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Agreement of spatio-temporal gait parameters between a vertical ground reaction force decomposition algorithm and a motion capture system

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ABSTRACT

Introduction: A ground reaction force decomposition algorithm based on large force platform measurements has recently been developed to analyze ground reaction forces under each foot during the double support phase of gait. However, its accuracy for the measurement of the spatiotemporal gait parameters remains to be established.
Objective: The aim of the present study was to establish the agreement between the spatiotemporal gait parameters obtained using (1) a walkway (composed of six large force platforms) and the newly developed algorithm, and (2) an optoelectronic motion capture system.
Methods: Twenty healthy children and adolescents (age range: 6–17 years) and 19 healthy adults (age range: 19–51 years) participated in this study. They were asked to walk at their preferred speed and at a speed that was faster than the preferred one. Each participant performed three blocks of three trials in each of the two walking speed conditions.
Results: The spatiotemporal gait parameters measured with the algorithm did not differ by more than 2.5% from those obtained with the motion capture system. The limits of agreement represented between 3% and 8% of the average spatiotemporal gait parameters. Repeatability of the algorithm was slightly higher than that of the motion capture system as the coefficient of variations ranged from 2.5% to 6%, and from 1.5% to 3.5% for the algorithm and the motion capture system, respectively.
Conclusion: The proposed algorithm provides valid and repeatable spatiotemporal gait parameter measurements and offers a promising tool for clinical gait analysis. Further studies are warranted to test the algorithm in people with impaired gait.

1. Introduction

Gait analysis, including kinematic and kinetic aspects of gait, is used to recommend therapeutic interventions [1] or to monitor the effect of an intervention on gait [2]. However, full gait analysis is time consuming and requires expensive devices as well as well-trained technicians [3]. The clinical need for simpler over-ground gait analysis instruments has driven the development of new tools, such as pressure sensor mats [4] or accelerometer-based devices [5]. Most of these systems measure spatiotemporal gait parameters (e.g., step length and time), which provide easy to collect and useful gait information, because spatiotemporal gait parameters are related to functional conditions such as risk and fear of falling [6], risk of cognitive decline and dementia [7] and early risks of mortality [8]. Spatiotemporal gait parameters are also useful to

Abbreviations: COP, center of pressure; CI, confidence interval; CV, coefficient of variation; GRF, ground reaction force; ICC, intra-class correlation coefficient; LoA, limit of agreement; SD, standard deviation; vGRF, vertical ground reaction force.

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monitor disease progression or in assessing the efficiency of a surgical or physical intervention [9]. However, most of these methods provide little or no information on the kinetic aspects of gait even though ground reaction forces (GRFs) are of major importance to characterize gait [10]. During the stance phase of a healthy walking cycle, vertical ground reaction forces present a characteristic sinusoidal curve with a typical ‘double bump’ [10]. Vertical ground reaction forces (vGRF) are also characterized by low intra-participant variability and high inter-limb symmetry [11]. In rehabilitation, the amount of weight bearing during walking is crucial after many orthopedic interventions on the lower extremities, as non weight bearing or excessive weight bearing can both lead to complications [12]. For this reason and given the consistent characteristics of vGRF mentioned above, this parameter is often used to assess gait asymmetry and joint loads in pathological populations such as cerebral palsy [13] or stroke [14].

Traditionally, to measure GRFs during walking the participant must place two consecutive steps on individual force platforms with no foot contact outside the surface of the platform. A large number of trials can be necessary before achieving valid measurements because it is key that participants do not voluntarily ‘target’ the force plate by adapting their step length [15]. Such targeting has been cited as a major limitation of gait studies [16] because it can modify both the vertical and horizontal component of GRFs [17–19]. Targeting also alters spatiotemporal parameters of the targeted steps as well as several steps preceding and following the target area [20].

An option to overcome the targeting problem is the use of large force plates, which offer many advantages over smaller ones. For instance, large force plates are easier to hit while walking, which reduces the time needed to gather the required valid trials. They are also more versatile as they can be used for large human movements such as manual materials handling [21] or for fast human movement such as running and jumping [22]. However, one important limitation of large force plates is their incapacity in dissociating the forces generated by both feet individually when they hit the platform simultaneously. To overcome this limitation Davis and Cavanagh [23] developed a method that uses force data measured with a single large force plate to decompose the left and right GRF profiles during the double support phase of walking and to determine the spatiotemporal gait parameters from the global values of the GRF. Nevertheless, the robustness of the method has not been extensively tested, and the variation in intra-subject gait pattern has not been taken into account in the method validation process.

