Gait temporal parameters estimation in toddlers using inertial measurement units: A comparison of 15 algorithms.

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Gait temporal parameters estimation in toddlers using inertial measurement units: A comparison of 15 algorithms

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ABSTRACT

Background: Children's motor development can be evaluated through the analysis of gait temporal parameters and their variability. This requires the detection of gait events in a real-world environment, which can be achieved using inertial measurement units. Algorithms have been previously developed for healthy adults; however, the performance of these algorithms in the detection of gait events in toddlers has not been analysed.
Research question: Can inertial measurement units be used to analyse gait temporal parameters in toddlers?
Methods: Fifteen previously published algorithms using sensors attached on the lower-back or the ankles were used to identify gait events and calculate gait temporal parameters. A total of 1388 initial and 1388 final foot contacts collected from 15 toddlers were included in the analysis. The performance of the algorithms was compared against a GAITRite mat in terms of accuracy and precision. Accuracy in the measurement of gait temporal parameters was evaluated using Bland Altman limits of agreement for repeated measurements, and precision was assessed through the evaluation of correctly identified, falsely identified and missed events.
Results: From our results, no algorithm emerged as a best option from all those analysed. Algorithms using the ankle sensors provide higher accuracy and perfect precision when using only angular velocity about the medio-lateral axis. The best algorithms using the sensor attached at the lower-back use the resultant or global acceleration that reduces the effect of the sensor's alignment. These lower-back-based algorithms compared to the best ankle-based ones have similar accuracy for the calculation of stride time and higher accuracy for step time; however, they do not have perfect precision.
Significance: Inertial measurement units can support research analysing the temporal parameters of toddlers' gait in controlled environments, and may allow future studies in natural, free-living environments that can improve the monitoring of gait in young children.

1. Introduction

Learning to walk is a long process. During the first 4–5 months of walking, toddlers' gait is marked by important changes [1]. McCollum et al. [2] identified three mechanical strategies adopted at the onset of walking, with toddlers using trunk twists to facilitate step progression, using gravity for the progression of the centre of mass, or controlling foot progression to stabilise the trajectory of the centre of mass. After this phase, toddlers' gait develops towards the pendulum mechanism [3]. Gait spatiotemporal parameters stabilise between 5 and 7 years of age [1,4,5]; with subsequent changes mostly occurring through growth [6]. Conversely, Hausdorff et al. [7] showed that although stride-to-stride variability was greatest for the youngest children (3 or 4 years old), it was still significantly larger at 6 or 7 years compared to 11–14 years. Therefore, gait at 7 years might not yet be fully mature.

Both the measurement of gait temporal parameters and the magnitude and structure of their variability have been used to monitor motor development, characterise gait patterns and identify changes due to medical intervention or the onset of pathologies [8,9]. As reported by Bisi et al. [10], the analysis and monitoring of young children's gait can help to identify mild motor deficits with long-term consequences, such as higher risks of obesity, cardiorespiratory problems, diabetes, and social integration problems [11]. Early identification of these mild motor deficits is crucial to allow effective interventions.

The measurement of gait temporal parameters requires the detection of gait events, i.e. foot initial and final contacts. Standard measurement

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methods are motion capture systems, force platforms and pressure mats; however, these systems are unsuitable to collect data on young children. Children's gait is unpredictable, due to high instability, difficulty in walking in a straight line and understanding instructions. Standard tools are limited by small testing volumes, the need to target specific measurement areas, and the possibility of occlusions or interference when children are guided by someone walking alongside. Additionally, a limited number of gait cycles can be captured in laboratory settings, with the common solution of treadmill walking being unsuitable for young children. A further limitation of laboratory settings is that movements are often not representative of real environments. Therefore, children's gait and its adaptations to real-world environments cannot be satisfactorily captured in laboratory settings.

Wearable sensors, such as inertial measurement units (IMUs), with their light weight, low cost, ability to capture gait wherever it occurs, and ease of use are an alternative to laboratory measurement systems and a suitable solution to collect data on young children. In addition, IMUs can be used to collect data for long periods of time without restricting movement and allow measurement whilst someone walks alongside young children. Wearable sensors and a gait event detection algorithm have been previously used to quantify temporal parameters, their variability, and nonlinear metrics of trunk kinematics, allowing to differentiate gait performance of toddlers born pre-term with full-term controls [10] and highlighting the possibility of identifying deviations from typical motor development using this technology [10]. Despite the advantages of the use of IMUs for toddlers' gait have been highlighted, algorithms' validity and usability should be demonstrated in laboratory settings [12] for the specific population for whom the algorithms are to be used. To the best of the authors' knowledge, no previous research has reported the performance of these algorithms in toddlers, with previous research [10] using an algorithm validated on healthy adults [13].

Several authors have proposed IMU-based algorithms to detect gait events. In their review of the literature, Pacini Panebianco et al. [14] identified 17 algorithms for gait event detection and compared their performances during overground walking. These algorithms used sensors on different body segments (i.e. feet, shanks and lower-back) with different processing approaches. Most algorithms were designed and validated on healthy adults; some were also validated for healthy children [15–17], children with cerebral palsy [15–17], and children with idiopathic toe walking [18]; but no algorithm was validated for toddlers or healthy children younger than 8 years of age. Therefore, the aim of this study was to compare the performance of previously published IMU-based algorithms to detect gait events in toddlers in a structured setting.

2. Methods

2.1. Participants

A convenience sample of 13 typically developing, healthy children born full-term (age: 3.26 $\pm$ 1.01 years, mass: 14.2 $\pm$ 2.4 kg, height: 94.6 $\pm$ 8.7 cm; walking experience: 27.2 $\pm$ 11.5 months) was recruited following informed consent given from their parents. Eight of these 13 children were in the 3/4 age group, and the remaining five were 1 or 2 years old, with three children of the younger age group having less than one year of walking experience. The study was approved by the University Ethics Committee.

