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The use of regression and normalisation for the comparison of spatio-temporal gait data in children

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ABSTRACT

Spatio-temporal parameters (STPs) are fundamental gait measures often used to compare children of different ages or gait ability. In the first case, non-dimensional normalisation (ND) of STPs using either leg-length or height is frequently conducted even though the process may not remove known inter-subject variability. STPs of children with and without disability can be compared through matched databases or using regression driven prediction. Unfortunately, database assignment is largely arbitrary and previous regressions have employed too few parameters to be successful. Therefore, the aims of this study were to test how well actual and ND STPs could be predicted from anthropometrics and speed and to assess if self-selected speed could be predicted from anthropometrics using multivariate regression in a cohort of eighty-nine typically developing children. Equations were validated on an extraneous dataset. We found that equations for actual step length, stride length, and cadence explained more than 84% of the variance compared to their ND counterparts. Moreover, only leg-length ND versions of these parameters were linearly proportional to speed. Prediction of single and double limb support times was weaker ($R^2 = 0.69$ and 0.72, respectively) and we were unable to predict self-selected speed ($R^2 < 0.16$) suggesting the use of anthropometrics is inappropriate for this purpose. Validation was successful for most STPs except in children lying near or outside the normal ranges and for gait speed. Clinically, regression could be used to quantify the difference between a patient's actual and theoretical STPs, allowing for monitoring of progress pre- and post intervention.

1. Introduction

Spatial-temporal parameters (STPs), such as self-selected speed, stride-length and cadence are basic measures of gait relating to foot-strike and foot-off placement and timing. There are differences in STPs between children with gait pathologies and their typically developing peers [1,2], adults and children [3,4], and amongst children of different ages. Amongst typically developing children, increased stride-length and decreased cadence lead to higher walking speeds with increasing age [5–8]. These differences can be attributed not only to anthropometric variability, such as leg-length or mass, but also to the neuromaturation effects of age [5]. Maturation plays a larger role in the early years whilst growth dominates the later stages of childhood [9–11].

STPs are often used to compare gait characteristics between children with varied anthropometrics or of different gait abilities, often walking at different speeds. There is therefore a requirement that comparisons account for the known variability between subjects. In the former case, the nondimensional normalisation (ND) approach of Hof [12] is often used and has been shown to effectively reduce inter-subject variability [13,14] and is used to compare subjects of different sizes, walking at similar ND speeds [15]. Yet the ND approach assumes proportional scaling and might not remove all age-related variability; in particular, variability arising from developmental differences may persist [5]. For the latter situation, STPs of children with and without gait pathology can be compared using large datasets grouped by age [6,8] or gait speed [16]; however, it remains unclear if grouping accounts for all the predictable variability in the subject groups. Alternatively, regression analysis may be used to predict expected gait parameters given no gait pathology and then determine how those with limited gait ability compare to their expected gait parameters. In a study by Stansfield et al. [15], ND STPs were regressed against ND speed only as maturation effects were assumed to be minimal in the cohort aged 7–12 years being

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investigated; however, the authors discouraged using their equations for predictive purposes. Possibly other factors, not included in the analysis, may have helped explain additional variability. An earlier study by the same lead author, investigating a slightly younger cohort, suggested that age might also be an important parameter [14]. It is conceivable that STPs could be best predicted by simultaneously analysing multiple anthropometric quantities such as height, leg-length, mass, and age as well as gait speed. In the aforementioned studies, gait speed was found to be a strong predictor of other STPs; yet, it remains unclear if self-selected speed itself can be reliably predicted from subject characteristics. In pathological populations this appears to be the case [17,18]; however, predictions in typically developing children are more rare. Vaughan et al. [5] reported that ND speed followed an exponential relationship with age: increasing rapidly in infants and reaching more stable values by age four. Perhaps additional anthropometric terms might further improve this relationship.

Therefore, the aims of this study were to test via multiple regression analysis whether (1) leg-length ND effectively removes the dependent relationship of speed, stride-length and cadence on anthropometrics and if (2) additional anthropometric terms could be used to generate better predictive equations for actual STPs. The first aim will allow critical evaluation of the use of leg-length normalised STPs for comparison of gait measures across different populations. The development of regression equations with strong predictive ability may improve the accuracy of comparison of gait data between children of different sizes, ages, and gait abilities.

