Chapter 17
Analysis of Temporospatial Gait Parameters

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Abstract Locomotion in post-stroke patients may be severely compromised. Assessment and treatment of gait disorders after stroke are crucial. Scientists and clinicians still look for more effective diagnostic and therapeutic tools. The aim of the study was to assess a new fuzzy-based tool for measurement of observed gait parameters (velocity, cadence, and stride length, and their normalized values), both in healthy people and post-stroke patients.

17.1 Introduction

Stroke is the second leading cause of preventable death and the fourth leading cause of lost productivity. At least of stroke survivors have limited independence. Thus efficient diagnosis, therapy, rehabilitation, and care in patients after stroke constitute important scientific, clinical, social, and economic challenges.

Assessment and treatment of gait disorders after stroke constitute a major component of post-stroke rehabilitation. Locomotion in post-stroke patients may be severely compromised. Disturbed (as a result of a stroke) motor control influences gait movements and the expected rate of recovery of walking function. Gait impairments can be, for example, a significant factor in falls and mobility limitations. The main element of the gait-related rehabilitation program of stroke survivors is task-related training

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with the strong dose of practice [22]. Diverse technologically complex interventions (from repetitive task-specific practice to complex games involving robotic systems, virtual reality, and augmented reality) may be applied to improve gait post-stroke. Availability, mode of application, and costs of the particular methods may vary, but the key issue focuses on their efficiency. Pure compensatory effects avoiding is also important.

Despite efforts of scientists and clinicians, the validity of many interventions within rehabilitation of gait post-stroke appears to be limited. Outcomes of gait recovery due to rehabilitation depend on many factors, including location and size of the lesion, kind and severity of impairment, available activity, cortical activation, and associated rehabilitation-induced activity-dependent neuroplasticity. To establish an adequate, flexible, and efficient rehabilitation program, the key element is a selection of the appropriate measurement tool according to the individual's level of function. Such a tool, used in everyday clinical conditions, should be simple, quick, cheap, exact, sensitive, valid, and relevant. What is more, possible impairments in gait coordination may be a cause of falls and diverse mobility limitations, thus therapy should be introduced as early as possible [7]. There should be a possibility to use the clinical tool for gait assessment at every stage, even early post-stroke, to assess both quantitative and qualitative parameters and compare results to the norm or other patients. Such an approach may help to restore the patient's best possible functioning [13, 14]. Improved assessment tools allow more detailed, valid, and reliable gait assessment independently of the phase of the rehabilitation program, and construction of efficient gait rehabilitation models in post-stroke patients. Current evidence does not demonstrate such a tool which is clinically, statistically, and economically important [5]. Gait velocity, although important, does not reflect changes in gait quality.

Gait quality is important for harmonic long-term efficiency of gait recovery. Even slower, but high-quality gait patterns at an early stage of rehabilitation may provide better long-term rehabilitation results reflected in various gait parameters.

The aim of the study was to assess a new fuzzy-based tool for measurement-observed gait parameters (velocity, cadence, and stride length and their normalized values), both in healthy people and post-stroke patients. The hypothesis is that this fuzzy-based tool for measurement-observed gait parameters is effective in the assessment of gait re-education in patients after ischemic stroke.

17.2 Methods

17.2.1 Subjects

The investigated group consisted of 50 patients: 25 healthy ones and 25 after ischemic stroke. Ischemic stroke is the most common stroke type; it constitutes approximately 80–85cases [3, 4]. A study group was established on the basis of the criteria described. Inclusion criteria for patients were as follows: age above 18 years,

Table 17.1 Patients' overall profiles

	Healthy people (n = 25)	Post-stroke patients (n = 25)
Sex:		
Females (K)	12 (48%)	12 (48%)
Males (M)	13 (52%)	13 (52%)
Age [years]:		
Min	51	49
Max	72	82
Mean	58.6	65.28
SD	6.29	9.56
Median	56	68
Side of paresis:		
left (L)	n.a.	13 (52%)
right (R)	n.a.	12 (48%)
Time after cerebrovascular accident (CVA):		
Min	n.a.	1
Max	n.a.	4
Mean	n.a.	2.56
SD	n.a.	1.17
Median	n.a.	3

time after cerebrovascular accident (CVA) from 6 weeks to 3 years, and diagnosis of ischemic stroke. The inclusion of patients was confirmed each time by medical records. Inclusion criteria for healthy people were: age above 18 years and lack of CVA and other diseases influencing gait function in the medical record. The patients' profiles are presented in Table 17.1.

