Studia i Materiały Informatyki Stosowanej, Tom 13, Nr 2, 2021
str. 21-25

Fraktalna analiza i predykcja zmian parametrów chodu

Dariusz Mikołajewski[1], Emilia Mikołajewska[2], Belco Sangho[1]

[1] *Uniwersytet Kazimierza Wielkiego, Instytut Informatyki, Chodkiewicza 30, 85-064 Bydgoszcz*
e-mail: dmikolaj@ukw.edu.pl
[2] *Uniwersytet Mikołaja Kopernika, Collegium Medicum im. Ludwika Rydygiera, Wydział Nauk o Zdrowiu, Katedra Fizjoterapii, Jagiellońska 13-15, 85-094 Bydgoszcz*

***Streszczenie**: Chód jest jedną z najbardziej złożonych i najczęściej wykonywanych czynności przez człowieka. Cel pracy był dwojaki: analiza metody obliczania miar fraktalnych chodu, klasyfikacja z wykorzystaniem sztucznych sieci neuronowych (ANN) i ich przydatność w codziennej praktyce klinicznej oraz ustalenie minimalnego zestawu parametrów odzwierciedlających z wystarczającą dokładnością kliniczną zmiany u chorych po udarze mózgu. Badania przeprowadzono na podstawie danych archiwalnych 50 zdrowych osób chodzących i 50 chorych po udarze mózgu. Wykazano, że mniejsza liczba parametrów (wymiar fraktalny, indeks Hursta) pozwala na lepszy opis chodu. ANN są w stanie dokonać automatycznej oceny jakościowej, a nie tylko ilościowej chodu.*

***Słowa kluczowe:** Analiza chodu, parametry fraktalne, klasyfikacja*

Fractal analysis and prediction of changes in gait parameters

***Abstract:** Walking is one of the most complex and most frequently performedhuman activities. The aim of the study was twofold: analysis of the methodof calculating fractal gait measures, classification using artificial neural net-works (ANNs) and their usefulness in everyday clinical practice and establish-ing a minimum set of parameters reflecting with sufficient clinical accuracythe change in stroke patients. The study was based on the following datafrom archival records of 50 healthy walkers and 50 stroke patients. The studyshowed that fewer parameters (fractal dimension, Hurst index) allow for betterdescription of the walk. ANNs are able to make an automatic qualitative, notjust quantitative assessment of the walk.*

***Key words:** Gait analysis, fractal parameters, classification*

1. Introduction

Walking is one of the most complex and most frequently performed human activities, occupying in an average person about 10 percent of the time of day. Despite technological progress, there is no single, universal tool to diagnose and evaluate the function of walking [16]. Solutions based on computational intelligence can complement traditional methods of clinical analysis of gait.The correct (physiological) human mobility is stereotypical, i.e., there is aglobal pattern of walking and the range of deviation from it is so narrow that an acceptable range of deviation from it can be established for the whole population. Despite progress in this area:

– there are no universal methods,
– simple, fast, and cheap methods are not accurate,
– accurate and reproducible methods are time-consuming, costly and require complex procedures and technical equipment.

Gait analysis based on computational intelligence (CI) can complement or even replace traditional methods of clinical walk analysis, especially when measureddata:

– must be extracted from normal patient activity,
– are incomplete,
– are fraught with errors, costly and require complex procedures and technical equipment,
– do not allow the construction of a mathematical model and must be analysed in a different way,
– have to get quickly from a large sample,
– it must be obtained in a cheap way.

Aforementioned methods can be useful screening tool since many injuries and diseases are reflected in gait features. The main problem is also to describe the qualitative parameters, and not only the quantitative parameters of gait. The potential of artificial intelligence in gait analysis is still untapped, especially inthe area of simple and cheap screening solutions that a primary care doctor or physiotherapist can run on a smartphone or tablet without using the gait analysis laboratory. Such simple and rapid screening tests make it possible to catch patients who require further diagnosis, which is already much more accurate, time consuming and expensive. This approach increases the effectiveness of capturing gait disorders and the conditions of which they are a symptom, and also facilitates early diagnosis, rehabilitation and care of risk groups, including the elderly. In some cases, the examination is possible at home, allowing for remote supervision of the patient's condition. We are deeply convinced artificial intelligence can significantly support the computational analysis of gait. The authors have shown this in earlier works, where they developed solutions based on it:

– aggregation of normalized spatio-temporal parameters of gait to one fuzzy number showing the degree of compliance of the results for a given patientwith the physiological gait pattern previously extracted from the study,
– fractal analysis, in which the fractal dimension reflected the smoothness and uniformity of the walk [1, 11, 12],
– classification by means of artificial neural networks for physiological (in healthy patients) and pathological (in patients with deficient gait function [2, 3, 4].

