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FUZZY LOGIC IN BIOMECHANICS OF THE HUMAN GAIT

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ABSTRACT
Computerized gait analysis using fuzzy logic has become an integral part of the treatment decision-making process. The integration of kinetic data, more specifically power joints in combination with fuzzy logic, is a relatively new addition to the other types of data including temporal and stride parameters. The power joints of the human leg are an important contribution to the understanding of the cause of certain gait abnormalities. This utility is not only limited to the surgical decision-making process in persons with spastic diplegia and myelomingocele but it can also be used in the rehabilitation decision-making process. The modelling of power joints and fuzzy logic applications in medicine will provide the reader with a detailed introduction to a new method of analysis of the human gait.
Keywords: biomechanics, fuzzy logic, gait analysis, human gait, myelomingocele, power joints, spastic diplegia.

1 INTRODUCTION

The study of human locomotion has aroused great interest in all periods of time from a mechanistic and heuristic point of view. Gait analysis and diagnosis still face some problems of application and knowledge of human locomotion is far from being complete. In carrying out a recent overview of the literature, one is struck by the importance of this problem today. In many clinical settings, computerized gait analysis has become an integral part of the clinical decision-making process of classifying human gait into different groups of pathology and of the treatment of gait abnormalities. The majority of clinical decisions derived from computerized gait analysis have been directed by kinematic and kinetic data in combination with fuzzy logic. The precise assessment of these types of information has been invaluable in contributing to the clinicians' understanding of the mechanisms in normal gait as well as in the pathological gait of persons with complex neuromuscular disorders such as spastic diplegia and myelomingocele. More recently, joint moments, joint powers and fuzzy logic have been available as additional tools in the assessment of normal and pathological gait. Joint kinetics provides an opportunity to better appreciate the role of trunk positioning and the relationship between joints and limbs during gait. The two primary avenues of classification and treatment of gait abnormalities in patients with spastic diplegia and myelomingocele are surgical treatment and rehabilitation. The purpose of this paper is to present the method of computation and examining the coefficients of the power's model of human gait in the classification and treatment decision-making process for persons with spastic diplegia and myelomingocele.

2 MATERIALS AND METHODS

Functional evaluation was carried out on 30 healthy subjects (average age 26 years), 40 patients with spastic diplegia (age ranging between 5 and 21 years) and 45 patients with myelomingocele (average age 10 years) after clinical evaluation. Patients were recruited into the Center of Bioingineeria in Milan (79 subjects) and into Glenrose Rehabilitation Hospital in Edmonton (36 subjects). The average height and weight of the subjects are listed in Table 1. The standard deviation values for the anthropometric data of each group are also given in Table 1. The difficulties that the patients most commonly complained about were: climbing stairs, walking uphill and bending down. Gait abnormalities of these persons are usually treated with a combination of rehabilitation, orthosis and surgery.

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Table 1: The anthropometric data (±SD) of subjects.

Subjects	Height (cm)	Weight (kg)
Healthy	168 ± 18	69 ± 10
Spastic diplegia	147 ± 27	46 ± 20
Myelomingocele	146 ± 21	57 ± 15

The optoelectronic systems—Elite-3D and Motion Analysis System—were used for the measurements. The systems are based on an online data processing of signals from a number of TV cameras. In the field of view of each TV camera it is possible to recognize those bright areas that are of interest for motion analysis. The optoelectronic systems have been designed to perform the following operations [1, 2]:

- recognize the shape of the marker placed on the subject;
- compute the x and y coordinates of the marker centroids;
- perform the previous operations in real time;
- classify the marker, so as to attribute each marker to the proper point of the basis of a suitable model of the body;
- perform routine data processing for: distortion correction by calibrating procedures, the reconstruction of point trajectories by test fitting techniques and three-dimensional analysis by stereometric techniques.