2. Methods

2.1. Subjects

Fifty girls and forty-four boys (3–16 years) performing barefoot walking trials whilst fitted with the plug-in gait marker set [19] were extracted from our laboratory database (Table 1). Criteria for inclusion were: no known motor system pathology, walking independently, and experiencing no pain whilst walking. Ethical approval was granted by the local healthcare research ethics committee.

2.2. Data collection and processing

Six walking trials at self-selected speed were collected of each subject using 12 MX cameras and Nexus Software (Vicon, Oxford Metrics, Oxford, UK). A single representative trial for each subject was selected based on visual inspection of lower-limb joint kinematic and kinetic traces. Gait events were determined from the force plate data using a 10 N threshold, and verified visually from toe, heel, and ankle marker trajectories. Stride-length (m) and cadence (steps/min) were extracted using a Nexus plug-in (Parameter Calculator, Vaquita, Zaragoza, Spain) and defined as the ankle marker displacement in the direction of travel between consecutive foot strikes of the same foot and the number of steps per minute, respectively. The average of both legs was taken for each parameter. Finally, the open-source Biomechanical Toolkit [20] was used to import c3d files into Matlab (v2012b, The Mathworks, Inc., Natick, USA) where gait speed was computed by taking the average of the derivative of the sacral (SACR) marker position over a number of consecutive steps.

2.3. Normalisation

The ND was applied to the STPs according to Hof [12] using leg-length (anterior superior iliac spine to medial malleolus, via the medial femoral condyle) for stride-length. Similarly, cadence and speed were normalised to gravity and leg-length:

$$\| \mathrm{SL} \| = \frac{\mathrm{SL}}{\mathrm{LL}} \tag{1}$$

$$\| \mathrm{c} \| \; \mathrm{c} \times \sqrt{\frac{\mathrm{LL}}{g}} \tag{2}$$

$$\| \mathrm{v} \| \; \frac{\mathrm{v}}{\sqrt{g \times \mathrm{LL}}} \tag{3}$$

where SL: stride-length; c: cadence; v: speed; LL: leg-length; g: gravity (9.81 m/s^2).

2.4. Regression analysis

Multicollinearity between predictors (height, leg-length, body mass, age, and self-selected speed) was tested using the variance inflation factor (VIF) before performing stepwise multiple regression analysis [21]. Regression equations for stride-length and cadence were derived using leg-length, body mass, age and self-selected speed as predictor variables, whilst self-selected speed was regressed against these anthropometric quantities only. Both actual (raw) and ND forms for each STP were considered for the regression analysis. All models were executed via the LinearModel function running the stepwise option in the Matlab statistical toolbox (v2012b, The Mathworks, Inc., Natick, USA). The model only considered linear terms without interactions between variables. R^2 (for a single predictor) or adjusted R^2 (otherwise)

Table 1
Subject anthropometrics, self-selected speed, and STPs by age group.

