https://doi.org/10.1007/s11517-019-02098-4

Gait event detection using inertial measurement units in people with transfemoral amputation: a comparative study

Emeline Simonetti[1,2,3] · Coralie Villa[1,2] · Joseph Bascou[1,2] · Giuseppe Vannozzi[3] · Elena Bergamini[3] · Hélène Pillet[2]

Abstract

In recent years, inertial measurement units (IMUs) have been proposed as an alternative to force platforms and pressure sensors for gait events (i.e., initial and final contacts) detection. While multiple algorithms have been developed, the impact of gait event timing errors on temporal parameters and asymmetry has never been investigated in people with transfemoral amputation walking freely on level ground. In this study, five algorithms were comparatively assessed on gait data of seven people with transfemoral amputation, equipped with three IMUs mounted at the pelvis and both shanks, using pressure insoles for reference. Algorithms' performance was first quantified in terms of gait event detection rate (sensitivity, positive predictive value). Only two algorithms, based on shank mounted IMUs, achieved an acceptable detection rate (positive predictive value > 99%). For these two, accuracy of gait events timings, temporal parameters, and absolute symmetry index of stance-phase duration (SPD-ASI) were assessed. Whereas both algorithms achieved high accuracy for stride duration estimates (median errors: 0%, interquartile ranges < 1.75%), lower accuracy was found for other temporal parameters due to relatively high errors in the detection of final contact events. Furthermore, SPD-ASI derived from IMU-based algorithms proved to be significantly different to that obtained from insoles data.

Keywords Inertial measurement units · Gait events · Gait temporal parameters · Asymmetry · Transfemoral amputee

1 Introduction

The accurate detection of gait events (GEs) is crucial for the biomechanical assessment of gait function in people with pathological walking patterns [1]. The identification of initial contact (IC) or final contact (FC) events, respectively marking stance initiation and termination, allows for gait cycle segmentation and is essential to extract and interpret relevant features from biomechanical and physiological gait variables such as joint angles or muscle activity [1].

✉ Emeline Simonetti
emeline.vacherand@ensam.eu

1 Institution nationale des Invalides (INI)/CERAH, 47 rue de l'Echat, 94000 Créteil, France

2 Arts et Métiers, Institut de Biomécanique Humaine Georges Charpak, 151 boulevard de l'Hôpital, 75013 Paris, France

3 Department of Movement, Human and Health Sciences, Interuniversity Centre of Bioengineering of the Human Neuromusculoskeletal System (BOHNES), University of Rome "Foro Italico", Piazza Lauro de Bosis, 6, 00135 Rome, Italy

In people with lower-limb amputation, whose gait is known to be highly asymmetrical due to joint function loss [2, 3], the identification of gait phases is particularly relevant for both prosthetic design and rehabilitation fields. For example, micro-processor-controlled prostheses generally adopt different behaviors according to the gait cycle phase [4]. Furthermore, stance or swing phase durations and temporal symmetry indices are widely used to evaluate gait in the clinical field. Quantifying these parameters can indeed assist therapists in decision-making during rehabilitation, as well as in prosthetics prescription, fitting, and alignment [3, 5, 6].

In recent years, wearable sensors, such as pressure insoles or inertial measurement units (IMUs), have been proposed as a portable and low-cost alternative to force platforms, instrumented mats, or treadmills for the detection of GEs. While some specific pressure insoles have been validated against force platforms [7, 8], their use is limited to the obtention of GEs and vertical ground reaction forces. On the other hand, IMUs, which include accelerometers and gyroscopes, can provide kinematic information in addition to GE detection. Thus, multiple algorithms have been developed for IC and FC identification from linear accelerations and/or angular velocities measured by IMUs [9]. Many authors have recommended the use of a single sensor at pelvis level to minimize invasiveness and gait alteration [3, 10–15]. However, in pathological gait, a robust detection of both IC and FC events is compromised because of gait inherent variability and stronger attenuation of feet-ground impacts at trunk level [9, 16]. Consequently, algorithms based on the use of two IMUs located on both shanks [4, 17–24] or feet [24–26] have been developed and are generally considered to be more accurate [9, 16, 21].

Given the number of available algorithms, the comparison of their accuracy in GE detection is relevant. However, most studies differ in their acquisition protocol, in the population investigated, and in the reported results, which make the comparison challenging. Indeed, while the accuracy of the timings of detected GEs is always discussed, the ability of the algorithms to detect all GEs without false positives, or the consequence of the timing errors on clinically relevant parameters, such as cycle durations or symmetry indices, is not always disclosed. Although there have been some attempts in performing comparative studies in the literature [16, 24, 27, 28], none focused on people with transfemoral amputation (TF). In addition, as most algorithms rely on the extraction of specific features from IMU signals, some may not be relevant for the population of TF because of deviations in their gait pattern, such as hip hiking, vaulting, delayed knee flexion, and temporal and spatial asymmetries [2, 8].

This work aimed at comparing the performance of different state-of-the-art algorithms in TF walking freely on level ground. Performance was quantified in terms of (i) sensitivity and positive predictive value of GE detection, (ii) accuracy of GEs timings, and (iii) accuracy of derived temporal parameters and of stance phase duration Absolute Symmetry Index (SPD-ASI) values. Furthermore, the robustness to different walking speeds was also investigated. Data from pressure insoles validated against force platforms in people with transfemoral amputation [8] were used for reference values assessment.

2 Material and methods

2.1 Participants

The study was designed according to the Declaration of Helsinki, and was granted ethical approval (CPP IDF VI, No. 2014-A01938-39). Seven TF (age, 47.3 ± 9.9 years; 5 males; mass, 74.5 ± 11.9 kg; height, 1.80 ± 0.10 m) gave written informed consent to participate in the study (Table 1). Inclusion criteria were people with transfemoral unilateral amputation due to trauma or tumor, fitted with a definitive prosthesis, able to walk at various speeds without any assistance. The participants walked with their usual passive microprocessor-controlled knee with an energy storing and return foot, the alignment of which was controlled by a prosthetist prior to data collection.

