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Artificial Neural Networks (ANN) Applied for Gait Classification and Physiotherapy Monitoring in Post Stroke Patients

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1. Introduction

1.1 Overview of the problem

Humans have an innate predisposition for ambulation (walking). The motor neuron stimulation involved in ambulation is generated by a natural neural network located in the spinal cord, known as the central pattern generator for locomotion. This network is strongly influenced both by super-spinal structures situated mainly in the hypothalamus and brainstem, and by signals coming from various types of peripheral receptors (Carter & Page 2009).

To facilitate research and analysis, free gait in humans is traditionally divided into phases and cycles. Each full gait cycle comprises two individual steps; a single step consists of a stance phase and a swing phase. The gait cycle includes a stage of single limb stance (when the body rests on a single lower extremity) and a double limb stance (on both lower extremities).

Kinematic gait analysis assumes a simplified, 15-segment model of the human body (feet, shins, thighs, forearms, upper arms, hands, head, torso, and pelvis) (Błaszczyk 2004). There are two kinds of basic parameters adopted for gait modelling and routine testing of ambulation in healthy and disabled individuals: spatial values of motion (including step length, velocity of the body mass centre, progressions of changes in joint angles, body mass oscillations) and dynamic values of gait mechanics (most often including ground reaction forces in 3 planes and the distribution of foot forces on the ground). These physical values are measured in parallel with bioelectric muscle activity (EMC), registered by surface electrodes as a subject walks (Perry & Burnfield, 2010).

Correct ambulation requires the precise integration of practically all the systems of the human body. When one of the elements, especially a motor organ, is damaged as a consequence of injury, degeneration, or deformation, this immediately finds reflection in divergences of the above parameters from normative values, which is in practice described as pathological gait (Perry & Burnfield, 2010). The field of clinical biomechanics therefore

seeks to identify normative values and limits for a broad range of parameters describing the mechanics of free gate, to help in detecting divergences in individual patients and in monitoring the process of gait rehabilitation following serious injury, surgical intervention, or neurological disorders – such as stroke.
In the remainder of Section 1 we will first outline the specifics of pathological gait classification in post-stroke patients and consider the link between brain lesion parameters and gait classification, then offer an overview of the application of artificial neural networks (ANNs) to physiotherapy in general and to gait classification in specific. In Section 2 we will present various findings from our own research dealing with the application of ANNs to post stroke gait classification (Kaczmarczyk et al., 2009; Kaczmarczyk et al., in preparation). In Section 3 we will more broadly discuss these findings in the light of other approaches to rehabilitation and in relation to other work dealing with ANNs.

1.2 Classification of pathological gait in post stroke patients

The traditional definition of stroke, devised by WHO in the 1970s, is a "neurological deficit of cerebrovascular cause that persists beyond 24 hours or is interrupted by death within 24 hours". Clinical symptoms of stroke depend on the type of stroke (ischemic caused by blockage in an artery that supplies blood to the brain, resulting in a deficiency in blood flow, and hemorrhagic caused by the bleeding of ruptured blood vessels in the brain), the size of the lesion, the location of the arterial blockage or hemorrhage, previous stroke damage, collateral circulation, and variability in areas supplied by individual arteries (Brust 2004). One consequence of stroke may be hemiparesis (weakness of one side of the body), which can have a profound effect upon the capacity for ambulation (Kinsella & Moran, 2008).
Recovery of functional ability after stroke is variable, with between 30% and 60% of subjects remaining dependent on others for some activities of their daily living (Duncan et al., 1994). Key functional tasks, such as regaining the ability to walk, have been identified by patients with hemiparesis as being of great significance in stroke rehabilitation (Bohannon et al., 1988, 1991).
The gait of post stroke patients is generally characterized by what is known as the Wernicke-Mann posture – the upper limb is adduced in the shoulder joint, flexed and rotated in the elbow joint, flexed in the brachiocarpal joint and the finger joints, whereas the lower limb is extended in the knee joint. However, a wide variety of gait deviation is observed in post stroke patients (Voigt & Sinkjaer, 2000; Burdett et al., 1988; Rodda et al., 2004). Many post stroke patients suffer from a foot drop problem during walking (an inability to move the ankle and toes upward). They might adopt different hemiplegic gait patterns with large variations, such as circumduction gait, high stepping pattern, etc. (Hermann 1987, Hong-yin et al., 2009). This variety of gait deviation poses a clinical problem, making it difficult to deliver targeted treatment. Clinical practice has therefore sought to develop methods for the appropriate (and early) classification of post-stroke gait dysfunction – the general idea being that once a given patient has been correctly classified as having a certain type of gait dysfunction, therapists may provide adopt a strategy of treatment best suited for their rehabilitation.
The observation-based classification of gait in neurological patients described by Hermann (1987) remains the primary method of gait diagnostics used for clinical purposes, supplying information that facilitates the qualitative evaluation of a given patient's dysfunction. Seeking to ensure better uniformity of evaluation methods, various forms of qualitative or

point-based ways of recording observations of pathological gait have been devised – such as various scales, questionnaires, gait evaluation indexes, etc. However, such widely used observation-based methods of classifying pathological gait quality, not being underpinned by objective measurement of mechanical gait parameters, are unfortunately fraught with a large degree of subjectivity and their effectiveness varies greatly depending on how experienced the observer is and on how systematically the criteria are applied. This shortcoming has given rise to various attempts at providing formal descriptions and classifications of various types of pathological gait.

