Gait event detection accuracy: effects of amputee gait pattern, terrain and algorithm

Abstract

Several kinematic-based algorithms have shown accuracy for gait event detection in unimpaired and pathological gait. However, their validation in subjects with lower limb amputation while walking on different terrains is still limited. The aim of this study was to evaluate the accuracy of three kinematic-based algorithms: Coordinate-Based Algorithm (CBA), Velocity-Based Algorithm (VBA) and High-Pass Filtered Algorithms (HPA) for detection of gait events in subjects with unilateral transtibial amputation walking on different terrains. Twelve subjects with unilateral transtibial amputation, using a hydraulic ankle prosthesis, walked at self-selected walking speed, on level ground and up and down a slope. Detection of Initial Contact (IC) and Foot Off (FO) by the three algorithms for intact and prosthetic limbs was compared with detection by force platforms using the True Error (TE) (time difference in detection). Mean TE found for over 100 events analysed per condition were smaller than 40 ms for both events in all conditions (approximately 6% of stance phase). Significant interactions ($p<0.01$) were found between terrain and algorithm, limb and algorithm, and also a main effect for the algorithm. Post-hoc analyses indicate that the algorithm, the limb and the terrain had an effect on the accuracy in detection.

If an accuracy of 40 ms is acceptable for the particular application, then all three algorithms can be used for event detection in amputee gait. However, if accuracy in detection of events is crucial for the intended application, an evaluation of the algorithms in pathological gait walking on the terrain of interest is recommended.

Keyword: Level Ground, Slope, Ramp, Initial Contact, Foot Off

1. Introduction

Initial Contact (IC) and Foot Off (FO) are gait events widely used in gait analysis, enabling time normalization of kinematic and kinetic data, thus facilitating comparisons between subjects and conditions (Hussain and Marmar, 2021; Theodorakos et al., 2022), and estimating spatiotemporal parameters (Dujmovic et al., 2017; Sagawa et al., 2011; Varrecchia et al., 2019). While force platforms are considered the gold standard for event detection, most laboratories only possess two platforms, thereby limiting the number of events analyzed per trial (Fonseca et al., 2022; Maeda et al., 2018). Kinematic-based algorithms have been proposed as one of the alternatives (De Asha et al., 2012; Desailly et al., 2009; Ulrich et al., 2019; Zeni Jr et al., 2008). Most of these algorithms have been validated on healthy subjects walking on level ground (De Asha et al., 2012; Eckardt and Kibele, 2017; Ulrich et al., 2019), with limited validation available for pathological gait or walking on different terrains (French et al., 2020). Evaluations on amputee gait are not usually conducted (Hendershot et al., 2016), especially when walking on slopes or stairs, even when robust event detection is crucial for assessing new prosthetic devices designed for diverse daily activities (Fajardo-Martos et al., 2018), on different terrains (Ernst et al., 2022; LeMoyne, 2016).

Using algorithms validated for healthy adults on amputee gait may not be ideal considering that kinematic-based algorithms may be affected by deviation of the kinematic parameters from normative values (Visscher et al., 2021; Zeni Jr et al., 2008). This is particularly so for amputee gait on level ground (Parker et al., 2013; Sandra Oliveira de Cerqueira Soares et al., 2009), and on slopes (McIntosh et al., 2006; Vrieling et al., 2008).

In the absence of kinematic-based algorithms proposed specifically for amputee gait, those that use a minimum number of markers and have been evaluated in unimpaired and some pathological gait are of interest. Such is the case of the Coordinate Based Algorithm (CBA), the Velocity Based Algorithm (VBA) (Zeni Jr et al., 2008) and the High Pass Filtered Algorithm (HPA) (Desailly et al., 2009), which were evaluated in unimpaired and pathological gait (Fonseca et al., 2022; French et al., 2020; Hendershot et al., 2016).

This study aims to assess the accuracy of CBA, VBA, and HPA algorithms for detecting gait events in amputee gait, while walking on level ground, uphill, and downhill slopes. The following hypothesis was tested: the accuracy of gait event detection is affected by amputee gait pattern, terrain and algorithm.

2. Material and Methods

2.1 Subjects

Data analysed in this study is part of a larger ongoing study investigating gait patterns of participants with unilateral transtibial amputation on level ground and slopes. The eligibility criteria for participants included: adults in the range of 18 to 70 years old, with unilateral transtibial amputation, who were physically active (K2-K4, according to the Medicare scale), and without comorbid conditions that could limit participation in study activities. For the present study, data from twelve subjects (8 males, 41.16 ± 15.94 years; mass 70.28 ± 12.45 kg; height 1.73 ± 0.08 m) wearing a hydraulic prosthesis (Echelon, Endolite, Blatchford Inc., Basingstoke, Hampshire, UK) was analysed. Data from subject 7 were discarded from the level ground analysis due to the limited number of clean hits on the platforms. Informed consent was obtained, and the protocol was approved by the University of Surrey Ethics Committee.

2.2 Protocol

Participants walked at self-selected speed on level ground (10 m) and on a 5° inclined ramp (6 m long, 1 m wide), with reflective markers on sacrum, on shoe (on the posterior aspect of calcaneus and on top of the first metatarsal head) and equivalent prosthetic foot positions. The ramp, built in sections, included two elevated parts that transmitted the force directly to the force platforms placed on the floor.