Age (yrs)	Mass (kg)	Leg length (m)	Speed (m/s)	Stride length (m)	Cadence (steps/min)	ND speed	ND stride length	ND cadence
3–4	16.81 (15.17, 18.45)	0.49 (0.46, 0.52)	1.28 (1.13, 1.44)	0.86 (0.77, 0.94)	176.34 (16.621, 18.648)	0.59 (0.52, 0.65)	1.76 (1.57, 1.95)	0.66 (0.61, 0.70)
5–6	19.62 (18.14, 21.09)	0.57 (0.55, 0.60)	1.31 (1.22, 1.40)	0.99 (0.94, 1.04)	157.27 (148.52, 166.02)	0.55 (0.51, 0.60)	1.73 (1.65, 1.81)	0.63 (0.60, 0.66)
7–8	24.87 (23.58, 26.16)	0.66 (0.65, 0.68)	1.36 (1.32, 1.40)	1.10 (1.07, 1.12)	147.54 (144.80, 150.27)	0.53 (0.52, 0.55)	1.67 (1.62, 1.71)	0.64 (0.63, 0.65)
9–10	32.81 (31.48, 34.14)	0.73 (0.71, 0.75)	1.37 (1.31, 1.42)	1.20 (1.17, 1.24)	135.03 (133.01, 137.05)	0.51 (0.49, 0.52)	1.65 (1.62, 1.68)	0.61 (0.60, 0.63)
11–12	39.23 (36.96, 41.44)	0.81 (0.80, 0.84)	1.35 (1.31, 1.40)	1.28 (1.24, 1.33)	126.42 (123.41, 129.28)	0.48 (0.46, 0.50)	1.57 (1.53, 1.63)	0.60 (0.59, 0.62)
13–14	54.41 (50.34, 58.48)	0.87 (0.86, 0.89)	1.49 (1.43, 1.54)	1.43 (1.37, 1.48)	123.90 (121.05, 126.74)	0.51 (0.49, 0.52)	1.63 (1.59, 1.67)	0.62 (0.60, 0.63)
15–16	62.68 (60.34, 65.03)	0.90 (0.88, 0.92)	1.40 (1.36, 1.44)	1.43 (1.39, 1.47)	117.12 (114.40, 119.84)	0.47 (046, 049)	1.59 (1.56, 1.62)	0.59 (0.58, 0.60)

Mean (confidence interval).

Table 2
Multiple regression results for actual and normalised STPs and self-selected speed.

STP	Regression equation	R^2	SEE
Speed	$0.412 \cdot LL + 1.069$	0.105	0.174
ND speed	$-0.008 \cdot A + 0.600$	0.182	0.068
Stride-length	$0.829 \cdot LL + 0.499 \cdot v + 0.013 \cdot A - 0.224$	0.904	0.070
ND stride-length	$1.836 \cdot v_L + 0.705$	0.645	0.102
Cadence	$-142.250 \cdot LL + 47.271 \cdot v + 177.51$	0.817	9.180
ND cadence	$0.500 \cdot v_L + 0.359$	0.500	0.038

Predictor variables: leg-length (LL), age (A), speed (v), and leg-length non-edimensionally normalised (ND) speed (v_L). All regressions significant at $p \leq 0.001$.

were reported to determine the percentage of variance explained by the models. Standard estimate of the error (SEE) were also computed. The predictive ability of the equations were validated using a 10-fold cross-validation process [22]. Finally, the standardised gradient, i.e., the slope, normalised by the average abscissa value, were computed for actual and ND STPs against leg-length to further assess the success of the ND approach. All correlations tested for significance at the $\alpha = 0.05$ level. No correction was made to significance level for multiple comparisons.

3. Results

3.1. Multiple regression analysis

Age, mass, leg-length, and speed were retained (height excluded) for multiple regression analysis with VIFs of 10.7, 6.4, 9.3, and 1.13, respectively. Regression equations are presented for all STPs (Table 2). For the prediction of actual self-selected speed, leg-length accounted for only 10.5% of the variability. For ND speed, the strongest, and single, predictor retained by the stepwise procedure, was age ($R^2 = 0.182$). For stride-length, a regression equation with leg-length, speed, and age accounted for 90.4% of the variance, whilst for cadence, the equation contained only leg-length and speed, and accounted for 81.7% of the variability. ND resulted in linear relationships with ND speed for stride-length and cadence (64.5 and 50.0% variance explained) (Fig. 1). All models were significant at $p < 0.001$. The average 10-fold cross-validation R^2 for speed, stride-length, and cadence were 0.095, 0.903, and 0.817, respectively, and 0.183, 0.645, 0.500 for their ND analogues, respectively.

3.2. Standardised gradient analysis

Both actual and ND STPs were linearly regressed against leg-length only and their standardised gradients and R^2 were analysed (Fig. 2 and Table 3). ND led to a greater dependence on leg-length for self-selected speed (standardised gradient changed from 30.2 to −42.4%). For stride-length and cadence, ND decreased the dependence on leg-length (from 115.7 to −26.1% and from −88.0 to −15.0%, respectively). All correlations significant at $p \leq 0.01$.

