Quantitative characterization of walking on sand inecological conditions: Speed, temporal segmentation, and variability

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

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Submitted to:

Gait & Posture

Word count:
(3130)

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Abstract

Background

The quantification of gait temporal parameters (i.e. step time, stance time) is crucial in human motion analysis and requires the accurate identification of gait events (i.e. heel strike, toe off). With the widespread use of inertial wearable sensors, many algorithms were proposed and applied for the purpose. Nevertheless, only few studies addressed the assessment of the actual performance of these algorithms, rather considering each proposed algorithm as a whole.

Research question

How different implementation characteristics influence the assessment of gait events and temporal parameters from inertial sensor measures in terms of accuracy and repeatability?

Methods

Seventeen different algorithms were identified from a systematic review and classified based on: 1) sensor position, 2) target variable, 3) computational approach. The influence of these characteristics was analysed on walking data of 35 healthy volunteers mounting 5 tri-axial inertial sensors. Foot contact events identified by 2 force platforms were assumed as gold standard. Temporal parameters were calculated from gait events. Algorithm performance was analysed in terms of accuracy (error median value) and repeatability (error 25th and 75th percentile values).

Results

Shank- and foot-based algorithms performed better (in terms of accuracy and repeatability) in gait events detection and stance time estimation than lower trunk-based ones, while sensor position did not affect step estimate, given the error bias characteristics. Angular velocity-based algorithms performed significantly better than acceleration-based ones for toe off detection in terms of repeatability (68ms and 102ms, 25th-75th percentile error range, respectively) and, for heel strike detection, showed better repeatability (40ms and 111ms) and comparable accuracy (65ms and 60ms median error, respectively) than acceleration-based ones. The performance of different computational approaches varied depending on sensor positioning.

Significance

Present results support the selection of the proper algorithm for the estimation of gait events and temporal parameters in relation to the specific application.

Keywords— *inertial wearable sensors, algorithm, gait events, temporal parameters, gait.*

Introduction

Gait analysis is extensively used for the quantitative assessment of motor function in basic research as well as clinical and sport applications, and gait timing is considered of primary importance for the characterization of gait alterations. The quantification of gait temporal parameters (GTP) (i.e. step and stance times) requires, first of all, to identify gait events (GE) (i.e. heel strike, HS, and toe off, TO). GTP can be estimated from measurements obtained using various sensing technologies, such as foot-switches, inertial sensors, pressure mats, or stereo-photogrammetric systems [1].

In particular, inertial measurement units (IMUs) have become widely used for quantitative motion analysis, thanks to their reliability and limited cost, as well as to the possibility to test gait in ecological conditions with limited invasiveness. This led to the need for appropriate gait segmentation methods [2] and to the development of a number of algorithms, which were proposed in the literature and applied in different conditions, exploiting different sensor positions, analysing different variables, with different computational approaches.

Most published works proposed and tested [3–19] the performance of one specific algorithm, rarely addressing a direct comparison with others. Studies approaching the comparisons of different algorithms usually limited the analysis to the positioning of IMUs [3–6]. Storm et al. [4] and Ben Mansour et al.[3] assessed the accuracy of two and three algorithms, respectively, based on shank-worn and lower trunk-worn IMUs. Storm et al. [4] demonstrated that lower trunk method performed worse than shank one in GE detection, but GTP estimation resulted satisfactory with both. Ben Mansour et al. [3] showed that shank method, analysing angular velocity, was the most accurate in estimating both GEs and GTPs, followed by lower trunk acceleration for GEs and shank acceleration for GTPs. Trojanello et al. [6] tested the performance of 5 different methods for GE detection using a single IMU attached to the lower trunk, showing an acceptable accuracy, sensitivity and robustness of all the evaluated methods in determining GTPs requiring the identification of HS, while a worse accuracy was found in determining GTPs requiring also TO identification (e.g. stance duration). These findings highlight differences in the performance of the analysed algorithms as related to different parameters, potentially suggesting that the choice of the most appropriate algorithm can also depend on the specific research question. Moreover, the few available comparison studies analysed each algorithm as a whole, not addressing the influence of specific implementation characteristics, except for sensor positioning, and not providing a comprehensive overview of the numerous solutions proposed in the literature. Only few studies [3,7] compared the combined effect of positioning and target variable, considering either linear acceleration or angular velocity at different positions, but still neglecting the analysis of the computational approach adopted.

To authors' knowledge, no comprehensive analysis has been published, investigating the performance of the available algorithms for GE detection as resulting from their specific implementation characteristics. The present study was designed to fill in this gap, starting from a systematic review of the available literature to identify the different proposed methods, aiming to provide relevant information for the selection of the most suitable algorithm for specific applications, and/or for the design and implementation of novel methods for GE detection. The performance of the algorithms was analysed in controlled conditions, to identify methodological intrinsic characteristics, without potential interferences of gait alterations.

Nomenclature

FIGURE 1 HERE

Materials and Methods

Literature review

Articles were searched in PubMed, Scopus and ISI Web of Knowledge until 20 November 2017. Searches consisted of a combination of the following keywords: (1) assessment or estimation or measurement; (2) wearable or inertial sensor or accelerometer or gyroscope or inertial measurement unit; (3) temporal or parameters; (4) gait or walking. Keyword search was performed to match words in the title, abstract, or keyword fields.

Studies published in English as full papers, involving original methods for the estimation of GEs using accelerometer attached to the lower trunk, shanks and feet were included based on criteria summarized in Table 1. These positionings were identified based on the higher number of citation (>500) in comparison with others (i.e. heel, pelvis on the right side, thigh, lateral tibial condyle).

TABLE 1 HERE

The search yielded 271 (PubMed), 191 (Scopus), and 350 (ISI Web of Knowledge) results.

A critical examination of the titles and abstracts allowed to exclude unrelated and duplicated articles. After the application of inclusion and exclusion criteria a set of 36 articles were identified. Articles purposing the same implementation rules for GE estimation were grouped together and the first published and most cited ones were considered as original references for the algorithms, resulting in a final set of 17 articles [7–23]. The remaining 19 articles were associated to the singular original articles as illustrated in the table A.1 (online supplementary material).

