Computer Methods and Programs in Biomedicine 220 (2022) 106808

Contents lists available at ScienceDirect

Computer Methods and Programs in Biomedicine

journal homepage: www.elsevier.com/locate/cmpb

Gait performance in toddlers born preterm: A sensor based quantitative characterization

Maria Cristina Bisi[a,b,*], Manuela Fabbri[c], Duccio Maria Cordelli[c,d], Rita Stagni[a,b]

[a] Department of Electrical, Electronic and Information Engineering, "Guglielmo Marconi" - DEI, University of Bologna, Italy
[b] Interdepartmental Center for Industrial Research – Life Sciences and Health Technologies, University of Bologna, Italy
[c] IRCCS Institute of Neurological Sciences of Bologna, UOC Neuropsychiatry of the Pediatric Age, Bologna, Italy
[d] Department of Medical and Surgical Sciences - DIMEC, University of Bologna, Italy

ARTICLE INFO

Article history:
Received 5 August 2021
Revised 11 March 2022
Accepted 9 April 2022

Keywords:
Wearable sensors
Motor biomarkers
Preterm children
Motor development
Variability
Complexity

ABSTRACT

Background and Objectives: Preterm children have an increased risk of motor difficulties. Gait analysis and wearable technologies allow the assessment of motor performance in toddlers, identifying early deviations from typical development. Using a sensor-based approach, gait performance of full-term and preterm toddlers at different risk of motor delay was analysed. The aim was to measure quantitative differences among groups.

Methods: Twenty-nine two-year old children born preterm (≤36 gestational weeks) and 17 full-term controls, matched for age and walking experience, participated in the study. Preterm children were further divided based on risk of motor delay: preterm at high risk ($n = 8$, born at ≤28 gestational weeks or with ≤1000 g of body weight), and at moderate risk ($n = 21$).

Children were asked to walk along a corridor while wearing 3 inertial sensors on the lower back and on the ankles. Gait temporal parameters, their variability, and nonlinear metrics of trunk kinematics (i.e. recurrence quantification analysis, multiscale entropy) were extracted from the collected data and compared among groups.

Results: Children born preterm showed significantly longer stance and double support phases, higher variability of temporal parameters, and lower multiscale entropy values than peers born full-term. No difference was found for the other parameters when comparing preterm and full-term children. When comparing children grouped according to risk of delay, with increasing risk, children showed longer stride-, stance- and double-support-time, higher variability of temporal parameters, higher recurrence- and lower multiscale entropy values.

Conclusions: Sensor-based gait analysis allowed differentiating the gait performance of preterm from full-term toddlers, and of preterm toddlers at different risk of motor delay. When analysing the present results with respect to the expected trajectory of locomotor development, children born preterm, in particular those at higher risk of motor delay, exhibited a less mature motor control performance during gait: lower stability (i.e. longer support phases), and higher variability, although not structured towards the exploration of more complex movements (i.e. higher recurrence- and lower multiscale entropy values). These indexes can serve as biomarkers for monitoring locomotor development and early detecting risk to develop persistent motor impairments.

1. Introduction

The earlier a baby is born the greater the risk of long-term consequences, with over 50% of children born <30 weeks facing motor, cognitive, and behavioural impairments [1]. Thanks to advances in medical care, younger and more vulnerable children born preterm (PT) have increased opportunities of survival, with evidence of an increasing number of PT infants worldwide (an estimated 11.1% of all livebirths in 2010 were born PT [2]).

One of the most frequent issues encountered by PT children is an increased risk of motor difficulties ranging from mild impairments to cerebral palsy, with prevalence 3 to 4 times greater than in the general population [3]. While a substantial evidence base has been established for risk factors, causal pathways, and neurological mechanisms for cerebral palsy [4], the knowledge regarding the non-cerebral palsy motor impairments is still limited, although affecting a much larger number of PT children (up to

* Corresponding author at: Via dell'Università 50, 47521, Cesena (FC), Italy.
E-mail address: mariacristina.bisi@unibo.it (M.C. Bisi).

https://doi.org/10.1016/j.cmpb.2022.106808
0169-2607/

50% of children born <30 weeks) [1]. Mild motor deficits, such as Developmental Coordination Disorder, can have long-term consequences, compromising physical function, academic achievement, and other health outcomes (e.g. higher risks of obesity, cardiorespiratory problems, diabetes, and problems related to social integration) [5]. Thus, to implement effective interventions for the future wellbeing of this growing population, the understanding as well as the early and timely identification of mild motor difficulties is crucial, given the key periods of brain plasticity and musculoskeletal development.

WHO defines preterm birth as any birth before 37 completed weeks of gestation and divides this further on the basis of gestational age (extremely/very preterm < 32 weeks of gestation; moderate/late preterm 32 - <37 weeks). These subdivisions are important since decreasing gestation age is associated with increasing short and long term consequences [2]. However, this subdivision is defined to support clinical data collection and management in general and not for subject-specific identification of risk of motor delays.

Nowadays, identification of potential gross motor impairment in toddlers is primarily based on motor-milestone history and clinical examination, which have demonstrated poor specificity [6]. Motor milestone assessments are made challenging by variability in parental report and the wide age range of normal in milestone attainment [6]. Clinical examinations, even when based on structured assessments of gross motor function (e.g. The Peabody Developmental Motor Scale-2 and Bayley Scales of Infant Development-3rd Edition), are long (90 min for the full BSID-III 18–22 month olds) and expensive, require trained personnel, thus limiting assessments only to the highest-risk children. Given these limitations, there is the need of quantitative and objective tests, easy to be administered, for a widespread application.

As recently highlighted in the review by Albesher et al. [7], walking is a central part of most basic and leisure daily activities; therefore, knowledge of the timing of walking onset and any alteration of gait is essential to understand the needs of children born PT. Several research studies [6,8–10] analysed and quantified gait of PT children during the first months of independent walking using lab-based measurement methods (i.e. instrumental walkways, 3-D motion analysis and force platforms) [7]. These studies showed that gait in toddlers born PT is generally characterized as being delayed and qualitatively less coordinated [8,11]. At 18 months of age, they exhibited shorter stride length than full-term (FT) peers [10], but it is not clear if these differences persist as children reach preschool and school age [7]. Recently, spatiotemporal gait parameters have been proposed as useful in building a clinically relevant, straightforward assessment of toddler gross motor development [6], but the need of laboratory assessment hinders their applicability for routine monitoring. Despite relevant findings [8–11], the quantitative characterization of gait in children born PT is still scarce and concentrates on the first few months after the child attains walking and at school age, while studies on walking characteristics of PT children in between those ages are lacking [7]. Wearable sensors can be a viable solution to overcome laboratory limitations and effectively fill this gap: they are easy to use, light, unobtrusive, and can be worn under the clothes, for long periods, facilitating the experiments with toddlers [12]. Human movement analysis methods exploiting measurements based on wearable inertial sensors allow the quantitative assessment of human movement in outpatient conditions at different ages, effectively integrating the information derived from qualitative observation with quantitative biomarkers [13] to attain a quantitative monitoring of motor development in PT children.

