Automatic Gait Event Detection in Paediatric Pathological Gait

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Automatic Gait Event Detection in Paediatric Pathological Gait

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Abstract

Introduction
Spatio-temporal parameters (STP), calculated from 3D gait analysis, are frequently used for treatment planning and evaluation in Cerebral Palsy (CP). To calculate these parameters, accurate determination of gait events (i. e. initial contact (IC) and foot off (FO)) is essential. Previous research on the performance of kinematic gait event detection algorithms on different walking patterns led to recommendations, which have not been verified on clinical populations.

Research questions
1) Which current kinematic approach is best capable of determining IC and FO for diverse gait patterns?
2) Does the use of automated kinematic algorithms affect clinical interpretation of STP compared to current clinical event detection (force-plate, visual identification)?

Methods
3D kinematic and kinetic data was retrospectively collected from 90 children with CP. Participants were classified in 3 categories – groups A (fore-foot IC), B (flat foot IC) and C (heel IC). Five kinematic algorithms (one modified) were implemented for two different foot marker configurations for both IC and FO and compared with clinical (visual and force-plate) identification using Bland-Altman analysis. The best-performing algorithm-marker configuration was used to compute STP, which were compared with those obtained clinically.

Results
In agreement with previous studies, sagittal velocity of the heel (Group C) or toe markers (Group A and B) was the most reliable indicator of IC, and the speed-dependent sagittal velocity coupled with the hallux marker worked best for FO across the entire dataset. A comparison of kinematic and clinical showed >1.78% differences in spatial parameters, and >6.3% differences in temporal parameters.

Significance
Outcomes showed that the choice of the best-performing algorithm was dependent on a combination of algorithm and marker choice. However, observing the high differences between clinical and kinematically calculated spatio-temporal parameters, clinicians need to be aware that the differences could likely affect clinical interpretation of gait analysis results. Hence, further research is needed to establish the efficacy of implementing automatic gait event detection algorithms in a clinical setting.

Keywords Cerebral Palsy, clinical gait analysis, kinematic detection, gait events, spatio-temporal parameters

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List of Abbreviations

BTX- Botulinum toxin

CGA- Clinical Gait Analysis

CP- Cerebral Palsy

FES- Functional Electrical Stimulation

FO- Foot Off

FSR- Force sensing resistors

IC- Initial Contact

ML- Machine Learning

QoL- Quality of Life

STP- Spatio-temporal Parameters

TD- Typically developing

vGRF- Vertical ground reaction force

1. Introduction

Cerebral Palsy (CP) is the most common and severe motor disorder in children. It has an estimated prevalence of 1.5 to 4 live births per 1,000 children, and it is associated with lifelong disability [1-3]. CP consists of a heterogeneous group of clinical syndromes which describe permanent disorders like muscle weakness, kinematic joint abnormalities, and reduced motor control [4, 5]. It typically occurs around birth and results from a non-progressive neurological disturbance in the developing fetal or infant brain [5]. Due to these neuromotor injuries, children with CP may develop a variety of musculoskeletal problems, which evolve throughout life and are related to physical growth, muscle spasticity, aging and other factors [4, 5]. These neuromuscular deficits of CP can lead to gait abnormalities and thereby decrease the quality of life (QoL) and reduce participation in activities of daily living [6].

With walking considered to be an important indicator of QoL, analysing gait deviations and optimizing gait towards that of their typically developing (TD) counterparts is an important aim in the treatment and rehabilitation of CP children [7].

In young children with CP, multiple treatment options are available, ranging from invasive i.e orthopaedic surgery to correct bony deformities and muscular contracture; and selective dorsal rhizotomy to address muscle spasticity, to minimally invasive (botulinum toxin (BTX)) to reduce muscle spasticity and, further to non-invasive techniques (orthotics, physical therapy) to address problems in everyday walking [8]. The progress of gait deterioration during growth, and the effect of various interventions are observed through tools such as clinical gait analysis (CGA) [9].

CGA is comprehensive analysis that quantifies how an individual's brain injury affects their walking patterns. Using CGA, spatio-temporal gait parameters (STP) such as step length and gait velocity are calculated, which in combination with other information such as joint kinematics and EMG activity of individual muscles collected during gait measurements, as well as physical examinations that determine muscle strength, spasticity and range of motion aid clinicians in assessing the causes of abnormal gait and selecting the right intervention for a patient. Post-intervention, CGA is used in monitoring and quantifying improvement in gait kinematics and motor control [7, 9-11].

In order to compute STP, it is necessary to estimate the exact moment the foot leaves or touches the ground. Therefore, accurate identification of gait events (Initial contact (IC) and Foot off (FO)), which discriminate between the two main phases of a gait cycle (stance v/s swing) is essential [12]. The timing of the IC often serves as the reference point to which all other gait data is correlated [13]. Hence, the timing information of the gait events allows not only for the extraction of comparable STP, but also allows for the temporal normalization of gait signals obtained during a clinical gait measurement, which is used for ensemble-averaging of kinematic and kinetic gait information. This, again, allows to quantify variabilities in gait parameters within-and between-subjects [14]. Since incorrect identification of gait events leads to errors in normalization of kinematic and kinetic data and ensemble-averaging of STP, their accurate identification is imperative for the comparison of gait patterns between subjects, as well as deficits in pathological conditions. Moreover, identification of accurate gait events has also investigated for use in triggering functional electrical stimulation (FES), wherein the peripheral nervous system is triggered to stimulate muscle contractions in muscles such as the tibialis anterior and gastrocnemius to assist walking and to correct foot drop in children with CP as well as subjects with stroke [15].

1.1 Problem Definition

Currently, gait events are identified in clinics through two main approaches (collectively referred to hereafter as clinical identification). The first approach, widely treated as the 'clinical gold standard',

involves entails using pressure-sensitive force platforms or force sensing resistors (FSR). IC and FO are determined when the value of the vertical ground reaction force (vGRF) measured by the force plates crosses or falls below a certain threshold respectively [16]. FSRs produce a voltage relative to the amount of force on the sensor. When placed on the plantar surface of the foot, a proportional change in plantar pressure allows for the detection of gait events [17].

However, at least two force plates are required to determine one stride, and thus the number of steps that can be captured is also generally constrained to the number of force platforms available in the gait laboratory. A large number of walking trials are thus sometimes necessary in order to achieve a clean, isolated force plate hits. Obtaining clean force plate hits is also often limited due to the use of assistive devices, short step lengths, or partial contact with the plate [18]. Furthermore, the acceptable force threshold to identify IC and FO events has not been standardized across clinics, especially for paediatric populations, and could lead to delays in event detection ranging upto 10 ms, when this threshold is changed from 10 N to 20 N [19]. FSRs, on the other hand, could impede the natural gait of the child, find difficulties in adhering to the subject's foot and could be prone to breakage [20]. Furthermore, a study also reported difficulty in choosing the right placement of FSRs on the foot surface, due to atypical plantar pressure patterns while walking in children with CP [21].

When force plate data is unavailable, gait events are detected through visual determination of gait events from video data by trained experts [22]. Trained experienced personnel observe video data and manually select the timing of gait events by observing segment kinematics. However, this approach is time-consuming and is often not feasible when dealing with a large dataset. Furthermore, while it is expected that the personnel are trained, the reliability of these measurements are dependent on the skills and experience of the rater, and is hence subjective. This subjectiveness can therefore lead to discrepancies in the reporting of event timings. Furthermore, accurate gait event detection is also limited by the frame rate of video cameras, which is low compared to force and pressure-based systems.

Due to the limitations of aforementioned clinical identification methods, researchers have attempted to find alternate methods by which gait events can be estimated using data from optoelectronic systems. Optoelectronic systems consist of multiple synchronized high-frequency infra-red cameras which capture the reflections of target points (markers) placed on bony landmarks that cover required body segments. Kinematic algorithms utilize information from markers and attempt to draw relations between the trajectories, velocities or algorithms of markers and the occurrence of gait events. Figure 1 below describes the general workflow of kinematic gait event detection. With the first kinematic algorithm developed in 1990 [23], many methods have been developed to estimate gait events in both TD and pathological gait [24-35]. However, these methods have not been tested on diverse gait patterns, nor have they been validated for use in a clinical setting.

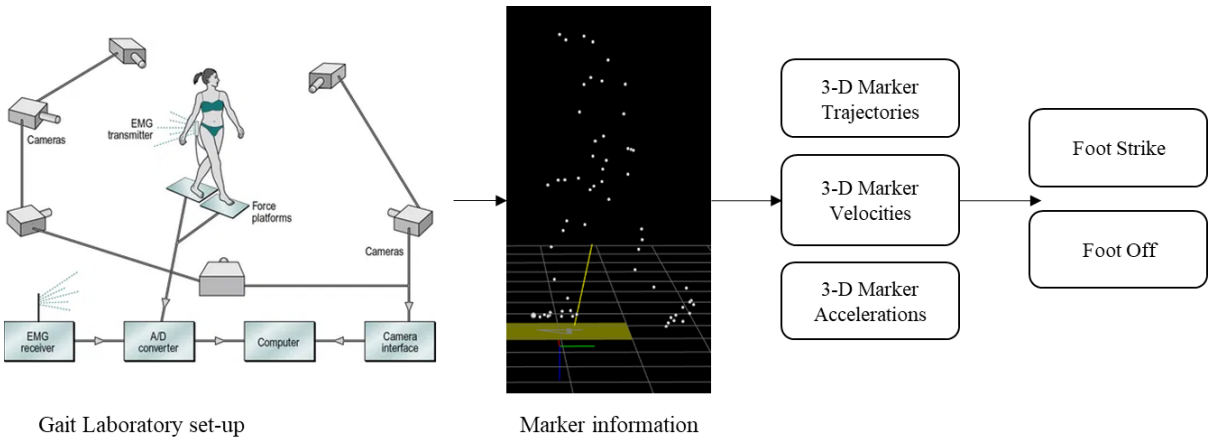


Figure 1: General Workflow of kinematic algorithms.

1.2 Research Goal

With CP causing severe movement deficits, and many existent studies attempting to correlate gait deviations with causes of underlying pathologies and muscle spasticity [36, 37], acquisition and interpretation of STP in children with CP remains an important research direction. In order to facilitate accurate acquisition of gait parameters, accurate identification of gait event events is essential. While many novel kinematic algorithms have been developed for both pathological and TD gait, validation and standardization of these methods for use in a diverse gait patterns is lacking. Since many children with CP do not demonstrate a fore-foot IC or a mid-foot IC - as opposed to a traditional heel IC as in TD children - traditional kinematic algorithms might thus provide lackluster results. Recommendations to improve performance for pathological gait patterns (regarding modification of existent algorithms, and the usage of the hallux markers to increase accuracy in FO detection [38]) have been introduced, but remain unverified. Furthermore, the influence of automatic identification on the estimation of STP has not been investigated, nor validated against clinical approaches.

Therefore, it is the primary goal of this study to incorporate the modifications suggested by previous publications into existent kinematic algorithms to determine if it causes improvements in gait event detection for different pathological walking patterns. Our second goal is to compare resulting spatio-temporal parameters obtained kinematically and clinically, to determine the feasibility of incorporating kinematic algorithms in a clinical setting.

2. Methods

2.1 Participants

This study utilized a retrospective database consisting of 3-D kinematic and kinetic data of 90 participants, aged 3-18 at the time of measurement, who underwent 3-D CGA at University Children's Hospital Basel (UKBB), Switzerland from 2015-2017. Participants were included in the study if they were classified as levels I, II or III of the Gross Motor Function Classification System (GMFCS) [39] and were able to complete a barefoot walking trial without the assistance of orthotic devices, crutches or walkers. A participant trial was included in the study in case of at least one clean force plate hit on either leg. Only one limb per participant was included in the study.

The participants fulfilling the inclusion criteria were classified into 3 groups of 30 individuals each, according to the region of the foot which initially contacted the ground. Informed consent was obtained from all children or their guardians, in accordance with the approval from the local ethical committee (EKNZ Nr. 2018-01640). All measurements were conducted according to the Declaration of Helsinki.

Participant characteristics per sub-group are described below in Table 1.

