Derivative Based Gait Event Detection Algorithm Using Unfiltered Accelerometer Signals

Rafael Escamilla-Nunez, Luis Aguilar, Gabriel Ng, Aliaa Gouda, and Jan Andrysek

Abstract—**Wearable sensors have been investigated for the purpose of gait analysis, namely gait event detection. Many types of algorithms have been developed specifically using inertial sensor data for detecting gait events. Though much attention has turned toward machine learning algorithms, most of these approaches suffer from large computational requirements and are not yet suitable for real-time applications such as in prostheses or for feedback control. Current rules-based algorithms for real-time use often require fusion of multiple sensor signals to achieve high accuracy, thus increasing complexity and decreasing usability of the instrument. We present our results of a novel, rules-based algorithm using a single accelerometer signal from the foot to reliably detect heel-strike and toe-off events. Using the derivative of the raw accelerometer signal and applying an optimizer and windowing approach, high performance was achieved with a sensitivity and specificity of 94.32% and 94.70% respectively, and a timing error of 6.52 ± 22.37 ms, including trials involving multiple speed transitions. This would enable development of a compact wearable system for robust gait analysis in real-world settings, providing key insights into gait quality with the capability for real-time system control.**

I. Introduction

Efficient and purposeful gait training is imperative for allowing those with mobility impairments to regain movement and improve quality of life [1]. Objective gait analysis is a crucial aspect in effective rehabilitation. Data on kinematics and gait timing provide insights into gait quality and can be applied to a range of applications such as powered prostheses, performance feedback systems, and better-informed therapy regiments [2], [3]. The rapid development of wearable sensor technology has allowed for increasingly portable gait analysis systems.

Quantitative gait analysis systems have been employed for many years in rehabilitation for motor-impaired populations and shown to be effective in improving rehabilitation outcomes [2], [4]. A common technique involves detecting gait events and segmenting the gait cycle into phases. For instance, heel-strike (HS) and toe-off (TO) denote the start of stance and swing phase, respectively. These can be used actively to control systems with actuation or feedback and also passively to calculate spatiotemporal gait parameters related to quality of gait and better inform rehabilitation.

Inertial measurement units consisting of accelerometer and gyroscope have emerged as a promising wearable sensor for gait analysis purposes [2], [5]. A wide assortment of algorithms have been investigated with gait event detection using inertial sensors attached to the shank, thigh, or foot. These include a variety of rules-based algorithms incorporating peak-detection or thresholding [3], [6] and frequency analysis [7]. Groups have also begun to investigate more powerful adaptive or machine learning models such as Bayes classifiers [8], Markov models [9], [10], and neural networks [11], [12]. Adaptable models are often desired for more complex analysis. They have been successfully applied to ankle angle estimation [11], eight-phase gait segmentation [8], and detecting the percentage of the gait cycle based on inertial data [12]. However, a key drawback to these models are their large computational requirements which limit many of them to offline use. There are many applications such as prosthesis control, stimulation, performance feedback, etc. that require online (i.e. real-time) performance. Robust rules-based algorithms can offer a computationally low-cost but still a high-accuracy alternative suitable for real-time gait analysis. In fact, a recent study comparing their thresholding algorithm to two machine-learning models (linear and quadratic discriminant analysis) for HS and TO detection found almost no difference in accuracy [3].

Previous studies have looked at accelerometer data for detecting HS and TO. According to the literature, HS and TO events can be detected by searching for the maximum local peaks in the X and Z axis of a 3-axis accelerometer [13], [14] aligned with the anteroposterior and longitudinal axis of the body, respectively. There are still many issues with these algorithms. They often require preprocessing and filtering [7], [14]. This is to eliminate noise and also the baseline drift over time exhibited by many inertial sensors. One study analyzing 41 acceleration algorithms reported difficulty achieving high accuracy with only a single accelerometer [15]. Nevertheless, a single accelerometer is desirable from a usability perspective by being less burdensome for the user, computationally more efficient to process, and overall simpler and more cost effective to implement.

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The aim of this study was to develop and validate a novel algorithm for detecting HS and TO using data from a single accelerometer signal from the dorsal side of the foot. Unlike traditional thresholding algorithms which look at the base linear acceleration values [13], [14], our algorithm calculates the derivative of the signal before applying windowing and a threshold to identify gait events. The goal of this work is to develop an algorithm that could potentially be embedded into a wearable system for both long-term and real-time gait event detection and control, allowing us to better guide patients during rehabilitation in and out of the clinical settings, improving outcomes and restoring individuals to healthy gait.

