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Short communication

# Automatic gait event detection in pathologic gait using an auto-selection approach among concurrent methods

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ABSTRACT

*Background:* Accurate gait event detection is crucial to analyze pathological gait data. Existing methods relying on marker trajectories were reported to be sensitive to different gait patterns, which is an inherent characteristic of pathologic gait.
*Research question:* We propose a new approach based on auto-selection among different methods, original and taken from the literature.
*Methods:* The auto-selection approach evaluates the accuracy of the implemented methods for both foot-strike and foot-off on all available events detected by the force platforms, independently, and automatically selects the most accurate one to be used on the whole gait session. Pathological gait data from 272 patients with cerebral palsy and idiopathic toe walking were used retrospectively to evaluate the accuracy of this approach. Three methods previously reported in literature together with original methods developed based on auto-correlation were implemented and constituted our auto-selection approach. The accuracy and precision were compared to a recently reported method based on deep events as it is the method that showed the best performance in literature.
*Results:* Results showed that the proposed approach outperformed all implemented methods used alone, with an accuracy of − 2.0 ms and − 0.9 ms for foot strike and foot-off, respectively. Additionally, more than 99% and 93% of events detected were detected within 20 ms and 10 ms of accuracy, respectively.
*Significance:* The proposed methodology has demonstrated to improve the accuracy and precision of gait event detection in gait analysis.

## 1. Introduction

Three-dimensional gait analysis requires accurate detection of events to align the different cycles and to identify their different phases. The gold standard for detecting events relies on the detection of a threshold on the vertical ground reaction force (GRF) measured by force-platforms [1]. However, this condition is generally applicable to a small number of steps during a gait session.

Several methods have been proposed to automatically estimate gait events based on kinematics [1–5]. However, none has yet been consensually accepted as the gold standard. The methods based on markers position, velocity or acceleration are highly sensitive to different gait patterns [1,6] and variations of walking speed [2]. Thus, their accuracy is reduced in a clinical context as pathological gait means higher heterogeneity at those levels [7].

The objective of this study is to design and evaluate an approach that automatically selects the best method for one gait session by concurrency of methods. Nine methods are implemented, six original methods based on auto-correlation between kinematic parameters and events detected by GRF and three methods from the literature.

## 2. Methods

### 2.1. Gait data

A total of 272 gait sessions collected from 184 patients, aged 13.0 (

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± 6.8) years, 129 diagnosed with cerebral palsy (CP) and 54 diagnosed with idiopathic toe-walking (ITW), were used retrospectively for this study. This study was approved by the "Comission Cantonale d'Éthique de la Recherche" (CCER-2018–00229). Two motion capture systems were used alternatively (Vicon MX3, Oxford Metrics, Oxford, UK and Oqus7+, Qualisys, Göteborg, Sweden) and two force platforms Accu-Gait, AMTI, (Watertown, MA, USA) with a sampling rate of 100 Hz and 1000 Hz, respectively. Participants were equipped with the conventional gait model marker set [8] and were asked to walk barefoot at self-selected speed. Marker trajectories and GRFs were filtered with a low-pass Butterworth filter at a cut-off frequency of 6 Hz.

### 2.2. *Auto-selection approach*

The code was developed in Matlab (v2019a, Mathworks Inc., Natick, MA, USA) and is fully available (https://gitlab.unige.ch/KLab/gev).

#### 2.2.1. *Reference*

For each gait session, events (foot-strike and foot-off) were automatically detected with GRFs using a generally accepted 20 N threshold