17.2.2 Methods

Healthy people were assessed once. Post-stroke patients participated in the rehabilitation program. Patients were treated by the same experienced physiotherapist (>15 years of experience in neurorehabilitation). Ten sessions of the therapy were provided in 2 weeks (10 days of the therapy). We used our own method of gait analysis, described in [12–14]. It is based on gait recording using a video camera with visual gait evaluation, measurement of temporospatial gait parameters (gait velocity, cadence, stride length) and their assessment, and calculating normalized values using the Clinical Gait Analyzer (free software developed by Ch. Kirtley). Measurements were performed in every post-stroke patient twice: on admission (before the therapy) and after the last session of the therapy to assess rehabilitation effects.

17.2.3 Statistical Analysis

Wherever possible, the results are given as mean, SD, median, minimal value, and maximal value. The Shapiro–Wilk test of normality was applied. The calculation of correlations (Spearman's rho) was made based on changes of parameters: gait velocity, cadence, and stride length, their normalized values, and results of the fuzzy-based assessment. The data were analyzed with the Statistica 9 software. The results were statistically analyzed using the Wilcoxon's test. The level of statistical significance (p value) was set at 0.05.

17.2.4 Fuzzy-Based Tool for Gait Assessment

The subject of the research-the quality of gait-is a difficult term for formal precise definition. It depends on the general public and varies depending on the group we consider to be the norm in terms of gait. If the precise model is out of reach, we can use the tools for imprecise information processing: fuzzy systems. Their main advantage is the flexibility, intuitiveness, and clarity of rules that are easy to describe linguistically.

The concrete proposition here is the multicriteria fuzzy evaluator of gait (MuFEG) defined for the purposes of the study presented in this chapter. This tool evolved from the multicriteria fuzzy evaluator proposed in [21], the purpose of which was evaluation of multicast routing algorithms. The measure of proper gait is presented as a percentage, where is an ideal quality. Defining MuFEG's basic model for a good quality of gait, assumptions have been made that the quality of gait in people with no stroke, that is, a reference group of respondents, cannot be lower than. The presented results were achieved by combining three different descriptors of a gait. In the version of MuFEG used in the present studies, these descriptors are represented by three fuzzy Mamdani-type systems. A general idea of such fuzzy systems and precise presentation can be found in many books, for example, [1, 15, 16]. Finally, their results are aggregated to one normalized outcome. Two concurrent MuFEG approaches are used. Their working names are 1b-25 and KFNc-25. Both are based on the same assumptions and the same rules. The first, 1b-25, is the classical fuzzy system with:

- Singleton fuzzification.
- Implication operator, MIN.
- Defuzzification is realized as implications and the middle of maxima (MOM) method defuzzification.

The fuzzy set representing the ideal value for each gait parameter is constructed from the data given for the reference group, people without stroke. Each of them is a triangular fuzzy set (see L-R fuzzy sets notation in [6]) and is determined on all the available data. For example, let's look at set *good gait velocity* (good-GV):

$$good - GV = \Lambda(x; x_{mean} - 2 \cdot \Delta_L, x_{mean}, x_{mean} + 2 \cdot \Delta_R) \tag{17.1}$$

where $\Delta_L = x_{mean} - x_{min}$, $\Delta_R = x_{max} - x_{mean}$, $x_{min}/x_{max}/x_{mean}$, the minimum/maximum/mean value of the gait velocity parameters for the available data about healthy (non-post-stroke) people.

