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

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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.

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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).