GAIT EVENT DETECTION DURING WALKING USING DEEP LEARNING AND THIGH-WORN ACCELEROMETRY

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Mobility and gait are important indicators of human health. However, measuring them outside of a laboratory setting can be challenging. To measure human physical behaviour in free-living conditions, thigh-worn accelerometers and data-driven algorithms are commonly used. This study explores a deep learning approach that utilises data from a single thigh-worn accelerometer. A temporal convolutional network was trained to predict gait events in healthy adults during various walking conditions. The model demonstrated a high level of detection accuracy (F_1 score ≥ 99%) and good time agreement for both gait events, with the 95% limits of agreement being -0.04s and 0.04s. Minor differences in spatiotemporal gait parameters were observed. The results indicate the potential of using a deep learning approach with thigh-worn accelerometry data for future research.

KEYWORDS: accelerometer, temporal convolutional network, gait analysis

INTRODUCTION: Thigh-worn accelerometers have become increasingly popular in physical activity research for monitoring the physical behaviour of individuals in real-world settings (Stamatakis et al., 2020). Wearable accelerometers, positioned on the thigh and utilizing data-driven algorithms, offer high accuracy in classifying various activity types under free-living conditions (Stevens et al., 2020). These devices offer the opportunity to extract additional outcomes, such as gait characteristics, by using the information contained within the raw acceleration signal.
Human gait patterns are sensitive indicators that can provide valuable insights into a range of health conditions, including neurological disorders, musculoskeletal issues, and age-related effects. Detecting changes in gait patterns can provide crucial information about emerging health problems, such as Parkinson's disease or the risk of falling (Del Din et al., 2019). Accurate detection of gait events is a critical step in gait analysis, enabling the computation of spatiotemporal gait variables and facilitating gait segmentation for further analysis or modelling (Slade et al., 2021). The application of deep learning techniques has demonstrated significant improvements in gait event detection using inertial measurement unit (IMU) data, as demonstrated in recent studies (Romijnders et al., 2022, 2023). Motivated by these advances, our study aims to evaluate the accuracy of a deep learning approach in estimating gait events based on thigh acceleration during walking. By expanding on the current knowledge, our study aims to provide valuable insights into the potential applications of thigh-worn accelerometers and further improve our ability to analyse gait in various health, sport, and research contexts.

METHODS: A total of 18 healthy adults (26.3 ± 4.1 years; 39% female; 23.3 ± 1.66 kg/m²) participated in the study. Each participant provided written informed consent prior to data collection, and the study was approved by the university's ethics committee (No. 107/2023). Participants completed four two-minute walking trials on a treadmill with walking speeds ranging from 2 to 5 km/h. The final trial consisted of a five-minute continuous walk on level ground outside the laboratory at the participant's preferred speed.
Vertical ground reaction force (GRF) was measured using wireless force-sensing insoles with a sampling frequency of 100 Hz (loadsol®, novel GmbH Munich, Germany). Triaxial acceleration of the thigh was measured using an IMU (AX6, Axivity Ltd, Newcastle upon Tyne, UK) placed on the lateral side of the dominant leg, midway between the hip and knee. The IMU

was attached directly on the skin using a standardised combination of medical adhesive tape. Acceleration data was sampled at 100 Hz with a dynamic range of ±8 g. The GRF and acceleration signals were time synchronised by using a series of standardised heel drops and manually identifying the peaks in each signal. The reference initial contacts (IC) and final contacts (FC) were identified based on the GRF using a 50 N threshold. Acceleration data were filtered using a fourth-order Butterworth filter with a cut-off frequency of 25 Hz. In addition, each axis was normalised using the channel-wise maximum absolute value.
All participant data was randomly split at the participant-level into two independent datasets, namely a training set and a test set, using a 3:1 ratio. The training set was used to optimise and train the deep learning model, while the test set was used to evaluate the model's performance on previously unseen data. Hyperparameter optimisation was performed using a hold-out sample from the training set (validation set). A single non-causal temporal convolutional network (TCN; Bai et al., 2018) was then trained to predict the occurrence of IC and FC events. The final model architecture was defined with 16 filters, a kernel size of 6 and dilations of [1, 2, 4, 8]. Two separate output layers were used with a sigmoid activation function, and the binary cross-entropy was used as the loss function. To evaluate the performance of the model, we compared its predictions on the test set with the corresponding reference labels. First, we identified all gait event predictions with a peak probability greater than 0.5 and a minimum interpeak distance of 0.5s. These gait events were subsequently considered predicted events for the analysis. This filtering was done to minimise false positive predictions. Correctly identified gait events were then defined as those that occurred within 0.25s before or after a true gait event (Romijnders et al., 2023). The evaluation assessed overall detection performance, temporal agreement between predicted and reference events, and gait-specific parameters. Recall was calculated as the proportion of true (reference) gait events that were predicted by the model, and precision was calculated as the proportion of predicted gait events that were true gait events. The F_1 score was calculated as the harmonic mean of recall and precision. Python 3.11 and open-source Python libraries were used for data processing, model training, and analysis. The TCN model was trained using Keras and KerasTCN (Rémy, 2020).

RESULTS: The test set comprised 6787 annotated steps, which were used to evaluate the model's performance. The trained TCN model demonstrated high recall (≥ 98%) and precision (≥ 99%) as well as an F_1 score (≥ 99%) for both IC and FC events across all walking conditions. The overall mean time error between the reference and predicted gait events for both IC and FC events was < 0.01s with the 95% limits of agreement being -0.04s and 0.04s. Figure 1 illustrates the distribution of time agreement errors for each walking condition. The mean differences between the predicted and reference values for gait-specific parameters ranged from -0.01s and 0.01s across all conditions, with 95% limits of agreement between -0.07s and 0.07s (see Table 1).

