Gait & Posture xxx (2012) xxx–xxx

Contents lists available at SciVerse ScienceDirect

Gait & Posture

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

Are clinical measurements linked to the Gait Deviation Index in cerebral palsy patients?

Yoshimasa Sagawa Jr.[a,b,c,*], Eric Watelain[a,b,c,d], Géraldo De Coulon[e], Andre Kaelin[e], Philippe Gorce[d], Stéphane Armand[e]

[a] UVHC, LAMIH, F-59313 Valenciennes, France
[b] Univ Lille Nord de France, F-59000 Lille, France
[c] CNRS, UMR 8201, F-59313 Valenciennes, France
[d] HandiBio, EA 4322, Univ du Sud Toulon Var, F-83957 La Garde, France
[e] Willy Taillard Laboratory of Kinesiology, Geneva University Hospitals and Geneva University, 4 Rue Gabrielle-Perret-Gentil, 1211 Geneva 14, Switzerland

ARTICLE INFO

Article history:
Received 17 February 2011
Received in revised form 30 October 2012
Accepted 27 November 2012

Keywords:
Cerebral palsy
Gait
Clinical measurements
Fuzzy decision tree

ABSTRACT

Objective: From a dataset of clinical assessments and gait analysis, this study was designed to determine which of the assessments or their combinations would most influence a *low* gait index (i.e., severe gait deviations) for individuals with cerebral palsy.
Design: A retrospective search, including clinical and gait assessments, was conducted from August 2005 to September 2009.
Population: One hundred and fifty-five individuals with a clinical diagnosis of cerebral palsy (CP) (mean age (SD): 11 (5.3) years) were selected for the study.
Method: Quinlan's Interactive Dichotomizer 3 algorithm for decision-tree induction, adapted to fuzzy data coding, was employed to predict a Gait Deviation Index (GDI) from a dataset of clinical assessments (i.e., range of motion, muscle strength, and level of spasticity).
Results: Seven rules that could explain severe gait deviation (a fuzzy GDI *low* class) were induced. Overall, the fuzzy decision-tree method was highly accurate and permitted us to correctly classify GDI classes 9 out of 10 times using our clinical assessments.
Conclusion: There is an important relationship between clinical parameters and gait analysis. We have identified the main clinical parameters and combinations of these parameters that lead to severe gait deviations. The strength of the hip extensor, the level of spasticity and the strength of the tibialis posterior were the most important clinical parameters for predicting a severe gait deviation.

1. Introduction

Cerebral palsy (CP) is a disorder caused by childhood brain damage that usually occurs before the age of 2 years. CP represents a group of permanent but not static disorders of locomotion, posture, and sensory and motor functions due to nonprogressive interference, lesions or abnormalities in brain development [1].

Currently, the complex locomotor characteristics of individuals with CP are assessed through clinical and gait assessments. The main clinical assessments evaluate the functionality of neuromuscular and musculoskeletal structures separately. These assessments are often divided into three test categories: (1) passive range of motion (ROM) [2], (2) muscle strength [3], and (3) level of spasticity [3]. The gait assessment is realised using a computer-aided three-dimensional gait analysis (3DGA). This method allows the quantification of a variety of measurements that provide a comprehensive description of human gait (e.g., 3D joint angles, moments, and powers). The 3DGA is used in clinical settings to assist in the development of therapeutic strategies to treat the motor deficits associated with CP [4]. However, interpreting CP gait analyses and related clinical analyses has traditionally been challenging when considering the large dataset available for the assessments and their interdependence.

To support the interpretation of gait analyses, understanding what roles the clinical parameters play in the gait deviations is important. Correlations and multiple regression analysis based on empirical datasets were the main methods

Abbreviations: AB, able-bodied individuals; CP, cerebral palsy; FDT, fuzzy decision tree; GDI, Gait Deviation Index; GMFCS, Gross Motor Function Classification System; RMSE, root mean square error; ROM, passive range of motion; 3DGA, three-dimensional gait analysis.