2.2 Measurement protocol

Three IMUs (MTw xSens, Netherlands, 100 samples s^{-1}), embedding a tri-axial accelerometer (± 16 g) and a tri-axial gyroscope (± 2000 deg/s), were used and positioned on the lower trunk (L4/L5 level) and on both shanks (laterally, below the tibial tuberosity level) of each participant (Fig. 1). IMUs were manually aligned with the anatomical axes of the underlying segments. Reference GEs were obtained using pressure insoles (Loadsol, Novel, Germany, 100 samples s^{-1}). These insoles have been reported to be reliable and to accurately estimate both vertical ground reaction force and stance phase duration in TF [8] and were, thus, considered a valid gold standard.

Participants walked freely along an 8-m level walkway, at three self-selected speeds (slow, comfortable, and fast), measured with a stopwatch. At least three trials of each condition were recorded. The average walking speeds of each participant are reported in Table 1. Participants were asked to stand upright for at least 3 seconds at the beginning and at the end of each trial, and to perform a downward kicking motion with the

Table 1 Participants' characteristics

	Age (years)	Height (m)	Mass (kg)	Gender	Etiology	Time since amputation (years)	Prosthetic knee	Prosthetic foot	Average self-selected walking speeds (ms^{-1})		
									Slow	Comfortable	Fast
TF01	47	1.54	72	F	Tumor	35	Rheo Knee	Variflex LP	0.72	1.02	1.25
TF02	52	1.69	75	M	Trauma	34	Rheo Knee	Variflex XC	0.92	1.13	1.48
TF03	34	1.70	51	F	Tumor	27	C-Leg	Trias	0.92	1.04	1.40
TF04	43	1.90	82	M	Trauma	5	C-Leg	Triton	1.00	1.16	1.35
TF05	64	1.84	86	M	Trauma	6	Rheo Knee	Talux	0.49	0.76	0.96
TF06	39	1.79	85	M	Trauma	3	C-Leg	Triton	0.89	1.06	1.25
TF07	52	1.84	72	M	Trauma	23	C-Leg	Pro-Flex	0.89	1.20	1.61

The prosthetic devices are from Ottobock (C-Leg, Triton, and Trias) and from Ossür (Rheo Knee, Variflex LP, Variflex XC, Talux, and Pro-Flex)

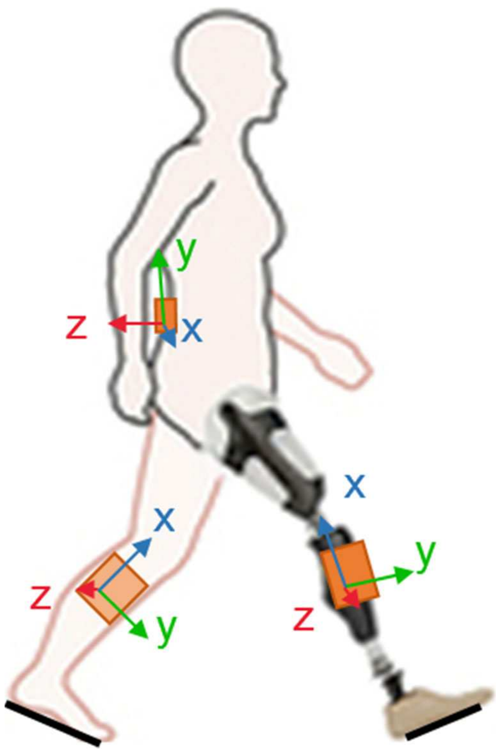

Fig. 1 Placement of the inertial measurement units and their associated local frames

heel of their sound foot to synchronize the IMUs with the insoles.

2.3 Data processing

IMUs and insoles data were post-processed using MATLAB® software (The MathWorks Inc., MA, US). Synchronization was performed semi-automatically by aligning the kicking-motion peaks in the sound-limb shank vertical acceleration and insole signals.

2.3.1 IC and FC events detection

Reference IC and FC events were identified using a 20 N threshold on the insoles' ground reaction force signals [8, 18].Regarding the IMUs' signals, five GE detection algorithms were selected based on a literature review. The first three algorithms were the only one retrieved that were specifically designed for people with lower-limb amputation. The two remaining algorithms were selected as they are representative of the state-of-the-art and appeared to be promising candidates in TF. Indeed, one of them was validated on an extensive cohort of people with different pathologies that significantly affected gait, and the second one used only one sensor, which is an interesting perspective for clinical applications. The algorithms, designated by the acronyms M-*N*, with *N* the initial(s) of the first author's name, are introduced hereafter:

(1) M-S: based on shank vertical and anteroposterior acceleration signals, validated against force platform data in ten people with transtibial amputation (TT) [18],
(2) M-M: based on shank mediolateral angular velocity, validated using footswitches in eight asymptomatic subjects and in two people with lower-limb amputation (one TT and one TF) [22],
(3) M-L: based on shank mediolateral angular velocity, flexion-extension angle, and axial acceleration, validated on five TF walking on an instrumented treadmill [4],
(4) M-T: based on shank mediolateral angular velocity and accelerations, validated against pressure mat data on an extensive cohort consisting of 80 elderly, 125 people with Parkinson's Disease, 31 people with mild cognitive impairment and on ten persons with hemiparesis [21, 23] as well as in ten asymptomatic subjects in an urban environment using pressure insoles [28],
(5) M-MC: based on pelvis vertical acceleration and angular velocity signals, validated in asymptomatic subjects compared to instrumented mat data [15] and in 30 people with pathological gait in a former comparative study [16].

M-L, M-MC, M-S, M-M, and M-T were implemented based on their descriptions in the literature [4, 15, 18, 22, 23], using only the target sensor signals as inputs. A brief description of the operating principles of each algorithm is reported in Table 2. Additional details can be found in the original articles. For M-MC, the pelvis angular velocity failed to discriminate between left- and right-side events, supposedly due to the asymmetrical gait pattern of TF [29]. Therefore, the mediolateral acceleration was used instead.