Participants walked during 1 min on each terrain, in both directions. At least six gait cycles with clean hits on the platforms were required on each terrain (level ground, slope up and slope down); otherwise, the test was repeated. All gait events were then visually inspected to ensure correct foot placement on the platform and away from its boundaries. For participants with a longer step length that the distance between platforms, only one event (for example, IC) may have been analysed, as the foot was properly placed for IC but not for FO, which occurred near the platform edge.

Kinematic and kinetic data was sampled at 200 Hz and 400 Hz respectively, using ProReflex cameras (Qualisys, Gothenburg, Sweden) and two force platforms (AMTI, MA, USA). Kinematic data was then interpolated to 400 Hz to match the sampling frequency of kinetic data.

2.3 Gait event detection algorithms

The following algorithms were used for detection:

vGRF: IC and FO were detected as the time when the vertical component of the ground reaction force (vGRF) exceeded and fell below the threshold set at 10 N, respectively (Eckardt and Kibele, 2017).

CBA (Zeni Jr et al., 2008): The algorithm uses the displacement of the heel, toe and sacrum markers in the X direction of the laboratory (direction of progression). IC was defined as the time of the maximum or minimum (depending on the direction of progression) in the referenced signal $X_{Heel} - X_{Sacrum}$ (Fig.1, a) and FO as the time of the minimum or maximum of the referenced signal $X_{Toe} - X_{Sacrum}$ occurs (Fig. 1, b).

VBA (Zeni Jr et al., 2008): The algorithm uses the velocity of the markers in the X direction of the laboratory (V_X). IC was defined as the time of the zero crossings of the velocity referenced signal, $V_{X(Heel - Sacrum)}$ (Fig. 1, c). Similarly, FO was defined at the time of the zero crossings of the velocity referenced signal, $V_{X(Toe - Sacrum)}$ (Fig. 1, d).

HPA (Desailly et al., 2009): X_{Heel} and X_{Toe} trajectories were first filtered using a high pass filter (Cut off Frequency, FCO = 0.5 * Gait-Frequency). IC was defined as the time of the first peak in X_{Heel} or X_{Toe} trajectories (Fig. 1, e). Then, the original trajectories were filtered using a high pass filter (FCO = 1.1 * Gait-Frequency), and FO was defined as the time of the last peak in X_{Heel} or X_{Toe} trajectories (Fig. 1, f).

In order to better understand the HPA algorithm performance, an extra analysis was performed. IC defined by HPA and the time of those two peaks which was closest to IC as detected by vGRF were both recorded. Similarly, FO as defined by HPA and the time of those peaks closest to FO by vGRF were both recorded. Then the differences between both IC and both FO were analyzed as a post-processing of HPA (HPApp).

The conditioning of the signals and the gait event detection was performed using the software Matlab® (v. R2019a, Mathwork Inc.,USA).

2.4 Data analysis and statistical analysis

The accuracy of the algorithms was assessed using the mean, standard deviation and confidence interval (CI) of the True Error (TE) between each algorithm (CBA, VBA and HPA) and the gold standard (vGRF). TE was calculated as the time difference between algorithm-detected events and vGRF-detected events. Positive values indicate an earlier detection of algorithm with respect to vGRF. Mean TE was computed for each subject's prosthetic and intact limb on every terrain.

A normality Kolmogorov-Smirnov test was applied to TE and homoscedasticity and sphericity compliance were evaluated and corrected if necessary. Then, a mixed ANOVA was used to evaluate the accuracy, using subjects as inter-subject factor and three intra-subject factors (limb: intact and prosthetic; terrains: level ground, uphill, downhill; Algorithm: CBA, VBA, HPA). Effect size ($\eta_p 2$) indicates association strength (Bakeman, 2005), with $\eta_p 2 > 0.8$ considered large, and $0.5 < \eta_p 2 < 0.8$ moderate.

TE for HPApp was compared to the one from HPA using a paired samples T-test. The percentage of the events for which each trajectory (X_{Heel} and X_{Toe}) was selected by the HPA algorithm and its post-process HPApp for detection of IC and FO was computed.

SPSS Statistics software (version 25, IBM Inc., USA) was used for statistical analysis.

3. Results

The total number of IC analyzed for intact and prosthetic limb, respectively, were: 196 and 194 for level ground, 144 for both legs on uphill slope and 111 and 114 for downhill slope. The total number of FO analyzed for intact and prosthetic limb, respectively, were: 172 and 183 for level ground, 143 and 144 on uphill slope and 115 and 114 for downhill slope.

Results for comparative mean TE are shown in Fig. 2 and Table in Supplementary material. Mean TE was positive for IC and negative for FO for all conditions (three methods, both legs and all terrains). Mean TE for both events, all algorithms, both limbs, and all terrains was under 40 ms.

TE variability, shown by standard deviation and confidence interval, was higher for IC than FO and generally higher for the prosthetic than the intact limb, with no clear trend across terrains or algorithms.

There was no algorithm that consistently outperformed others across conditions. CBA and VBA provided similar accuracy for all conditions.

Significant interactions ($p<0.01$) were found between terrain and algorithm, limb and algorithm, and also a main effect for the algorithm (post-hoc analyses reveal differences between all three algorithms, Table 1).

