify ground contact time and swing/flight time within the Mymo platform to further inform the assessment of a runner's gait. A large cohort of healthy adult and adolescents (n=203, 91M:112F) were recruited to run on a treadmill while wearing the Mymo wearable. Validity of the inertial-based algorithm to quantify ground contact time was established through manual labelling of reference standard ground truth video data, with a presented accuracy between 96.6-98.7% across the two classes with respect to each foot.

Clinical Relevance: This establishes the validity of a ground contact and swing times for runner with a low-cost IoT wearable.

Introduction

Recreational and competitive running is popular, due to its low-cost accessibility, social community and significant health benefits [1]. As a runner looks to improve, multiple factors must be considered to maximize their running performance. For example, a runner could adopt High Intensity Interval Training (HIIT)-based exercises for endurance and muscle strengthening [2]. A runner could also optimize their ground contact time (GCT, time the foot is in contact with the ground) to minimize the metabolic cost of running [3] and/or decrease the rate of stiffness experienced over long periods of running [4], which can reduce risk of injury [5]. However, there are few methods of measuring intricate running gait characteristics such as GCT outside of a controlled setting, where supervision and observation with expensive equipment is often required. Moreover, traditional running gait assessment methods typically require manual visual analysis of a runner's kinematics, which can be subject to bias or adoption of inadequate techniques [6].

Wearable technology has allowed for a more personalized data-driven approach to running gait analysis, beyond the confines of specialist environments [7]. Consumer-grade products show promise in quantifying various running gait features, including step rate and vertical ground reaction force [8]. Wearable devices can take shape in many forms, with common technologies such as Pressure-Sensitive Resistors (PSR) [9, 10] and Inertial Measurement Units (IMU) [11, 12] often found within. Furthermore, the proliferation and integration of Cloud-computing [13] through the ubiquity of smartphones, enables complex, computationally expensive data-analysis in any environment. This is exemplified through the Internet of Things (IoT), ensuring feasibility of remote running gait assessment to everyone, everywhere.

This study implements a low-cost, Cloud-based solution to quantify GCT and swing time (ST) of runners with a foot-mounted IMU tethered to a smartphone application via Bluetooth. This work extends the functionality of a commercial device (Mymo) by proposing an algorithm and validating it with a large dataset gathered from a synchronized gold/reference standard. The work will enable consumers to better understand their running gait characteristics from their habitual environment.

Related work

A. IMU-based gait analysis

Use of IMUs in healthcare and bioinformatic applications are becoming more common as a result of the quality of data produced in comparison to their PSR counterpart. Their increasingly small form factor and low-cost allows for easily scalable and remote deployment [14, 15]. Despite their low-cost, studies have shown them to perform in equivalent accuracy to their respective gold-standards in running gait assessment [16, 17].

IMUs are well suited to running analysis due to their typical inclusion of both accelerometer and gyroscope units. For instance, accelerometers excel at the detection of initial contact (IC) and final contact (FC, or toe-off, TO) events through observation of acceleration in multiple planes, segmenting gait events for quantification of spatial and temporal characteristics

[18]. Equally, gyroscopes provide 3D-angular velocity, allowing for the understanding of the rotational kinematics a runner may exhibit [19].

B. Ground contact time (GCT)

GCT has been shown to be critical in improving a runner's biomechanical economy [4, 20]. In general, GCT is defined through the distance between identified points of IC (the point where the foot first strikes the ground during a stride) and TO, the point where the foot leaves the ground [3]. Quantifying GCT from an IMU, therefore, must rely upon known gait segmentation methods for the identification of IC and TO events.

It is shown that different levels of support-cushioning technology within a running shoe can adversely affect an individual's GCT [21]. For example, shoes utilizing Air® chamber technology often increase GCT, whereas 'barefoot' style shoes exhibit a shorter GCT.

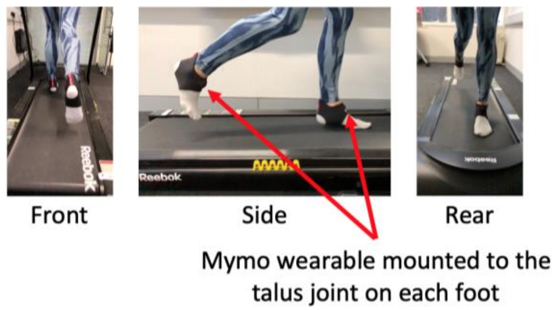

Figure 1: Example of video capture with Mymo sensor from front, side and rear perspectives

C. Swing time

Swing time (ST) refers to the period of time the foot spends off the ground during a stride [22], often described as the opposite of GCT. Although not as critical a measure as GCT, understanding a runner's ST can lead to indirect gains in running performance in relation to oxygen-use optimization through increased cadence as a result of less time spent in the air [23].