2.3.2 Temporal parameters and symmetry index computation

The following temporal parameters were estimated for each trial and method (insoles- and IMU-based algorithms):

- Stride duration (time between two consecutive ICs of the same foot), computed based on prosthetic ICs;
- Prosthetic and sound limb stance phase duration (time between an IC and the subsequent FC of the same foot);
- Prosthetic and sound limb initial double support duration (time between an IC and the subsequent FC of the contralateral foot), further referred to as prosthetic or sound limb double support duration.

Stance phase duration symmetry between the prosthetic and sound limbs was also assessed for each stride using the Absolute Symmetry Index (ASI): $\mathrm{ASI} = \frac{S-P}{0.5(S+P)} \times 100$, where S and P are the stance phase durations for the sound and prosthetic limbs respectively [2].

Table 2 Description of the operating principle of the implemented algorithms

Algorithm	Signal used for IC	Signal used for FC	General principle
M-S [18]	Vertical acceleration of the shank	Vertical and AP acceleration of the shank	Gait is segmented into approximate strides by identifying the minima in the low-pass filtered shank vertical acceleration. Within each identified stride, the vertical acceleration is low-pass filtered with a cut-off frequency depending on the estimated stride duration. Peaks identified in the filtered signal enable to define intervals in which to look for gait events. ICs are then identified as maxima in the vertical acceleration and FCs are identified as minima in the AP acceleration in their respective intervals.
M-M [22]	Shank ML angular velocity		Mid-swing instants are detected as maxima in the filtered ML shank angular velocity. ICs are then defined as the first or subsequent negative local minima following mid-swing, associated with negative slope and FCs are defined as local minima occurring at least 300 ms after ICs, with speed lower than a set threshold.
M-L [4]	Shank vertical acceleration, ML angular velocity, and flexion/extension angle		This state-machine algorithm uses the shank ML angular velocity, the shank vertical acceleration, and the shank angle (obtained using a complementary filter of the shank acceleration and angular velocity) as inputs to detect transitions between the "swing" state and the "stance" state. Stance is detected at zero-crossings in the vertical acceleration, if the angular velocity is negative and the shank angle is above a threshold. It should occur after at least 200 ms of swing. Swing is detected when the vertical acceleration is increasing above a negative threshold, the angular velocity is negative, and the shank angle is below a negative threshold. It occurs after at least 400 ms of stance. A set of similar conditions enable to identify the first transition to swing (FC) or stance (IC).
M-T [21]	Shank sagittal angular velocity and AP acceleration		Peak identification in the ML angular velocity signal enables to define intervals in which to look for gait events. In these intervals, ICs are identified as the minima in ML angular velocity preceding a maximum AP acceleration and FCs are identified as minima in the AP acceleration preceding the last maximum in AP acceleration.
M-MC [15]	Vertical and ML acceleration of the pelvis		The vertical acceleration is filtered with a Gaussian continuous wavelet transform. ICs are identified as the minima in the filtered acceleration. FCs are identified as the maxima in the differentiated signal. In this study, the ML acceleration was used to distinguish right and left gait events occurrence, while the vertical angular velocity was used in the original study.

AP, anteroposterior; *ML*, mediolateral; *IC*, initial contact event; *FC*, final contact event

2.4 Algorithms performance assessment

2.4.1 Sensitivity and positive predictive value of GE detection

Sensitivity, defined as the number of correctly detected algorithm-derived GEs divided by the number of reference GEs, and positive predictive value (PPV), i.e., the number of correctly detected algorithm-derived GEs divided by the total number of detected GEs (including extra events), are often used in the literature to assess algorithms' performance in terms of detection rate [16, 17]. However, the criterion used to classify an algorithm-detected event as either correct, missed, or extra is usually missing. In this work, we propose to compute the number of algorithm-detected events such that $|t_{\mathrm{rGE}} - t_{\mathrm{aGE}}| \leq \frac{1}{2}\mathrm{StD}_{\mathrm{ref}} \quad (1)$ with:

- t_{rGE} the timing of a reference GE,
- t_{aGE} the timing of algorithm-derived GEs,
- $\mathrm{StD}_{\mathrm{ref}}$ the median stride duration computed from reference ICs.

If no algorithm-detected event fulfilled condition (1), an event was missed. Conversely, if several algorithm-detected events fulfilled condition (1), only the closest to the reference event was considered as correctly detected, and the others were discarded as extra events.

Sensitivity and PPV were computed for all the algorithms to compare their GE detection rate. While the occurrence of a missed event can be detected based on the duration between successive detected events, the identification of a correct event among several possible candidates is not possible without a reference. Therefore, to be used in real-life settings, an algorithm must be extremely robust in this respect. Consequently, for the subsequent accuracy analysis, only the algorithms scoring a PPV above 99%, representing a negligible number of extra events, were considered.

For each algorithm, PPV and sensitivity were quantified for the entire trials in order to assess the algorithm ability to detect all events, including those of the first and last steps which mark gait initiation and termination. For the rest of the analysis, the initiation and termination steps were not considered for the sake of comparison with the literature.

2.4.2 Accuracy of GEs timings

For each algorithm, the difference between the timing of each IMU-based and the corresponding reference GE was computed. Positive and negative errors respectively indicate delayed and anticipated event detection.

2.4.3 Impact of GEs timings errors on estimates of gait temporal parameters and symmetry index

For each algorithm, stride, stance and double support durations, as well as symmetry derived from IMU-based GEs were computed. IMU-based temporal parameter estimates errors were expressed in seconds and in percentage of the reference parameter, with positive and negative values indicating, respectively, overestimation and underestimation of temporal parameters.

2.5 Statistical analysis

Descriptive statistics (medians and interquartile ranges (IQR)) were computed over all participants for each walking speed for reference GE timings and temporal parameters, for IMU-based GE and temporal parameter errors as well as for SPD-ASI derived from the insoles and the algorithms.

