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IMU-based gait analysis in lower limb prosthesis users: Comparison of step demarcation algorithms

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ABSTRACT

Background: Inertial Measurement Unit (IMU)-based gait analysis algorithms have previously been validated in healthy controls. However, little is known about the efficacy, performance, and applicability of these algorithms in clinical populations with gait deviations such as lower limb prosthesis users (LLPUs).
Research question: To compare the performance of 3 different IMU-based algorithms to demarcate steps from LLPUs.
Methods: We used a single IMU sensor affixed to the midline lumbopelvic region of 17 transtibial (TTA), 16 transfemoral (TFA) LLPUs, and 14 healthy controls (HC). We collected acceleration and angular velocity data during overground walking trials. Step demarcation was evaluated based on fore-aft acceleration, detecting either: (i) maximum acceleration peak, (ii) zero-crossing, or (iii) the peak immediately preceding a zero-crossing. We quantified and compared the variability (standard deviation) in acceleration waveforms from superposed step intervals, and variability in step duration, by each algorithm.
Results: We found that the zero-crossing algorithm outperformed both peak detection algorithms in 65% of TTAs, 81% of TFAs, and 71% of HCs, as evidenced by lower standard deviations in acceleration, more consistent qualitative demarcation of steps, and more normally distributed step durations.
Significance: The choice of feature-based algorithm with which to partition IMU waveforms into individual steps can affect the quality and interpretation of estimated gait spatiotemporal metrics in LLPUs. We conclude that the fore-aft acceleration zero-crossing serves as a more reliable feature for demarcating steps in the gait patterns of LLPUs.

1. Introduction

Inertial measurement units (IMUs) are portable, low-cost tools used for objective gait assessment in patient populations with diverse pathologies [1–3]. Objective assessment of lower limb prosthesis user (LLPU) walking performance in the clinic, using IMUs, could help optimize prosthetic fitting, alignment, and individualized component selection, enhancing and expediting care. By extracting spatiotemporal gait parameters from acceleration and angular velocity data, IMUs can potentially track changes in gait over time. One approach involves placement of a single IMU sensor on the lower trunk or pelvis. Prior studies validated this approach [4,5] and confirmed the test-retest reliability of using IMU sensors in healthy subjects [6,7]. However, previously published literature (e.g., [8]) suggest that step demarcation algorithms in commercial IMU systems may be inadequate for individuals with gait deviations.

Automated algorithms are used to partition IMU waveforms into step intervals and estimate parameters such as mean step duration, walking speed, and symmetry [7,9,10]. However, there is little data on the efficacy, performance, and applicability of existing algorithms in populations that exhibit gait deviations, i.e. those with variable or asymmetric gait patterns. This highlights the need to explore whether step demarcation algorithms, previously validated on healthy subjects, are also effective and reliable in assessing pathologic gait. In clinical populations, reliable step demarcation could be leveraged for analysis of step-by-step execution consistency, speaking to locomotor control, stability, characterization of gait deviations, side-to-side symmetry, and to monitor longitudinal changes in these parameters.

To date, a limited number of studies have used IMUs to evaluate LLPUs. Previous studies [8,9,11–14] have looked at pelvis or trunk IMU

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parameters that may be indicative of gait stability or symmetry. Studies have reported mean spatiotemporal parameters to be reliable; however, systematic errors have been reported between estimated and observed e.g. intact vs. prosthetic limb metrics. Furthermore, there is a lack of studies that use, or validate the use of, IMUs to reliably capture step execution variability. Our study is motivated by empirical observation of high intra- and inter-subject LLPU gait acceleration variability, reflecting known deviations from healthy subject movement patterns [15–17]. Prior literature (e.g., [5,8]) and our own experience, suggest these deviations confound step demarcation algorithms that were not explicitly developed for, or validated in, this clinical population.

The purpose of this study was to evaluate the ability of different algorithms to demarcate steps from IMU-based LLPU walking patterns. We evaluated three step-demarcating strategies by comparing step variability metrics using LLPUs and healthy controls (HCs). The results have broad implications for IMU-based analysis of pathologic gait in clinical settings.