* Corresponding author at: Laboratoire d'Automatique et de Mécanique d'Informatique Industrielles et Humaines (UMR CNRS 8201) Université le Mont Houy, Bâtiment Malvache, 59313 Valenciennes cedex 9, France.
Tel.: +33 03 27 51 13 49/06 65 17 79 36; fax: +33 03 27511317.
E-mail address: Yoshimasa.SagawaJunior@univ-valenciennes.fr (Y. Sagawa Jr.).

0966-6362/$ – see front matter © 2012 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.gaitpost.2012.11.026

employed toachieve this aim [5–7]. However, these methods showed poor correlations between gait analyses and clinical assessments [5–7]. Alternatively, numerous supervised learning methods (e.g., artificial neural networks, random forest, and support vector machines) have been developed to extract knowledge from large datasets and could be further adapted to identify clinical parameters that are the most indicative of alterations in gait. Among these methods, the fuzzy decision tree (FDT) approach seems particularly appropriate for identifying and explaining gait deviations [8]. FDT combines fuzzy logic with decision tree. The fuzzy logic makes it possible to simplify the knowledge extraction process, address data imprecision, and increase the interpretability. The decision tree makes it possible to induce automatic and intelligible readable rules from a dataset. This is the main advantage of FDT compared with other supervised learning methods that are currently based on a black box system (i.e., a system that can be viewed only in terms of its input and outputs) [8,9].

Although FDT has rarely been used in gait analysis, we believe that it could be used to gain relevant insights into the complexity of CP gait. Therefore, the aim of this article is to determine which of the clinical parameters or their combinations in a dataset of clinical assessments would most influence a *low* gait index of individuals with CP. Our hypothesis is that some of the clinical parameters or their combinations are more important than others for explaining the severity of gait deviations. The identified clinical parameters might be considered key factors for gait analysis interpretation and could be used to optimise treatment strategies in individuals with CP.

2. Methods

A retrospective search in the laboratory database, including clinical and gait assessments, was conducted for the period from August 2005 to September 2009. This study was approved by the local ethics committee.

2.1. Population

For selecting the individuals, the following inclusion criteria were used: (1) individuals had to have a clinical diagnosis of CP; (2) individuals could be male or female; (3) the individual's age had to be in the range of 3–30 years on the exam date; and (4) individuals had to have completed a clinical exam and a gait analysis on the same date. Individuals who underwent a lower limb surgery 6 months prior to the clinical exam and gait analysis were excluded.

2.2. Materials

2.2.1. Clinical assessments

The clinical assessments consisted of 17 functional tests of the lower limb (Table 1). They were chosen by a multidisciplinary team. These tests were divided into three main categories: (1) ROM, measured with a handheld goniometer and using gentle slow manoeuvres to avoid spastic muscle responses; (2) muscle strength, according to a manual five-point scale [3]; and (3) the level of spasticity measured with a modified Ashworth Scale, ranging from 0 to 4 [3]. These clinical assessments were performed by three well-trained physical therapists.

2.2.2. Gait analysis

The 3DGAs were performed using a 7-camera motion measurement system (Vicon MX3+, Oxford Metrics, UK). Reflective markers for video measurements were placed at defined anatomical points on the pelvis and lower limbs according to the Davis protocol [10]. Kinematic variables were calculated using Nexus software (Oxford Metrics, UK) and Matlab (MathWork, USA). All individuals were asked to walk barefoot at a self-selected speed along a 12-m walkway. Data were collected for at least five trials for each participant. The same biomechanical engineer performed these 3DGAs.

Among the multivariate measurements of overall gait pathology based on kinematic data [11–13], we chose to use the Gait Deviation Index (GDI) developed by Schwartz and Rozumalski [12]. The GDI is computed with kinematic gait data from the pelvis, hip, knee, ankle, and foot. A GDI around 100 indicates an individual whose gait is as close as possible to typical able-bodied (AB) individuals. Every 10 points below 100 corresponds to one standard deviation away from the mean for AB individuals.

2.3. Analyses

2.3.1. Fuzzy window coding and the definition of linguistic modalities

Fuzzy window coding simplifies the knowledge extraction process and increases interpretability. This method transforms data into a ''natural language'' while minimising the loss of information due to the transformation of quantitative data in qualitative data [8]. Contrary to a classical-binary approach in which just 1 value is possible for representing the modality for such a variable (e.g., Low, Average, High—1, 0, 0), the fuzzy approach permits different membership values (e.g., Low, Average, High—0.7, 0.3, 0) as a probability of belonging to a modality and then addresses data imprecision by defining fuzzy numbers that can be expressed in linguistic variables [14].