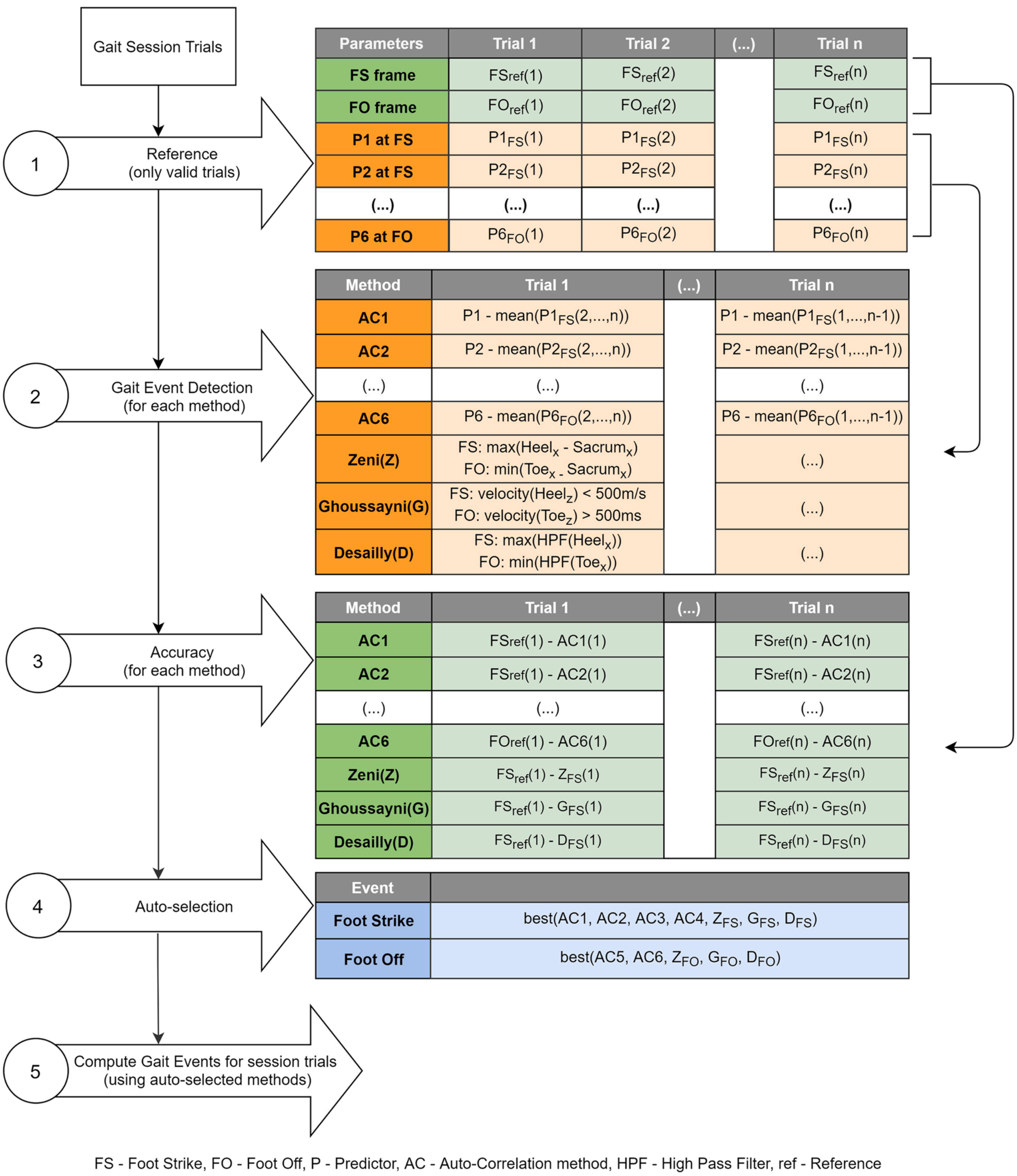


**Fig. 1.** Workflow of the Auto-selection approach. 1) Reference: Event frames are detected by GRF (green). Marker trajectories (P) are extracted at those events (orange). 2) Gait Event Detection: Marker trajectories stored at Reference stage are used to build AC methods and calculate gait events for each trial. The P obtained at the same trial is not included. Methods Z, G and D are also computed. 3) Accuracy: Event frames calculated in Reference are used to calculate the accuracy of each method outcome. 4) Auto-Selection: The method with higher accuracy for the entire session is selected, for FS and FO separately. 5) Compute Gait Events: The two methods selected in Auto-Selection are used to detect the event frames on the entire session. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

[2], respectively. Steps without an unique and entire foot position on the force-platform were automatically excluded. The detected frames were stored for posterior accuracy calculation. For these events, foot and pelvic marker positions were extracted at foot-strike and foot-off and normalized (target values of the parameters).

*2.2.2. Gait event detection*

Normalized marker trajectories from each trial were extracted. The difference between those trajectories and the respective target values was calculated. Thus, different combinations of those parameters served to detect the event frames by minimum peak detection of this difference. Four auto-correlation methods were built for detecting foot-strike (AC1-AC4) and two for detecting foot-off (AC5-AC6). The description of the auto-correlation methods is fully described in Supplementary Information (S1).

Additionally, three methods from the literature were implemented and used in the auto-selection approach: *Ghoussayni*, *Zeni*, *Desailly* [2,3,5].

