Gait & Posture 64 (2018) 30–37

Contents lists available at ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Full length article

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

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ARTICLE INFO

Keywords:
Inertial measurement unit
Accelerometer
Prosthesis
Gait
Amputation

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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https://doi.org/10.1016/j.gaitpost.2018.05.025
Received 21 December 2017; Received in revised form 13 April 2018; Accepted 21 May 2018

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.

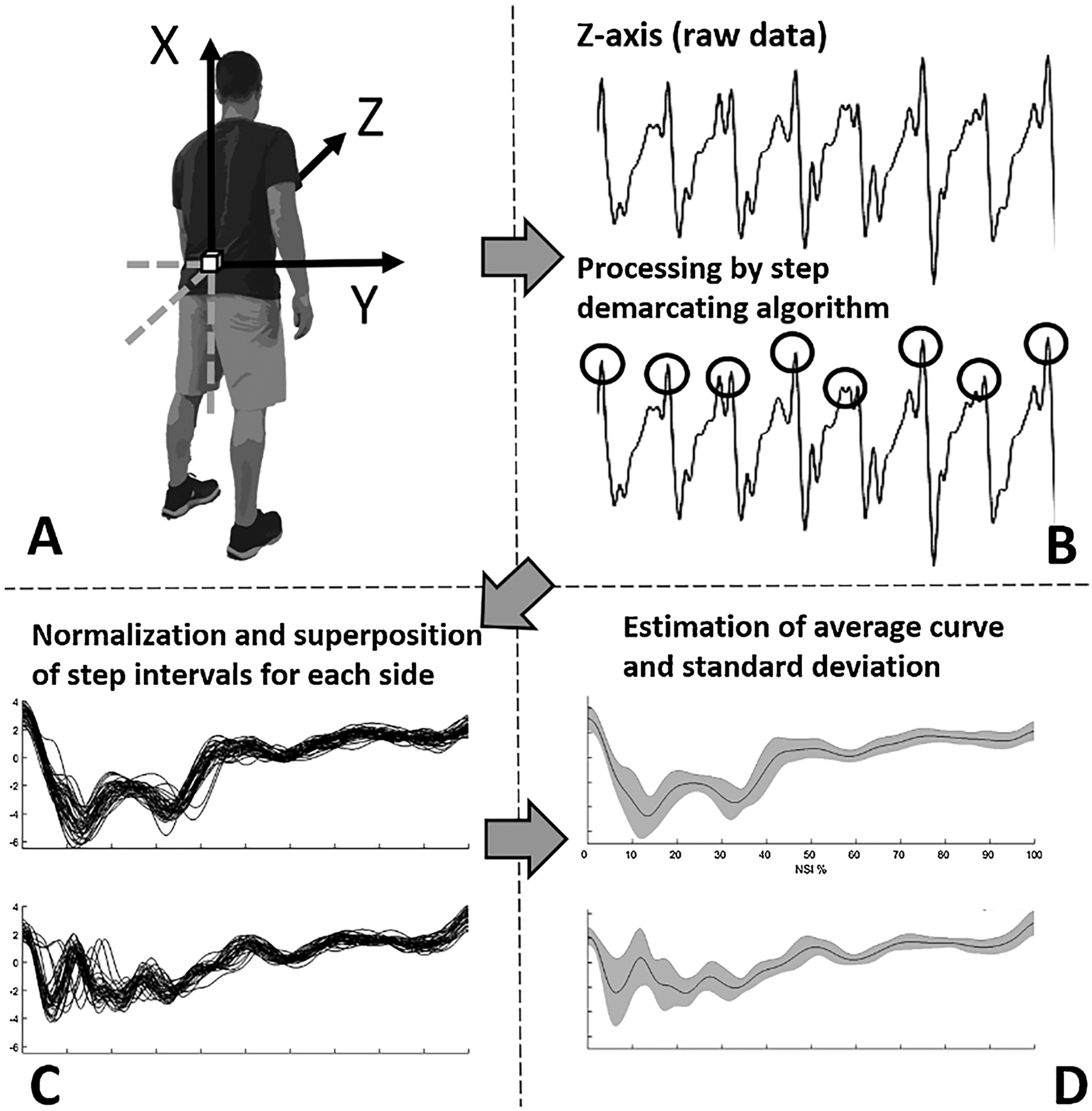

Fig. 1. Depicted are IMU sensor placement, direction of local coordinate axes (A), and signal processing workflow: application of algorithm to demarcate step intervals based on z-axis acceleration data (B), superposition of acceleration waveforms over normalized step intervals (C), and estimation of average acceleration waveform and standard deviation (D).