In terms of post stroke dysfunction, numerous authors (Mulroy et al., 2003; Olney & Richards, 1996; Knutsson & Richards, 1979; Perry et al., 1995; Kramers de Quervain et al., 1996; Kinsella & Moran, 2008) have attempted to identify homogeneous subgroups of post stroke walking patterns. Knutsson & Richards (1979) used EMG signals to distinguish three types of pathological gait. Kramers de Quervain et al. (1995) 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. (2003), analyzing gait based on temporal distance and sagittal plane joint kinematics, using a non-hierarchical cluster analysis to categorise four subgroups of walking patterns. Kinsella & Moran (2008) used hierarchical cluster analysis to identify three gait patterns in hemiplegics with equinus deformity of the foot based on temporal distance parameters and joint kinematic and kinetic measures in the sagittal and coronal planes.

Overall, irrespective of the parameters measured or technique used, this line of investigation seems to show some convergence of results: suggesting that post stroke patients can be usefully classified into more or less three–four types of dysfunctional gait based on quantitative data.

Wong et al. (2004) proposed another, simple gait classification technique based on evaluating foot position at ground contact. This study looked at 65 post stroke patients and distinguished between three gait types by analyzing the motion of the point of application of the resultant reaction force on the foot. Wong et al. (2004) found a correlation between the results of their classification, the neurological condition of the patients, and the temporal-spatial data obtained from kinematic analysis. However, they did not attempt to find a link between foot position at ground contact and the progression of lower limb angle values over the gait cycle. The work of Wong et al. (2004), one of the few papers in the literature attempting to classify post stroke patients based on the analysis of foot motion during ambulation, served as the inspiration for the methodology used in our research.

None of these studies discussed above attempted (as we have) to categorize walking patterns based on the full progression of joint angle changes as a function of the gait cycle in post stroke subjects – an avenue of research that is made possible by the use of Artificial Neural Networks (ANNs), as described in detail in the next section below.

1.3 Association between brain lesion and gait classification

Relatively little is known about the specific association between the parameters of the brain lesion causing a stroke and the gait type found in post stroke patients. Elucidating this relationship could enhance our understanding of the neural circuitry involved in locomotion and could have important clinical implications, underscoring the need to prioritize gait retraining for patients in the early stages after stroke.

In view of this need for early rehabilitation, many studies (Jørgensen et al., 1995; Viosca et al., 2005; Dominkus et al., 1990) have discussed the association between motor recovery and

the most predictive factors that can be identified. However, none of these authors attempted to identify any link between CT scan parameters and the characteristic gait patterns seen in post-stroke patients – as we have explored in the work described below.

The various types of pathological gait have a neurophysiological basis, due to post stroke changes in the brain. Clinical evidence suggests that the site of damage of the sensorimotor cortex influences the pattern of motor deficits (Glymour et al., 2007). This raises the possibility of exploring CT scan parameters as a way to predict gait patterns. Studies mostly evaluated the association of only one parameter of brain lesion with motor and functional outcomes after stroke. While several studies have suggested that brain lesion parameters correlate with final outcomes (Bear & Smith 2001; Dominkus et al., 1990; Alexander et al., 2009; Laufer et al., 2003; Pérennou et al., 1999; Turney et al., 1984; Kwolek & Spławiński 1996), other studies have found no such association (Chen et al., 2003; Viosca et al., 2005; Binkofski et al., 2001; Nakayama et al., 1994; Chae et al., 2000). The reason for this controversy might be that outcomes actually correlate with some combination of brain lesion factors together, rather than individually. Chen et al. (2000) showed that recovery and functional outcomes correlate with "brain lesion profiles" that combine two factors: size and location. However, all the cited authors have concentrated on finding an association between brain lesion parameters and motor recovery and functional outcome in hemiplegic stroke patients, rather than objectively identified gait patterns – this led us to further investigate the possibility of the latter link using Artificial Neural Networks (ANNs), as described in detail below.

1.4 Introduction to Artificial Neural Networks

Artificial neural networks (ANN), also known as connectionist systems or parallel distributed processing models, are computer-based, self-adaptive models that were first developed in the 1960s, but gained broad popularity only in the 1980s after the development of the backpropagation algorithm by Rumelhart et al. (1986). It is hard to ascertain today what sort of motivation initiated the development of neural network theory, but we can assume that a fascination with the human brain was a fundamental factor. Neural network research can be traced back to the work of McCulloch and Pitts (1943), who put forward the first formal arithmetic-logical model of the neuron.

ANNs are simulations of the nervous system: a computational model consisting of an interconnected group of artificial neurons, often situated in distinct layers, which can be used for processing information. An ANN system is adaptive, responding to information that flows through the network during a learning phase. In a testing phase, ANNs generate on output signals as a response to previously unknown inputs. ANNs offer an extraordinarily flexible tool for inductive, nonlinear modelling of complex input-output relationships and finding complex patterns in data. The effectiveness of generalization can be expressed as the ratio of correctly recognised input patterns to all of the presented patterns in the test phase. The advantage of ANNs is that they can process large numbers of data simultaneously and because of their internal structure the pieces of data do not have to be isolated from each other, preserving the inherent relationships amongst the data set. The attractive features of simultaneous data handling and the concept of contextuality make ANNs potentially useful tools in the automated recognition of various gait patterns.

Three types of neural network architecture can be distinguished: feedforward networks, recurrent networks, and cellular neural networks. In the feedforward type of network

mainly discussed below, the information moves in only one direction – forward – from the input nodes, through any hidden layers of nodes to the output nodes, and there are no cycles or loops in the network. In a recurrent network, in turn, some connections between units form a directed cycle, enabling the network to exhibit dynamic temporal behaviour.