4. Discussion

4.1. Summary

This study presented regression equations for common STPs of gait in both actual and ND form for typically developing children between the ages of 3 and 16. The equations were derived using a stepwise multiple linear regression approach and their predictive ability were cross validated [22]. Furthermore, standardised gradients and correlations between each STP and leg-length were computed to determine the effectiveness of normalisation by leg length. The results suggest that ND, although appropriate for stride-length and cadence, does not successfully remove anthropometric variability from self-selected speed. Comparison of ND speed across non-homogeneous groups should therefore be conducted with caution.

4.2. STP normalisation

Self-selected speed was found to increase with leg-length, in agreement with previous work [8,23]; however, predictive ability using anthropometric quantities was poor. The process of ND of self-selected speed does not remove anthropometric dependence. This was revealed not only via the multiple linear regression analysis (ND speed decreasing with increasing age), but also through the strong standardised gradient (ND speed decreasing with increasing leg-length).

Stride-length and cadence were seen to increase and decrease, respectively, throughout childhood as seen in previous studies [8]. Stride-length was well predicted by leg-length and speed, with age also appearing as an additional factor, whilst cadence was only predicted by leg-length and speed. The dependence of these STPs on speed and leg-length is well known; however, the appearance of age suggests that neuromaturation effects are also important. After ND, both stride-length and cadence were found to be related to ND speed only, in agreement with previous work [14]. Although anthropometric quantities such as leg-length were rejected by the stepwise regression, our further analysis of standardised gradients shows that trends of decreasing ND stride-length and ND cadence with increasing leg-length remains.

There is a known relationship between speed, stride-length, and cadence: if two of the variables are known, the other can be computed. Therefore, at first glance it appears incongruent that ND speed could depend on leg-length (or age), whilst both ND stride-

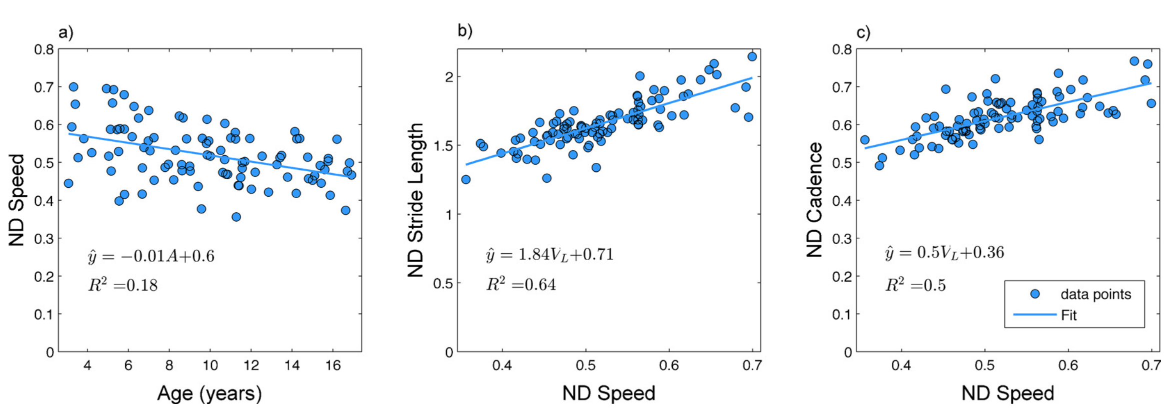

Fig. 1. Data points and stepwise multiple regression lines for nondimensionally normalized (ND) spatio-temporal parameters: (a) ND speed vs. age (years), (b) ND stride length vs. ND speed, and (c) ND cadence vs. ND speed. Pearson's squared correlation coefficients (R^2) and regression equation ($\hat{y}$) also shown.

