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Gait event detection using kinematic data in children with bilateral spastic cerebral palsy

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A R T I C L E I N F O

Keywords:
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A B S T R A C T

Background: Ground reaction forces are the gold standard for detecting gait events, but they are not always applicable in cerebral palsy. Ghoussayni's algorithm is an event detection method based on the sagittal plane velocity of heel and toe markers. We aimed to evaluate whether Ghoussayni's algorithm, using two different thresholds, was a valid event detection method in children with bilateral spastic cerebral palsy. We also aimed to define a new adaptation of Ghoussayni's algorithm for detecting foot strike in cerebral palsy, and study the effect of event detection methods on spatiotemporal parameters.
Methods: Synchronized kinematic and kinetic data were collected retrospectively from 16 children with bilateral spastic cerebral palsy (7 males and 9 females; age 8.9 ± 2.7 years) walking barefoot at self-selected speed. Gait events were detected using methods: 1) ground reaction forces, 2) Ghoussayni's algorithm with a threshold of 0.5 m/s, and 3) Ghoussayni's algorithm with a walking speed dependent threshold. The new adaptation distinguished how foot strikes were performed (heel and/or toe) comparing the timing when the foot markers velocities fell below the threshold. Differences between the three methods, and between spatiotemporal parameters calculated from the two Ghoussayni's thresholds were analyzed.
Findings: There were statistically significant ($P < 0.05$) differences between methods 1 and 3, and between some spatiotemporal parameters calculated from methods 2 and 3. Ghoussayni's algorithm showed better performance for foot strike than for toe off.
Interpretation: Ghoussayni's algorithm using 0.5 m/s is valid in children with bilateral spastic cerebral palsy. Event detection methods affect spatiotemporal parameters.

1. Introduction

Cerebral palsy (CP) is the most common cause of chronic childhood motor disability (Pakula et al., 2009) with a prevalence of above 2 per 1000 live births (Odding et al., 2006), and it describes a group of permanent disorders affecting movement and posture that are attributed to non-progressive lesions in the developing fetal or infant brain (Rosenbaum et al., 2007). Spasticity is often the dominant motor disorder (Rethlefsen et al., 2010), along with loss of selective motor control and impaired balance, and secondary musculoskeletal problems like

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muscle contractures, bony deformities, and joint instability appear as a consequence of growth and development of the musculoskeletal system (Narayanan, 2007). Their interaction, occurring at multiple levels, affects the quality and efficiency of gait, contributing to activity limitation and participation restriction (Narayanan, 2007).

The instrumented gait analysis (IGA) allows a precise quantification of gait deviations through objective data that cannot be appreciated visually (Chang et al., 2010) and it is often used in the assessment of children with CP for multiple purposes (Theologis and Wright, 2015): 1) classification: six reliable and valid multiple joint patterns based on IGA have reached consensus (Papageorgiou et al., 2019); 2) decision-making: IGA can modify treatment decisions in case of disagreement with expert clinical evaluation or reinforce the decision in case of agreement (Benedetti et al., 2017; Wren et al., 2011); and 3) evaluation of treatment effects: IGA provide responsive outcome measures (Gómez-Pérez et al., 2019).

Gait events are essential in different stages of IGA (Ghoussayni et al., 2004), for example the determination of the gait cycle (from one foot strike (FS) to the successive FS on the same side), and stance and swing phases (separated by the toe off (TO)) (Chambers and Sutherland, 2002). FS is defined as the timing when foot contacts the ground and foot forward progression stops, and TO as the timing when toe leaves the ground or toe starts forward progression (Bruening and Ridge, 2014). These comprehensive definitions cover both healthy and pathological subjects, and include kinetic and kinematic components (Bruening and Ridge, 2014).