The 17 algorithms were revised and classified based on:

i) IMU position (i.e. lower trunk[1], shanks, feet)

ii) Target variable (i.e. acceleration, angular velocity)

iii) Computational approach: 'peak identification' and 'zero crossing', on raw or filtered target variable (i.e. FIR, IIR, WT filtering). 'Peak identification' aims to identify specific peaks on the target variable, corresponding to specific temporal events: local maxima or minima of the vertical or antero-posterior component for acceleration-based algorithms; local minima of the sagittal component for angular velocity-based algorithms. 'Zero crossing' aims to identify the instants of sign change in the target variable, corresponding to specific temporal events: in the antero-posterior component for acceleration-based algorithms; in the sagittal component for angular velocity-based algorithms.

Experimental analysis

Participants:

Thirty-five young healthy participants (17 females, 18 males; 26.0±3.8 years; 1.72±0.08 m; 69.0±13.1 Kg) were recruited in the study. All participants were physically active and self-reported no musculoskeletal or neurological disorder. The Bioethics Committee of the University of Bologna approved the study on 12/6/2017 with protocol number 60193, and informed consent was signed by all participants.

Data acquisition:

Each participant walked for 2 minutes back and forth along a 10 m straight pathway at self-selected speed (normalized gait speed: 0.41±0.06 [24]) wearing own comfortable footwear. Five tri-axial IMUs (Cometa, Milano, Italy) equipped with accelerometer (sensitivity: 156,3 mV/g; range: ± 8g) and gyroscope (sensitivity: 1,3 mV/g; range: ±1000°/s) were attached to the trunk (at L5 level), shanks (about five centimetres above lateral malleolus), and feet (on the dorsal surface of each shoe) (Figure 1). 3D acceleration and 3D angular velocity were acquired from each sensor with a sampling frequency of 285Hz, higher than that in all referred works. Ground reaction forces were recorded (sampling frequency 1000Hz) by two force platforms (Kistler, Winterthur, Switzerland) mounted half-way along the path, assumed as gold standard reference for GE detection.

A trigger signal was generated by IMU system at the beginning of each trial for synchronization. The online version of this article contains the collected data.

[1] From here, for the sake of concision, the term "trunk" will be used meaning "lower trunk".

Data analysis:

The identified 17 algorithms were implemented in MATLAB (MathWorks 2017a, NATHSK, USA), and HS and TO were estimated from IMU data for each participant with each algorithm.

A 20N threshold was applied to ground reaction force (GRF) vertical component for the automatic detection of HS and TO [25] for each participant.

For each algorithm, the error (E) was calculated for GEs (E_{GE}) and GTPs (E_{GTP}) as follow:

$$E_{GE} = GE_{IMU} - GE_{GRF}$$

$$E_{GTP} = GTP_{IMU} - GTP_{GRF}$$

Where GE subscripts denote methods of estimation.

If an algorithm allowed identifying only HS, errors were calculated for HS and step time.

Statistical analysis:

12 contacts per participants were included in the statistical analysis. For each parameter (GEs and GTPs), a linear mixed model [26] was applied to test the dependency of error values on each implementation criterion, with a significance level of 0.05. First, the statistical analysis was performed to investigate the influence of IMU position and target variable, alone. Then, the influence of computational approach was investigated separately for each IMU position.

Med of the error was calculated to characterize accuracy, and to characterize repeatability Dmed, calculated as 75th percentile minus 25th percentile value of the error.

Data processing was performed in MATLAB (MathWorks, Natick, USA), and statistical analysis using R software (R-Core Team., Vienna, Austria, version 3.4.3 2017).

Results

Of the 17 algorithms, as summarised in Table 2:

- 6 were trunk-based (of which only 2 provided both HS and TO [12,16], while 4 defined only HS [9,13,19,21]), all analysing acceleration, 3 using 'peak identification', of which 1 with IIR [9], 1 with FIR [13] and 1 with WT filtering (detecting HS and TO) [16], and 3 using 'zero crossing' approach, of which one with raw signal [19], 1 with FIR filtering (detecting HS and TO) [12] and 1 with IIR filtering [21];
- 7 were shank-based, of which 3 analysing acceleration with 'peak identification', 1 with raw signal [20], 1 with IIR [14] and 1 with WT filtering [23], and 4 analysing angular

velocity with ‘peak identification’, 2 with raw signal [18,27], 1 with IIR [10] and 1 with WT filtering [8];

- 4 were foot-based, of which 1 analysing acceleration with ‘peak identification’ of raw signal [7], and 3 analysing angular velocity, 2 with ‘peak identification’, 1 adopting raw signal [11] and 1 with IIR filtering [17] and 1 with ‘zero crossing’ of IIR filtered signal [15].

TABLE 2 HERE

For each subject at least 12 contacts on the force platform were detected, for a total of 420 analysed strides. No false positive or negatives were identified for all the analysed algorithms.
Statistical analysis highlighted significant differences for all three implementation characteristics, although the magnitude of errors was comparable.

IMU Position

For HS detection error, no significant difference was found between shank- and trunk-based algorithms ($p=0.978$), while significant differences ($p<0.001$) were found for foot-based algorithms with respect to the others. By analysing error results in detail, shank- and foot-based algorithms resulted more accurate and repeatable in HS detection than trunk-based ones. Foot-based algorithms showed comparable accuracy (Med 63 ms and 62 ms, respectively) and repeatability (Dmed 59 ms and 44 ms, respectively) to shank-based ones, while trunk-based ones resulted less accurate (Med 70 ms) and less repeatable (Dmed 113 ms).
For TO detection, statistically significant differences were found for all IMU positions ($p<0.001$). In particular, foot-based algorithms showed the highest accuracy and repeatability, with Med 2 ms and Dmed 57 ms; shank-based algorithms followed with Med -29 ms and Dmed 96 ms; trunk-based ones provided the worst performance with Med -66 ms and Dmed 164 ms.
For step time estimation, results showed comparable accuracy and repeatability among all IMU positions (Med/Dmed: 6/41 ms, 6/32 ms, 2/47 ms, for trunk, shank, and foot, respectively). For stance time, foot-based algorithms showed the highest accuracy and repeatability (Med/Dmed -64/120 ms), followed by shanks-based (Med/Dmed -88/151 ms) and trunk-based ones (Med/Dmed -111/159 ms).