1.5 Application of Artificial Neural Networks in physiotherapy

The use of neural networks in medicine and rehabilitation has grown enormously in the past decade (Carter 2007). They have been applied as statistical tool to solve problems including the following: i) prediction of diagnosis, e.g. for several types of cancer (Rogers et al., 1994), ii) prognoses, e.g. for heart disease (Katz et al., 1993), iii) the interpretation of diagnostic tests, e.g. for pancreatic enzymes (Kazmierczak et al., 1993), and iv) decision support, e.g. (Doornewaard et al., 1999).

Neural networks are especially useful if the main goal of building a model is to predict outcomes for new cases. Grigsby et al. (1994) attempted to predict functional outcome, length of stay, and cost for patients with hip fractures who were undergoing inpatient rehabilitation. This study was one of the first to apply ANN methodology to the analysis of patients undergoing rehabilitation. The input data included age and selected Function Independence Measure scores at admission. An accurate prediction was defined as a value within ±15% of the actual outcome: the functional outcome model predicted the mean rating of the 13 FIM motor items score at discharge with an accuracy of 86%; the length of stay model prediction was 87% accurate, the cost model 91% accurate. Oczkowski & Barreca (1997) attempted to predict functional outcomes and discharge placement for moderately impaired stroke patients. The input data used to predict outcome included age, days since stroke, motor recovery of leg strength and postural control, the presence of sensory loss, neglect, a care-giver, and the admission FIM score. The network demonstrated an accuracy of 88% for the prediction of discharge FIM score, and 75% for the prediction of discharge placement. Both studies used separate training and test sets to evaluate model performance and back propagation methods for error reduction. Ohno-Machado et al. (1999) created neural network models to predict early mortality and ambulation for patients with spinal cord injuries. Their model included 15 variables for example, day from injury to admission, age gender level of presented neurologic function, and American Spinal Injury Association (ASIA) impairment score (Rowland et al., 1998), achieving an 97% rate of accuracy.

Neural networks have also been applied to the study of functional electrical stimulation (FES). FES is one of the most used technologies for restoring the functions of patients affected by neurological pathologies. By electrically activating the muscular system, FES is increasingly recognized as a method of therapy and treatment for subjects impaired by stroke, multiple sclerosis and cerebral palsy (Popovic et al., 2002; Galen & Granat 2002). Electrical stimulation generates control signals that effectively activate paralyzed upper limb muscle for standing up, walking and maintaining body balance. A radial-basis neural network was used by (Popovic, Radulovic et al., 2003) for controlling FES in eight muscles in six subjects with paraplegia as a result of spinal cord injury. Their input data consisted of a function of hip, knee, ankle angles, flexors and extensors activation and ground reaction force (GRF) during the gait cycle in able-bodied individuals. Another study by (Muniz, Liu et al., 2010) evaluated three different models, including a probabilistic neural network (PNN) for discriminating between normal and Parkinson disease subjects in terms of ground reaction force during walking. Their experimental protocol included medications

and deep brain stimulation of the subthalamic nucleus. They found that neural networks, as well as the other models, showed high performance indexes for classifying ground reaction forces of normal and Parkinson subjects.

ANNs can be also used for gleaning a better understanding of the mechanisms of motor control. Bernabucci, Conforto et al. (2007) simulated a simplified version of the biomechanical arm model, constructed with two mono-articular pairs of muscles for each joint (elbow and shoulder) and a bi-articular third pair of muscles connecting the two joints. The proposed system was only able to make ballistic plantar movements. As a crucial part of the system, ANNs were engaged for synchronizing the muscle activation during arm movement. Such theory-based investigations are important because they commonly open up wide fields of application. For instance the system developed by Bernabucci, Conforto et al. (2007) can be adapted to FES and could enhance paretic patients' capacity to control their arm movements with reduced effort during therapy.

Encouraging results achieved in overcoming simple functional limb substitution (Liberson et al., 1961) and successful therapy both in lower (Bogataj et al., 1995) and in upper limb movements (Wang et al., 2002) have recently led to the development of FES-assisted rehabilitation programs for hemiplegic patients (Gritsenko & Prochazka 2004; Goffredo et al., 2008). Restoration of upper limb movements in post stroke patients is one of the keystones of rehabilitative practices. Rehabilitation of arm movements is usually more difficult than for the lower extremities (Goffredo et al., 2008). Goffredo et al. introduced a non-invasive FES-assisted rehabilitation system for the upper limb, called smartFES (sFES). The system includes a markless motion estimation algorithm and a biologically inspired neural inverse dynamics model, fed by the kinematic information that drives a biomechanical arm model, which could be used to drive an sFES. The algorithm is based on the design of a specific ANN, which works on a two-step basis: ANN1 was used to estimate the dynamics of shape and ANN2 to generate the muscular activation that will make the artificial muscles produce the forces necessary to drive the arm model. ANN1 is a two-hidden-layers network. The network inputs consisted of horizontal and vertical components of position, velocity and acceleration of all the contour points n (n=1,..,N) in the current frame (i-1), which means the number of the input neurons is N*6. The (N*2) outputs are given by the horizontal and vertical components of the position of the contour points in the subsequent frame i. ANN2 is also a two-hidden-layer network, fed by four inputs, representing the coordinates of the starting and the ending points of the movement to be generated. The output layer yields: the time of contraction of the muscle pairs of both the shoulder and the elbow joint, together with the duration of the overall neural activations. In the stimulation of movements of a synthetic arm with a length of ±20cm, the model has shown an unbiased angular error, and a mean position error of about 1.5 cm, thus confirming the ability of the system to reliably drive the model to the desired targets.