*2.2.3. Accuracy and auto-selection approach*

The accuracy of each implemented method was calculated by the time difference between the reference and the predicted events for each trial and side. The overall session accuracy for each method was estimated by the mean accuracy among the session. The method with the lowest averaged time difference was selected, one method for each event (foot-strike and foot-off). No correlation was observed between the accuracy of the methods and the number of trained events used (Supplementary Information S2).

## 2.3. Validation

For the evaluation of each method and the auto-selection approach, the averaged time difference was completed by the confidence interval and compared to *DeepEvent* [9], which was not included in the auto-selection approach. The distribution of the methods selected by the auto-selection approach on the different patients and sessions was used to rank them. Fig. 1.

# 3. Results

## 3.1. Validation

The auto-selection approach predicted foot-strike within a mean accuracy of − 1.2 ms and − 2.0 ms for CP and ITW groups, respectively (Table 1). Moreover, it predicted foot-off with a mean accuracy of − 0.1 ms and − 0.9 ms for both groups, respectively. The auto-selection approach resulted in better accuracy and precision (Fig. 2). In general, most of the methods showed relatively good accuracy (median of accuracies close to zero) but poor precision (most have a wide range of dispersion). The auto-selection approach detected 99.3% of events within 20 ms of accuracy and 93% within 10 ms (Table 1).

**Table 1**
Description of the construction of each method. AC [1–6] - Auto-correlation methods, FS – Foot Strike, FO – Foot Off, p – parameter, HEEz – vertical component of the heel marker, STEPx – horizontal component of the distance from the heel to the anterior posterior iliac spine markers, FOOTα – Foot angle with respect to the ground, HIPx – horizontal component of the distance between the anterior iliac spine markers.

| Method | Predictors of Methods |
|---|---|
| AC1 | p(HEEz) + p(STEPx) |
| AC2 | p(HEEz) + p(STEPx) + p(FOOTα) |
| AC3 | p(STEPx) + p(HIPx) |
| AC4 | p(HEEz) + p(STEPx) + p(FOOTα) + p(HIPx) |
| AC5 | p(TOEz) + p(STEPx) |
| AC6 | p(TOEz) + p(STEPx) + p(FOOTα) |
| *Zeni* et al. *(2007)* | Maximum distance between Heel and Sacrum (FS) and minimal distance between Toe and Sacrum (FO) markers in the horizontal plane |
| *Ghoussayni* et al. *(2004)* | Sagittal velocity of the Heel (FS) and Toe (FO) markers goes bellow and above a threshold of 500 m/s, respectively |
| *Desailly* et al. *(2008)* | High pass filtered maximum horizontal Heel (FS) and minimal horizontal Toe (FO) markers, respectively. |

## 3.2. Distribution of selected methods

For detecting foot-strike, AC1 was the most selected method for both groups. Contrarily, the methods implemented from literature were generally less selected.

Regarding the detection of foot-off, *Zeni* method was the most selected method for both groups with a percentage of selection above 70%.

# 4. Discussion

The purpose of the present study was to define and evaluate an improved approach for gait event detection in pathological gait. Our approach proposed the implementation of existing methods, together with original ones based on auto-correlation and an auto-selection of the best predicting method within a gait session. After testing different combinations of parameters, we have proposed six methods for detecting foot-strike and foot-off. The parameters used on those methods (i.e. foot and pelvis marker positions with the exception of anterior iliac spine markers) were previously used [6], which support them as indicators of gait events. Parameters based on velocity and acceleration of markers were not included as they showed higher sensitivity to gait velocity and patterns [6,9]. Most of the velocity-based or acceleration-based methods reported in the literature have only been validated for normal gait [2,3,5].

The performance of the implemented methods was observed similar to what was reported in the literature [2,3,5,6,9] but the auto-selection approach outperformed all tested methods. *Lempereur* et al. reported an absolute accuracy of 5.5 ms and 10.7 ms with a confidence interval of [0.9;10.2] and [5.4;15.9], for foot-strike and foot-off, respectively [9]. In this study, *DeepEvents* resulted in considerably lower accuracy regarding foot-off, but *DeepEvent* was trained on their own entire database, acquired in a different laboratory, while our model is trained for each session. Our proposed approach requires considerably lower computation time than *DeepEvent* (approximately 70 s by trial with *DeepEvent* compared to 0.2 s with auto-selection). The considerably lower confidence interval and percentage of predicted events within 10 ms and 20 ms reported in Table 1 (99.3% and 93% of the predictions within one frame for foot-strike and foot-off, respectively) demonstrate the high performance of the auto-selection approach.