Providing a valid algorithm that could decompose GRFs measured by large force plates would allow minimizing the number of walking trials which is critical in many clinical settings as fatigue may affect results [24]. It would be innovative to have a device not limited to the measurement of the vertical GRF under each foot but that can also estimate spatiotemporal gait parameters, without any additional equipment on the subject and with a minimum time requirement. Recently, Ballaz et al. [25] developed an algorithm (referred to as the ‘force decomposition algorithm’ throughout the remaining of the manuscript) which uses single large force platform measurements to estimate spatiotemporal gait parameters as well as the left and right vertical ground reaction forces. The original description of the method validated the decomposition of vertical force into left and right GRFs [25], but the validity of this method to determine the spatiotemporal gait parameters remained to be tested. Consequently, the primary aim of the present study was to assess the agreement between the spatiotemporal gait parameters obtained with the approach developed by Ballaz et al. [25] and those measured with optoelectronic (3D) motion capture system, viewed as a ‘gold standard’ method [4,26,27]. The secondary aim was to determine the intra-session repeatability of both methods.

2. Method

Twenty healthy children and adolescents (age range: 6–17 years; mean age [standard deviation; SD]: 10 [3] years; mean height [SD]: 1.46 [0.17] m; mean body mass: 40 [14] kg; 14 males) and nineteen healthy adults (age range: 19–51 years; mean age [SD]: 26 [8] years; mean height [SD]: 1.59 [0.09] m; mean body mass: 67 [12] kg; 8 males) participated in this study. Participants were recruited from hospital and research staff and students. This study was approved by the ethics committee of the Sainte-Justine University Hospital Research Center. Informed consent was provided by participants or for minors by their parents. Assent was provided by participants aged 7–17 years.

2.1. Measurement equipment

2.1.1. Force measuring walkway

Vertical GRFs were recorded using the Leonardo Mechanograph® Gangway system (Novotec Medical GmbH, Pforzheim, Germany) sampled at 800 Hz, as described in detail elsewhere [28,29]. Six force plate modules (dimensions of each module:150 cm long × 78 cm wide × 7 cm high) were placed on the floor to form a 9 m long walkway on which ground reaction forces were measured. A 2 m long custom-build wooden platform was added at the end of the walkway in order to obtain at least a 10 m long walkway, the length classically used in clinical gait analysis [3]. The first two meters of the walkway allowed participants to accelerate and reach steady state walking velocity whereas the last two meters of the walkway were used to decelerate. This allowed us to assess gait during steady state walking [4].

2.1.2. Optoelectronic motion capture system

Displacement of the lower legs and the feet in space and time were measured using an 8-camera motion capture system sampled at 60 Hz (Vicon®, 512, Oxford Metrics, Oxford, United Kingdom). Six reflective markers were placed by the same experienced examiner on the lower limbs at the following anatomic landmarks: lateral malleoli, heels and second metatarsals, as usually done to assess spatiotemporal gait parameters with an optoelectronic motion capture system [30]. To ensure that gait cycles measured by the motion capture system corresponded to that of the force measuring gangway system, 2 reflective markers were placed on each corner of the third walkway platform. This served as a spatial landmark which was used to detect the first step that was concurrently measured by the motion capture and walkway system. Using this approach, spatiotemporal parameters were calculated on the same steps with each of the two methods.

2.2. Test procedure

For each participant, the experimenter provided a description of the procedure and a task demonstration. The force measuring platform was zeroed before a participant stepped onto it. Participants performed the walking trials in two different conditions: at a normal/preferred speed (‘Preferred’ condition) and at a speed that was faster than your preferred speed (‘Faster’ condition). Different walking speeds were tested because walking speed is known to influence GRFs [31]. Prior to the beginning of testing, the participant received one of the two following instructions depending on the testing condition: “Start walking at your preferred speed or a speed comfortable for you. The test ends when you step off the walkway" or "Start walking at a speed that is faster than your preferred speed without running. The test ends when you step off the walkway". Participants performed a total of three blocks of three trials in each of the two conditions. Each block of three trials in a condition was followed by three trials in the other condition. The order of testing the two conditions was equally distributed across participants: half of the participants initiated their trials with the 'Preferred' condition while the other half started with the 'Faster' condition.