2.2. Algorithm selection

In this study, we selected the algorithms identified in [14] excluding those using sensors attached to the feet, since their size and weight would likely affect gait for toddlers. We performed a literature search for algorithms published subsequent to [14]. Fifteen algorithms using sensors attached to the shank and lower-back were selected (Table 1). Algorithms used accelerometer and/or gyroscope data, raw or filtered – using either infinite impulse response (IIR), finite impulse response (FIR) or wavelet transform (WT) - signals, and different rules to identify the features corresponding to the gait events of interest based on thresholds, zero crossing, and search windows. Algorithms also differed as to whether they used signals recorded in the sensor coordinate system or transformed them into a horizontal-vertical coordinate system to

Table 1
Details of the algorithms selected from the literature.

Algorithms	Sensor location	Variable used	Raw/ Filter data	Approach
Aminian et al., 2002 [26]	Ankles	Angular velocity about the medio-lateral axis	WT	Local peak identification based on search window
Behboodi et al., 2015 [27]	Ankles	Angular velocity about the medio-lateral axis	Raw	Zero crossing and local peak identification
Catalfamo et al., 2010 [17]	Ankles	Angular velocity about the medio-lateral axis	IIR	Local peak identification based on search window
Digo et al., 2023 [19]	Ankles	Angular velocity about the medio-lateral axis	Raw	Local peak following and preceding mid-swing
Greene et al., 2010 [28]	Ankles	Angular velocity about the medio-lateral axis	IIR	Local peak identification based on adaptive threshold calculations
Khandelwal and Wickström, 2014 [29]	Ankles	Resultant acceleration	WT	Local peak identification based on threshold
Lee et al., 2010 [22]	Ankles	Resultant acceleration	IIR	Local peak identification based on threshold
Salarian et al., 2004 [13]	Ankles	Angular velocity about the medio-lateral axis	Raw	Local peak identification within search window and using threshold
Trojaniello et al., 2014 [32]	Ankles	Angular velocity about the medio-lateral axis and acceleration along the antero-posterior axis	Raw	Local peak identification within search window and using threshold
Del Din et al., 2016 [23]	Lower-back	Vertical acceleration after transformation into horizontal-vertical coordinate system	WT	Peak identification
Digo et al., 2023 [19]	Lower-back	Acceleration along the antero-posterior axis	Raw	Peak identification
González et al., 2010 [30]	Lower-back	Acceleration along the antero-posterior and vertical axes	FIR	Peak identification based on threshold, heuristic rules and zero crossing
McCamley et al., 2012 [34]	Lower-back	Acceleration along and angular velocity about the vertical axis	WT	Peak identification
van Gelder et al., 2023 [24]	Lower-back	Resultant acceleration	WT	Zero crossing
Zijlstra and Hof, 2003 [25]	Lower-back	Angular velocity about the medio-lateral axis	IIR	Peak identification based on zero crossing

remove the effect of sensor alignment.

Changes to these algorithms were only necessary to reflect the shorter gait cycle in toddlers compared to adults by adjusting the window size between subsequent mid-swing phases.

2.3. Experimental set-up

Three IMUs (RunScribes, Scribe Labs, California, USA) were used; each of 9 g in weight and 35 × 25 x 7.5 mm in size. The sensors' accelerometer and gyroscope sampled data at 200 Hz within ranges of ± 16 g and ± $2000^{\circ}s^{-1}$, respectively. Two sensors were positioned approximately two centimetres above the participants' lateral malleoli and fixed using self-adhesive elastic bandage. Although different shank locations were specified in previously published algorithms, this location was selected as it was less affected by soft tissue artifacts, was easier to access for toddlers and sensor readings are similar as the shank acts as a rigid body. The third sensor was mounted on the lower-back via a clip attached to the participants' trouser waistband or for participants wearing dresses by wrapping self-adhesive elastic bandage around their waist. This sensor was used to represent the point closest to the centre of mass; however, its position was affected by the participants' use of different styles of nappies.

A 4.88 m long pressure mat (GAITRite, CIR Systems, NJ, USA) was used as the gold standard for measurement of gait temporal parameters. The mat sampled data at 120 Hz and was positioned between 5 and 10 m of a 15 m straight walkway marked on a wooden floor with adhesive tape. The pressure mat was chosen as gold standard to provide a larger target area compared to force platforms and to allow someone to walk alongside the toddlers avoiding markers' occlusions if using an optoelectronic motion capture system.

A GoPro camera positioned approximately 2 m behind the walkway recording at 60 Hz was used to determine which steps were over the GAITRite.

2.4. Protocol

Participants walked at a self-selected speed, with a researcher walking at their side to motivate and guide the participant without holding hands. Participants completed the walking trials in three different conditions as part of a wider data collection: barefoot and wearing two pairs of shoes of different stiffnesses. All three conditions were included in the analysis to increase the data variability. Three valid trials for each condition were completed by participants older than 3 years, and two valid trials were completed by younger participants. Trials were considered valid if the participant walked in a straight line without deviations from normal walking, such as pauses, running or stamping.

2.5. Data processing

The 15 algorithms selected from the literature and all other analysis were implemented in MATLAB (Mathworks R2023b, Natick, MA, USA). The IMUs used were not synchronized amongst themselves or to the GAITRite. Therefore, corresponding steps between IMUs and the GAITRite had to be found.