The aim of the study was twofold: analysis of the method of calculating fractal gait measures, classification using artificial neural networks (ANNs) and their usefulness in everyday clinical practice and establishing a minimum set ofparameters reflecting with sufficient clinical accuracy the change in strokepatients.

2. Materials and Methods

2.1 Material

The research was based on the following data in the archive records of 50 healthy people's gait and 50 post-stroke patients, both men and women, aged 38-72 years (mean 55, SD=5.67). Selection method in both groups was convenience samples based on archival data sets. Stroke is one of the most serious neurological diseases, and one of the three most common civilisation diseases (i.e. its incidence increases with the development of civilization of a given community). In addition, changes after a stroke are often reflected in gait parameters. Better diagnosis and quicker rehabilitation influences higher health-related quality of life in stroke survivors.

2.2 Methods

Normalized spatio-temporal parameters of gait were calculated based on anthropometric measures of patients and their gait parameters (gait velocity, cadence and stride length) measured in every patient. Fuzzy parameter was calculated using original algorithm previously described [2]. The study analyses time series, generated from films made during the 10 m walk test recording. For generation of time series Open Source Tracker Video Analysis and Modelling Tool in version 5.1.5 was used. The generated time series were exported to the Matlab for fractal analysis and multifractal time series. Fractal dimension (D, also FD, value in the range 1-2) was calculated:

$$a= 1/s^{D} \quad (1)$$

$$D= (\log A)/\log(1/s) \quad (2)$$

where: a - number of elements obtained as a result of scaling up the object, D– fractal dimension, self-similarity dimension s - a scaling factor.

Box-counting dimension was compared with and Higuchi's fractal dimension, but the first of them is much quicker and easier-to-use in environments featured by low computational power. Hurst index (also called Hurst Exponent) was then calculated:

$$SD=a^{H} \quad (3)$$

where: SD - standard deviation, a - the length of the time series. It takes valuesfrom the range (0, 1).

The interpretation of the H value is following:

– H in the range 0-0,5 - a highly volatile time series with frequent changes of direction in short-term trends,
– H=0.5 - random character, equal probability of changing and maintaining the trend,
– H in the range 0.5-1 - an orderly course, with a higher probability of maintaining the current trend.

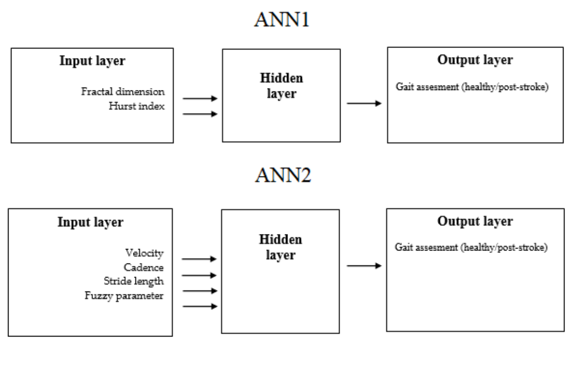

Fig. 1. ANNs structure

ANN-based analysis was performed respectively using various architecturesbased on:

– ANN1 based on current results,
– ANN2 based on archival results (Figure 1).

Results from both aforementioned ANNS were compared and assessed. The statistical analysis was carried out with the Statistica package. The MATLAB 16.0 software was used for training and optimisation purposes. The results for various ANNs architectures were compared - only the best of them are described in this paper.. Results of the analysis were compared to the results of the traditional analysis of the spatio-temporal gait parameters i.e., velocity, pace, stride length and gait classification in the same people calculated in CGA Gait Analyzer software by Chris Kirtley as far as fuzzy analysis by Prokopowicz et al.

Table 1. Results in the group of healthy people

	Fractal dimension	Hurst Index
Mean	1.15	0.21
SD	0.06	0.05
Min	1.04	0.11
Q1	1.06	0.16
Median	1.12	0.19
Q3	1.15	0.26
Max	1.18	0.33

Table 2. Results in the group of post stroke people

	Fractal dimension	Hurst Index
Mean	1.38	0.29
SD	0.32	0.07
Min	1.12	0.15
Q1	1.26	0.23
Median	0.26	0.28
Q3	1.44	0.34
Max	1.53	0.39

Table 3. Difference between groups of healthy people and post stroke patients

	Fractal dimension	Hurst Index
Średnia	0.24	0.08
SD	0.08	0.02
Min	0.08	0.04
Q1	0.19	0.07
Mediana	0.25	0.09
Q3	0.3	0.11
Max	0.35	0.14