Thus, in this study, the clinical assessments and the GDI for each limb were coded using three triangular fuzzy membership functions related to the following three modalities—Low, Average, and High (Fig. 1)—as used by Armand et al. [8]. The membership values were determined based on expert advice and the data distribution of the clinical assessments and the GDI. The Low and High boundaries of these assessments correspond to the 5th and 95th percentiles, respectively, and the Average boundary corresponds to the median. Table 1 shows the main clinical assessments chosen by the experts, the GDI chosen and their window boundaries for the fuzzy coding. For example, for the Thomas test, the scores were distributed around 10° (median – Average), 0° (5th percentile – Low) and 25° (95th percentile – High). For the muscle strength and level of spasticity tests, we used the same scale for all the joints. In our study, the fuzzy coding transformed the variables without changing their meaning. For example, in clinical settings, we look for low values of strength and high values of spasticity. The results need to be interpreted in the same manner, but using just three modalities. To facilitate analysis, we added a colour code in Tables 1 and 2 to indicate the modalities related to normal and abnormal values.

Table 1
The main clinical parameters chosen by the experts and their window boundaries for fuzzy coding, based on expert advice and the clinical measurements' data distribution. The green areas represent normal values; the yellow areas, abnormal values; and the red areas, very abnormal values.

Premise of the rules	Clinical assessment	Low	Aver	High
Hip	Thomas test[a]	0	10	25
	ROM abduction[a]	10	30	55
	ROM internal rotation[a]	30	55	80
	Strength extensors[b]	1	3	5
	Spasticity adductors[c]	0	2	4
Knee	ROM extension[a]	−15	0	15
	Strength extensors[b]	1	3	5
	Spasticity flexors[c]	0	2	4
	Duncan-Ely Test[c]	0	2	4
Ankle	ROM flexion knee at 90° [a]	−10	10	30
	ROM flexion knee at 0° [a]	−15	0	20
	Strength triceps[b]	1	3	5
	Strength tibialis anterior[b]	1	3	5
	Strength tibialis posterior[b]	1	3	5
	Spasticity triceps[c]	0	2	4
	Spasticity soleus[c]	0	2	4
	Spasticity tibialis posterior[c]	0	2	4
Conclusion	GDI	43	77.5	108

Abbreviations – Aver: average; ROM: range of motion.
[a] ROM in degrees.
[b] Muscle strength according to a manual five-point scale.
[c] Level of spasticity measured by a modified Ashworth Scale (range from 0 to 4).

Please cite this article in press as: Sagawa Jr Y, et al. Are clinical measurements linked to the Gait Deviation Index in cerebral palsy patients? Gait Posture (2012), http://dx.doi.org/10.1016/j.gaitpost.2012.11.026

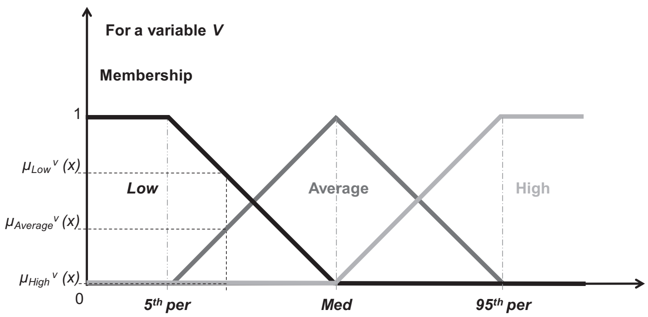

Fig. 1. The principle of fuzzy windowing with triangular membership functions is used to characterise clinical and GDI measurements as Low, Average, and High. The membership values of the clinical and GDI measurements were determined based on expert advice and the data distributions of each parameter (Low and High boundaries correspond to the 5th and 95th percentiles, respectively, and the Average boundary corresponds to the median). x is a measured value of a given clinical variable V; $\mu^{V}_{\text{Average}}(x)$ and $\mu^{V}_{\text{Low}}(x)$ are, respectively, the membership values of the Average and Low modalities. In this example, the membership value of the High modality is equal to zero ($\mu^{V}_{\text{High}}(x) = 0$).