Participants started from a static position at the starting line, marked with tape 5 m prior to the GAITRite mat. The GoPro video was used to synchronize the IMU sensors and the GAITRite mat: the number of left and right strides required to cover these 5 m were identified by counting steps for each trial from the GoPro video; the angular velocity about the medio-lateral axis and the acceleration along the antero-posterior axis were used for step counting for the malleolar and sacrum sensors, respectively. These data and the initial contact detection approach were chosen following Digo et al. [19], since clear trends were present across participants for these data. The angular velocity about the medio-lateral axis recorded from the malleolar sensors showed a minimum corresponding with the mid-swing phase of gait preceded and followed by two peaks, which correspond to the final and initial foot contact, respectively. Similarly, the sacrum acceleration along the antero-posterior axis presented local maxima and minima corresponding to initial and final foot contacts, respectively. These features were used to count the number of steps (from the sacral sensor) and left and right strides (from the ankle sensors) starting from the static position. This counting procedure was used to match corresponding steps for the IMUs and GAITRite. Hence, each IMU recording was cropped to only include steps over the GAITRite. To compare step time from the ankle-based algorithms with the GAITRite, an additional processing step was necessary to synchronize the malleolar sensors between themselves. To achieve this, from the cropped IMU recordings of each trial, the initial foot contacts identified from the malleolar IMUs were used to calculate the time of each step over the GAITRite. These times present a constant error due to the lack of synchronization between the sensors plus the errors related to the accuracy of the gait event detection approach considered, with the true step time provided by the GAITRite measurements. Therefore, the difference between each step time estimated from the IMUs and the corresponding value measured by the GAITRite was calculated and these differences averaged to find the time lag between the ankle sensors for that trial. The correction was then applied to synchronize the malleolar sensors for each trial and checked by visual observation of the alignment of right and left IMU traces.

Once the time window was identified and the time lags applied, all algorithms were implemented to detect the gait events corresponding to the steps over the GAITRite. The following temporal parameters were calculated from the gait events detected from each algorithm for comparison with the GAITRite: stride, step, stance and swing times.

Stride and step times were calculated from initial foot contacts. Stride time was calculated for both left and right strides to match the GAITRite data.

2.6. Statistical analysis

Algorithms were compared against the GAITRite data using Bland Altman limits of agreement (95 % confidence intervals) defined for repeated measurements [20] and calculated for each temporal parameter. Regression lines were added to the Bland Altman plots with an asterisk highlighting if the p-value of the slope term is significant (alpha = 0.05).

The detection performance for correctly identified events (true positives, TP), falsely identified events (false positives, FP) and missed events (false negatives, FN) was evaluated. From the detection performance, recall precision - defined as how many gait events were detected (R = TP/(TP+FN)) - and precision - defined as how many of the detected gait events were genuine (P = TP/(TP+FP)) - were calculated [21].

3. Results

For each trial, between 7 and 27 steps were recorded over the GAITRite; these differences were due to participants' differing gait. This resulted in a total of 1388 initial and 1388 final foot contacts that should be detected by the algorithms.

For ankle sensors, the best limits of agreement for stride times were obtained for algorithms using only the angular velocity about the medio-lateral axis (Table 2). The best lower-back sensor algorithms performed similarly (Fig. 1).

For step times (Fig. 2), similar accuracy was obtained for all algorithms based on the ankle sensors, with the exception of the algorithm developed by Lee et al. [22], which results show larger limits of agreement. And all algorithms using only the angular velocity about the medio-lateral axis showed worse results for step time compared to stride time. All algorithms using the lower-back sensor provide higher accuracy for step times compared to stride times, with the algorithms developed by Del Din et al. [23] and van Gelder et al. [24] providing the

Table 2
Results from Bland Altman limits of agreement for repeated measurements for each algorithm and temporal parameter calculated. Values are reported as mean bias ± SD (lower and upper 95 % limits of agreement). Gait events detection performance for initial and final foot contact (IC and FC, respectively) is reported as number of true positives (TP), false negatives (FN), false positives (FP), recall precision (R) and precision (P). Data refer to a total of 13 children, and 1388 IC and 1388 FC.

						IC					FC				
	Algorithm	Stride time [ms]	Step time [ms]	Stance time [ms]	Swing time [ms]	TP	FN	FP	R [%]	P [%]	TP	FN	FP	R [%]	P [%]
Ankle	Aminian et al., 2002	−1 ± 37 (−75, 72)	−1 ± 48 (−96, 94)	38 ± 37 (−35, 111)	−39 ± 31 (−101, 23)	1388	0	0	100	100	1388	0	0	100	100
	Behboodi et al., 2015	−1 ± 35 (−70, 68)	−1 ± 47 (−92, 90)	−14 ± 38 (−89, 61)	13 ± 28 (−42, 68)	1388	0	0	100	100	1388	0	0	100	100
	Catalfamo et al., 2010	−1 ± 34 (−69, 66)	−1 ± 46 (−91, 89)	47 ± 34 (−20, 115)	−49 ± 26 (−99, 2)	1388	0	0	100	100	1388	0	0	100	100
	Digo et al., 2023	−1 ± 37 (−74, 72)	−1 ± 48 (−96, 94)	38 ± 38 (−38, 113)	−39 ± 33 (−103, 26)	1388	0	0	100	100	1388	0	0	100	100
	Greene et al., 2010	−1 ± 37 (−74, 72)	−1 ± 47 (−94, 92)	53 ± 38 (−21, 128)	−54 ± 28 (−108, 0)	1386	2	0	99.9	100	1387	1	0	99.9	100
	Khandelwal and Wickström, 2014	4 ± 56 (−106, 114)	−1 ± 47 (−93, 90)	39 ± 64 (−87, 164)	−35 ± 28 (−89, 19)	1369	19	0	98.6	100	1359	29	0	97.9	100
	Lee et al., 2010	22 ± 72 (−119, 163)	−2 ± 55 (−109, 106)	33 ± 71 (−107, 173)	−10 ± 33 (−75, 55)	1324	64	0	95.4	100	1326	62	0	95.5	100
	Salarian et al., 2004	0 ± 42 (−83, 83)	−1 ± 46 (−91, 89)	6 ± 46 (−84, 96)	−5 ± 30 (−64, 53)	1382	6	0	99.6	100	1382	6	0	99.6	100
	Trojaniello et al., 2014	3 ± 50 (−95, 100)	−1 ± 46 (−91, 88)	−50 ± 60 (−169, 68)	53 ± 43 (−32, 138)	1375	13	0	99.1	100	1375	13	0	99.1	100
Lower-back	Del Din et al., 2016	−1 ± 37 (−74, 73)	0 ± 30 (−60, 60)	−7 ± 76 (−157, 143)	8 ± 74 (−138, 153)	1381	7	0	99.5	100	1323	65	0	95.3	100
	Digo et al., 2023	−2 ± 55 (−110, 106)	0 ± 52 (−103, 103)	−28 ± 78 (−181, 125)	25 ± 68 (−109, 158)	1374	14	0	99.0	100	1374	14	0	99.0	100
	González et al., 2010	19 ± 100 (−176, 214)	10 ± 90 (−165, 186)	39 ± 159 (−272, 349)	−16 ± 165 (−340, 308)	1362	26	0	98.1	100	1381	7	0	99.5	100
	McCamley et al., 2012	−4 ± 56 (−113, 104)	−2 ± 44 (−89, 85)	−24 ± 54 (−129, 82)	20 ± 45 (−68, 108)	1359	29	0	97.9	100	1245	143	0	89.7	100
	van Gelder et al., 2023	−1 ± 38 (−76, 74)	0 ± 33 (−65, 65)			1385	3	16	99.8	98.9					
	Zijlstra and Hof, 2003	−1 ± 54 (−108, 105)	−1 ± 53 (−104, 102)			1366	22	21	98.4	98.5					