3. Results

Results in the group of healthy people are presented in Table 1. Results in the group of post stroke people (not always with with clear hemiplegia) are pre-sented in Table 2. Difference between aforementioned groups was statistically significant ($p<0.05$, Table 3). ANN analysis: the input variables were scaled using the same max and min values from the in-sample data. Initial network weight values were estimated values between -1 and 1. To prevent startup weight deviation, weights randomly selected on initialisation were standardised. Samples were divided into three groups: 70 percent (learning), 20 percent (testing), and 10 percent (validation). ANN1 was able to minimise the MSEfor the data in the training set to very small values (0.01), was faster, its accuracy was very good (95 percent) even in very simple networks such as MLP 2-7-1(ANN1) compared to MLP 4-9-1 (ANN2). Quality of learning and testing was high (0.8813-0.9275).

4. Discussion

Gait has been evaluated for decades and used as a proxy indicator to high-light impairments of various origins. In most studies, classical linear analyses of spatio-temporal gait parameters have been adopted. Advanced, but no less practical, non-linear, automatic or semi-automatic techniques can be used to analyze the time series of gait parameters of both healthy and sick people. Clinicians and scientists still look for more sensitive indicators related to spatio-temporal gait parameters than previously used, in the hope of better, quicker, and simpler identification of movement disorders. Similar current studies are rare, but it is widely believed that an analysis of gait can help clinicians to improve targeted treatment. Karczmarczyk et al. showed efficiency of ANN-based classification of gait [1]. They have used three methods to classify stroke patients' gait patterns into homogeneous groups with an average success rate of 85 percent. Similar methods can be used to catch small, slowly increasing changes in gait parameters, as in Parkinson's disease [6]. The first completed attempts to use the fractal parameters for automatic analysis of gait took place in the 1990s [7]. Study by Phinyomark et al. showed that depending on the purpose of the research, careful selection of the methods of fractal analysis and their parameters is required [7]. Dierick et al. compared H and FD, including walking backward, and assessed that complementary application of the Hurst exponent and the fractal dimension can significantly improve walking classification [10]. Study by Gates and Dingwell based on fractal analysis of gait showed, that normal long-range correlation structure of stride intervals remained unaltered despite significant peripheral sensory loss. Such phenomenon may be significant factor taken into consideration during further research on gait analysis, gait itself, and sensory/motor control within the central nervous system and peripheral nervous system [9]. But the proposed observation of the long term correlations in the gait cycle requires much longer duration of the diagnostic process, not always available in clinical and home settings. The use of fractal parameters in the analysis of gait in Parkinson's disease patients is moving towards increasing computational complexity in laboratory setting, which goes beyond the scope of this study [13], [14]. Main limitation of the study is following: our solution is adjusted to the diagnosis of healthy person's gait and patients' gait with a specific condition (post-stroke, sometimes with the characteristic hemiplegic gait). There is a need to explore a solution for much larger groups of people, not always homogeneous, with a va-riety of walking dysfunctions. Despite aforementioned limitation our finding scan have immediate applications in rehabilitation, especially gait diagnosis and classification procedures. During the further work we plan to determine the chaotic dynamic parameters: the variation in time of the Hurst exponent, the multifractal spectrum, and the distribution of probabilities in order to assess the predictability of the value of the complex system so described (i.e. the ability to predict the results of self-medication and therapy-assisted self-medication). The ultimate goal is to develop an automated solution for the diagnosis, classification and prediction of gait. Our previous tool, developed jointly with Prof. Prokopowicz, based on the analysis of fuzzy parameters of spatio-temporal gait parameters, won two awards. Novel, not fully explored auxiliary solutions for our software can constitute wearable devices developed within Internet of Things (IoT) paradigm [15].

5. Conclusions

Fewer parameters (D, H) allow better description of the walk. Higher (i.e. worse) values of parameters were observed as well as greater variability of the fractal parameters of gait in the group of patients after the stroke. The Hurst'sindex indicates that these are time series with high variability, with frequent changes of direction of short-term trends, which allows to think positively about the influence of therapy (possible trend reversal). ANNs are able to make an automated qualitative and not only quantitative assessment of the gait by comparing spatial-temporal gait patterns (form of curves) and the correct course of the gait cycle, extracted by the network. Clear expressing predictability and complexity of gait interval time series, exactly computedand properly interpreted can significantly influence gait diagnosis and further therapy and care [16-19].