Sensor-based approaches allowed the estimation of temporal gait parameters in different children populations with typical and atypical development [13] as well as toddlers at the onset of walking [12]. On the other hand, the analysis and monitoring of motor control development requires to address the maturation of different underlying control mechanisms, such as automaticity and complexity, that can be investigated by means of advanced metrics [13,14].

To this purpose, nonlinear metrics, derived from dynamical system theory, provide tools for investigating the dynamics of motor control resulting from interactions between nervous system, musculoskeletal system, and the surrounding environment while performing of a specific task [15].

Among these nonlinear metrics, previous works from the same authors showed that multiscale entropy (MSE) [16] and recurrence quantification analysis (RQA) of trunk 3D acceleration during gait, allowed to quantitatively assess motor development during the life-span [17,18], highlighting differences related to age maturation [17], and providing information complementary to standard clinical tests in toddlers and school-children [19,20]. In particular, RQA and MSE have been associated to the quantification of motor regularity and complexity during locomotion and their changes with age to changes in the maturation of motor control [19,20]. Increase or decrease of these metrics with (age) maturation depends on the analysed motor task and, specifically, on the stage of motor learning process of the population under study with respect to the specific task [20,21]. When considering toddlers at the onset of independent walking, MSE was found to increase with maturation and/or walking experience, as during the first stage of the fundamental movement phase [22], there is a gradual increase in agility, adaptability, and ability to make complex movements, which children show manifesting more and more flexibility in performance [18,23].

When considering PT children motor development, entropy-based metrics have been applied for the analysis of infant postural control maturation [24–27], highlighting that infants born PT show a decreased postural complexity compared to infants born FT. These results, although not specifically referred to gait, support the use of nonlinear metrics for the investigation of motor development to highlight consequences of PT births and/or risk of possible delays.

The aim of the present study was to assess gait performance of toddlers born PT as compared to a control group born at FT, using a sensor-based approach that allows quantifying a cluster of metrics [17] that include gait temporal parameters, their variability, as well as nonlinear metrics quantitatively characterizing the dynamics of the lower trunk, related to the control of the progression of the center of mass [19]. Only PT children without diagnosis of cerebral palsy were included in the study. Based on previous literature [7,23,25], it was hypothesized that PT children at risk of motor delay would show a less mature gait performance, corresponding to a delayed maturation of the control of the trunk and a higher variability of gait temporal parameters.

2. Materials and methods

2.1. Study subjects

PT children were recruited at the Ceredilico – IRCCS Institute of Neurological Sciences of Bologna, where they were already enrolled in a neurodevelopment follow-up program. Children born at FT were recruited at a local kindergarten (Istituto San Giuseppe, Lugo, Ravenna). The local Ethical Committee approved this study (ASL_BO n° 0018081 08/02/2017), and informed consent was obtained from the participants' parents.

Twenty-nine two-year old PT (median/min-max value of months of adjusted age: 25/18–27; months of walking experience: 12/2–16; gestational weeks: 30.5/24–35) and 17 FT children (median/min-max value of age: 28/14–34; months of walking

Table 1a
Preterm (PT) participants' details, divided into children at high risk (Hrisk-PT) and children at moderate risk (Mrisk-PT) of motor delays: age and adjusted age (months), sex (male(M)/female(F)), twins (yes(y)/no(n)), walking experience (months), weeks of pregnancy, body mass at birth (kg), length (cm) and body mass (kg) at 24 months, Bayley Scales of Infant Development-3rd Edition (BSID-III) cognitive standardized score at 24 months.

							at birth		at 24 months	
	age (months)	adjusted age	sex	twins	walking experience (months)	weeks of pregnancy	body mass (kg)	length (cm)	body mass (kg)	BSID-III cognitive standardized scores
Hrisk-PT	22.3	18.3	F	n	4.3	23+4	0.530	84	9.2	85*
	27.4	24.2	F	y	12.2	26+2	0.900	86	11.0	105
	27.4	24.2	M	y	11.2	26+2	1.020	86	13.0	90
	28.8	25.7	F	n	9.7	27+2	0.755	80	10.5	85
	30.2	27.2	F	y	15.2	27+2	1.040	92	13.0	80
	30.2	27.2	F	y	16.2	27+2	1.085	90	15.0	105
	27.6	24.8	F	n	12.8	28+2	1.020	77	9.5	90
	26.9	24.1	F	n	12.1	28+2	0.810	85	11.0	100
Mrisk-PT	30.0	27.2	F	n	14.2	28+4	1.430	91	12.4	100
	28.8	26.0	M	n	15.0	28+3	1.170	89	12.5	95
	27.6	25.3	F	y	13.3	30+1	1.470	90	11.0	100
	27.6	25.3	M	y	14.3	30+1	1.410	92	12.0	95
	26.3	24.0	F	n	8.0	30	1.200	90	12.0	95
	25.3	22.9	F	y	6.9	30+3	1.480	86	12.5	95
	25.3	22.9	F	y	6.9	30+3	1.411	86	11.5	90
	26.7	24.6	M	n	14.6	31	1.990	90	12.5	95
	27.1	25.0	F	n	12.0	31	1.530	84	11.4	100
	27.0	25.1	M	n	15.1	31+2	1.600	89	13.0	95
	21.3	19.2	M	y	7.2	31+3	1.795	88	13.0	75
	21.3	19.2	M	y	7.2	31+3	1.410	85	12.5	75
	26.2	24.4	F	n	11.4	32	1.580	85	11.3	NA**
	27.3	25.4	F	y	10.4	32	1.590	88.5	12.3	100
	27.3	25.4	F	y	11.4	32	1.490	88.5	12.3	100
	26.7	24.6	F	n	2.6	31+6	1.400	92	13.0	105
	27.4	25.6	F	y	10.6	32+3	1.675	80.5	10.1	95
	27.5	25.6	F	y	12.6	32+3	1.375	80.5	10.1	90
	26.7	24.9	F	n	14.9	32+4	2.090	87	12.5	95
	27.3	25.5	F	n	13.5	32+6	1.690	85	12.0	100
	26.2	25.1	F	n	12.1	35	1.545	82	10.0	90

* test administered when the child was 29 months old.
** test score not available.

experience: 15/2–24; ≥38 gestational weeks) participated in the study.

All PT children had a diagnosis of "Disorders related to short gestation and low birth weight", ICD10-GM-2018 P07, and no other diagnosed developmental delay. Children with congenital malformations and/or blindness were excluded. PT children were further divided into two groups based on the risk of motor delay. Since gestational age and body weight at birth are both determinant of long-term neurodevelopmental outcomes [28,29], the children born extremely PT (≤28 gestational weeks [2]) or with extremely low body weight (≤1000 g [30]) were considered at high risk (Hrisk-PT), and the other PT children at moderate risk (Mrisk-PT). FT children had no diagnosed developmental delay. Characteristics of PT and FT children participating in the study are shown in Table 1a and 1b, respectively.