best results overall.

Stance and swing times were not calculated by Gelder et al.'s [24] and Zijlstra and Hof's [25] algorithms, as they detected only initial foot contact. For the remaining algorithms, stance and swing times showed lower agreement compared to step and stride times (Figs. 3 and 4).

In Table 2, the gait event detection performance for each algorithm is reported in terms of true positives (TP), false negatives (FN) and false positives (FP). Events were falsely identified (FP) only by the algorithms developed by van Gelder et al. [24] and Zijlstra and Hof [25], with all other algorithms showing perfect (100 %) precision. Whereas most algorithms missed events (FN) for both initial and final foot contact, with the exception of four of the six algorithms based only on the ankle sensors' angular velocity about the medio-lateral axis. Despite missed events, all algorithms performed with recall precision higher than 89.7 %.

4. Discussion

The aim of this study was to compare the performance of 15 published IMU-based algorithms for the detection of gait events in toddlers. These algorithms were developed for healthy adults [22,25–31], healthy older adults [13,19,26,32], adults with pathological gait [13,23,24,32], and only one was developed for children between 8 and 16 years [17]. To the best of the authors' knowledge, no algorithms have been specifically developed or validated for toddlers or healthy children aged under 8.

A previous study by Pacini Panebianco et al. compared 17 algorithms for the detection of gait events in healthy adults including algorithms based on sensors located on feet, shanks and the lower-back [14]. In the current study, only sensors located on the ankles above the lateral malleoli and on the lower-back were considered. We chose to do this because placing sensors on toddlers' feet might alter their gait as they would have a significant impact on the foot segment weight.

The correct identification of gait events is of critical importance when the use of sensors is intended for ecological environment applications, therefore, the recall precision and precision obtained in this study are of great relevance. All algorithms using ankle sensors showed perfect precision and four of six algorithms using ankle angular velocity about the medio-lateral axis correctly identified all gait events, showing perfect recall precision (Table 2). On the other hand, all lower-back algorithms failed to identify some gait events (FN in Table 2), and two algorithms (van Gelder et al. [24] and Zijlstra and Hof [25]) falsely identified some gait events (FP in Table 2). Despite this, algorithms based on the lower-back sensor still performed with very high precision in both the detection of initial and final contact events. In contrast, Pacini Panebianco et al. [14] did not find any false positives or negatives. This might be explained by the fact the algorithms were originally developed for adults, and that toddlers present a more varied gait due to their wider range of size and walking experience, with toddlers in our study ranging from 7 to 46 months of walking experience.

In terms of accuracy, no single algorithm emerged as a best option from our results. Algorithms using sensors located on the ankles were consistently more accurate in the calculation of step and stride time when using only angular velocity about the medio-lateral axis, compared to when acceleration was used. For sensors located on the lower-back, the algorithms developed by Del Din et al. [23] and van