The subjects were analysed while walking barefoot along a straight pathway 10 m long. The quantization of the biomechanical variables and the spatio-temporal parameters of walking was performed by means of a computerized system for automatic acquisition of kinematics and ground reaction forces. A working volume 3 m long, 2.5 m high and 1.2 m wide was calibrated by a precision grid, which was displaced in three different parallel planes. The resulting accuracy was assessed by measuring the movement of a special stick with three retroreflective markers placed on it. In these conditions, the only errors that can appreciably affect the kinematic measurements are skin motion artefacts and deformation of the anatomical structure. Pre-processing of raw data involved a tracking procedure, three-dimensional reconstruction of the marker's coordinates, correction for optoelectronic distortion and filtering. The frequency of acquisition was set at 50 Hz. All the subjects were analysed with the same protocol (SAFLo) of gait analysis in the SAFLo laboratory in Milan and in the Syncrude Centre for Motion & Balance in Edmonton. The markers were placed at the following locations on each subject: two on the posterior superior iliac spines, one on the sacrum bone, two on the lateral femoral condyles, two on the lateral malleoli and one on the wrist. The inertial parameters were also derived using the measurement and some kinematic data from the optimization, according to the adjustments of the Zatsiorsky–Seluyanov's parameters [1]. In this work, ground reaction data were collected using AMTI and KISTLER platforms placed in these labs. Three forces and three moments relative to each force plate were recorded. Force plates were also calibrated by leaving the special eight marker devices on each force plate one at a time. The mean distance computed between the two spheres on the stick differed, in general, from the actual distance (400 mm) by less than 0.3 mm. Using data from the ground reaction platform, the kinematic data (trajectories, joint angles, acceleration, etc.) have been combined with ground reaction forces and inertial parameters in order to compute the joint moments and powers. All the variables were time-normalized taking the whole stride duration as 100%. Moments, powers and ground reaction forces were expressed as percentages of the individual body weight to make them comparable between different subjects.

2.1 The power's model of human gait using regression functions

Current technology does not allow the direct measurement of power joint. The power joint must be estimated through the combination of kinematic data associated with body segment locations and spatial orientations with force platform data. The calculation of power joint over the gait cycle requires the following data sets:

- the location of the hip, the knee and the ankle joints;
- the location of the centre of mass (CM) of the thigh, the shank and the foot;
- the linear acceleration of the CM of the thigh, the shank and the foot;
- the angular velocity and the acceleration of the thigh, the shank and the foot;
- the ground reaction forces and the vertical torque;
- the location of the point of application of the ground reactions.

These data are then incorporated into equations of motion along with estimates of the mass and the mass of inertia of each lower extremity segment. The computation of power joint is a relatively straightforward application of Newtonian mechanics. The mechanical power associated with joint rotation is computed from the combination of the joint moment and the joint angular velocity (the rotational velocity of one segment relative to another) [1, 2]. The formula for power joint is facilitated by the use of eqn (1):

$$P_i = \vec{M}_i \cdot \vec{\omega}_i, \tag{1}$$

where P is the joint power, M is the joint moment and ω is the angular velocity. The computation of the joint moment is faciliated by the use of eqn (2) of rotational motion:

$$M_i = F \cdot r, \tag{2}$$

where M is the join moment, F is the joint force and r is the vector from the joint centre to the CM of the segment.

The external forces considered were: ground reaction components and gravitational and inertial forces applied at the barycentre of each body segment. Mass, moments of inertia and positions of centres of gravity of each body segment were obtained from anthropometric tables [1].

The power's model proposed by the author is based on the instantaneous power joints of the lower limbs. The procedure of identification in the power's model of human gait, using regression functions, is presented in Fig. 1.