Gait event detection is one of the most time-consuming processes in IGA (Bruening and Ridge, 2014). Accurate automated event detection is important to increase the efficiency and repeatability of IGA (Bruening and Ridge, 2014; Ghoussayni et al., 2004). Force plate measurements (ground reaction forces (GRF)) are considered the gold standard in the detection of gait events (Bruening and Ridge, 2014; Gonçalves et al., 2019). However, this equipment is not always available in gait analysis laboratories (Bruening and Ridge, 2014; Ghoussayni et al., 2004) and/or applicable in pathological populations such as CP (Bruening and Ridge, 2014; Gonçalves et al., 2019), as some subjects step with more than one foot on each force plate (Gonçalves et al., 2019) or slide or drag their feet in swing phase, creating false force thresholds (Bruening and Ridge, 2014). In these cases, marker detection systems (three-dimensional (3D) marker coordinates) take relevance as alternative methods to GRF (Bruening and Ridge, 2014). Moreover, they present some advantages in comparison to GRF, such as the possibility of detecting gait events for several strides within the measurement volume, or their applicability in treadmill walking (Ghoussayni et al., 2004).

There exist different gait event detection methods based on kinematic data (Desailly et al., 2009; Ghoussayni et al., 2004; Hreljac and Marshall, 2000; Hsue et al., 2007; Zeni et al., 2008). When comparing these automated algorithms for the detection of gait events in children with CP, using visual inspection (Bruening and Ridge, 2014) or force plates (Gonçalves et al., 2019) as a reference, the algorithm reported by Ghoussayni et al. (Ghoussayni et al., 2004) (hereafter called Ghoussayni's algorithm) shows the best results. This algorithm is based on the velocity in the sagittal plane of two foot markers (heel and toe) (Ghoussayni et al., 2004). Two empirically set thresholds have been used: 0.05 m/s (Ghoussayni et al., 2004) (in healthy adult subjects) and 0.5 m/s (Bruening and Ridge, 2014; Gonçalves et al., 2019) (in children with CP). Another threshold, walking speed dependent, was proposed to increase the accuracy of Ghoussayni's algorithm in children with CP (Bruening and Ridge, 2014). However, in that case, no statistical results were reported in the study (Bruening and Ridge, 2014).

In children with CP, six different gait patterns have reached consensus (genu recurvatum, drop foot, true equinus, jump gait, apparent equinus and crouch gait) (Papageorgiou et al., 2019). Beyond the gait pattern, children with CP perform FS in different ways (with the heel, toe, and/or both at the same time) (Read et al., 2003), and it is not always possible to distinguish them visually. This fact should be taken into account when detecting FS. Ghoussayni et al. (Ghoussayni et al., 2004) validated their automated algorithm with healthy adults, so they did not address this issue. Bruening and Ridge (Bruening and Ridge, 2014) classified the children in different gait patterns, and used the toe marker in place of the heel marker for the detection of FS in the equinus group. Gonçalves et al. (Gonçalves et al., 2019) also considered different gait patterns, but they detected FS using the heel marker in all cases.

Validation of a new measurement method requires comparison with the gold standard (Doğan, 2018). The objective of the present study is to compare Ghoussayni's algorithm, both using a threshold of 0.5 m/s (hereafter called Gho05) and using a walking speed dependent threshold (hereafter called GhoWS), with the gold standard (GRF) in order to evaluate if Gho05 and GhoWS can be used as alternative methods for the detection of gait events in children with bilateral spastic CP. Based on Ghoussayni et al. (Ghoussayni et al., 2004), Bruening and Ridge (Bruening and Ridge, 2014) and Gonçalves et al. (Gonçalves et al., 2019), our hypotheses are: 1) both Gho05 and GhoWS are valid alternatives to GRF for detecting gait events in children with bilateral spastic CP, and 2) GhoWS provides closer results to GRF than Gho05. We also aimed to define a new adaptation of Ghoussayni's algorithm for the detection of FS in children with CP, according to the following requirement: the capability to distinguish the way any child with CP performs each FS (with the heel, toe, or both at the same time), independently of the gait pattern. Finally, we aimed to study the effect of gait event detection methods on spatiotemporal (ST) parameters.

2. Methods

Data were collected retrospectively from a previous study made at the Motion Analysis Laboratory of the Institut Guttmann (Badalona, Spain).

2.1. Participants

The potentially eligible participants were children with a diagnosis of bilateral spastic or mixed CP, age between 4 and 14 years, Gross Motor Function Classification System (GMFCS) (Reid et al., 2011) levels I to III, and ability to carry out simple verbal instructions. No child had moderate or severe pain, or severe visual impairment. Exclusion criteria were: 1) disability to walk 7 m independently without assistive devices; and 2) unavailability to detect at least one valid gait event using GRF. The study was approved by the Research Ethics Committee of the Institut Guttmann (Badalona, Spain), and parents gave written informed consent for participating in the study.

