Gait & Posture 30 (2009) 207–210

Contents lists available at ScienceDirect

Gait & Posture

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

Gait classification in post-stroke patients using artificial neural networks

Katarzyna Kaczmarczyk [a,*], Andrzej Wit [a,b], Maciej Krawczyk [a,c], Jacek Zaborski [d]

[a] Jozef Pilsudski University of Physical Education, Marymoncka 34, Warsaw, Poland
[b] Almamer High School of Economics, Warsaw, Poland
[c] Institute of Psychiatry and Neurology, Warsaw, Poland
[d] Institute of Neurology, Międzylesie, Poland

ARTICLE INFO

Article history:
Received 25 November 2008
Received in revised form 22 April 2009
Accepted 25 April 2009

Keywords:
Stroke
Hemiplegia
ANN analysis
Gait patterns

ABSTRACT

The aim of this study was to test three methods for classifying the gait patterns of post-stroke patients into homogenous groups. First, qualitative test results were found to correctly classify patients' gait patterns with an average success rate of 85%. Seeking further improvement, two quantitative methods were then tested. Analysis of min/max angle values in three lower limb joints, however, was less successful, showing a correct classification rate of below 50%. The best classification results were seen using an artificial neural network (ANN) to analyze the full progression of lower limb joint angle changes as a function of the gait cycle (with success rates from 100% for the knee joint to 86% for the frontal motion of the hip joint). These findings may help clinicians improve targeted therapy.

1. Introduction

The wide variety of gait deviations observed in post-stroke patients [1–3] makes it difficult to deliver targeted treatment. Devising a method for identifying homogeneous subgroups of stroke patients could enable clinicians to develop more effective interventions. This is particularly the case with clinicians who do not have access to motion analysis equipment [4]; such a method would also facilitate communication between clinicians [5].

Many authors [4,6–10] have attempted to identify homogeneous subgroups of walking patterns. Knutsson and Richards [7] used EMG signals to distinguish three types of pathological gait. Kramers de Quervain et al. [9] used the Mahalanobis distance statistical technique on five temporal distance parameters to distinguish four gait patterns. A similar study was carried out by Mulroy et al. [4], analyzing gait based on temporal distance and sagittal plane joint kinematics, using a non-hierarchical cluster analysis to categorize four subgroups of walking patterns. Kinsell and Moran [10] used cluster analysis to identify the gait pattern of hemiplegics with equinus deformity.

Wong et al. [11] proposed another, simple gait classification technique based on evaluating foot position at ground contact, which we take as our point of departure here. These authors distinguished between three gait types by analyzing the motion of the point of application of the resultant reaction force on the foot. They did not, however, attempt to identify any link between foot position on the ground and lower limb joint angles during the gait cycle. This led us to further investigate the possibility of such a link in the present study.

Artificial neural networks (ANNs) are an extraordinarily flexible tool for nonlinear modelling, especially useful in gait analysis. Many papers [12–15] have shown ANNs to be useful in distinguishing gait patterns, but no previous studies have attempted to categorize walking patterns based on the full progression of joint angle changes as a function of the gait cycle in post-stroke subjects.

The aim of this study was to test three methods for classifying post-stroke patients into gait pattern types, based around Wong et al.'s three types of foot position. The methods we considered were: (1) qualitative test results of gait kinematics, as well as two different types of quantitative investigation: (2) min/max joint angle values and (3) the full progression of joint angle changes.

2. Materials and methods

2.1. Participants

Seventy-four hemiplegic patients (31 female and 43 male) participated in this study. The average (±standard deviation) age, mass and height of the participants were as follows: 55.6 ± 9.4 and 58.9 ± 9.3 years, 69.6 ± 11.6 and 78.7 ± 9.9 kg, 162 ± 5 and 173.8 ± 5.2 cm (females and males, respectively). Fifty-five were diagnosed with ischemic stroke, 20 with hemorrhagic stroke. The inclusion criteria were: age 40–70 years, first incident of hemorrhagic or ischemic stroke within the past six months, capable of walking independently using no aids, with no other disorders of an orthopedic, rheumatologic, etc., nature that could affect gait kinematics and no cognitive disorders. Participants and their physicians and physiotherapists provided consent for their participation in this study. The sample size, 74, consisted of all patients treated by the host institution in 2005–2007 who met these inclusion criteria.