Target variable

For HS detection, algorithms exploiting angular velocity showed higher repeatability and comparable accuracy than those exploiting acceleration (Med/Dmed 65/40 ms and 60/111 ms, for angular velocity and acceleration, respectively).

For TO detection, angular velocity-based algorithms performed significantly ($p<0.001$) higher than acceleration-based ones in terms of repeatability, with Dmed 68 ms, smaller than the 122 ms of acceleration-based ones, but a lower accuracy, with Med -25 ms versus 6 ms.

Acceleration-based algorithms resulted more and equally accurate for stance and step time, respectively, but less repeatable than angular-velocity ones for both parameters (step time Med/Dmed: 7/34 ms and 2/43 ms; stance time Med/Dmed: -84/65 ms, -69/106 ms, for angular velocity and acceleration, respectively).

Error characteristics for HS and TO as related to IMU position and target variable are schematically depicted in Figure 2, and for step and stride time in Figure 3. Numerical values as related to IMU position and target variable are reported in Table A.2 and A.3, respectively (online supplementary material).

FIGURE 2 HERE

FIGURE 3 HERE

Computational approach

Considering the trunk-based algorithms, statistically significant differences were found between the two approaches ($p<0.05$). In particular, 'peak identification' approach with FIR filtering resulted to be the most accurate (Med 2ms) and repeatable (Dmed 16ms) in HS detection. The 'zero crossing' approach with FIR filtering resulted the most accurate (Med 26ms) in TO detection, while 'peak identification' with WT filtering resulted to be the most repeatable (Dmed 54ms). For step time, no significant difference was found among different filtering for each approach ($p>0.597$ for all comparisons among filtering). For stance time, 'zero crossing' with FIR filtering resulted to be the most accurate, while 'peak identification' with WT filtering highlighted the highest repeatability (Med/Dmed: -22/186 ms, -159/32 ms, respectively).

Shank-based algorithms exploited only 'peak identification' approach: WT filtering reported the highest accuracy and repeatability in HS detection (Med 47 ms and Dmed 36 ms), while raw data resulted to be the most accurate and repeatable in TO detection (Med -2 ms and Dmed 89 ms). Raw or filtered signals resulted to be equally accurate and repeatable in step time estimation; significant differences were found only between raw signal and IIR filtering, which showed comparable accuracy and repeatability (Med/Dmed: 8/33 ms and 2/31 ms, respectively). For stance time estimation, raw signal resulted to be the most accurate (Med -46ms), while WT filtering showed the highest repeatability (Dmed 45ms).

Considering foot position of IMUs, statistically significant differences ($p<0.05$) were found between the two computational approaches. In particular, 'peak identification' on raw signal resulted to be the most accurate (Med 44 ms) in HS detection, while 'zero crossing' with IIR filtering resulted to be the most repeatable both for HS and TO (Dmed 19 ms and 24 ms, respectively). Referring to the accuracy in TO estimation, 'peak identification' with IIR filtering (Med -1 ms) resulted the most accurate. For GTPs, 'zero crossing' with IIR filtering (Med/Dmed 1/17 ms) resulted the most accurate and repeatable in step detection. No statistically significant difference was found between approaches for stance time ($p=0.676$).

Numerical values of error characteristics for GE and GTP as related to computational approach are reported in Table A.4 (online supplementary material).

Results are summarized in Figure 4.

FIGURE 4 HERE

Discussion

The present study analysed the performance of 17 published algorithms proposed for GE detection from IMU data. The algorithms were selected based on a systematic review and analysed with respect to the influence of IMU position, target variable and computational approach on estimated errors on GEs and derived GTPs.

IMU position

Trunk-based algorithms exhibited a worse performance than shank- and foot-based ones in GE detection. Taking into account the IMU sampling period of 3.5ms, minor differences between the latter two can be considered negligible for HS detection, while foot-based algorithms performed better than shank-based ones both in terms of accuracy and repeatability for TO detection. Generally, error bias resulted in a delay of HS (the largest for trunk-based algorithms, the lowest for shank- and feet-based algorithms) and an anticipation of TO (the smallest for foot-based algorithms, increasing moving towards shank and trunk) as illustrated in Figure 4. This behaviour justifies the trend observed in the analysed GTPs: step time estimate (derived from HS alone) does not result significantly affected by IMU positioning, while stance time (derived from HS and TO) resulted always underestimated, increasingly from the foot to the trunk. These results provide more detail but are in line with the literature [7, 17, 21, 25].

Target variable

Acceleration-based algorithms: i) resulted more accurate than angular velocity-based ones for TO detection, while differences in accuracy were negligible for HS detection; ii) resulted less repeatable for both HS and TO detection, as supported by the lower values of the intra-class correlation coefficient obtained for shanks and feet acceleration compared to the angular velocity; iii) provided always lower repeatability but better accuracy in stance time and similar accuracy in step time estimation. Jasiewicz et al. [7] found that either linear acceleration or angular velocity of IMUs attached to the foot performed equally in terms of accuracy in GE detection, while Ben Mansour et al. [3], comparing trunk and shank position, showed that shank angular velocity allowed better accuracy for both GEs and GTPs, followed by trunk and shank acceleration for GEs and GTPs, respectively. These differences can be justified considering that their analysis focused only on foot- or shank/trunk- based algorithms, neglecting the influence of different IMU positioning and/or computational approach.