Normality of the median values was verified using the Shapiro-Wilk test and, according to the test result, either a Friedman test or a one-way repeated-measure ANOVA was performed to investigate the effect of the "walking speed" factor on the errors. Post-hoc pairwise comparisons (Wilcoxon signed-rank tests or *t* tests depending on the normality of the data) with Holm-Bonferroni correction were then performed where any difference was found.

If the main effect of "walking speed" persisted, pairwise comparisons were used to investigate the presence of significant differences between each pair of methods, for each level of walking speed, considering separately prosthetic- and sound-limb parameters when relevant. Conversely, if no main effect of "walking speed" was found, medians and IQR were computed over all three walking speeds for each participant and method, and pairwise comparisons were then executed on this new dataset.

Wilcoxon signed-rank tests were used to investigate the effect of the limb considered, that is, to determine whether errors where significantly different at the sound and prosthetic side for each parameter and each algorithm.

The statistical analysis was performed using SPSS (IBM SPSS Statistics 23, NY, USA). The level of significance was set to 0.05 for all statistical tests.

3 Results

Due to technical issues with the insoles, GEs of two participants had to be discarded at the sound limb, leaving a total of 454 sound steps for 623 prosthetic steps considered in the analysis. Table 3 reports the descriptive statistics of the temporal parameters derived from the insoles.

3.1 GE detection rate

Sensitivity and PPV for each algorithm are reported in Table 4. Only M-T and M-L showed a PPV higher than 99% and were further analyzed. Both algorithms had extra and missed detections; however, those of M-T never occurred outside of the first and last steps of gait.

Table 3 Reference temporal parameters derived from insoles data

Walking speed level	Gait velocity (ms^{-1})	Stride duration (s)*	Side	Stance phase duration		Double support duration	
				(s)	(% stride)	(s)	(% stride)
	med (IQR)	med (IQR)		med (IQR)	med (IQR)	med (IQR)	med (IQR)
Slow	0.89 (0.12)	1.33 (0.14)	Sound	0.91 (0.14)	68.9 (5.2)	0.17 (0.04)	13.2 (2.4)
			Prosthetic	0.81 (0.11)	60.9 (2.4)	0.22 (0.06)	16.4 (4.0)
Comfortable	1.06 (0.12)	1.16 (0.13)	Sound	0.77 (0.10)	67.0 (3.4)	0.14 (0.02)	12.1 (2.2)
			Prosthetic	0.68 (0.08)	58.7 (3.3)	0.16 (0.04)	13.3 (2.1)
Fast	1.35 (0.19)	1.00 (0.13)	Sound	0.65 (0.12)	64.7 (4.9)	0.10 (0.03)	10.5 (1.4)
			Prosthetic	0.56 (0.07)	56.9 (2.6)	0.12 (0.04)	11.6 (3.4)

[*] Stride durations were estimated based on prosthetic IC timings; med, median

Table 4 Sensitivity and positive predictive value of the five IMU-based algorithms in gait event detection

Method	Sensitivity				Positive predictive value			
	Prosthetic limb		Sound limb		Prosthetic limb		Sound limb	
	Initial contact	Final contact	Initial contact	Final contact	Initial contact	Final contact	Initial contact	Final contact
M-S	93.4%	92.7%	94.0%	92.8%	99.1%	97.3%	95.2%	95.7%
M-M	98.6%	98.8%	97.4%	98.2%	99.7%	100.0%	98.3%	99.8%
M-L	88.4%	88.8%	84.2%	85.0%	100.0%	100.0%	100.0%	100.0%
M-T	99.1%	99.1%	98.8%	98.8%	100.0%	100.0%	99.8%	99.8%
M-MC	93.4%	91.9%	91.2%	90.6%	97.1%	96.0%	96.1%	96.1%

3.2 Accuracy of GEs timings

No significant effect of the "walking speed" factor was found on the errors obtained for GE timings, neither for M-T nor for M-L. GEs were generally detected with a small anticipation with M-L and with a short delay using M-T (Fig. 2). There was no effect of the "limb" on the IC timings estimated with either algorithm. Conversely, FC timings estimated with M-T were significantly more accurate ($t(4) = -3.626$, p value = 0.022) at the sound limb than at the prosthetic limb while the contrary was observed with M-L ($t(4) = -5.171$, p value = 0.007).

When comparing the algorithms in terms of errors, M-T was found to be less accurate than M-L for prosthetic FC detection ($t(6) = 4.890$, p value = 0.003), but more accurate for both prosthetic IC ($Z = -2.214$, p value = 0.027) and sound FC detection ($t(4) = 6.674$ p value = 0.003).

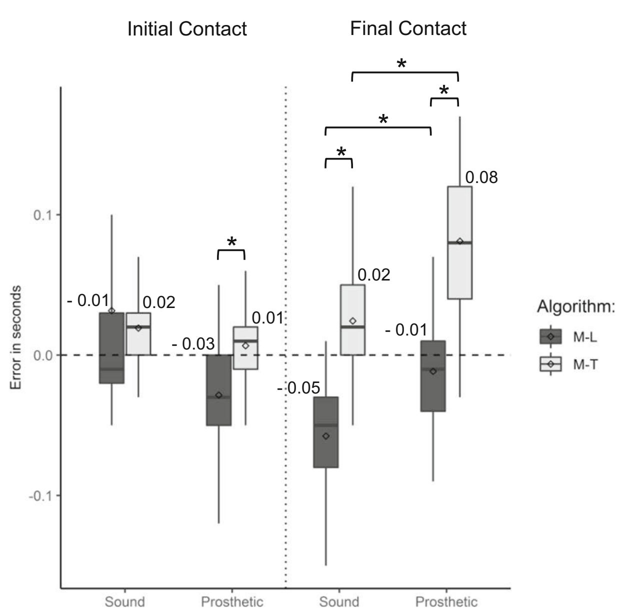

Fig. 2 Errors (s) of IC and FC timings obtained with M-T and M-L algorithms at all speeds with respect to reference events estimated with the insoles. Mean values are indicated with a diamond-shaped point and median values are reported above each boxplot. Significant differences ($p < 0.05$) are marked with an asterisk*. Outliers are not represented. In general, M-T and M-L resulted in a low number of outliers (< 3%), but M-L resulted in 8.02% of outliers for sound IC

3.3 Impact of GEs timings errors on estimates of gait temporal parameters and symmetry index

There was no effect of the "walking speed" factor on the median errors of gait temporal parameter estimates. While there was no difference between the algorithms for the stride duration, statistically significant differences were obtained for stance phase and double support duration estimates (Fig. 3 and Table 5). Furthermore, a significant effect of the "limb" was observed for stance phase durations for both algorithms (M-T: $t(4) = -3.940$, p value = 0.017; M-L: $t(4) = -2.781$, p value = 0.05) and for double support duration for M-T ($t(4) = 4.877$, p value = 0.008).