2.3. Gait parameters computation

The following spatiotemporal parameters were computed: average gait velocity, step length (right and left foot) and time per step (right and left foot). These parameters were computed using the motion capture system and the force decomposition algorithm [25], which is based on force platform measurements. Between one and three gait cycles were assessed during each trial depending on stride's length of the participants. A gait cycle corresponded to the heel strike until the heel strike of the same leg.

Using the motion capture system, heel strike and toe-off events were defined for every trial. Vicon (Oxford Metrics, Oxford, United Kingdom) Polygon software (version 2.0) was then used to compute the spatiotemporal parameters. Heel strike and toe off were defined visually by an experience examiner for every trial based on positional changes of markers on the foot through multiple frames. Heel strike was defined as the frame before the horizontal trajectory of the heel markers changed direction. Toe off was defined as the first frame where the toe marker change direction in the anterior–posterior axis.

We tested the repeatability of our visual detection method on five healthy adults who have been previously tested in our gait laboratory. Three trials per participants including two steps on separated floor mounted force plates were selected. A total of 30 heel-strike and toe-off instants were determined. First, for each trial the heel-strike and toe-off instants were determined twice with the kinematic data (based on the same heel and toe markers than in the present study). A 2-h "washout period" was imposed to the assessor between the two evaluations. Secondly, the heel-strike and toe-off instants were determined with the two separated force plates (gold standard method). We computed the intra-rater reliability (ICC) as well as the absolute constant error made when visual detection was used to determine heel-strike and toe-off events as compared to that detected by a force plate (see Table 1).

Using the force decomposition algorithm, gait parameters were computed from the raw data of the walkway force sensors in two distinct steps. The vertical GRFs and the corresponding COPs under the left and right feet were decomposed from the global vertical GRF on the multiple platforms set-up. The transitions between single and double stance phases, especially the heel strikes and toe-offs, are identified using thresholds on a variable called ΔCOP^2, defined as the squared Euclidian norm in the horizontal plane between two given samples of the global center of pressure [20]. These thresholds depend on the white noise magnitude measured in the trials. For further details on the process, the reader is invited to consult the following subsections: 'COP-related definitions', 'Detection of stance transitions', and 'Decomposition of the GRFs', pp. 238–240 of Ballaz et al. [20].

Using these data, the following gait parameters were computed: average velocity, step length and time per step. These parameters are computed for each foot as follows:

The average *velocity* [m/s], v, is defined as the distance between the beginning of the first step and the end of the last step, divided by the time, t, to move this distance, as formulated by Eq. (1).

$$v = \frac{\sqrt{(COP_{x,last} - COP_{x,first})^2 + (COP_{y,last} - COP_{y,first})^2}}{t} \quad (1)$$

where $COP_{x,first}$ and $COP_{y,first}$ denote the antero-posterior and lateral components, respectively, of the COP at the beginning of the first step, called t_{first} further in the paper, and $COP_{x,last}$ and $COP_{x,last}$ denote the antero-posterior and lateral coordinates, respectively, of the COP at the end of the last step, called t_{last} further in the paper.

The average *step length* [m], l, is defined as the average distance between antero-posterior COP components at consecutive heel-strikes, as formulated by Eq. (2).

$$l = |COP_{x,heel-strike} - COP_{x,heel-strike-1}| \quad (2)$$

where $COP_{x,heel-strike}$ and $COP_{x,heel-strike-1}$ denote the antero-posterior components of the COP of consecutive heel-strikes (left to right or right to left, respectively). This step length is then averaged from the beginning of the first step, t_{first}, to the end of the last step, t_{last}.

The average *time per step* [s], Δt, is the difference between the instants at consecutive heel-strike of one foot and that of the opposite foot, as formulated by Eq. (3).

$$\Delta t = t_{heel-strike} - t_{heel-strike-opp} \quad (3)$$

where $t_{heel-strike}$ and $t_{heel-strike-opp}$ denote the instants at consecutive heel-strikes of one foot ($t_{heel-strike}$) and that of the opposite foot ($t_{heel-strike-opp}$; left to right or right to left). This time per step is then averaged from t_{first} to t_{last}.

The results of the three consecutive trials in the same condition were averaged after normalization for the number of steps. This average result for three trials was called a 'block'. A minimum of four steps and a maximum of eight steps per trial were recorded for each participant, depending on step length. Therefore, a minimum of 12 and a maximum of 24 steps were included in a given block.