Acknowledgements

The paper is a part of work financed by statutory audits of the Institute of Computer Science, Kazimierz Wielki University in Bydgoszcz, Poland.

Conflict of interest

The authors declare that they have no conflict of interest.

References

1. Mandelbrot B. B. The fractal geometry of nature,W.H. Freeman, San Francisco (1982).
2. Prokopowicz P., Mikołajewski D., Tyburek K., Mikołajewska E. Computational gait anal-ysis for post-stroke rehabilitation purposes using fuzzy numbers, fractal dimension andneural networks. Bull Pol Acad Sci Tech Sci 2020, 68(2), 191-198 (2020).
3. Mikołajewski D., Mikołajewska E., Fractal analysis of gait, Studies and Materials in Applied Computer Science, 12 pp. 23-26 (2020).
4. Mikołajewska E. Nowe markery chodu w klinicznej analizie chodu w grupie pacjent́ow poudarze ḿozgu usprawnianych metoda NDT-Bobath. Wydawnictwo CM UMK, Bydgoszczy2017.
5. Kaczmarczyk K., Wit A., Krawczyk M., Zaborski J. Gait classification in post-strokepatients using artificial neural networks, Gait Posture, 30(2), 207-210 (2009).
6. Kostek B., Kupryjanow A. Wykorzystanie sieci neuronowych i metody wektoŕow nośsnychSVM w procesie rozpoznawania aktywnośsci ruchowej pacjent́ow dotknietych chorobaParkinsona. [W:] Tadeusiewicz R., Korbicz J., Rutkowski L., Duch W. (red.) Sieci neuronowe w inżynierii biomedycznej. Tom 9. monografii: Torbacz W., Maniewski R., ẂojcickiJ. M., Liebert A. (red.) Inżynieria biomedyczna – podstawy i zastosowania. AkademickaOficyna Wydawnicza EXIT, Warszawa 2013, ss. 239-262.
7. Ripoli A., Belardinelli A., Palagi G., Franchi D., Bedini R. An effective algorithm forquick fractal analysis of movement biosignals. J Med Eng Technol, 23(6), 216-221 (1999).
8. Phinyomark A., Larracy R., Scheme E. Fractal analysis of human gait variability viastride interval time series. Frontiers in Physiology, 11, 333 (2020).
9. Gates D. H., Dingwell J. B. Peripheral neuropathy does not alter the fractal dynamicsof stride intervals of gait, J Appl Physiol , 102(3), 965-971 (2007).
10. Dierick F., Nivard A.-L., White O., Buisseret F. Fractal analyses reveal independentcomplexity and predictability of gait, PLoS ONE 12(11), e0188711 (2017).
11. Lopes R., Betrouni N. Fractal and multifractal analysis: a review. Med Image Anal.,13(4), 634-49 (2009).
12. Chau T. A review of analytical techniques for gait data. Part 1: fuzzy, statistical andfractal methods. Gait Posture 13, 49–66 (2001).
13. Chakraborty M., Das T., Ghosh D. Characterization of gait dynamics using fractalanalysis for normal and

Parkinson disease patients, 2015 IEEE Power, Communication andInformation Technology Conference (PCITC), Bhubaneswar, 367–372 (2015). ImmersiveVirtual Reality to Restore Natural Long-Range Autocorrelations in Parkinson's DiseasePatients' Gait During Treadmill Walking.

14. Lheureux A., Lebleu J., Frisque C., Sion C., Stoquart G., Warlop T., Detrembleur C.,Lejeune T. Immersive Virtual Reality to Restore Natural Long-Range Autocorrelations inParkinson's Disease Patients' Gait During Treadmill Walking, Front Physiol. 11, 572063,2020.
15. Mikołajewski D., Mikołajewska E., Prokopowicz P., Nedashkovskyy M. Wearable devicesin clinical gait analysis, Studies and Materials in Applied Computer Science, 10(1), 5-8(2018).
16. Mikołajewska E. Normalized gait parameters in NDT-Bobath post-stroke gait rehabilitation, Central European Journal of Medicine, 7(2), 176-182 (2012).
17. Mikołajewska E., Mikołajewski D. Roboty rehabilitacyjne. Rehabil. Prakt 4, 49-53 (2010).
18. Mikołajewska E., Mikołajewski D. Zastosowania automatyki i robotyki w wózkach dla niepełnosprawnych i egzoszkieletach medycznych. Pomiary Automatyka Robotyka 15, 58-63 (2011).
19. Mikołajewska E., Mikołajewski D. Roboty rehabilitacyjne i pielęgnacyjne. Mag. Pielęg. Położ 12, 42 (2009).