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Gait Event Detection Using a Thigh-Worn Accelerometer

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Abstract

Background: Gait event detection is critical for remote gait analysis. Algorithms using a thigh-worn accelerometer for estimating spatiotemporal gait variables have demonstrated clinical utility in monitoring the gait of patients with gait and balance impairment. However, one may obtain accurate estimates of spatiotemporal variables, but with biased estimates of foot contact and foot off events. Some biomechanical analyses depend on accurate gait phase segmentation, but previous studies using a thigh-worn accelerometer have not quantified the error in estimating foot contact and foot off events.

Methods: Gait events and spatiotemporal gait variables were estimated using a thigh-worn accelerometer from 32 healthy subjects across a range of walking speeds (0.56 – 1.78 m/s). Ground truth estimates were obtained using vertical ground reaction forces measured using a pressure treadmill. Estimation performance was quantified using absolute error, root mean square error, and correlation analysis.

Results: Across all strides (N = 3,898), the absolute error in estimating foot contact, foot off, stride time, stance time, and swing time was similar to other accelerometer-based techniques (39 ± 28 ms, 28 ± 28 ms, 11 ± 14 ms, 46 ± 31 ms, and 45 ± 30 ms, respectively). The correlation between reference measurements and estimates of bout-average stride time, stance time, and swing time were 1.00, 0.92, and 0.80, respectively. The (5^{th}, 95^{th}) percentiles of the foot contact and foot off estimation errors were (−91 ms, 51 ms) and (−70 ms, 60 ms), the largest of which amounts to about three samples using the 31.25 Hz sampling frequency used in this study.

Significance: Use of the proposed algorithm for estimating spatiotemporal gait variables is supported by the strong correlations with reference measurements. The gait event estimation error distributions provide bounds on the estimated gait events for enforcing gait phase-dependent task constraints for biomechanical analysis.

Keywords

event detection; accelerometer; wearable sensor; gait analysis

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Conflict of interest
RSM owns stock in MC10, Inc. This conflict is being managed by the University of Vermont.

1. Introduction

Recent developments in remote gait analysis promise improved monitoring of patients with both neurological and musculoskeletal conditions [1–5]. Gait event detection is doubly important for remote analyses as it provides the information needed to compute spatiotemporal gait variables, which alone are clinically informative, and enables more complex analyses that require accurate gait phase segmentation (e.g., see [1]). For example, knowledge of gait phase can aid in the use of simplifying assumptions such as zero foot velocity during stance for pedestrian tracking [6] or zero distal contact forces during swing for inverse dynamics-based estimates of joint moment [7].

Several gait event detection methods have been proposed and differ according to algorithm used and the number, type, and location of wearable sensors [8]. Methods utilizing a single, thigh-worn accelerometer are practically deployable as they present minimal burden to the patient and have demonstrated clinical utility [1,9]. Aminian et al. (1999) validated an algorithm using a thigh-worn accelerometer for estimating spatiotemporal variables for preferred walking speeds which relied on constant low-pass filter cutoff frequencies. We used a modified version of the Aminian algorithm with adaptable cutoff frequencies for monitoring patients' gait following knee surgery [1]. It is important to note that accurate estimates of spatiotemporal gait variables do not infer accurate estimation of the actual foot contact or foot off events. These errors should be characterized so that gait phase-dependent task constraints can be applied appropriately. However, errors in thigh-worn accelerometer-based estimates of foot contact and foot off events have not been reported in previous studies [9–11]. Therefore, the purpose of this study was to quantify the error in estimating foot contact and foot off events during gait using a modified version of the algorithm proposed in [1]. We also report spatiotemporal gait variable estimation performance for comparison to previous studies.

2. Methods

2.1 Experimental Design

Thirty-two healthy subjects (16 female, 21 ± 3 years old, height (data available from 31 subjects): 1.74 ± 0.09 m) walked for one-minute at various self-selected walking speeds on a pressure treadmill (h/p/cosmos quasar, Nussdorf-Traunstein, Germany, 100 Hz) with a three-axis accelerometer (Opal, APDM, Inc., Portland, OR, USA) on the left and right lateral thigh. The range of walking speeds (0.56 – 1.78 m/s) and stride times (0.91 – 1.57 s) analyzed well encompass those observed for young and elderly healthy populations [2,12] as well as for patients with neurological and musculoskeletal impairment [1,3]. Ground truth foot contact and foot off instances were identified from the vertical ground reaction force measurements provided by the treadmill using a 20 N threshold. Accelerometer data were downsampled from the original sampling frequency (128 Hz) to 31.25 Hz to mimic sampling frequencies used for remote monitoring [1]. All subjects provided written consent to participate and study activities were approved by the local Institutional Review Board.

