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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

AUTHORS

Giulia Pacini Panebianco¹, Maria Cristina Bisi¹, Rita Stagni^{1,2*}, Silvia Fantozzi^{1,2*}

AFFILIATIONS

¹Department of Electrical, Electronic and Information Engineering "Guglielmo Marconi"-Viale del Risorgimento, 2, 40136, University of Bologna, Bologna, Italy;

²Health Sciences and Technologies - Interdepartmental Center for Industrial Research, Via Tolara di Sopra, 50, 40064-Ozzano dell'Emilia – ITALY

* Both authors contributed equally to this work

AUTHORS' E-MAILS

Giulia Pacini Panebianco: giulia.pacini2@unibo.it

Maria Cristina Bisi: mariacristina.bisi@unibo.it

Rita Stagni: rita.stagni@unibo.it

Silvia Fantozzi: silvia.fantozzi@unibo.it

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Corresponding author:

Giulia Pacini Panebianco, Ph.D student.

e-mail: giulia.pacini2@unibo.it

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.*

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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

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180 performance of the available algorithms for GE detection as resulting from their specific
181 implementation characteristics. The present study was designed to fill in this gap, starting from a
182 systematic review of the available literature to identify the different proposed methods, aiming to
183 provide relevant information for the selection of the most suitable algorithm for specific applications,
184 and/or for the design and implementation of novel methods for GE detection. The performance of the
185 algorithms was analysed in controlled conditions, to identify methodological intrinsic characteristics,
186 without potential interferences of gait alterations.
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192 **Nomenclature**

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195 *FIGURE 1 HERE*
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198 **Materials and Methods**

200 *Literature review*

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202 Articles were searched in PubMed, Scopus and ISI Web of Knowledge until 20 November 2017.
203 Searches consisted of a combination of the following keywords: (1) assessment or estimation or
204 measurement; (2) wearable or inertial sensor or accelerometer or gyroscope or inertial measurement
205 unit; (3) temporal or parameters; (4) gait or walking. Keyword search was performed to match words
206 in the title, abstract, or keyword fields.
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209 Studies published in English as full papers, involving original methods for the estimation of GEs
210 using accelerometer attached to the lower trunk, shanks and feet were included based on criteria
211 summarized in Table 1. These positionings were identified based on the higher number of citation
212 (>500) in comparison with others (i.e. heel, pelvis on the right side, thigh, lateral tibial condyle).
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218 *TABLE 1 HERE*
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220 The search yielded 271 (PubMed), 191 (Scopus), and 350 (ISI Web of Knowledge) results.
221 A critical examination of the titles and abstracts allowed to exclude unrelated and duplicated articles.
222 After the application of inclusion and exclusion criteria a set of 36 articles were identified. Articles
223 purposing the same implementation rules for GE estimation were grouped together and the first
224 published and most cited ones were considered as original references for the algorithms, resulting in
225 a final set of 17 articles [7–23]. The remaining 19 articles were associated to the singular original
226 articles as illustrated in the table A.1 (online supplementary material).
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239 The 17 algorithms were revised and classified based on:
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- 241 i) IMU position (i.e. lower trunk¹, shanks, feet)
- 242 ii) Target variable (i.e. acceleration, angular velocity)
- 243
- 244 iii) Computational approach: ‘peak identification’ and ‘zero crossing’, on raw or filtered
245 target variable (i.e. FIR, IIR, WT filtering). ‘Peak identification’ aims to identify specific
246 peaks on the target variable, corresponding to specific temporal events: local maxima or
247 minima of the vertical or antero-posterior component for acceleration-based algorithms;
248 local minima of the sagittal component for angular velocity-based algorithms. ‘Zero
249 crossing’ aims to identify the instants of sign change in the target variable, corresponding
250 to specific temporal events: in the antero-posterior component for acceleration-based
251 algorithms; in the sagittal component for angular velocity-based algorithms.
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258 ***Experimental analysis***