In this paper, a new method for the diagnosis of human gait is proposed. The method is based on regression functions. The human gait model using regression functions is determined by eqn (3) [3, 4]:

$$\hat{Y}_n = \underline{u}_n \cdot \underline{a}, \quad n = 1, 2, \ldots, N, \tag{3}$$

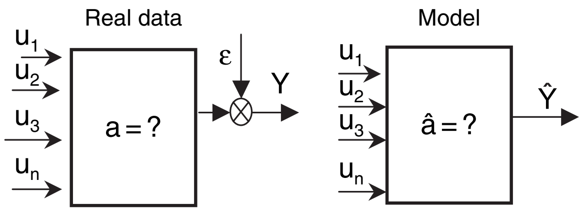

Figure 1: The identification model of human gait.

where $\hat{Y}$ is the model's output (power joints in the n instant), $\underline{u}_n$ is the model's input (power joints in the n instants before), $\underline{a}$ represents the unknown parameters of human gait and N is the sample size. The unknown vector $\underline{a}$ is determined by eqns (4) and (5):

$$a = (\underline{U}^{\mathrm{T}} \cdot \underline{U})^{-1} \cdot \underline{U}^{\mathrm{T}} \cdot \underline{Y}, \tag{4}$$

where $\underline{U}$ is the matrix of the input data and $\underline{Y}$ is the vector of the output data,

$$a = [a_1 \quad a_2 \quad \ldots \quad a_k]^{\mathrm{T}}, \quad k = 1, 2, \ldots, K, \tag{5}$$

where K is the coefficient size.

The power's model coefficients determined using regression functions are presented in Table 2. They were calculated for the hip, the knee and the ankle joints in two phases: in the stance phase and in the swing phase. The standard deviation values of the model's coefficients for each group are also given in Table 2.

Statistical analysis was performed on the whole population of healthy subjects and those with spastic diplegia and myelomingocele. A characterization of the difference was obtained by computing the following parameters: the standard deviation, correlation, variance and confidence intervals. The average value of coefficients a_1 for the hip joint is the highest for patients with myelomingocele in the stance phase and for patients with spastic diplegia in the swing phase. The average value of coefficients a_2 is the highest for patients with spastic diplegia in the stance phase and for healthy subjects in the swing phase. There are no significant differences between the values of coefficients a_3 for each group. The analysis of the model's coefficients for the knee joint shows that the average value of coefficients a_1 is the highest for healthy subjects in the stance phase. There are no significant differences between coefficients a_1 for each group in the swing phase. The average value of coefficients a_2 is the highest for patients with spastic diplegia in the stance phase and in the swing phase. The average value of coefficients a_3 is the highest for patients with spastic diplegia and myelomingocele in the stance phase and for healthy subjects in the swing phase. The analysis of the ankle joint shows, that the average value of coefficients a_1 is the highest for patients with spastic diplegia in the stance and in the swing phase. There are no significant differences between coefficients a_2 for each group in the swing phase. The average value of coefficients a_2 is the highest for patients with myelomingocele in the swing phase. In the stance phase, the coefficients a_3 do not change the value a lot for each group and it is the highest for healthy subjects in the swing phase.

Table 3 presents the power's model coefficients in seven phases of human gait: the initial contact (IC), the loading response (LR), the midstance (MSt), the terminal stance (TSt), the initial swing (ISw), the midswing (MSw) and the terminal swing (TSw), obtained using regression functions. The standard deviation values of the model's coefficients for each group are also given in Table 3.

The analysis of the model's coefficients in the initial contact shows that the average value of coefficients a_2 is the lowest for patients with myelomingocele, but the average value of coefficients a_3 is the highest for healthy subjects. In the loading response, the average value of coefficients a_2 is the lowest for healthy subjects. In the midstance, the average value of coefficients a_1 is the lowest for patients with spastic diplegia and the average value of coefficients a_3 is the highest for patients with myelomingocele. Moreover, in the terminal stance, the average value of coefficients a_1 is the highest for patients with spastic diplegia, a_2 is the lowest for healthy subjects and a_3 is the highest for patients with myelomingocele. In the initial swing, there are no significant differences between the values of the model's coefficients for each group. In the midswing, we can see that the coefficients a_2 are the lowest and a_3 are the highest for patients with spastic diplegia. Finally, in the terminal swing the coefficients a_2 are the lowest for patients with spastic diplegia and a_3 are the lowest for

Table 2: The power's model coefficients (±SD) for healthy subjects and for patients with spastic diplegia and myelomingocele in the stance and the swing phases.