Median SPD-ASI values were averaged across all participants and walking speeds for each method (insoles, M-T and M-L) as no significant effect of the "walking speed" factor was found. SPD-ASI estimates obtained with M-T and M-L were found to be significantly different than those derived from the insoles (Table 6).

4 Discussion

This study aimed at (i) comparing the accuracy of state-of-the-art IMU-based algorithms in detecting both IC and FC events and (ii) assessing the impact of GE timing errors on the estimation of gait temporal parameters and symmetry in TF.

Gait temporal parameters and walking speeds obtained with pressure insoles were similar to those reported in the literature for the considered population [29, 30].

4.1 GE detection rate

To be relevant in an ecological context, GE detection algorithms must not detect extra events as they would be impossible to identify without a reference. Given their PPV values inferior to 99%, two of the algorithms developed for lower-

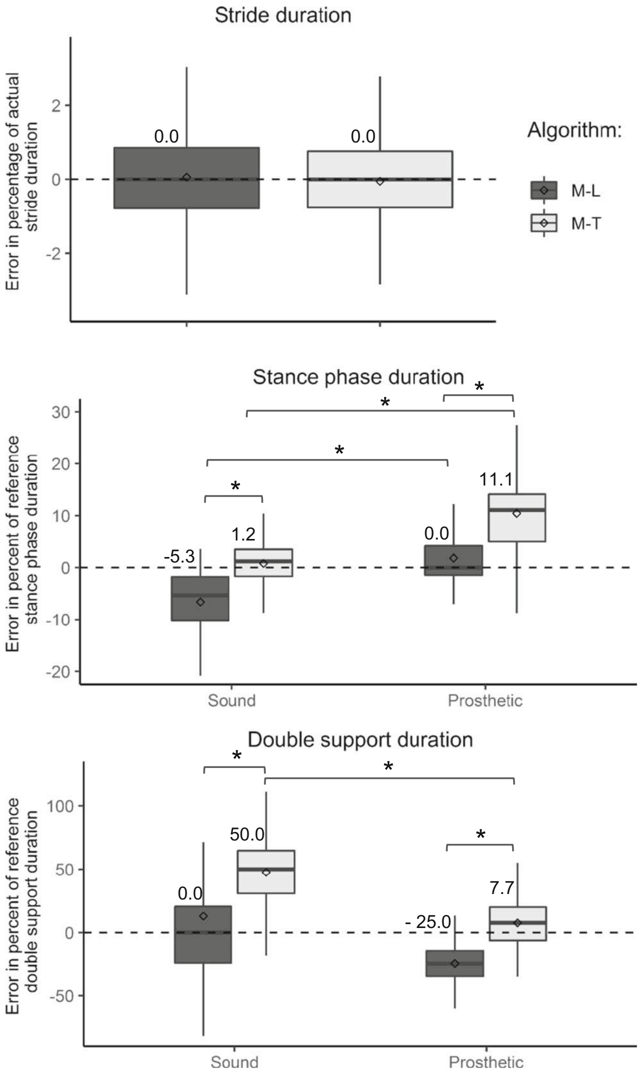

Fig. 3 Errors (%) of gait temporal parameters estimated with M-T and M-L expressed in percentage of the actual gait temporal parameters derived from the insoles data, at all speeds. From top to bottom: stride duration, stance phase duration, double support duration. Mean values are indicated with a diamond-shaped point and median values are reported above each boxplot. Significant differences ($p < 0.05$) are marked with an asterisk*. Outliers are not represented. In general, M-T and M-L resulted in a low number of outliers (< 4.5%), except for strides for M-T (13.7% of outliers) and for sound double support estimates for M-L (9.1% of outliers)

limb amputees (M-S and M-M) and the single-sensor-based algorithm (M-MC) were discarded from the analysis.

The modification applied to M-MC algorithm allowed to improve the discrimination between right- and left-side events, thus reducing the number of extra events (less than 4% of extra FC in our data, while up to 11.2% of extra FC were found in hemiparetic patients in a former study [4]), although not sufficiently. However, the number of missed events was higher than in the literature [4, 19], which might be due to specific gait alterations of prosthetic gait, such as the lack of propulsion inherent to prosthetic components [2].

Neither missed nor extra events were reported by the authors of the two other algorithms M-S and M-M. However, it should be noted that M-S was designed and validated in TT, whose gait pattern differs from that of TF. Furthermore, while all steps were considered in our analysis, including transition, acceleration, and deceleration steps, Selles and coworkers only analyzed steps that occurred on a force platform, ensuring to consider only steady-state steps [10].

Maqbool and coworkers reported a 100% detection rate by comparing the absolute number of events detected by M-M and by footswitches, without considering an objective criterion to ensure that each detected event would correspond to a footswitch event [24]. Furthermore, the algorithm was developed and validated on asymptomatic subjects and on only one TF and one TT who might have presented very few gait alterations, thus preventing the generalization of their results to the population of lower-limb amputees.

In what follows, only results obtained with M-L and M-T algorithms will be discussed.