Table 1: Participant Description

	Group A	**Group B**	**Group C**
Group definition	The forefoot is in contact with the ground during FS.	The entire sole or the side of the foot is in contact with the ground during FS.	The heel is in contact with the ground during FS.
GMFCS level [I/II/III]	17/12/1	25/5/0	29/1/0
Sagittal Foot-floor angle [Mean (SD)]	−20.7 (14.0)	−0.7 (2.5)	7.5 (6.7)
Sagittal Ankle-dorsiflexion angle [Mean (SD)]	−17.0 (11.8)	−2.6 (7.8)	−1.1 (5.7)
Age in years [Mean (SD, range)]	11.2 (3.2, 5.9−17.3)	11.6 (3.4, 5.6−17.3)	12.6 (2.6, 7.7−17.6)
Sex (M/F)	15/15	18/12	18/12
GMFCS level [I/II/III]	17/12/1	25/5/0	29/1/0

2.2 Measurement Procedure

All participants walked barefoot on an equipped walkway at a self-selected walking speed for at least 6 trials. Kinematic data was collected at a sampling frequency of either 150 (for data collected after 2016) or 300 Hz (for data collected until 2016). A total of 64 markers were attached to the subjects according to a modified Plug-in Gait (PiG) model (9.5-mm diameter, see Appendix 2.1). 3D ground reaction forces (GRFs) were collected through force platforms embedded in the walkway (Kistler, Switzerland, sampling frequency 1500 Hz). Walking trials were only included for data processing when at least one step with clean force plate contact was achieved. Trials with occluded or missing marker data from the heel, toe, hallux or posterior superior iliac markers were excluded. In total, 90 trials were included for analysis.

2.3. Data processing

Kinematic data was pre-processed in Vicon Nexus software (v2.8.2., VICON, Oxford, UK) following the standard PiG procedure. 3-D trajectories of the posterior superior iliac (PSI), calcaneous (HEE), second metatarsal head (TOE) and hallux (HLX) were extracted and filtered through a 2nd order Butterworth filter with a cut off-frequency of 10 Hz in MATLAB (v. 2019a, Mathworks Inc.). Initially, five algorithms recommended by previous studies [40] [38] (Zeni [35], Desailly [24] , Ghoussayni [26], Hrejac and Marshall [27], Hsue [28]), and the algorithm by O'Connor et al. (due to its reported accuracy in typically developing gait) [32] were incorporated on the dataset. Of these, two algorithms [27, 28] were excluded from the study due to difficulty in identifying true events automatically (see Appendix 2.2). The algorithm by Ghoussayni et. al. ([26] was further modified to tune event detection as a function of the walking speed, according to the recommendations of [38]. The algorithms were implemented using the toe (1) and the hallux marker (2) for FO detection. For IC detection, markers positioned at the heel (1) and toe (2) were used for all 3 groups.

A visual description of the kinematic signals used in the selected algorithms is detailed in Figure 2. More information on the exclusion of algorithms can be found in supplementary information S2. The algorithm description and marker choices are summarized in Table 2.

Table 2: Definition of gait events (IC, FO) according to included algorithms. For convenience, the algorithms have been listed according to the primary author's last names.

Author	Description of IC	Markers used for IC determination	Description of FO	Markers used for FO determination
Zeni (2008)	Maximum horizontal heel position relative to sacrum	HEE, TOE	Minimum horizontal toe position relative to sacrum	TOE, HLX
Desailly (2009)	High pass filtered maximum heel position (Cut-off frequency set at 0.5* cadence)	HEE, TOE	High pass filtered minimum toe position (Cut-off frequency set at 0.5* cadence)	TOE, HLX
O' Connor (2004)	Minimum vertical velocity of virtual foot centre.	Virtual foot centre calculated between HEE and TOE	Minimum vertical velocity of virtual foot centre.	Virtual foot centre calculated between TOE and HLX
Ghoussayni (2007)	IC occurs when the sagittal velocity of the heel marker falls below a threshold of 500 m/s.	HEE, TOE	FO occurs when the sagittal velocity of the toe marker crosses a threshold of 500 m/s.	TOE, HLX
Modified Ghoussayni	IC occurs when the sagittal velocity of the heel marker falls below	HEE, TOE	FO occurs when the sagittal velocity of the heel marker	TOE, HLX

	a threshold of 0.78* walking speed		reaches a threshold of 0.66* walking speed.	
Hrejac and Marshall (2000)	IC occurs at the local maxima in the vertical acceleration of the marker and the point of zero-crossing of the jerk (as it decreases)	HEE, TOE	FO occurs at the local maxima in the horizontal acceleration of the marker and the point of zero-crossing of the jerk (as it increases)	TOE, HLX
Hsue (2007)	Minima in the horizontal acceleration of the marker	HEE, TOE	Maxima in the horizontal acceleration of the marker	TOE, HLX

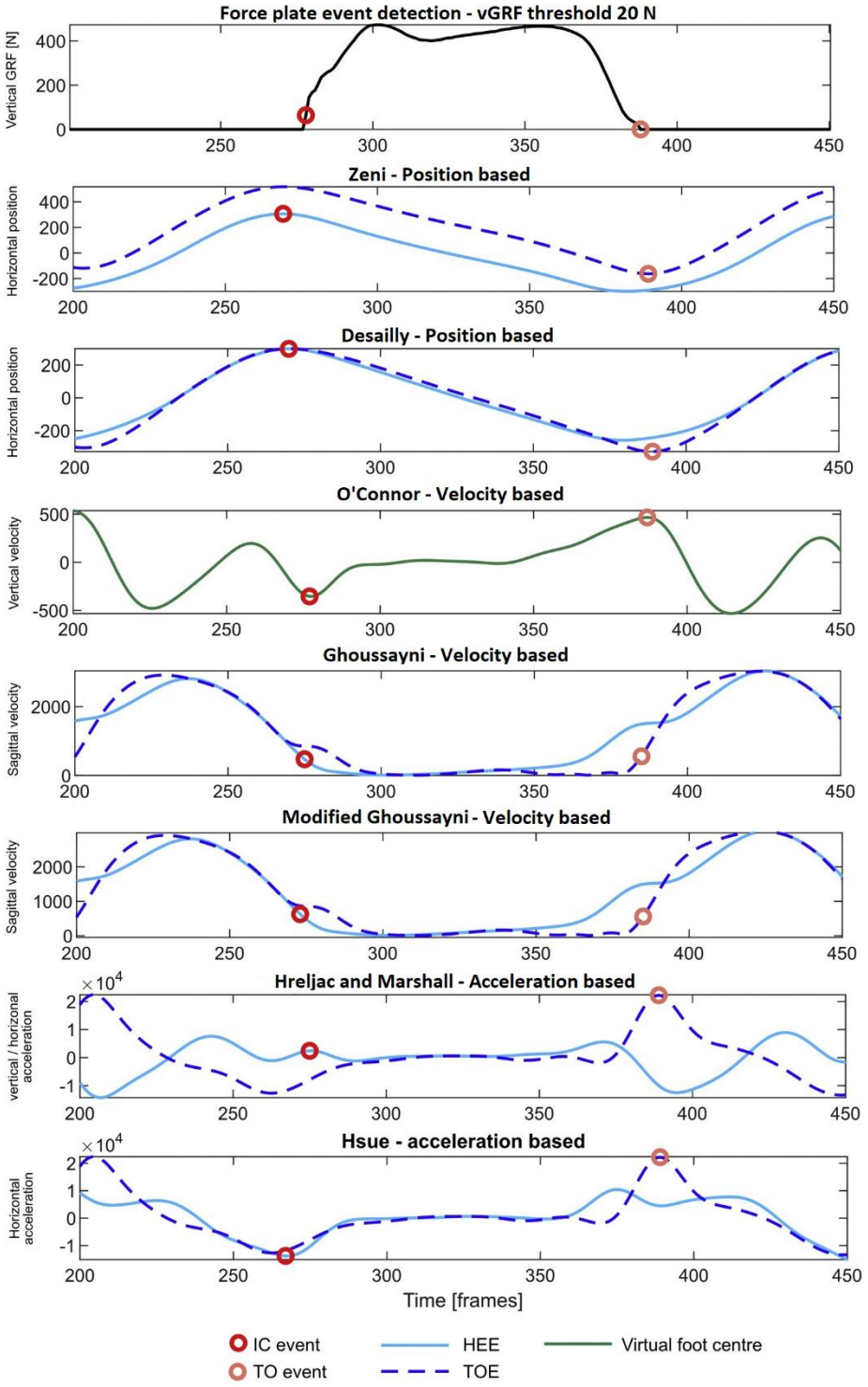


Figure 2: Signals used in the selected methods for gait event detection. GRF: ground reaction force; IC: initial contact; FO: foot off. Velocity and acceleration are in mm/s and mm/s2. Sampling rate, 150 Hz; 1 frame is equivalent to 7 ms.

Algorithms using the above described marker configurations were compared against event detection by force plates (vGRF), set at a threshold of 20 N, with the difference between the two values was expressed as an event detection error. The best-performing algorithm for each group was determined

on the basis of sensitivity and accuracy, explained below under statistical analysis. To examine efficacy for use in clinical settings, spatio-temporal parameters (step length (mm), stride length (mm), stride width (mm), step time (ms), stride time (ms), single limb support time (ms), double support time (ms) and walking speed (m/s)) were calculated using the best-performing algorithm for each group. Event detection by force plates was also compared against 3 different thresholds – 10 N, 15 N, 20 N and 2% of the maximum vGRF to determine whether a change in threshold yields significant offset values.

All data processing was performed in MATLAB (v. 2019a, Mathworks Inc.). Codes related to this report are attached in the appendix (see Appendix 2.3).

2.4 Statistical Analysis

The error values obtained for each algorithm and group were analyzed for normal distribution with a Kolmogorov-Smirnov test. Bland-Altman analyses [41, 42] were performed to compare a) the timing of gait events obtained using the implemented algorithms against the 'gold standard', and b) the STP obtained automatically and clinically, with the coefficient of determination (R^2 value) used to evaluate the linear association between the clinically and kinematically identified STP per subgroup. Specifically, we looked for R^2 values greater than 0.95. The best performing algorithm was chosen on the basis of a) sensitivity i.e. the number of subjects for which the algorithm was able to detect a gait event within +- 33 ms of the force plate-detected event; and b) accuracy, determined by the median event detection error.

3. Results

3.1 Identification of the best-performing algorithm

The Kolmogorov Smirnov test accepted the normalcy hypothesis for the error values in almost all groups except groups A and B when using the O'Connor algorithm.

For FO detection, a combination of the speed-dependent sagittal velocity approach and the hallux marker yielded the best results with median errors of 0 ms for all 3 groups. With regards to sensitivity, for groups A and C, all error values were within the accepted 33 ms threshold, whereas for group B, 96.67% of the errors were within the threshold.

In the case of IC estimation, the sagittal velocity approach (threshold: 500 mm/s) combined with the toe marker yielded the best results for Groups A (100% sensitivity, median error 0 ms) and B (96.67% sensitivity, median error 0 ms) while the heel marker provided the lowest median values for group C (96.67% sensitivity, median error 3.33 ms). Overall, all algorithms had a higher sensitivity when detecting FO than IC.

The results of the Bland Altman analysis revealed high agreement (R^2 >0.95) for every algorithm and marker combination for both IC and FO, except for the combination of the toe marker with the algorithm by O'Connor et al. The R^2 values were 0.4221 for IC estimation for group C, and 0.4590 for FO estimation in group A.