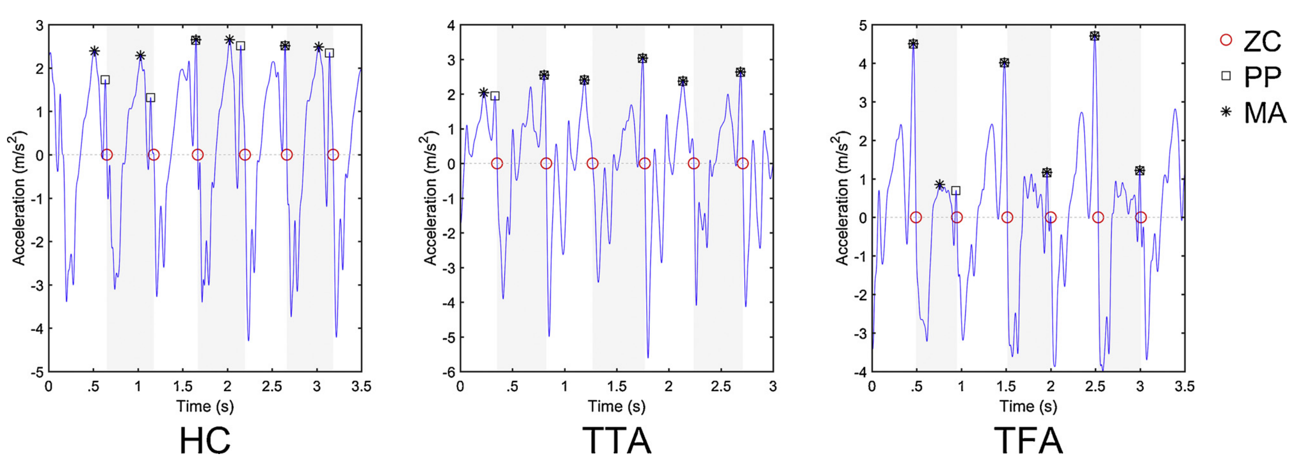

Fig. 2. Raw acceleration waveforms from a representative HC (healthy control), TTA (transtibial) and TFA (transfemoral) subject, with demarcation indices by zero-crossing (ZC), proximal peak (PP) and maximal acceleration (MA) algorithms.