FT, Mrisk-PT, and Hrisk-PT showed no difference in terms of age (when considering both adjusted and not adjusted age for PT children) and walking experience (Kruskalwallis test, level of significance 5%).

2.2. Experimental setup

Three tri-axial wireless inertial sensors (OPAL, Apdm, USA) were mounted on the lower back (at L5 level) and on the shanks (above lateral malleolus) using Velcro straps (Fig. 1) [12]; 3D acceleration and angular velocity were recorded at 128 Hz. Tests were performed at the clinical center Ceredilico – IRCCS Institute of Neurological Sciences of Bologna during the day of the follow-up visit for PT children, and at the kindergarten (Istituto San Giuseppe, Lugo, Ravenna) for FT children.

Sensors had coloured stickers attached on in order to help participants familiarize. After sensor positioning, children were distracted with toys and free walks. Tests started only when participants were comfortable and forgot about the sensors (given the unobtrusiveness of the sensors, this took typically less than 2 min).

The participants were asked to walk at self-selected speed along a 15 m long corridor while moms or nannies called them at the other end of the corridor. The trials were video recorded to later check if they either were helping themselves with something (wall, shelves etc.), were curving, stopping, running, or crying. In those cases, the identified steps were excluded from the analysis.

2.3. Data analysis

Only inline straight strides were considered for data analysis.

Foot contacts and foot offs were identified from the angular velocity around the medio-lateral axis of the leg, identifying local minima at the beginning and at the end of the swing phase [12,31,32]. For all participants, 14 consecutive strides were analysed, being the maximum number of inline strides identified for all subjects.

The following temporal parameters were calculated as described in [17] and [31]:

- Stride- (StrideT, in seconds) and normalized stride-time (nStrideT, adimentional [33]);
- Step- (StepT, in seconds) and normalized step-time (nStepT, adimentional [33]);
- Stance-time (StanceT, expressed in% of StrideT),
- Double support-time (DS, expressed in% of StrideT).

Table 1b
Full-term (FT) participants' details: age (months), sex (male(M)/female(F)), twins (yes(y)/no(n)), walking experience (months), weeks of pregnancy, body mass at birth (kg), length (cm) and body mass (kg) at 24 months.

					at birth	at 24 months	
age (months)	sex	twins	walking experience (months)	weeks of pregnancy	body mass (kg)	length (cm)	body mass (kg)
32.0	M	n	19.0	38+4	3.790	96	14.4
28.0	F	n	10.0	41	3.550	86	12.2
28.0	F	n	15.0	40	2.685	85.5	10.8
25.0	F	n	14.0	38	2.800	85	12.5
29.0	F	n	16.0	41	3.270	91	13.4
31.0	M	n	18.0	40	3.560	92	13.3
29.0	F	n	17.0	36	3.960	97	15.7
31.0	F	n	19.0	39	3.520	91	14.5
20.0	M	n	7.0	38+3	3.090	82	11.2
21.0	F	n	8.0	39	3.265	83	13.2
19.0	M	n	7.0	40	3.500	85	12.5
19.0	F	n	3.0	37+4	2.645	95	14.2
33.0	M	n	24.0	40+3	4.050	96.5	14.8
27.0	M	n	15.0	38	4.000	92	15.9
14.0	M	n	2.0	38	3.190	92	16.1
34.0	M	n	19.0	38+2	2.600	96	17.5
27.0	M	n	13.0	41	3.215	90	14.0

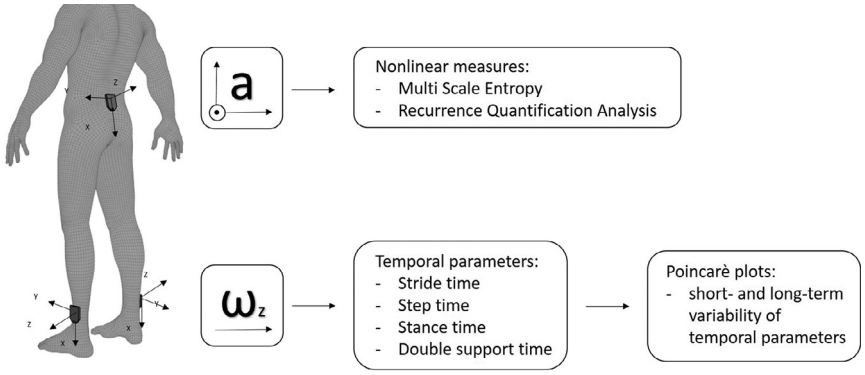

Fig. 1. On the left, inertial sensor positions (lower trunk and shanks) and axis orientations. On the right, data analysis flowchart.

Symmetry between right and left StrideT, StanceT and StepT was tested per each subject using the Kruskal–Wallis test with a level of significance of 5%. As no significant difference between right and left parameters was found, data from both legs were considered together for each participant.

Intra-subject variability was evaluated using Poincarè plots [34], calculating short (SD1) and long term (SD2) variability [35] of the estimated temporal parameters (i.e. StrideT, StepT, StanceT, DS).

RQA and MSE were calculated for the three trunk acceleration components (vertical, V, medio-lateral, ML, and antero-posterior, AP) [17].

MSE was calculated as the Sample Entropy (SEN) of trunk acceleration components (SENv, SENml, SENap) at time scales (τ) from 1 to 6: i) coarse-grained time series were calculated by averaging increasing numbers of data points in non-overlapping windows of length τ, τ=1:6; ii) length of sequences to be compared, *m*, was fixed at 2, and tolerance for accepting matches, *radius*, at 0.2 [20]. To guarantee reliability of MSE results [36], sensitivity to radius values was verified (*radius* = 0.10, 0.15, 0.20, 0.25, and 0.30) for each τ for the two groups, and relative consistency was verified for radius values below and above the selected one.

For RQA [37], the state space was constructed by using the delay-embedded state space of each component of the trunk acceleration separately (embedding dimension = 5, time delay = 10 samples) [20]. After the generation of recurrence plots (threshold = 40%) [20], the following features were extracted for each acceleration component: recurrence rate (RR), determinism (DET) and averaged diagonal line length (AvgL).

Fig. 1 shows sensor placement and a schematic flowchart of data analysis.

Full description of parameters extractions for both temporal and nonlinear parameters is provided in Table 2a and 2b, respectively.

2.4. Statistical analysis

Jarque-Bera test was performed to test the normal distribution of the estimated parameters in the different groups (i.e. FT, PT, Hrisk-PT, Mrisk-PT): since the normal distribution was not verified on all groups, Kruskal-Wallis test (level of significance 0.1) was used to analyze influence of (i) PT birth and (ii) risk of motor delay on the calculated parameters (i.e. temporal parameters, variability of temporal parameters, RQA, MSE).