II. Methods

A. Algorithm Design

The algorithm utilizes raw acceleration data from the X-axis (anteroposterior axis) of a 3-axis accelerometer. As a first step, pilot testing was conducted in one healthy subject to identify a pattern in the peak sequence and amplitude from one gait cycle to another. Within a single gait cycle, we could consistently identify two periods featuring prominent acceleration spikes corresponding approximately with HS and TO timing. However, the large variations in those peak amplitudes over time accompanied by occasional noise spikes make it difficult to choose a single threshold that will capture only gait events while avoiding erroneous detections. Since the maximums occur as a result of drastic changes in acceleration (foot hitting – HS – or leaving the ground – TO), it was postulated that analyzing the derivative of the raw signal could more reliably identify maximum peaks at each gait cycle (Fig. 1).

The algorithm first looks at a window made up of consecutive derivative values and computes the total absolute change which we refer to as the total derivative (d_{total}). After d_{total} is computed for a given window, the second step is to apply an initial threshold to determine if there is enough total change to indicate a possible gait event (Fig. 2). Since the signal fluctuates considerably around gait events, multiple windows nearby will have d_{total} values above the threshold (i.e., local maximums). The third step is to determine where the global maximum change occurs, which corresponds to the actual gait event. The global maximum is determined by comparing consecutive windows and selecting the window with the largest total derivative (Fig. 2). Early pilot testing showed that a data window with 10 samples and a comparison size of 5 windows was adequately robust to accommodate three different rates of walking (i.e., slow, self-selected, and fast).

B. System Instrumentation

An accelerometer (ADXL 355Analog Devices, MA, USA) and two force sensitive resistor (FSR) sensors (FSR 406, Interlink Electronics, CA, USA) were utilized to detect desired gait events (i.e., HS and TO) (Fig. 3). The accelerometer was affixed on the dorsal side of the left foot. The accelerometer was aligned in the transverse plane where the X, Y and Z axes aligned with the anteroposterior, frontal and longitudinal axes, respectively (Fig. 3). Two FSR sensors were placed at the bottom of the shoe on the left foot, one at the heel and one at the toe (Fig. 3). The accelerometer and FSR sensor data were sampled at a frequency of 100 Hz, with an accelerometer range of ±3g. The data was processed on the Arduino Mega on-board system and logged directly onto a computer via Bluetooth. Dual-beam timing gates (Smartspeed PT, Fusion Sport, CO, US) were used to measure the time for each trial to validate speed difference.

C. Experimental Protocol

A convenience sample of four (n=4) healthy subjects (two males; age: 22–31 years) were recruited to participate in this study. During data collection, subjects were instructed to walk at three different speeds: slow (S1), self-selected (S2), and fast (S3). Each participant completed four 20-m straight-line walking trials, one at each of the three speeds and one at varying speeds. For the variable-speed case (SV), subjects were instructed to walk at varying speeds in a randomized sequence (i.e., S3-S2-S1, S3-S1-S2, S2-S3-S1, S2-S3-S1 for

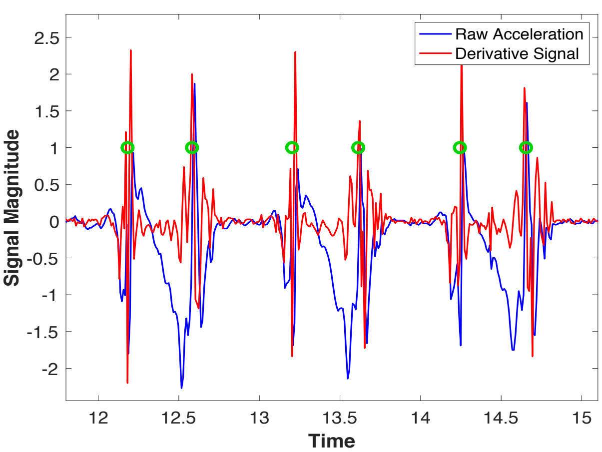

Figure 1. Plot of raw acceleration data (blue) with the equivalent derivative signal (red). The derivative of the acceleration signal displays rapid changes around gait events. Gait events (green) can be identified by the time when the greatest total change occurs.