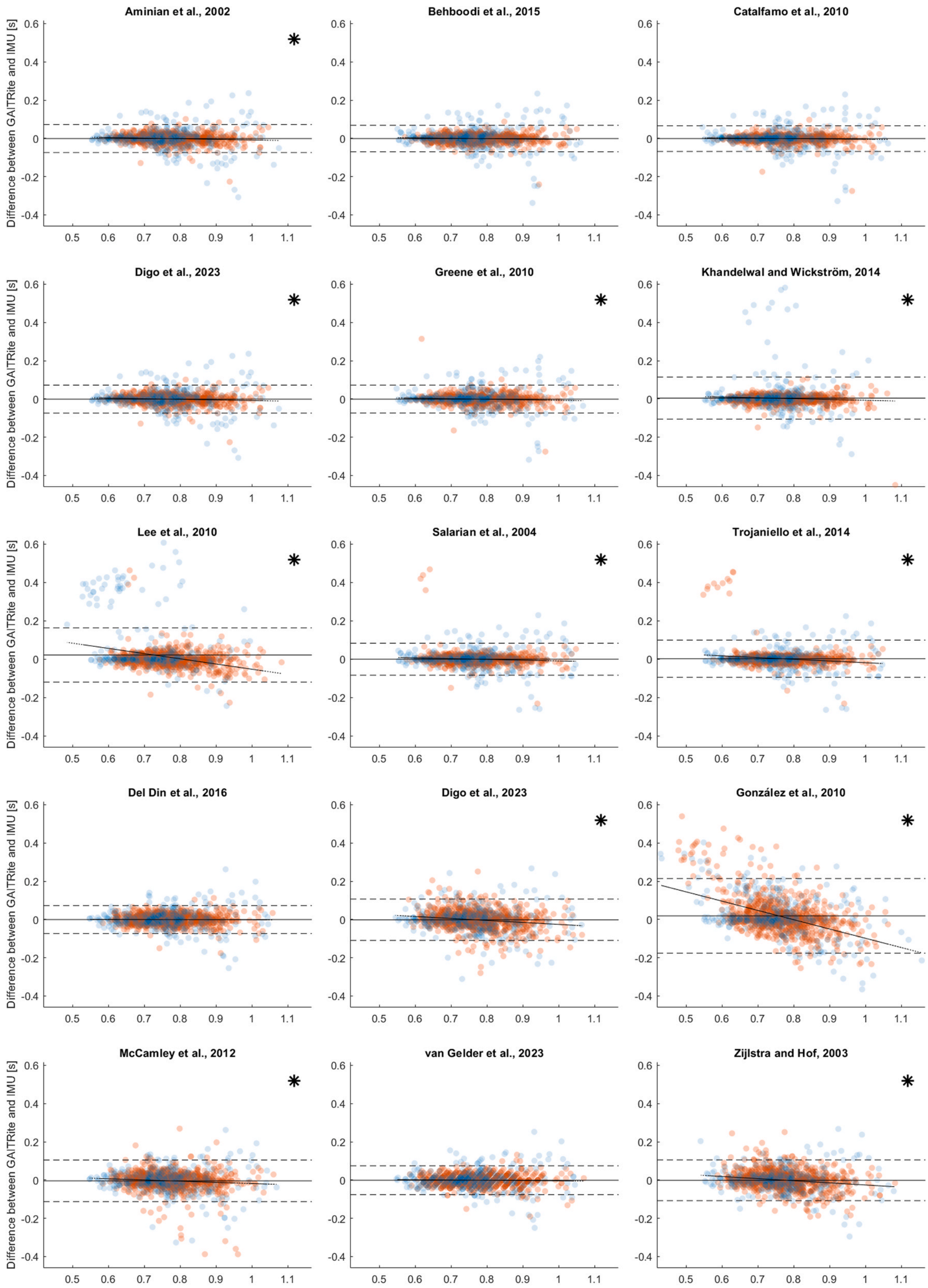

Fig. 1. Bland Altman limits of agreement for repeated measurements with 95 % confidence intervals for stride time. The results for each algorithm are reported through separate scatter plots showing the difference between IMU and GAITRite measurement against the average of the two measurements with lines representing mean bias (horizontal solid line), upper and lower limits of agreement (horizontal dashed lines) and regression line (dotted line). Plots with an asterisk present significant bias. Blue refers to the 3 children with less than one year of walking experience, red for children with more than one year of walking experience. Data refer to a total of 13 children, and 1388 IC and 1388 FC.