Statistical analysis was performed to test:

i Influence of preterm birth: PT vs FT;
ii Influence of risk of motor delay: FT, Mrisk-PT and Hrisk-PT. When a significant effect was found, a multiple comparison test [38] was performed to evaluate which of the analysed groups showed significant differences from the others. Dunn–Sidak correction was considered for post-hoc analysis [39].

Table 2a
Temporal parameters: acronyms, descriptions and details for parameter calculation.

Temporal parameters		
Acronym	Measure (unit)	Description
StrideT	Stride time (s)	Time difference between two consecutive initial contacts of the same foot
nstrideT	normalized stride time (adimentional)	Adimentional stride time, calculated according to Hof [33].
stepT	Step time (s)	Time difference between the initial contact of one foot and the initial contact of the opposite foot.
nstepT	normalized step time (adimentional)	Adimentional step time, calculated according to Hof [33].
stanceT	stance time (% of StrideT)	Time difference between initial contact and the consecutive terminal contact of the same foot, expressed in percentage of StrideT.
DS	double support time (% of StrideT)	Time difference between the initial contact of one foot and the terminal contact of the opposite foot, expressed in percentage of StrideT.
SD1 StrideT	short term variability of StrideT	Poincaré plots were created plotting temporal parameters data between successive gait cycles, showing variability of temporal parameters data. The plots display the correlation between temporally consecutive data in a graphical manner: SD1 and SD2 are calculated as width and length of the long and short axis, respectively, describing the elliptical nature of the plots, and represent the short-term and long- term variability of the analysed temporal parameter [34].
SD2 StrideT	long term variability of StrideT	
SD1 StepT	short term variability of StepT	
SD2 StepT	long term variability of StrideT	
SD1 StanceT	short term variability of StrideT	
SD2 StanceT	long term variability of StrideT	
SD1 DS	short term variability of StrideT	
SD2 DS	long term variability of StrideT	

Table 2b
Nonlinear parameters: acronyms, descriptions and details for parameter calculation.

Nonlinear parameters		
Acronym	Measure	Description
MSE	multiscale entropy	MSE was calculated as the Sample Entropy (SEN) of trunk acceleration components (SENv, SENml, SENap) at time scales (τ) from 1 to 6.
SEN	sample entropy	Trunk acceleration time series have been normalized to have standard deviation 1. Consecutive coarse-grained time series were calculated by averaging increasing numbers of data points in non-overlapping windows of length τ. Each element of the coarse grained time series $y_j(\tau)$, was calculated starting from the original time series {x1,...,xi,..., xN}, according to $y_j^{(\tau)} = 1_\tau \sum_{i=(j-1)}^{jx} xi$, where τ represents the scale factor and $1 \le j \le N/\tau$. For each coarse grained time series, SEN was calculated as the conditional probability that two sequences of m consecutive data points ($m = 2$) similar to each other will remain similar (i.e. distance of data points inferior to a fixed radius (radius fixed at 0.2), when one more consecutive point is included.
RQA	Recurrence quantification Analysis	State space was reconstructed by using the delay embedded state space of each trunk acceleration component separately (V, AP and ML). Embedding dimension was fixed at 5; time delay was obtained using the first minimum of the average mutual information algorithm and set at 10 samples (corresponding to 0.078 s given the sampling frequency of 128 Hz). Distance between all the points of the embedded time series was calculated. If this distance was less than or equal to a threshold the point is a recurrence. The recurrence plot was obtained by selecting a threshold of 40% of the max distance, and all cells with values below this threshold were identified as recurrent points.
RR	Recurrence Rate	RR was calculated as the number of recurrent points in the recurrence plot expressed as a percentage of the number of possibly recurrent points (percentage of points within a threshold distance of one another).
DET	Determinism	DET was calculated as the percentage of recurrent points falling on upward diagonal line segments. Number of points forming a line segment was fixed at 4.
AvgL	Averaged Diagonal Line Length	AvgL was calculated as the average upward diagonal line length, where the diagonal lines are defined following determinism definition.

3. Results

3.1. Temporal parameters

No significant difference was found for StrideT, nStrideT, StepT, and nStepT when comparing FT and PT. When comparing the 3 groups based on risk of motor delay, a significant effect was found for both StrideT and nStrideT ($p = 0.007$ and $p = 0.001$, respectively) and for stepT and nStepT ($p = 0.09$ and $p = 0.05$, respectively): StrideT, nStrideT, stepT, and nStepT all resulted shorter for groups at lower risk of motor delay; post-hoc analysis showed that Hrisk-PT had significantly longer StrideT than Mrisk-PT and longer nStrideT than Mrisk-PT and FT, and had significantly longer nStepT than Mrisk-PT and FT children.

PT children also showed significantly longer StanceT ($p = 0.02$) and DS ($p = 0.06$) with respect to FT. When considering the three groups based on risk of motor delay, a significant effect was found on StanceT, showing longer stance for increasing risk of motor de-

lay ($p = 0.04$); however, post-hoc analysis highlighted no significant differences between groups.

Intra-subject variability of all temporal parameters resulted significantly higher in PT children than in FT control peers for all estimated parameters except for SD2 of StrideT ($p = 0.3$). When dividing PT participants based on risk of motor delay, a significant effect was found for SD1 of StrideT ($p = 0.03$), SD1 of StepT ($p = 0.03$), SD1 and SD2 of StanceT ($p = 0.04$ and $p = 0.07$, respectively), and SD1 of DS ($p = 0.07$), highlighting an increasing trend of variability with increasing risk of motor delay; post-hoc analysis showed that FT children had significantly lower values of SD1 of StrideT, of StepT and of StanceT than Mrisk-PT.

Median values and 25th and 75th percentiles of temporal parameters for each group are reported in Table 3.

3.2. Non-linear metrics

No significant difference was found for RQA parameters when comparing FT and PT. When considering the three groups based on risk of motor delay, among RQA parameters, a significant effect was found for DETml ($p = 0.02$) showing higher values in children at higher risk of motor delay: post-hoc analysis showed DETml to be significantly higher in Hrisk-PT than Mrisk-PT.

When comparing FT vs PT, SEN values calculated in the frontal plan, i.e. V and ML directions, showed significant differences for τ=1 ($p = 0.01$), and τ=1 and 2 ($p = 0.007$ and 0.01), respectively. In particular, PT children showed lower complexity values than FT peers. No significant difference was found for the other values of τ and in AP direction (for all the values of τ). When considering participants divided into three groups, a significant effect of risk of motor delay was found again for SEN values calculated in the frontal plane, i.e. V and ML directions, in particular for τ=1 ($p = 0.03$) on the V axis, and τ = from 1 to 4 (p<0.02) on the ML axis. In all cases, lower SEN values were found for increasing risk of motor delay. Post hoc analysis highlighted that, in ML direction, Hrisk-PT children had significantly lower SEN values than FT.