The median errors, sensitivity values for all groups studied are summarized in Figure 3 below. Further details on the comparison of the implemented algorithms can be found in supplementary information (see Appendix 3.1)

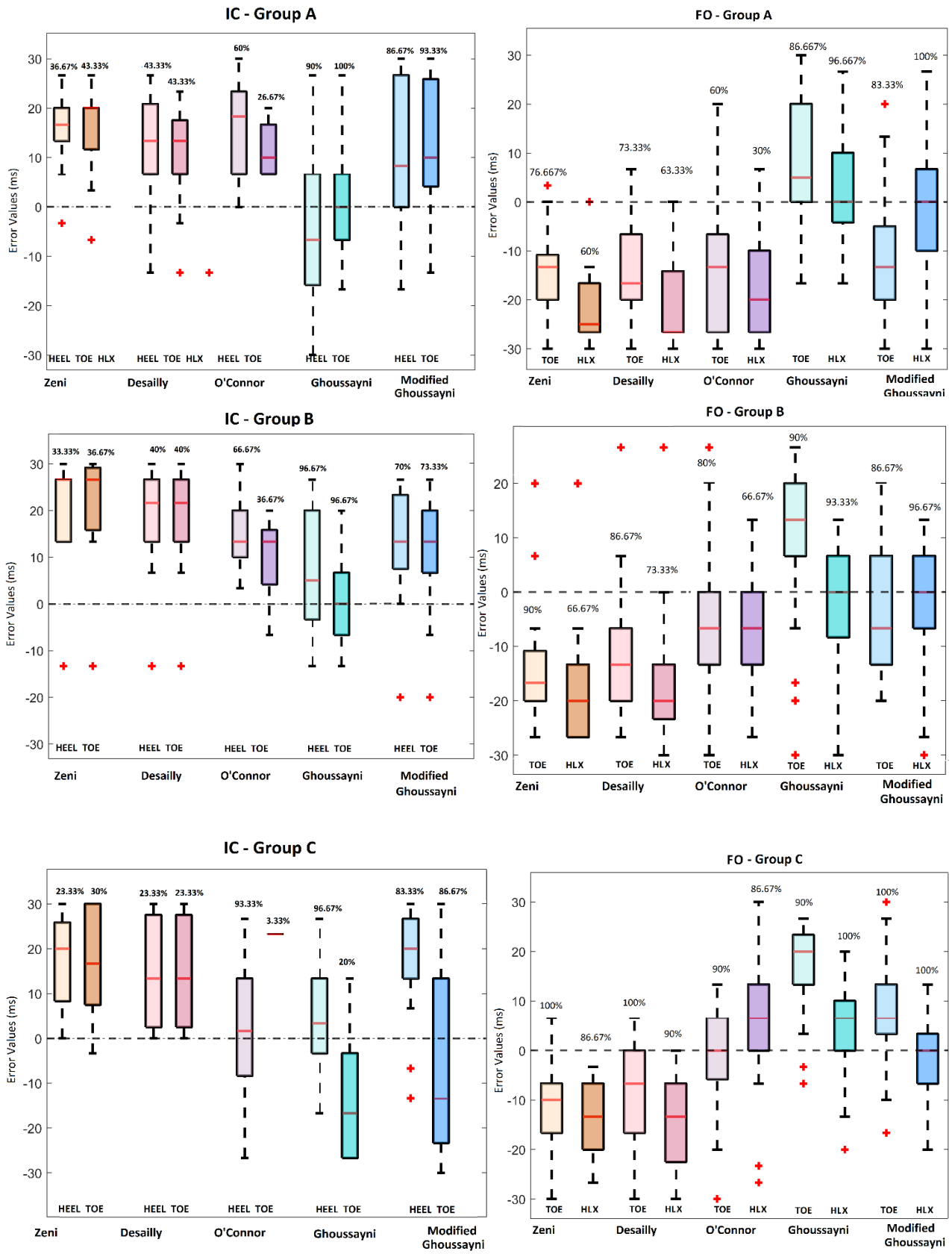


Figure 3:Box-plots representing the error distribution for the algorithms. Positive values indicate a delay in the detection of gait events, compared to force plate event detection, whereas negative values indicate that the algorithm detected events before the force plate. The sensitivity values are listed above the box plots.

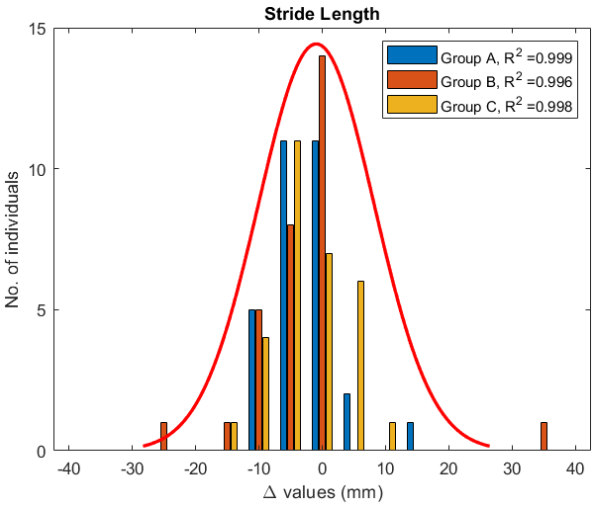
3.2 Comparison of clinically and kinematically determined spatio-temporal parameters

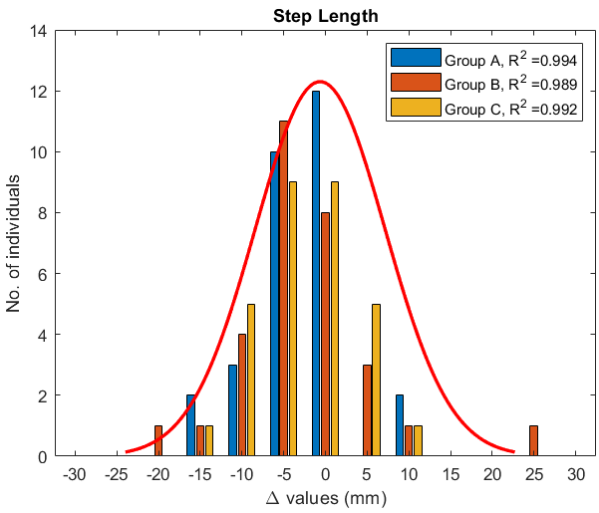
The Δ values describing the difference between the clinically and kinematically calculated spatio-temporal parameter were not normally distributed for any parameter or participant group. The median Δ values between the two methods ranged between -0.0300 to -0.312 mm for stride length, 0.021 to -0.899 mm for step length, -0.0236 to -1.541 mm for stride width, -1.667 to -6.667 ms for stride time, 0 to -3.333 ms for step time, 0 to 6.667 ms for single limb support time, 0 to -13.33 ms for double limb support time and 0.0021 to 0.0034 m/s for walking speed. Positive/negative values indicate over/underestimation of kinematically determined STP. The median and range of Δ values per participant group are listed in supplementary information S4.

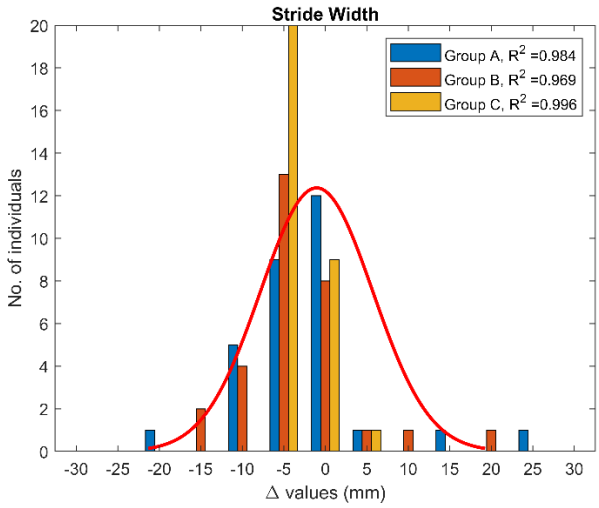
The maximum percentage differences for each computed spatio-temporal parameter were as follows: stride length, 3.13%; stride time, 6.3%; step length, 9.03% ; step time, 9.66%; stride width, 1.68%; single limb support time, 20.45%; double limb support time, 36.62% and 3.97% for walking speed.

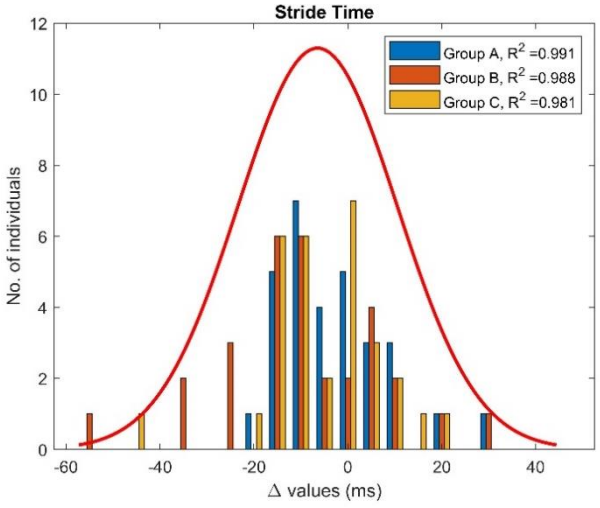
Results of the Bland Altman analysis showed high agreement (R^2>0.95) for most STP except step time for group C (R^2 = 0.923), single limb support time for which the R^2 values were 0.722 for group A, 0.875 for group B and 0.879 for group C) and double limb support time, wherein the R^2 values were 0.632 for group A, 0.921 for group B and 0.769 for group C.

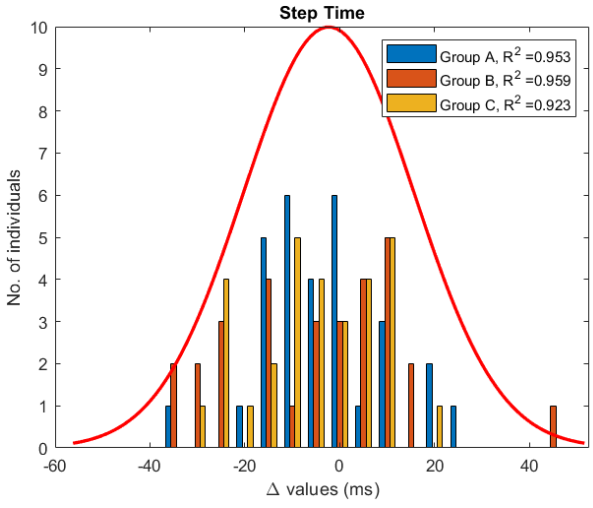
The histogram distribution and R^2 values is shown in Figure 4 below.

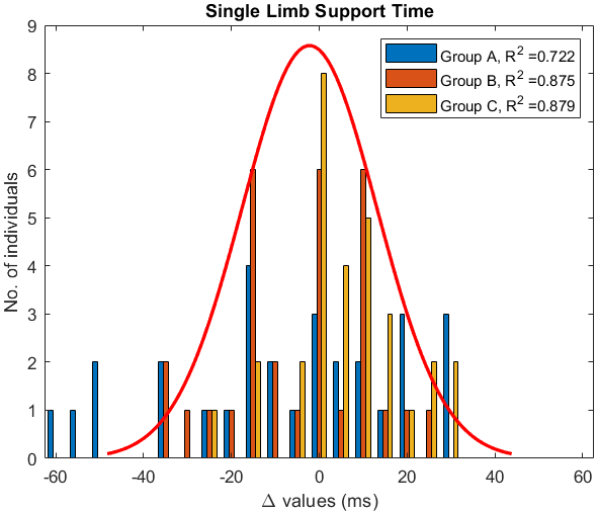

Stride Length
Group A, R2 =0.999
Group B, R2 =0.996
Group C, R2 =0.998
No. of individuals
Δ values (mm)


Step Length
Group A, R2 =0.994
Group B, R2 =0.989
Group C, R2 =0.992
No. of individuals
Δ values (mm)


Stride Width
Group A, R2 =0.984
Group B, R2 =0.969
Group C, R2 =0.996
No. of individuals
Δ values (mm)


Stride Time
Group A, R2 =0.991
Group B, R2 =0.988
Group C, R2 =0.981
No. of individuals
Δ values (ms)


Step Time
Group A, R2 =0.953
Group B, R2 =0.959
Group C, R2 =0.923
No. of individuals
Δ values (ms)


Single Limb Support Time
Group A, R2 =0.722
Group B, R2 =0.875
Group C, R2 =0.879
No. of individuals
Δ values (ms)

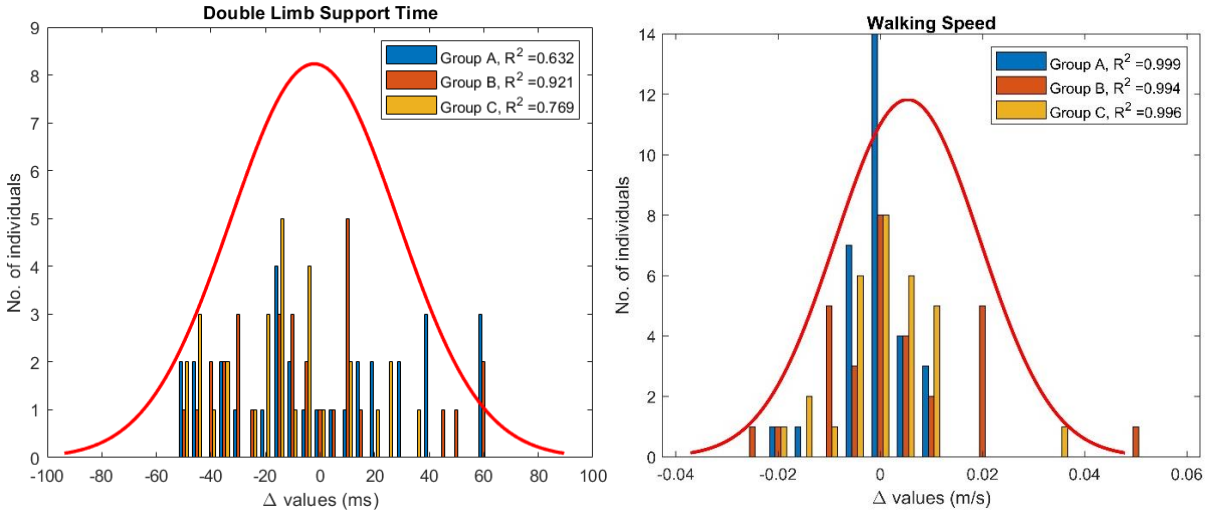


Figure 4: Histogram of the differences in STP between kinematic and clinical identification. Participants were grouped according to the region of foot that initially contacted the ground – Group A (fore-foot), Group B (flat foot or side of foot) and Group C (heel strike). Red line indicates normal distribution.