The post-processing of the HPA showed that HPA detects the events similarly in the intact and prosthetic limbs (Table 2). For IC in the intact limb, the HPA algorithm mostly used X_{Heel} (i.e. X_{Heel} was the first peak) for uphill and downhill slope (77% and 71%, respectively). These agreed with the events closer to those detected by the vGRF (73% uphill and 79% downhill). For IC in the prosthetic limb, the HPA algorithm mostly uses X_{Heel} for detection, but this is not always the closest to the vGRF event (in fact, it was the closest only in 54% of IC events on slope down). For FO detection in the intact limb, the HPA algorithm mostly used the X_{Toe} (i.e. X_{Toe} was the last peak), which agrees with the vGRF event. However, for FO detection in the prosthetic limb, the HPA algorithm still mostly used the X_{Toe} but these are the closest only in 8% of the events detected on level ground.

HPA exhibited significantly larger mean TE for IC ($t=11.05$, $p<0.01$) and FO ($t= -12.088$, $p<0.01$) than the post-processing HPApp. The marker selection resulted in differences of mean TE as high as 30 ms (Fig. 3).

4. Discussion

This study evaluated the accuracy of CBA, VBA, and HPA algorithms for detecting gait events in participants with unilateral transtibial amputation fitted with a hydraulic prosthesis, while walking on level ground, uphill, and downhill slopes. Results showed the accuracy of detection of gait events is influenced by the algorithm used, the gait pattern of intact and prosthetic limbs and the terrain.

Mean TE found were smaller than 40 ms for both events in all conditions. This represents approximately 6% of stance phase (and 3.5% of gait cycle), considering mean stance duration of 679 ms on level ground.

Mean TE were generally smaller for FO than IC detection and for the intact limb than the prosthetic limb, possibly attributed to detection rules based on unimpaired gait patterns. In fact, the results from the HPApp analysis showed that the rules used for detection in the HPA algorithm (first and last peak of X_{Heel} and X_{Toe}) may not provide the event closest to the gold standard for the prosthetic limb. These differences suggest that the change in the pattern of amputee gait affects the accuracy of detection.

The standard deviation of TE was up to 50% of the mean and even higher for some of the tested conditions, particularly for IC. Similar variability has been reported in studies comparing kinematic algorithms to force platforms (Bruening and Ridge, 2014; Catalfamo et al., 2014b; Desailly et al., 2009; French et al., 2020; Hendershot et al., 2016). This may result from differences in detection methods, as kinematic algorithms rely on marker movement, while force platforms measure the force applied. In the present study, all kinematic algorithms detected IC earlier than the gold standard, likely due to markers reaching the IC position before substantial loading is applied. Moreover, the time difference between marker movement and force may depend on factors such as gait pattern and walking speed, thereby increasing the variability of the TE.

Terrain also affected accuracy. IC on uphill slopes had a smaller mean TE than other terrains, a trend consistent across algorithms. Similarly, FO mean TE is smaller on downhill slopes. The consistency in accuracy from the algorithms may be explained by different slopes prompting a change in the horizontal position and velocity of the foot, which are used for detection by the three algorithms.

The difference in accuracy between algorithms was also significant, although the clinical relevance of the difference should be evaluated for each particular application. What is more, the results of accuracy found in this study are in the order of those reported by the original authors (Desailly et al., 2009; Zeni Jr et al., 2008) and similar or better than other studies using kinematic-based algorithms in pathological gait (Fonseca et al., 2022; Gómez-Pérez et al., 2021; Hendershot et al., 2016; Zahradka et al., 2020) or sensor-based algorithms (Catalfamo et al., 2014a; Ledoux, 2018; Maqbool et al., 2017; van der Veen et al., 2018). They are also in the order of results reported from sensor-based algorithms evaluated in unimpaired participants on level ground and ramps using an accelerometer (Joshi et al., 2016) and force myography signals (Godiyal et al., 2018), and using an infrared sensor in participants with transfemoral amputation (Tiwari and Joshi, 2020).

If an accuracy of 40 ms (approximately 3.5% of gait cycle) is acceptable for the particular use, then all three algorithms can be used for event detection in amputee gait. However, the decision regarding the accuracy needed in pathological gait will depend on the specific application and should be decided by each researcher (French et al., 2020).

This study imposed strict inclusion criteria, such as the prosthesis used, to avoid confounding effects on detection accuracy. Future research could explore other prosthetic devices to evaluate whether the prosthesis type affects detection. If confirmed, machine learning could help mitigate its impact, given sufficient and representative data on the wide variety of gait patterns of individuals with amputation. Future research could also include individuals with different levels of amputation.

5. Conclusion

The results confirmed the hypothesis that accuracy of IC and FO events detection is influenced by the algorithm chosen, the amputee gait pattern and the terrain. Mean TE was smaller than 40 ms for evaluated conditions (three algorithms, both limbs and three terrains). Consequently, if an accuracy of 40 ms is acceptable for the particular use, then all three algorithms can be used for event detection in amputee gait. However, if accuracy in detection of events is crucial for the intended application, an evaluation of the algorithms in pathological gait walking on the terrain of interest is recommended.

6. Acknowledgments

We would like to thank the participants who kindly volunteered for this study.