Approval for the study was obtained from the Institute's Research Ethics Commission and all the participants provided written informed consent.

* Corresponding author. Tel.: +48 604777670.
E-mail address: katarzyna.kaczmarczyk@gmail.com (K. Kaczmarczyk).

0966-6362/$ – see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.gaitpost.2009.04.010

2.2. Data collection and processing

Patients taking part in the experiment were twice evaluated by a neurologist and a physiotherapist: once after admission to a neurological ward with the diagnosis of stroke and once prior to gait analysis.

Gait analysis was performed once for each subject using the Ariel Performance Analysis System (APAS). Participants walked unassisted at a self-selected speed along a 10 m walkway being recorded by two analogue cameras set perpendicularly to one another, 7 m from the subject (one standard setup for 3D analysis). 18 markers were placed on each patient, at specific points according to a standard protocol for full body motion analysis using the APAS system: the base of the first metatarsal bone, the calceneal tuberosity, the lateral malleolus, the articular space of the knee joint, the greater trochanter of the femur, the radiocarpal joint, the elbow joint, the greater tubercle of the humerus, the jugular notch of the sternum and the root of the nose to define joint centres and the axes of rotation.

In the first stage, patients' gait was evaluated based on qualitative criteria. Each of the following parameters was evaluated based on video observation, using a two-valued scale of either a positive (+) or negative (−) evaluation: position of foot during first contact with ground—forefoot (A1), flatfoot (A2), heel (A3); position of knee joint on the affected side during the stance phase—flexion (A4), hyperextension (A5); position of hip joint in flexion during the stance phase (A6); position in flexion in knee joint on the unaffected side (A7); foot position on the ground at first contact (A8); broader stance plane (A9); absence of pectoral girdle movement (A10); associated reactions of the lower limbs (A11).

In the second stage, gait was evaluated quantitatively, based on min/max angle values and absolute angle values in the lower limb joints as a function of time. Since the foot position was considered a dependent variable, the values were collected for the knee and hip in the frontal and sagittal planes.

2.3. Statistics

The data from the study were subjected to detailed statistical analysis using the STATISTICA software, adopting a significance level of $\alpha = 0.05$. The methods used for gait classification were cluster analysis, discriminant function analysis and ANNs.

Cluster analysis (CA) was utilized to group kinematic gait parameters into clusters of similar statistical strength and to identify which variables best enabled the given set of cases to be classed into groups. The calculations used two types of cluster analysis methods: agglomeration via the single linkage (nearest neighbour) method and grouping via the *k*-means method, striving to minimize variability within clusters and maximize variability between clusters.

Discriminant function (DF) analysis, in turn, was used to classify patients and to identify parameters that made a significant contribution to distinguishing between gait types in post-stroke patients. To illustrate the progression of the analysis, the forward stepwise method was used.

Lastly, artificial neural networks (ANNs) were used to assign each case, as represented by the corresponding set of input data, to one of the selected gait pattern types. The input variables were discrete (continuous) values on the progression of knee and hip angle changes. The input variables were joint angles previously normalized for the gait cycle (expressed in percent), resampling to 50 points. The input signals from each of the subjects, a total of 74 cases, were coded on a scale from 0 to 1. The output cell was a dependent variable of a nominal value (GROUP), represented using the "one-of-N" technique. In the "one-of-N" coding, one neuron corresponds to only one of 3 possible values of the GROUP variable, containing information about 3 types of gait in post-stroke patients. The classification was implemented with the STATISTICA™ v7.0 Neural Networks software, using the MultiLayer Perceptron (MPL) network type. The program Statistica Neural Network was used to establish a network of 51 input cells, one hidden layer of 27 cells and one three-level output cell (MLP 51:51–27–3:1). For the three different network-creation subsets, i.e. the training, validation and test subsets, different quality measures were selected. Cases (subjects) were assigned to the individual subsets automatically and randomly.