D. Running gait analysis and shoe recommendation

Mymo is a product that uses an IoT-enabled foot-mounted IMU to recommend running shoes based on a runner's gait (www.mymo.co.uk). Informed by a runner's pronation and foot-strike location extracted through a zero-crossing gradient maxima identification algorithm, the system utilizes deep learning to recommend neutral or support cushioned running shoes [18]. As an extension of the latter study, providing runners with GCT could better inform the selection of the correct running shoe; i.e. a runner with slow GCT may prefer a shoe that allows for faster GCT such as a 'barefoot' shoe [21].

Methods

A. Data capture and labelling

Healthy adults and adolescents (i.e. those with no physical impairments and who could run for a sustained period of time) were recruited from community-based leisure centers and running clubs in the North East of England. Ethical approval was granted by Northumbria University Research Ethics Committee (Ref: 21603). All participants gave verbal consent before providing data during treadmill-based testing.

Participants were asked to wear the Mymo wearable as per the manufacturer's guidelines: on each foot via a neoprene sock while they ran on a treadmill, mounting the IMU to the talus joint. Participants lower-extremities were then video recorded while running at 5mph/8kmph from three angles (front/side/rear) with a frame rate of 240FPS to allow for a high-resolution frame-by-frame analysis of the runner's GCT and ST. Participants ran for a period of 1 minute/foot, providing >7200 data points per runner (IMU polling at 60Hz, 1 minute/foot), Fig 1.

Upon completion of data capture, each video was manually labelled by a trained researcher, such that videos were loaded into video-processing software (VLC), where the frames between points of IC and TO events were counted and averaged for every stride in the footage. Videos were then cross-referenced between each data stream, wherein (i) the timestamp of IC is located, (ii) the timestamp of TO is located, (iii) GCT is calculated as the difference between these two points and (iv) ST was quantified as the distance from TO to the proceeding IC event. The process was repeated for each stride in the signal and averaged to provide a final GCT and ST of the runner in seconds compared video labels.

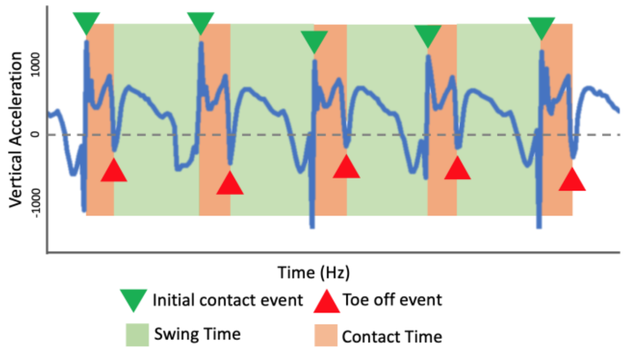

Figure 2: Visualization of contact and swing time calculation with both IC/TO identification (green and red markers respectively)

B. *Gait signal filtering and segmentation*

Inertial signals from the Mymo IMU were filtered by a Butterworth filter performing at 60Hz with a cutoff frequency of 5Hz and a sampling period of 3Hz to remove extraneous noise [18]. Once complete, a dynamic signal segmentation method utilizing zero-crossing gradient maxima detection was applied to the vertical acceleration (a_v) of the inertial signal to locate the points of IC within the filtered signal, splitting the signal into multiple gait cycles defined between two points of IC.

C. *Locating toe-off events*

As the proposed running gait cycle segmentation is focused on points of IC, to calculate GCT and ST, locations of TO events proceeding any given IC event are required. Inertial signals were compared to videos and it was identified that a TO event is denoted by the first negative gradient sign-change in a_v after crossing zero, Fig. 2.

The absolute signal of a_v is calculated and applied to our zero-crossing gradient maxima method [18] for identification of peaks proceeding an IC event. Peaks identified from this approach are then identified as TO events. During testing, false positives were identified within 5Hz (0.083s) from any respective point of IC, causing the calculation of GCT and ST to significantly under-perform. In response, a 5Hz threshold was applied from the point of IC to ensure TO events are not quantified within.