259 *Participants:*

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

273 Each participant walked for 2 minutes back and forth along a 10 m straight pathway at self-selected
274 speed (normalized gait speed: 0.41±0.06 [24]) wearing own comfortable footwear. Five tri-axial
275 IMUs (Cometa, Milano, Italy) equipped with accelerometer (sensitivity: 156,3 mV/g; range: ± 8g)
276 and gyroscope (sensitivity: 1,3 mV/g; range: ±1000°/s) were attached to the trunk (at L5 level), shanks
277 (about five centimetres above lateral malleolus), and feet (on the dorsal surface of each shoe) (Figure
278 1). 3D acceleration and 3D angular velocity were acquired from each sensor with a sampling
279 frequency of 285Hz, higher than that in all referred works. Ground reaction forces were recorded
280 (sampling frequency 1000Hz) by two force platforms (Kistler, Winterthur, Switzerland) mounted
281 half-way along the path, assumed as gold standard reference for GE detection.
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288 A trigger signal was generated by IMU system at the beginning of each trial for synchronization. The
289 online version of this article contains the collected data.
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293 ¹ From here, for the sake of concision, the term “trunk” will be used meaning “lower trunk”.

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298 *Data analysis:*
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300 The identified 17 algorithms were implemented in MATLAB (MathWorks 2017a, NATHSK, USA),
301 and HS and TO were estimated from IMU data for each participant with each algorithm.
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303 A 20N threshold was applied to ground reaction force (GRF) vertical component for the automatic
304 detection of HS and TO [25] for each participant.
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308 For each algorithm, the error (E) was calculated for GEs (E_{GE}) and GTPs (E_{GTP}) as follow:
309

$$310 E_{GE} = GE_{IMU} - GE_{GRF}$$

$$311 E_{GTP} = GTP_{IMU} - GTP_{GRF}$$

312 Where GE subscripts denote methods of estimation.
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316 If an algorithm allowed identifying only HS, errors were calculated for HS and step time.
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319 *Statistical analysis:*
320

321 12 contacts per participants were included in the statistical analysis. For each parameter (GEs and
322 GTPs), a linear mixed model [26] was applied to test the dependency of error values on each
323 implementation criterion, with a significance level of 0.05. First, the statistical analysis was
324 performed to investigate the influence of IMU position and target variable, alone. Then, the influence
325 of computational approach was investigated separately for each IMU position.
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328 Med of the error was calculated to characterize accuracy, and to characterize repeatability Dmed,
329 calculated as 75th percentile minus 25th percentile value of the error.
330

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

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340 Of the 17 algorithms, as summarised in Table 2:
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- 342 - 6 were trunk-based (of which only 2 provided both HS and TO [12,16], while 4 defined
343 only HS [9,13,19,21]), all analysing acceleration, 3 using ‘peak identification’, of which
344 1 with IIR [9], 1 with FIR [13] and 1 with WT filtering (detecting HS and TO) [16], and
345 3 using ‘zero crossing’ approach, of which one with raw signal [19], 1 with FIR filtering
346 (detecting HS and TO) [12] and 1 with IIR filtering [21];
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348 - 7 were shank-based, of which 3 analysing acceleration with ‘peak identification’, 1 with
349 raw signal [20], 1 with IIR [14] and 1 with WT filtering [23], and 4 analysing angular
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355 velocity with ‘peak identification’, 2 with raw signal [18,27], 1 with IIR [10] and 1 with
356 WT filtering [8];

- 357 - 4 were foot-based, of which 1 analysing acceleration with ‘peak identification’ of raw
358 signal [7], and 3 analysing angular velocity, 2 with ‘peak identification’, 1 adopting raw
359 signal [11] and 1 with IIR filtering [17] and 1 with ‘zero crossing’ of IIR filtered signal
360 [15].
361

362 **TABLE 2 HERE**

363 For each subject at least 12 contacts on the force platform were detected, for a total of 420 analysed
364 strides. **No false positive or negatives were identified for all the analysed algorithms.**

365 Statistical analysis highlighted significant differences for all three implementation characteristics,
366 although the magnitude of errors was comparable.

367 **IMU Position**

368 For HS detection error, no significant difference was found between shank- and trunk-based
369 algorithms ($p=0.978$), while significant differences ($p<0.001$) were found for foot-based algorithms
370 with respect to the others. By analysing error results in detail, shank- and foot-based algorithms
371 resulted more accurate and repeatable in HS detection than trunk-based ones. Foot-based algorithms
372 showed comparable accuracy (Med 63 ms and 62 ms, respectively) and repeatability (Dmed 59 ms
373 and 44 ms, respectively) to shank-based ones, while trunk-based ones resulted less accurate (Med 70
374 ms) and less repeatable (Dmed 113 ms).