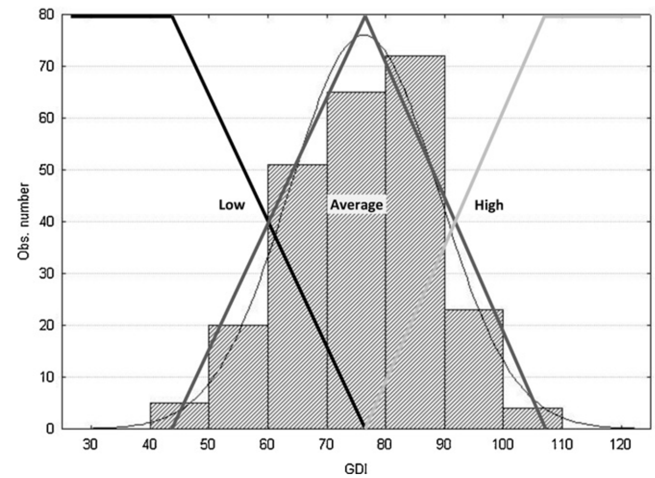

Fig. 2. The GDI distribution of 240 spastic sides and the fuzzy windows determining the three GDI classes: Low (black), Average (dark grey), and High (light grey).

2.3.2. A learning set of observations

The learning set of observations corresponds to the set of variables for the lower limbs of our individuals. An observation is characterised by several inputs and one output, which consist of the fuzzy membership values related to the linguistic modalities. In our case, the inputs are represented by the set of linguistic variables from the clinical assessments (Table 1). The output, also called the conclusion of the rule, is represented by the set of linguistic variables from the GDI (Table 1 and Fig. 2).

2.3.3. Rule induction using fuzzy decision trees (FDT)

The process of generating rules from data is called induction. Quinlan's Interactive Dichotomizer 3 algorithm for decision-tree induction was first described in 1986 [9]. Several methods for adapting this algorithm to fuzzy data have been proposed [15,16]. The method was explained in detail by Marsala [17] and applied to biomechanical data by Armand et al. [8].

In the FDT method, the experts express system knowledge as fuzzy rules. Fuzzy rules take the following form: "If input A and input B are true, then conclusion C can be made". Both the inputs and the conclusion are described in linguistic terms (Section 2.3.1), which simplifies the knowledge extraction process and increases the interpretability of rules because the fuzzy rule is expressed in terms similar to the expert's natural language [14].

The learning set is then subjected to a 4-step procedure:

(1) A discriminating measure is used to determine which clinical variable best explains the distribution of the individuals among the classes, and a node is created. In our study, a discrimination measure based on information entropy was used [17].
(2) The dataset is partitioned to build as many subsets as there are linguistic modalities for the variable chosen in step 1.
(3) A termination condition is tested using a termination criterion, β. In our study, the termination condition is defined for a given node level, with the condition probability p of being in a class, thus verifying the conjunction of fuzzy conditions from the "root" to the node. In our study, β was initially set at $\beta = 0.7$ [17].
(4) If the termination condition is verified, then the subset is considered to be a "leaf" of the tree. If the termination condition is not verified, then steps 1–3 are repeated.

Once the FDT has been created, each branch of the tree (i.e., the path from the root to the leaf of a FDT) can be converted into a rule. The rule ends at the leaf level, indicating the membership in the class for which the tree was induced. Following the four steps of the rule induction procedure, the other two steps can be executed to simplify and optimise the knowledge base. These steps were performed according to Yuan and Shaw's method [15].

2.3.4. Individual classification

The fuzzy rules are a sort of knowledge repository, in which each rule containing a probable explanation for the GDI classes. Thus, this rule base can be used objectively and automatically to assign selected individuals to the fuzzy GDI classes to which they most likely belong—which is precisely what we hoped to achieve. To test the accuracy of this rule-based classification system, a stratified 10-fold cross-validation [18] was performed. In this paper, we present the rules that explain the fuzzy GDI *low* class because they are the most interesting for a clinical point of view: discover the clinical parameters or their combination that lead to severe gait

Table 2
The rules induced from the FDT that produced a GDI *Low*. The green areas represent normal values; the yellow areas, abnormal values; and the red areas, very abnormal values.