3. Results

3.1. Qualitative gait assessment and classification

Eleven parameters were arbitrarily chosen for individual evaluation of gait quality (±marks). Three parameters (A1, A2, A3) – concerning foot position on the ground at first contact – served as dependent variables classifying patients into three groups characterized by the gait types *forefoot* (*F*1), *flatfoot* (*F*2), *heel* (*H*) (selected *a priori* based around Wong et al.'s three types of foot position). The remaining parameters were treated as eight independent variables, labelled A4–A11.

Firstly, we used cluster analysis (CA) to group patients according to qualitative kinematic gait parameters. This CA indicated that the most clear-cut classification occurred with precisely three types of gait, showing the greatest divergence between clusters. Further analysis showed that the classification obtained with this method coincided with the previously assumed, arbitrary classification into three groups: forefoot, flatfoot, heel (thus verifying and lending further justification to the *a priori* selection of these three gait pattern groups).

Table 1
Significance of various parameters in building a model of gait types in post-stroke patients ($n = 74$).

Variable	Summary of discriminant function analysis (pluses/minuses)					
	Wilks lambda	Partial Wilks	*F* to remove (2.63)	*p*-Level	Toler.	1-Toler. (R^2)
A4	0.256	0.876	4.461	0.015	0.351	0.649
A5	0.270	0.829	6.502	0.002	0.368	0.632
A6	0.301	0.743	10.865	0.000	0.800	0.200
A7	0.246	0.912	3.022	0.055	0.595	0.406
A8	0.315	0.712	12.720	0.000	0.741	0.259
A9	0.232	0.967	1.055	0.354	0.859	0.141
A10	0.261	0.858	5.221	0.007	0.907	0.093
A11	0.229	0.977	0.742	0.479	0.795	0.205

A4–A11: various qualitative values taken from video observation of gait.

Next, a discriminant analysis was used to identify the individual contribution of each of these variables to the classification of subjects into the three gait groups (Table 1). Variables A7, A9 and A11 did not contribute much information towards building a three-component model of post-stroke patient gait, yet further calculations indicated that reducing the number of parameters worsened the outcome of prediction to a level around 60% of correct classifications.

The next step used generalized models of discriminant analysis to evaluate the systems with any combination of independent qualitative variables and discriminant data. Table 2 shows the outcome of discriminant function analysis, indicating a satisfactory effect of classifying the subjects into the same three gait groups. The highest rates of correct classification were observed in group H: 94% and group F1: 87%, with the worst rate seen in group F2, with 6 individuals (23%) mistakenly classified into other groups. The statistical differences in classifying all patients into the three gait types are presented in Table 3.

3.2. Quantitative gait assessment and classification

We subsequently performed two stages of gait assessment using quantitative methods. The first stage was based on min/max stance phase angles in the knee and hip joints in the sagittal and frontal planes. This stage of discriminant analysis showed that none of these variables were significant ($p > 0.05$) in predicting classification into groups (Table 4). Discriminant analysis correctly classified patients into the three gait patterns with accuracy below 50 percent (Table 5).

Table 2
Percentage breakdown of correct classification of post-stroke patients into gait types, based on ($n = 74$).

Group	Classification matrix (pluses/minuses)			
	Percent correct	Forefoot, $p = .4110$	Flatfoot, $p = .3562$	Heel, $p = .2329$
Forefoot ($n = 30$)	86.7	26	3	1
Flatfoot ($n = 26$)	76.9	3	22	1
Heel ($n = 18$)	94.1	1	1	16
Total	84.9	30	26	18

The first column lists groups identified *a priori* on the basis of foot position at first contact. The remaining columns then represent the number of patients correctly or incorrectly classified based on qualitative parameters A4–A11 taken from video observation of gait.

Table 3
Degree of significance in classifying patients ($n = 74$) into three gait types.