375 For TO detection, statistically significant differences were found for all IMU positions ($p<0.001$). In
376 particular, foot-based algorithms showed the highest accuracy and repeatability, with Med 2 ms and
377 Dmed 57 ms; shank-based algorithms followed with Med -29 ms and Dmed 96 ms; trunk-based ones
378 provided the worst performance with Med -66 ms and Dmed 164 ms.

379 For step time estimation, results showed comparable accuracy and repeatability among all IMU
380 positions (Med/Dmed: 6/41 ms, 6/32 ms, 2/47 ms, for trunk, shank, and foot, respectively). For stance
381 time, foot-based algorithms showed the highest accuracy and repeatability (Med/Dmed -64/120 ms),
382 followed by shanks-based (Med/Dmed -88/151 ms) and trunk-based ones (Med/Dmed -111/159 ms).
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416 ***Target variable***
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418 For HS detection, algorithms exploiting angular velocity showed higher repeatability and comparable
419 accuracy than those exploiting acceleration (Med/Dmed 65/40 ms and 60/111 ms, for angular velocity
420 and acceleration, respectively).
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423 For TO detection, angular velocity-based algorithms performed significantly ($p < 0.001$) higher than
424 acceleration-based ones in terms of repeatability, with Dmed 68 ms, smaller than the 122 ms of
425 acceleration-based ones, but a lower accuracy, with Med -25 ms versus 6 ms.
426
427

428 Acceleration-based algorithms resulted more and equally accurate for stance and step time,
429 respectively, but less repeatable than angular-velocity ones for both parameters (step time
430 Med/Dmed: 7/34 ms and 2/43 ms; stance time Med/Dmed: -84/65 ms, -69/106 ms, for angular
431 velocity and acceleration, respectively).
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436 Error characteristics for HS and TO as related to IMU position and target variable are schematically
437 depicted in Figure 2, and for step and stride time in Figure 3. Numerical values as related to IMU
438 position and target variable are reported in Table A.2 and A.3, respectively (online supplementary
439 material).
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443 ***FIGURE 2 HERE***

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445 ***FIGURE 3 HERE***
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448 ***Computational approach***
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450 Considering the trunk-based algorithms, statistically significant differences were found between the
451 two approaches ($p < 0.05$). In particular, ‘peak identification’ approach with FIR filtering resulted to
452 be the most accurate (Med 2ms) and repeatable (Dmed 16ms) in HS detection. The ‘zero crossing’
453 approach with FIR filtering resulted the most accurate (Med 26ms) in TO detection, while ‘peak
454 identification’ with WT filtering resulted to be the most repeatable (Dmed 54ms). For step time, no
455 significant difference was found among different filtering for each approach ($p > 0.597$ for all
456 comparisons among filtering). For stance time, ‘zero crossing’ with FIR filtering resulted to be the
457 most accurate, while ‘peak identification’ with WT filtering highlighted the highest repeatability
458 (Med/Dmed: -22/186 ms, -159/32 ms, respectively).
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464 Shank-based algorithms exploited only ‘peak identification’ approach: WT filtering reported the
465 highest accuracy and repeatability in HS detection (Med 47 ms and Dmed 36 ms), while raw data
466 resulted to be the most accurate and repeatable in TO detection (Med -2 ms and Dmed 89 ms). Raw
467 or filtered signals resulted to be equally accurate and repeatable in step time estimation; significant
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475 differences were found only between raw signal and IIR filtering, which showed comparable accuracy
476 and repeatability (Med/Dmed: 8/33 ms and 2/31 ms, respectively). For stance time estimation, raw
477 signal resulted to be the most accurate (Med -46ms), while WT filtering showed the highest
478 repeatability (Dmed 45ms).
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481 Considering foot position of IMUs, statistically significant differences ($p < 0.05$) were found between
482 the two computational approaches. In particular, 'peak identification' on raw signal resulted to be the
483 most accurate (Med 44 ms) in HS detection, while 'zero crossing' with IIR filtering resulted to be the
484 most repeatable both for HS and TO (Dmed 19 ms and 24 ms, respectively). Referring to the accuracy
485 in TO estimation, 'peak identification' with IIR filtering (Med -1 ms) resulted the most accurate. For
486 GTPs, 'zero crossing' with IIR filtering (Med/Dmed 1/17 ms) resulted the most accurate and
487 repeatable in step detection. No statistically significant difference was found between approaches for
488 stance time ($p = 0.676$).
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490 Numerical values of error characteristics for GE and GTP as related to computational approach are
491 reported in Table A.4 (online supplementary material).
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500 Results are summarized in Figure 4.
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503 ***FIGURE 4 HERE***
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505 506 507 **Discussion**