All methods used alone demonstrated high accuracy but low precision. All methods were selected in the auto-selection approach (Table 1), some methods more often selected for foot-strike and others for foot-off, and with differences between CP and ITW. Such observation reinforces the idea that existing methods are sensitive to heterogeneus gait. The Auto-selection approach allows to find the adjusted solution according to the patient's gait characteristics. demonstrating that all methods implemented have different performance for both gait events and that by separating the selection by the type of event, results in more accurate detection. In addition, our proposed approach requires considerably lower computation time than *DeepEvent.*

In conclusion, the proposed approach has demonstrated to improve the accuracy and precision of gait event detection in pathological gait. Thus, we propose its use in clinical practice. The implementation of additional existing methods is possible and expected to further improve its performance.

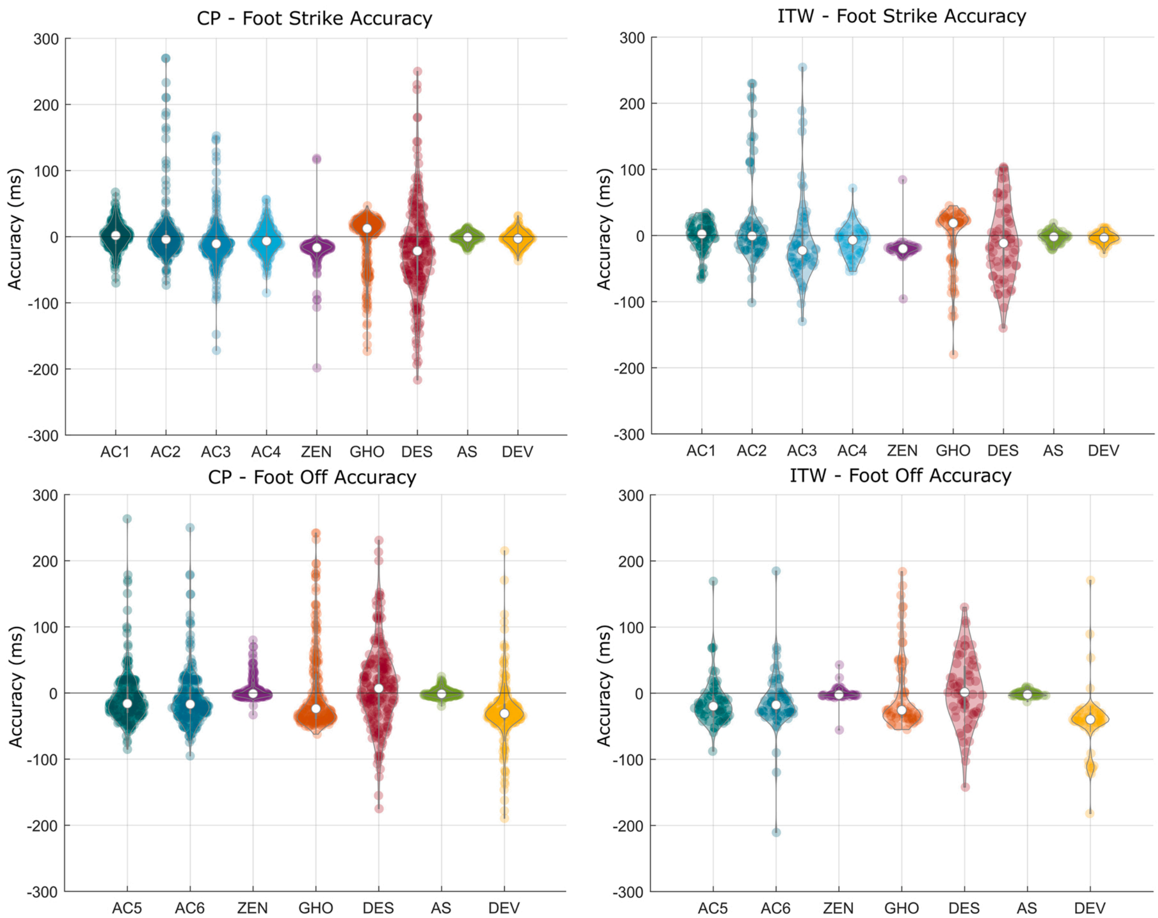


**Fig. 2.** Violin plot for visualization of accuracy distribution for all sessions in milliseconds with respect to the two populations. White point represents the median of the observations. Auto-correlation (AC [1–6]), Zeni (ZEN), Ghoussayni (GHO), Desailly (DES), DeepEvent (DEV) and Auto-selection (AS).


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## Conflict of interest statement

The authors declare no conflict of interest.

## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gaitpost.2022.06.001.

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