2.2. Procedures

Each child walked barefoot, without orthosis or assistive devices, at self-selected speed on a 7-m walkway. A minimum of three trials were collected. Two reflective markers (radius 15 mm) were placed on each foot (right and left), one on the posterior end of the calcaneus (heel marker) and the other on the second metatarsal head (toe marker), based on the Plug-in-Gait model (Kainz et al., 2017). 3D marker coordinates were measured using a six infrared cameras system (SMART-D, BTS Bioengineering, Milan, Italy). GRF were measured using two force plates (9286BA, Kistler, Granollers, Spain). Data were synchronously recorded at 140 Hz and filtered using a fourth order low pass Butterworth filter with a cutoff frequency of 6 Hz. Additionally, lateral and frontal views of feet motion were video recorded.

2.2.1. Gait event detection using GRF (Gold Standard)

Gait events were detected using a 10 N threshold from the vertical component of GRF. FS was estimated as the first frame with GRF vertical component above 10 N, and TO as the first frame below 10 N. Events were considered valid when only one foot was in contact with the force plate and its heel or toe (depending on the event type) was clearly located on the force plate.

2.2.2. New adaptation of Ghoussayni's algorithm for the detection of foot strike in children with cerebral palsy

We defined a new adaptation of Ghoussayni's algorithm for detecting FS in children with CP. The new adaptation consisted of calculating sagittal plane velocities of the two foot markers (heel and toe) (Ghoussayni et al., 2004), and comparing the timing (in frames) when each one fell below a given threshold. Three different situations made it possible to distinguish three types of FS: 1) heel strike: when heel marker velocity fell below the threshold before than toe marker velocity, 2) toe strike: when toe marker velocity fell below the threshold before than heel marker velocity, and 3) both at the same time: when both (heel and toe) marker velocities fell below the threshold at the same time. FS was estimated as the first frame with sagittal plane velocity of at least one of the two foot markers (heel and/or toe) below the threshold.

In the present study, this new adaptation of Ghoussayni's algorithm was applied using two different thresholds: 0.5 m/s (Gho05, see Section 2.2.3), and a walking speed dependent threshold (GhoWS, see Section 2.2.4).

2.2.3. Gait event detection using Gho05

The gait events previously detected with GRF were estimated using Ghoussayni's algorithm (Ghoussayni et al., 2004) with a threshold of 0.5 m/s (Bruening and Ridge, 2014). FS was estimated as the first frame with sagittal plane velocity of at least one of the two foot markers (heel and/or toe) below 0.5 m/s, using the new adaptation of Ghoussayni's algorithm. TO was estimated as the first frame with sagittal plane velocity of the toe marker above 0.5 m/s.

2.2.4. Gait event detection using GhoWS

The gait events previously detected using GRF and Gho05 were also estimated using Ghoussayni's algorithm (Ghoussayni et al., 2004) with a walking speed dependent threshold (Bruening and Ridge, 2014). Bruening and Ridge (Bruening and Ridge, 2014) defined the threshold (for FS and TO) as a simple function of walking speed, according to the correlation between walking speed and sagittal plane velocity of foot markers at the gait events (FS and TO) (see Eqs. (1) and (2)). Walking speed was calculated as stride speed (m/s), dividing stride length by stride time (Carcreff et al., 2018; Hollman et al., 2011). Stride length (m) was computed as the distance between the heel marker at two successive FS of the same foot (Carcreff et al., 2018), and stride time (s) as the time difference between two successive FS of the same foot (Carcreff et al., 2018). Both variables were computed from a gait cycle containing the gait event that was being estimated, in order to obtain a stride speed as close as possible to the true walking speed at that moment. The two successive FS used to calculate the stride speed were estimated using Gho05 due to the difficulty to detect two successive FS from GRF only.

$$FS\ threshold = 0.78 \times Walking\ Speed \tag{1}$$

$$TO\ threshold = 0.66 \times Walking\ Speed \tag{2}$$

FS was estimated as the first frame with sagittal plane velocity of at least one of the two foot markers (heel and/or toe) below the FS threshold (see Eq. (1)), using the new adaptation of Ghoussayni's algorithm. TO was estimated as the first frame with sagittal plane velocity of the toe marker above the TO threshold (see Eq. (2)).