A surprisingly high number of events were missed by M-L in the present study, despite its reported excellent sensitivity in TFs [4]. The thresholds originally proposed in [4] were specifically devised for treadmill ambulation, which was shown to reduce gait inherent inter-stride variability compared to level ground ambulation [31]. This may have hindered the algorithm's capacity to detect all events when walking in a less constraining situation. Furthermore, if an event is undetected by the algorithm, the following event will also be missed because of the state-machine design of M-L. Regarding M-

Table 5 Errors (ms) of gait temporal parameters estimated with M-T and M-L compared to insoles. Results of the statistical tests are reported, with significant differences between M-T and M-L values marked with asterisks (*p value ≤ 0.05)

Temporal parameter (in milliseconds)	M-T		M-L		Statistical tests (on % values)	
	Median	(IQR)	Median	(IQR)	p value	Score
Stride duration	0	(20)	0	(20)	0.317	$Z = -1.000$
Sound stance phase duration	10	(40)	−40	(70)	0.017*	$t(4) = 3.927$
Prosthetic stance phase duration	70	(60)	0	(40)	0.003*	$t(6) = 4.817$
Sound double support duration	70	(53)	0	(60)	0.009*	$t(4) = -4.788$
Prosthetic double support duration	10	(40)	−40	(40)	0.001*	$t(4) = -8.953$

Table 6 Mean and standard deviation over all participants of the median stance phase duration ASI derived from insoles and obtained with M-T and M-L algorithms. Results of the statistical tests are reported, with significant differences between insoles- or IMU-based ASI values marked with an asterisk

Algorithm	ASI algorithm		ASI insoles		*T* test	
	Mean	(Sd)	Mean	(Sd)	*p* value	Score
M-L	6.72%	(3.44%)	12.79%	(2.85%)	0.048*	$t(4) = 2.807$
M-T	4.16%	(5.05%)			0.013*	$t(4) = 4.274$

T, no extra or missed events occurred in the steady phase of gait, as reported in former studies [21, 23]. This directly results from the efficient design of M-T: the algorithm first detects maxima in the shank angular velocity and uses this information at both sides to segment gait into cycles and to identify restrained intervals of time where one and only one event (either an IC or a FC) has to occur. For all the investigated parameters, both algorithms were found to be robust to various self-selected walking speeds, confirming results reported for M-T [21, 23].

4.2 GE detection accuracy

Prosthetic IC and FC detections with M-L were as accurate as those reported in the original study [4], but slightly less precise. This may also result from the higher gait variability of overground- compared to treadmill-walking. Estimated FC timings were less accurate for the sound limb than the prosthetic limb, likely due to the adoption of identical thresholds for both limbs, as reported by the author [4]. Defining limb-specific thresholds was beyond the scope of this study, but it might improve sound FC timing accuracy.

M-T achieved similar or even improved GE timing accuracy compared to that reported using other algorithms specifically designed for people with lower-limb amputation [18, 22]. Furthermore, the achieved accuracy for IC detection in our participants is comparable to that of people with Parkinson's disease [21]. Both these results corroborate previous statements that M-T might be suitable for clinical routine detection of gait events [21, 23]. All in all, M-T achieved equivalent or higher accuracy than M-L in GE detection except for prosthetic FC. The algorithms differ not only in the signals that are used as inputs, but also in their design: M-T is based on peak-detection while M-L is a threshold-based algorithm. The latter strategy might be more efficient for prosthetic FC detection: the smoother movement occurring at FC compared to IC [27] and the attenuated propulsion at the prosthetic limb [2] might result in a smoothed signal, detrimental to the peak-identification strategy.

It should be noted that the sampling frequency (100 Hz) might have induced a delay of up to 10 ms between algorithms-derived and insoles-detected events. This constant delay has however no impact on the estimated durations.

4.3 Impact of GEs timings errors on estimates of gait temporal parameters and symmetry index

Both algorithms provide stride duration estimates acceptable for clinical use [27], with null median errors and IQR of 20 ms.

Regarding stance and double support durations, errors result from the discrepancy between IC and FC timing errors. In our study, temporal parameters errors were mostly driven by relatively high errors in FC detection at the sound limb for M-L and at the prosthetic limb for M-T compared to IC.

The errors achieved for stance phase duration are acceptable at the prosthetic limb with M-L and at the sound limb with M-T [27], with a similar accuracy to that of the original article [21]. Furthermore, the achieved errors with either algorithm at either limb are inferior to the minimal change detectable by pressure insoles in people with lower limb amputation [32]. Combining both algorithms by using M-T approach for gait segmentation and interval identification, and then taking advantage of either M-T or M-L detection approaches for the sound or prosthetic limb respectively, might provide more accurate estimates of stance phase duration at both limbs. This would in turn enable a long-term monitoring of a patient's progress during his rehabilitation, but test-retest reliability should be evaluated prior to using the combined algorithm in a clinical setting for longitudinal monitoring.

Regarding double support duration, percentage errors achieved high values and variability at both sides with both algorithms. Therefore, although double support duration is a clinically relevant parameter reflecting stability and weight shifting ability in TF [30, 33], the use of either M-T or M-L algorithms for its estimation is not recommended.

Regarding temporal gait symmetry, the discrepancy between sound and prosthetic stance phase duration errors explains the observed SPD-ASI inaccuracy. The algorithms tend to significantly underestimate sound stance-phase duration or to overestimate prosthetic stance-phase duration, resulting in a falsely low asymmetry index. Thus, neither M-T nor M-L can be safely used to assess stance phase duration asymmetry between the prosthetic and the sound limb.

This confirms the need of a more robust algorithm at both the prosthetic and sound limbs for temporal parameters, which in turn would enable to obtain reliable SPD-ASI estimates in TF.

Although the participants of the study were found to be representative of the population with TF [29, 30], the small sample size in this study should be considered prior to results generalization.