A similar study, this time concerning the lower limb, was undertaken by Chen et al. (2004). Hemiplegic patients very often suffer from the drop-foot problem. Chen et al. (2004) established a neural network and fuzzy feedback control FES system for adjusting the optimum electrical stimulating current to control the motion of an ankle joint. Three hemiplegics and a healthy individual participated in their study. Their three-level neural network structure used back-propagation. The network was used to estimate the current volume input into the body for electrical stimulation of the tibialis anterior of the hemiplegic patients. The fuzzy controller solved the nonlinear problem by compensating for the motion trace errors between neural networks control and actual system. Locomotion of the

hemiplegics was effectively improved by applying the neural network to electrical stimulation therapy.
On the whole, therefore, we can conclude that ANNs have proven to be effective tools in medicine and rehabilitation.

1.6 Gait classification using ANNs

Artificial neural networks have a lot to offer to gait analysis in particular, facilitating the study of complicated gait variable relationships that have traditionally been difficult (Chau, 2001). A standard three-layered feedforward network works as a universal function approximator (Lapedes & Farber, 1988). This property allows one to model any relationship among gait variables, provided adequate data are available and the requisite network complexity is computationally feasible.
Another notable aspect of neural networks is that they can analyze great amounts of gait data, as evidenced in the studies of Holzreiter & Kohle (1997) and Lafuente et al. (1997). Other benefits to gait analysis include their inherent non-linear mapping ability, demonstrated aptitude at capturing temporal dependence (Savelberg & Herzog, 1997), and short processing time (Miller, 2009). Another advantage is the ability to capture patterns in the data within their internal parameters known as weights and biases which may influence gait patterns (Hinton, 1992).
A significant number of papers (Holzreit & Kohle, 1993; Barton & Lees, 1997, 1995; Gioftsos & Grieve, 1995; Lafuente et al., 1998; as well as our own research outlined in the next section) have shown ANNs to be useful in distinguishing gait patterns. Recent efforts generally fall into three categories of application: i) classification of human gait, ii) biomechanical modelling, iii) prediction of gait variables and parameters (Chau, 2001). It is the first and third of these applications – classification and prediction – that we will explore in detail below, reporting the results of our own research.
One of the first attempts at classifying gait in patients using ANNs was made by Holzreiter and Kohle (1993), using the standard network structure (i.e. with one hidden layer) and showing a 95% rate of successfully distinguishing gait patterns of healthy individuals from those of physically disabled individuals. Gioftsos & Grieve (1995) investigated the application of ANNs (again with one hidden layer) to the recognition of temporal gait parameters associated with altered gait patterns. Their network had a mean accuracy of 73% in correctly recognizing the unknown patterns. Similar studies were undertaken by Barton & Lees (1995, 1997) – their first study expanded the ANN classification to three categories and achieved a successful classification rate of 77% to 100% based on foot position, whereas their second study concluded that angle changes in the hip and knee joints offer a good basis for automatic identification of gait types (with an average correct classification rate of 83.3%). In both tests, Barton & Lees (1995, 1997) used a complex neural network with two hidden layers concealed between the input and output cells. Lafuente et al. (1997) reverted to the standard network structure (i.e. with one hidden layer); here 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%. The review of Miller et al. (1992) described other neural networks applied in different areas of investigation, with similar results. In turn, Aminian et al. (1995) used accelerometer to recognize the speed and incline of walking. The neural networks were first "trained" by known patterns of treadmill walking. Then the inclines, the speeds, and the distance covered during overground

walking (outdoor circuit) were estimated. The results show a good agreement between actual and predicted variables. 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.
The various approaches and findings of these studies are summarized in Table 2.

Author	Measured parameters	Inputs	Network type	Outputs	Conclu-sions
Holzreiter & Kohle (1993)	Ground reaction forces	128 FFT coefficients	Feed forward (one hidden layer)	1) Able-bodied gait 2) Pathological gait	Up to 95% accuracy
Barton & Lees (1995)	Maximum pressure prints	1316 maximum pressure values	Feed forward (two hidden layers)	1) Heathy feet 2) Pes cavus 3) Hallux vagus	77-100% accuracy
Gioftsos & Grieve (1995)	Duration of the double, right and left support phases	three temporal measuremen ts	Recurrent network	Three walking conditions; 7 walking speeds	73% accuracy
Barton & Lees (1997)	Hip and knee angles	30 FFT coefficients	Feed forward (two hidden layers)	1) Normal walking 2) 20 mm thick sole 3) 3.5 kg mass	83.3% accuracy
Lafuente (1997)	Cadence Velocity 5 kinetic parameters	Kinetic and kinematic parameters	Feed forward (one hidden layer)	1) Healthy 2) Ankle arthrosis 3) Knee arthrosis 4) Hip arthrosis	80% accuracy
Aminian et al. (1995)	10 parameterizations of accelerations of the trunk and right heel	Forward, vertical and lateral accelerations	Two feed forward networks	Speed and incline	

Table 1. Summary of studies applying neural networks for gait classification

2. Example application of ANNs in post stroke gait rehabilitation

Overall, therefore, ANNs have been shown to be a promising avenue of research in post stroke gait rehabilitation. As an illustration of this, in the remainder of this chapter we will describe in detail the findings of our own research in this direction, which may be viewed as a single study reported in two separate papers, Kaczmarczyk et al. (2009, in preparation).
As we noted above, the ability to correctly classify gait patterns in post stroke patients is now recognized as a crucial aspect for improving the rehabilitation process and providing targeted therapy tailored to the patient's individual needs. ANNs offer an advantage over

existing methods for characterizing post stroke gait types – which are mainly based on verbal descriptions, hence their use in clinical practice involves considerable risk and is strongly dependent upon the experience of the observer. At the same time, the use of traditional statistical methods, based on analysis of min/max values, may involve a certain error: two individuals may exhibit similar ranges of motion, yet have significantly different progressions of joint angle values over the course of their gait cycles.