Joint	Coefficient	Stance phase	Swing phase
Healthy subjects			
Hip	a_1	1.964 ± 0.570	1.562 ± 0.491
	a_2	-1.252 ± 1.067	0.904 ± 0.591
	a_3	0.203 ± 0.186	0.180 ± 0.090
Knee	a_1	2.033 ± 0.545	1.834 ± 0.447
	a_2	-1.501 ± 0.798	-1.187 ± 0.574
	a_3	0.464 ± 0.223	0.290 ± 0.203
Ankle	a_1	1.759 ± 0.530	1.001 ± 0.363
	a_2	-1.168 ± 0.640	-0.212 ± 0.160
	a_3	0.288 ± 0.106	-0.039 ± 0.015
Patients with spastic diplegia			
Hip	a_1	2.005 ± 0.508	1.952 ± 0.488
	a_2	-0.955 ± 0.350	-0.849 ± 0.344
	a_3	0.378 ± 0.210	0.351 ± 0.173
Knee	a_1	1.865 ± 0.590	1.788 ± 0.648
	a_2	-0.901 ± 0.317	-0.859 ± 0.425
	a_3	0.275 ± 0.169	0.408 ± 0.208
Ankle	a_1	1.997 ± 0.334	1.340 ± 0.605
	a_2	-1.002 ± 1.427	-0.561 ± 0.388
	a_3	0.371 ± 0.213	0.045 ± 0.024
Patients with myelomingocele			
Hip	a_1	2.084 ± 0.386	1.743 ± 0.234
	a_2	-1.501 ± 0.676	-1.154 ± 0.168
	a_3	0.386 ± 0.312	0.285 ± 0.091
Knee	a_1	1.801 ± 0.328	1.909 ± 0.343
	a_2	-1.114 ± 0.557	-1.369 ± 0.585
	a_3	0.241 ± 0.127	0.422 ± 0.249
Ankle	a_1	1.848 ± 0.464	1.145 ± 0.306
	a_2	-1.275 ± 0.768	-0.435 ± 0.286
	a_3	0.299 ± 0.198	0.044 ± 0.021

healthy subjects. The Kolmogorow–Smirnow statistical test with $p < 0.05$ was used to compare the average values of the coefficients in each group [5]. The hypothesis regarding the same coefficient's distribution in three groups was rejected.

2.1.1 The system of supported clinical decision-making in medicine

Since the 1980s new techniques using fuzzy logic have appeared in medical systems. Many of these intelligent systems are based on fuzzy control strategies with the description of complex systems of mathematical models in terms of linguistic rules. Fuzzy logic needs a full description of the rules of relations between the inputs and the outputs that can occur in a considered engineering context. When complexity increases, the list of rules becomes extremely large and needs a great deal

Table 3: The power's model coefficients (±SD) for healthy subjects and for patients with spastic diplegia and myelomingocele in the seven phases of human gait.

Coefficient	IC	LR	MSt	TSt	ISw	MSw	TSw
Healthy subjects							
a_1	0.636 ± 0.102	1.232 ± 0.117	1.039 ± 0.154	0.576 ± 0.122	0.641 ± 0.107	0.610 ± 0.151	1.226 ± 0.221
a_2	−0.068 ± 0.003	−0.350 ± 0.045	−0.138 ± 0.035	−0.408 ± 0.101	−0.187 ± 0.050	−0.061 ± 0.005	−0.263 ± 0.051
a_3	0.046 ± 0.008	−0.076 ± 0.007	−0.091 ± 0.009	−0.057 ± 0.005	−0.097 ± 0.021	−0.051 ± 0.008	−0.151 ± 0.080
Patients with spastic diplegia							
a_1	0.620 ± 0.151	0.992 ± 0.422	0.856 ± 0.101	0.914 ± 0.307	0.750 ± 0.150	0.759 ± 0.152	1.215 ± 0.250
a_2	−0.060 ± 0.006	−0.113 ± 0.070	−0.235 ± 0.100	−0.196 ± 0.071	−0.126 ± 0.052	−0.190 ± 0.401	−0.500 ± 0.100
a_3	−0.040 ± 0.035	−0.050 ± 0.030	−0.093 ± 0.006	−0.179 ± 0.077	−0.025 ± 0.005	0.024 ± 0.030	−0.011 ± 0.004
Patients with myelomingocele							
a_1	0.635 ± 0.403	0.965 ± 0.150	1.086 ± 0.040	0.676 ± 0.352	0.797 ± 0.551	0.736 ± 0.300	0.947 ± 0.500
a_2	−0.109 ± 0.100	−0.100 ± 0.045	−0.273 ± 0.850	−0.234 ± 0.114	−0.139 ± 0.101	−0.067 ± 0.032	−0.295 ± 0.150
a_3	0.012 ± 0.009	−0.070 ± 0.054	0.035 ± 0.020	−0.080 ± 0.050	−0.066 ± 0.065	−0.055 ± 0.035	−0.090 ± 0.075