Table 1: Algorithm output vs. with (ground-truth) video

Left Foot				
Gait Feature	**Algorithm (s)**	**Video (s)**	***p***	**ICC$_{(2,1)}$**
GCT	0.306	0.302	0.951	0.974
ST	0.429	0.424	0.912	0.952
Right Foot				
Gait Feature	**Algorithm (s)**	**Video (s)**	***p***	**ICC$_{(2,1)}$**
GCT	0.327	0.316	0.818	0.894
ST	0.431	0.426	0.924	0.96

Algorithm Output and Video Reference refer to mean values of respective outputs, GCT=Ground Contact Time, ST=Swing Time. *p* refers to Pearson's Correlation

D. *Calculating GCT and ST*

Where GCT is defined as the quantified time the foot spends on the ground (i.e., between a point of IC and TO), GCT is calculated such that:

$$GCT_n = \frac{TO_n - IC_n}{SR} \qquad (1)$$

where, GCT_n is the GCT of any given stride in seconds and SR is the sampling rate of the device (60Hz). By normalising GCT into seconds, a direct comparison between the output of the GCT algorithm can be made against labels provided by video data.

To calculate ST, the time spent off the ground, an inverse of the calculation was performed by evaluating the time between a TO event and the proceeding IC:

$$ST_n = \frac{IC_{n+1} - TO_n}{SR} \qquad (2)$$

GCT and ST are calculated for every stride in a runner's signal, the mean GCT and ST is then provided to account for any anomalous strides within the signal.

E. Statistical analysis

Validating the performance of the proposed algorithms and their respective videos was conducted in SPSS v26. Shapiro-Wilks tests indicated a normal distribution of all data (p>0.105). Consequently, Pearson's correlation and intra-class correlation ($ICC_{(2,1)}$) models examined absolute agreement between algorithms and video. As defined by Koo and Mae, 2016 [24], ICC performance was rated as poor (< 0.5), moderate (0.5-0.75), good (0.75-0.9) or excellent (>0.9). Mean differences were calculated between algorithms and video for descriptive purposes.

Results

203 participants were recruited and undertook the protocol described. No data loss occurred across the cohort of participants. IMU and video-recorded running data were gathered while participants were on a treadmill for one minute per-foot (2mins total) whilst wearing the Mymo wearable. Results of the proposed algorithm were compared against the manually labelled data to assess the overall performance of the algorithms.

A. GCT and ST

Our approach to quantify GCT and ST with a foot-mounted IMU performs exceptional compared to ground-truth (video) reference ($ICC_{(2,1)}$ ≥0.894), Table 1. Figure 3 illustrates the algorithm performance across the cohort of participants, displaying results within close boundaries of their respective video reference range, while procuring few outliers.

Correlation and $ICC_{(2,1)}$ were excellent across left-foot GCT, ST and right-foot ST (≥0.952), with right-foot GCT classed as good (0.894), showing that the approach performs within low-variance of their respective video reference. Equally, observing the mean difference between algorithm output and video reference respective to class, our accuracy ranges from 96.6%-98.7% across all classes.

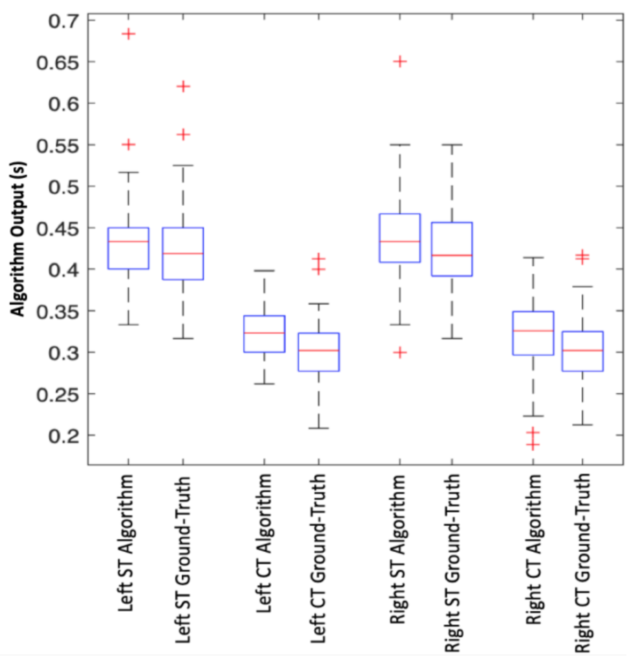

Figure 3: Boxplots of gait parameters for left/right foot, compared between algorithm and ground truth, video