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509 The present study analysed the performance of 17 published algorithms proposed for GE detection
510 from IMU data. The algorithms were selected based on a systematic review and analysed with respect
511 to the influence of IMU position, target variable and computational approach on estimated errors on
512 GEs and derived GTPs.
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514 515 516 517 ***IMU position***

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

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

565 Computational approach resulted to affect performance differently, depending on IMU position. For
566 the computational approach, IMU position have to be taken into account. Considering trunk-based
567 algorithms, ‘peak identification’ with FIR filtering showed the best performance in HS detection, due
568 to the effectiveness of the filter in emphasizing the main acceleration peak associated to HS [13]. For
569 TO detection, ‘peak identification’ with WT filtering resulted the most repeatable while ‘zero
570 crossing’ with FIR filtering resulted the most accurate, in line with the literature [12,16]. No
571 statistically significant difference was found in step time estimation, demonstrating that gait cycle
572 duration can be estimated from the recording of a single IMU, independently from the computational
573 approach [6]. Conversely, stance time was affected by the approach used as observed for TO
574 identification.
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582 Considering IMUs positioned on the shanks, the best performance was obtained using ‘peak
583 identification’ with WT filtering for HS and on raw signal for TO detection, in line with the literature
584 [20,28]. Similarly to trunk-based algorithms, computational approach did not influence step time
585 estimation, while stance estimation varied significantly depending on signal pre-processing:
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591 estimation on raw signal resulted to be the most accurate, while a pre-processing with WT filtering
592 provided the best repeatability.

593 Regarding foot positioning, the best accuracy was obtained with ‘peak identification’ on raw and IIR
594 filtered signal for HS and TO, respectively: this result could be expected, since sharp peaks in angular
595 velocity or acceleration during HS and TO are the more empathized and easy to detect, the closer to
596 the ground the IMU is located [20]. On the other hand, the best repeatability in GE detection was
597 obtained from ‘zero crossing’ with IIR filtering, which represented a robust way for detecting gait
598 cycles both in healthy and pathological populations [15]. The delay introduced by this approach in
599 HS detection (positive Med), resulted compensated in step estimation (Med 1 ms), exhibiting the best
600 accuracy and reproducibility in the parameter estimation. Conversely, no significant difference was
601 found for stance time estimation between the two approaches.
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612 The potential concurrent influence of different factors was analysed and did not result to affect the
613 performance at the same extent for all analysed factors. Eventual concurrent influence was reported
614 where relevant (e.g. sensor position when discussing computational approach).
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617 Most of the algorithms (independently from IMU position, target variable and computational
618 approach) showed comparable performance when estimating step time, while attention is needed for
619 stance duration and GEs.
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622 Future studies will address different situations (e.g. ecological conditions, varying walking speed),
623 different sensor type and sampling frequency, as well as populations characterized by altered gait
624 patterns (e.g. children, elderlies, pathological populations) [8,20,29], and will include the assessment
625 of algorithms’ specificity and sensitivity, as possible false positive/negatives may occur in these
626 conditions.
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633 **Conclusion**

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

Figures

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

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

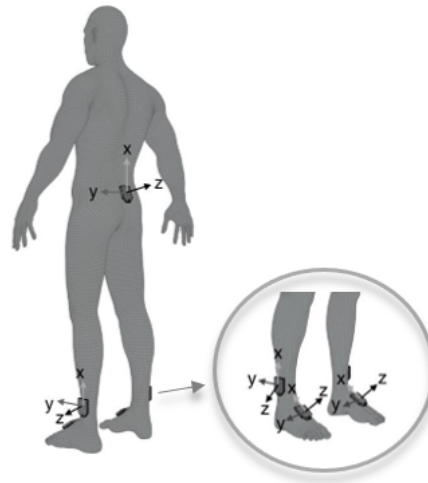


Figure 2.