Median values and 25th and 75th percentiles of nonlinear metrics for each group are reported in Table 4.

Based on statistical analysis results, the following significant parameters were selected for a polar representation [17]:

1) 'Temporal parameters': nStrideT, StanceT, DS.
2) 'Motor complexity': SENv (τ=1), SENml (τ=1), SENml (τ=2).
3) 'Short term variability': SD1 for strideT, stanceT and DS.
4) 'Long term variability': SD2 for strideT, stanceT and DS.

Fig. 2 shows polar reference bands representing median, 25th and 75th percentiles of each parameter for FT and PT, and for Mrisk-PT and Hrisk-PT.

4. Discussion

In the present work, a sensor-based approach was used to characterize and compare gait performance of toddlers born PT with FT controls, allowing to quantify differences in temporal parameters, their variability, and non-linear metrics for the quantification of motor control. PT children showed significantly longer StanceT, higher variability of temporal parameters (SD1 of StrideT, StepT, StanceT and DS, SD2 of StepT, StanceT and DS), and lower motor complexity than FT (lower MSE values in the frontal plane). When dividing PT children according to risk of motor delay (Hrisk-PT and Mrisk-PT), the estimated parameters confirmed the expected trends, showing a significant effect of risk of motor delay and Mrisk-PT values in between those of FT and Hrisk-PT (see Tables 3 and 4).

Although literature providing quantitative characterization of gait characteristics in PT children is scarce [7], some of the re-

Table 3
On the left, estimated temporal parameters (25th, 50th, and 75th percentiles) for FT and PT children. Asterisks indicate significant differences between FT and PT (*p<0.1; ** p<0.05). Significant differences are described between brackets. On the right, estimated temporal parameters (25th, 50th, and 75th percentiles) for PT children at moderate risk (Mrisk-PT) and children at high risk (Hrisk-PT) of motor delay. Asterisks indicate a significant effect of risk of motor delay when comparing FT, Mrisk-PT and Hrisk-PT (*p<0.1; ** p<0.05). Significant differences between groups resulting from the multiple comparison test are described between brackets.

	FT			PT				Mrisk-PT				Hrisk-PT			
	25th	50th	75th	25th	50th	75th		25th	50th	75th		25th	50th	75th	
StrideT	0.74	0.82	0.87	0.75	0.80	0.89		0.72	0.78	0.84		0.84	0.88	0.92	** (Hrisk-PT > Mrisk-PT)
nstrideT	2.48	2.61	2.86	2.54	2.71	2.98		2.39	2.65	2.77		2.83	3.00	3.05	** (Hrisk-PT > FT; Hrisk-PT > Mrisk-PT)
stepT	0.37	0.41	0.44	0.37	0.40	0.44		0.37	0.38	0.43		0.42	0.44	0.45	*
nstepT	1.24	1.32	1.42	1.27	1.35	1.50		1.22	1.32	1.42		1.42	1.50	1.51	** (Hrisk-PT > FT; Hrisk-PT > Mrisk-PT)
stanceT	56.4	58.2	59.9	57.4	60.2	62.0	** (PT > FT)	56.6	60.2	62.0		58.2	60.2	62.6	**
DS	13.1	17.2	19.8	17.2	20.0	24.0	* (PT > FT)	16.3	20.4	24.0		17.8	19.8	24.1	
SD1 StrideT	0.04	0.04	0.06	0.05	0.06	0.08	** (PT > FT)	0.05	0.07	0.08		0.05	0.06	0.07	** (FT < Mrisk-PT)
SD2 StrideT	0.05	0.08	0.11	0.07	0.09	0.12		0.06	0.08	0.11		0.07	0.10	0.13	
SD1 StepT	0.02	0.03	0.04	0.03	0.04	0.07	** (PT > FT)	0.03	0.05	0.08		0.03	0.04	0.04	** (FT < Mrisk-PT)
SD2 StepT	0.04	0.04	0.07	0.05	0.06	0.08	** (PT > FT)	0.04	0.06	0.18		0.05	0.06	0.07	
SD1 StanceT	2.53	3.05	3.94	3.16	4.16	4.82	** (PT > FT)	3.16	4.18	4.97		3.21	3.93	4.33	** (FT < Mrisk-PT)
SD2 StanceT	3.22	3.68	4.17	3.72	4.31	5.41	** (PT > FT)	3.40	4.31	5.25		3.92	4.82	5.69	*
SD1 DS	3.41	4.06	5.44	4.34	5.39	6.60	** (PT > FT)	4.34	5.39	6.81		4.12	5.71	6.46	*
SD2 DS	4.10	5.21	5.73	4.63	5.94	7.35	** (PT > FT)	4.54	5.94	7.77		5.10	5.81	7.29	

Table 4
On the left, estimated nonlinear parameters (25th, 50th, and 75th percentiles) for FT and PT children. Asterisks indicate significant differences between FT and PT (** $p<0.05$). Significant differences are described between brackets. On the right, estimated nonlinear parameters (25th, 50th, and 75th percentiles) for PT children at moderate risk (Mrisk-PT) and children at high risk (Hrisk-PT) of motor delay. Asterisks indicate a significant effect of risk of motor delay when comparing FT, Mrisk-PT and Hrisk-PT (** $p<0.05$). Significant differences between groups resulting from the multiple comparison test are described between brackets.

	FT			PT				Mrisk-PT			Hrisk-PT			
	25th	50th	75th	25th	50th	75th		25th	50th	75th	25th	50th	75th	
DETml	5.11	5.50	5.69	5.29	5.47	5.69		5.28	5.42	5.55	5.62	5.82	6.04	** (Hrisk-PT > Mrisk-PT)
SENv (τ=1)	0.47	0.54	0.58	0.38	0.46	0.54	** (PT < FT)	0.38	0.46	0.55	0.38	0.45	0.51	**
SENml (τ=1)	0.51	0.60	0.67	0.43	0.51	0.55	** (PT < FT)	0.43	0.52	0.55	0.35	0.46	0.51	** (Hrisk-PT < FT)
SENml (τ=2)	0.83	1.01	1.09	0.74	0.83	0.90	** (PT < FT)	0.78	0.87	0.93	0.60	0.75	0.80	** (Hrisk-PT < FT)