3.3 Comparison of force plate event detection at different thresholds

Comparing the IC events identified at a 20 N threshold against 10 N, 15 N, and 2% of the maximum vGRF, the mean absolute differences were 3.11 ms, 1.20 ms and 2.82 ms respectively. The maximum absolute differences observed were 20 ms, 6.66 ms and 26.67 ms respectively.

The mean absolute differences were higher in FO, with the observed values being 9.96 ms, 4.28 ms and 12.50 ms respectively. The maximum absolute differences were also higher, with values 26.67 ms, 33.33 ms and 60 ms respectively. The Bland Altman analysis revealed a high agreement between the different thresholds, with the R^2 values greater that 0.99 for ever case.

4. Discussion

The purpose of this study was to compare existent kinematic gait event detection algorithms for accuracy and sensitivity for different walking patterns (groups A (fore-foot IC), B (flat foot IC) and C (heel-strike IC)) and to determine if differences between kinematically and clinically identified (force plate or visually determined) gait events could influence clinical interpretation. Outcomes showed that accuracy and sensitivity of kinematic algorithms was dependent on a combination of algorithm and marker choice. For IC, the best-performing algorithm was the sagittal velocity approach across all 3 groups, with the toe as the preferred marker for Groups A and B, and the heel for Group C. For FO, sagittal velocity with a walking speed-dependent threshold with the hallux marker worked best across all groups. When comparing kinematically and clinically determined STP, differences of >1.7% were observed in spatial parameters despite high R^2 values (>0.95). For temporal parameters, observed R^2 values were relatively lower (>0.63), and the percentage differences in temporal parameters were especially high in the case of single and double limb support times (>20%).

4.1 Evaluation of outcomes

For IC, the accuracy and sensitivity values for the sagittal velocity approach are consistent with those reported previously. This is possibly because it was the only algorithm that considered movement in the sagittal plane, while other algorithms considered movement only in one direction. However, contrary to Bruening and Ridge's reported sensitivities of 96%+ for the two algorithms utilizing horizontal position (for equinus, steppage and slide/drag walking patterns), our observed values of sensitivity were lower. This could be attributed to the differences in sampling frequencies for kinematic data (150 or 300 Hz) used in this study to that of the publication (120 Hz), since a lot of absolute errors computed for our dataset were at 33.3 ms and hence discarded. The inclusion of the toe marker also did not improve the accuracy of IC detection for group A for any other algorithms, barring the sagittal velocity approaches, possibly because the other algorithms relied on local maxima in horizontal position or vertical velocity and hence marker choice would not severely affect event detection. It is also noteworthy that for group B, both heel and toe markers yielded similar results for the sagittal velocity approach. A possible reason for the same is that in many participants from the group, the side of the foot initially contacted the ground. Hence, we propose the investigation of markers at the proximal and distal ends of the fifth metatarsal (PMT5 and DMT5 [43]) for IC detection, as it may improve the robustness of the sagittal velocity approach.

For FO detection, inclusion of the speed-dependent threshold and the hallux marker improved identification for the sagittal velocity approach, as recommended by Bruening and Ridge [38]. However, inclusion of the hallux marker was ineffective for other algorithms. These results are not in agreement with recommendations of the publication, which expected FO detection to improve across all algorithms. This could again be explained by the reliance on local maxima/minima of the other algorithms. For group C, all algorithms had a high sensitivity value of 86%+ which could be explained by most participants having a distinct toe-off enabling FO detection from all 3 planes.

4.2 Limitations

The methodology used for the identification of the best-performing algorithm did not account for errors occurring due to marker misplacement and marker trajectories. Marker misplacement occurs due to anatomical deformations or difficulties in identifying underlying anatomical landmarks. Marker trajectory errors are influenced by the number of cameras, calibration volume and calibration procedures, and could lead to errors upto 1.7 mm [44]. A combination of both could exacerbate the differences in kinematic and kinetic event detection, and hence influence identification of the best-performing

algorithm. We tried to minimize the effect of marker displacement by only including data measured by trained experts from the gait laboratory.

Furthermore, the reference clinical method for gait event detection (force plate identification) is threshold dependent. Despite the high R^2 value (>0.99), absolute mean differences in the thresholds were greater than 1.2 ms for IC, and 4.2 ms for FO. Since the choice of threshold can influence event detection and hence calculation of STP, this suggest the need for further research in identifying the most suitable threshold for pediatric pathological populations.

4.3 Clinical relevance

To evaluate whether differences in clinically and kinematically identified STP influence clinical interpretation, the obtained differences were compared to previously reported values of clinically meaningful differences. Clinically meaningful changes for step width (3- 8 mm), step length (2.4- 6.1 mm), stance time (5-14 ms) and swing time (3- 9 ms) were reported in ambulatory adults over the age of 70 [45]. Comparing and extrapolating these values to the maximum differences reported in this study, clinical interpretation is likely to be affected if kinematic algorithms are implemented in a clinical setting, especially in the case of temporal parameters. However, further research is needed to establish values of clinically meaningful differences for STP for CP gait.

It is also important to consider that, while in this study, results were computed for one gait cycle, these differences could increase over multiple consecutive gait cycles. Therefore, evaluating the intra-subject reliability in the computation of STP using the two methods for multiple gait cycles is recommended for evaluating kinematic algorithms for clinical use. Furthermore, determining the influence of these differences on the determination and interpretation of the Movement Analysis Profile is also recommended.

4.4 Conclusion

Current findings suggest that overall, the sagittal velocity approach for gait event detection is most robust to a wide variety of walking patterns, and while the speed-dependent threshold improved FO detection, further research is needed to establish a better threshold for IC estimation. Evaluation of the resultant STP showed that kinematic gait event algorithms cannot yet be implemented in a clinical setting due to the differences possibly crossing clinically meaningful differences and hence influencing clinical interpretation. Furthermore, it also seems that the 33 ms threshold defined by previous studies as an acceptable error for kinematic algorithms is too high, considering the high differences observed between kinematic and clinical STP. Therefore, we recommend investigating the resultant spatio-temporal values obtained from gait events determined from machine learning algorithms utilizing kinematic data, as they have been reported to detect gait events within a 10.7 ms window and could be robust to a variety of pathological gait patterns [46]. Overall, our findings suggest that correct selection of the marker-algorithm choice for automatic gait event detection could ensure that misinterpretation of STPs is avoided.

5. References

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Appendix

1. Background Theory

1.1 Gait Cycle

Walking can be described as a "a cyclic pattern of body movements which advances an individual's position". A gait cycle is usually described in context of one leg, termed as the ipsilateral leg. It begins at the initial contact or initial contact of the ipsilateral leg and continues until the initial contact of the same leg in preparation for the next step to occur [47].

Typically, a gait cycle can be divided into two main phases-the stance phase i.e. the period the ipsilateral leg is in contact with the ground and bears the body weight which comprises of approximately 60% of the entire cycle, and the swing phase wherein the period the limb is not in contact with the ground, comprising of 40% of the cycle. Two events occur during the gait cycle – **Initial Contact** (which defines the start and end of a gait cycle) and **Foot Off** (occurring at the end of the stance phase), which determine the length and time of the gait phases.

Therefore, the gait cycle can be divided into the following phases, as described in figure 1 below.

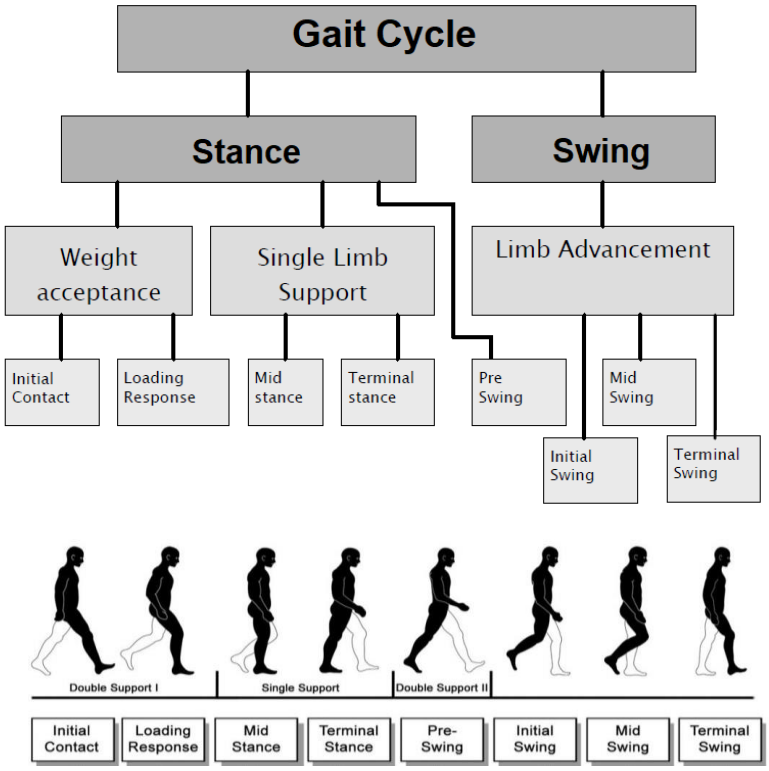

Figure 4: Phases of the gait cycle. Adapted from [48].

Typically, the timing of one gait cycle is normalized as a percentage (100%), and gait events and phases are described as occurring at a percentage of the gait cycle. The phases and events of a gait cycle are described as follows:

Ipsilateral Initial contact (0% and 100% of the gait cycle): The point in time in stance phase when the ipsilateral foot comes in contact with the ground.

Loading Response (0-10%): The first period of **double support** (i.e. the period both legs are in contact with the ground) wherein the body weight is transferred from one lower limb to another.

Contralateral Foot-Off (10%): The point in time in the stance phase when the contralateral foot leaves the ground.

Single Support phase (10-50%): Consists of the **mid-stance** phase (10%-30%), which is described as a period where the ipsilateral limb moves from a shock-absorption to a stability function, and the **terminal stance** (30-50%) which starts with the heel rise of the ipsilateral leg, and is defined as a period where the body weight progresses beyond the ipsilateral foot.

Contralateral Initial contact (50%): The point in time in the stance phase when the contralateral leg touches the ground.

Pre-Swing (50-60%): The second period of **double support** wherein the ipsilateral limb is prepared for swing.

Ipsilateral Foot-Off (60%): The point in time wherein the ipsilateral leg leaves the ground. This event also marks the beginning of the swing phase.

Initial Swing (60-73%): This phase is defined as the period of limb advancement and foot clearance.

Mid-Swing (73% to 87%): The point in time when the swinging limb is forward. The functional objectives in this phase are again foot clearance and limb advancement.

Terminal Swing (87-100%): The last phase of a gait cycle which is defined by a period of deceleration of the ipsilateral leg and preparation for its next initial contact.