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2.2 Event Detection Algorithm

All accelerometer data were first projected onto the long axis of the thigh (identified during a standing calibration trial [1]). Next, the step frequency (f_{str}) and stride frequency (f_{str}) were estimated from the power spectral density of the accelerometer signal during the walking bout (Figure 1a). The signal was then low-pass filtered with cutoff frequencies equal to f_{stp}, f_{str}, and $5 \cdot f_{str}$ (Figure 1b) where the cutoff frequency $5 \cdot f_{str}$ was chosen to remove soft-tissue artefact while accounting for variable stride frequencies (as is characteristic in other sensing modalities [13]). Foot off events were estimated as the instants associated with the larger peaks in the f_{stp} -filtered signal (arrow 3 in Figure 1b) just prior to a local minima in the f_{str} -filtered signal (arrow 1 in Figure 1b). Foot contact events were estimated as the instants associated with the positive going 1 g crossings (arrow 2 in Figure 1b) of the $5 \cdot f_{str}$ filtered signal (determined via linear interpolation where necessary) following each identified foot off event. Source code is provided in the online supplemental material as well as a more detailed description of the algorithm.

2.3 Statistical Analysis

Estimation performance was quantified across all strides using the absolute error (AE) and root mean square error (RMSE) between the reference measurements and accelerometer-based estimates of foot contact and foot off events as well as stride time, stance time, and swing time. The bout-average stride, stance, and swing time estimates were further evaluated using Pearson's correlation coefficient and Bland-Altman analysis for repeated measures [14,15].

3. Results

Across all strides (N = 3,898), the estimation error was 39 ± 28 ms AE (47 ms RMSE) for foot contact; 28 ± 28 ms AE (40 ms RMSE) for foot off; 11 ± 14 ms AE (17 ms RMSE) for stride time; 46 ± 31 ms AE (55 ms RMSE) for stance time; and 45 ± 30 ms AE (54 ms RMSE) for swing time. The correlation between the estimated and measured bout-average stride, stance, and swing times were 1.00, 0.92, and 0.80, respectively. The bias and 95% limits of agreement (lower limit, upper limit) for the bout-average stride, stance, and swing time estimates were 0 (−2, 3) ms, 13 (−85, 110) ms, and −12 (−109, 85) ms, respectively. The (5^{th}, 95^{th}) percentiles (mean ± 1.65 SD) of the foot contact and foot off estimation errors were (−91, 51) ms and (−70, 60) ms.

4. Discussion

The RMSE in estimating foot contact and foot off events (47 ms and 40 ms) present improvements over that reported for a shank accelerometer (80 ms and 68 ms) [16]. Methods using a sacral accelerometer appear more accurate for foot contact estimation (28 ms RMSE), but with comparable foot off estimation errors (40 ms RMSE) [16]. Based on the error distributions in estimating these gait events (5^{th} and 95^{th} percentiles), biomechanical analyses enforcing task constraints dependent on the stance (swing) phase of gait should force the assumption only for data at least 51 ms after (91 ms before) the estimated foot contact event and 70 ms before (60 ms after) the estimated foot off event. This knowledge provides the intervals of time during which one may apply stance phase- (e.g., zero velocity updates) and/or swing phase- (e.g., zero distal contact force) based assumptions with 95% confidence. The largest of these (91 ms) amounts to less than three samples for the 31.25 Hz sampling frequency. In a post-hoc analysis we found nearly identical results in foot contact and foot off estimation error with data sampled at 128 Hz (40 ms and 28 ms AE, respectively) and thus inaccuracies in the proposed algorithm cannot be attributed to the relatively low sampling frequency. Bland-Altman analysis revealed an apparent relationship between stance and swing time errors and their magnitudes (Figure 2). Similar results have been observed previously [16] and warrants further investigation. Nevertheless, spatiotemporal gait variables were estimated with strong correlations ($r \geq 0.80$) and low absolute errors (11 to 46 ms) comparable to other methods [16]. These results were observed for a large sample size relative to previous studies of similar aim [9,10,16] and for a broad range of gait speeds and stride times which are representative of a multitude of subject populations [1,2,12], supporting the use of this approach for remote gait analysis.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgements

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Highlights

- Validation of a gait event detection algorithm using a thigh-worn accelerometer
- Strong correlations between estimated and measured spatiotemporal gait variables
- Low mean absolute error in gait event detection (28 to 39 ms)
- Source code for the algorithm has been made available

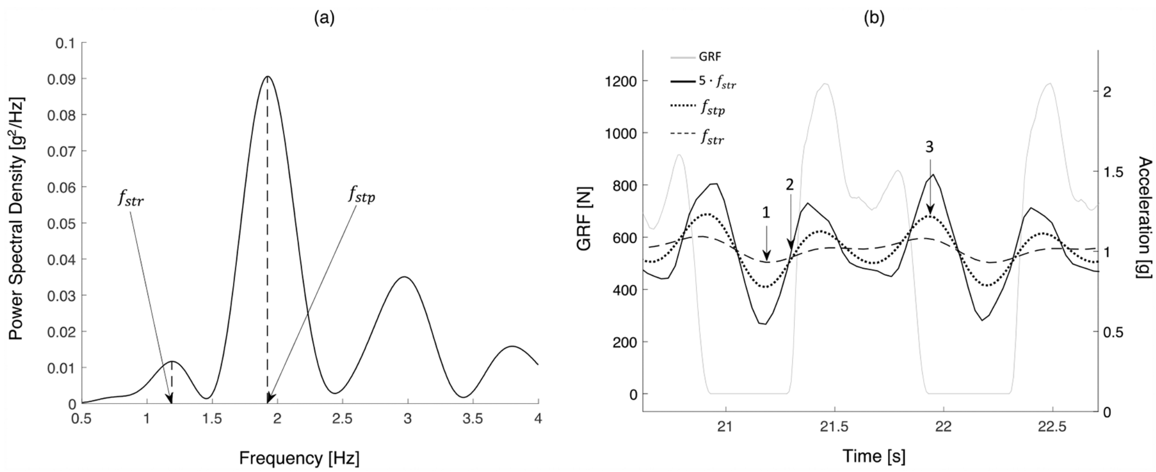

Figure 1.

Gait event detection algorithm. First, step (f_{stp}) and stride (f_{str}) frequencies are approximated from the power spectral density of the raw accelerometer signal (a). Foot contact and foot off events are then determined algorithmically by associating consistently identifiable features in the processed accelerometer signals (b, arrows 1–3) with ground truth data obtained from the measured vertical ground reaction forces (b, GRF, solid grey line, left vertical axis). The minimum in the f_{str}-filtered signal (b, dashed black line) preceding foot contact (b, arrow 1) are id entified first. The estimate of foot contact is then associated with the positive going 1 g crossing (b, arrow 2) in the 5 · f_{str} Hz-filtered signal (b, solid black line) following minimum. Finally, the foot off event is associated with the second peak (b, arrow 3) in the f_{stp}-filtered signal (b, dotted black line) following foot contact.

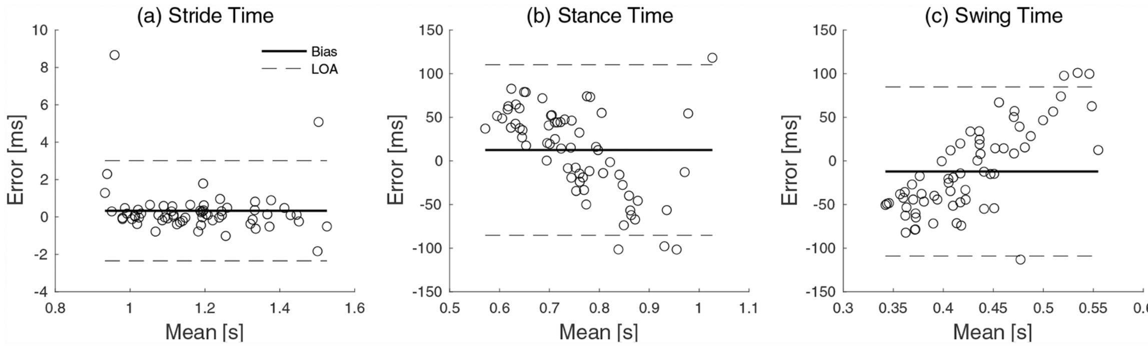

Figure 2.

Bland-Altman plots of the estimation error (vertical axis) between the measured and estimated bout-average stride time (a), stance time (b), and swing time (c) against the mean of the measured and estimated values (horizontal axis). The solid black line in each figure is the bias (mean error) and the dashed black lines denote the 95% limits of agreement (LOA).