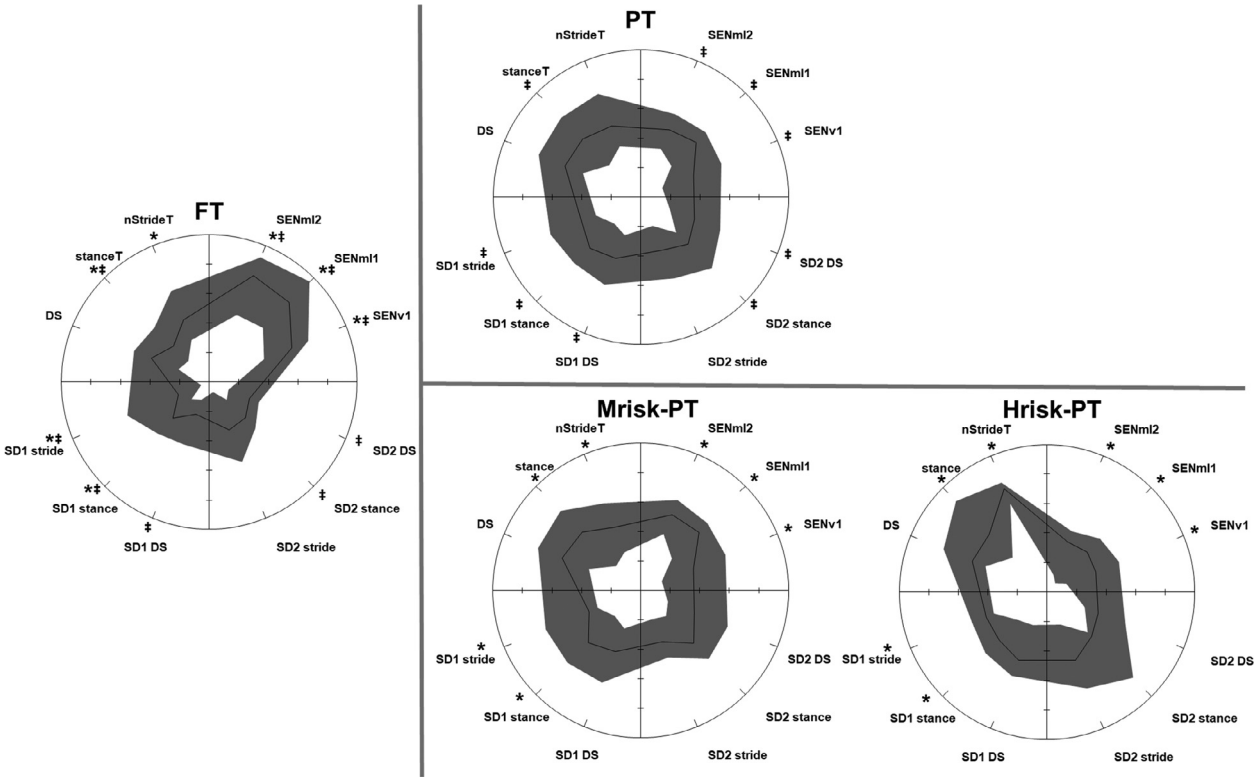

Fig. 2. Polar bands (median, 25th and 75th percentiles) for FT and PT children and for Mrisk-PT and Hrisk-PT. Double daggers indicate significant differences between FT and PT ($p<0.05$), asterisks significant effect of risk of motor delay when considering FT, Mrisk-PT and Hrisk-PT ($p<0.05$).

sults of the comprehensive analysis performed in the present work confirm previous findings. The proposed sensor-based approach showed a tendency towards longer (not significant) StepT in Hrisk-PT (median 0.44 s) with respect to Mrisk-PT and FT (median 0.38 s and 0.41 s) and significantly longer nStepT (median nStepT 1.50 for Hrisk-PT, 1.32 for Mrisk-PT, 1.32 for FT). In addition, stride duration (i.e. StrideT and nStrideT) resulted significantly longer in Hrisk-PT than in Mrisk-PT and FT, while they did not significantly differ between PT and FT. This result confirms the longer step duration already observed in PT children with moderate motor delay when compared to FT children [7,8]. No significant differences were found between Mrisk-PT and FT for these parameters.

Moreover, significantly longer StanceT and a tendency towards longer DS (not significant) were found for PT children when compared to FT. PT children at 18 months were previously shown to have a stance duration inversely correlated to walking experience [10] and those with lower gross motor function to have longer StanceT and DS phases [8]. The combination of the mentioned [8,10] and present findings suggests that PT children manifest a delayed gait maturation, characterized by longer support phases, which can be interpreted as driven by the need of a stabilizing strategy [35].

Both short- and long-term intra-subject variability of temporal parameters showed a decrease from Hrisk-PT to Mrisk-PT to FT children. Increased gait variability was already reported in the literature for PT schoolchildren when analysing stride velocity- and stride length variability [9]. Considering gait development, the increased gait variability in PT can be interpreted as the manifestation of a less mature gait performance, as a decrease in StrideT variability with age maturation (from toddlers to schoolchildren) is expected [18,40].

Among non-linear metrics, RQA showed DETml significantly higher in Hrisk-PT than Mrisk-PT and FT, and MSE highlighted significantly lower values of SEN in PT children on the V and the ML direction. These results suggest that PT children manifest a more regular and less complex pattern of gait on the frontal plane, corresponding to a more simple early form of gait [12] and a possible delay in the manifestation of flexibility and ability to make complex movements [41].

With respect to previous works from the same authors [17,18], highlighting the significance of MSE for τ values higher than 4 when characterizing gait at different ages from school children to adults, in the population analysed in the present work, the lowest time scales resulted the ones highlighting significant differences

between groups (i.e. τ=1 for V and τ=1,2 for ML). Considering that coarse graining procedures (i.e. averaging on a moving window, as performed for the calculation of MSE) on gait acceleration signal for increasing values of τ can be related to low pass filtering at decreasing cut-off frequencies (e.g. τ =4 corresponding to 16 Hz, τ =5 corresponding to 13 Hz etc.), this result suggests that, when considering toddlers, differences between PT and FT are related to faster signal components. This could suggest that proprioceptive-based control loops (short-loops) associated to postural control play a more relevant role for the characterization of the early development of gait, while visuo-vestibular based control loops (long-loops), characterized by longer time scale, influence and characterize the development of gait later in life (e.g. starting from middle and/or late childhood) [42]. Clearly, specific future studies are necessary to investigate this hypothesis and improve the understanding of underlying physiology of motor control development.

It has to be highlighted that MSE on the ML axis (τ = from 1 to 2) was the only metric allowing to differentiate both PT from FT and Hrisk-PT from the other two groups, supporting the potential of this metric in the assessment of motor control development. As previously suggested for postural control in infants [24], also in gait, decreased early complexity not only may contribute to motor delays but may also limit exploration of the environment impacting cognitive development.

To authors' knowledge, this is the first study investigating gait performance differences in PT children using wearable sensors, highlighting the possibility of identifying early motor biomarkers with non-intrusive technology [13]. This solution will facilitate longitudinal monitoring, which, as suggested in literature [7], is fundamental to understand the relationship between early biomarkers of gait and long-term developmental problems and/or to understand if affected children catch up later or continue to have issues.

The advantage of the polar representation of the results is again confirmed in this application as in previous studies [17,19]: when aiming at characterizing a specific population, it allows to relate the proposed metrics at first glance to an 'age equivalent' in order to understand if possible delays in motor development are present and in which area (variability, motor complexity etc.). Clearly, given the very young age of the participants of the present study, only natural walking was considered. In the future, using the same approach, it will be possible to analyze locomotor performance of PT schoolchildren, by assessing gait and tandem gait, as proposed in the literature [19].