2.2.5. Spatiotemporal parameters

We compared ST parameters calculated from gait events detected using Gho05 and GhoWS. Gait cycles containing at least one of the gait events detected previously (using GRF, Gho05 and GhoWS) were selected (see Fig. 1). The fundamental events of each gait cycle (initial FS, opposite TO, opposite FS, TO and final FS) were detected using Gho05 and GhoWS. The following ST parameters were calculated: stride length, stride time, stride speed, first double support (percentage of the gait cycle from initial FS to opposite TO), single support (percentage of the gait cycle from opposite TO to opposite FS), and time of TO (percentage of the gait cycle from initial FS to TO). We could not detect the five fundamental events of a gait cycle using GRF so it was not possible to calculate ST parameters from GRF.

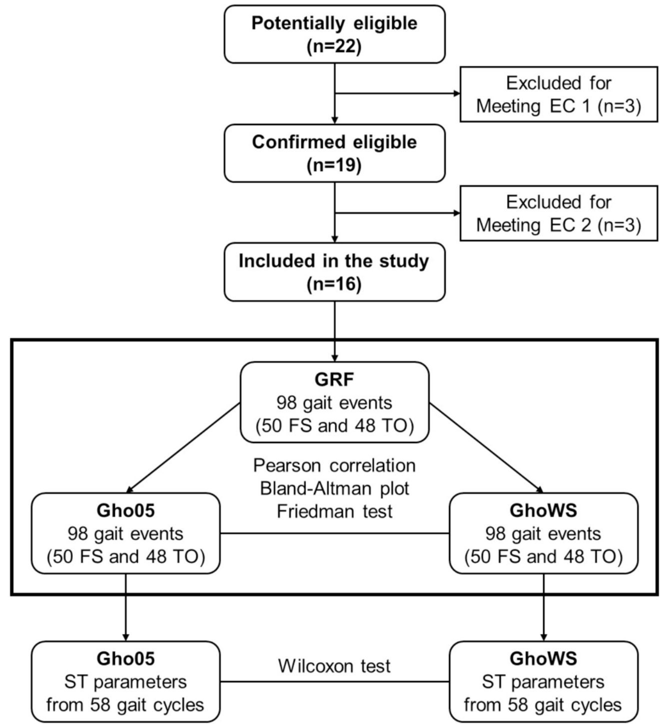

Fig. 1. Study flow diagram. EC, Exclusion criteria; GRF, Ground reaction forces; Gho05, Ghoussayni's algorithm using a threshold of 0.5 m/s; GhoWS, Ghoussayni's algorithm using a walking speed dependent threshold; FS, Foot strike; TO, Toe off; ST, Spatiotemporal.

2.3. Statistical analysis

Statistical analysis was done separately for FS and TO. Pearson correlation coefficients (r) were used to evaluate the linear relationship between the gold standard (GRF) and the two Ghoussayni's thresholds (Gho05 and GhoWS). Bland-Altman plots (Bland and Altman, 1986) were used to evaluate the degree of agreement between GRF and the other methods. In Bland-Altman plots, mean bias was calculated as the average of the differences (in frames) between GRF and the other methods, and limits of agreement (LoA) as the mean bias ±2SD (Bland and Altman, 1986). Bland-Altman plots only define LoA, without assessing whether these limits are acceptable or not (Giavarina, 2015). Acceptable limits must be previously defined, based on clinical needs, biological considerations or other goals (Giavarina, 2015). We defined acceptable limits of −5 and 5 frames, that is, −35.7 and 35.7 ms, based on the accuracy window of 33 ms used by Bruening and Ridge (Bruening and Ridge, 2014). Difference of means tests for non-normal distribution paired data were used to analyze the statistical significance of differences between the three methods (Friedman test), and between ST parameters calculated from Gho05 and GhoWS (Wilcoxon test). Mean differences (and 95% confidence intervals for differences) were also reported. A *P*-value lower than 0.05 was considered. Microsoft Excel and the Statistical Package for the Social Sciences (SPSS v.26) were used.