Computational approach

Computational approach resulted to affect performance differently, depending on IMU position. For the computational approach, IMU position have to be taken into account. Considering trunk-based algorithms, 'peak identification' with FIR filtering showed the best performance in HS detection, due to the effectiveness of the filter in emphasizing the main acceleration peak associated to HS [13]. For TO detection, 'peak identification' with WT filtering resulted the most repeatable while 'zero crossing' with FIR filtering resulted the most accurate, in line with the literature [12,16]. No statistically significant difference was found in step time estimation, demonstrating that gait cycle duration can be estimated from the recording of a single IMU, independently from the computational approach [6]. Conversely, stance time was affected by the approach used as observed for TO identification.

Considering IMUs positioned on the shanks, the best performance was obtained using 'peak identification' with WT filtering for HS and on raw signal for TO detection, in line with the literature [20,28]. Similarly to trunk-based algorithms, computational approach did not influence step time estimation, while stance estimation varied significantly depending on signal pre-processing:

estimation on raw signal resulted to be the most accurate, while a pre-processing with WT filtering provided the best repeatability.

Regarding foot positioning, the best accuracy was obtained with 'peak identification' on raw and IIR filtered signal for HS and TO, respectively: this result could be expected, since sharp peaks in angular velocity or acceleration during HS and TO are the more empathized and easy to detect, the closer to the ground the IMU is located [20]. On the other hand, the best repeatability in GE detection was obtained from 'zero crossing' with IIR filtering, which represented a robust way for detecting gait cycles both in healthy and pathological populations [15]. The delay introduced by this approach in HS detection (positive Med), resulted compensated in step estimation (Med 1 ms), exhibiting the best accuracy and reproducibility in the parameter estimation. Conversely, no significant difference was found for stance time estimation between the two approaches.

The potential concurrent influence of different factors was analysed and did not result to affect the performance at the same extent for all analysed factors. Eventual concurrent influence was reported where relevant (e.g. sensor position when discussing computational approach).

Most of the algorithms (independently from IMU position, target variable and computational approach) showed comparable performance when estimating step time, while attention is needed for stance duration and GEs.

Future studies will address different situations (e.g. ecological conditions, varying walking speed), different sensor type and sampling frequency, as well as populations characterized by altered gait patterns (e.g. children, elderlies, pathological populations) [8,20,29], and will include the assessment of algorithms' specificity and sensitivity, as possible false positive/negatives may occur in these conditions.

Conclusion

All analysed factors resulted to affect GE and GTP estimation. No proposed algorithm can be generally preferred over the others, but the reported results can support researchers in the choice of the most suitable algorithm/algorithms based on experimental condition (e.g. number/type/placement of sensors) and research question (e.g. mean/variability of the selected gait variable). Finally, these results can support future design of novel and more efficient detection algorithms.

Conflict of interest statement

The authors have no conflicts of interest to report.

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Figure captions:

Figure 1: Tables glossary for acronyms; attachment of IMUs on the different body location and relative axis orientations.

Figure 2: Box plot (minimum, 25^{th} percentile, median, 75^{th} percentile, maximum values) for HS (a) and TO (b) estimation errors as related to IMU position and target variable (angular velocity contoured in dots, acceleration no contour) (* $p<0.001$).

Figure 3: Box plot (minimum, 25^{th} percentile, median, 75^{th} percentile maximum values) for step time (a) and stance time (b) estimation errors as related to IMU position and target variable (angular velocity contoured in dots, acceleration no contour) (* $p<0.001$).

Figure 4: Estimated error for HS (a) and TO (b) as related to IMU position, target variable and computational approach.

Figures

Figure 1.

Tables glossary for acronyms; attachment of IMUs on the different body location and relative axis orientations.

Acronym	***Description***
GE	Gait Event
GTP	Gait Temporal Parameter
HS	Heel Strike
TO	Toe Off
IMU	Inertial Measurement Unit
FIR	Finite Impulse Response
IIR	Infinite Impulse Response
WT	Wavelet Transform
Med	Median
Dmed	Dispersion around median value

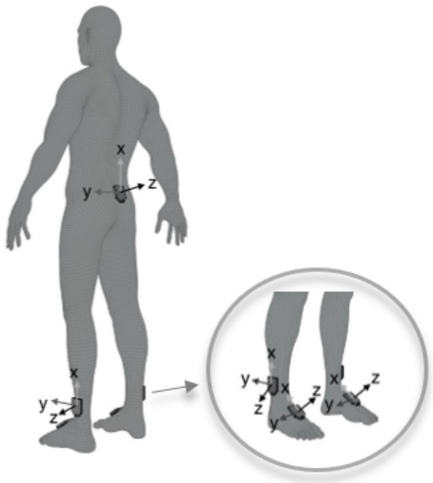


Figure 2.

Box plot (minimum, 25th percentile, median, 75th percentile, maximum values) for HS (a) and TO (b) estimation errors as related to IMU position and target variable (angular velocity contoured in dots, acceleration no contour) (* p<0.001).