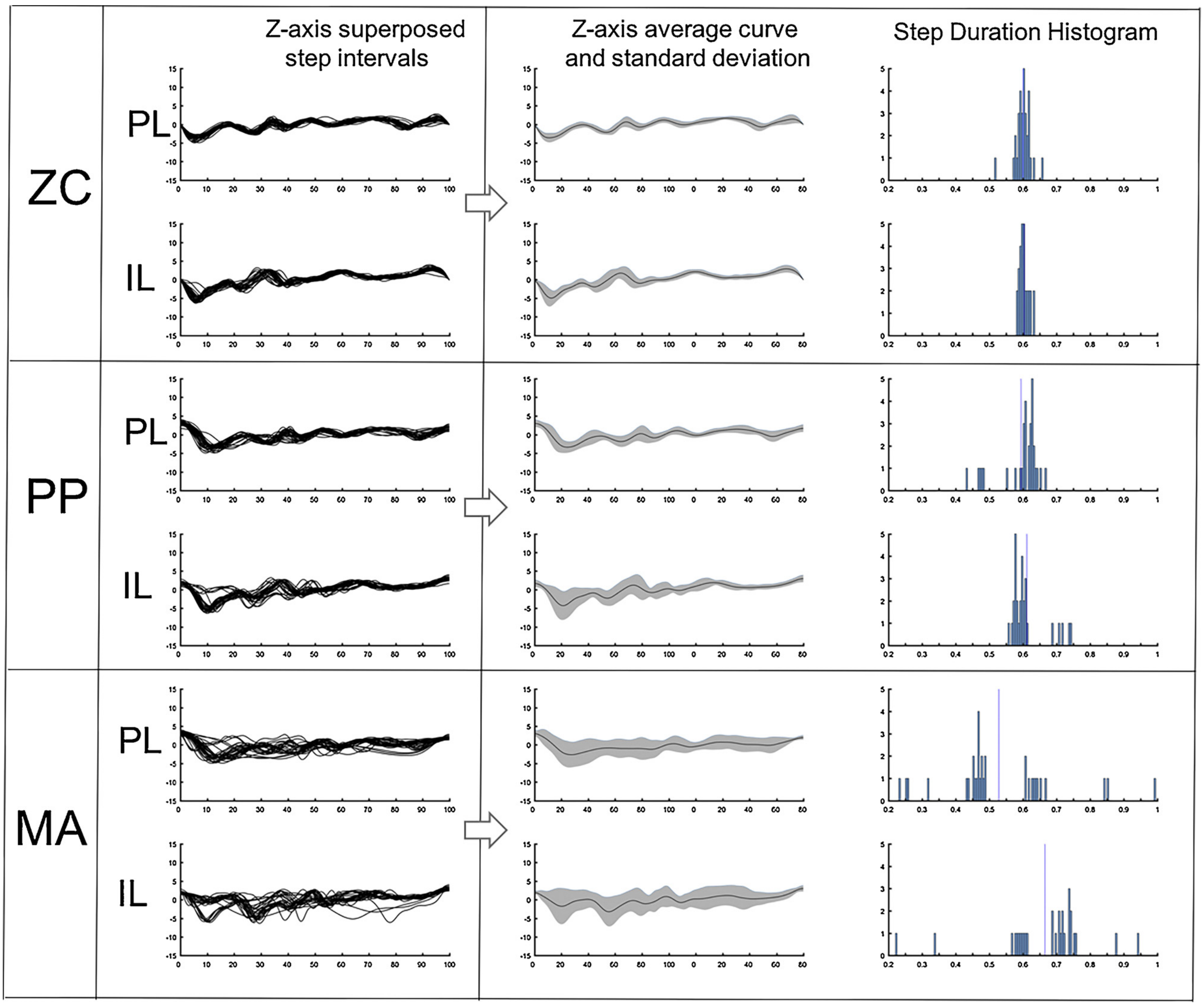

Fig. 3. Depicted is a single TTA subject's post-demarcation superposition of z-axis acceleration waveforms, normalized as step intervals, for each side (PL: prosthetic limb; IL: intact limb) and by each method (ZC: zero-crossing, PP: proximal peak, MA: maximal acceleration). Each black line in the plots of the first column represents data from a single step interval. In the middle column are depicted the resulting average curves with a band representing the upper and lower border of the standard deviation throughout the NSI (normalized step interval). The right column shows step duration histograms resulting from each method, highlighting how different algorithms can result in different step duration and step duration variability estimates.

2.10. Laterality assignment

Laterality of steps (left vs. right for HCs, or prosthetic vs. intact limb for LLPUs) was identified based on angular velocity. Specific implementation details are provided in the Appendix.