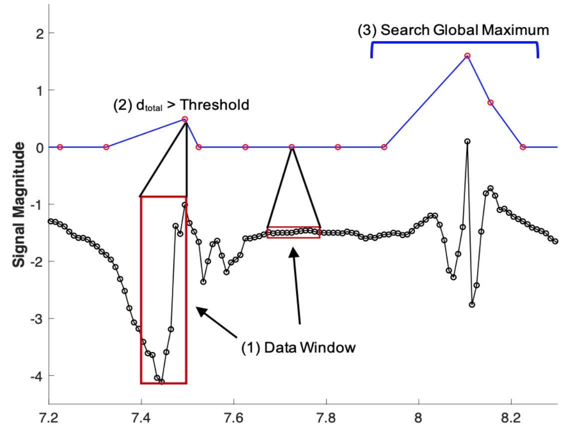

Figure 2. Sample signal to show windowing technique. (1) The total change within a data window is computed and stored. (2) These are passed through a threshold which zeroes any windows that do not exceed this value. (3) The algorithm then searches through consecutive windows to identify the global maxima (i.e. gait events).

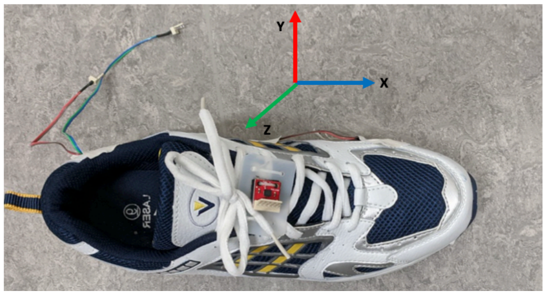

Figure 3. Participant instrumentation using accelerometer (ADXL 355, Analog Devices) affixed to the top of the shoe and FSR sensors (FSR 406, Interlink Electronics) on the sole.

subject 1, 2, 3 and 4 respectively). The experimental protocol previously described was approved by the Research Ethics Board at Holland Bloorview Kids Rehabilitation Hospital, Canada. Informed written consent from each participant was obtained before conducting the study.

D. Data Analysis

The accuracy of the proposed algorithm was evaluated by comparing the gait events detected against timing provided by the two FSR sensors located at the plantar surface of the shoe (heel x1, toe x1). FSR and acceleration data were analyzed using MATLAB software (R2019a, Mathworks, MA, USA). HS was identified by the maximum slope in the heel sensor data. TO data was identified when the slope of the TO signal reached a minimum (i.e. has plateaued at 0) as shown in the bottom plot of Fig. 4. This allowed us to calculate algorithm sensitivity and specificity.

A basic optimizer was also designed to search for optimal parameters for the algorithm, namely the total window size and d_{total}. Based on preliminary tests, we provided ranges for these parameters. For each test, the optimizer iterates over all combinations of the parameters within the specified ranges to determine optimal performance based on weights allocated to sensitivity and specificity. For results shown in Table I, specificity was weighted 5x sensitivity. This was determined through trial and error to achieve high sensitivity and specificity. However, weights could be adjusted based on the application to achieve different results.

III. Results

The experimental results show the algorithm's ability to detect HS and TO events for different walking conditions.

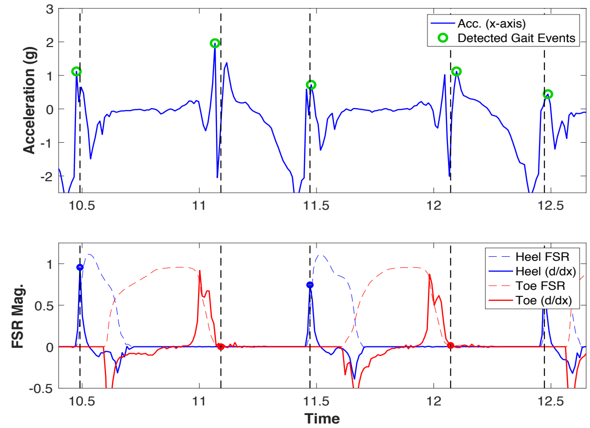

Figure 4. (top) raw acceleration signal from single subject with gait events identified by the algorithm in green. (bottom) FSR data was used to calculate ground truth events shown by the black dashed lines in both plots. HS was a peak in the derivative of the heel FSR signal (blue circles). TO was a plateau in the toe FSR (red circles).