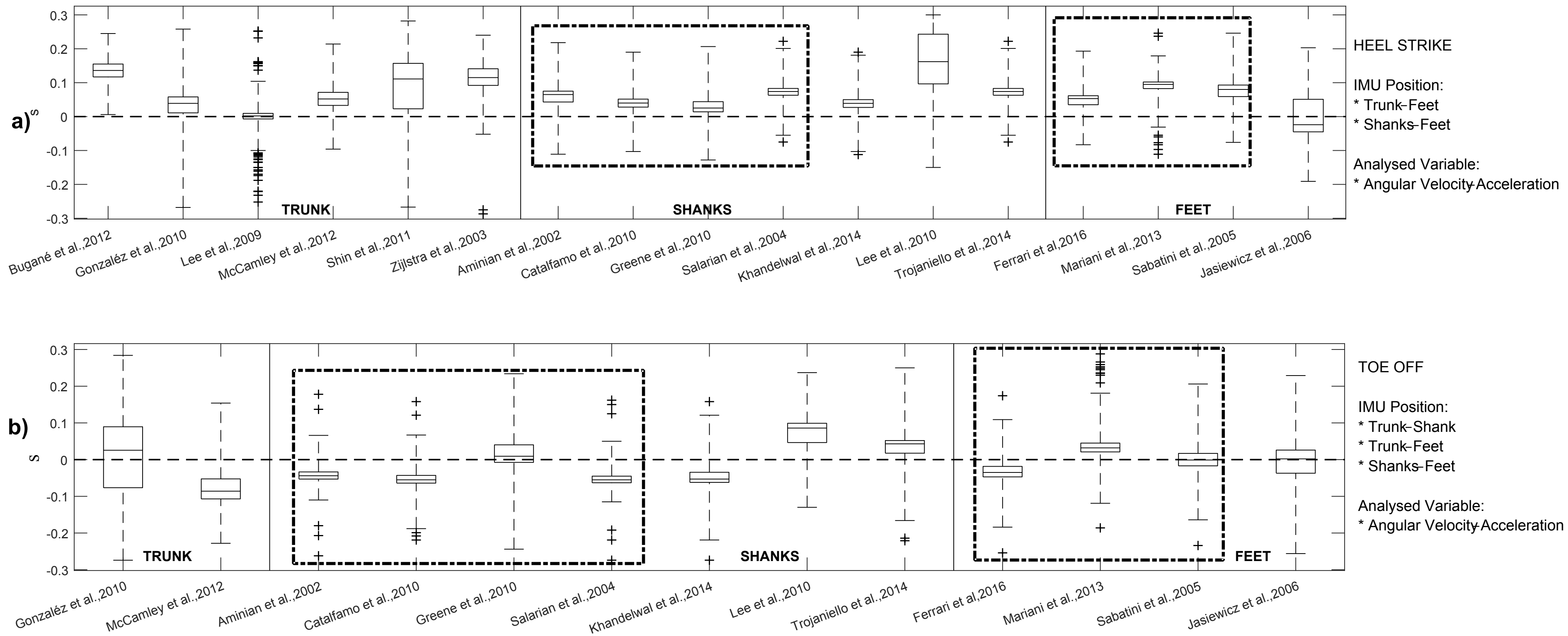


Figure 3.

Box plot (minimum, 25th percentile, median, 75th percentile maximum values) for step time (a) and stance time (b) estimation errors as related to IMU position and target variable (angular velocity contoured in dots, acceleration no contour) (* p<0.001).

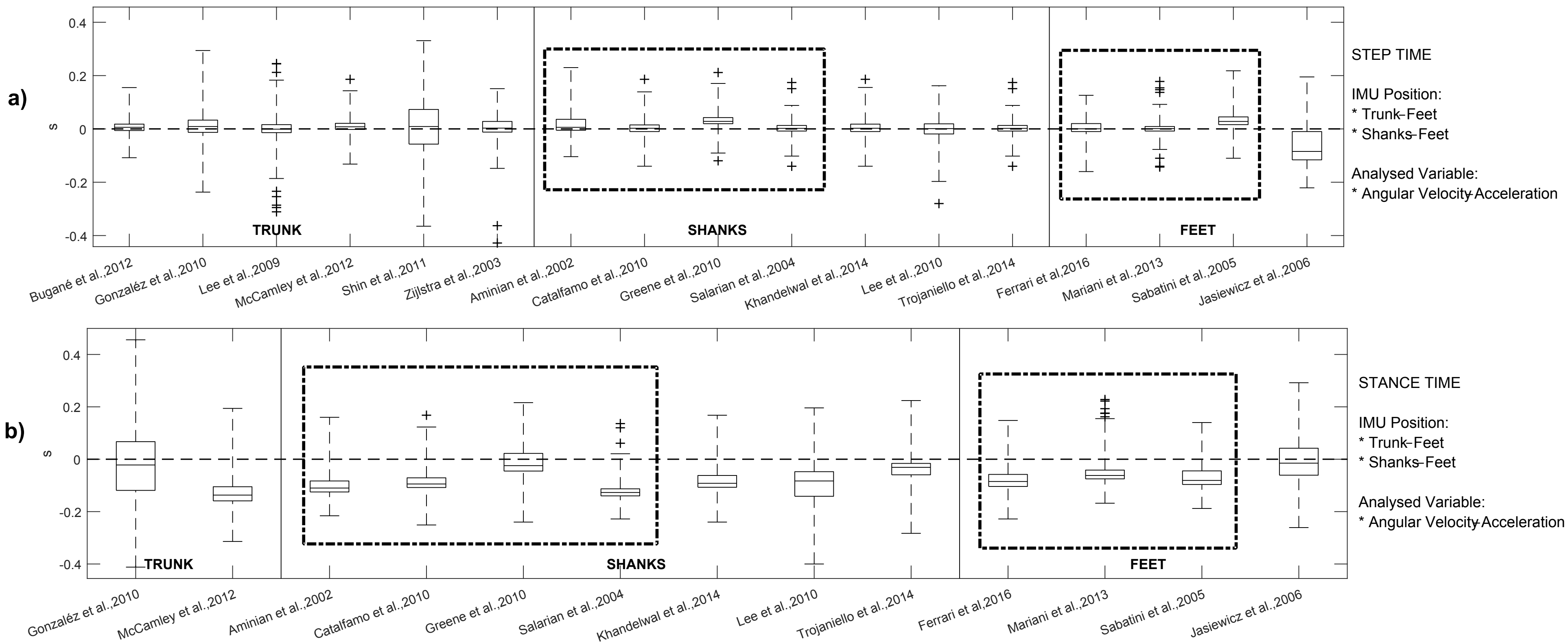
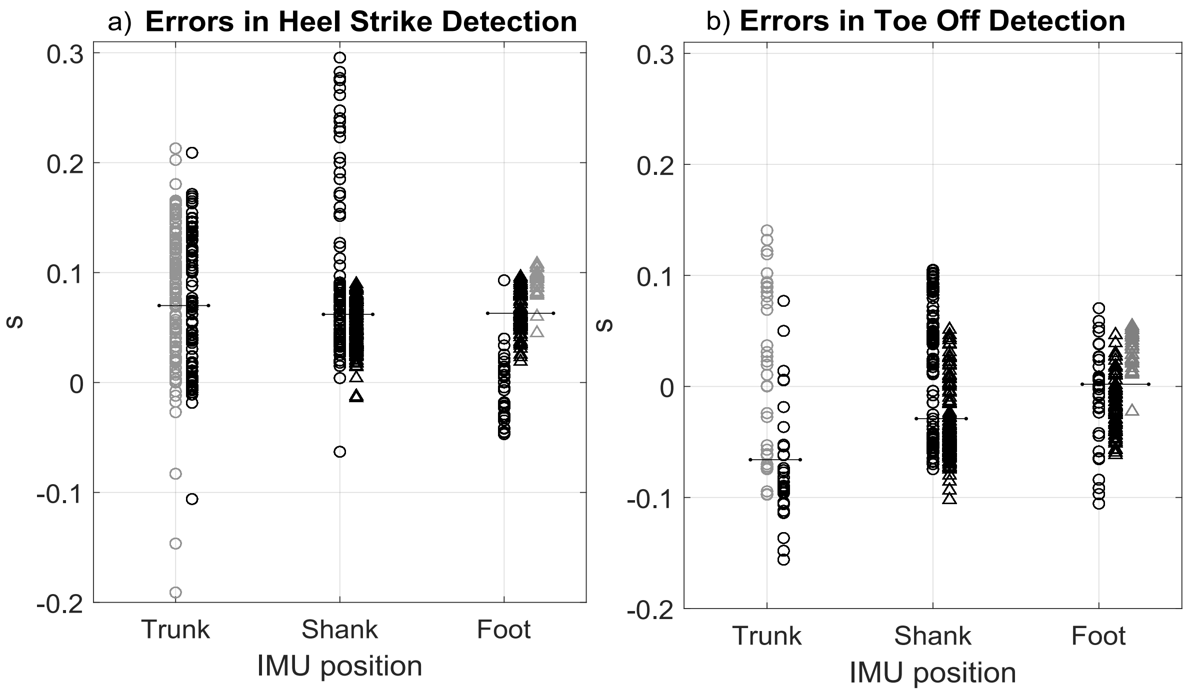