Finally, due to the natural variability of human gait, it is generally recommended to average spatiotemporal gait parameters from several gait cycles [4,28,32,33]. Therefore it is expected that errors might be also averaged in the process.

2.4. Statistical analysis

2.4.1. Visual detection of heel-strike and toe-off study with the motion capture system

To assess intra-rater reproducibility (evaluation 1 vs. evaluation 2) of visual heel-strike and toe-off detection based on the motion capture system measurements we used intra-class coefficients with a two-way mixed effect model – consistency definition [34]. Thus, ICC(C,k) and their 95% confidence intervals (95% CIs) were computed. For the intra-rater assessment, we also determined the absolute constant error the rater did when comparing heel-strike and toe-off visual frames detection for evaluation 1 and 2. Finally, to establish the precision of heel-strike and toe-off visual detection, we computed the absolute constant error that was done when comparing the visual detection data to the automatic force plate detection data (gold standard).

2.4.2. Main study

Results are presented as mean [SD]. Differences in gait parameters between the force decomposition algorithm and the optoelectronic motion capture system were assessed by comparing the mean of the nine trials performed in adults and in children for each of the two walking speed conditions using paired t-tests. Differences in gait parameters between the 'Preferred' and 'Faster' walking speed conditions were assessed by comparing the mean of the nine trials performed in each condition using paired *t*-tests. Calculations were performed using PASW 20® (SPSS Inc., Chicago, IL, USA).

As in our previous studies [28,29], repeatability of both the algorithm and the motion capture system approach was assessed by calculating the coefficient of variation (CV) and the intraclass correlation coefficient (ICC), as they are widely used repeatability parameters for human performance measures [6]. CV was calculated for each parameter in each of the two conditions ('Preferred', 'Faster'), as previously described [29]. Regarding ICC, a two-way mixed effect model with a consistency definition was used following the algorithm proposed by McGraw and Wong [8]. In the mixed model the participant is treated as a random effect, whereas measurement error is considered as a fixed effect. Thus, ICC(C,k) and their 95% confidence intervals (95% CIs), where 'C' refers to a 'consistency' definition of the ICC and 'k' refers to the fact that the analysis was done on averaged measurements, were computed.

To assess validity of the proposed algorithm, Bland and Altman plots and limits of agreement [35] were calculated for both the adult and the children group and for each of the six spatiotemporal parameters to determine the level of agreement between the algorithm and the motion capture data [9]. The bias between the algorithm computed data and the motion capture computed data was calculated as the mean difference between measurements by each method. To detect the presence of heteroscedasticity, i.e., to determine if the difference between both methods was proportional to the measured value, a Kendall's tau test was done [36]. No significant correlation between the difference and the measurements were observed (all P values >0.11) and therefore no data transformations were needed to perform the Bland and Altman plots. The upper and lower limits of agreement, which define the range in which 95% of the differences between methods are expected to lie, were calculated as bias ±1.96 SD. The precision of the limits of agreement, are reported as a 95% confidence interval. Bland and Altman analyses, assessing the agreement between both the force decomposition algorithm and the motion capture system, showed that the limits of agreement of the 'Children' and 'Adults' group were very similar in each of the five spatiotemporal parameters (see Supplementary data). Thus, for sake of simplicity the data of the child and adult groups were pooled and the Bland and Altman analyses were performed with this regrouped set of data.

3. Results

3.1. Visual detection of heel-strike and toe-off study

Comparison between visual and automatic force plate detection showed that the absolute constant error was 1.3 frames, i.e., 21 ms of error, for heel-strike detection and 0.95 frames, i.e., 15 ms of error, for toe-off detection (Table 1). The average absolute constant error in assessing the same trial 2 h appart was of 0.13 frame (2 ms) for heel-strike detection and 0.96 frames (15 ms) for toe-off detection. ICCs showed that reproducibility was excellent (Table 1).

Table 1
Absolute Constant Error for visual vs. automatic force plate detection comparison and for the comparison of evaluation 1 vs. 2 expressed in number of 'frames' as well as the intra-rater reproducibility (ICC [95% CI]).