2. Methods

2.1. Participants

We recruited 14 HCs (10 male, 4 female, 23.0 ± 2.5 years old, 1.77 ± 0.10 m height, 74.5 ± 11.0 kg), 17 with transtibial amputation (TTA) (14 male, 3 female, 47 ± 12 years old, 1.79 ± 0.06 m height, 95 ± 18 kg), and 16 with transfemoral amputation (TFA) (11 male, 5 female, 44 ± 13 years old, 1.74 ± 0.10 m height, 77 ± 15 kg). LLPUs self-reported K-level [18] to be K3 or K4. Study exclusion criteria for controls were: (i) age < 18 years, or (ii) lower limb pathology or other medical condition (e.g., neuromuscular or cardiopulmonary impairments) affecting walking ability. For LLPUs, inclusion criteria were: (i) ≥6 months following limb loss procedure, (ii) unilateral lower limb loss, (iii) current daily use of prosthesis, (iv) adequate self-reported comfort and perceived enablement by prosthesis at time of testing. Exclusion criteria for LLPUs: (i) age < 18 years, (ii) use of assistive devices (e.g. crutches, rolling walker, or cane) to walk, and (iii) contralateral lower limb pathology or other medical conditions (e.g., neuromuscular or cardiopulmonary impairments) affecting walking ability. Subjects gave informed consent, as approved by the Vanderbilt University Medical Center Institutional Review Board.

2.2. Experimental protocol

We collected data at 100 Hz with a single IMU (G-walk by BTS Bioengineering, Brooklyn, NY, USA) containing a 3-axis accelerometer and 3-axis gyroscope, transmitted via Bluetooth to a data-logging laptop computer. Following identification of the top level of the iliac crests (L4) by palpation, subjects wore a neoprene belt affixing the sensor to the midline lumbopelvic area (over the L5 vertebra). Belt tightness was adjusted to maintain placement and comfort. Subjects stood upright and still for a calibration period of 3–5 s before walking in a straight line over a level, indoor surface, traversing a distance of 25 m at a self-selected pace. Data collection was stopped as subjects crossed the 20-m mark, before deceleration or gait termination. Five such walking trials were recorded for each subject. An overview of sensor placement and IMU signal processing workflow is provided in Fig. 1. Translational acceleration and angular velocity data for x, y and z (per the sensor's local coordinate system) were exported into MATLAB (MathWorks, Natick, MA, USA).

2.3. Data reduction and analysis

We filtered raw data at 30 Hz using a 3rd order, dual-pass Butterworth filter to reduce signal noise. For each trial, the mean acceleration and angular velocity was subtracted, such that each waveform was centered about zero. A period of steady-state walking [19] for each trial was isolated for further processing by trained experimenters. These filtered and de-meaned data are referred to as the processed data, and were used in the step demarcation analysis.

2.4. Step demarcation

Steady-state data from each walking trial were analyzed using 3 different algorithms (Fig. 2). The demarcation points detected by each algorithm were used to divide walking data into step intervals. A separate laterality assignment algorithm parsed left vs. right (or prosthetic vs. intact) steps. Step-demarcated acceleration patterns and other derived metrics from the 5 walking trials were combined for each subject, respectively for intact and prosthetic limb. There was an average of 61 ± 12 jointly considered steps for each subject. Considered step intervals from each trial were contiguous, with no omitted steps.

2.5. Zero-crossing (ZC) algorithm

This algorithm demarcated steps by searching for z-axis acceleration zero-crossings, similar to Zijlstra et al. [5]. Lower trunk acceleration waveforms contain at least two zero-crossings during step intervals (as acceleration changes from positive to negative, later reversing, as shown in Fig. 2). Additional zero-crossings may be present due to noise or subject-specific walking variation. We identified falling-edge zero-crossings (i.e., transitioning from positive to negative acceleration) following the maximal acceleration peak. This rapid deceleration has been shown to coincide with weight transfer onto the leading limb [4,5].

2.6. Maximum acceleration (MA) peak detection algorithm

This algorithm identified the maximum peak occurring between successive zero-crossings (identified from ZC algorithm), similar to Zijlstra et al. [5].

2.7. Proximal peak (PP) detection algorithm

This algorithm identified the first major peak occurring prior to falling-edge zero-crossings. Starting from each zero-crossing (identified by ZC), the algorithm searched backwards until the first peak was located. Simple heuristic criteria were used to avoid detecting minor or transient noise peaks common to IMU data. Though this peak detection algorithm was not explicitly defined/used in Zijlstra et al. [5], we consider it a variant of the MA peak algorithm they published.

2.8. Absolute step duration

The durations of demarcated step intervals were recorded, and used to calculate mean step duration and standard deviation for each algorithm.

2.9. Normalized step interval

Step intervals demarcated by the respective algorithms, were normalized over time 0–100%, termed the Normalized Step Interval (NSI). Data from each step were resampled to 1000 samples (representing 0–100% of NSI), enabling us to calculate average step acceleration waveform and standard deviation. Left and right (or prosthetic and intact) steps were analyzed and plotted separately. The NSI was used to graphically superpose data from each step, for a given side, permitting visualization of movement variability in the captured waveforms (Fig. 3) and inspection of step demarcation consistency.