Figure 4.

Estimated error for HS (a) and TO (b) as related to IMU position, target variable and computational approach.



Legend

Target Variable:
Acceleration (O)
Angular velocity (Δ)

Computational Approach:
Zero crossing (grey)
Peak identification (black)

Tables

Table 1.
Inclusion criteria considered for the systematic review

Criteria	***Definition***
Measurement instruments	Wearable inertial sensors
Body positioning of IMUs	Trunk, both shanks and both feet
Motor tasks	Walking
Areas of interest	Gait events definition: Heel Strike and Toe Off Temporal parameters estimation
Publication type	Journal articles and papers in English
Participants under investigation	Healthy adults and able-bodied humans

Table 2.
Details of algorithms identified from the literature review classified according to the three criteria.

Algorithms	*Sensor position*	*Target Variable*	*Computational Approach*	*Analysed subjects*
Bugané et al., 2012 [9]	Trunk	Acceleration	'peak identification' (IIR)	Healthy
Lee et al., 2009 [14]	Trunk	Acceleration	'peak identification' (FIR)	Healthy Hemiplegic after stroke
McCamley et al., 2012 [17]	Trunk	Acceleration	'peak identification' (WT)	Healthy
Gonzaléz et al., 2010 [12]	Trunk	Acceleration	'zero crossing' (FIR)	Healthy
Shin et al., 2011 [20]	Trunk	Acceleration	'zero crossing' (Raw)	Healthy
Zijlstra et al., 2003 [22]	Trunk	Acceleration	'zero crossing' (IIR)	Healthy
Lee et al., 2010 [15]	Shank	Acceleration	'peak identification' (IIR)	Healthy
Trojaniello et al., 2014 [21]	Shank	Acceleration	'peak identification' (Raw)	Healthy Hemiparetic Choreic Parkinson's disease
Khandelwal et al., 2014 [13]	Shank	Acceleration	'peak identification' (WT)	Healthy
Catalfamo et al., 2010 [10]	Shank	Angular velocity	'peak identification' (IIR)	Healthy
Greene et al., 2010 [23]	Shank	Angular velocity	'peak identification' (Raw)	Healthy
Salarian et al., 2004 [19]	Shank	Angular velocity	'peak identification' (Raw)	Healthy Parkinson's disease
Aminian et al., 2002 [8]	Shank	Angular velocity	'peak identification' (WT)	Healthy
Jasiewicz et al., 2006 [7]	Foot	Acceleration	'peak identification' (Raw)	Healthy Spinal-cord injured
Sabatini et al., 2005 [18]	Foot	Angular velocity	'peak identification' (IIR)	Healthy
Ferrari et al, 2016 [11]	Foot	Angular velocity	'peak identification' (Raw)	Healthy Parkinson's disease
Mariani et al., 2013 [16]	Foot	Angular velocity	'zero crossing' (IIR)	Healthy Parkinson's disease

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

We further confirm that any aspect of the work covered in this manuscript that has involved either experimental animals or human patients has been conducted with the ethical approval of all relevant bodies and that such approvals are acknowledged within the manuscript.

We understand that the Corresponding Author is the sole contact for the Editorial process (including Editorial Manager and direct communications with the office). She is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs. We confirm that we have provided a current, correct email address (giulia.pacini2@unibo.it) which is accessible by the Corresponding Author and whic has been configured to accept email from the Journal.

Signed by all authors as follows:

Giulia Pacini Panebianco, 03/08/2018

Maria Cristina Bisi, 04/07/2018

Rita Stagni, 04/07/2018

Silvia Fantozzi, 04/07/2018

On-line additional material

Table A.1: Original algorithms selected for the study with position, relative number of citations, and the list of studies proposing algorithms that follow the same implementation rules, with relative number of citations.