3. Results

Twenty-two potentially eligible participants were identified. Six children were excluded (see Fig. 1). Sixteen children (seven males and

Table 1
Participants' characteristics.

ID	Sex	CP, type	GMFCS, level	Age, y	Weight, kg	Height, m	Mean walking speed[a] (SD), m/s	Foot strike[b],type (n)	Orthosis	Assistive device
1	Male	Mixed	III	6.3	17.4	1.10	0.55 (0.08)	Toe (2), both (1)	Yes	No
2	Female	Spastic	II	9.4	22.5	1.30	0.95 (0.19)	Heel (2), both (2)	Yes	No
3	Male	Spastic	III	9.9	34.9	1.32	0.50 (0.05)	Heel (4)	Yes	Crutches
4	Female	Spastic	III	12.1	41.5	1.47	1.11 (0.12)	[c]	Yes	Crutches
5	Male	Spastic	II	7.9	26.8	1.32	0.92 (0.08)	Toe (1)	Yes	No
6	Female	Spastic	III	8.1	46.2	1.25	0.66 (0.03)	Heel (1), both (2)	No	Walker
7	Male	Spastic	II	12.1	50.2	1.57	0.91 (0.01)	Heel (1), both (1)	No	No
8	Female	Spastic	II	8.8	24.2	1.25	0.95 (0.01)	Both (3)	Yes	No
9	Female	Mixed	II	11.5	28.5	1.32	0.43 (0.08)	Toe (2)	No	Walker
10	Male	Spastic	II	12.8	33.4	1.45	1.01 (0.03)	Heel (2)	No	No
11	Female	Spastic	I	4.9	21.3	1.09	1.08 (0.05)	Heel (5), both (1)	Yes	No
12	Male	Spastic	II	8.3	29.9	1.31	0.91 (0.11)	Heel (1), both (1)	Yes	No
13	Female	Mixed	II	12.5	34.4	1.44	1.03 (0.06)	Heel (6), toe (1)	No	No
14	Female	Spastic	II	6.9	18.1	1.10	0.93 (0.17)	Heel (2), both (2)	Yes	No
15	Female	Mixed	I	5.6	18.4	1.08	1.15 (0.04)	Heel (6)	No	No
16	Male	Spastic	II	5.8	27.9	1.20	0.99 (0.15)	Both (1)	Yes	No

ID, identification; CP, cerebral palsy; GMFCS, Gross Motor Functional Classification System; SD, standard deviation.
[a] Mean value of the walking speeds calculated for the detection of gait events using Ghoussayni's algorithm with a walking speed dependent threshold (GhoWS).
[b] Estimated using the new adaptation of Ghoussayni's algorithm with a threshold of 0.5 m/s (Gho05): heel strike (heel marker velocity fell below the threshold before than toe marker velocity), toe strike (toe marker velocity fell below the threshold before than heel marker velocity), both at the same time (both -heel and toe-marker velocities fell below the threshold at the same time)
[c] No valid foot strikes were detected using ground reaction forces (GRF).

nine females) with a diagnosis of bilateral spastic CP and a mean age of 8.9 ± 2.7 years were included in the present study (see Table 1). Sixty-two trials were collected and 51 of them contained at least one valid event. Ninety-eight gait events (50 FS and 48 TO) were detected, first with GRF, and afterwards with Gho05 and GhoWS. Three types of FS were distinguished: heel strike ($n = 30$), toe strike ($n = 6$), and both at the same time ($n = 14$) (see Table 1).

Correlation coefficients between the gold standard (GRF) and the other methods were $r = 0.99$ ($P < 0.01$) both for Gho05 and GhoWS, and both for FS and TO. Bland-Altman plots are shown in Fig. 2. For FS, the mean bias was smaller between GRF and Gho05 than between GRF and GhoWS (−0.18 and 1.08 frames, respectively); and LoA were −4.60 and 4.24 frames between GRF and Gho05, and −3.49 and 5.65 frames between GRF and GhoWS, exceeding (GhoWS) the acceptable limits (−5 and 5 frames). For TO, the mean bias was also smaller between GRF and Gho05 than between GRF and GhoWS (−1.08 and −1.58 frames, respectively); and LoA were −7.10 and 4.94 frames between GRF and Gho05, and −6.44 and 3.28 frames between GRF and GhoWS, exceeding (both Gho05 and GhoWS) the acceptable limits.