7. Declaration of interest

None

8. Funding sources

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

9. References

Bruening, D.A., Ridge, S.T., 2014. Automated event detection algorithms in pathological gait. Gait Posture 39, 472–477. https://doi.org/10.1016/j.gaitpost.2013.08.023

Catalfamo, P., Acevedo, R., Ghoussayni, S., Ewins, D.J., 2014a. Gait Event Detection on Stairs using a Rate Gyroscope. Sensors 14, 5470–5485.

Catalfamo, P., Acevedo, R.R., Ghoussayni, S., Ewins, D., 2014b. Comparison of kinematic and pressure measurement reference methods used in gait event detection. Footwear Sci. 6, 193–202. https://doi.org/10.1080/19424280.2014.917123

De Asha, A.R., Robinson, M.A., Barton, G.J., 2012. A marker based kinematic method of identifying initial contact during gait suitable for use in real-time visual feedback applications. Gait Posture 36, 650–652. https://doi.org/10.1016/j.gaitpost.2012.04.016

Desailly, E., Daniel, Y., Sardain, P., Lacouture, P., 2009. Foot contact event detection using kinematic data in cerebral palsy children and normal adults gait. Gait Posture 29, 76–80.

Dujmovic, I., Radovanovic, S., Martinovic, V., Dackovic, J., Maric, G., Mesaros, S., Pekmezovic, T., Kostic, V., Drulovic, J., 2017. Gait pattern in patients with different multiple sclerosis phenotypes. Mult. Scler. Relat. Disord. 13, 13–20.

Eckardt, N., Kibele, A., 2017. Automatic identification of gait events during walking on uneven surfaces. Gait Posture 52, 83–86.

Ernst, M., Altenburg, B., Schmalz, T., Kannenberg, A., Bellmann, M., 2022. Benefits of a microprocessor-controlled prosthetic foot for ascending and descending slopes. J. Neuroeng. Rehabil. 19, 1–12. https://doi.org/10.1186/s12984-022-00983-y

Fajardo-Martos, I., Roda, O., Zambudio-Periago, R., Bueno-Cavanillas, A., Hita-Contreras, F., Sánchez-Montesinos, I., 2018. Predicting successful prosthetic rehabilitation in major lower-limb amputation patients: a 15-year retrospective cohort study. Brazilian J. Phys. Ther. 22, 205–214. https://doi.org/10.1016/j.bjpt.2017.08.002

Fonseca, M., Dumas, R., Armand, S., 2022. Automatic gait event detection in pathologic gait using an auto-selection approach among concurrent methods. Gait Posture 96, 271–274. https://doi.org/10.1016/j.gaitpost.2022.06.001

French, M.A., Koller, C., Arch, E.S., 2020. Comparison of three kinematic gait event detection methods during overground and treadmill walking for individuals post stroke. J. Biomech. 99, 109481. https://doi.org/10.1016/j.jbiomech.2019.109481

Godiyal, A.K., Verma, H.K., Khanna, N., Joshi, D., 2018. A force myography-based system for gait event detection in overground and ramp walking. IEEE Trans. Instrum. Meas. 67, 2314–2323. https://doi.org/10.1109/TIM.2018.2816799

Gómez-Pérez, C., Martori, J.C., Puig Diví, A., Medina Casanovas, J., Vidal Samsó, J., Font-Llagunes, J.M., 2021. Gait event detection using kinematic data in children with bilateral spastic cerebral palsy. Clin. Biomech. 90. https://doi.org/10.1016/j.clinbiomech.2021.105492

Hendershot, B.D., Mahon, C.E., Pruziner, A.L., 2016. A comparison of kinematic-based gait event detection methods in a self-paced treadmill application. J. Biomech. 49, 4146–4149. https://doi.org/10.1016/j.jbiomech.2016.10.046

Hussain, R., Marmar, Z., 2021. Gait dataset of 14 Syrian above-knee amputees and 20 healthy subjects. Data Br. 38, 107365. https://doi.org/10.1016/j.dib.2021.107365

Joshi, D., Nakamura, B.H., Hahn, M.E., 2016. A novel approach for toe off estimation during locomotion and transitions on ramps and level ground. IEEE J. Biomed. Heal. Informatics 20, 153–157. https://doi.org/10.1109/JBHI.2014.2377749

Ledoux, E.D., 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

LeMoyne, R., 2016. Advances for prosthetic technology: From historical perspective to current status to future application, Advances for Prosthetic Technology: From Historical Perspective to Current Status to Future Application. https://doi.org/10.1007/978-4-431-55816-3

Maeda, T., Ishizuka, T., Yamaji, S., Ohgi, Y., 2018. A Force Platform Free Gait Analysis. Proceedings 2. https://doi.org/10.3390/proceedings2060207

Maqbool, H.F., Husman, M.A.B., Awad, M.I., Abouhossein, A., Iqbal, N., Dehghani-Sanij, A.A., 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

McIntosh, A.S., Beatty, K.T., Dwan, L.N., Vickers, D.R., 2006. Gait dynamics on an inclined walkway. J. Biomech. 39, 2491–2502. https://doi.org/10.1016/j.jbiomech.2005.07.025

Parker, K., Hanada, E., Adderson, J., 2013. Gait variability and regularity of people with transtibial amputations. Gait Posture 37, 269–273. https://doi.org/10.1016/j.gaitpost.2012.07.029

Sagawa, Y., Turcot, K., Armand, S., Thevenon, A., Vuillerme, N., Watelain, E., 2011. Biomechanics and physiological parameters during gait in lower-limb amputees: a systematic review. Gait Posture 33, 511–26. https://doi.org/10.1016/j.gaitpost.2011.02.003

Sandra Oliveira de Cerqueira Soares, A.I., Yuji Yamaguti, E.I., Mochizuki III, L., Carlos Amadio, A.I., Cerca Serrão, J. V, 2009. Biomechanical parameters of gait among transtibial amputees: a review Parâmetros biomecânicos da marcha de amputados transtibiais: revisão. Sao Paulo Med J 127, 302–311.