Original algorithms	*Position*	*Number of citation*	*Algorithms following the same implementation rules and relative number of citation*	
Bugané et al., 2012 [1]	Trunk	59	M. Pau et al., «Clinical assessment of gait in individuals with multiple sclerosis using wearable inertial sensors: Comparison with patient-based measure», Mult. Scler. Relat. Disord., vol. 10, pagg. 187–191, nov. 2016.	7
Lee et al., 2009 [2]		7	-	
McCamley et al., 2012 [3]		51	F. A. Storm, C. J. Buckley, e C. Mazzà, «Gait event detection in laboratory and real life settings: Accuracy of ankle and waist sensor based methods», Gait Posture, vol. 50, pagg. 42–46, 2016	11
			A. Godfrey, S. Del Din, G. Barry, J. C. Mathers, e L. Rochester, «Instrumenting gait with an accelerometer: a system and algorithm examination», Med. Eng. Phys., vol. 37, n. 4, pagg. 400–407, apr. 2015.	36
Gonzaléz et al., 2010 [4]		85	-	
Shin et al., 2011 [5]		26	-	
Zijlstra et al., 2003 [6]		384	E. Grimpampi, S. Oesen, B. Halper, M. Hofmann, B. Wessner, e C. Mazzà, «Reliability of gait variability assessment in older individuals during a six-minute walk test», J. Biomech., vol. 48, n. 15, pagg. 4185–4189, nov. 2015.	10
			C. Little, J. B. Lee, D. A. James, e K. Davison, «An evaluation of inertial sensor technology in the discrimination of human gait», J. Sports Sci., vol. 31, n. 12, pagg. 1312–1318, 2013.	9
			W. Zijlstra, «Assessment of spatio-temporal parameters during unconstrained walking», Eur. J. Appl. Physiol., vol. 92, n. 1–2, pagg. 39–44, giu. 2004.	155
			R. Senden, H. H. C. M. Savelberg, B. Grimm, I. C. Heyligers, e K. Meijer, «Accelerometry-based gait analysis, an additional objective approach to screen subjects at risk for falling», Gait Posture, vol. 36, n. 2, pagg. 296–300, giu. 2012.	43
			W. Johnston, M. Patterson, N. O'Mahony, e B. Caulfield, «Validation and comparison of shank and lumbar-worn IMUs for step time estimation», Biomed. Tech. (Berl), vol. 62, n. 5, pagg. 537–545, ott. 2017.	0
			A. Hartmann, K. Murer, R. A. de Bie, e E. D. de Bruin, «Reproducibility of spatio-temporal gait parameters under different conditions in older adults using a trunk tri-axial accelerometer system», Gait Posture, vol. 30, n. 3, pagg. 351–355, ott. 2009.	52
			X. Chen, S. Liao, S. Cao, D. Wu, e X. Zhang, «An Acceleration-Based Gait Assessment Method for Children with Cerebral Palsy», Sensors, vol. 17, n. 5, pag. 1002, mag. 2017.	1
			I. González, J. Fontecha, R. Hervás, e J. Bravo, «Estimation of Temporal Gait Events from a Single Accelerometer Through the Scale-Space Filtering Idea», J. Med. Syst., vol. 40, n. 12, pag. 251, dic. 2016.	4
Lee et al., 2010 [7]	Shank	41	-	
Trojaniello et al., 2014 [8]		42	F. A. Storm, C. J. Buckley, e C. Mazzà, «Gait event detection in laboratory and real life settings: Accuracy of ankle and waist sensor based methods», Gait Posture, vol. 50, pagg. 42–46, 2016	11
Khandelwal et al., 2014 [9]		8	-	
Catalfamo et al., 2010 [10]		60	P. C. Formento, R. Acevedo, S. Ghoussayni, e D. Ewins, «Gait Event Detection during Stair Walking Using a Rate Gyroscope», Sensors, vol. 14, n. 3, pagg. 5470–5485, mar. 2014.	16
			D. Gouwanda e A. A. Gopalai, «A robust real-time gait event detection using wireless gyroscope and its application on normal and altered gaits», Med. Eng. Phys., vol. 37, n. 2, pagg. 219–225, feb. 2015.	24
Greene et al., 2010 [11]		77	B. R. Greene, D. McGrath, K. J. O'Donovan, R. O'Neill, A. Burns, e B. Caulfield, «Adaptive estimation of temporal gait parameters using body-worn gyroscopes», Conf. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf., vol. 2010, pagg. 1296–1299, 2010.	15
			W. Johnston, M. Patterson, N. O'Mahony, e B. Caulfield, «Validation and comparison of shank and lumbar-worn IMUs for step time estimation», Biomed. Tech. (Berl), vol. 62, n. 5, pagg. 537–545, ott. 2017.	0
Salarian et al., 2004 [12]		276	S. Wüest, F. Massé, K. Aminian, R. Gonzenbach, e E. D. de Bruin, «Reliability and validity of the inertial sensor-based Timed "Up and Go" test in individuals affected by stroke», J. Rehabil. Res. Dev., vol. 53, n. 5, pagg. 599–610, 2016.	3
Aminian et al., 2002 [13]		396	-	
Jasiewicz et al., 2006 [14]	Foot	165	S. Sessa, M. Zecca, L. Bartolomeo, T. Takashima, H. Fujimoto, e A. Takanishi, «Reliability of the step phase detection using inertial measurement units: pilot study», Healthc. Technol. Lett., vol. 2, n. 2, pagg. 58–63, mar. 2015.	5
Sabatini et al., 2005 [15]		326	D. Hamacher, D. Hamacher, W. R. Taylor, N. B. Singh, e L. Schega, «Towards clinical application: repetitive sensor position re-calibration for improved reliability of gait parameters», Gait Posture, vol. 39, n. 4, pagg. 1146–1148, apr. 2014.	23
Ferrari et al, 2016 [16]		14	-	
Mariani et al., 2013 [17]		76	-	

Table A.2: Results of statistical analysis for IMU positioning: minimum, 25th quartile, median, 75th quartile, maximum value of estimation error for HS, TO, step time and stance time (* p<0.001)