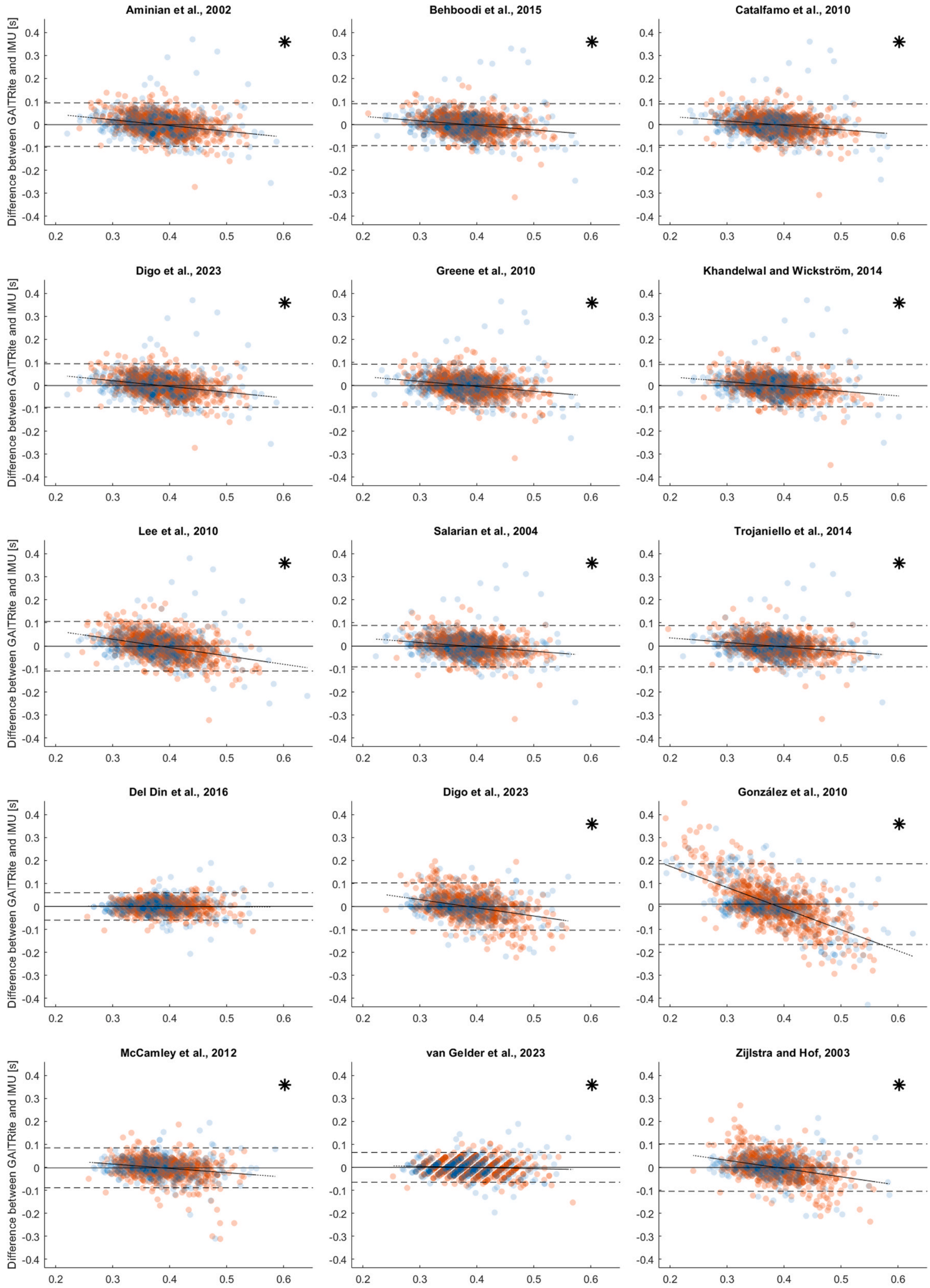

Fig. 2. Bland Altman limits of agreement for repeated measurements with 95 % confidence intervals for step time. The results for each algorithm are reported through separate scatter plots showing the difference between IMU and GAITRite measurement against the average of the two measurements with lines representing mean bias (horizontal solid line), upper and lower limits of agreement (horizontal dashed lines) and regression line (dotted line). Plots with an asterisk present significant bias. Blue refers to the 3 children with less than one year of walking experience, red for children with more than one year of walking experience. Data refer to a total of 13 children, and 1388 IC and 1388 FC.