Group	Mahalanobis distance (pluses/minuses)					
	Forefoot		Flatfoot		Heel	
	F	*p*	*F*	*p*	*F*	*p*
Forefoot ($n = 30$)			1.775	0.045	6.532	0.000
Flatfoot ($n = 26$)	1.775	0.045			5.170	0.000
Heel ($n = 18$)	6.532	0.000	5.170	0.000		

The first column lists groups identified *a priori* on the basis of foot position at first contact. The remaining columns then represent the statistical distance of classification based on qualitative parameters A4–A11 taken from video observation of gait.

Table 4
Significance of min/max parameters in building a model of gait types in post-stroke patients ($n = 74$).

Variable	Summary of discriminant function analysis (min/max)					
	Wilks lambda	Partial Wilks	*F* to remove (2.63)	*p*-Level	Toler.	1-Toler. (R^2)
α_{min}	0.839	0.955	1.554	0.219	0.204	0.796
α_{max}	0.807	0.993	0.232	0.793	0.194	0.806
β_{min}	0.813	0.986	0.478	0.622	0.224	0.776
β_{max}	0.811	0.988	0.404	0.669	0.227	0.773
δ_{min}	0.831	0.964	1.243	0.295	0.196	0.804
δ_{max}	0.859	0.932	2.394	0.099	0.202	0.798

Table 5
Percentage breakdown of correct classification of post-stroke patients into gait types ($n = 74$).

Group	Classification matrix (min/max)			
	Percent correct	Forefoot, $p = .405$	Flatfoot, $p = .3562$	Heel, $p = .2329$
Forefoot ($n = 30$)	66.7	20	8	2
Flatfoot ($n = 26$)	38.5	13	10	3
Heel ($n = 18$)	38.9	3	8	7
Total	48.3	30	26	18

The first column lists groups identified *a priori* on the basis of foot position at first contact. The remaining columns then represent the number of patients correctly or incorrectly classified based on min and max angle values in lower limb joints.

The second stage of quantitative result analysis involved classifying the gait of patients based on the progression of angle values in the knee and hip joints in the frontal and sagittal planes using artificial neural networks. For ANN training, the input cells were the successive values of the knee joint angle progression $\alpha = f(t)$ during gait, sampled with step $k = 2$.

The outcome of the classification for individual joints is presented in Table 6. Classification based on changes in knee joint angle values as a function of time placed all subjects correctly for all three gait types. Analysis of hip joint angle values in the sagittal plane placed all the subjects into the appropriate groups for two gait types (with a rate of nearly 97% for the third). For hip joint angle values in the frontal plane, successful classification rates were around 95% for two gait types, and 85% for the third gait type.

Table 6
Classification obtained using a neural network, with knee and hip joint angle values during gait as input parameters.

Joint	Forefoot ($n = 30$), correct [%]	Flatfoot ($n = 26$), correct [%]	Heel ($n = 18$), correct [%]
Knee	100	100	100
Hip, sagittal	96.7	100	100
Hip, frontal	96.7	84.6	94.4

4. Discussion

Performing qualitative gait evaluation in post-stroke patients based on kinematic parameters, ground reaction force and muscle activity is a challenging procedure in clinical practice. Wong et al. [11] proposed a simple classification of post-stroke patients based on analysis of foot motion during gait. We adopted and verified with cluster analysis their classification, based on evaluating foot position at initial contact.

Wong et al. [11] concluded that patients with hemiplegia were often unable to place their heel on the ground for initial foot contact and experienced problems with the propulsion mechanism. Depending on the severity of neurological deficiency, they often shift the trajectory of the centre of pressure towards the front of the foot. This is consistent with our results. Different results were obtained by von Schroeder et al. [16], who observed only one case involving toe-contact, the remaining subjects showing flatfoot contact. This was confirmed by Karsznia et al. [17], who observed flatfoot position in their subjects both during initial contact and during the propulsion stage. We would assume that both these studies involved subjects with similar neurological deficiency and little differentiation in gait pattern, although the authors did not present detailed data on this in their papers. However, Karsznia [17] attempted to identify a link between foot position on the ground and angle progression in lower limb joints during the gait cycle.