R	If	and	and	and	and	and	and	and	Then
	Hip		Knee	Ankle					
1	Str Hip ext **Average**	Spa Hip add **High**	ROM Knee ext **High**	ROM Ankle flex knee at 0° **Average**	Str Ankle tibialis post **High**			Spa Ankle tibialis post **Average**	**GDI – Low**
2	Str Hip ext **Average**	ROM Hip int rot **Average**	ROM Knee ext **Average**			Str Ankle triceps **Low**		Spa Ankle tibialis post **High**	
3	Str Hip ext **Average**		Duncan-Ely Test **Low**	ROM Ankle flex knee at 0° **High**	Str Ankle tibialis post **High**		Spa Ankle triceps **High**	Spa Ankle tibialis post **Average**	
4	Str Hip ext **Average**	ROM Hip abd **Low**		ROM Ankle flex knee at 0° **High**	Str Ankle tibialis post **Average**			Spa Ankle tibialis post **Average**	
5	Str Hip ext **Average**		Duncan-Ely Test **Average**	ROM Ankle flex knee at 0° **Average**	Str Ankle tibialis post **Average**	Str Ankle triceps **Low**	Str Ankle tibialis ant **Average**	Spa Ankle tibialis post **Average**	
6	Str Hip ext **Average**	ROM Hip int rot **Average**	ROM Knee ext **Average**		Str Ankle tibialis post **Low**		Spa Ankle triceps **High**	Spa Ankle tibialis pos **High**	
7	Str Hip ext **Average**	ROM Hip int rot **Average**	Spa Knee flex **High**					Spa Ankle tibialis post **Average**	

Abbreviations – R: rules; ROM: range of motion; Str: strength; Spa: spasticity; Ext: extension; Flex: flexion; Add: adduction; Abd: abduction; Ant: anterior; Post: posterior; Int rot: internal rotation.

Please cite this article in press as: Sagawa Jr Y, et al. Are clinical measurements linked to the Gait Deviation Index in cerebral palsy patients? Gait Posture (2012), http://dx.doi.org/10.1016/j.gaitpost.2012.11.026

alterations. These rules explain severe gait deviations based on GDI values between 43 and 77.5 (Fig. 2).

3. Results

3.1. Population

According to our criteria, 155 individuals (45% with hemiplegia and 55% with diplegia) were selected to perform the study. The individuals had a mean age (SD) of 11 (5.3) years, a mean mass (SD) of 34.5 (14.7) kg, a mean height (SD) of 1.37 (0.2) m, and mean (SD) Gross Motor Function Classification System (GMFCS) level of 1.5 (0.6). These 155 individuals corresponded to 240 ''spastic side'' observations.

3.2. FDT rule inductions

Seven rules were induced to explain the fuzzy GDI *low* class. For the entire FDT system, using our stratified 10-fold cross-validation, we computed the mean (SD) of the following parameters: coverage, root mean square error (RMSE), maximum error, and accuracy. The accuracy represents the ratio between the correctly classified values and all values of our rules. All of the observations tested, caused at least 1 of our rules to fire, thus ensuring a coverage of 100%. The RMSE—which measures the differences between the net GDI values predicted by our inductions and the GDI values observed—was 2.35 (0.4) GDI. The absolute maximum error observed was 26.3 (5.12) GDI, and the accuracy was 0.9 (0.01).

3.3. Rule characterisation

The 7 rules that characterise a fuzzy GDI *low* class are shown in Table 2. These rules are composed of 4–7 premises and are classified according to their firing strengths. Except for rule 4, all rules are composed of premises from the hip, knee, and ankle joints. All rules have premises based on our three clinical assessment categories, and except for rules 1 and 7, all rules have premises based on our three fuzzy linguistic modalities.