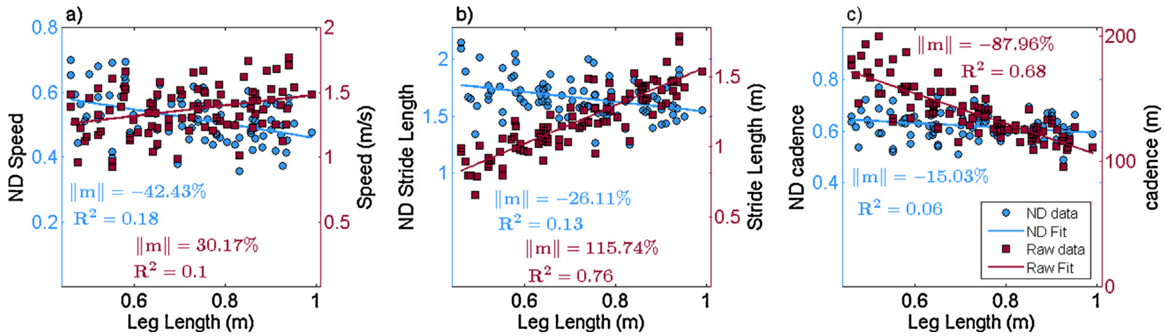

Fig. 2. Data points and linear regression lines for nondimensionally normalized (ND) and actual (raw) spatio-temporal parameters: (a) speed, (b) stride length, and (c) cadence vs. leg length (m). Pearson's squared correlation coefficients (R^2) and standardized gradients (||m||) shown for each regression.

length and ND cadence do not. Closer inspection of the standardised gradients might help answer this seemingly contradictory finding. Starting with the actual measures, the oppositely directed trends of increasing (115.7%) and decreasing (−88.0%) stride-length and cadence with increasing leg-length, respectively, result in a slowly increasing speed (30.2%) with leg-length. After ND, both stride-length and cadence reveal a tendency to decrease with leg-length (−26.1 and −15.0%, respectively). These trends were too small (not-significant) to appear in the regression equations, leading these STPs to appear invariant (at least statistically) with respect to anthropometrics. For ND speed, however, these two small trends reinforce each other. The regression analysis revealed that ND speed decreases with age, whilst the standardised gradients show a decrease of ND speed with leg-length. In fact the standardised gradients show that ND speed has a greater dependence on leg-length than raw speed (−42.4 vs. 30.2%). Although, no formal statistical test was conducted to determine if this change was significant, the trend should still be taken into account. Although the ND process is designed to remove the dimension of length, the underlying influence of leg-length remains. For ND stride-length and cadence, the effect is small enough to consider these parameters invariant with anthropometrics, but the same cannot be said for ND speed. Further studies might investigate other normalisation schemes that do not assume proportional scaling in the hopes of completely removing this dependence.

The fact that actual (raw) self-selected speed is poorly predicted by anthropometrics (only leg-length) is also of great interest. Perhaps other, non-anthropometric, factors are driving self-selected speed choice. Past research has shown that children with neuromuscular disease tend to walk more quickly in a laboratory environment (10 m walk) than in a community setting (10 min walk) [24]. Although this may be more related to fatigue effects occurring over a longer time interval, nervousness may also have contributed to quicker speeds within the gait lab. A study measuring STPs in children consecutively for a number of years reported an increase in ND speed after the laboratory set-up had changed to include a longer walkway [25], suggesting that walkway length might influence STPs. However, in older patients recovering from stroke, walkway length did not seem to play a role in determining self-selected speed [26]. Further investigation of possible psychosocial and environmental factors and their effects on self-selected speed may need to be conducted to achieve better prediction. Meantime, it cannot be assumed that normalising speed by leg length accounts for inter-subject variation in the non-pathological population. It appears that the determination of self-selected speed is far more complex than initially believed.

Table 3
Summary of correlation between STPs and leg-length.

STP	R^2	Standardised gradient (%)
Speed	0.105	30.167
ND speed	0.180	−42.433
Stride-length	0.762	115.743
ND stride-length	0.133	−26.107
Cadence	0.676	−87.959
ND cadence	0.063	−15.026

4.3. Recommendations

The researcher or clinician whose aim is to compare stride-length and/or cadence of typically developing children across different ages and sizes may rely on leg-length ND analogues of these parameters, whilst keeping in mind that some underlying dependency on leg-length might remain. For speed, use of ND appears inadequate for this purpose. It may be that a statistical approach using actual speed with age and/or leg-length as a covariate might be superior to using ND speed directly. For populations with gait pathologies, a similar approach, possibly using measures of pathology as additional covariates, could also be useful.