Our cluster analysis, based on the type of foot position on the ground at first contact, classified patients into three groups: *forefoot*, *flatfoot* and *heel*. CA has been put to similar use in studies by other authors, i.e. for tailoring therapy based on the type of dysfunction characteristic for a given group of patients [18], for distinguishing characteristic groups of patients with pain syndromes in the vicinity of the shoulder joint [19] for identifying pathological gait patterns in children with cerebral palsy [20] and for classifying post-stroke patients [4].

The first method we tested for classifying patients' gait patterns into these three gait groups, using qualitative variables, achieved successful classification on an average level of 85%. Despite this relatively satisfactory outcome, we went on to test whether two methods of qualitative gait analysis could further improve the accuracy of classification.

Burdett et al. [2] found certain leg joint angle values at certain gait phases to be most important qualitative traits distinguishing gait in post-stroke patients from that of able-bodied subjects. Other authors concluded that the greatest differences between pathological and normal gait involve the maximal and minimal angles in the knee and ankle joints during the toe-off stage and at first foot contact with the ground [7,21]. With respect to post-stroke patients, in particular, impressive classification results (98%) were obtained by Mulroy et al. [4], utilizing the maximal and minimal values of only three kinematic parameters. Kim and Eng [22] attempted to classify gait in post-stroke patients using the extreme values of angles in selected lower limb joints, successfully distinguishing two types of gait.

Our study, however, did not find min/max angle values of the leg joints to serve as a useful indicator for classifying post-stroke patients into gait types, showing a correct classification rate of below 50 percent. The unsatisfactory result in our case may be explained by the fact that peak values characteristic for a specific phase of pathological gait are subject to random fluctuation. The very procedure of filtering and normalizing the registered positions in the kinematic analysis could also be a source of additional error.

In view of this unsatisfactory result, the next stage of our study analyzed the full progression of joint angle changes as a function of the gait cycle, using artificial neural networks as the method of analysis.

One of the first attempts at classifying gait in patients using ANNs was made by Holzreiter and Kohle [12]. They classified pathological gait based on measurements of ground reaction force, showing a 95% rate of successfully distinguishing gait patterns of healthy and physically disabled individuals.

Similar studies were undertaken by Barton and Lees [14], expanding the ANN classification to three categories – healthy, adducted and abducted foot – achieving a successful classification rate of 77–100%. In 1997, Barton and Lees [13] concluded that angle changes in the hip and knee joints are characteristic for various types of gait and offer a basis for automatic identification of gait types. The authors analyzed changes in hip and knee joint angles in eight healthy individuals, with an average correct classification rate of 83.3%. In both tests, Barton and Lees used a complex neural network with two hidden layers concealed between the input and output cells.

Lafuente et al. [15] reverted to the standard network structure (i.e. with one hidden layer), similarly used by Holzreiter and Kohle [12] when attempting a classification into four gait categories. Data concerning gait rhythm, speed and five kinetic values were fed into the neural network, based on which, four gait types were correctly distinguished at a rate of 80%.

All the above studies showed rates of correct classification within the 77–100% range, reaffirming the great potential of neutral networks in distinguishing gait patterns. Among the studies cited, only Barton and Lees [13] used kinematic parameters similar to those used in the current study. The rates of correct classification they obtained (83.3%) were poorer than the average result of our study (92.5%), most likely due to the small size of the group they analyzed ($n = 8$).

In conclusion, this study found ANN analysis to be superior to two other methods – qualitative variable analysis and analysis of min/max joint angles – in classifying post-stroke patients' gait patterns into three types. ANN classification may allow for more effective treatment with appropriately targeted intervention. This study has helped confirm the appropriate use of neural networks in gait research. Further work should focus on more in-depth description of gait kinematics in the identified groups and, subsequently, in developing more targeted methods of therapy for each group.

Acknowledgement

Partly supported by Grant No. 404 3302 33, Ministry of Science and Higher Education.

Conflict of interest statement

The authors have no conflict of interests with the submitted article.