The aim of our work, reported in two separate papers but described in conjunction in the remainder of this section, was to compare methods for classifying post stroke patients into gait pattern types, taking as a point of departure Wong et al.'s (2004) three types of foot position. The methods we considered were: 1) min/max joint angle values and 2) the full progression of joint angle changes analyzed with ANNs, concluding that the ANN method yielded superior results (as reported in Kaczmarczyk et al., 2009). We also used these ANN gait classification predictions as a reference against which to test the association between the simultaneous impact of four brain lesion parameters and different pathological gait patterns (as reported in Kaczmarczyk et al., in preparation)

2.1 Materials and methods

2.1.1 Participants

Seventy-four hemiplegic patients (31 females and 43 men) participated in this study; their characteristics are shown in Table 2. The inclusion criteria were: 40-70 years old, first incidence of hemorrhagic or ischemic stroke within the past six months, capable of walking independently (without any orthopedic walking aid), with no other disorders of an orthopedic, rheumatologic, etc., nature that could affect gait kinematics, with no cognitive disorders and with consent from their physician and physiotherapist for their participation in this study.

Group	Height [cm]	Body mass [kg]	Age [years]	Time since stroke [weeks]	Type of stroke
Women (n = 31)	162 ± 5 (150 ÷ 172)	69,6 ± 11,6 (51 ÷ 105)	55,6 ± 9,4 (40 ÷ 70)	7 ± 2,9 (4 ÷ 12)	I = 25 H = 6
Men (n = 43)	173,8 ± 5,2 (164 ÷ 186)	78,7 ± 9,9 (59 ÷ 100)	58,9 ± 9,3 (40 ÷ 70)	7,2 ± 3,0 (3 ÷ 12)	I = 30 H = 14

I – ischemic, H – hemorrhagic (from Kaczmarczyk et al., 2009)

Table 2. Average (±SD) values and ranges (min÷max) for selected characteristics of study participants

Both the men and women subjects had experienced their stroke incident at a similar timeframe (7 months prior to the study), with the scatter coefficient of this parameter in both groups being 41%. One difference between the male and female groups was that hemorrhagic stroke accounted for 32% of the cases in the male group (n = 44) involved but 19% of the cases in the female group (n = 31) – consistent with WHO data indicating that hemorrhagic stroke accounts for about 20% of all stroke incidents.

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

2.1.2 Data collection and processing

Firstly, 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 selected characteristic points (following 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.

Gait was evaluated quantitatively, based on local extremes (min/max) angle values and absolute angle values in the leg joints as a function of time. Because foot position was considered a dependent variable, the values collected were for the knee joint and for the hip joint in the frontal and sagittal planes.

Secondly, all the patients had CT brain scans performed within 7 days after stroke. The images were evaluated in line with accepted diagnostic criteria, following American Stroke Association guidelines. The scans were performed without using a contrast medium, with slice thickness of 8 to 10 mm. A stroke lesion is treated as being a hypodensive ischemic area situated in the cortex, subcortically, or in the deep structures of white or grey matter, according to vascularization from one of the cerebral arteries. Lesion number was evaluated for each patient as follows: 1) one, 2) two, 3) multiple. Lesion size was classified according to Brott et al. (1989) as: 1) lacunar – up to 1 cm, 2) small lesion – less than ½ lobe but more than 1 cm, 3) medium-size lesion – between ½ and 1 lobe, 4) large lesion encompassing more than 1 lobe. Lesion location was defined according to the criteria of Damasio (1984) by vascularization area: 1) middle cerebral artery, 2) anterior cerebral artery, 3) posterior cerebral artery, 4) basilar artery, and by structures occupied: 1) deep structures, 2) frontal lobe 3) temporal lobe, 5) occipital lobe, 6) cerebellum, 7) brainstem.

2.1.3 Statistics

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

DF analysis was used to classify patients and to identify parameters that make 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.

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 Multi Layer Perceptron (MLP)

network type, 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.
To identify the weight, in the range of 0 to 1, for each of the predicting values, one of the multivariate exploratory techniques was applied: analysing the robustness of the classification tree for the three gait types as dependent variables and for the four independent variables, lesion size and lesion location (as opposed to lesion number or lesion type). The classification tree was built performing discriminant-based split, bottom up running, generalizing Chi-square goodness of fit measures. Prior and misclassification cost were specified as equal, estimated from the data.

2.2 Results

We performed two stages of gait assessment using quantitative methods. The first such stage was based on local min/max angle values in the knee joint and the hip joint in the sagittal and frontal planes during the stance phase. This stage of discriminant analysis showed that none of these variables were significant ($p>0.05$) in predicting classification into groups (Tab. 2).