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).

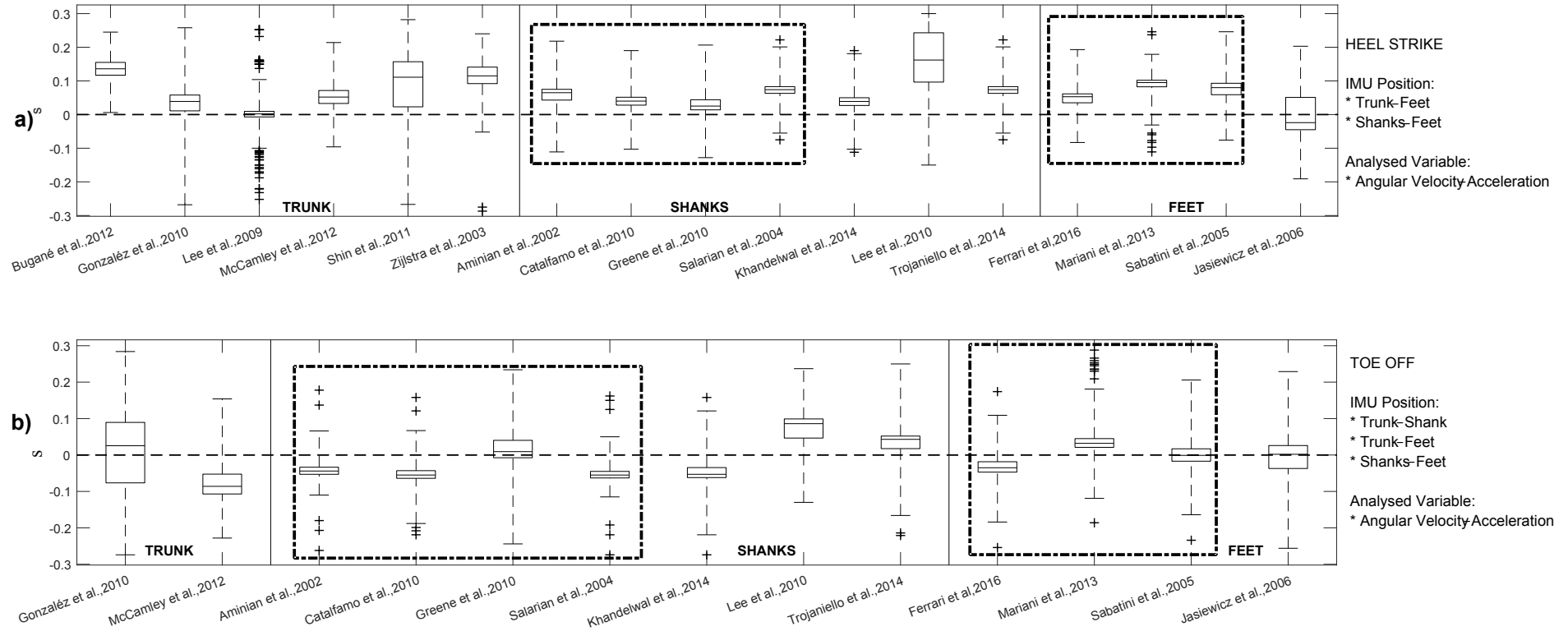


Figure 3.

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).