of expert information. Fuzzy logic resembles the way of thinking of actors left with an agreed set of decision options, a list of rules of behaviour and of instructions how to use them so as to solve a specific problem. Fuzzy logic, as any other type of logic, cannot transcend its own limits as a tool of inference and thus cannot be used as a holistic criterion of reality. Fuzzy logic provides a means for encapsulating the subjective decision-making process in an algorithm suitable for computer implementation. As such, it appears to be eminently suited to aspects of medical decision-making. Furthermore, the principles behind fuzzy logic are straightforward and its implementation in software is relatively easy. Nevertheless, the applications of fuzzy logic in medicine are few [6–8].

This section will illustrate the application of fuzzy logic into the system of supported clinical decision-making in biomechanics of the human gait. MATLAB 6.5 as well the Borland C++ Builder and the fuzzy Dempster-Shafer (FDS) classifier were used to build this system [9–11]. The FDS fuzzy logic has a particular advantage in areas where precise mathematical description of the control process is impossible and is thus especially suited to support medical decision-making. The knowledge base is managed in the Center of Bioingineeria in Milan (Italy) and in the Glenrose Rehabilitation Hospital in Edmonton (Canada). The subjects' data were divided into two sets: the teaching set and the testing set. The teaching set included subjects' data from the Center of Bioingineeria in Milan, while the testing set included subjects' data from the Glenrose Rehabilitation Hospital in Edmonton. The numbers of subjects in both sets are presented in Table 4.

The first step in implementing a fuzzy logic control algorithm is to 'fuzzify' the measured variables. In the proposed system, the rules were generated using the power's model coefficients presented in Tables 2 and 3. The patient's state in terms of diagnosis was a fuzzy set with the following square membership function given by eqn (6) [12]:

$$y = \frac{(X - x_i)^2}{(x_i - x_{i+1})}, \tag{6}$$

where y is the membership function and X is a variable. The operator's adjustment is presented by eqn (7):

$$\max(0, x \cdot p), \tag{7}$$

where x is the new rule and p is the rule of the operator's adjustment.

The maximum of the operator's adjustment was defined as follows:

1. The value of the operator's adjustment was tested at the borders $\langle 0, 1 \rangle$. The threshold value was 0.75. If the threshold value was crossed, the number of well-chosen rules was increased (the addition of the rule to the report required 50% + 1 attribute with the threshold value). In a different case, point 2 was carried out.
2. The method of gold division was used for determining the operator's adjustment.

Table 4: The number of subjects in the teaching set and the testing set.

Subjects	Teaching set	Testing set
Healthy	15	15
Spastic diplegia	26	14
Myelomingocele	26	19

During the system's teaching three relations were used: healthy subjects—15 rules; patients with spastic diplegia—26 rules; patients with myelomingocele—26 rules. The coefficient's ranges, which allow the classification of human gait into different groups of pathology, are presented in Table 5. The use of power joints in the treatment decision-making process is relatively new. Choosing the best method of improvement of human gait for these particular diseases may not be easy. Certain points have to be taken into consideration—the side effects of the method of improvement, the effect of the treatment on the patient, whether the patient is taking any other treatment, and the effect of the combination of the treatments, whether the patient is infected with some other disease and so on. Hence, determining an appropriate method of improvement of human gait becomes important as well as complicated. Here, fuzzy decision-making plays a major role [12, 13].