Discussion

Our approach to the quantification of GCT and ST from a single foot-mounted IMU from Mymo, uses a zero-gradient crossing approach to the location and comparison of IC and TO events of a runner's stride. Deployed as part of an IoT system, Mymo aims to provide the need for transition from observer-based running gait assessment, to analysis beyond controlled settings, i.e. natural running situations [25].

Our segmentation algorithms as described in previous work [18] effectively identify and split inertial signals into their respective gait cycles through the use of standardized zero-crossing gradient maxima peak detection methods; providing an accurate basis for the quantification of GCT and ST.

The approach presented here can accurately assess both GCT and ST of runners as compared to their corresponding video reference data, Table 1. Our findings are concurrent with similar approaches in the field utilizing the gold-standard approach of pressure-sensitive technology for gait analysis [26, 27].

A. *Limitations and future work*

Participants were asked to run at a pace of 5mph/8kmph for 1 minute/foot. The study is limited in its accuracy across different running speeds/abilities, due to the relationship between running speed and impact forces [28]. Future work will require research into a variation of runner levels (i.e., beginner/amateur/elite) at their respective comfortable speeds to ensure the approaches validity in a diverse cohort of runners displaying a wide range of impact forces. Equally, testing within a range of locations (i.e., off the treadmill) is necessary to assess the validity of running gait assessment over ground.

Video data were captured in different low-resource environments, exhibiting a range of brightness levels and running orientations (i.e., running left to right/right to left). As such, it is speculated that findings for right-foot GCT are slightly lower in accuracy because of reduced clarity pertaining to the exact identification of IC in darker environments when the right foot is behind the left. Even lighting across video capture settings in future work will help to improve identification of gait events from video streams.

Conclusion

Presented is a novel approach to the quantification of GCT and ST of runners from a single foot mounted commercial IMU wearable. Our approach works to improve the overall functionality of the system (Mymo), an IoT device to help runners choose the correct running shoe by providing a real-world running gait assessment. The proposed method exhibits a high accuracy of GCT and ST across a large cohort of runners upon a treadmill.

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References

[1] S. Haake, "Gotta run?," *New Scientist,* vol. 245, no. 3273, pp. 34-38, 2020.

[2] F. García-Pinillos, J. C. Cámara-Pérez, V. M. Soto-Hermoso, and P. Á. Latorre-Román, "A high intensity interval training (HIIT)-based running plan improves athletic performance by improving muscle power," *The Journal of Strength & Conditioning Research,* vol. 31, no. 1, pp. 146-153, 2017.

[3] I. S. Moore, K. J. Ashford, C. Cross, et al, "Humans Optimize Ground Contact Time and Leg Stiffness to Minimize the Metabolic Cost of Running," *Frontiers in Sports and Active Living,* vol. 1, p. 53, 2019.

[4] J.-B. Morin, G. Dalleau, H. Kyröläinen, T. Jeannin, and A. Belli, "A simple method for measuring stiffness during running," *Journal of applied biomechanics,* vol. 21, no. 2, pp. 167-180, 2005.

[5] R. J. Butler, H. P. Crowell III, and I. M. Davis, "Lower extremity stiffness: implications for performance and injury," *Clinical biomechanics,* vol. 18, no. 6, pp. 511-517, 2003.

[6] B. K. Higginson, "Methods of running gait analysis," *Current sports medicine reports,* vol. 8, no. 3, pp. 136-141, 2009.

[7] L. C. Benson, C. A. Clermont, E. Bošnjak, and R. Ferber, "The use of wearable devices for walking and running gait analysis outside of the lab: A systematic review," *Gait & posture,* vol. 63, pp. 124-138, 2018.

[8] B. P. de Fontenay, J. Roy, B. Dubois, L. Bouyer, and J. Esculier, "Validating commercial wearable sensors for running gait parameters estimation," *IEEE Sensors Journal,* vol. 20, no. 14, pp. 7783-7791, 2020.