As there are three systems with one input each there is no need for the aggregation of premise parts of the rules. The second fuzzy system, KFNc-25, is based on the new model of processing imprecise data, the Ordered Fuzzy Numbers (OFN; see Chap. 4). In the papers [18, 19] the name "Kosinski's Fuzzy Numbers" (KFNs) model is also used alternatively. For the calculations of MuFEG results the tool implemented by the first author (P. Prokopowicz) was used. Its basic functionality is the modeling of fuzzy systems with the OFN model as well as with classical fuzzy sets. The variant of MuFEG for classical fuzzy sets was also implemented using the fuzzy logic toolbox for MATLAB for the reference purposes. The results were the same, thus it proved the author tool in this scope is correct. As OFN is a relatively new conception, the tool in this aspect is completely a pioneer.

17.2.5 Main Ideas of the OFN Model

The OFN mathematical model [10, 11] takes into account the order of the characteristic parts of a membership function of a fuzzy number. As a result, it extends the general idea of fuzzy numbers with an additional feature, a direction. As the result of using the direction in calculations, we have the opportunity to reduce the imprecision of the following operations. The OFN computational model has a number of properties. Some of them were presented in [17]. Apart from good calculations, the direction also gives additional potential in the interpretation of fuzzy data. It can be treated as a direction of the process, for example, "Velocity is high and is growing," is a different situation from, "Velocity is high, but is decreasing." The direction of the OFN can be used to represent the difference between these sentences. Because we deal with additional information, there is a need for the new methods which benefit the full potential of OFNs in modeling of linguistic data. The papers [10, 17–20] describe the research of the OFN processing methods that consider the direction.

Thanks to the new property, a new potential for the practical use of OFNs also appears with a new quality associated with the direction. The work [8] presents the practical use of this property in modeling financial data, and [9] diversity of opinions in social networks. In [2] the application of OFNs for an ant colony optimization algorithm is presented. Here we use the new model for defining an assessment tool for gait.

17.2.6 OFN Model in Gait Assessment

At the present stage of the research presented in this chapter, considering the direction is not a key element. However, for the future extent of this research OFN gives additional potential. It presents the possibility of trend processing (see Chap. 4). In a gait assessment, measuring the trend of changes can be more valuable than the only present quality. It is especially appropriate when we want to evaluate the effectiveness of different therapeutic approaches. The MuFEG system in the OFN variant used here is designed as generally preferring higher values of inputs. For example, for the stride length, the value near the lower limit of healthy people's interval gives a worse result than the value near the upper limit.

17.3 Results

The results are presented in Tables 17.2, 17.3, and 17.4.

Changes in the six main temporospatial parameters were reflected in the changes of MuFEG-generated percentages both in healthy people and post-stroke patients. The main statistically relevant correlations observed in the study were similar in both groups.

17.4 Discussion

Post-stroke patients often suffer from multiple limitations of the ability to perform everyday activities. Thus they need rehabilitation in more than one area. But an assumption may be true that it is hard to achieve simultaneous recovery in all areas (including gait function, hand function, activities of daily life) in a relatively short period of rehabilitation (10 sessions) [13, 14]. In the described research we focused on gait rehabilitation. The study has focused on determination of changes in gait parameters (gait velocity, cadence, and stride length) observed as a result of the therapy in a group of patients after ischemic stroke. No doubt, there were observed statistically relevant changes in gait parameters as the result of the therapy. A good quality of the gait depends on many different factors. We must remember that we compare the gait of people after stroke with a reference gait of people without stroke. However, in the context of the evaluation, these model people are considered as healthy; in fact, their gait may be affected by many different factors, ranging from diseases other than stroke, through bad habits of posture or finally physical fatigue on examination day. Thus it is obvious that the good quality of gait evaluation is not a crisp value.

The proposed solution is an element of the broader concept, using fuzzy numbers, fractal dimension, and artificial neural networks to analyze the human gait in a more