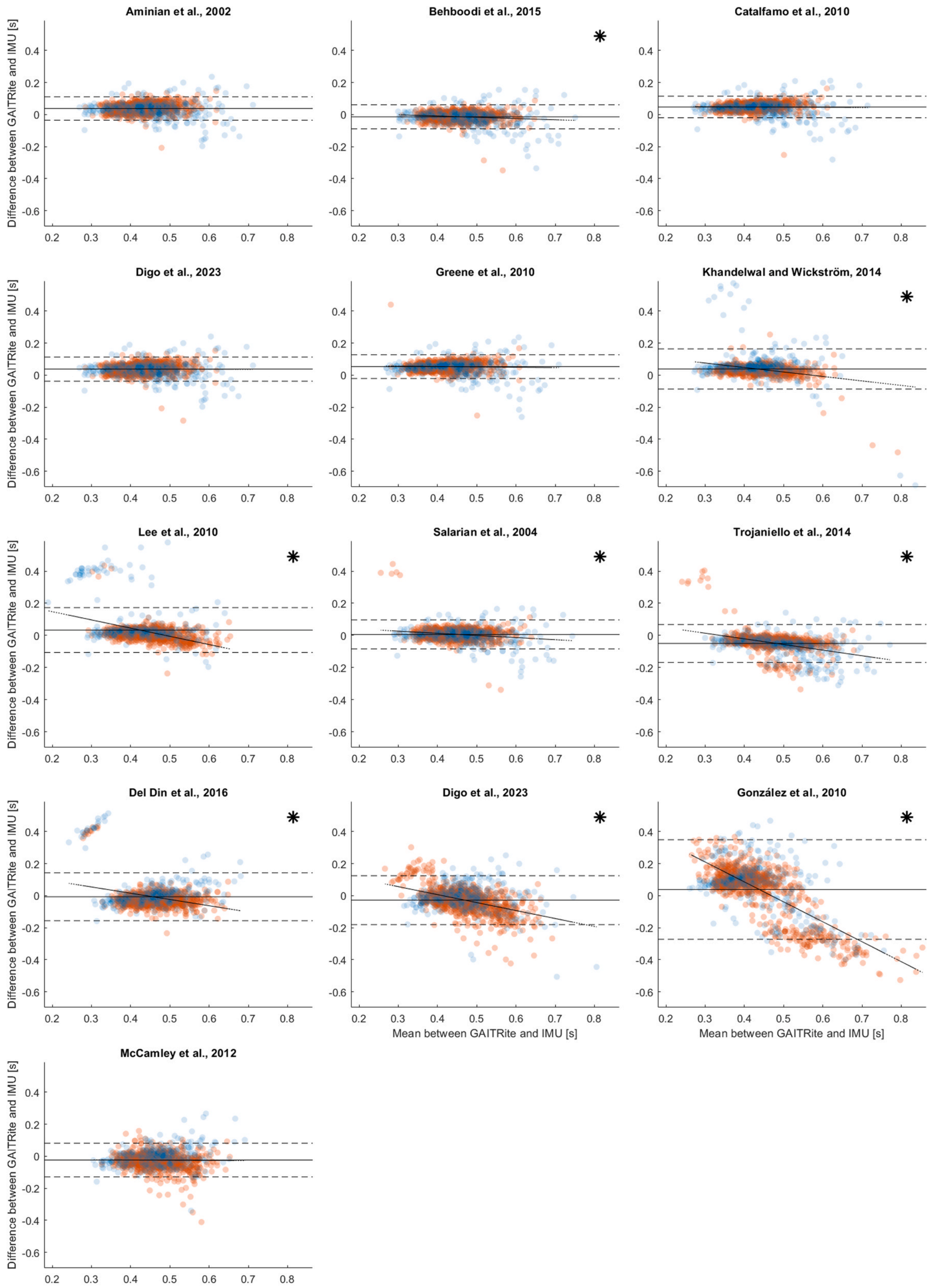

Fig. 3. Bland Altman limits of agreement for repeated measurements with 95 % confidence intervals for stance time. The results for each algorithm are reported through separate scatter plots showing the difference between IMU and GAITRite measurement against the average of the two measurements with lines representing mean bias (horizontal solid line), upper and lower limits of agreement (horizontal dashed lines) and regression line (dotted line). Plots with an asterisk present significant bias. Blue refers to the 3 children with less than one year of walking experience, red for children with more than one year of walking experience. Data refer to a total of 13 children, and 1388 IC and 1388 FC. Algorithms from van Gelder et al. [24] and Zijlstra and Hof [25] are not reported since they were designed only to calculate the initial contact, therefore, stance time could not be calculated.

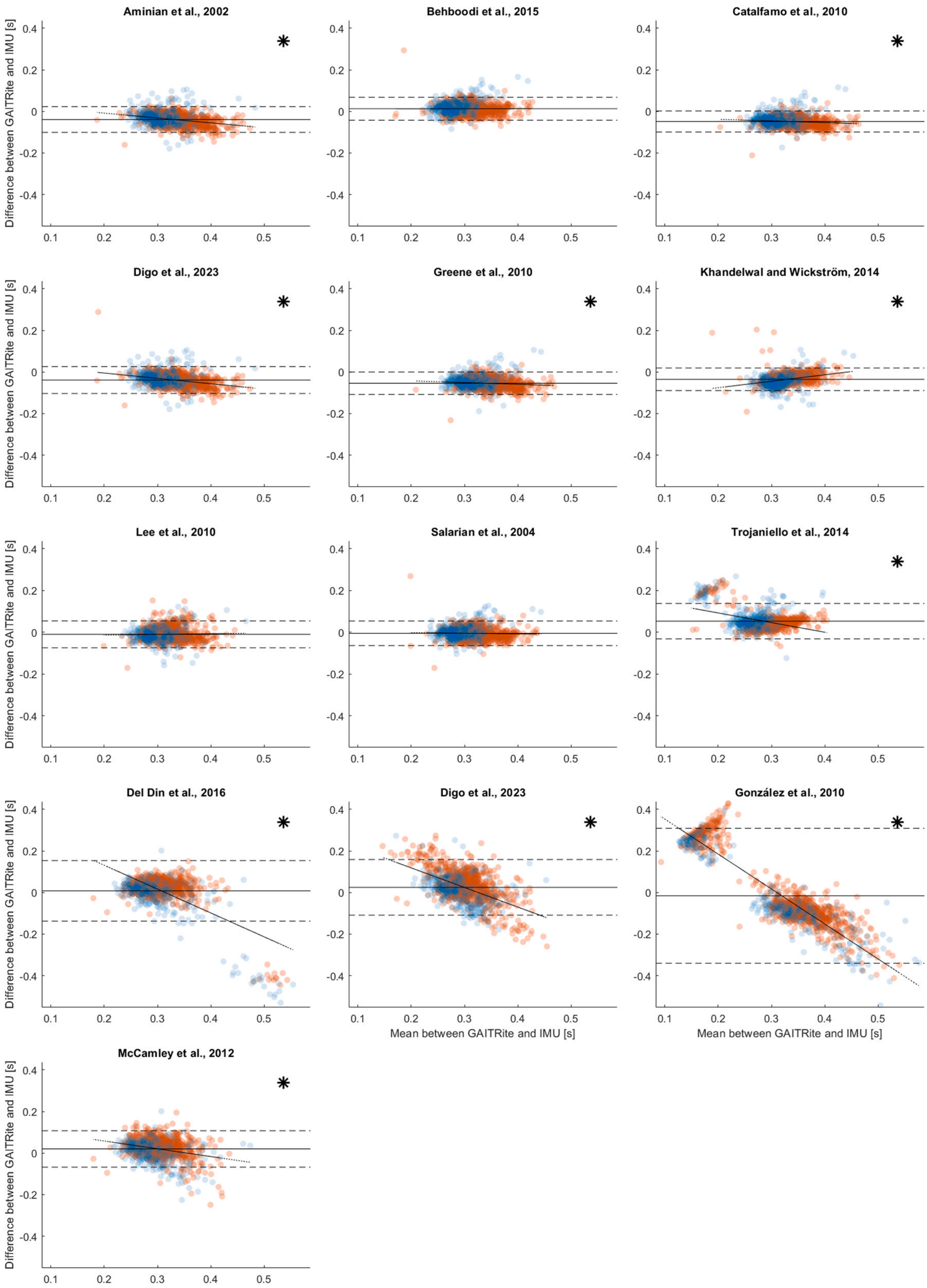

Fig. 4. Bland Altman limits of agreement for repeated measurements with 95 % confidence intervals for swing time. The results for each algorithm are reported through separate scatter plots showing the difference between IMU and GAITRite measurement against the average of the two measurements with lines representing mean bias (horizontal solid line), upper and lower limits of agreement (horizontal dashed lines) and regression line (dotted line). Plots with an asterisk present significant bias. Blue refers to the 3 children with less than one year of walking experience, red for children with more than one year of walking experience. Data refer to a total of 13 children, and 1388 IC and 1388 FC. Algorithms from van Gelder et al. [24] and Zijlstra and Hof [25] are not reported since they were designed only to calculate the initial contact, therefore, stance time could not be calculated.