The statistical significance of differences, mean difference, and 95% confidence interval for the difference between the three methods are shown in Table 2. For FS, there were no statistically significant ($P < 0.05$) differences between GRF and the two Ghoussayni's thresholds. For TO, there were statistically significant differences between GRF and GhoWS, but not between GRF and Gho05. In both cases (FS and TO), there were statistically significant differences between Gho05 and GhoWS.

ST parameters from 58 gait cycles defined using Gho05 and GhoWS were compared. There were statistically significant differences between ST parameters calculated from Gho05 and GhoWS in the following cases: first double support, single support, and time of TO (see Table 3).

4. Discussion

We compared two different thresholds of Ghoussayni's algorithm (Gho05 and GhoWS) with the gold standard gait event detection method (GRF) in order to validate them as alternative event detection methods in children with bilateral spastic CP. Ghoussayni's algorithm (Ghoussayni et al., 2004) is based on kinematic data, so it can be applied in severely involved or very young patients walking with small steps, when the assessment with GRF cannot be done, or on treadmills where force plates were not build in. Gho05 had already shown good performance in children with CP (Bruening and Ridge, 2014; Gonçalves et al., 2019). However, no statistical results about GhoWS had been published before the present study (Bruening and Ridge, 2014).

Ninety-eight valid gait events from 16 children with bilateral spastic CP were detected. This number was conditioned by the gold standard event detection method. In optimal conditions (healthy gait pattern and force plates configuration adapted to stride length), it would have been possible to obtain a maximum of 4 gait events per trial (right FS, left FS, right TO and left TO). We collected 62 trials, so that would have resulted in 248 gait events. The pathological gait of children with CP (short, irregular, slide and drag steps) reduced the applicability of force plate data and we actually detected 98 gait events, the 39.5% of all potential events. This result reinforces the need to develop alternative methods to GRF based on kinematic data, such as Ghoussayni's algorithm. Moreover, methods based on kinematic data are not conditioned to the number of force plates and all the gait events occurring within the measurement volume can be detected (Ghoussayni et al., 2004).

Our results indicated that both Gho05 and GhoWS were significantly close enough to GRF (in terms of equal means) in the detection of FS, but only Gho05 was significantly close enough to GRF in the detection of TO, so our hypotheses were rejected. These results are consistent with those reported by Gonçalves et al. (Gonçalves et al., 2019), who validated Gho05 for children with unilateral or bilateral spastic CP. However, they are not aligned with those of Bruening and Ridge (Bruening and Ridge, 2014), who found that GhoWS improved Ghoussayni's algorithm accuracy. Our results also indicated better performance of Ghoussayni's algorithm for FS than for TO. These results are also in agreement with those reported by Ghoussayni et al. (Ghoussayni et al., 2004), who showed smaller average differences between GRF and the automated algorithm in relation to FS (within 1.5 frames) than to TO (between 9 and 10 frames). Inaccuracies in TO detection could be improved by using a Hallux marker, but its placement presents some problems depending on the CP gait pattern (Bruening and Ridge, 2014).

The new adaptation of Ghoussayni's algorithm for the detection of FS in children with CP made it possible to distinguish the way each child performed each FS. This is an advantage over the method used by Gonçalves et al. (Gonçalves et al., 2019), who detected FS using the heel marker in all cases, although some children perform FS with the toe. It is also an advantage over the method used by Bruening and Ridge (Bruening and Ridge, 2014), who first classified children into different gait patterns, and then detected FS using the toe or heel marker according to this classification, without taking into account that some children do not