In order to compare a patient's STPs to typically developing peers, there are two options: the first is to construct regression equations based on known patient characteristics such as leg length and age. The second is to use a carefully matched dataset. The first approach has the potential to provide adequate estimation of stride-length and cadence, but is still difficult to implement for speed, given its poor predictability. Using regression, the difference between a patient's actual and predicted STP values could be calculated and serve as an indicator of severity of pathology. Improvement pre-post intervention could also be monitored. The second method requires a large database that must be appropriately split into well-defined groups. At present, group assignment is fairly arbitrary and considers only a few factors [6,8,16]. More complete databases where children are matched to a wide range of quantities might actually be needed.

4.4. Limitations

The present regression equations have not been tested in other laboratories. It is possible that differences in data collection protocols, marker sets, computation methods, walkway lengths, and populations may influence the parameters of the equations. Individual laboratories should query their own databases in order to build bespoke regression equations using the techniques described herein. We also suggest that the present regression equations not be used for prediction of STPs for children outside or at the extreme ranges of age or gait speeds used in this study.

The anthropometric parameters included in the regression equations were correlated with each other. It is therefore possible that the appearance of a specific predictor in the equations might obscure other existing relationships. For example, stepwise multiple regression found that age was the single most important predictor of speed ($R^2 = 0.182$ in Table 2), but when speed was regressed with leg-length only, the prediction was only slightly weaker ($R^2 = 0.180$, Fig. 2a). We assessed multi-collinearity between predictors and used the recommendation of a VIF < 10 to guide our choice of which variables to retain [21]. Although age had a slightly higher VIF (10.7) it was kept as it alone best describes maturation of motor control.

The children in our sample trended towards greater self-selected speed, stride-length, and cadence compared to age-matched peers from previous studies [6,8,27]; however, comparison of confidence intervals for the current results and those of Lythgo et al. [8] shows overlap across some age groups. It is important to note that in the studies of Dusing and Thorpe [6] and by Lythgo et al. [8] data were collected on the GAITRite® instrumented walkway (CIR Systems Inc. Haverton, USA) within the familiar school environment, whilst the study of Müller et al. [27] used a mobile walkway (location and type not reported). Our cohort was instructed to walk at habitual speed in the gait laboratory. We did not pace the children nor did we provide specific feedback about their speed choice. As it remains unclear which factors most strongly influence the selection of comfortable speed, it may be that some other environmental factor was responsible.

Conclusions

From these results, it appears that stride length and cadence are determined primarily by walking speed in combination with leg-length. However, the determination of self-selected speed is more complex, and is not merely determined by the length of the subject's legs. Even including other anthropometric variables did not improve this prediction.

In summary, we were able to show that leg-length ND is appropriate for stride-length and cadence: anthropometric predictors were not strong enough to appear in the regression equations and further analysis showed that their dependence on leg-length was effectively reduced. For ND of self-selected speed, age appeared to be the driving factor. Moreover, speed showed an increased dependence on leg-length after normalisation, rather than the other way round. Therefore, caution should be exercised when attempting to compare normalised speeds across groups with different anthropometric characteristics.

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Conflicts of interest

The authors have no conflicts of interests or financial relationships that could bias this work.