5 Conclusions

This study analyzed the performance of different IMU-based algorithms and gives indications about their accuracy for GE detection in people with transfemoral amputation. Two of the investigated algorithms, using one IMU on each shank, provide acceptable estimates of stride and stance phase durations considering the minimal detectable change of these parameters by pressure insoles. However, test-retest reliability of the IMU-derived estimates remains to be evaluated prior to using these algorithms for longitudinal monitoring of gait. Furthermore, both algorithms lack in accuracy when estimating either double support duration or the temporal asymmetry index. A new algorithm, combining the strengths of M-T and M-L should be devised to improve gait event detection and temporal parameters estimation in people with transfemoral amputation. The results of the present study support the use of a priori gait cycle segmentation using the shank mediolateral angular velocity and tend to indicate that threshold-based detection should be preferred to peak-based detection at the prosthetic limb, at least for FC event detection.

Acknowledgments The authors would like to thank Dr. Loiret, IRR Nancy, and Florian Guillaume (MSc) for their help in the data acquisition.

Author statement Emeline Simonetti: Conceptualization, investigation, methodology, software, formal analysis, writing—original draft, visualization. Elena Bergamini: Conceptualization, software, formal analysis, writing—review and edition, visualization, supervision.

Coralie Villa: Conceptualization, investigation, supervision.

Joseph Bascou: Software.

Giuseppe Vannozzi: Formal analysis, Writing—review and edition

Hélène Pillet: Conceptualization, writing—reviewing and editing, supervision, project administration.

Funding information Research reported in this publication was supported by grants from the Fédération des Amputés de Guerre de France and the Université Franco-Italienne [Call VINCI 2018–C2-881, attributed to E. Simonetti].

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the national research committee (CPP IDF VI, No. 2014-A01938-39) and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent Informed consent was obtained from all individual participants included in the study.

Disclaimer 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.

References

1. Perry J (1992) Gait analysis normal and pathological function. Thorofare, NJ, Slack Incorporated. https://doi.org/10.1097/01241398-199211000-00023
2. Nolan L, Wit A, Dudziñski K, Lees A, Lake M, Wychowañski M (2003) Adjustments in gait symmetry with walking speed in trans-femoral and trans-tibial amputees. Gait Posture 17:142–151. https://doi.org/10.1016/S0966-6362(02)00066-8
3. Bastas G, Fleck JJ, Peters RA, Zelik KE (2018) IMU-based gait analysis in lower limb prosthesis users: comparison of step demarcation algorithms. Gait Posture 64:30–37. https://doi.org/10.1016/j.gaitpost.2018.05.025
4. Ledoux E (2018) Inertial sensing for gait event detection and transfemoral prosthesis control strategy. IEEE Trans Biomed Eng 65:2704–2712. https://doi.org/10.1109/TBME.2018.2813999
5. AG AC, Raggi M, Andreoni G, Sacchetti R (2015) Clinical gait analysis for amputees: innovation wishlist and the perspectives offered by the outwalk protocol. G Ital Med Lav Ergon 37:45–48
6. Aminian K, Najafi B, Büla C, Leyvraz P-F, Robert P (2002) Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes. J Biomech 35:689–699. https://doi.org/10.1016/S0021-9290(02)00008-8
7. Barnett S, Cunningham JLJ, West S (2001) A comparison of vertical force and temporal parameters produced by an in-shoe pressure measuring system and a force platform. Clin Biomech 16:353–357. https://doi.org/10.1016/S0268-0033(01)00026-2
8. Loiret I, Villa C, Dauriac B, Bonnet X, Martinet N, Paysant J, Pillet H (2019) Are wearable insoles a validated tool for quantifying transfemoral amputee gait asymmetry? Prosthetics Orthot Int 43(5):492–499. https://doi.org/10.1177/0309364619865814
9. Pacini Panebianco G, Bisi MC, Stagni R, Fantozzi S (2018) Analysis of the performance of 17 algorithms from a systematic review: influence of sensor position, analysed variable and computational approach in gait timing estimation from IMU measurements. Gait Posture 66:76–82. https://doi.org/10.1016/j.gaitpost.2018.08.025
10. Zijlstra W, Hof AL (2003) Assessment of spatio-temporal gait parameters from trunk accelerations during human walking. Gait Posture 18:1–10. https://doi.org/10.1016/S0966-6362(02)00190-X
11. Brandes M, Zijlstra W, Heikens S, Van Lummel R, Rosenbaum D (2006) Accelerometry based assessment of gait parameters in children. Gait Posture 24:482–486. https://doi.org/10.1016/j.gaitpost.2005.12.006
12. Houdijk H, Appelman FM, Van Velzen JM, Van der Woude LHV, Van Bennekom CAM (2008) Validity of DynaPort GaitMonitor for assessment of spatiotemporal parameters in amputee gait. J Rehabil Res Dev 45:1335–1342. https://doi.org/10.1682/JRRD.2007.12.0209
13. González RC, López AM, Rodriguez-Uría J, Álvarez D, Alvarez JC (2010) Real-time gait event detection for normal subjects from lower trunk accelerations. Gait Posture 3:322–325. https://doi.org/10.1016/j.gaitpost.2009.11.014
14. Köse A, Cereatti A, Della Croce U (2012) Bilateral step length estimation using a single inertial measurement unit attached to the pelvis. J Neuroeng Rehabil 9:1–10. https://doi.org/10.1186/1743-0003-9-9
15. McCamley J, Donati M, Grimpampi E, Mazzà C (2012) An enhanced estimate of initial contact and final contact instants of time using lower trunk inertial sensor data. Gait Posture 36:316–318. https://doi.org/10.1016/j.gaitpost.2012.02.019
16. Trojaniello D, Ravaschio A, Hausdorff JM, Cereatti A (2015) Comparative assessment of different methods for the estimation of gait temporal parameters using a single inertial sensor: application to elderly, post-stroke, Parkinson's disease and Huntington's