Possible limitations of the present study regard the number and the characteristics of the participants: i) the number of participants per group, especially when considering Hrisk-PT and Mrisk-PT separately, is relatively small and ii) even if groups had no significant differences in term of age and walking experience, when compared to PT children, FT characteristics were more dispersed (PT, 24 $\pm$ 2 months of adjusted age, FT, 26 $\pm$ 5 months). Nonetheless, the number of participants is similar to that of previous studies investigating gait in PT [7], and the larger dispersion of the FT group characteristics is more likely to have hindered rather than promoted the identification of significant differences with respect to the PT group; despite a higher variability of FT characteristics, the inter-subject variability of FT children gait results was comparable to that of PT children (see band widths in Fig. 2), highlighting that locomotor development has a similar trajectory in children with typical development, while it is more heterogeneous in PT children.

However, the limited number of participants included in the present study has to be taken into consideration when drawing the conclusions of the study: the present results demonstrated the feasibility of the proposed quantitative sensor-based approach [17] for monitoring gait performance in PT children, confirming, in a relatively small group of children, the hypothesis that PT children at risk of motor delay show a less mature gait performance, corresponding to a delayed maturation of the control of the trunk (i.e. lower complexity) and a higher variability of gait temporal parameters. The proposed approach will support the implementation of further longitudinal studies on more numerous groups, in order to attain a more robust and deeper understanding of motor development pathways in PT children, assessing the predictive capacity and usability of the identified quantitative parameters as biomarkers of locomotor development and risk of motor delay.

Conflict of Interest

The Authors declare that there is no conflict of interest.

Acknowledgments

Authors would like to thank the participants and their parents. The present study was approved by the local Ethical Committee (ASL_BO n° 0018081 08/02/2017). This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

[1] A.J. Spittle, J.L. McGinley, D. Thompson, R. Clark, T.L. FitzGerald, B.F. Mentiplay, K.J. Lee, J.E. Olsen, A. Burnett, K. Treyvaud, E. Josev, B. Alexander, C.E. Kelly, L.W. Doyle, P.J. Anderson, J.L. Cheong, Motor trajectories from birth to 5 years of children born at less than 30 weeks' gestation: early predictors and functional implications. Protocol for a prospective cohort study, J. Physiother. 62 (2016) 222–223 https://doi.org/10.1016/j.jphys.2016.07.002.

[2] H. Blencowe, S. Cousens, D. Chou, M. Oestergaard, L. Say, A.-.B. Moller, M. Kinney, J. Lawn, Born too soon: the global epidemiology of 15 million preterm births, Reprod. Health. 10 (2013) S2https://doi.org/10.1186/1742-4755-10-S1-S2.

[3] J. Williams, K.J. Lee, P.J. Anderson, Prevalence of motor-skill impairment in preterm children who do not develop cerebral palsy: a systematic review, Dev. Med. Child Neurol. 52 (2010) 232–237 https://doi.org/10.1111/j.1469-8749.2009.03544.x.

[4] J. Williams, C. Hyde, A. Spittle, Developmental coordination disorder and cerebral palsy: is there a continuum? Curr. Dev. Disord. Rep. 1 (2014) 118–124 https://doi.org/10.1007/s40474-014-0009-3.

[5] P. Caçola, Physical and mental health of children with developmental coordination disorder, Front. Public Health. 4 (2016) https://doi.org/10.3389/fpubh.2016.00224.

[6] K. Cahill-Rowley, J. Rose, Toddle temporal-spatial deviation index: assessment of pediatric gait, Gait Posture 49 (2016) 226–231 https://doi.org/10.1016/j.gaitpost.2016.06.040.

[7] R.A. Albesher, A.J. Spittle, J.L. McGinley, F.L. Dobson, Gait characteristics of children born preterm, NeoReviews. 20 (2019) e397–e408 https://doi.org/10.1542/neo.20-7-e397.

[8] K. Cahill-Rowley, J. Rose, Temporal-spatial gait parameters and neurodevelopment in very-low-birth-weight preterm toddlers at 18–22 months, Gait Posture 45 (2016) 83–89 https://doi.org/10.1016/j.gaitpost.2016.01.002.

[9] P. Hagmann-von Arx, O. Manicolo, N. Perkinson-Gloor, P. Weber, A. Grob, S. Lemola, Gait in very preterm school-aged children in dual-task paradigms, PLoS ONE 10 (2015) e0144363 https://doi.org/10.1371/journal.pone.0144363.

[10] S.-.F. Jeng, T.-.W. Lau, W.-.S. Hsieh, H.-.J. Luo, P.-.S. Chen, K.-.H. Lin, J.-.Y. Shieh, Development of walking in preterm and term infants: age of onset, qualitative features and sensitivity to resonance, Gait Posture 27 (2008) 340–346 https://doi.org/10.1016/j.gaitpost.2007.04.012.

[11] L. de Groot, C.J. de Groot, B. Hopkins, An instrument to measure independent walking: are there differences between preterm and fullterm infants? J. Child Neurol. 12 (1997) 37–41 https://doi.org/10.1177/088307389701200106.

[12] M.C. Bisi, R. Stagni, Evaluation of toddler different strategies during the first six-months of independent walking: a longitudinal study, Gait Posture 41 (2015) 574–579 https://doi.org/10.1016/j.gaitpost.2014.11.017.

[13] C.C.T. Clark, M.C. Bisi, M.J. Duncan, R. Stagni, Technology-based methods for the assessment of fine and gross motor skill in children: a systematic overview of available solutions and future steps for effective in-field use, J. Sports Sci. 0 (2021) 1–41 https://doi.org/10.1080/02640414.2020.1864984.

[14] S.C. Dusing, Postural variability and sensorimotor development in infancy, Dev. Med. Child Neurol. 58 (2016) 17–21 Suppl 4https://doi.org/10.1111/dmcn.13045.

[15] N. Stergiou, Nonlinear Analysis for Human Movement Variability, Taylor & Francis Inc, 2016.

[16] M. Costa, C.-.K. Peng, A.L. Goldberger, J.M. Hausdorff, Multiscale entropy analysis of human gait dynamics, Phys. Stat. Mech. Its Appl. 330 (2003) 53–60 https://doi.org/10.1016/j.physa.2003.08.022.