Variable	Summary of discriminant function analysis (local min/max)					
	Wilks Lambda	Partial Wilks	F to remove (2.63)	p-level	Toler.	1-Toler. (R-Sqr.)
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 3. Significance of min/max parameters in building a model of gait types in post stroke patients (n = 74) (from Kaczmarczyk et al., 2009)

The Lambda Wilks values in the second column close to 1.0 indicate that the variables do not make a significant contribution to discriminating between groups. This is because the proposed variables do not individually carry sufficient information to build a good model of three gait type groups based on the proposed kinematic gait parameters (extreme range values of lower limb joints).
In the next stage in our research, we tested the use of discriminant analysis for gait classification. The results are shown in Table 4.
This unsatisfactory result of classification for discriminant analysis (below 50% both for each gait classification group and overall) can be explained in terms of the fact that the peak values characteristic for a specific gait phase may be distorted by random variations in extreme values or by the data processing itself, especially the filtering and smoothing of raw values in kinematic analysis. That is why our next step was to check whether it was possible to analyze the entire progression of angle values as a function of the cycle of a single step.

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

Table 4. Percentage breakdown of correct classification of post stroke patients into gait types (n = 74) (from Kaczmarczyk et al., 2009)

The next stage of our research, therefore, 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 joint angle progression $\alpha = f(t)$ during gait, sampled with step k = 2. Networks were built manually (i.e. not using the automatic option), and multi layer networks were ultimately selected for training. The network that most faithfully recreated the real values involved angle changes in the knee joint during walking. Figure 1 illustrates the configuration of the network we used for classifying post stroke patient gait on the basis of the progression of knee joint values during walking – a feedforward network using a single layer of hidden nodes. A network of identical configuration was built for post stroke gait classification based on the progression of hip joint values in both the frontal and sagittal planes.

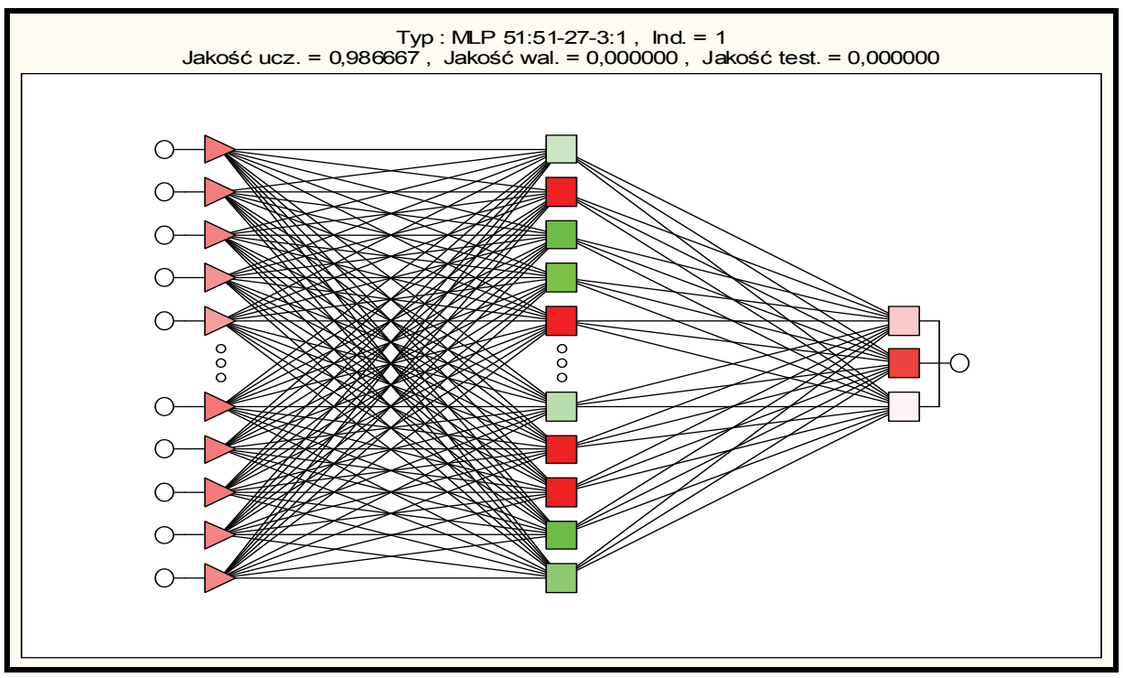

Fig. 1. Configuration of ANN for post stroke gait classification based on the progression of knee joint values during walking (from Kaczmarczyk et al., 2009)

The main measure of the quality of the configured network during the learning process were errors in the training, validation, and test sets. The sets we used were of equal size and each constituted 1/3 of all patients; the selection of patients for each of the three sets was random. Table 5 shows data concerning the quality of the best sets accepted for further analysis.

Joint	Training error	Validation error	Testing terror
Knee	0.07	0.00	0.00
Hip sagittal	0.01	0.03	0.19
Hip frontal	0.39	0.00	0.00

Table 5. Error report for training of MLP51:51-27-3:1 neural network configured for 3 joint angles (from Kaczmarczyk et al., 2009)

The critical error level is assumed to be 0.1, and the smaller the error value the better adapted the network is. The data in Table 5 shows that a fully satisfactory network was built solely on the basis of knee joint angle changes. For the other two hip joint angles, the program was unable to create a network so well adjusted to the measurement data set. As a result, classification of individual patients based on information from hip joint angle progressions is not as accurate as for the knee joint.