	Visual vs. force plate detection	Visual detection Evaluation 1 vs. Evaluation 2	ICC [95% CI] Evaluation 1 vs. Evaluation 2
Heel-strike	1.33 (1.03)	0.13 (0.86)	1.00 [1.00–1.00]
Toe-off	0.95 (1.43)	0.96 (0.97)	1.00 [1.00–1.00]

Table 2
Spatiotemporal parameters (mean [± SD]) of the Children group in both the 'Preferred' and 'Faster' conditions as determined by the Ballaz et al.'s algorithm and the motion capture method (Vicon).

Children	Algorithm	Motion capture	*Δ%*	P^*
Preferred condition				
Velocity (m/s)	1.40 [0.16]	1.38 [0.16]	1.2	<0.001
Step Length-Right Foot (cm)	70.4 [10.0]	69.9 [10.2]	0.8	0.37
Step Length-Left Foot (cm)	69.1 [9.9]	69.3 [9.7]	−0.4	0.64
Time per Step-Right Foot (s)	0.51 [0.03]	0.51 [0.03]	−0.2	0.59
Time per Step-Left Foot (s)	0.51 [0.03]	0.50 [0.03]	0.1	0.67
Faster condition				
Velocity (m/s)	1.86 [0.20]	1.85 [0.21]	0.2	0.68
Step Length-Right Foot (cm)	78.4 [10.9]	79.1 [12.0]	−0.9	0.35
Step Length-Left Foot (cm)	77.6 [11.7]	79.0 [11.5]	−1.8	0.05
Time per Step-Right Foot (s)	0.42 [0.04]	0.43 [0.04]	−0.7	0.28
Time per Step-Left Foot (s)	0.42 [0.03]	0.43 [0.04]	−1.0	0.27

* Paired *t*-test; all significant effects are reported at $P < 0.05$.

3.2. Main study

Systematic differences between the outcomes of both methods were observed in the child and adult populations. For the children (Table 2) in the 'Preferred' condition, the algorithm significantly overestimated velocity by 1.2%. For the adult group (Table 3) in the 'Preferred' speed condition the algorithm significantly overestimated the time per step of the left foot by 0.9% compared to the motion capture system. In the 'Faster' speed condition, the algorithm underestimated by 1.6% the values of the motion capture system for step length of the right foot.

Repeatability data for the children group (Table 4) and the adult group (Table 5) showed that all ICCs were between 0.72 and 0.98 for the force decomposition algorithm data and all over 0.90 for the motion capture computed data. Consistent with the ICCs, the CVs were slightly larger for the algorithm (2–7%) than for the motion capture (1–5%). The ICCs and CVs were very similar across conditions and groups.

The Bland and Altman plots showed that step lengths at the right and left feet were the parameters with the largest limits of agreement. The limits of agreement of these two parameters represented around 6% of the averaged measurements of both methods: (force decomposition algorithm data + motion capture data)/2. For the remaining parameters, i.e. velocity, time per step right and left foot, the limits of agreement was under 5% of the averaged method measurements (Fig. 1A–E).

Table 3
Spatiotemporal parameters (mean [±SD]) of the Adult group in both the 'Preferred' and 'Faster' conditions as determined by the Ballaz et al.'s algorithm and the motion capture method (Vicon).

Adults	Algorithm	Motion capture	*Δ%*	P^*
'Preferred' condition				
Velocity (m/s)	1.47 [0.19]	1.46 [0.19]	0.7	0.09
Step length-Right Foot (cm)	76.0 [7.2]	75.8 [7.9]	0.2	0.71
Step length-Left Foot (cm)	75.5 [8.3]	75.6 [7.6]	−0.2	0.79
Time per Step-Right Foot (s)	0.52 [0.03]	0.53 [0.03]	−0.6	0.20
Time per Step-Left Foot (s)	0.52 [0.03]	0.52 [0.03]	1.0	0.01
'Faster' condition				
Velocity (m/s)	1.95 [0.22]	1.95 [0.21]	0.1	0.71
Step Length-Right Foot (cm)	86.0 [8.1]	87.5 [7.8]	−1.6	0.04
Step Length-Left Foot (cm)	86.7 [7.4]	87.2 [7.3]	−0.5	0.47
Time per Step-Right Foot (s)	0.45 [0.03]	0.46 [0.02]	−1.4	0.05
Time per Step-Left Foot (s)	0.45 [0.02]	0.45 [0.03]	0	0.99

* Paired *t*-test; all significant effects are reported at $P < 0.05$.