1.2 Spatio-temporal gait parameters

Further characterisation of human walking can be done with distance or spatial measurements such as step length and stride length. When these are combined with temporal parameters, additional descriptors of gait characteristics such as walking velocity and cadence can be defined. Below is a short description of the most common spatio-temporal gait parameters that help provide an objective analysis of gait [12].

Step length (m) is defined as the longitudinal distance between the two feet generally. It is the distance from a point of initial contact of one foot with the ground to the following occurrence of the same point of contact of the other foot with the ground (Figure 2).
In normal walking, **the right step** length is defined as the distance measured from
heel strike of the left foot to heel strike of the right foot. Consequently, the **left step length** is defined as the distance measured from heel strike of the right foot to heel strike of the left foot.

Step time (s) is the time taken for one step and is measured as the period of time from an event of the ipsilateral foot to the following same event of the contralateral foot.

Stride length (m) is the distance covered during a complete gait cycle, and extends from the initial contact of the ipsilateral foot to the following initial contact of the same foot. It is a summation of the right and left step lengths (Figure 2).

Stride time (s) is the time taken to complete one stride.

Step width (mm) is defined as the mediolateral distance between the feet which is typically measured from the ankle joint centre.

Single limb support time (ms) is the amount of time that passes during the period when only one limb is in contact with the ground during a gait cycle.

Double limb support time (ms) is the time in the gait cycle when both feet are in contact with the ground.

Cadence (steps/min) is the number of steps taken during a given amount of time.

Walking velocity (m/s) is the rate of change of linear displacement along the direction of progression measured over one or more strides.

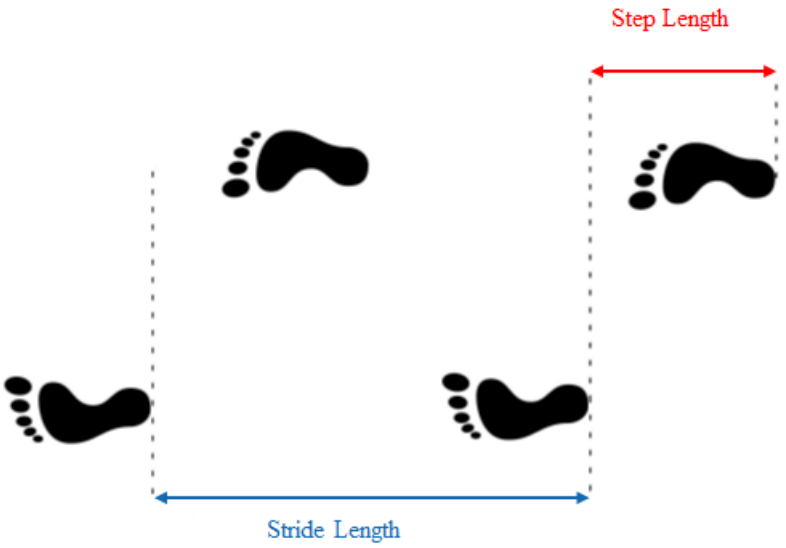

Figure 5: Depiction of stride and step lengths

1.3 The role of gait parameters in the treatment and management of CP

While STP serve as indicators of walking behaviour, they do not consider the motion of individual joints. For example, it is possible for children exhibiting mild equinus gait to walk with a comparative walking speed as that of a TD child [49]. Therefore, diagnostic tools such as the Gait Deviation index and the Gilette Gait index make use of joint kinematics in combination with STP order to quantify the degree of deviation from TD gait [50].

As an example of how gait parameters are used in the diagnosis and management of cerebral palsy, below is an example report retrieved from a clinical gait report of child diagnosed with cerebral palsy, who had undergone clinical gait analysis at the University of Basel Children's Hospital, Switzerland in 2018 (Figure 3). As seen in the figure, both spatio-temporal and kinematic parameters were extracted, ensemble-averaged and compared to controls in order to quantify gait abnormalities. Similarly, such figures are also generated when the patient is fitted with an orthoses, after the injection of BTX, and post-surgeries that target muscle and bony abnormalities. STP are also used to gauge stride-to-stride variability occurring in a subject. Therefore, while not absolute, STP nevertheless assist clinicians in assessing and characterising functional gait performance.

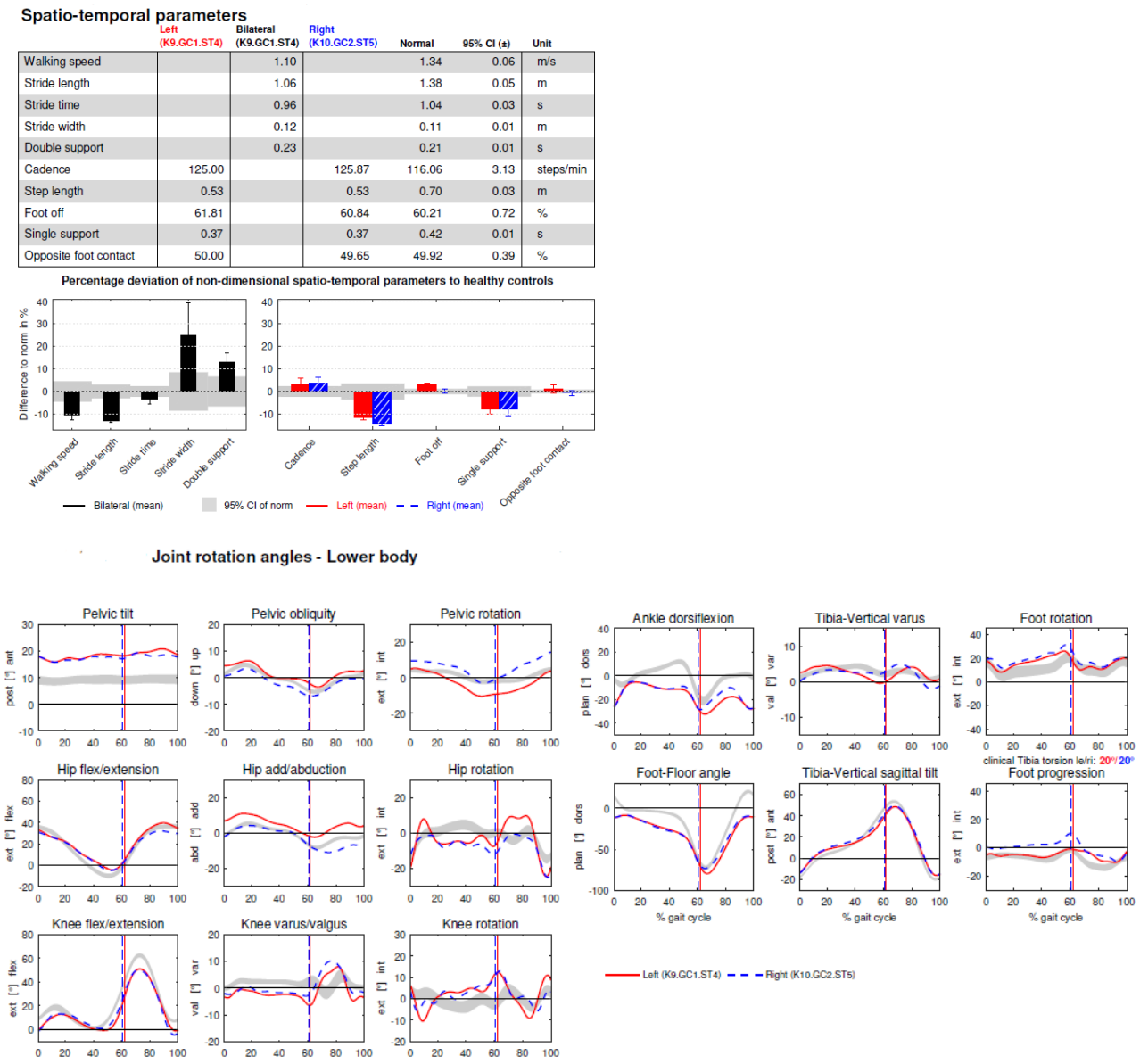

Figure 6: Example of data in a clinical gait analysis report for bilateral spastic cerebral palsy: a) Spatio-temporal parameters; b) Joint kinematics

2. Supplementary information - Methods

2.1 Marker List

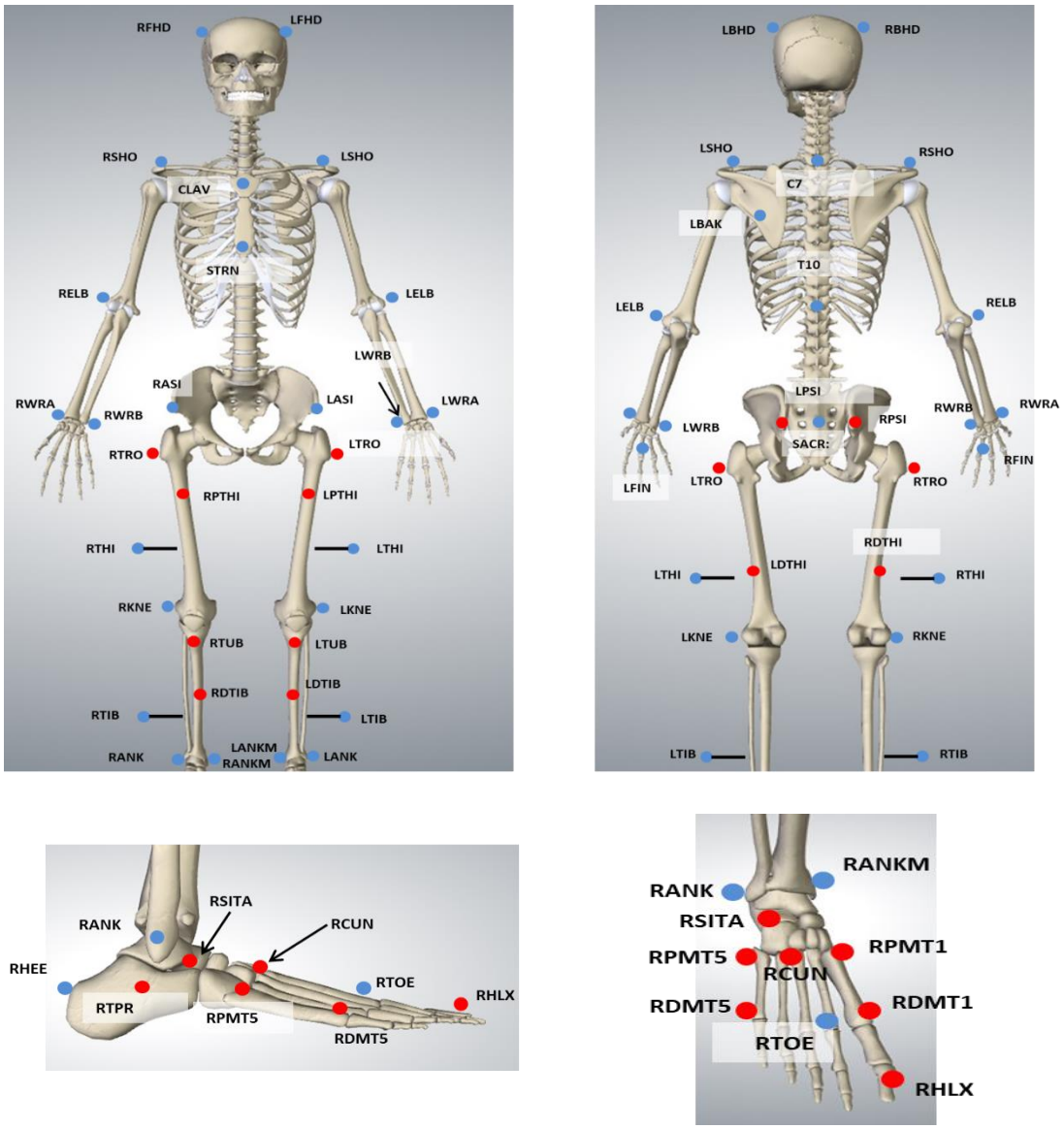

Figure 7: Marker list

2.2 Plug-In Gait Model:

- LFHD/RFHD: Left/Right front head
- LBHD/RBHD: Left/Right Back Head
- LSHO/RSHO: Left/Right Shoulder (acromio-navicular joint)
- CLAV: Where the clavicle meets the sternum
- C7: 7th Cervical Vertebra
- LBAK: Left Back
- T10: 10th Thoracic Vertebra
- STRN: Xiphoid process of the Sternum
- LELB/RELB: Left/Right Elbow (lateral epicondyle)
- LWRA/RWRA: Left/Right Wrist thumb side
- LWRB/RWRB: Left/Right Wrist pinkie side
- LFIN/RFIN: Left/Right Dorsum of the hand