Table 17.2 Results of the study-traditional approach

	Healthy people (n = 25)	Post-stroke patients (n = 25)		
		Before the therapy	After the therapy	Change
Gait velocity [m/s]				
Min	1.6	0.1	0.1	−0.5
Max	2.2	0.8	1.6	0.8
Mean	1.81	0.48	0.57	0.06
SD	0.17	0.11	0.16	0.02
Median	1.8	0.5	0.5	0.05
Normalized gait velocity [-]				
Min	0.52	0.05	0.04	−0.07
Max	0.72	0.28	0.53	0.25
Mean	0.61	0.16	0.19	0.07
SD	0.06	0.05	0.04	0.02
Median	0.58	0.16	0.17	0.02
Cadence [steps/min]				
Min	102	36	24	−34
Max	142	100	151	67
Mean	123.72	78.24	82.56	4.4
SD	11.54	16.92	21.29	17
Median	126	81	88	4
Normalized cadence [-]				
Min	0.54	0.17	0.12	−0.18
Max	0.73	0.51	0.76	0.34
Mean	0.62	0.39	0.41	0.12
SD	0.05	0.09	0.12	0.02
Median	0.61	0.41	0.43	0.13
Stride length [m]				
Min	1.54	0.57	0.61	−0.55
Max	2	2.22	2.5	0.5
Mean	1.76	1.44	1.61	0.21
SD	0.18	0.46	0.53	0.05
Median	1.67	1.54	1.54	0.14
Normalized stride length [-]				
Min	1.7	0.38	0.72	−0.6
Max	2.23	2.5	2.94	1.19
Mean	1.93	1.62	1.86	0.24
SD	0.21	0.36	0.6	0.06
Median	1.84	1.73	1.85	0.18

(continued)

Table 17.2 (continued)

	Healthy people (n = 25)	Post-stroke patients (n = 25)		
		Before the therapy	After the therapy	Change
MuFEG assessment [%] (1b-25)				
Min	64.17	0	0	−26.67
Max	92.34	33. 83	57	53.67
Mean	82.46	12.49	20.19	6.33
SD	0.08	0.14	0.17	0.19
Median	83.5	5	26	1.17
MuFEG assessment [%] (KFNc-25)				
Min	59.93	0	0	−21.39
Max	95.93	36.71	54.31	41.41
Mean	78.25	14.44	20.95	6.51
SD	0.09	0.13	0.16	0.16
Median	79.79	11.45	19.53	0

comprehensive way, without any wearable devices. Finally, the described system could be used both for gait analysis of runners and for developmental issues of children. Three possible results of the therapy (recovery, no change, and relapse) may confuse analysts. But the main result of short-term therapy may be varied. Sometimes gait re-education aims at increasing gait quality, and the changes in gait velocity or cadence will be observed during the next rehabilitation periods. Fuzzy-based software should provide full support for the data analysis in such cases.

The most important advantage of the MuFEg is that it does not require any additional procedure: temporospatial gait analysis is a part of normal clinical practice in neurorehabilitation. Moreover, the result of our analysis reflected in one number has enough informative and predictive power and allows the assessment of the general tendency. Thus the EBM-based clinical decision-making process may be quicker and easier. Of course, if necessary, detailed temporospatial gait parameters also may be used. The main limitation of the research is a small sample, but we regard this study as a preliminary one. The discrepancy between results shown in Tables 17.3 and 17.4 proves the necessity of further calibration of the MuFEG algorithms, including various samples of healthy people and patients, even on much bigger retrospective datasets.

The next step will also be establishing an online version of our gait analyzer, to gather opinions of other MuFEG users and medical data analysts. Bigger samples should provide further comparative studies on validity and reliability of the proposed fuzzy-based measurements. Results of the pure study show that physiotherapy interventions significantly influence gait function and coordination. However, even the most promising approaches aiming at restoring gait coordination require reliable