Table 4
Repeatability of the spatiotemporal data as computed by both the algorithm and the motion capture method for the Children group at both walking speed conditions.

	Preferred		Faster	
	ICC(C, k) [95% CI]	CV (%)	ICC(C, k) [95% CI]	CV (%)
Algorithm				
Velocity (m/s)	0.98 [0.91–0.98]	4.43	0.98 [0.86–0.97]	4.75
Step length-Right Foot (cm)	0.72 [0.87–0.97]	2.76	0.72 [0.71–0.94]	5.07
Step length-Left Foot (cm)	0.94 [0.83–0.97]	3.15	0.94 [0.82–0.96]	4.32
Time per Step-Right Foot (s)	0.81 [0.96–0.99]	3.78	0.81 [0.91–0.98]	5.27
Time per Step-Left Foot (s)	0.94 [0.94–0.99]	4.67	0.94 [0.89–0.98]	5.39
Motion Capture				
Velocity (m/s)	0.96 [0.91–0.98]	4.82	0.96 [0.92–0.99]	3.91
Step Length-Right Foot (cm)	0.97 [0.93–0.99]	2.12	0.97 [0.94–0.99]	2.05
Step Length-Left Foot (cm)	0.90 [0.78–0.96]	3.50	0.96 [0.91–0.98]	2.87
Time per Step-Right Foot (s)	0.98 [0.96–0.99]	3.96	0.99 [0.98–1.00]	2.42
Time per Step-Left Foot (s)	0.99 [0.97–0.99]	3.00	0.99 [0.99–1.00]	1.93

Table 5
Repeatability of the spatiotemporal data of both the Ballaz et al.'s algorithm and the motion capture method for the Adult group at both walking speed conditions.

	Preferred		Faster	
	ICC(C, k) [95% CI]	CV (%)	ICC(C, k) [95% CI]	CV (%)
Algorithm				
Velocity (m/s)	0.98 [0.96–0.99]	3.66	0.98 [0.96–0.99]	2.73
Step Length-Right Foot (cm)	0.72 [0.39–0.88]	5.74	0.82 [0.62–0.93]	3.73
Step Length-Left Foot (cm)	0.94 [0.87–0.97]	2.72	0.87 [0.71–0.94]	3.92
Time per Step-Right Foot (s)	0.81 [0.59–0.92]	4.68	0.93 [0.85–0.97]	3.92
Time per Step-Left Foot (s)	0.94 [0.86–0.97]	4.10	0.95 [0.89–0.98]	4.23
Motion capture				
Velocity (m/s)	0.98 [0.96–0.99]	3.49	0.98 [0.96–0.99]	2.71
Step Length-Right Foot (cm)	0.98 [0.96–0.99]	1.53	0.98 [0.96–0.99]	1.75
Step Length-Left Foot (cm)	0.96 [0.91–0.98]	2.52	0.95 [0.90–0.98]	2.22
Time per Step-Right Foot (s)	0.98 [0.97–0.99]	2.39	0.98 [0.94–0.99]	2.23
Time per Step-Left Foot (s)	0.99 [0.98–1.00]	1.72	0.99 [0.98–1.00]	1.37

4. Discussion

The main finding of this study is the high degree of agreement between the spatial and temporal gait parameters measured with the optoelectronic motion capture system (Vicon®) and those computed with the proposed algorithm [25] using large force platforms from the Leonardo gangway® system [28,29]. This was true for both groups (children and adults) and for both walking speed conditions ('Preferred' and 'Faster'). While significant differences between methods were found for selected gait parameters, these differences, in average, did not exceed 2.4%. The fact that these small differences were significant may reflect the very low inter-system variability of the measures estimated by each method or may reflect the presence type I error (false positive), i.e., that a difference have been observed when, in fact, there was no real difference.

Both systems showed excellent repeatability for temporal and spatial parameters, as indicated by high ICCs (0.74–0.99) with narrow confidence intervals and low coefficients of variation (under 6%). These data were comparable to the ones reported for other clinical gait analysis systems/methods [26,37]. The overall parameter variability can result from the technical variability of the measurement devices. For the motion capture system, the low sampling rate (60 Hz) and the subjective visual detection of heel strike/toe-off are the most likely candidate contributing to the overall variability of the parameters. However, our validation/reproducibility study showed errors ranging between 15 ms (toe-off) and 21 ms (heel-strike) when visual detection was compared to automatic force plate detection. The intra-rater error was between 2 ms for heel-strike and 15 ms for toe-off detection. To give an idea of the size of these error a 21 ms represent 4.2% of the right and left time per step (0.50 s/500 ms), as reported in Table 3. The ICCs also revealed excellent reproducibility for the visual detection of heel strike and toe-off. These errors are very similar to the 16 ms of error reported by Connor et al. who developed an automatic detection algorithm based on foot markers velocity [38], Therefore, it is suggested that for the motion capture system, the overall parameter variability results more from the gait variability than on the technical variability of the measurement device [30].