2.11. Outcome metrics and statistical analysis

The primary outcome metric was acceleration step interval variability. The acceleration standard deviation over the NSI was calculated to provide a single value for each respective side and axis of acceleration. To compare which algorithm resulted in the lowest overall variability, the six acceleration standard deviations (i.e., in all three directions and for both sides) were averaged (mean) to a single value, which we termed the *combined standard deviation*. When multiple step demarcation algorithms were applied to the same data set, the algorithm that yielded the lowest *combined standard deviation* was interpreted as the best. This interpretation is based on the observation that errors in partitioning a cyclical task into periods tend to increase the variability (standard deviation) seen when those individual periods are superposed. Thus, higher variability signifies more and/or larger errors in partitioning steps (periods) in a given steady-state walking trial. An extended rationale for this metric and justification of the interpretation is provided in the Appendix. To evaluate which demarcation algorithm was best for the most number of individuals, we enumerated the number of subjects for whom each algorithm yielded the lowest variability. For each group of subjects (HC, TTA, TFA), we also performed a repeated measures ANOVA with Holm-Sidak correction to statistically compare how demarcation algorithms affected the primary outcome metric. Significance level of 0.05 was used. For brevity, statistical differences are presented graphically in box-and-whisker plots. Secondary outcome metrics were mean and standard deviation of step duration. Step durations were plotted as histograms to enable direct comparison of left vs. right, or intact vs. prosthetic limb. Step time metrics provide insight related to (inter-limb) asymmetry and (intra-limb) differences in the consistency of step execution.

3. Results

3.1. Acceleration variability

The ZC algorithm generally provided the best demarcation of step

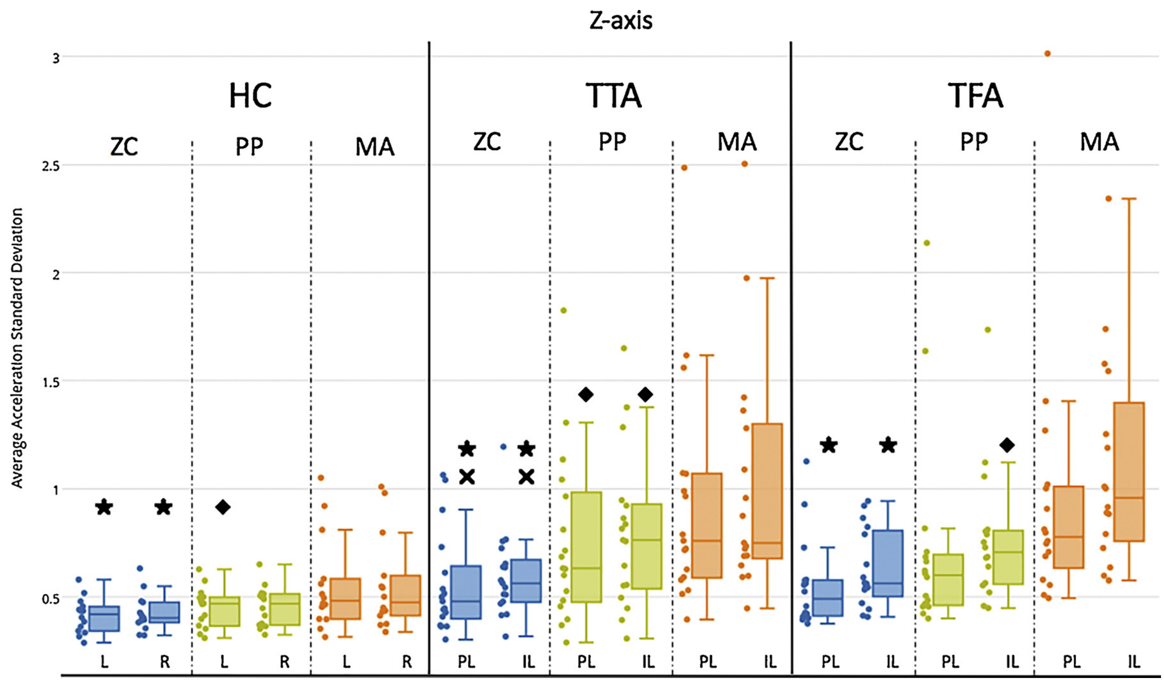

Fig. 4. Box-and-whisker plots of the acceleration standard deviation for HC (n = 14), TTA (n = 17) and TFA (n = 16) subjects in the fore-aft (z-axis) direction, per side (L: left; R: right; PL: prosthetic limb; IL: intact limb), following demarcation of step intervals by the respective processing algorithms. On average, the ZC algorithm yielded the lowest z-axis standard deviation, indicating that acceleration waveforms exhibited the most consistency (least variability) when superposed using ZC step demarcation. Within group (HC, TTA, TFA), per limb, statistically significant differences are noted (★: ZC/MA; ◆: PP/MA; x: ZC/PP).