References

[1] Voigt M, Sinkjaer T. Kinematic and kinetic analysis of the walking pattern in hemiplegic patients with drop foot using a peroneal nerve stimulator. Clin Biomech 2000;15:340–51.
[2] Burdett RG, Borello-France D, Blatchly C, Poptter C. Gait comparison of subjects with hemiplegia walking unbraced, with ankle–foot orthosis, and with air-stirrup brace. Phys Ther 1988;68:1197–203.
[3] Rodda JM, Graham HK, Carson L, Galea MP, Wolfe R. Sagittal gait patterns in spastic diplegia. J Bone Joint Surg 2004;86:251–8.
[4] Mulroy S, Gronley JoAnne, Wiess W, Newsam C, Perry J. Use of cluster analysis for gait pattern classification of patients in the early and late recovery phases following stroke. Gait Posture 2003;18:114–25.
[5] O'Byrne JM, Jenkinson A, O'Brien TM. Quantitative analysis and classification of gait patterns in cerebral palsy using a three-dimensional motion analyzer. J Child Neurol 1998;13:101–8.
[6] Olney SJ, Richards C. Hemiparetic gait following stroke. Part II. Recovery and physical therapy. Gait Posture 1996;4:149–62.
[7] Knutsson E, Richards C. Different types of disturbed motor control in gait of hemiparetic patients. Brain 1979;102:405–30.
[8] Perry J, Garrett M, Gronley JK, Mulroy SJ. Classification of walking handicap in the stroke population. Stroke 1995;26(6):982–9.
[9] Kramers de Quervain IA, Simon SR, Leurgans S, Pease WS, McAllister D. Gait pattern in the early recovery period after stroke. J Bone Joint Surg 1996;78:1506–14.
[10] Kinsella S, Moran K. Gait pattern categorization of stoke participants with equines deformity of the foot. Gait Posture 2008;27:144–51.
[11] Wong AM, Pei Y-C, Hong WH, Chung Ch-Y, Lau Y-Ch, Chen CP. Foot contact pattern analysis in hemiplegic stroke patients: an implication for neurologic status determination. Arch Phys Med Rehabil 2004;85:1625–30.
[12] Holzreiter SH, Kohle ME. Assessment of gait patterns using neural networks. J Biomech 1993;26:645–51.
[13] Barton JG, Lees A. An application of neural networks for distinguishing gait patterns on the basis of hip–knee joint angle diagrams. Gait Posture 1997;5:28–33.
[14] Barton JG, Lees A. Development of a connectionist expert system to identify foot problems based on under-foot pressure patterns. Clin Biomech 1995;10(7):385–91.
[15] Lafuente R, Belda JM, Sanchez-Lacuesta J, Soler C, Prat J. Design and test of neural networks and statistical classifiers in computer-aided movement analysis: a case study on gait analysis. Clinical Biomechanics 1998;3(3):216–20.
[16] von Schroeder HP, Coutts RD, Lyden PD, Billings Jr E. Gait parameters following stroke: a practical assessment. J Rehabil Res Dev 1995;32:25–33.
[17] Karsznia A, Oberg T, Dworak L. Gait in subjects with hemiplegia. Acta Bioeng Biomech 2004;6(2):65–76.
[18] McLachlan GJ. Cluster analysis and related techniques in medical research. Stat Methods Med Res 1992;1:27–48.
[19] Winters TF, Groenier KH, Sobel JS, Arendzen HH, Meyboom-de Jongh B. Classification of shoulder complaints in general practice by means of cluster analysis. Arch Phys Med Rehabil 1997;78:1369–74.
[20] Toro B, Nester CJ, Farren PC. Cluster analysis for the extraction of sagittal patterns in children with cerebral palsy. Gait Posture 2007;25:157–65.
[21] Intiso D, Santilli V, Grasso MG, Rossi R, Caruso I. Rehabilitation of walking of electromyographic biofeedback in foot-drop after stroke. Stroke 1996;25:1189–92.
[22] Kim CM, Eng JJ. Magnitude and pattern of 3D kinematic and kinetic gait profiles in person with stroke: relationship to walking speed. Gait Posture 2004;20:140–6.