Theodorakos, I., Healy, A., Chatzistergos, P., Andersen, M.S., Chockalingam, N., 2022. Assessment of the effect of a total contact cast on lower limb kinematics and joint loading. Gait Posture 98, 203–209. https://doi.org/10.1016/j.gaitpost.2022.09.075

Tiwari, A., Joshi, D., 2020. An Infrared Sensor-Based Instrumented Shoe for Gait Events Detection on Different Terrains and Transitions. IEEE Sens. J. 20, 10779–10791. https://doi.org/10.1109/JSEN.2020.2994956

Ulrich, B., Santos, A.N., Jolles, B.M., Benninger, D.H., Favre, J., 2019. Gait events during turning can be detected using kinematic features originally proposed for the analysis of straight-line walking. J. Biomech. 91, 69–78. https://doi.org/10.1016/j.jbiomech.2019.05.006

van der Veen, S.M., Hammerbeck, U., Baker, R.J., Hollands, K.L., 2018. Validation of gait event detection by centre of pressure during target stepping in healthy and paretic gait. J. Biomech. 79, 218–222. https://doi.org/10.1016/j.jbiomech.2018.07.039

Varrecchia, T., Serrao, M., Rinaldi, M., Ranavolo, A., Conforto, S., De Marchis, C., Simonetti, A., Poni, I., Castellano, S., Silvetti, A., Tatarelli, A., Fiori, L., Conte, C., Draicchio, F., 2019. Common and specific gait patterns in people with varying anatomical levels of lower limb amputation and different prosthetic components. Hum. Mov. Sci. 66, 9–21. https://doi.org/10.1016/j.humov.2019.03.008

Visscher, R.M.S., Sansgiri, S., Freslier, M., Harlaar, J., Brunner, R., Taylor, W.R., Singh, N.B., 2021. Towards validation and standardization of automatic gait event identification algorithms for use in paediatric pathological populations. Gait Posture 86, 64–69. https://doi.org/10.1016/j.gaitpost.2021.02.031

Vrieling, A.H., van Keeken, H.G., Schoppen, T., Otten, E., Halbertsma, J.P.K., Hof, A.L., Postema, K., 2008. Uphill and downhill walking in unilateral lower limb amputees. Gait Posture 28, 235. https://doi.org/10.1016/j.gaitpost.2007.12.006

Zahradka, N., Verma, K., Behboodi, A., Bodt, B., Wright, H., Lee, S.C.K., 2020. An evaluation of three kinematic methods for gait event detection compared to the kinetic-based ‘gold standard.’ Sensors (Switzerland) 20, 1–15. https://doi.org/10.3390/s20185272

Zeni Jr, J.A., Richards, J.G., Higginson, J.S., 2008. Two Simple Methods for Determining Gait Events During Treadmill and Overground Walking Using Kinematic Data. Gait Posture 27, 710.