intervals (Fig. 4 and Supplemental materials), as indicated by the lowest acceleration standard deviations in each direction of movement. This was confirmed by visual inspection of demarcated and superposed acceleration waveforms of normalized step interval plots (Supplemental materials). The ZC algorithm provided the lowest acceleration combined standard deviation in 71.4% of HC, 64.7% of TTA and 81.2% of TFA LLPUs (Fig. 5). The PP algorithm provided the lowest acceleration standard deviation in 14.3% of HC, 35.3% of TTA and 18.8% of TFA LLPUs. The MA algorithm provided the most consistent step demarcation in 14.3% of HC, but for none of the LLPUs. For all LLPUs in which PP demarcation yielded the lowest acceleration combined standard deviation, the ZC algorithm was typically an exceedingly close second. The ZC algorithm always outperformed the MA algorithm. On average, combined standard deviation for acceleration by the ZC method was 23% lower than by PP, and 65% lower than by MA for HC subjects, 48% lower than by PP, and 62% lower than by MA for TTA subjects, and finally 54% lower than by PP, and 65% lower than by MA for TFA subjects. ANOVA comparisons further corroborated the strength of the aforementioned observations. We found statistical significance for differences between ZC vs. MA (all groups, both limbs), and ZC vs. PP (TFA prosthetic limb).

3.2. Step duration and variability

For HC subjects, mean step duration and standard deviation for each side were similar for all algorithms; however, for TTA and TFA subjects, there was large discordance of estimated mean step durations and duration variability by the different algorithms. The ZC algorithm resulted in the lowest step duration variability in 8 of 14 (57%) HC, 11 of 17 (64%) TTA, and 14 of 16 (87.5%) TFA subjects. The step duration histograms also demonstrated that lower estimated standard deviations corresponded with more typical normal distributions of demarcated step times, and fewer outlier steps (Fig. 3).

3.3. Subject-specific results

Subject-specific acceleration and step duration histograms are provided for all HC, TTA and TFA subjects in the Supplementary materials. These results depict the higher variability of acceleration waveforms in TTA and TFA subjects as compared to HC subjects, and highlight why the choice of an appropriate demarcation strategy is critical for reliably capturing spatiotemporal gait parameters for LLPUs.

4. Discussion

IMU-based lumbopelvic motion tracking is an inexpensive, non-invasive, fast and easy, objective gait analysis that captures clinically relevant spatiotemporal parameters. It can reflect the locomotor control and stability afforded through the action of each lower limb and the head-arms-trunk during walking [20–22]. However, the potential clinical utility is contingent on automated algorithms being able to reliably demarcate step intervals.

In this study, we show that step demarcation algorithms that work reliably on control subjects do not necessarily translate well to the analysis of pathological gait. While prior studies have shown that both peak and zero-crossing detection algorithms provide reasonable step demarcation for controls [5], we found the more feature-rich acceleration waveforms of LLPUs cause larger systematic errors when peak detection is used. These findings suggest that step demarcation algorithms based on zero-crossings are preferable to peak detection algorithms for gait assessment of LLPUs via pelvis-mounted IMU.

4.1. Zero-crossing vs. peak detection algorithms

Lower average acceleration standard deviations for all axes (z, y, x), were interpreted to signify more consistent step demarcation. This objective evaluation was also supported by visual confirmation for which algorithm provided the most consistent superposition of step-demarcated acceleration waveforms (Fig. 3). The choice of demarcation algorithm was most important for LLPUs, who typically exhibit more