- LASI/RASI: Left/Right Anterior Superior Iliac
- LPSI/RPSI: Left/Right Posterior Superior Iliac
- SACR: Sacrum (middle of the LPSI/RPSI)
- LTHI/RTHI: Left/Right lateral Thigh
- LKNE/RKNE: Left/Right Knee
- LTIB/RTIB: Left/Right lateral Tibia
- LANKM/RANKM: Left/Right Medial Malleoli
- LANK/RANK: Left/Right lateral Malleoli
- LHEE/RHEE: Left/Right Heel (same level as the TOE marker)
- LTOE/RTOE: Left/Right Metatarsal II head

Additional Markers:

- LTRO/RTRO: Left/Right Trochanter Major
- LDTHI/RDTHI: Left/Right Distal posterior Thigh
- LPTHI/RPTHI: Left/Right Proximal anterior Thigh
- LTUB/RTUB: Left/Right Tibial Tuberosity
- LDTIB/RDTIB: Left/Right Medial Tibial Edge
- LSITA/RSITA: Left/Right Sinus Tarsi
- LPTR/RPTR: Placed under ankle, lateral on the calcaneus
- LPMT5/RPMT5: Left/Right Metatarsal V base
- LPTM1/RPTM1: Left/Right Metatarsal I base
- LCUN/RCUN: Placed between Metatarsal I and V basis
- LDMT5/RDMT5: Left/Right Metatarsal V head
- LDMT1/RDMT1: Left/Right Metatarsal I head
- LHLX/RHLX: Left/Right Hallux

2.2 Explanation for exclusion of acceleration-based kinematic algorithms

Two algorithms, recommended by previous comparison studies, were excluded from the study due to low sensitivity. The two algorithms and the reason for their exclusion have been detailed below:

1. **Hreljac and Marshall (2000)** developed an algorithm that uses local maxima in the vertical acceleration and the point of zero-crossing of the jerk (as it decreases) of the heel marker to determine the location of IC. TO is computed as the local maxima in the horizontal acceleration and the point of zero-crossing of the jerk (as it increases) of the toe marker. The below example illustrates the difficulty in automatic isolation of these peaks.
   3-D kinematic data was taken from a participant belonging to group C (participants with a defined heel strike). The below figure plots the vertical acceleration and the jerk of the heel marker against frame number. Please note that the units of acceleration have been scaled by a factor of 10 for visual clarity.

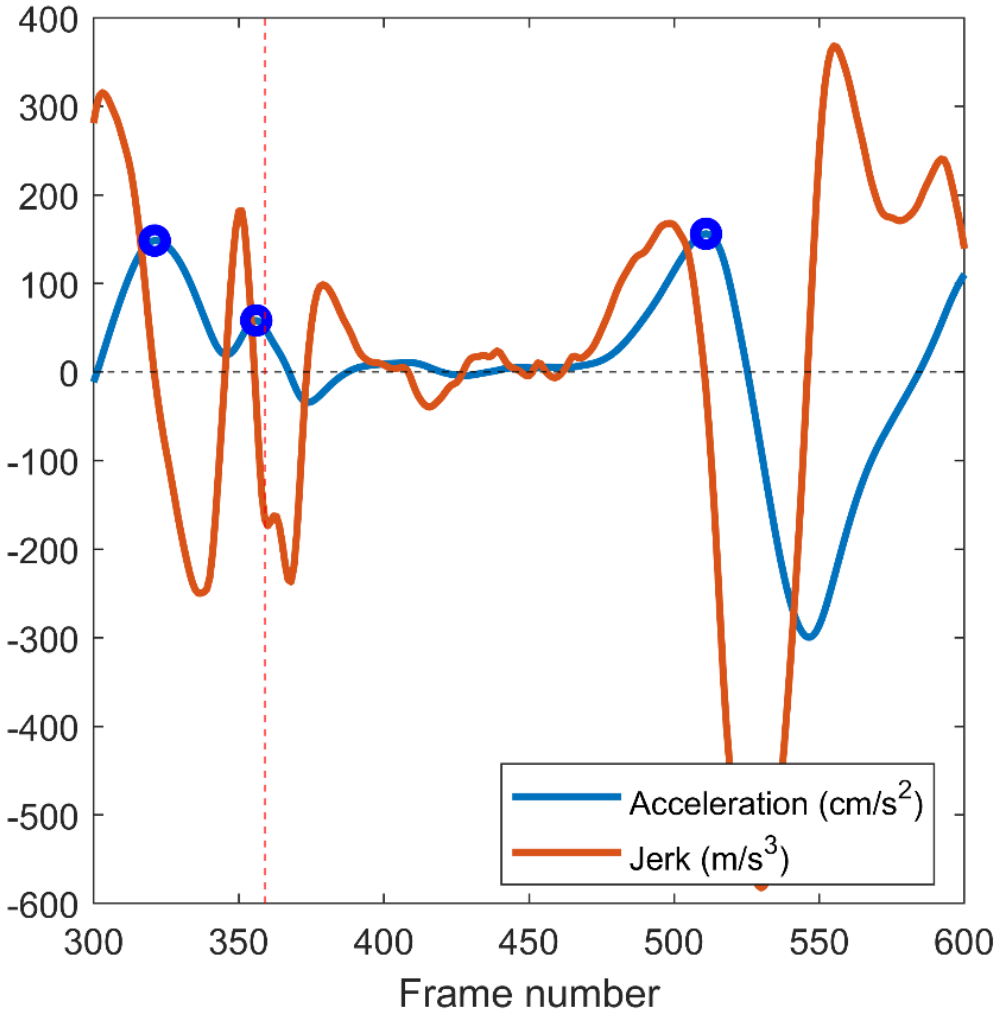

Figure 8: Detection of false positives for IC.

As is evident from the figure, the algorithm detects 3 possible instances of local maxima and zero-crossing of jerk, despite the true IC occurring only at frame 356 (dashed red vertical line). Similarly, the algorithm detected multiple false instances of TO, especially in participants from Group A and B. Therefore, the algorithm was excluded due to high false positives, and hence, difficulty in automation.

2. **Hsue et al. (2007)** recommended the minima and the maxima of the horizontal acceleration of the toe marker for IC and TO detection respectively. While the algorithm was able to detect distinct peaks for some individuals, for other individuals, there were often 2 peaks occurring close to the true event. While shorter peaks could be eliminated by setting appropriate thresholds for peak height per individual, due to the high range of differences in the heights of the maximum horizontal acceleration peaks across individuals, this process could not be automated. Hence, the algorithm was excluded due to feasibility of incorporating in a clinical setting.

2.3 Codes for data analysis

All codes used in the thesis are available at the following link:

https://github.com/Roosje95/AGED_gait-event-detection

2.3.1 Generation of result matrices for all algorithms

Main_Algorithms

```
% Needed to run:
% 1. btk installed [http://biomechanical-toolkit.github.io/]
% 2. Matlab functions

% Outcomes: after running the code table1 reports the frame on which
event
% is detected per method, if you want ms instead of frame



close all;
clc;
```

Initial set-up

```
% TestDIR=uigetdir([], ?Select the folder with the test data?); test
out to
% automatic select the folder
btkFolder     =
'P:\Projects\NCM_CP\read_only\Codes\Codes_Basics\Codes_UKBB\btk';%ad
d location were btk folder from biomechanical toolkit is saved
addpath(btkFolder);
addpath('P:\Projects\NCM_CP\project_only\NCM_CP_GaitEventDetection\M
anuscript\G&P_v1\GitLab_Codes'); %add path to where zyou saved our
matlab functions
addpath('P:\Projects\NCM_CP\project_only\NCM_CP_GaitEventDetection\M
anuscript\G&P_v1\GitLab_Codes\example_c3d'); %add path towards c3d
files

table1=readtable('Trails_info.xlsx');% replace Trails_Info.
cd
P:\Projects\NCM_CP\project_only\NCM_CP_GaitEventDetection\Manuscript
```

```
\G&P_v1\GitLab_Codes\example_c3d %go to folder in which c3d files
are saved
```

Initialize variables

```
c3dlist=table1{:,1}; % names of c3d files which you would like to
evaluate
FP = table1{:,2}; % numbers refering to which force platform was hit
during each trail (c3d file)
Side = table1{:,3}; % indicates is this trail is with force plate
hit on left or right side

% for-loop to perform calculations for all c3d files
for i=1:length(c3dlist)
    c3dfile = c3dlist(i);
    btkData=btkReadAcquisition(c3dfile{1,1});
    btkClearEvents(btkData);
    metadata=btkGetMetaData(btkData);
    ff=btkGetFirstFrame(btkData);
    Markers = btkGetMarkers(btkData);
    angles=btkGetAngles(btkData);
    f = btkGetPointFrequency(btkData);
    freq(i,1)=f;

    n = btkGetPointFrameNumber(btkData);
    FPnumber=FP(i);
```

Determine Force Plate events

```
    temp = btkGetGroundReactionWrenches(btkData);
    for t = 1:length(temp(FPnumber).F(:,3))
        if temp(FPnumber).F(t,3) < 20 % 15 N threshold on Z axis
(vertical)
            temp(FPnumber).F(t,:) = 0;
        end
    end
    Forces = interpft(temp(FPnumber).F(:,3),n); % Z axis (vertical)
    mFS = NaN;
    if min(find(Forces>1e-4))
        mFS = min(find(Forces>1e-4));
    end
    if ~isnan(mFS)
```

```
        mFO = min(find(Forces(mFS+20:end)<1e-4)+mFS+20-1);
    else
        mFO = NaN;
    end
    mFO_ms=(mFO/f)*1000    ;
    mFS_ms=(mFS/f)*1000    ;
```

Define Markers

```
    if (strcmp(Side{i,1},'Left') ||strcmp(Side{i,1},'left'))
        heelMarkerName = 'LHEE';
        toeMarkerName = 'LHLX';
    else
        heelMarkerName = 'RHEE';
        toeMarkerName = 'RHLX';
    end

    % Zeni Markers
    sacralMarkerName='SACR';
    LPSI='LPSI';
    RPSI='RPSI';
    LASI='LASI';
    RASI='RASI';
```

Correct for Walking Direction

```
    SACR = Markers.SACR;

    % delete zeros at the beginning or end of an trial

    dir_i = abs(SACR(end, 1) - SACR(1, 1));
    dir_j = abs(SACR(end, 2) - SACR(1, 2));

    walkdir = 1;  % x is walkdir

    if (dir_i < dir_j)
        walkdir = 2;  % y is walkdir
    end

    % pos. or neg. direktion on axis
    sgn = sign(SACR(end, walkdir) - SACR(1, walkdir));
    walkdir = walkdir * sgn;
```

```
    [Markers_Corrected]=f_rotCoordinateSystem(Markers, walkdir, 1);
    gaitAxis=1;
    verticalAxis=3;
```

Filtering Markers and preprocessing

```
    [B,A] = butter(4,6/(f/2),'low');
    velfootcentre=[];
    Hvelocity_sagittal= [];
    Fvelocity_sagittal= [];
    Hvelocity_horizontal=[];
    Fvelocity_horizontal=[];
    Hvelocity_vertical=[];
    Fvelocity_vertical=[];
    filtheelmarker = [];
    Hacc_sag=[];
    Hacc_hor=[];
    Hacc_ver=[];
    Facc_sag=[];
    Facc_hor=[];
    Facc_ver=[];
    filttoemarker = [];
    filtsacrmarker=[];
    filtRPSI=[];
    filtLPSI=[];
    filtRASI=[];
    filtLASI=[];
    filtheelmarker(:,:,1) = filtfilt(B, A,
Markers_Corrected.(heelMarkerName));
    filttoemarker(:,:,1) = filtfilt(B, A,
Markers_Corrected.(toeMarkerName));
    filtsacrmarker(:,:,1) = filtfilt(B, A,
Markers_Corrected.(sacralMarkerName));
    filtLPSI(:,:,1) = filtfilt(B, A, Markers_Corrected.(LPSI));
    filtRPSI(:,:,1) = filtfilt(B, A, Markers_Corrected.(RPSI));
    filtLASI(:,:,1) = filtfilt(B, A, Markers_Corrected.(LASI));
    filtRASI(:,:,1) = filtfilt(B, A, Markers_Corrected.(RASI));

    ysacr=filtsacrmarker(:,gaitAxis,:);
    zsacr=filtsacrmarker(:,verticalAxis,:);
    yheel=filtheelmarker(:,gaitAxis,:);
    ytoe=filttoemarker(:,gaitAxis,:);
```

```
    %Determine approximate walking speed
    [vel,time]=f_approxVelocity(ysacr,zsacr,f);
    vel2=vel/100;
```