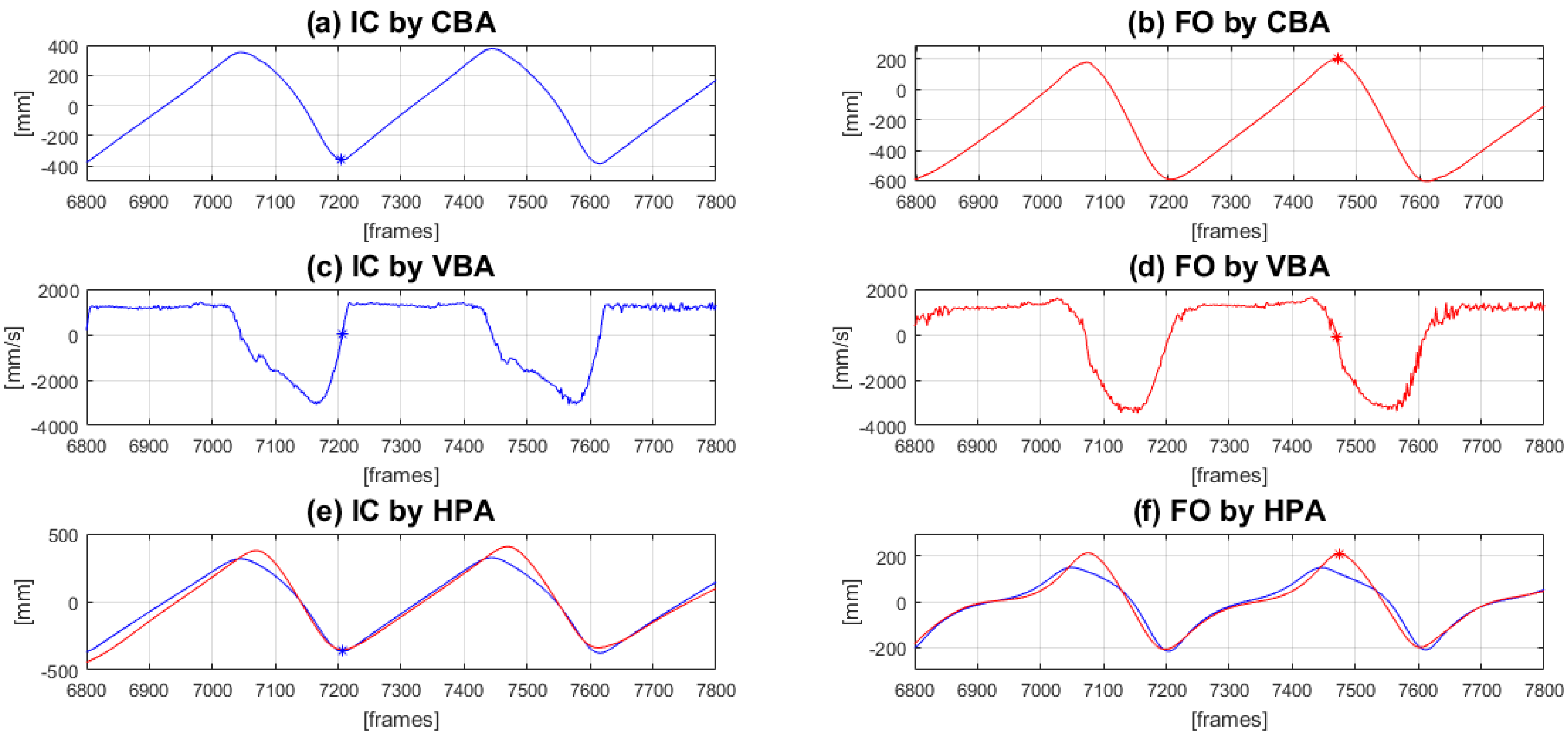

Fig. 1: Initial Contact (IC) and Foot Off (FO) event detection from the Coordinate Based Algorithm (CBA) (a and b), Velocity Based Algorithm (VBA) (c and d) and High Pass Filtered Algorithm (HPA) (e and f). The blue and red asterisk show the frame of IC and FO, respectively. (a) Displacement referenced signal X_{Heel}– X_{Sacrum} and IC detection by CBA. (b) Displacement referenced signal X_{Toe} – X_{Sacrum} and FO detection by CBA. (c) Velocity referenced signal $V_{x\ (Heel\text{-}Sacrum)}$ and detection of IC by VBA. (d) Velocity referenced signal $V_{x\ (Toe\text{-}Sacrum)}$ and detection of FO by VBA. (e) X_{Heel} (blue line) and X_{Toe} (red line) displacement signals filtered by a high pass filter (with cut of frequency as 0.5 of gait frequency) and detection of IC by HPA. (f) X_{Heel} (blue line) and X_{Toe} (red line) displacement signals filtered by a high pass filter (with cut of frequency of 1.1 of gait frequency) and detection of FO by HPA.