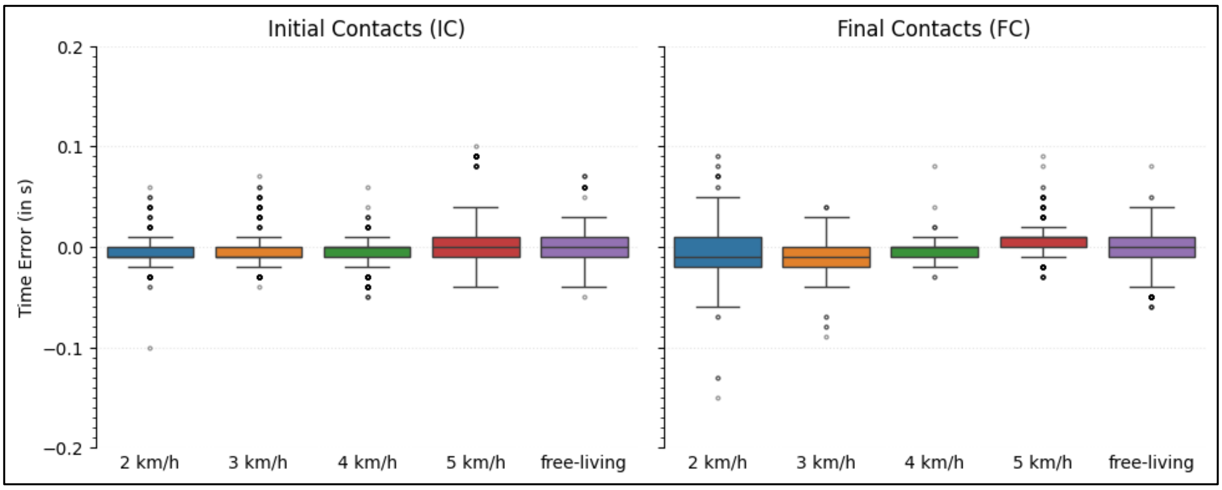

Figure 1: Time errors of the predicted initial contacts (left) and final contacts (right).

Table 1: Agreement between the deep learning model and the reference for gait-specific parameters.

Condition	Gait parameter	Mean difference (s)	95% Limits of Agreement (s / s)
2 km/h	Stride time	0.00	(-0.04 / 0.04)
	Stance time	0.00	(-0.07 / 0.07)
	Swing time	0.00	(-0.06 / 0.06)
3 km/h	Stride time	0.00	(-0.04 / 0.04)
	Stance time	0.01	(-0.04 / 0.05)
	Swing time	-0.01	(-0.05 / 0.04)
4 km/h	Stride time	0.00	(-0.03 / 0.03)
	Stance time	-0.01	(-0.04 / 0.03)
	Swing time	0.01	(-0.03 / 0.04)
5 km/h	Stride time	0.00	(-0.05 / 0.05)
	Stance time	0.00	(-0.05 / 0.05)
	Swing time	0.00	(-0.05 / 0.05)
Free-living	Stride time	0.00	(-0.03 / 0.03)
	Stance time	-0.01	(-0.05 / 0.04)
	Swing time	0.01	(-0.04 / 0.05)

DISCUSSION: Thigh-worn accelerometers which can be used to detect gait events and measure gait characteristics, could provide researchers with new outcomes to analyse within existing large-scale datasets. This study aimed to evaluate the performance of a deep-learning approach in estimating gait events during walking in healthy adults. The model achieved excellent accuracy in detecting gait events when compared to the reference. The level of agreement for the timing of gait events and derived gait-specific parameters was high. These results are comparable to previous studies that used a similar deep learning approach based on IMU data from the shank or foot (Romijnders et al., 2022, 2023). The agreement of the derived gait-specific parameters, specifically stance and swing time, was superior to that of a previous study using thigh-acceleration and a deterministic filtering approach. The study reported 95% limits of agreement of -0.085s and 0.110s for stance time and -0.109s and 0.085s for swing time (Gurchiek et al., 2020).
While several studies have developed algorithms for gait event detection, they are often limited to laboratory data. We incorporated both laboratory and free-living data into the model's training and testing, which increases the generalisability of our results. However, this study has limitations due to the small and homogeneous sample, which makes it difficult to generalize the results to a broader population. The model's ability to accurately predict gait events may be affected by the prevalence of musculoskeletal or neurological diseases, as well as aging, which can impact individual gait patterns. Therefore, further external validation of our performance results is necessary, including a more heterogeneous sample. The walking conditions in our study were homogeneous, consisting of flat surfaces without any incline. It is important to note that these conditions may not reflect the diverse real-world walking conditions.
The sensor type, settings and placement used in our study are common in physical activity research. This increases the applicability of our results to other studies and datasets. As a next step, we will work on combining the gait event detection with a walking classifier. This will enable the classification of multi-day raw acceleration data from epidemiological cohort studies such as the HUNT4 study (Åsvold et al., 2023). If successful, this will allow researchers to gain new insights into real-world walking and gait characteristics and their association with various health-related parameters. In addition, our findings can serve as a basis for future research to extend the approach to other sports, such as running and race walking.

CONCLUSION: To our knowledge, this study presents the first deep learning model that uses only the acceleration signal of the thigh. The findings suggest that deep-learning approaches can be used to detect gait events in healthy adults during walking. When combined with an accurate walking classifier, which is readily available for thigh-worn accelerometry, the deep learning approach can support physical activity researchers in studying free-living human gait. However, it is necessary to conduct further model training and validation in other cohorts, such as older adults or individuals with impaired gait, and under more diverse conditions. If applied to a sports setting, this approach has the potential to enable accurate gait analysis during running and walking in the field.

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