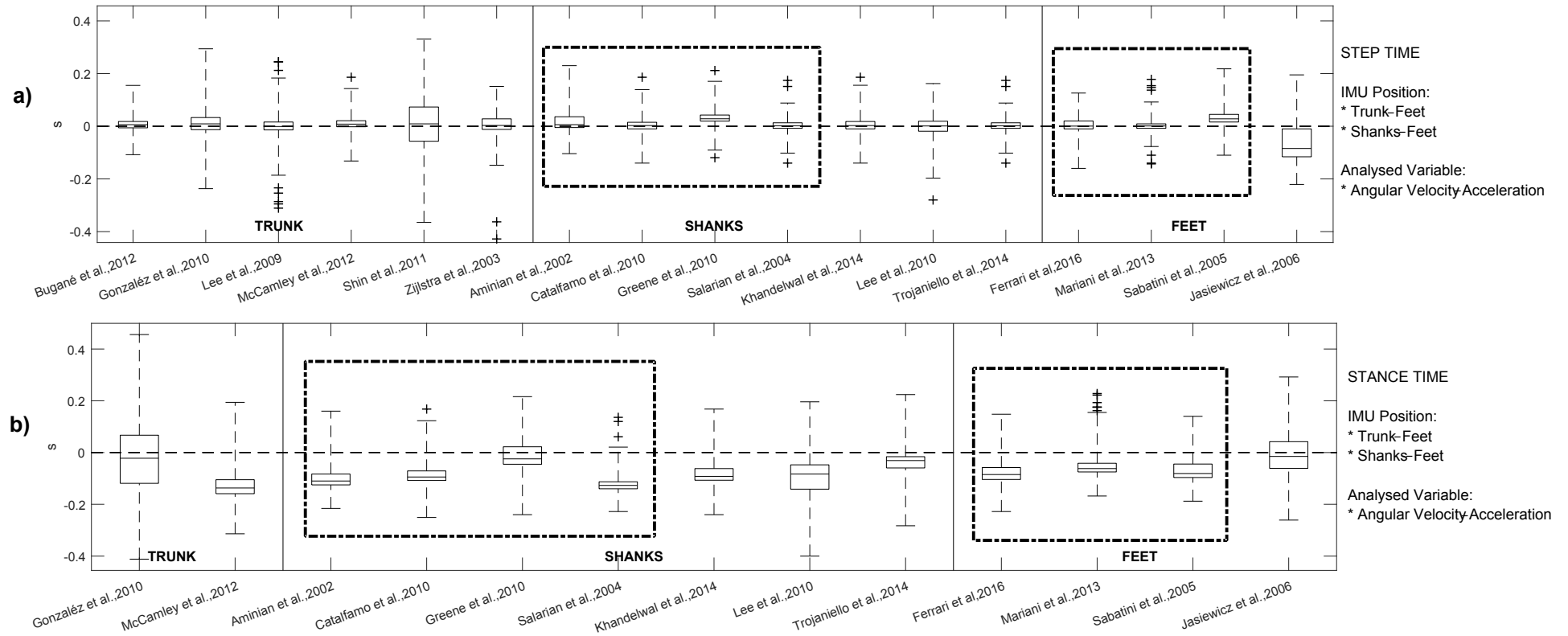
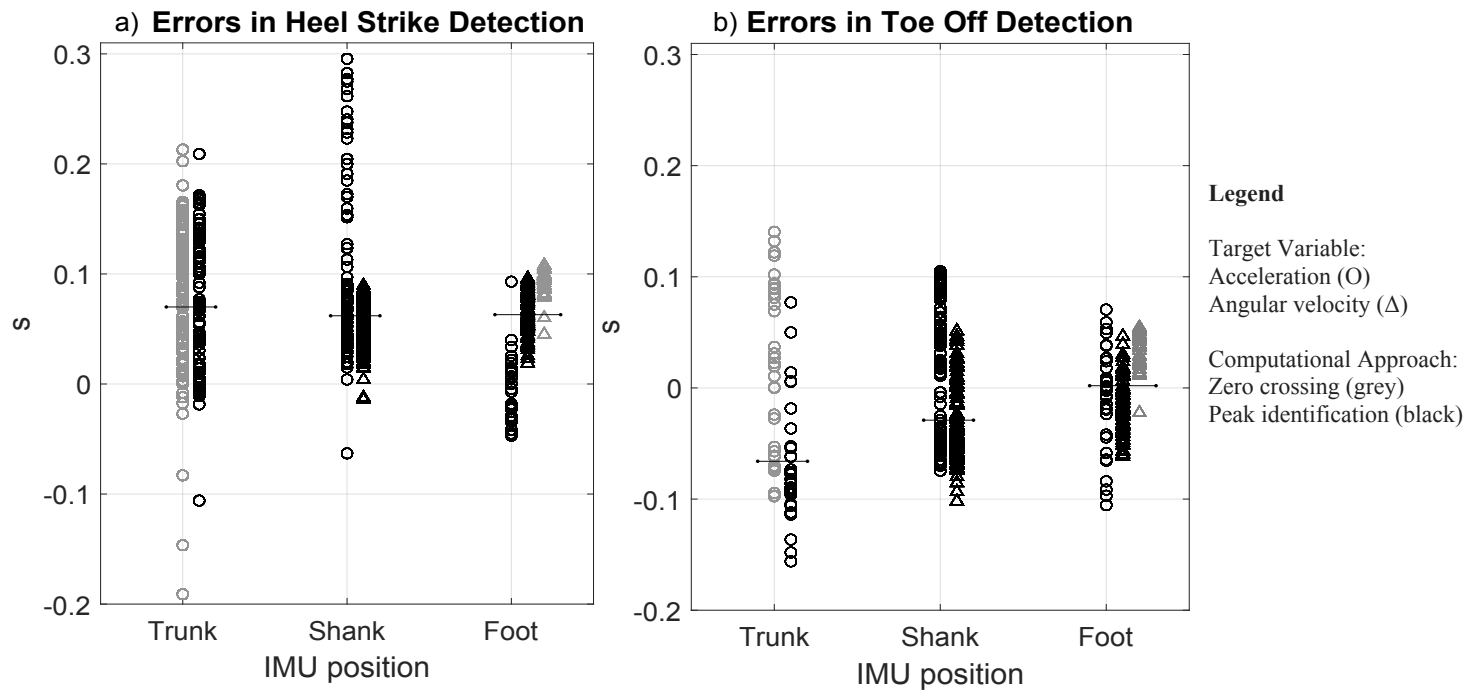