Parameter	***Estimation of errors: IMU position (s)***			***Level of significance***
	Trunk	***Shanks***	***Feet***	
HS	-0.287, 0.015, 0.070, 0.128, 0.282	-0.150, 0.037, 0.062, 0.081, 0.300	-0.191, 0.032, 0.063, 0.091, 0.246	Trunk – Shank Trunk – Feet * Shanks – Feet *
TO	-0.228, -0.097, -0.066, 0.067, 0.284	-0.262, -0.055, -0.029, 0.041, 0.250	-0.256, -0.027, 0.002, 0.030, 0.288	Trunk – Shank * Trunk – Feet * Shanks – Feet *
Step Time	-0.484, -0.013, 0.006, 0.028, 0.484	-0.421, -0.008, 0.006, 0.024, 0.230	-0.221, -0.021, 0.002, 0.026, 0.218	Trunk – Shank Trunk – Feet * Shanks – Feet *
Stance Time	-0.412, -0.145, -0.111, 0.014, 0.456	-0.400, -0.117, -0.088, -0.034, 0.224	-0.261, -0.090, -0.064, -0.030, 0.292	Trunk – Shank Trunk – Feet * Shanks – Feet *

Table A.3: Results of statistical analysis for Target variable: minimum, 25th quartile, median, 75th quartile, maximum value of estimation error for HS, TO, step time and stance time (* p<0.001)

Parameter	***Estimation of errors: Target variable (s)***		***Level of significance***
	Angular velocity	***Acceleration***	
HS	-0.128, 0.043, 0.065, 0.083, 0.246	-0.287, 0.014, 0.060, 0.125, 0.300	Angular Velocity – Acceleration *
TO	-0.262, -0.051, -0.025, 0.017, 0.288	-0.256, -0.062, 0.006, 0.060, 0.284	Angular Velocity – Acceleration *
Step Time	-0.160, -0.006, 0.007, 0.028, 0.230	-0.484, -0.021, 0.002, 0.022, 0.484	Angular Velocity – Acceleration *
Stance Time	-0.251, -0.111, -0.084, -0.046, 0.228	-0.412, -0.117, -0.069, -0.011, 0.456	Angular Velocity – Acceleration *

Table A.4: Results of statistical analysis for computational approach: minimum, 25th quartile, median, 75th quartile, maximum value of estimation error for HS, TO, step time and stance time (* p<0.001, ** p≤0.05)

IMU position	*Parameter*	*Level of significance 'peak identification' vs 'zero crossing'*	*Estimation of errors: Filtering (s) Level of significance*			
			Filtering within 'peak identification'	*Level of significance for filtering within 'peak identification'*	*Filtering within 'zero crossing'*	*Level of significance for filtering within 'zero crossing'*
Trunk	HS	*	FIR: -0.252, -0.007, 0.002, 0.009,0.252 IIR: 0.006, 0.117, 0.136, 0.155, 0.245 WT: -0.096, 0.033, 0.052, 0.071, 0.214	FIR – IIR * FIR – WT * IIR – WT *	Raw: -0.267,0.024, 0.111, 0.157, 0.282 FIR: -0.268, 0.011, 0.039, 0.058,0.258 IIR: -0.287, 0.092, 0.115, 0.141, 0.240	FIR – IIR * FIR – Raw * IIR – Raw *
	TO	*	WT: -0.228, -0.107, -0.086, -0.053, 0.154	-	FIR: -0.223, -0.077,0.026, 0.089, 0.284 Raw: -0.365, -0.057,0.009,0.073,0.331	FIR – Raw
	Step Time	**	FIR: -0.484, -0.014, -0.001, 0.016, 0.484 IIR: -0.428, -0.009, 0.005, 0.022, 0.155 WT: -0.132, -0.002, 0.008, 0.021, 0.186	FIR – IIR FIR – WT IIR – WT	FIR: -0.237, -0.012,0.009,0.033,0.294 Raw: -0.365, -0.057,0.009,0.073, 0.331	FIR – Raw
	Stance Time	*	WT: -0.314, -0.159, -0.137, -0.105, 0.194	-	FIR: -0.412, -0.119, -0.022,0.067,0.456	-
Shank	HS	-	Raw: -0.128, 0.038, 0.066, 0.079, 0.222 IIR: -0.150, 0.050, 0.076, 0.163, 0.300 WT: -0.112, 0.031, 0.047, 0.067, 0.218	IIR – Raw * IIR – WT * Raw – WT *	-	
	TO		Raw: -0.244, -0.047, -0.002, 0.042, 0.250 IIR: -0.234, -0.017, -0.001, 0.017, 0.206 WT: -0.262, -0.059, -0.048, -0.034, 0.178	IIR – Raw * IIR – WT * Raw – WT *		
	Step Time		Raw: -0.140, -0.005, 0.008, 0.028, 0.212 IIR: -0.280, -0.014, 0.002, 0.017, 0.186 WT: -0.421, -0.008, 0.005, 0.023, 0.230	IIR – Raw ** IIR – WT Raw – WT		
	Stance Time		Raw: -0.283, -0.118, -0.046, -0.018, 0.224 IIR: -0.400, -0.116, -0.092, -0.058, 0.196 WT: -0.240, -0.117, -0.099, -0.072,0.168	IIR – Raw * IIR – WT Raw – WT *		
Foot	HS	*	Raw: -0.191, -0.028, 0.044, 0.059, 0.203 IIR: -0.076, 0.059, 0.080, 0.093, 0.246	IIR – Raw *	IIR: -0.111, 0.083, 0.095,0.102,0.246	-
	TO	*	Raw: -0.256, -0.046, -0.024, 0.009, 0.229 IIR: -0.234, -0.017, -0.001, 0.017, 0.206	IIR – Raw *	IIR: -0.186, 0.021,0.032, 0.045, 0.288	
	Step Time	**	Raw: -0.221, -0.087, -0.010, 0.011, 0.195 IIR: -0.110, 0.016, 0.028, 0.045, 0.218	IIR – Raw *	IIR: -0.143, -0.008, 0.001, 0.009, 0.178	
	Stance Time	-	Raw: -0.261, -0.093, -0.059, 0.001, 0.292 IIR: -0.188, -0.096, -0.081, -0.045, 0.140	IIR – Raw *	IIR: -0.168, -0.075, -0.062, -0.042,0.228	