To induce the rules for a fuzzy GDI *low* class, 13 out of 17 clinical assessments were used. As shown in Table 2, the strength of hip extension, the ROM of hip internal rotation, and the strength of the tibialis anterior all had globally *average* values. The level of spasticity of the tibialis posterior, the ROM of the ankle in flexion, the level of spasticity of the triceps surae, the ROM of the knee in extension, the level of spasticity of the hip adductors, the level of spasticity of the knee flexors, and the strength of the tibialis posterior all had globally *average* to *high* values. The strength of the triceps surae, the level of spasticity of the knee extensors (using the Duncan Ely test), and the ROM of the hip in abduction all had globally *average* to *low* values.

4. Discussion

4.1. The accuracy and originality of our FDT method

Some studies in the literature found significant but poor correlations when clinical and gait assessments were correlated in pairs. Orendurff et al. [5] and McMulkin et al. [6] used ROM parameters, while Desloovere et al. [7] used 32 clinical assessments involving ROM, muscle strength, level of spasticity, and selectivity. After examining the correlations, all of these authors concluded that clinical assessments did not seem to be good predictors of gait deviation. Still, Desloovere et al. [7] found better results for muscle strength, the level of spasticity, and selectivity than for ROM.

In contrast, the classification accuracy of our method (87–93%) is in the same range as the studies using artificial neural networks combined with clinical biomechanics. The accuracy of the gait data classifications with neural networks varies from study to study but can be estimated at approximately 80% [19]. In Chau's review [20], the accuracy of gait parameter prediction using other data types yielded a correlation coefficient that varied between 0.71 and 0.98. The accuracy of our classification indicates that the chosen clinical assessments provide a good explanation of the individuals' gait deviation. Many of our *low* fuzzy rules (severe gait deviations) are composed of premises from three joints, three clinical assessment categories, and three linguistic modalities. The multiple origins and complexity of CP gait could explain why this rule diversity works.

Because the clinical assessments performed by clinical experts have a modest repeatability [21], fuzzy logic appears to be an ideal tool for dealing with the impreciseness and variability of clinical assessments [14].

4.2. Interpreting the rules

Many of the parameters used in our *low* fuzzy rules have already been used to characterise CP [3]. Considering the number of occurrences of clinical parameters in the rules, the strength of the hip extensor, the level of spasticity and the strength of the tibialis posterior were the most important parameters for predicting a severe gait deviation. In the following paragraphs, the clinical parameters involved in 7 fuzzy GDI *low* rules are discussed.

Unsurprisingly, at the hip level, the strength of the hip extensor is the main clinical parameter that makes it possible to predict a *low* GDI. This is in line with the results of Eek and Beckung [22], which highlight a significant loss of strength in the hip extensors, according to GMFCS. These hip extensors are involved in generating the power needed to walk. Riad et al. [23] and Lee et al. [24] suggest that muscle strengthening physiotherapy should be directed towards the power generators in the hip because hip extensors compensate for the lack of power at the ankle.

In the frontal plane of the hip, limited abduction and spasticity in the adductor are the parameters involved in the rules predicting a *low* GDI. The results of limited abduction and spasticity in the adductor can disrupt stability during stance and limb advancement during swing [25]. Internal hip rotation (found in 3 rules) and excessive femoral anteversion are common alterations with CP [26] and can lead to severe misalignment, including external tibia torsion and a valgus position of the foot [25].

At the level of the knee, recurvatum (''ROM Knee ext *high*''), spasticity of the knee flexor or spasticity of the knee extensor can lead to a *low* GDI in our rules. Recurvatum could be linked with an insufficient quadriceps strength to preserve weight-bearing stability [25]. Surprisingly, the strength of the knee extensors is not involved in our rules. Eek and Beckung [22] have identified this muscle as a key muscle group in the gait of individuals with CP. Further investigations are needed to determine the associations between quadriceps strength and recurvatum in this CP group. With respect to the spasticity of the knee, the spasticity of the extensor and the spasticity of the knee flexor were found separately in one rule (R5, R7 respectively). The spasticity of the knee extensor could contribute to a stiff knee gait [27], whereas the spasticity of the knee flexor could contribute to a crouch gait [27].