With regard to the algorithm, Tables 4 and 5 show that the repeatability of the spatiotemporal parameters was slightly lower for the algorithm than for the motion capture method. The algorithm itself is not expected to generate variability as it is deterministic, i.e. the algorithm will always provide the same value for a given GRF input. However, there are other sources of variability that could have contributed to the slightly lower repeatability of the algorithm's data as compared to the motion capture system. First, the variability of the spatiotemporal parameters will mostly depend on the variability of the inputs fed to the algorithm that in turn can be affected by the noise of the force transducers included in the force platform. Second, when the algorithm uses the data from two force platform, i.e. when a foot is in contact with two force plates, the noise of the algorithm's input signal is expected to slightly increase. Finally, the noise associated with the high sampling frequency of the force platform could be another potential factor contributing to the slightly higher variability observed for the algorithm's data as compared to the motion capture system.

There are an increasing number of gait analysis systems that can measure spatiotemporal gait parameters such as pressure mats [4], insole pressure systems [39], foot worn accelerometer devices [26,37], webcam and silhouettes [27]. These approaches have been validated through comparisons to an optoelectronic

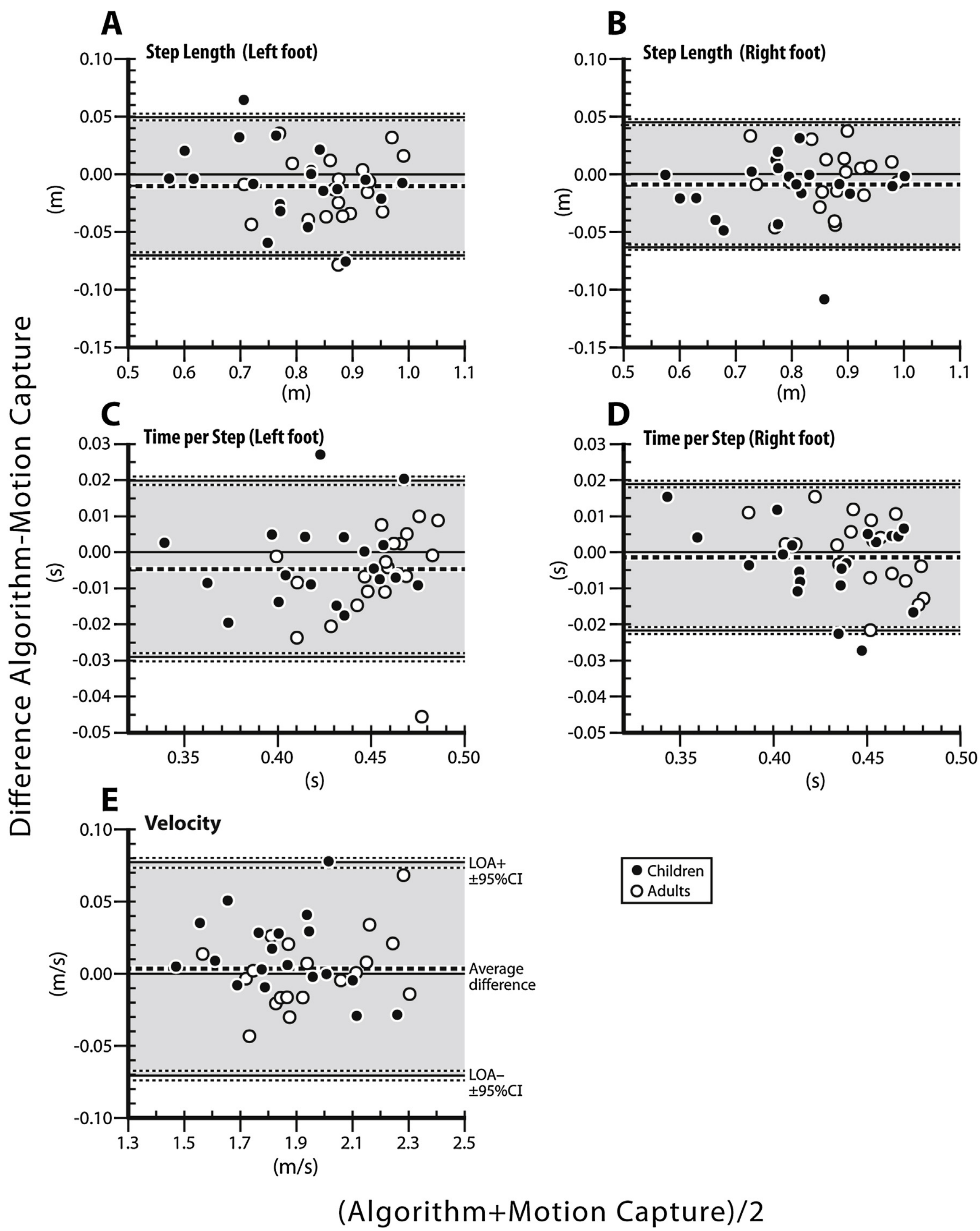

Fig. 1. (A–F) Bland and Altman plots depict the differences (thick dotted line) between spatiotemporal gait parameters as computed by the algorithm method and the motion capture method, with 95% limits of agreement (black lines). 95% confidence intervals of the limits of agreements are also depicted (small dotted lines). White filled squares represents data of the 'Adult' group patients and black filled squares represents data of the 'Children' group. Spatiotemporal parameter: (A) Step Length-Left Foot (cm), (B) Step Length-Right Foot (cm), (C) Time per Step-Left Foot (s), (D) Time per Step-Right Foot (s) and (E) Velocity (m/s).

motion capture system (Vicon®) and using the Bland and Altman's limits of agreement statistical approach, as done in the present study. In the current study, the limits of agreement did not exceed 8% of the averaged measurements, regardless of the gait parameters, walking speed conditions or group that were analyzed. On average, step length parameters had limits of agreement around 6% of the average measurements whereas velocity and step time parameters limits of agreement were lower at around 4% of the average gait parameters measurements. This is very similar to the limits of agreement reported for pressure mat [4,40], insole pressure systems [39] as well