[17] M.C. Bisi, P. Tamburini, R. Stagni, A 'Fingerprint' of locomotor maturation: motor development descriptors, reference development bands and data-set, Gait Posture 68 (2019) 232–237 https://doi.org/10.1016/j.gaitpost.2018.11.036.
[18] M.C. Bisi, R. Stagni, Complexity of human gait pattern at different ages assessed using multiscale entropy: from development to decline, Gait Posture 47 (2016) 37–42 https://doi.org/10.1016/j.gaitpost.2016.04.001.
[19] M.C. Bisi, Human motor control: is a subject-specific quantitative assessment of its multiple characteristics possible? A demonstrative application on children motor development, Med. Eng. Phys. (2020) 8.
[20] M.C. Bisi, P. Tamburini, G. Pacini Panebianco, R. Stagni, Nonlinear analysis of human movement dynamics offer new insights in the development of motor control during childhood, J. Biomech. Eng. (2018) https://doi.org/10.1115/1.4040939.
[21] M.C. Bisi, R. Stagni, Changes of human movement complexity during maturation: quantitative assessment using multiscale entropy, Comput. Methods Biomech. Biomed. Engin. 21 (2018) 325–331 https://doi.org/10.1080/10255842.2018.1448392.
[22] D.L. Gallahue, J.C. Ozmun, Understanding Motor Development. Infants, Children, Adolescents, Adults, McGrow Hill, 2006 Sixth Edition.
[23] M.C. Bisi, F. Riva, R. Stagni, Measures of gait stability: performance on adults and toddlers at the beginning of independent walking, J. Neuroengineering Rehabil. 11 (2014) 131https://doi.org/10.1186/1743-0003-11-131.
[24] S.C. Dusing, T.A. Izzo, L.R. Thacker, J.C. Galloway, Postural complexity differs between infant born full term and preterm during the development of early behaviors, Early Hum. Dev. 90 (2014) 149–156 https://doi.org/10.1016/j.earlhumdev.2014.01.006.
[25] S.C. Dusing, L.R. Thacker, J.C. Galloway, Infant born preterm have delayed development of adaptive postural control in the first 5 months of life, Infant Behav. Dev. 44 (2016) 49–58 https://doi.org/10.1016/j.infbeh.2016.05.002.
[26] S.C. Dusing, A. Kyvelidou, V.S. Mercer, N. Stergiou, Infants born preterm exhibit different patterns of center-of-pressure movement than infants born at full term, Phys. Ther. 89 (2009) 1354–1362 https://doi.org/10.2522/ptj.20080361.
[27] J.E. Deffeyes, R.T. Harbourne, S.L. DeJong, A. Kyvelidou, W.A. Stuberg, N. Stergiou, Use of information entropy measures of sitting postural sway to quantify developmental delay in infants, J. Neuroengineer. Rehabil. 6 (2009) 34https://doi.org/10.1186/1743-0003-6-34.
[28] J.J. Hollanders, N. Schaëfer, S.M. van der Pal, J. Oosterlaan, J. Rotteveel, M.J.J. Finken, O. behalf of the Dutch POPS-19 collaborative study group, long-term neurodevelopmental and functional outcomes of infants born very preterm and/or with a very low birth weight, Neonatology 115 (2019) 310–319 https://doi.org/10.1159/000495133.
[29] N.M. Davis, G.W. Ford, P.J. Anderson, L.W. Doyle, Victorian Infant Collaborative Study Group, Developmental coordination disorder at 8 years of age in a regional cohort of extremely-low-birthweight or very preterm infants, Dev. Med. Child Neurol. 49 (2007) 325–330 https://doi.org/10.1111/j.1469-8749.2007.00325.x.
[30] C.L. Cutland, E.M. Lackritz, T. Mallett-Moore, A. Bardají, R. Chandrasekaran, C. Lahariya, M.I. Nisar, M.D. Tapia, J. Pathirana, S. Kochhar, F.M. Muñoz, Low birth weight: case definition & guidelines for data collection, analysis, and presentation of maternal immunization safety data, Vaccine 35 (2017) 6492–6500 https://doi.org/10.1016/j.vaccine.2017.01.049.
[31] G. Pacini Panebianco, M.C. Bisi, R. Stagni, S. Fantozzi, Analysis of the performance of 17 algorithms from a systematic review: influence of sensor position, analysed variable and computational approach in gait timing estimation from IMU measurements, Gait Posture 66 (2018) 76–82 https://doi.org/10.1016/j.gaitpost.2018.08.025.
[32] A. Salarian, H. Russmann, F.J.G. Vingerhoets, C. Dehollain, Y. Blanc, P.R. Burkhard, K. Aminian, Gait assessment in Parkinson's disease: toward an ambulatory system for long-term monitoring, IEEE Trans. Biomed. Eng. 51 (2004) 1434–1443 https://doi.org/10.1109/TBME.2004.827933.
[33] A.L. Hof, Scaling gait data to body size, Gait Posture 4 (1996) 222–223 https://doi.org/10.1016/0966-6362(95)01057-2.
[34] A.H. Khandoker, S.B. Taylor, C.K. Karmakar, R.K. Begg, M. Palaniswami, Investigating scale invariant dynamics in minimum toe clearance variability of the young and elderly during treadmill walking, IEEE Trans. Neural Syst. Rehabil. Eng. Publ. IEEE Eng. Med. Biol. Soc. 16 (2008) 380–389 https://doi.org/10.1109/TNSRE.2008.925071.
[35] G. Pacini Panebianco, M.C. Bisi, A.L. Mangia, S. Fantozzi, R. Stagni, Quantitative characterization of walking on sand inecological conditions: speed, temporal segmentation, and variability, Gait Posture 86 (2021) 211–216 https://doi.org/10.1016/j.gaitpost.2021.03.019.
[36] J.M. Yentes, P.C. Raffalt, Entropy analysis in gait research: methodological considerations and recommendations, Ann. Biomed. Eng. (2021). https://doi.org/10.1007/s10439-020-02616-8.
[37] F. Sylos Labini, A. Meli, Y.P. Ivanenko, D. Tufarelli, Recurrence quantification analysis of gait in normal and hypovestibular subjects, Gait Posture 35 (2012) 48–55 https://doi.org/10.1016/j.gaitpost.2011.08.004.
[38] Y. Hochberg, A.C. Tamhane, References, in: Mult. Comp. Proced, John Wiley & Sons, Inc., 2008, pp. 417–438. http://onlinelibrary.wiley.com/doi/10.1002/9780470316672.refs/summary (accessed September 9, 2013).
[39] Z. Šidák, Rectangular confidence regions for the means of multivariate normal distributions, J. Am. Stat. Assoc. 62 (1967) 626–633 https://doi.org/10.1080/01621459.1967.10482935.
[40] J.M. Hausdorff, L. Zemany, C. Peng, A.L. Goldberger, Maturation of gait dynamics: stride-to-stride variability and its temporal organization in children, J. Appl. Physiol. Bethesda Md 1985 86 (1999) 1040–1047.
[41] M. Hadders-Algra, Variation and variability: key words in human motor development, Phys. Ther. 90 (2010) 1823–1837 https://doi.org/10.2522/ptj.20100006.
[42] P. Gilfriche, V. Deschodt-Arsac, E. Blons, L.M. Arsac, Frequency-specific fractal analysis of postural control accounts for control strategies, Front. Physiol. 9 (2018) https://doi.org/10.3389/fphys.2018.00293.