At the level of the ankle, the high level of spasticity of the triceps is present in 2 rules. This spasticity leads to ankle equines, which is one of the most common gait abnormalities in individuals with CP [28]. The lack of strength of the triceps is present in 2 rules. The weakness of the triceps is associated with a lack of propulsion at the end of the stance phase [25]. Moreover, the gastrocnemius controls the tibia advancement and could be associated with a crouch gait [25]. The spasticity of the tibialis posterior is always present in rules predicting *low* GDI. The spasticity of this muscle is associated with equinovarus of the foot [27,29].

4.3. Limitations

This study has some limitations. Despite the fact that the medical staff examined various clinical aspects and the capacity of each individual to undergo a 3DGA, 8% of our individuals received a Botulinum Toxin injection at 3.5 months from the clinical exams and 3DGA. Graham et al. recommended a more conservative delay of approximately 6 months to guarantee that individuals recover their initial gait performance [30]. In addition, 10% of our patients were under 6 years old when the 3DGA was conducted: two were 3 years old; five were 4 years old; and nine were 5 years old. To insure gait reproducibility, 3DGA should be performed in children older than 6 years old.

We emphasised the advantages of using FDT methods, and then we presented only the results for the GDI *low* class. We identified the clinical parameters that permitted us to predict a severe gait deviation. If individuals with CP exhibit these parameters within their modalities, they might have a severe gait deviation. A future study with a large sample should be conducted to identify parameters that explain the longitudinal modification of the GDI classes after an intervention (e.g., passing from a fuzzy GDI *low* class to a fuzzy GDI average/high class or the inverse).

5. Conclusions

We have identified the main clinical parameters and combinations of these parameters that lead to severe gait deviations in individuals with CP. The strength of the hip extensor, the level of spasticity and the strength of the tibialis posterior were the most important clinical parameters for predicting a severe gait deviation. These clinical parameters have to be considered as key factors for gait analysis interpretation and for optimising treatment strategies in CP individuals with severe gait alterations.

Acknowledgments

This research was funded by OSEO (Project Number A0607009N), the International Campus on Safety and Intermodality in Transportation, the *Nord/Pas-de-Calais* Region, the European Community, the Regional Delegation for Research and Technology, the Ministry of Higher Education and Research, and the French National Center for Scientific Research (CNRS). The authors gratefully acknowledge the support of these institutions.

Conflict of interest

The authors state that no conflicts of interest are present in this research.