The average gait speeds per condition across participants were S1 = 0.93 ± 0.10 m/s, S2 = 1.18 ± 0.05 m/s, S3 = 1.47 ± 0.04 m/s, and SV = 1.23 ± 0.06 m/s.

The overall sensitivity and specificity averaged across all conditions were 94.32% and 94.70%, respectively (Table I). Sensitivity and specificity results for each specific condition (S1, S2, S3, and SV) showed that the algorithm performs better under SV (i.e., variable-speed); followed by S1, S3, and S2 speeds (i.e., slow, fast, and self-selected speed) (Table I). The overall time error between the proposed and referenced methods (i.e., using accelerometer vs. FSR sensors) was 6.52 ± 22.37 ms.

Optimizer analysis showed the majority of the datasets achieved best results with similar parameters, 35-50 samples and a threshold value of 0.200-0.500 in the derivative.

IV. Discussion

The proposed study presents a novel algorithm for real-time detection of HS and TO events using a single accelerometer signal from the foot. The algorithm is demonstrated to be robust enough to achieve a high detection rate under various walking speeds (S1, S2, S3, and SV) across participants. The development and assessment of robust, low-cost computational algorithms is crucial to meet the design requirements of wearable gait detection systems.

Table I. Evaluation of algorithm performance

Subject	*Sensitivity (%)*				*Specificity (%)*			
	S1	*S2*	*S3*	*SV*	*S1*	*S2*	*S3*	*SV*
1	90.63	97.14	84.85	97.30	90.63	94.29	84.85	94.59
2	96.97	100.00	97.37	96.67	96.97	96.55	97.37	96.67
3	96.77	90.32	100.00	97.14	96.77	93.55	96.97	97.14
4	93.55	80.00	91.89	96.97	96.77	83.33	97.30	100.00
Average	**94.49**	**92.00**	**93.62**	**97.04**	**95.28**	**92.00**	**94.33**	**97.04**

With respect to time error, the algorithm performed comparably to previous studies [3], [6], [10]. The overall sensitivity of the proposed algorithm is lower than those reported by other studies [3], [7]. This could be because we do not filter the raw signal. Further work is required for the algorithm to perform with unfiltered signals at a level comparable with those that use filtered signals. Our algorithm performed best for the randomized gait speed walking trials with an average sensitivity of 97.04%, and performed worst for self-selected data with an average sensitivity of 92.00%. This was opposite to expectations, as we predicted the introduction of speed transitions in the random-speed trials would negatively impact performance. Further investigation is needed with a larger data set to determine the significance and potential reasons for these results. Regardless, the initial success in the variable-speed trials is promising for a system capable of dealing with the increased variation and noise present in real-world or unsupervised walking [16].

We did not find any direct correlation between the parameters (e.g. window size, d_{total}) which achieved the best results for trials, across either participants or speeds. Future considerations, however, should examine the optimization of parameters. It remains unclear whether constant parameters will work over a broad range of mobility conditions (i.e. greater range of walking speeds, variable terrains, etc.), or whether the parameters will need to be customized or adjusted. We would also like to analyze the algorithm's performance on a larger sample size and identify common parameter values between subjects for each speed that would be suitable for implementing more generalized models and eliminate the need of an online optimizer.

It was observed that occasionally the algorithm's peak detections would lag a true peak just beyond the defined window size, and these instances were instead counted as misdetections. Also, the current algorithm does not differentiate between HS and TO or evaluate for temporal accuracy. Thus, it would be interesting to observe the lag and lead time differences for detected events to determine whether there was a tendency toward either detecting HS or TO late.

Future work should focus on improving the robustness of gait event detection algorithm. One way this could be achieved is by implementing a windowed version of the optimization algorithm. This could identify suitable selection of parameter which meet predefined sensitivity and specificity specifications and adjust parameters in real time to achieve the highest possible accuracy. The combination of weight adjustment (for sensitivity and specificity), as well as online parameter tuning could provide adaptability at a lower computational cost than full machine learning models. Additionally, we would like to explore ways to improve the responsiveness of our algorithm for real-time implementation. One method would be to incorporate a sliding window with overlap. This would allow for a relatively large window so as to have an accurate depiction of the acceleration signal and not misidentify any local or global maxima, while reducing the step size to allow the algorithm to update and quickly respond to the gait signal in real-time. This can bring the algorithm's performance to a level comparable with more powerful machine-learning architectures.

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