It has been noticed that more information can be obtained from the proportion between the power's model coefficients. The proportions between coefficients are determined by eqn (8):

$$\begin{bmatrix} a_{\mathrm{I}} \\ a_{\mathrm{II}} \end{bmatrix} = \begin{bmatrix} \dfrac{a_1}{a_3} \\ \dfrac{a_2}{a_3} \end{bmatrix}, \tag{8}$$

where a_1, a_2 and a_3 are the power's model coefficients of human gait.

The coefficient's ranges, which allow choosing the method of improvement of human gait (surgical treatment or rehabilitation), are presented in Table 6. The ranges are presented together for both spastic diplegia and myelomingocele.

Table 5: The rules for healthy subjects and for patients with spastic diplegia and myelomingocele.

Joint	Phases of the human gait	Coefficient	Value of the coefficient
Healthy subjects			
Hip	Stance	a_1	$1.395 \div 2.534$
		a_2	$-2.319 \div -0.185$
		a_3	$0.017 \div 0.389$
	Swing	a_1	$1.071 \div 2.053$
		a_2	$-0.313 \div 1.495$
		a_3	$0.090 \div 0.270$
Knee	Stance	a_1	$1.489 \div 2.578$
		a_2	$-2.299 \div -0.703$
		a_3	$0.241 \div 0.687$
	Swing	a_1	$1.387 \div 2.281$
		a_2	$-1.761 \div -0.613$
		a_3	$0.087 \div 0.493$
Ankle	Stance	a_1	$1.229 \div 2.289$
		a_2	$-1.808 \div -0.528$
		a_3	$0.182 \div 0.470$
	Swing	a_1	$0.639 \div 1.364$
		a_2	$-0.372 \div 0.052$
		a_3	$-0.054 \div 0.177$

(*Continued*)

Table 5: *Continued*

Joint	Phases of the human gait	Coefficient	Value of the coefficient
Patients with spastic diplegia			
Hip	Stance	a_1	1.497 ÷ 2.513
		a_2	−1.345 ÷ −0.605
		a_3	0.168 ÷ 0.588
	Swing	a_1	1.464 ÷ 2.440
		a_2	−1.193 ÷ −0.505
		a_3	0.178 ÷ 0.524
Knee	Stance	a_1	1.275 ÷ 2.455
		a_2	−1.218 ÷ −0.584
		a_3	0.106 ÷ 0.444
	Swing	a_1	1.140 ÷ 2.436
		a_2	−1.284 ÷ −0.434
		a_3	0.200 ÷ 0.616
Ankle	Stance	a_1	1.663 ÷ 2.331
		a_2	−2.429 ÷ 0.424
		a_3	0.158 ÷ 0.584
	Swing	a_1	0.736 ÷ 1.945
		a_2	−0.949 ÷ −0.173
		a_3	0.021 ÷ 0.067
Patients with myelomingocele			
Hip	Stance	a_1	−11.778 ÷ 23.780
		a_2	−10.007 ÷ 1.775
		a_3	−558.000 ÷ 7.491
	Swing	a_1	−21.821 ÷ 1.317
		a_2	−15.470 ÷ 10.600
		a_3	−5.353 ÷ 2.222
Knee	Stance	a_1	−40.760 ÷ 19.575
		a_2	−12.964 ÷ 0.998
		a_3	−8.634 ÷ 43.002
	Swing	a_1	−13.011 ÷ 16.008
		a_2	−8.710 ÷ 29.504
		a_3	−11.845 ÷ 1.282
Ankle	Stance	a_1	−11.832 ÷ 47.579
		a_2	−17.219 ÷ 3.612
		a_3	−11.778 ÷ 23.780
	Swing	a_1	−10.007 ÷ 1.775
		a_2	−558.000 ÷ 7.491
		a_3	−21.821 ÷ 1.317