Kinematics

```
    %Calculate velocity of markers
    for t = 1:n-1
        Hvelocity_sagittal(t) = sqrt((filtheelmarker(t+1,gaitAxis)-
filtheelmarker(t,gaitAxis))^2+(filtheelmarker(t+1,verticalAxis)-
filtheelmarker(t,verticalAxis))^2)/(1/f);
        Fvelocity_sagittal(t) = sqrt((filttoemarker(t+1,gaitAxis)-
filttoemarker(t,gaitAxis)).^2+(filttoemarker(t+1,verticalAxis)-
filttoemarker(t,verticalAxis)).^2)/(1/f); % mm/s
        Hvelocity_horizontal(t)=(filtheelmarker(t+1,gaitAxis)-
filtheelmarker(t,gaitAxis))/(1/f);
        Fvelocity_horizontal(t)=(filttoemarker(t+1,gaitAxis)-
filttoemarker(t,gaitAxis))/(1/f);
        Hvelocity_vertical(t)=(filtheelmarker(t+1,verticalAxis)-
filtheelmarker(t,verticalAxis))/(1/f);
        Fvelocity_vertical(t)=(filttoemarker(t+1,verticalAxis)-
filttoemarker(t,verticalAxis))/(1/f);
    end

    %Calculate accelerations
    %
    for j = 1:size(Hvelocity_sagittal,2)-1
        Hacc_sag(j)=(Hvelocity_sagittal(j+1)-
Hvelocity_sagittal(j))/(1/f);
        Hacc_hor(j)=(Hvelocity_horizontal(j+1)-
Hvelocity_horizontal(j))/(1/f);
        Hacc_ver(j)=(Hvelocity_vertical(j+1)-
Hvelocity_vertical(j))/(1/f);
    end
    for j = 1:size(Fvelocity_sagittal,2)-1
        Facc_sag(j)=(Fvelocity_sagittal(j+1)-
Fvelocity_sagittal(j))/(1/f);
        Facc_hor(j)=(Fvelocity_horizontal(j+1)-
Fvelocity_horizontal(j))/(1/f);
        Facc_ver(j)=(Fvelocity_vertical(j+1)-
```

```
Fvelocity_vertical(j))/(1/f);
    end
```

Kinematic Algorithm_Zeni

```
[eFO_zeni_frame,eFS_zeni_frame,eFO_zeni_ms,eFS_zeni_ms]=f_zeni_event
(f,yheel,ytoe,ysacr,mFO,mFS);
```

Kinematic Algorithm_Ghoussayni

```
    vThreshold=500;
    FS=[];
    FO=[];
    [FS_G,FO_G] =
f_Ghoussayni_500(filtheelmarker,filttoemarker,gaitAxis,verticalAxis,
n,f);
    [eFO_G_frame,eFS_G_frame,eFO_G_ms,eFS_G_ms]=f_mG_event(FO_G,
FS_G,mFO,mFS,f);
```

Kinematic Algorithm_ModifiedGhoussayni

```
[FS_mG,FO_mG]=f_Ghoussayni_variablethreshold(filtheelmarker,filttoem
arker,gaitAxis,verticalAxis,n,f,vel2);

[eFO_mG_frame,eFS_mG_frame,eFO_mG_ms,eFS_mG_ms]=f_mG_event(FO_mG,
FS_mG,mFO,mFS,f);
```

Kinematic algorithm_Desailly

```
    [B,A] = butter(4,(7/(f/2)));
    filttoemarker_d = filtfilt(B, A,
Markers_Corrected.(toeMarkerName));
    filtheelmarker_d = filtfilt(B, A,
Markers_Corrected.(heelMarkerName));
    fhm2 = filttoemarker_d(1:end,gaitAxis);
    fhm=filtheelmarker_d(1:end,gaitAxis);
    [z,p,k] = butter(4,0.5/(f/2),'high');
    [sos,g] = zp2sos(z,p,k);
    L_toe_high  = filtfilt(sos,g,fhm2);
    L_heel_high=filtfilt(sos,g,fhm);
```

```
    [location_d_TO,index_d_TO]=findpeaks(-L_toe_high);
    [location_d_FS,index_d_FS]=findpeaks(L_heel_high);

    [eFS_D_frame,eFS_D_ms]=
f_desailly_event(L_heel_high,mFS,f,location_d_FS,index_d_FS );
    [eFO_D_frame,eFO_D_ms]=
f_desailly_event(L_heel_high,mFO,f,location_d_TO,index_d_TO );
```

Kinematic algorithm_O'Connor

```
    zheel= filtheelmarker_d(:,verticalAxis);
    ztoe=filttoemarker_d(:,verticalAxis);
    zCoordfootcentre = 1/2 * (zheel + ztoe);
    for j=1:length(zheel)
        footcentre(j)=(zheel(j)+ztoe(j))/2;
    end
    p=1;
    for j=1:length(ztoe)-1
        velfootcentre(p)=(footcentre(j+1)-footcentre(j))/(1/f);
        p=p+1;
    end

    [eFO_oconnor_frame,eFS_oconnor_frame,eFO_oconnor_ms,
eFS_oconnor_ms]=f_oConnor_event(f,zheel,velfootcentre,mFS,mFO);

%     %% Kinematic algorithm_Hreljac
%     threshold=0.3 * max(Facc_hor);
%     [vFS_hreljac,FSindex_hreljac]=findpeaks(Hacc_ver);
%     [vFO_hreljac,FOindex_hreljac]=findpeaks(Facc_hor);
%
%
[eFO_hreljac_frame,eFS_hreljac_frame,eFO_hreljac_ms,eFS_hreljac_ms]=
f_hreljac_event(Hacc_hor, Facc_hor,Hacc_ver, Facc_ver,mFO,mFS,f);
%
```

Collect outcomes in table

```
    table1.FP_FS(i)= mFS;
    table1.Zeni_FS(i)= eFS_zeni_frame;
    table1.Ghoussayni_FS(i)= eFS_G_frame;
    table1.mGhoussayni_FS(i)= eFS_mG_frame;
    table1.Desailly_FS(i)= eFS_D_frame;
```

```
    table1.Oconnor_FS(i)= eFS_oconnor_frame;
    table1.FP_FO(i)= mFO;
    table1.Zeni_FO(i)= eFO_zeni_frame;
    table1.Ghoussayni_FO(i)= eFO_G_frame;
    table1.mGhoussayni_FO(i)= eFO_mG_frame;
    table1.Desailly_FO(i)= eFO_D_frame;
    table1.Oconnor_FO(i)= eFO_oconnor_frame;
```

```
end %FOR-loop c3d files

disp(table1)% show results in command Window
```

2.3.2 Rotating coordinate systems for standardizing the walking direction across all subjects to be analysed

```
%Change coordinate system from vicon xyz to x'y'z'


function [xyz] = f_rotCoordinateSystem(xyz, walkdir, i)

    walksgn = 1;  % case x+
    saggdir = 2;
    saggsgn = 1;

    if (walkdir < -1)

        walkdir = 2;  % case y-
        walksgn = -1;
        saggdir = 1;
        saggsgn = 1;


    elseif (walkdir < 0)

        walkdir = 1;  %case x-
        walksgn = -1;
        saggdir = 2;
        saggsgn = -1;

    elseif (walkdir > 1)
```

```
        walkdir = 2;  % case y+
        walksgn = 1;
        saggdir = 1;
        saggsgn = -1;


    end %IF (walkdir < -1)

    tm = fieldnames(xyz);
    nm = length(tm);

    for j = 1 : nm
        xyz(i).(tm{j}) = [walksgn * xyz(i).(tm{j})(:, walkdir) ...
                          saggsgn * xyz(i).(tm{j})(:, saggdir) ...
                                    xyz(i).(tm{j})(:, 3)];
    end %FOR j = 1 : nm

end  %FUNCTION f_rotCoordinateSystem
```

2.3.3 Approximating the walking velocity of the subject.

```
function [vel,time]=f_approxVelocity(Xmid, Ymid, SF)
%Calculates velocity per track

%Xmid=X_coord from SACR marker
%Ymid=Y_coord from SACR marker

start=(1);
stop=length(Xmid);

%make sure there are no NaN
%start and stop are the same for X and Y
Xstop=Xmid(stop);
while isnan(Xstop) ;
    stop=stop-1;
    Xstop=Xmid(stop);
end

Xstart=Xmid(start);
```

```
while isnan(Xstart);
    start=start+1;
    Xstart=Xmid(start);
end

%calculate the spatial difference
Xdiff=abs(Xstop-Xstart);
Ydiff=abs(Ymid(stop)-Ymid(start));
diff_mm=sqrt(Xdiff^2+Ydiff^2);
diff_mm=diff_mm*100;
time=(abs(stop-start))/SF;

%velocity [mm/s]
vel=diff_mm/time;
```

2.3.4 Ghoussayni Algorithm

```
function [FS,FO] =
f_Ghoussayni_500(Hmarkers,Fmarkers,gaitAxis,verticalAxis,n,f)

% ------------------------------------------------------------------
-------
% Initialisation
% ------------------------------------------------------------------
-------
FS = [];
FO = [];

% ------------------------------------------------------------------
-------
% Calculate the 2D velocity of the markers in the plane containing
% gait (V1) and vertical (V2) axes
% ------------------------------------------------------------------
-------
for t = 1:n-1
    % Hindfoot markers velocity
    for i = 1:size(Hmarkers,3)
        Hvelocity(t,i) = sqrt((Hmarkers(t+1,gaitAxis,i)- ...
            Hmarkers(t,gaitAxis,i))^2+ ...
            (Hmarkers(t+1,verticalAxis,i)- ...
            Hmarkers(t,verticalAxis,i))^2)/ ...
```

```
            (1/f);
    end
    % Forefoot markers velocity
    for i = 1:size(Fmarkers,3)
        Fvelocity(t,i) = sqrt((Fmarkers(t+1,gaitAxis,i)- ...
            Fmarkers(t,gaitAxis,i)).^2+ ...
            (Fmarkers(t+1,verticalAxis,i)- ...
            Fmarkers(t,verticalAxis,i)).^2)/ ...
            (1/f);
    end
end

% -------------------------------------------------------------------
-------
% Calculate the 2D velocity of the markers barycenter in the plane
% containing gait (V1) and vertical (V2) axes (ONLY FOR CASE 3)
% -------------------------------------------------------------------
-------
for t = 1:n
    % Hindfoot markers barycenter
    Hbarycenter(t,1) = sum(Hmarkers(t,1,:))/size(Hmarkers,3);
    Hbarycenter(t,2) = sum(Hmarkers(t,2,:))/size(Hmarkers,3);
    Hbarycenter(t,3) = sum(Hmarkers(t,3,:))/size(Hmarkers,3);
    % Forefoot markers barycenter
    Fbarycenter(t,1) = sum(Fmarkers(t,1,:))/size(Fmarkers,3);
    Fbarycenter(t,2) = sum(Fmarkers(t,2,:))/size(Fmarkers,3);
    Fbarycenter(t,3) = sum(Fmarkers(t,3,:))/size(Fmarkers,3);
end
for t = 1:n-1
    % Hindfoot barycenter velocity
    HBvelocity(t) = sqrt((Hbarycenter(t+1,gaitAxis)- ...
        Hbarycenter(t,gaitAxis))^2+ ...
        (Hbarycenter(t+1,verticalAxis)- ...
        Hbarycenter(t,verticalAxis))^2)/ ...
        (1/f);
    % Forefoot barycenter velocity
    FBvelocity(t) = sqrt((Fbarycenter(t+1,gaitAxis)- ...
        Fbarycenter(t,gaitAxis))^2+ ...
        (Fbarycenter(t+1,verticalAxis)- ...
        Fbarycenter(t,verticalAxis))^2)/ ...
        (1/f);
```

```
end

% -------------------------------------------------------------------
-------
% Velocity threshold (empirically set)
% 50 mm/s in the original article for barefoot gait
% 500 mm/s in Bruening et al., 2014
% -------------------------------------------------------------------
-------
vThreshold = 500;
% -------------------------------------------------------------------
-------
% Detect events using the velocity threshold
% CASE #1: The event is defined when a first marker has a velocity
under
%          threshold for FS, the last marker over threshold for FO
% -------------------------------------------------------------------
-------
twindow = fix(30/150*f); % two consecutive events must be at least
distant of 30 frame (at 150 Hz)
for t = 1:n-1
    % Foot strike defined using heel marker
    if isempty(FS) && isempty(FO)
        temp = [];
        for i = 1:size(Hvelocity,2)
            if Hvelocity(t,i) <= vThreshold
                temp = t;
            end
        end
        if ~isempty(temp)
            FS = [FS temp];
        end
    elseif ~isempty(FS) && isempty(FO)
        % Do nothing: wait for a first FO (assume that we detect
first a FS)
    elseif ~isempty(FS) && ~isempty(FO) && ...
            length(FS) > length(FO)
        % Do nothing: wait for the next FO (assume that we detect
first a FS)
    elseif ~isempty(FS) && ~isempty(FO) && ...
            length(FS) == length(FO)
```

```
        temp = [];
        for i = 1:size(Hvelocity,2)
            if Hvelocity(t,i) <= vThreshold && ...
               t >= FO(end)+twindow
                temp = t;
            end
        end
        if ~isempty(temp)
            FS = [FS temp];
        end
    end
    % Foot off defined using forefoot marker
    if isempty(FS) && isempty(FO)
        % Do nothing: wait for a first FS (assume that we detect
first a FS)
    elseif ~isempty(FS) && isempty(FO)
        temp = [];
        for i = 1:size(Fvelocity,2)
            if Fvelocity(t,i) >= vThreshold && ...
               t >= FS(end)+twindow
                temp = t;
            end
        end
        if ~isempty(temp)
            FO = [FO temp];
        end
    elseif ~isempty(FS) && ~isempty(FO) && ...
            length(FO) < length(FS)
        temp = [];
        for i = 1:size(Fvelocity,2)
            if Fvelocity(t,i) >= vThreshold && ...
               t >= FS(end)+twindow
                temp = t;
            end
        end
        if ~isempty(temp)
            FO = [FO temp];
        end
    elseif ~isempty(FS) && ~isempty(FO) && ...
            length(FO) == length(FS)
        % Do nothing: wait for the nest FS (assume that we detect
```

```
first a FS)
    end
end
```