Gelder et al. [24] provided the best results. Del Din et al.'s algorithm [23] was based on the one developed by McCamley et al. [31], with the addition of a transformation from the local sensor coordinate system into the vertical-horizontal global system; whereas, the algorithm developed by van Gelder et al. [24] was based on resultant acceleration. All other algorithms for sensors located on the lower-back used acceleration or angular velocity recorded in the sensor's local coordinate system. These results suggest that the data recorded from a lower-back sensor might be influenced by the sensor's alignment due to the use of different nappies and clothing, and that by reducing the effect of the sensor's different orientation between participants, global or resultant accelerations provide better accuracy.

In healthy adults, Pacini Panebianco et al. [14] found comparable accuracy in the detection of initial foot contact between foot and shank-based algorithms, with lower-back-based algorithms performing worse. Whereas, in the detection of final contact, foot-based algorithms had the best accuracy, followed by shank-based and then lower-back-based algorithms. This lower precision in the detection of the final contact event, compared to the initial contact for algorithms based on ankle and lower-back sensors, explains the lower accuracy found in this study for all the algorithms in the calculation of stance and swing time. In contrast to the results obtained for healthy adults [14], in toddlers the algorithms developed by Del Din et al. [23] and van Gelder et al. [24] provided similar results to the best ankle-based algorithms in the calculation of stride time, and the best overall accuracy when calculating step time (Table 2). Minimal detectable difference between the measurement systems corresponds to a single GAITRite frame for stride, stance and swing time; whereas the need to synchronize the two malleolar IMUs for the calculation of step time leads to errors up to two GAITRite frames. Therefore, the decreased accuracy in the calculation of step time compared to stride time for the ankle-based algorithms might be explained by the sensors' synchronization, which was not an issue for the single-sensor lower-back algorithms, even if this error can be quantified as less than 17 ms, which is still small compared to the 90 ms confidence intervals obtained comparing the measurement methods. The algorithm developed by Del Din et al. [23] is also the only one that does not present a significant slope in the Bland Altman plot for step time (Fig. 2), and for stride time together with three other algorithms [17,24,27]. This highlights that most ankle-based algorithms and those on the lower-back using recordings in the sensor's local coordinate system underestimate quicker step or stride times and overestimate slower ones, suggesting a dependence on walking speed.

The accuracy of the algorithms was also compared between younger and older toddlers, and due to the wide range in participants' characteristics, a one-year walking experience was chosen as threshold. The comparison shows wider differences between IMUs and GAITRite for the detection of stride (Fig. 1) and stance time (Fig. 3) in the younger group, especially for the ankle-based algorithms. This suggests that the use of these algorithms with toddlers with more walking experience might lead to improved accuracy for these temporal parameters. Whereas the results for step time (Fig. 2), despite a small number of outliers, suggest the algorithms have similar performance for toddlers with varying walking experience. Swing time shows less spread in the mean difference between systems for the toddlers with less than one-year walking experience. Toddlers, when first starting to walk, present longer stance phase to maintain stability and consequently shorter swing phase [3], which explain these differences in mean. These results suggest that ankle-based algorithms using angular velocity about the medio-lateral axis would be the preferred choice for the measurement of stride time in toddlers with more walking experience, whereas for step time walking experience does not seem to influence the algorithms' accuracies; however, more data collected on participants with little walking experience would allow more definitive results.

For future studies, the development of a hybrid algorithm that combines the accuracy of the best algorithms using lower-back sensors with the precision of the best ankle-based algorithms could reduce the number of false positives and negatives and simplify the distinction between right and left foot contact. When trying to reduce the number of sensors to be used, the lower-back is the favourable location for a single device, being close to the centre of mass, it can be used to detect fall risk, trunk stability and balance control [33]. In addition, a lower-back sensor can lead to the detection of more features of gait in toddlers where the typical gait pendulum mechanism is not yet fully developed, and the effect of stamping and other gait deviations is more evident in the sensors attached to the lower limbs. The results of this study, therefore, support the use of a single sensor on toddlers' lower-back using resultant or global acceleration, since it is less affected by walking speed for step time estimation and by walking experience, however, attention must be placed on the potential to miss some gait events leading to erroneous estimation of temporal parameters.

In this study, we analysed the usability of IMUs to detect gait events in toddlers in a structured environment. Future work should consider the usability of the sensors in semi-structured environments (e.g. walking path including obstacles, steps and uneven terrains) to determine the ability of IMUs to evaluate children's gait and its adaptations due to real-world environmental changes. The use of IMU sensors to detect gait events should also be validated for young children with pathological gait, this would support clinical practice, particularly to monitor disease progression and consequently improve diagnosis and treatment benefitting the children and their families' quality of life. When deciding which algorithm to use, we suggest researchers select the best algorithm based on the characteristics of their study population, the parameters they wish to measure and the accuracy they require.

Limitations of this study are related to the need to synchronise the IMU sensors to each other and to the GAITRite. The synchronisation between measurement methods relied on step counting from a reference video, the use of synchronized devices with the same sample frequency would provide a more accurate comparison and reduce additional sources of errors. The lack of inbuilt IMU synchronisation increased the complexity of the analysis and might have introduced errors in the estimation of step time. To be used in the real world, sensors should be small, lightweight, simple to use, and for algorithms using multiple sensors should have inbuilt synchronisation.

5. Conclusion

In this study we showed the potential of IMUs to detect gait events and measure gait temporal parameters in toddlers. No single algorithm showed overall better performance than others, with lower-back algorithms producing better step time measures, but having lower precision than ankle-based algorithms. IMUs can support research analysing the spatio-temporal parameters of toddlers' gait in controlled environments, and may allow future studies in natural, free-living environments that can improve the monitoring of gait in young children.

CRediT authorship contribution statement

Penitente Gabriella: Writing – review & editing, Resources, Project administration, Methodology, Conceptualization. **Wheat Jonathan:** Writing – review & editing, Conceptualization. **Heller Ben:** Writing – review & editing, Conceptualization. **d'Andrea Francesca:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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