References

[1] Krägeloh-Mann I, Cans C. Cerebral palsy update. Brain and Development 2009;31(7):537–44.
[2] Somers DL, Hanson JA, Kedzierski CM, Nestor KL, Quinlivan KY. The influence of experience on the reliability of goniometric and visual measurement of forefoot position. Journal of Orthopaedic and Sports Physical Therapy 1997;25(March (3)):192–202.
[3] Bleck EE. Orthopedic management of cerebral palsy. Philadelphia, Toronto: Saunders; 1979.
[4] Filho MCdM, Yoshida R, Carvalho WdS, Stein HE, Novo NF. Are the recommendations from three-dimensional gait analysis associated with better postoperative outcomes in patients with cerebral palsy? Gait & Posture 2008;28(2):316–22.
[5] Orendurff MS, Chung JS, Pierce RA. Limits to passive range of joint motion and the effect on crouch gait in children with cerebral palsy. Gait & Posture 1998;7:165–6.
[6] McMulkin ML, Gulliford JJ, Williamson RV, Ferguson RL. Correlation of static to dynamic measures of lower extremity range of motion in cerebral palsy and control populations. Journal of Pediatric Orthopedics 2000;20(May–June (3)):366–9.
[7] Desloovere K, Molenaers G, Feys H, Huenaerts C, Callewaert B, Van de Walle P. Do dynamic and static clinical measurements correlate with gait analysis parameters in children with cerebral palsy? Gait & Posture 2006;24(November (3)):302–13.
[8] Armand S, Watelain E, Roux E, Mercier M, Lepoutre FX. Linking clinical measurements and kinematic gait patterns of toe-walking using fuzzy decision trees. Gait & Posture 2007;25(3):475–84.
[9] Quinlan JR. Induction of decision trees. Machine Learning 1986;1:81–106.
[10] Davis RB. Reflections on clinical gait analysis. Journal of Electromyography and Kinesiology 1997;7(December (4)):251–7.
[11] Schutte LM, Narayanan U, Stout JL, Selber P, Gage JR, Schwartz MH. An index for quantifying deviations from normal gait. Gait & Posture 2000;11(February (1)):25–31.
[12] Schwartz MH, Rozumalski A. The Gait Deviation Index: a new comprehensive index of gait pathology. Gait & Posture 2008;28(October (3)):351–7.
[13] Baker R, McGinley JL, Schwartz MH, Beynon S, Rozumalski A, Graham HK, et al. The gait profile score and movement analysis profile. Gait & Posture 2009;30(October (3)):265–9.
[14] Guillaume S. Designing fuzzy inference systems from data: an interpretability-oriented review. IEEE Transactions on Fuzzy Systems 2001;9(3):427–43.
[15] Yuan Y, Shaw MJ. Induction of fuzzy decision trees. Fuzzy Sets and Systems 1995;69:125–39.
[16] Olaru C, Wehenkel L. A complete fuzzy decision tree technique. Fuzzy Sets and Systems 2003;138:221–54.
[17] Marsala C. Apprentissage inductif en présence de données imprécises: construction et utilisation d'arbres de décision flous. Paris: Paris VI; 1998.
[18] Kohavi R, editor. A study of cross-validation and bootstrap for accuracy estimation and model selection. Montreal, Canada: International Joint Conference on Artificial Intelligence (IJCAI); 1995.
[19] Schollhorn WI. Applications of artificial neural nets in clinical biomechanics. Clinical Biomechanics (Bristol Avon) 2004;19(November (9)):876–98.
[20] Chau T. A review of analytical techniques for gait data. Part 2: neural network and wavelet methods. Gait & Posture 2001;13(April (2)):102–20.
[21] Kilgour G, McNair P, Stott NS. Intrarater reliability of lower limb sagittal range-of-motion measures in children with spastic diplegia. Developmental Medicine and Child Neurology 2003;45(June (6)):391–9.
[22] Eek MN, Beckung E. Walking ability is related to muscle strength in children with cerebral palsy. Gait & Posture 2008;28(October (3)):366–71.
[23] Riad J, Haglund-Akerlind Y, Miller F. Power generation in children with spastic hemiplegic cerebral palsy. Gait & Posture 2008;27(May (4)):641–7.
[24] Lee JH, Sung IY, Yoo JY. Therapeutic effects of strengthening exercise on gait function of cerebral palsy. Disability and Rehabilitation 2008;30(19): 1439–44.
[25] Perry J, Burnfield JM. Gait analysis: normal and pathological function, 2nd ed., Thorofare, NJ: Slack Inc.; 2010.
[26] O'Sullivan R, Walsh M, Hewart P, Jenkinson A, Ross LA, O'Brien T. Factors associated with internal hip rotation gait in patients with cerebral palsy. Journal of Pediatric Orthopedics 2006;26(July–August (4)):537–41.
[27] Wren TA, Rethlefsen S, Kay RM. Prevalence of specific gait abnormalities in children with cerebral palsy: influence of cerebral palsy subtype, age, and previous surgery. Journal of Pediatric Orthopedics 2005;25(January–February (1)):79–83.
[28] Wren TA, Do KP, Kay RM. Gastrocnemius and soleus lengths in cerebral palsy equinus gait – differences between children with and without static contracture and effects of gastrocnemius recession. Journal of Biomechanics 2004;37(September (9)):1321–7.
[29] Michlitsch MG, Rethlefsen SA, Kay RM. The contributions of anterior and posterior tibialis dysfunction to varus foot deformity in patients with cerebral palsy. Journal of Bone and Joint Surgery 2006;88(August (8)):1764–8.
[30] Graham HK, Harvey A, Rodda J, Nattrass GR, Pirpiris M. The functional mobility scale (FMS). Journal of Pediatric Orthopedics 2004;24(September–October (5)):514–20.

Please cite this article in press as: Sagawa Jr Y, et al. Are clinical measurements linked to the Gait Deviation Index in cerebral palsy patients? Gait Posture (2012), http://dx.doi.org/10.1016/j.gaitpost.2012.11.026