as for a webcam-silhouette approach [27] for which the limits of agreement reported between the two systems ranged between 1.4 and 6%. The agreement between portable/wearable gait analysis systems and an optoelectronic motion capture system for spatiotemporal gait parameters has also been assessed. However, for these systems the limits of agreement analyses were done on velocity and step/stride length but not on temporal parameters [26,37] and were generally higher than the limits reported in the current study. Therefore, the validity of the force decomposition algorithm for the assessment of spatiotemporal gait parameters is comparable to pressure mats or insole pressure systems or better than less conventional system such as foot-worn accelerometers.

The suggested algorithm has many potential applications that demarks it from other existing and established methods. The algorithm could be useful in current clinical gait laboratory settings using motion capture systems and force plates. Given the capacity of the algorithm to reconstruct forces from multiple force sensors, it would be possible to use data from trials in which one footfall felt on two distinct force plates laterally or consecutively. These trials are typically rejected, contributing to increase the usually large amount needed to perform this kind of gait analysis. It could also favor the implementation of large force plates in new gait/movement analysis laboratories leading to a decrease testing time through a decreased number of trials needed to gather a sufficient amount of valid trials.

Systems such as insole pressure mats allow measurement of GRFs and temporal parameters but not spatial ones [41] whereas others, such as pressure mats, allow temporal and spatial parameters but not GRFs [4]. Accelerometer would possibly allow the measurement of all three parameters i.e.: GRFs [42], temporal and spatial parameters [43]. However, to the best of our knowledge there is currently no algorithm allowing any systematic analysis of spatiotemporal and GRF parameters using three dimensional accelerometers. Therefore, it appears that the proposed force decomposition algorithm is the first method to provide estimates of temporal, spatial and force parameters in automatic mode [25].

5. Conclusion

The current data show that the force decomposition algorithm [25] is valid for the estimation of spatiotemporal gait parameters in healthy children and adults. Based on these results, it is now justified to further evaluate the reliability of the system in different patient populations.

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Conflict of interest statement

The authors declare no conflict of interest.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.gaitpost.2015.10.007.

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