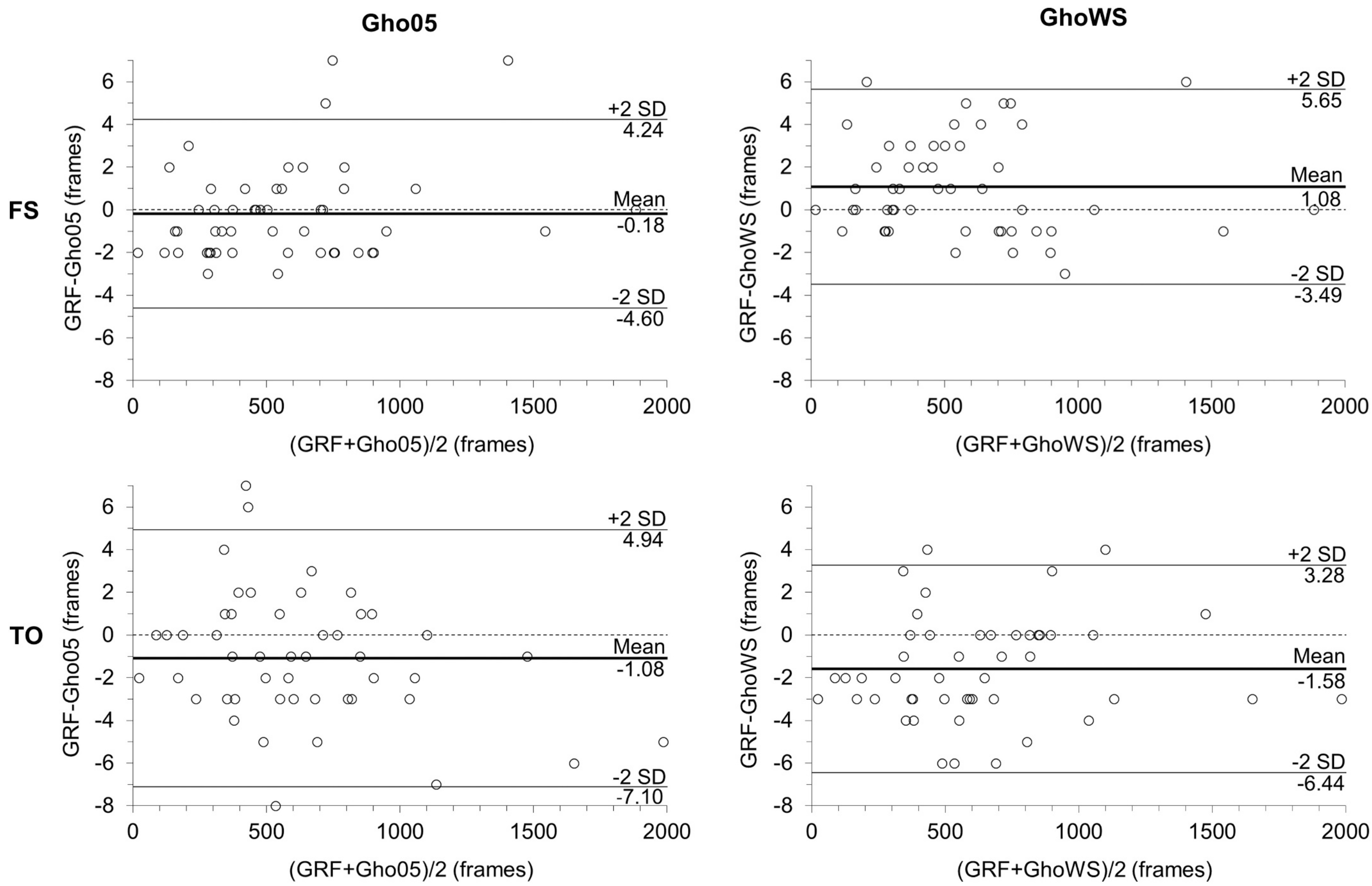

Fig. 2. Bland-Altman plots between GRF and Ghoussayni's thresholds (Gho05 and GhoWS), for foot strike (FS) and toe off (TO). GRF, Ground reaction forces; Gho05, Ghoussayni's algorithm using a threshold of 0.5 m/s; GhoWS, Ghoussayni's algorithm using a walking speed dependent threshold; SD, Standard deviation.