References

[1] Prosser LA, Lauer RT, VanSant AF, Barbe MF, Lee SCK. Variability and symmetry of gait in early walkers with and without bilateral cerebral palsy. Gait Posture 2010;31:522–6.
[2] Bregou Bourgeois A, Mariani B, Aminian K, Zambelli PY, Newman CJ. Spatio-temporal gait analysis in children with cerebral palsy using, foot-worn inertial sensors. Gait Posture 2014;39:436–42.
[3] Grieve DW, Gear RJ. Relationships between length of stride step frequency time of swing and speed of walking for children and adults. Ergonomics 1966;9:379–99.
[4] Stolze H, Kuhtz-Buschbeck JP, Mondwurf C, Johnk K, Friege L. Retest reliability of spatiotemporal gait parameters in children and adults. Gait Posture 1998;7:125–30.
[5] Vaughan CL, Langerak NG, O'Malley MJ. Neuromaturation of human locomotion revealed by non-dimensional scaling. Exp Brain Res 2003;153:123–7.
[6] Dusing SC, Thorpe DE. A normative sample of temporal and spatial gait parameters in children using the GAITRite electronic walkway. Gait Posture 2007;25:135–9.
[7] Sutherland D, Olshen R, Biden E. The development of mature walking. London: Mac Keith Press; 1988. p. 277.
[8] Lythgo N, Wilson C, Galea M. Basic gait and symmetry measures for primary school-aged children and young adults whilst walking barefoot and with shoes. Gait Posture 2009;30:502–6.
[9] Sutherland D. The development of mature gait. Gait Posture 1997;6:163–70.
[10] Beck RJ, Andriacchi TP, Kuo KN, Fermier RW, Galante JO. Changes in the gait patterns of growing children. J Bone Joint Surg Am 1981;63:1452–7.
[11] Norlin R, Odenrick P, Sandlund B. Development of gait in the normal child. J Pediatr Orthop 1981;1:261–6.
[12] Hof AL. Scaling gait data to body size. Gait Posture 1996;4:222–3.
[13] Pierrynowski MR, Galea V. Enhancing the ability of gait analyses to differentiate between groups: scaling gait data to body size. Gait Posture 2001;13:193–201.
[14] Stansfield BW, Hillman SJ, Hazlewood ME, Lawson AM, Mann AM, Loudon IR, et al. Normalisation of gait data in children. Gait Posture 2003;17:81–7.
[15] Stansfield BW, Hillman SJ, Hazlewood ME, Robb JE. Regression analysis of gait parameters with speed in normal children walking at self-selected speeds. Gait Posture 2006;23:288–94.
[16] Schwartz MH, Rozumalski A, Trost JP. The effect of walking speed on the gait of typically developing children. J Biomech 2008;41:1639–50.
[17] Mizelle C, Rodgers M, Forrester L. Bilateral foot center of pressure measures predict hemiparetic gait velocity. Gait Posture 2006;24:356–63.
[18] Allet L, Kim H, Ashton-Miller JA, Richardson JK. Which lower limb frontal plane sensory and motor functions predict gait speed and efficiency on uneven surfaces in older persons with diabetic neuropathy? Pm R 2012;4:726–33.
[19] Kadaba MP, Ramakrishnan HK, Wootten ME. Measurement of lower extremity kinematics during level walking. J Orthop Res 1990;8:383–92.
[20] Armand S., Barre A., Biomechanical Toolkit. 2013. Retrieved from: https://code.google.com/p/b-tk/.
[21] Neter J, Wasserman W, Kutner MH. Applied linear regression models. Illinois, USA: Irwin; 1989. p. 409.
[22] Kohavi RA. Study of cross-validation and bootstrap for accuracy estimation and model selection. Proceedings of the 14th international joint conference on artificial intelligence 1995.
[23] Muller J, Muller S, Baur H, Mayer F. Intra-individual gait speed variability in healthy children aged 1–15 years. Gait Posture 2013;38:631–6.
[24] Pirpiris M, Wilkinson AJ, Rodda J, Nguyen TC, Baker TJ, Nattrass GR, et al. Walking speed in children and young adults with neuromuscular disease: comparison between two assessment methods. J Pediatr Orthop 2003;23:302–7.
[25] Hillman SJ, Stansfield BW, Richardson AM, Robb JE. Development of temporal and distance parameters of gait in normal children. Gait Posture 2009;29:81–5.
[26] Ng SSM, Ng PCM, Lee CYW, Ng ESW, Tong MHW. Walkway lengths for measuring walking speed in stroke rehabilitation. J Rehabil Med 2012;44:43–6.
[27] Muller J, Muller S, Baur H, Mayer F. Intra-individual gait speed variability in healthy children aged 1–15 years. Gait Posture 2013.