2.3.5 Modified Ghoussayni Algorithm

```
function [FS,FO] =
f_Ghoussayni_variablethreshold(Hmarkers,Fmarkers,gaitAxis,verticalAx
is,n,f,vel2)

% ------------------------------------------------------------------
-------
% Initialisation
% ------------------------------------------------------------------
-------
FS = [];
FO = [];

% ------------------------------------------------------------------
-------
% Calculate the 2D velocity of the markers in the plane containing
% gait (V1) and vertical (V2) axes
% ------------------------------------------------------------------
-------
for t = 1:n-1
    % Hindfoot markers velocity
    for i = 1:size(Hmarkers,3)
        Hvelocity(t,i) = sqrt((Hmarkers(t+1,gaitAxis,i)- ...
            Hmarkers(t,gaitAxis,i))^2+ ...
            (Hmarkers(t+1,verticalAxis,i)- ...
            Hmarkers(t,verticalAxis,i))^2)/ ...
            (1/f);
    end
    % Forefoot markers velocity
    for i = 1:size(Fmarkers,3)
        Fvelocity(t,i) = sqrt((Fmarkers(t+1,gaitAxis,i)- ...
            Fmarkers(t,gaitAxis,i)).^2+ ...
            (Fmarkers(t+1,verticalAxis,i)- ...
            Fmarkers(t,verticalAxis,i)).^2)/ ...
            (1/f);
    end
```

```
end


 vThreshold_FS = 0.78*vel2;
 vThreshold_FO=0.66*vel2;
%Calculate threshold, which is dependent on walking speed
% -------------------------------------------------------------------
-------
% Detect events using the velocity threshold
% CASE #1: The event is defined when a first marker has a velocity
under
%          threshold for FS, the last marker over threshold for FO
% -------------------------------------------------------------------
-------
twindow = 15; % two consecutive events must be at least distant of
30 frame (at 150 Hz)
for t = 1:n-1
    % Foot strike defined using heel marker
    if isempty(FS) && isempty(FO)
        temp = [];
        for i = 1:size(Hvelocity,2)
            if Hvelocity(t,i) <= vThreshold_FS
                temp = t;
            end
        end
        if ~isempty(temp)
            FS = [FS temp];
        end
    elseif ~isempty(FS) && isempty(FO)
        % Do nothing: wait for a first FO (assume that we detect
first a FS)
    elseif ~isempty(FS) && ~isempty(FO) && ...
            length(FS) > length(FO)
        % Do nothing: wait for the next FO (assume that we detect
first a FS)
    elseif ~isempty(FS) && ~isempty(FO) && ...
            length(FS) == length(FO)
        temp = [];
        for i = 1:size(Hvelocity,2)
            if Hvelocity(t,i) <= vThreshold_FS && ...
               t >= FO(end)+twindow
```

```
                temp = t;
            end
        end
        if ~isempty(temp)
            FS = [FS temp];
        end
    end
    % Foot off defined using forefoot marker
    if isempty(FS) && isempty(FO)
        % Do nothing: wait for a first FS_ghoussayni (assume that we
detect first a FS_ghoussayni)
    elseif ~isempty(FS) && isempty(FO)
        temp = [];
        for i = 1:size(Fvelocity,2)
            if Fvelocity(t,i) >= vThreshold_FO && ...
               t >= FS(end)+twindow
                temp = t;
            end
        end
        if ~isempty(temp)
            FO = [FO temp];
        end
    elseif ~isempty(FS) && ~isempty(FO) && ...
            length(FO) < length(FS)
        temp = [];
        for i = 1:size(Fvelocity,2)
            if Fvelocity(t,i) >= vThreshold_FO && ...
               t >= FS(end)+twindow
                temp = t;
            end
        end
        if ~isempty(temp)
            FO = [FO temp];
        end
    elseif ~isempty(FS) && ~isempty(FO) && ...
            length(FO) == length(FS)
        % Do nothing: wait for the nest FS_ghoussayni (assume that
we detect first a FS_ghoussayni)
    end
end
```

3. Supplementary information – Results

3.1 Comparison of kinematic algorithms

Table 3: Comparison of the implemented algorithms and marker configurations for IC and FO, Median error [ms] (Sensitivity [%]). For convenience, the algorithms are listed with the primary author's last name. The best-performing algorithms for each group are highlighted in red.

INITIAL CONTACT

GROUP A – FOREFOOT IC

Algorithm	Median Error-Heel	R^2 value	Median Error-Toe	R^2 value
Zeni	16.67 (36.67%)	0.9983	20 (43.33%)	0.9981
Desailly	13.33 (43.33%)	0.9978	13.33 (43.33%)	0.9977
O'Connor	18.33 (60%)	0.9727	10 (26.67%)	0.9766
Ghoussayni	-6.67 (90%)	0.9989	**0 (100%)**	0.9997
Modified Ghoussayni	8.33 (86.67%)	0.9988	10 (93.33%)	0.9991

GROUP B – MIDFOOT IC

Algorithm	Median Error-Heel	R^2 value	Median Error-Toe	R^2 value
Zeni	26.67 (33.33%)	0.9968	26.67 (36.67%)	0.9967
Desailly	21.67 (40%)	0.9971	21.67 (40%)	0.9971
O'Connor	13.33 (66.67%)	0.9282	13.33 (36.67%)	0.9610
Ghoussayni	5.00 (96.67%)	0.9986	**0 (96.67%)**	0.9991
Modified Ghoussayni	13.33 (70%)	0.9987	13.33 (73.33%)	0.9987

GROUP C – HEEL IC

Algorithm	Median Error-Heel	R^2 value	Median Error-Toe	R^2 value
Zeni	20 (23.33%)	0.9979	16.67 (30%)	0.9976
Desailly	13.33 (23.33%)	0.9971	13.33 (23.33%)	0.9972

O'Connor	1.67 (93.33%)	0.9981	23.33 (3.33%)	0.4221
Ghoussayni	**3.33 (96.67%)**	0.9989	-16.67 (20%)	0.9956
Modified Ghoussayni	20 (83.33%)	0.9983	-13.33 (86.67%)	0.9947

FOOT OFF

GROUP A – FORE-FOOT IC

Algorithm	Median Error-Heel	R^2 value	Median Error-Toe	R^2 value
Zeni	-13.33 (76.67%)	0.9993	-25 (60%)	0.9993
Desailly	-16.67 (73.33%)	0.9992	-26.67 (63.33%)	0.9993
O'Connor	-13.33 (60%)	0.4590	-20 (30%)	0.9841
Ghoussayni	5 (86.67%)	0.9993	0 (96.67%)	0.9995
Modified Ghoussayni	-13.33 (83.33%)	0.9994	**0 (100%)**	0.9995

GROUP B – MID-FOOT IC

Algorithm	Median Error-Heel	R^2 value	Median Error-Toe	R^2 value
Zeni	-16.67 (90%)	0.9993	-20 (66.67%)	0.9987
Desailly	-13.33 (86.67%)	0.9991	-20 (73.33%)	0.9987
O'Connor	-6.67 (80%)	0.9549	-6.67 (66.67%)	0.9840
Ghoussayni	13.33 (90%)	0.9991	0 (93.33%)	0.9993
Modified Ghoussayni	-6.67 (86.67%)	0.9986	**0 (96.67%)**	0.9995

GROUP C – HEEL IC

Zeni	-10 (100%)	0.9994	-13.33 (86.67%)	0.9992
Desailly	-6.67 (100%)	0.9991	-13.33 (90%)	0.9990
O'Connor	0 (90%)	0.9980	6.67 (86.67%)	0.9954
Ghoussayni	20 (90%)	0.9986	6.67 (100%)	0.9992
Modified Ghoussayni	6.67 (100%)	0.9991	**0 (100%)**	0.9996

3.2 Comparison of clinically and kinematically identified Spatio-temporal parameters

Table 4:Median and range of Δ values between clinically and kinematically identified gait events. Positive/negative values indicate over/underestimation of kinematically determined spatio-temporal parameters.

STP	**Group A**		**Group B**		**Group C**	
	Median Δ values (range)	**R^2 value**	**Median Δ values (range)**	**R^2 value**	**Median Δ values (range)**	**R^2 value**
Stride Length (mm)	-0.0334 (27.974)	0.999	-0.0300 (59.361)	0.996	-0.312 (26.247)	0.998
Step Length (mm)	-0.5387(56.592)	0.994	-0.899 (41.2901)	0.989	0.021 (25.711)	0.992
Stride Width (mm)	-0.0236 (44.045)	0.984	-1.541 (35.6810)	0.969	-1.152 (9.9573)	0.996
Stride Time (ms)	-3.333 (46.667)	0.991	-6.667 (86.6667)	0.988	-1.667 (60.000)	0.981
Step Time (ms)	-3.333 (60.000)	0.953	0 (80.000)	0.959	-1.667 (46.667)	0.923
Single Limb Support Time (ms)	-3.333 (93.333)	0.722	0 (60.000)	0.875	6.667 (56.667)	0.879
Double Limb Support Time (ms)	0 (133.333)	0.632	-6.667 (120.000)	0.921	-13.333(106.667)	0.769
Walking Speed (m/s)	0.0021 (0.0342)	0.999	0.0034 (0.0738)	0.994	0.0027 (0.0549)	0.996

4. Scientific activity resulting from the thesis

1**. Sansgiri, S.**, Visscher R.M.S., Singh, N. B., Freslier, M., Harlaar J., Taylor, W. R., Brunner, R.(2020). A comparison of clinically and kinematically identified spatio-temporal parameters in cerebral palsy gait. Poster presentation at ESMAC 2020.
https://doi.org/10.1016/j.gaitpost.2020.08.057

2. 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