Table 2
Statistical significance of differences and mean difference (95% confidence interval for the difference) between GRF, Gho05 and GhoWS.

Gait event	GRF and Gho05		GRF and GhoWS		Gho05 and GhoWS	
	F	Mean difference (95% CI)	F	Mean difference (95% CI)	F	Mean difference (95% CI)
Foot strike (frame)	2.300	−0.18 (−0.81;0.45)	2.000	1.08 (0.43;1.73)	4.300***	1.26 (0.89;1.63)
Toe off (frame)	1.633	−1.08 (−1.96;−0.21)	4.338***	−1.58 (−2.29;−0.88)	2.705*	−0.50 (−1.07;0.07)

GRF, Ground reaction forces; Gho05, Ghoussayni's algorithm using a threshold of 0.5 m/s; GhoWS, Ghoussayni's algorithm using a walking speed dependent threshold; F, standardized Friedman test statistic in absolute value; CI, confidence interval for the difference. * $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$.

Table 3
Statistical significance of differences and mean difference (95% confidence interval for the difference) between spatiotemporal parameters calculated from Gho05 and GhoWS.

Spatiotemporal parameter	Standardized Wilcoxon test statistic in absolute value	Mean difference (95% CI)
Stride length (m)	1.217	−0.0005 (−0.0012;0.0003)
Stride time (s)	0.570	−0.0011 (−0.0025;0.0002)
Stride speed (m/s)	1.217	0.0005 (−0.0003;0.0013)
First double support (%)	3.714***	−1.3729 (−2.0071;−0.7386)
Single support (%)	3.782***	1.4347 (0.7737;2.0958)
Time of toe off (%)	3.643***	−1.2682 (−1.8748;−0.6616)

Gho05, Ghoussayni's algorithm using a threshold of 0.5 m/s; GhoWS, Ghoussayni's algorithm using a walking speed dependent threshold; CI, confidence interval for the difference. * $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$.

perform all FS in the same way.

ST parameters are calculated from gait events. Focusing on the methods' mean bias, Gho05 showed a negative difference both for FS and TO, so it tends to delay the gait events in comparison to GRF. GhoWS showed a positive difference for FS and a negative difference for TO, so it tends to advance FS and delay TO in comparison to GRF (the same was observed in comparison to Gho05). This fact could result in bigger differences between GRF (or Gho05) and GhoWS in terms of ST parameters such as first double support, single support, and time of TO; which are calculated from FS to TO, or vice versa. When comparing ST parameters calculated from Gho05 and GhoWS, statistically significant differences were found in the three mentioned ST parameters. Our results reinforce the thought that, in IGA, careful consideration should be given when comparing ST parameters obtained using different methods (Ghoussayni et al., 2004).

Some limitations should be considered when interpreting the results of this study: 1) severely involved or very young patients walking with small steps are the target population of kinematic based event detection methods, but these characteristics do not allow comparison with the gold standard (GRF), which is the most accurate validation method; 2) the number of gait events was small due to the low percentage of valid events detected from GRF in the included CP population; 3) the walking speed used in GhoWS was calculated using FS detected from Gho05, due to the difficulty to obtain two successive FS from GRF (which only occurred in one trial); 4) the different types of FS were not equally represented: heel strike (60%), toe strike (12%), both at the same time (28%); and 5) It was not possible to calculate ST parameters from gait events detected using GRF, so we could only compare ST parameters obtained from Gho05 and GhoWS.

5. Conclusions

In conclusion, Gho05 is a valid method for detecting gait events in children with bilateral spastic CP. GhoWS is only valid for detecting FS, so it can be dismissed as a general gait event detection method for this population. Ghoussayni's algorithm showed better performance for FS than for TO. The new adaptation of Ghoussayni's algorithm for the detection of FS distinguishes the way that any child with CP performs each FS. GRF showed low efficiency to detect valid events in children with bilateral spastic CP. Significantly different gait event detection methods can result in significantly different ST parameters. Further research should be conducted to improve the detection of TO, and to establish which is the best method to detect FS in children with CP.

Conflict of interest statement

No benefits in any form have been received or will be received from a commercial party related directly or indirectly to the subject of this article. The authors have stated that they had no interests which might be perceived as posing a conflict or bias.

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