Figure 4.

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



Tables

Table 1.
Inclusion criteria considered for the systematic review

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

Table 2.

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

<i>Algorithms</i>	<i>Sensor position</i>	<i>Target Variable</i>	<i>Computational Approach</i>	<i>Analysed subjects</i>
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
González 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.

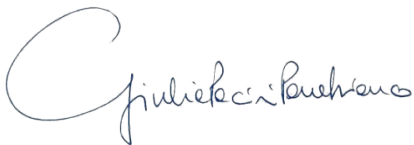
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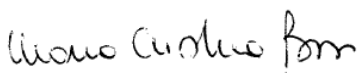
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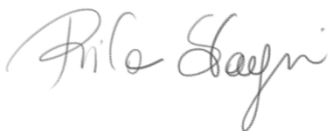
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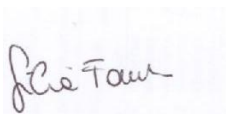
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Rita Stagni, 04/07/2018



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.

<i>Original algorithms</i>	<i>Position</i>	<i>Number of citation</i>	<i>Algorithms following the same implementation rules and relative number of citation</i>	
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», <i>Mult. Scler. Relat. Disord.</i> , 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», <i>Gait Posture</i> , 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», <i>Med. Eng. Phys.</i> , vol. 37, n. 4, pagg. 400–407, apr. 2015.	36
González 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», <i>J. Biomech.</i> , 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», <i>J. Sports Sci.</i> , vol. 31, n. 12, pagg. 1312–1318, 2013.	9
			W. Zijlstra, «Assessment of spatio-temporal parameters during unconstrained walking», <i>Eur. J. Appl. Physiol.</i> , 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», <i>Gait Posture</i> , 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», <i>Biomed. Tech. (Berl)</i> , 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», <i>Gait Posture</i> , 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», <i>Sensors</i> , 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», <i>J. Med. Syst.</i> , 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», <i>Gait Posture</i> , 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. Ghousayni, e D. Ewins, «Gait Event Detection during Stair Walking Using a Rate Gyroscope», <i>Sensors</i> , 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», <i>Med. Eng. Phys.</i> , 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», <i>Conf. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf.</i> , 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», <i>Biomed. Tech. (Berl)</i> , 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», <i>J. Rehabil. Res. Dev.</i> , 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», <i>Healthc. Technol. Lett.</i> , vol. 2, n. 2, pagg. 58–63, mar. 2015.
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», <i>Gait Posture</i> , 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)

<i>Parameter</i>	<i>Estimation of errors: IMU position (s)</i>			<i>Level of significance</i>
	<i>Trunk</i>	<i>Shanks</i>	<i>Feet</i>	
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)

<i>Parameter</i>	<i>Estimation of errors: Target variable (s)</i>		<i>Level of significance</i>
	<i>Angular velocity</i>	<i>Acceleration</i>	
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	Level of significance for filtering within 'peak identification'	Level of significance for filtering within 'zero crossing'	Level of significance for filtering within 'zero crossing'
			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	