disease subjects Gait Posture 42:310–316. doi:https://doi.org/10.1016/j.gaitpost.2015.06.008
17. Salarian A, Russmann H, Vingerhoets FJG, Dehollain C, Blanc Y, Burkhard PR, Aminian K (2004) Gait assessment in Parkinson's disease: toward an ambulatory system for long-term monitoring. IEEE Trans Biomed Eng 51:1434–1443. https://doi.org/10.1109/tbme.2004.827933
18. Selles RW, Formanoy MAG, Bussmann JBJ, Janssens PJ, Stam HJ (2005) Automated estimation of initial and terminal contact timing using accelerometers; development and validation in transtibial amputees and controls. IEEE Trans Neural Syst Rehabil Eng 13:81–88. https://doi.org/10.1109/TNSRE.2004.843176
19. Catalfamo P, Ghoussayni S, Ewins D (2010) Gait event detection on level ground and incline walking using a rate gyroscope. Sensors 10:5683–5702. https://doi.org/10.3390/s100605683
20. Greene BR, McGrath D, O'Neill R, O'Donovan KJ, Burns A, Caulfield B (2010) An adaptive gyroscope-based algorithm for temporal gait analysis. Med Biol Eng Comput 48:1251–1260. https://doi.org/10.1007/s11517-010-0692-0
21. Trojaniello D, Cereatti A, Pelosin E, Avanzino L, Mirelman A, Hausdorff JM, Della Croce U (2014) Estimation of step-by-step spatio-temporal parameters of normal and impaired gait using shank-mounted magneto-inertial sensors: application to elderly, hemiparetic, parkinsonian and choreic gait. J Neuroeng Rehabil 11:152. https://doi.org/10.1186/1743-0003-11-152
22. Maqbool HF, Husman MAB, Awad MI, Abouhossein A, Iqbal N, Dehghani-Sanij AA (2017) A real-time gait event detection for lower limb prosthesis control and evaluation. IEEE Trans neural Syst Rehabil Eng 25:1500–1509. https://doi.org/10.1109/TNSRE.2016.2636367
23. Bertoli M, Cereatti A, Trojaniello D, Avanzino L, Pelosin E, Del Din S et al (2018) Estimation of spatio-temporal parameters of gait from magneto-inertial measurement units: multicenter validation among Parkinson, mildly cognitively impaired and healthy older adults. Biomed Eng Online 17:58. https://doi.org/10.1186/s12938-018-0488-2
24. Jasiewicz JM, Allum JHJ, Middleton JW, Barriskill A, Condie P, Purcell B, Li RC (2006) Gait event detection using linear accelerometers or angular velocity transducers in able-bodied and spinal-cord injured individuals. Gait Posture 24:502–509. https://doi.org/10.1016/j.gaitpost.2005.12.017
25. Sabatini AM, Martelloni C, Scapellato S, Cavallo F (2005) Assessment of walking features from foot inertial sensing. IEEE Trans Biomed Eng 52:486–494. https://doi.org/10.1109/TBME.2004.840727
26. Mariani B, Rouhani H, Crevoisier X, Aminian K (2013) Quantitative estimation of foot-flat and stance phase of gait using foot-worn inertial sensors. Gait Posture 37:229–234. https://doi.org/10.1016/j.gaitpost.2012.07.012
27. Trojaniello D, Cereatti A, Della Croce U (2014) Accuracy, sensitivity and robustness of five different methods for the estimation of gait temporal parameters using a single inertial sensor mounted on the lower trunk. Gait Posture 40:487–492. https://doi.org/10.1016/j.gaitpost.2014.07.007
28. Storm FA, Buckley CJ, Mazzà C (2016) Gait event detection in laboratory and real life settings: accuracy of ankle and waist sensor based methods. Gait Posture 50:42–46. https://doi.org/10.1016/j.gaitpost.2016.08.012
29. Goujon-Pillet H, Sapin E, Fodé P, Lavaste F (2008) Three-dimensional motions of trunk and pelvis during transfemoral amputee gait. Arch Phys Med Rehabil 89:87–94. https://doi.org/10.1016/j.apmr.2007.08.136
30. Goujon H, Bonnet X, Sautreuil P, Maurisset M, Darmon L, Fode P, Lavaste F (2006) A functional evaluation of prosthetic foot kinematics during lower-limb amputee gait. Prosthetics Orthot Int 30:213–223. https://doi.org/10.1080/03093640600805134
31. Hollman JH, Watkins MK, Imhoff AC, Braun CE, Akervik KA, Ness DK (2016) A comparison of variability in spatiotemporal gait parameters between treadmill and overground walking conditions. Gait Posture 43:204–2019. https://doi.org/10.1016/j.gaitpost.2015.09.024
32. Timmermans C, Cutti AG, van Donkersgoed H, Roerdink M (2019) Gaitography on lower-limb amputees: repeatability and between-methods agreement. Prosthetics Orthot Int 43:71–79. https://doi.org/10.1177/0309364618791618
33. Kendell C, Lemaire ED, Dudek NL, Kofman J (2010) Indicators of dynamic stability in transtibial prosthesis users. Gait Posture 31:375–379. https://doi.org/10.1016/j.gaitpost.2010.01.003

Emeline Simonetti is completing a joint PhD in Biomechanics at Arts et Métiers (Paris, France) and Foro Italico (Rome, Italy). Her research aims at developing wearable methods for the assessment of people with lower-limb amputation.

Coralie Villa received a PhD in Biomechanics in 2014. Her research aims at developing methods in motion analysis for the development of clinical evaluation and rehabilitation protocols for people with lower-limb amputation.

Joseph Bascou works as a researcher at Institution nationale des Invalides/CERAH since 2009 and obtained his PhD in Biomechanics in 2012. His research interests include manual wheelchair and gait analysis of amputee people.

Giuseppe Vannozzi got a PhD in Bioengineering (2004) and the Habilitation as Associate Professor. His research focuses on assessing human motor function for clinical rehabilitation, physical training, and life-span development.

Elena Bergamini received a joint PhD in Bioengineering at the University of Bologna (Italy) and Arts et Métiers (France) in 2011. Her research concerns the development of methods to assess persons' motor function.

Hélène Pillet has a PhD in Biomechanics (2006) and an accreditation to supervise research (2015). Her research involves motion analysis for the understanding of musculoskeletal systems for clinical evaluation and rehabilitation.