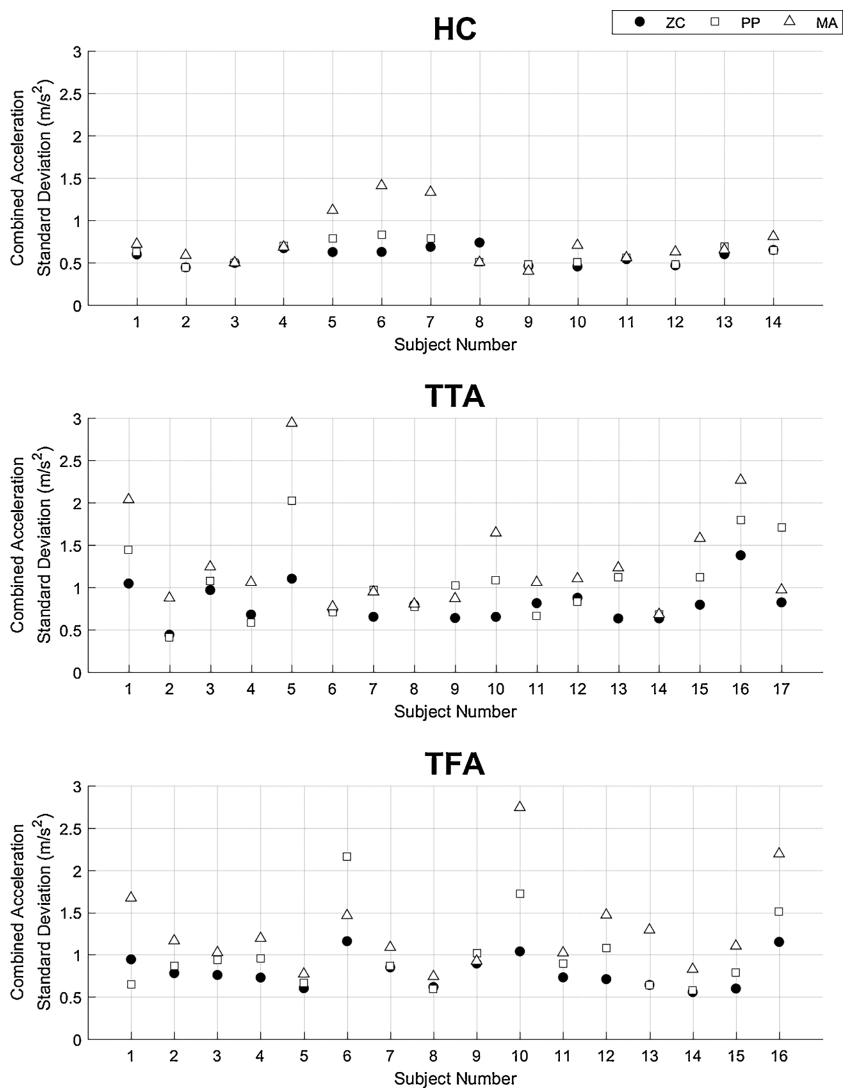

Fig. 5. HC, TTA and TFA subject-specific lowest acceleration combined standard deviation by each processing algorithm (considers all 3 axes, and both sides averaged into a single value). This calculation revealed which algorithm provided the greatest consistency in step demarcation for each subject, with the algorithm affording the lowest value considered the best.

pronounced gait deviations, especially at proximal levels of limb loss.

4.2. Potential benefits of tracking lumbopelvic motion

Tracking lumbopelvic motion permits objective quantification of gait, including effects due to impairments that are remote to the pelvis itself [6,23–25]. A single midline lumbopelvic region IMU is appealing for routine clinical use, given that fully-instrumented motion analysis labs [26] are available in a small subset of clinics. Our results demonstrate that the choice of step demarcation algorithm is critical for LLPUs, and potentially other patients with gait asymmetry or deviations.

4.3. Benefits of gait analysis using step demarcation

Step-by-step analysis provides a means of assessing gait spatiotemporal movement variability and overall symmetry. Analyzing how successive walking cycles are executed is of high interest for clinical populations, such as LLPUs. This type of analysis can reflect gait deviations (whether due to impairments or adaptations) arising from discomfort, improper prosthesis fit or device misalignment. Symmetry is of high significance for LLPUs, partly for psychosocial reasons (e.g., many individuals want the appearance of normal gait), and partly for biomechanical reasons (e.g., it has been suggested that substantial asymmetry may contribute to secondary disorders such as osteoarthritis [27] or low back pain [28]).