The system of supported clinical decision-making in medicine was verified on patients from the Glenrose Rehabilitation Hospital in Edmonton (15 healthy subjects, 14 patients with spastic diplegia and 19 patients with myelomingocele). The results of the verification of the system are presented in Table 7. The verification was based on the comparison of the results obtained from the system with the

Table 6: The rules for patients with myelomingocele and spastic diplegia—surgical treatment and rehabilitation.

Phases of the human gait	Coefficient	Value of the coefficient
Surgical treatment		
IC	a_{I}	$-154.004 \div 345.011$
	a_{II}	$-87.155 \div 34.999$
LR	a_{I}	$-73.759 \div 140.000$
	a_{II}	$-86.004 \div 9.905$
MSt	a_{I}	$-36.004 \div 135.341$
	a_{II}	$-48.012 \div 11.008$
TSt	a_{I}	$-607.000 \div 95.313$
	a_{II}	$-18.020 \div 148.009$
ISw	a_{I}	$-1347.111 \div 24.212$
	a_{II}	$-5.425 \div 339.016$
MSw	a_{I}	$-52.000 \div 62.990$
	a_{II}	$-8.612 \div 5.446$
TSw	a_{I}	$-210.004 \div 289.994$
	a_{II}	$-229.758 \div 70.001$
Rehabilitation		
IC	a_{I}	$-11.778 \div 23.780$
	a_{II}	$-10.007 \div 1.775$
LR	a_{I}	$-558.000 \div 7.491$
	a_{II}	$-21.821 \div 1.317$
MSt	a_{I}	$-15.470 \div 10.600$
	a_{II}	$-5.353 \div 2.222$
TSt	a_{I}	$-40.760 \div 19.575$
	a_{II}	$-12.964 \div 0.998$
ISw	a_{I}	$-8.634 \div 43.002$
	a_{II}	$-13.011 \div 16.008$
MSw	a_{I}	$-8.710 \div 29.504$
	a_{II}	$-11.845 \div 1.282$
TSw	a_{I}	$-11.832 \div 47.579$
	a_{II}	$-17.219 \div 3.612$

medical doctor's diagnosis. The effectiveness of the system in classifying the subjects into different pathological groups is 91.6 %. The probability of wrong classification is 0% for healthy subjects, 7.1% for patients with spastic diplegia and 15.8% for patients with myelomingocele. The system properly determined the method of improvement of human gait in over 90.0% of the cases. The probability of wrong diagnosis of treatment is about 10.0% for both spastic diplegia and myelomingocele.

3 CONCLUSIONS

It is very likely that applying kinetics data, especially power joints, helps to define gait pathology and treatment in a large number of patients. A lot of work remains to be done in the modelling area. Hopefully, the accurate computation and interpretation of power joints in combination with the other

Table 7: The verification of the system—classification of patients into different groups of pathology and the method of improvement of human gait.

	Correct classification (%)
Classification of patients into different groups of pathology	
Healthy	100.0
Spastic diplegia	92.9
Myelomingocele	84.2
The method of improvement of human gait	
Surgical treatment (spastic diplegia and myelomingocele)	91.6
Rehabilitation (spastic diplegia and myelomingocele)	88.9

components of the computerized analysis system will eventually lead to significant improvements in treatment decision-making for complex gait abnormalities such as spastic diplegia and myelomingocele. This method of identification represents human movement in a very accurate way during walking in the sagittal plane. It could be used in bioengineering for the assessment of walking recovery.

The considerations introduce an incomplete analysis of spacious problems concerned with the classification and the improvement of the apparatus of human gait, which is a result of the limited amount of the collected data. However, scientific results obtained lead to the conclusion that the model's method of identification (regression functions) can be applied to determine the dynamic properties of human gait, and consequently to diagnose a patient's apparatus of movement.

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