The outcome of the ANN classification for individual joints – which we believe to be impressive given the unsatisfactory results obtained using the quantitative methods described so far – is presented in Table 5. 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.

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**

Table 5. Classification obtained using a neural network, with knee and hip joint angle values during gait as input parameters (from Kaczmarczyk et al., 2009)

The above findings were reported in Kaczmarczyk et al. (2009), drawing the major conclusion that ANN analysis is superior to qualitative variable analysis for classifying post stroke patients' gait patterns into three gait types, as well as superior to the analysis of min/max joint angle values. Next, as reported in Kaczmarczyk et al. (in preparation), we used this ANN-derived classification method (which placed post stroke patients into one of three groups – F1 (*forefoot*), F2 (*flat foot*), H (*heel*)) as a reference gait classification against which we looked at the influence of four individual brain lesion parameters on the nature of gait in the same set of early stage post stroke patients. The results of comparing CT scan parameters against this ANN-derived gait classification are presented in Table 6.

Observed	Predicted by CT scan parameters			Correct classified (%)
	F1(forefoot)	*F2 (flat foot)*	*H (heel)*	
F1(forefoot) (n=30)	22	4	4	**73.3**
F2 (flat foot) (n=26)	5	18	3	**69.2**
H (heel) (n=18)	2	3	13	**72.2**

Table 6. The relationship between CT scan and gait pattern classification (from Kaczmarczyk et al., in preparation)

The best correspondence between CT scan classification and the reference gait pattern from the previous study (listed as "observed" in Table 6) was seen in the *F1(forefoot)* group (of the 30 individuals to be correctly placed into this group, CT scan parameters classed 22 individuals correctly, 8 incorrectly). In general, all three groups showed similar levels of correct classification based on CT scan parameters, with the overall average result of 71.3% correct classification for all patients – a result that may be described as relatively good.

Our next analysis looked into the classification trees techniques. The analysis followed a pairwise principle, comparing each pair to identify how each of the individual CT parameters contributes to classification into the different gait types. Table 7 lists the results of the comparisons – the values stated are weights that range from 0 to 1. The comparisons indicate that the influence of the individual parameters varies and depends on the configuration (accompanying parameter). The parameter whose contribution is analyzed is listed in the first column of Table 7, and the accompanying parameters are listed in order in the first row of the table 7.

	Number	**Size**	**Location**	**Type**
Number		0.60	0.56	0.79
Size			0.33	0.8
Location				0.89

Table 7. The individual CT parameters' contribution to classification into the three different gait types (from Kaczmarczyk et al., in preparation)

The data in Table 6 indicate that considering only two stroke parameters derived from CT scans may be used to identify the importance (influence) of each CT scan parameter for the type of patient gait. Comparisons of all parameters against each other indicate a clearly lower importance of type of stroke, whereas for "number–type", "size–type", and "location–type" comparisons the first parameter is always of dominant importance in predicting the type of gait in the future course of rehabilitation.

The results of this analysis seem to indicate that to obtain a full picture of the influence of each of the parameters on the result of gait classification, analysis should be carried out considering all the CT scan parameters simultaneously. Therefore, next the individual significance of the four lesion geometry parameters was considered. Of these four, lesion size and lesion location (as opposed to lesion number or lesion type) appeared to influence gait pattern in post stroke patients most strongly (Fig. 2).

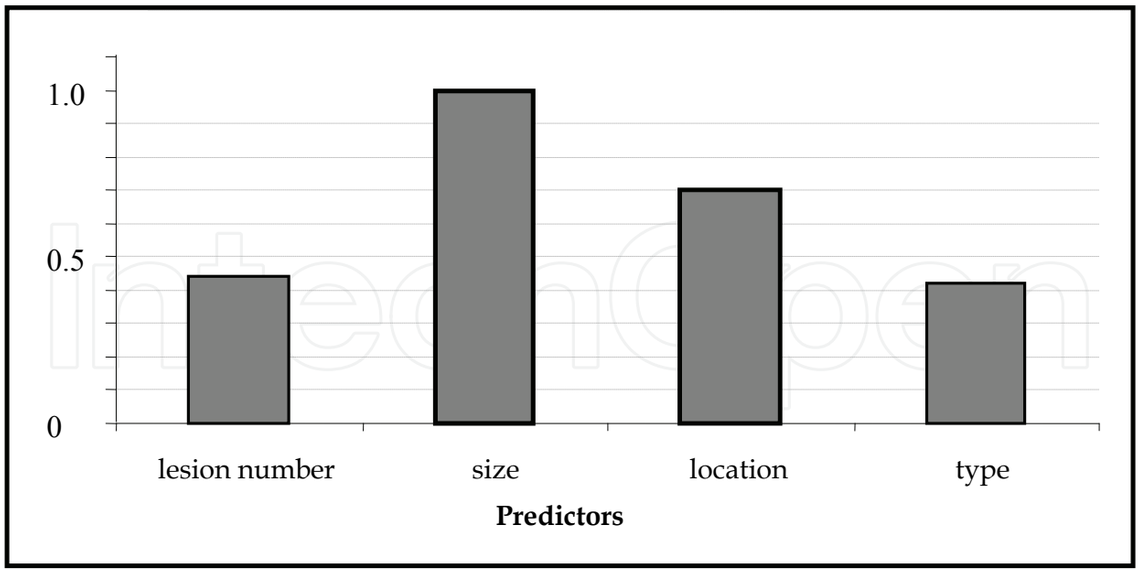

Fig. 2. Weight of the influence of individual CT parameters on the type of post stroke gait disorders in patients studied (from Kaczmarczyk et al., in preparation)

These main findings obtained by recursive partitioning methods suggest that CT scan parameters, specific lesion size and lesion location may serve as a useful early gait classification strategy, nearly as accurate as the ANN method previously presented by Kaczmarczyk et al. (2009), which provided a useful reference classification.
In the next section, we will discuss these various findings of ours in the broader context of other studies.