[9] S. W. Park, P. S. Das, and J. Y. Park, "Development of wearable and flexible insole type capacitive pressure sensor for continuous gait signal analysis," *Organic Electronics,* vol. 53, pp. 213-220, 2018.

[10] R. Nagahara and J.-B. Morin, "Sensor insole for measuring temporal variables and vertical force during sprinting," *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology,* vol. 232, no. 4, pp. 369-374, 2018.

[11] M. Mansoubi, P. Esser, A. Meaney, R. Metz, K. Beunder, and H. Dawes, "Evaluating of the Axivity accelerometers algorithm in measurement of physical activity intensity in boys and girls," 2019.

[12] M. Falbriard, F. Meyer, B. Mariani, G. P. Millet, and K. Aminian, "Drift-Free Foot Orientation Estimation in Running Using Wearable IMU," *Frontiers in Bioengineering and Biotechnology,* vol. 8, p. 65, 2020.

[13] D. Byrne, C. Corrado, and D. E. Sichel, "The rise of cloud computing: minding your P's, Q's and K's," National Bureau of Economic Research, 0898-2937, 2018.

[14] Y.-S. Cho *et al.*, "Evaluation of validity and reliability of inertial measurement unit-based gait analysis systems," *Annals of rehabilitation medicine,* vol. 42, no. 6, p. 872, 2018.

[15] V. Chandel, S. Singhal, V. Sharma, N. Ahmed, and A. Ghose, "PI-Sole: A Low-Cost Solution for Gait Monitoring Using Off-The-Shelf Piezoelectric Sensors and IMU," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2019: IEEE, pp. 3290-3296.

[16] G. Bailey and R. Harle, "Assessment of foot kinematics during steady state running using a foot-mounted IMU," *Procedia Eng,* vol. 72, pp. 32-37, 2014.

[17] T. Tan, Z. A. Strout, and P. B. Shull, "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,* 2020.

[18] F. Young, G. Coulby, I. Watson, C. Downs, S. Stuart, and A. Godfrey, "Just find it: The Mymo approach to recommend running shoes," *IEEE Access,* vol. 8, pp. 109791-109800, 2020.

[19] Y. Celik, S. Stuart, W. L. Woo, and A. Godfrey, "Gait analysis in neurological populations: Progression in the use of wearables," *Medical Engineering & Physics,* 2020.

[20] R. Di Michele and F. Merni, "The concurrent effects of strike pattern and ground-contact time on running economy," *Journal of science and medicine in sport,* vol. 17, no. 4, pp. 414-418, 2014.

[21] A. Roca-Dols *et al.*, "Effect of the cushioning running shoes in ground contact time of phases of gait," *Journal of the mechanical behavior of biomedical materials,* vol. 88, pp. 196-200, 2018.
[22] S. A. Dugan and K. P. Bhat, "Biomechanics and analysis of running gait," *Physical Medicine and Rehabilitation Clinics,* vol. 16, no. 3, pp. 603-621, 2005.
[23] N. Tam, R. Tucker, J. Santos-Concejero, D. Prins, and R. P. Lamberts, "Running Economy: Neuromuscular and Joint Stiffness Contributions in," *International Journal of Sports Physiology and Performance*.
[24] T. K. Koo and M. Y. Li, "A guideline of selecting and reporting intraclass correlation coefficients for reliability research," *Journal of chiropractic medicine,* vol. 15, no. 2, pp. 155-163, 2016.
[25] R. J. Mobbs, D. Ho, W. J. Choy, C. Betteridge, and H. Lin, "COVID-19 is shifting the adoption of wearable monitoring and telemedicine (WearTel) in the delivery of healthcare: opinion piece," *Annals of Translational Medicine,* vol. 8, no. 20, 2020.
[26] W. Seiberl, E. Jensen, J. Merker, et al, "Accuracy and precision of loadsol® insole force-sensors for the quantification of ground reaction force-based biomechanical running parameters," *European journal of sport science,* vol. 18, no. 8, pp. 1100-1109, 2018.
[27] G. T. Burns, J. D. Zendler, and R. F. Zernicke, "Wireless insoles to measure ground reaction forces: step-bystep validity in hopping, walking, and running," *ISBS Proceedings Archive,* vol. 35, no. 1, p. 255, 2017.
[28] S. Mo and D. H. Chow, "Accuracy of three methods in gait event detection during overground running," *Gait & posture,* vol. 59, pp. 93-98, 2018.