There are alternative ways to process IMU data without step demarcation, such as e.g. autocorrelation approaches to estimate mean step duration [12]. However, such approaches are not intended to capture step-by-step variability metrics. The advantage of reliable step demarcation is that it enables additional exploration of gait relating to consistency and symmetry, important to LLPUs and other populations of clinical interest.

Step demarcation algorithms must be identified and validated for LLPUs to permit the deployment of appropriate clinical tools to aid practitioners and benefit patients. Objective assessment tools in the clinic could help optimize prosthetic fitting, alignment, and individualized component selection, greatly enhancing care.

4.4. Importance of choosing an appropriate step demarcation algorithm

LLPUs exhibited acceleration waveforms that differed substantially from HCs, in both average pattern and variability. The choice of acceleration waveform feature (i.e., peak vs. zero-crossing) by which to demarcate steps affected the quality and consistency of the output. Although ZC and peak detection algorithms performed similarly well for HC, larger differences in step demarcation efficacy were evident in LLPUs. In LLPUs, the different algorithms impacted the estimation of mean step duration and step duration variability (Fig. 3). We found many examples where MA and PP algorithms led to considerable misestimation of mean prosthetic vs. intact step time, as compared to the ZC algorithm (see Supplementary material). Such errors can lead to incorrect interpretations related to LLPU gait symmetry.

4.5. Implementation of step demarcation algorithms

We envision multiple ways step demarcation algorithms could be implemented for a single IMU sensor placed in the lumbopelvic region. Since the ZC algorithm generally performed the best, one option would be to use it as the default algorithm. However, in a subset of LLPUs PP yielded a slightly lower standard deviation than ZC. Therefore, alternatively, all three algorithms evaluated in this study could be implemented, employing a post-processing selection for whichever algorithm worked best to minimize estimated variability in acceleration waveforms (i.e., signifying maximized consistency for demarcation of step intervals).

4.6. Study limitations

Our step demarcation algorithms primarily analyzed z-axis acceleration. Integration of data from other acceleration and gyroscope axes may further enhance the reliability of step demarcation. This may require use of additional computational approaches such as neural networks or deep learning to inform data fusion. Our use of z-acceleration was based on previously published and validated methods on HCs (e.g., [5]); however, we similarly concluded (by visual inspection of IMU data from LLPUs) that z-axis acceleration appears the most repeatable waveform for feature-based algorithms. Higher data sampling rates or additional signal processing, such as implementing a subject-to-IMU alignment calibration or resolving accelerations into a tilt-corrected reference frame (e.g., [29]) might further improve demarcation results. We did not collect ground truth step interval data (e.g., using force plates, foot switches or motion capture). Zijlstra and Hof [5] previously performed such a validation of IMU vs. ground reaction force data for HC. In our study, we instead evaluated step demarcation algorithms based on the consistency of their outputs. Most of our data collection was performed in clinical settings, where additional instrumentation was not available. Future research is also warranted to study the sensitivity of demarcation algorithms to imperfect sensor placement or variability in belt tightness.

5. Conclusion

In summary, IMU-based tracking of lumbopelvic motion is an objective measurement tool that could feasibly be introduced into the clinical setting to aid practitioners with longitudinal monitoring of patient gait, and with decision-making surrounding interventions. However, successful clinical use depends on first understanding how to process recorded IMU data to reliably extract spatiotemporal gait parameters in clinical populations of interest. In this study, comparison of three feature-based step demarcation algorithms demonstrated that a zero-crossing detection provided more consistent step demarcation for LLPU walking data, compared to peak detection algorithms. Our study demonstrates the importance of validating IMU step-demarcation algorithms for LLPUs and other populations of clinical interest.

Conflict of interest statement

None of the authors have any conflicts of interest to report.

Acknowledgements

Research reported in this publication was supported by the National Institutes of Health (NIH) [2K12HD043483, K12HD073945]. Study sponsors, did not have a role in the study design, collection, analysis and interpretation of data, writing of the manuscript or the decision to submit the manuscript for publication.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.gaitpost.2018.05.025.

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