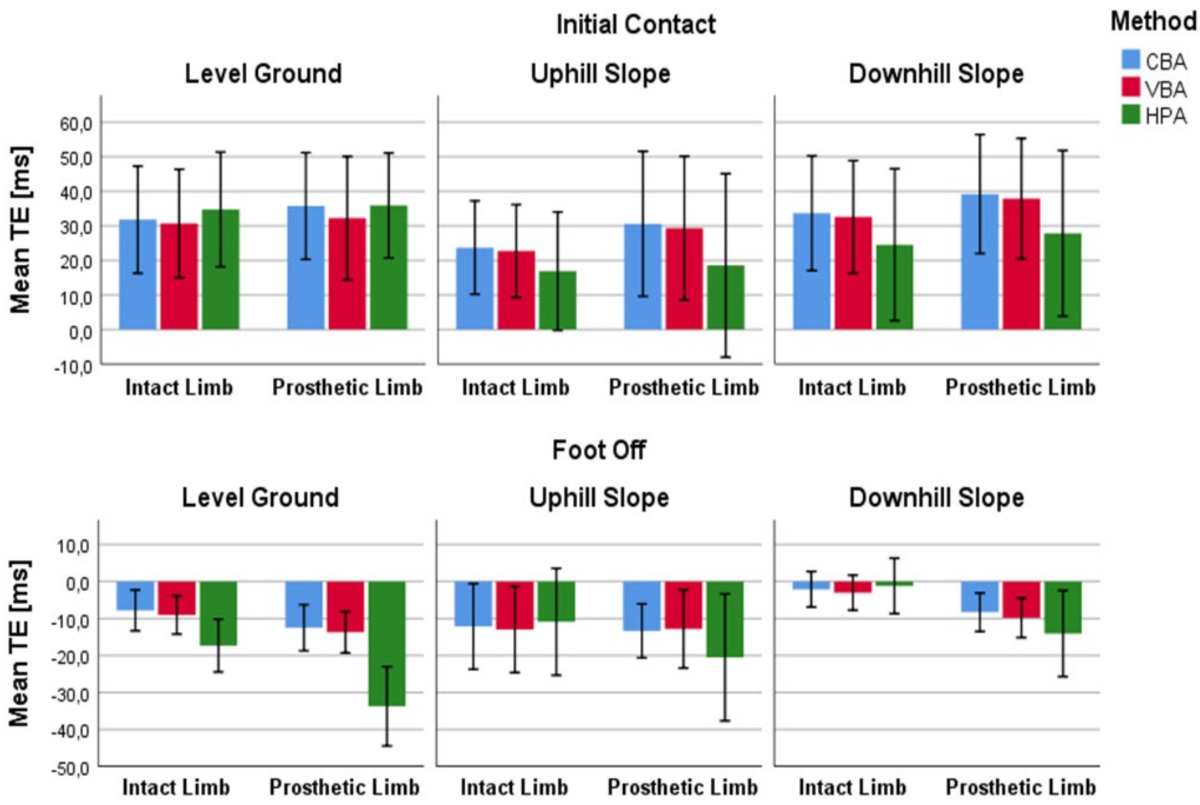

Fig. 2. Mean TE (ms) for IC (top row) and FO (bottom row) for level ground, uphill and downhill slope, for the intact and prosthetic limb, and for the three algorithms: CBA, VBA and HPA. Error bars show +/- 1 standard deviation.

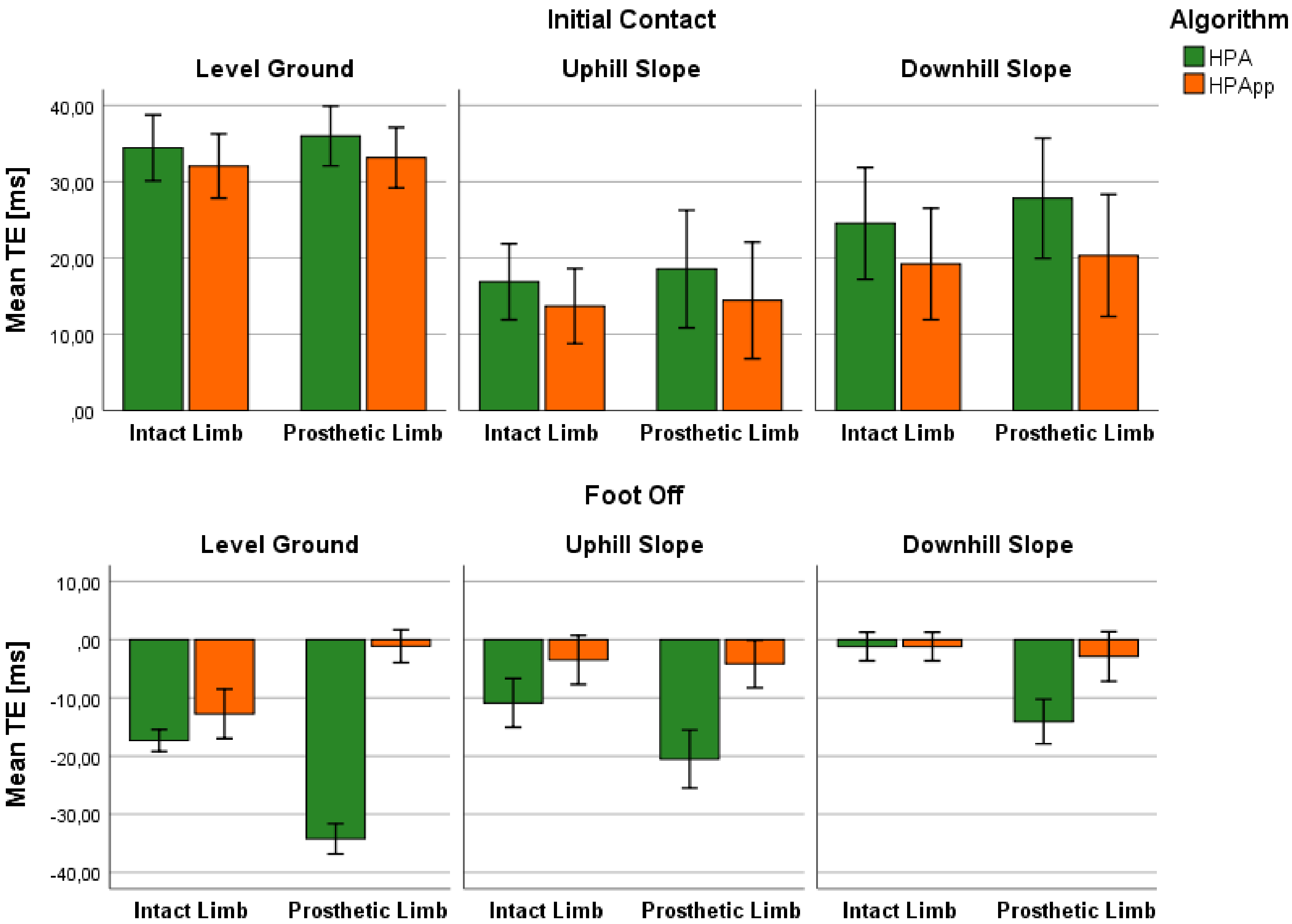

Fig. 3. Mean TE (ms) for HPA and HPApp for IC (top row) and FO (bottom row) for level ground, uphill and downhill slope, for the intact and prosthetic leg. Error bars show +/- 1 standard deviation.