Table 17.3 Correlations (Spearman's rho values) for healthy people

	Age	Gait velocity	Cadence	Stride length	Normalized gait velocity	Normalized cadence	Normalized stride length	Fuzzy evaluator	
								MuFEG (Ib-25)	MuFEG (KFNc-25)
Age	–	−0.952	ns	−0.397	−0.948	−0.452	−0.449	−0.42	−0.399
		p = 0.000		p = 0.032	p = 0.000	p = 0.045	p = 0.047	p = 0.007	p = 0.004
Gait velocity		–	ns	0.458	0.956	ns	0.518	0.650	0.519
				p = 0.042	p = 0.000		p = 0.019	p = 0.032	p = 0.017
Cadence			–	−0.620	ns	0.905	−0.516	0.414	0.457
				p = 0.004		p = 0.000	p = 0.020	p = 0.012	p = 0.040
Stride length				–	ns	−0.467	0.922	0.520	0.478
						p = 0.038	p = 0.000	p = 0.005	p = 0.000
Normalized gait velocity					–	ns	0.482	0.413	0.45
							p = 0.031	p = 0.004	p = 0.007
Normalized cadence						–	ns	0.412	0.542
								p = 0.017	p = 0.019
Normalized stride length							–	0.531	0.490
								p = 0.021	p = 0.042
MuFEG								–	0.936
(Ib-25)									p = 0.000
MuFEG									–
(KFNc-25)									

ns = not significant

Table 17.4 Correlations (Spearman's rho values) for post-stroke patients

	Age	Gait velocity	Cadence	Stride length	Normalized gait velocity	Normalized cadence	Normalized stride length	Fuzzy evaluator	
								MuFEG (Ib-25)	MuFEG (KFNc-25)
Age	–	−0.931	ns	−0.325	−0.902	−0.407	−0.399	−0.447	−0.315
		p = 0.007		p = 0.000	p = 0.003	p = 0.007	p = 0.043	p = 0.020	p = 0.002
Change of gait velocity		–	ns	0.425	0.923	ns	0.499	0.571	0.478
				p = 0.045	p = 0.000		p = 0.031	p = 0.020	p = 0.000
Change of cadence			–	−0.513	ns	0.925	−0.522	0.397	n.s.
				p = 0.000		p = 0.007	p = 0.006	p = 0.021	
Change of stride length				–	ns	−0.413	0.910	0.457	0.428
						p = 0.002	p = 0.000	p = 0.010	p = 0.009
Change of normalized gait velocity					–	ns	0.437	0.404	0.432
							p = 0.010	p = 0.002	p = 0.019
Change of normalized cadence						–	ns	0.377	0.446
								p = 0.012	p = 0.034

(continued)

Table 17.4 (continued)

	Age	Gait velocity	Cadence	Stride length	Normalized gait velocity	Normalized cadence	Normalized stride length	Fuzzy evaluator	
								MuFEG (Ib-25)	MuFEG (KFNc-25)
Change of normalized stride length							–	0.457	0.422
								p = 0.002	p = 0.015
MuFEG								–	0.912
(Ib-25)									p = 0.002
MuFEG (KFNc-25)									–

ns = not significant

clinical diagnostic tools. Such tools allow for more objective diagnosis and reassessment (performed at every stage of the rehabilitation to check progress in the therapy), and may help to achieve a better understanding of the nature of both neuroplasticity and coordination deficits in functional tasks after stroke and their optimal role in the neurorehabilitation.

Future research also requires work with the MuFEG system. In particular, the OFN variant provides an interesting potential of flexibility. Considering trends in the information will allow for searching the solutions that estimate therapy methods in the various contexts. For example, we can prefer the improvement of the quality of gait which is small but regular over a large but occasional one. For the future, it is also worthwhile considering distinguishing the differences in bad estimations, particularly in the cases when results are too low and too high. Moreover, based on the good arithmetical properties of the OFN model it is possible to provide fluent use of such imprecise data in further processing without additional transformations.

17.5 Conclusions

In the previous sections tools for measurement of the quality of gait were presented. They are based on the fuzzy system conception that allows for creation of the formal model from linguistic opinions. It is, in general, the main advance of the fuzzy system approach. The model formulation is intuitive and easy to understand not only for a computer science researcher but also for medical personnel. Analysis of the results presented in Tables 17.3 and 17.4 confirm that the proposed new fuzzy-based tool for measurement-observed gait parameters (MuFEG) may be efficient both in healthy people and post-stroke patients.

One of the tools was based on the specific OFN model. The research presented here shows that is possible to use that kind of fuzzy system in similar situations as the classical fuzzy systems. In addition, the use of an OFN model-based tool seems more appropriate as it has more flexibility for future expansion of the research. It seems to be a good direction to search for a tool to obtain a measure of tendency in the changes of results after long-term rehabilitations.

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