Table 1

Results of the mixed ANOVA test, with three intra-subject factors (limb: intact and prosthetic limb; terrains: Level Ground, Uphill Slope and Downhill Slope; Algorithm: CBA, VBA, HPA), and with subjects as inter-subject factor- *indicates significant effect, ** indicates moderate effect size, and *** indicates large effect size.

			IC			FO		
Mixed ANOVA Effect			**F(df, Error)**	**p-value**	**Effect Size η_p^2**	**F(df, Error)**	**p-value**	**Effect Size η_p^2**
Main Effect	Algorithm		F(1.094,40) = 101.445	<0.01*	0.835***	F(1.11,40)=236.16	<0.01*	0.922***
	Between Levels	VBA Vs CBA	F(1,20) = 97.812	<0.01*	0.830***	F(1,20)=27.882	<0.01*	0.581**
		VBA Vs HPA	F(1,20) = 84.83	<0.01*	0.809***	F(1,20)=220.690	<0.01*	0.917***
		CBA Vs HPA	F=(1,20) = 114.359	<0.01*	0.851***	F(1,20)=267,567 ;	<0.01*	0.930***
Interaction	Between Factors	Algorithm *Leg	F(1.445,40) = 40.748	<0.01*	0.671**	F(1.3,40)=233.212	<0.01*	0.921***
		Algorithm * Terrain	F(1.204,40) = 70.272	<0.01*	0.778***	F(4,40)=101.464	<0.01*	0.835***

Table 2

A) Number of IC events (expressed as a percentage of the total number of IC events analysed), detected using the heel marker trajectory when using the HPA and the HPApp algorithms. B) Number of FO events (expressed as a percentage of the total number of FO events analysed), detected using the toe marker trajectory when using the HPA and the HPApp algorithms.

	Intact Limb		**Prosthetic Limb**	
	A) Initial contact detected by the heel marker			
	HPA	**HPApp**	**HPA**	**HPApp**
Level Ground	39	**92**	57	**72**
Uphill Slope	77	**73**	93	**64**
Dowhill Slope	71	**79**	80	**54**
	B) Foot Off detected by the toe marker			
Level Ground	79	**90**	92	**8**
Uphill Slope	100	**94**	98	**36**
Dowhill Slope	100	**94**	100	**71**

Supplementary Material

True Error (mean ± standard deviation) expressed in ms, and 95% Confidence Interval of the kinematic-based gait event detection algorithms (CBA, VBA, HPA) when compared to force platform during walking on level ground, uphill and downhill slope for the intact and prosthetic leg. n: total number of events analysed per condition.

	Intact Limb			**Prosthetic Limb**		
	CBA	**VBA**	**HPA**	**CBA**	**VBA**	**HPA**
Level Ground						
Initial Contact						
n		196			194	
TE	30.9 ±13.5	29.8±13.5	34.1 ±14.2	33.3 ±12.5	30.4 ±16.0	35.0 ±12.9
CI	[26.0 35.9]	[24.8 34.8]	[28.8 39.3]	[28.6 37.9]	[24.5 36.3]	[30.3 39.8]
Foot Off						
n		172			183	
TE	-8.14 ±6.0	-9.4 ±5.9	-18.1 ±5.7	-12.5 ±6.6	-13.9 ±6.2	-32.9 ±11.8
CI	[-10.3 -5.9]	[-11.6 -7.2]	[-20.2 -16.0]	[-14.9 -10.0]	[-16.2 -11.6]	[-37.3 -28.3]
Uphill Slope						
Initial Contact						
n		144			144	
TE	25.0 ±14.5	23.8 ±14.3	16.2 ±18.8	31.7 ±22.1	30.7 ±21.9	18.0 ±28.1
CI	[19.6 33.3]	[18.6 29.1]	[9.3 23.11]	[23.6 39.9]	[22.6 38.7]	[7.7 28.3]
Foot Off						
n		143			144	
TE	-11.5 ±12.0	-12.8 ±11.6	-10.4 ±15.4	-14.9 ±6.0	-13.2 ±11.9	-22.8 ±16.8
CI	[-15.9 -7.1]	[-17.0 -8.5]	[-16.0 -4.7]	[-17.1 -12.7]	[-17.6 -8.8]	[-28.9 -16.6]
Downhill Slope						
Initial Contact						
n		111			114	
TE	33.9 ±17.7	32.9 ±17.3	24.5 ±23.2	38.7 ±18.5	37.4 ±18.8	27.3 ±24.7
CI	[27.4 40.4]	[26.5 39.2]	[16.0 33.1]	[31.9 45.4]	[30.5 44.3]	[18.2 36.4]
Foot Off						
n		115			114	
TE	-2.1 ±5.11	-3.3 ±4.1	-1.0 ±7.5	-9.1 ±4.8	-10.6 ±4.9	-15.5 ±11.13
CI	[-4.0 -0.3]	[-4.8 -1.8]	[-3.8 1.7]	[-10.9 -7.3]	[-12.4 -8.8]	[-19.9 -11.4]