3. Discussion

The process of post stroke rehabilitation is protracted and costly. There are many papers arguing that post stroke patients engaged in a rehabilitation program achieve higher degrees of independence than patients without rehabilitation, and that the former do not acquire pathological gait patterns (Prescott et al., 1982). Even so, the effectiveness of such programs continues to raise many doubts. For the rehabilitation process to be effective, it has to be initiated as early as possible and properly targeted. One of the criteria for including patients in our research, reported above, was the relatively short time that had elapsed since their incidence of stroke.
Functional reorganization after stroke is a commonly-hypothesized phenomenon. It is thought to play an essential role in the functional recovery that occurs during the first 3 to 6 months after stroke through the recruitment of alternative neural paths (Fujii & Nakada 2003). This opinion is confirmed by the results of research on various populations of post stroke patients using such tests and scales for evaluating neurological condition as the Fugl-Meyer test and the Bartel scale. Using them it has been shown that the largest improvement in functional condition is achieved during the first 6 months after the occurrence of the stroke incident (Kwolek i Spławiński 1996). After that the process of improvement slows down, although in certain cases progress has been noted even up to 5 years later (Bach-y-Rita 1981). Richards & Olney (1996) confirmed previous research that the time of rehabilitation onset is important, showing at the same time that rehabilitation during the

first 6 weeks is the most effective. All these findings serve to confirm the premise of early rehabilitation.

Accurate gait classification in post stroke patients could aid the effectiveness of therapy. Performing qualitative gait evaluation in post stroke patients (especially early stage post stroke patients) based on kinematic parameters, ground reaction force and muscle activity is not an easy procedure in clinical practice. Wong et al. (2004) therefore proposed a simple classification of post stroke patients based on the analysis of foot movement during gait. Their classification corresponds to the criterion we adopted and verified with cluster analysis, based on evaluating foot position at the onset of the single stance phase.

Wong et al. (2004) concluded that patients with hemiplegia have a tendency not to place their heel on the ground at the moment of first foot contact and to experience disturbances in the propulsion mechanism. Depending on the degree of neurological deficiency, they are observed to shift the trajectory of the centre of pressure towards the front of the foot, which is consistent with our results. Different results were obtained by von Schroeder et al. (1995), who observed only one case involving first contact of the toes with the ground, the remaining subjects seen to position their whole foot. This was confirmed by Karsznia et al. (2004), who in turn observed flatfoot position in their subjects both during first contact and during the propulsion stage. We can surmise that in both these experiments this finding resulted from the small degree of group differentiation in terms of neurological deficiency, although the authors did not present detailed data on this in their papers. However, Karsznia (2004) attempted to identify a link between foot position on the ground and angle progression in leg joints during the gait cycle.

Burdett et al. (1988) 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 (Knutsson & Richards 1979, Intiso et al., 1996). With respect to post stroke patients, in particular, impressive classification results (98%) were obtained by Mulroy et al. (2003), utilizing the maximal and minimal values of only three kinematic parameters. Kim and Eng (2004) attempted to classify gait in post stroke patients using the extreme values of angles in selected leg 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 might 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 (1993). Holzreiter and Kohle measured two successive ground reaction forces during normal walking from 94 subjects with various lower limb conditions, including calcaneus fracture and limb deficiencies. The authors computed fast-Fourier transforms (FFT) of vertical components of the two ground reaction forces. The FFT coefficients served as inputs to a standard network with one hidden layer achieved 95% rate of successfully distinguishing gait patterns of healthy individuals from those of physically disabled

individuals. This early work demonstrated simple two-category gait classification with a fairy large number of input parameters. Gioftsos & Grieve (1995) measured the duration of the double support and right and left single support phases at seven speeds under three walking conditions (normal walking, walking with a 3.5 kg mass strapped to the right ankle, walking with the right knee fixed in an extended position) in 20 subjects. The network they applied showed a mean accuracy of 73% in correctly recognizing gait patterns.

Similar studies were undertaken by Barton & Lees (1995), who expanded the ANN classification to three categories: healthy feet, pes cavus (high arch) and hallux valgus (bunion). They achieved a successful classification rate of 77% to 100% based on foot position. Below-foot pressure patterns were recorded from 18 subjects during normal walking. The patterns were rotated to a common orientation, scaled to a common size and normalized to the interval [0,1]. The network inputs consisted of a great number of 1316 measured pressure values. Unlike the three-layer network used by Holzreiter & Kohle (1993) and Gioftsos & Grieve (1995), Barton & Lees (1995) developed a more complex neural network with two hidden layers. In 1997, Barton & Lees concluded that hip-knee join angle diagrams offer a good basis for automatic identification of gait types. The diagrams show the changes in the knee-joint angle as a function of the hip-joint angle. These curves combine the temporal changes of two joint angles, which allow interpretation of the relationships between the two angles, although the time dimension is lost on the graphical representation. The hip-knee joint angle diagrams represent the movement of nearly the entire body, and could be representative of the subject's gait pattern and serve as a basis for distinguishing different gait patterns (Barton & Lees, 1997). These authors distinguished three gait patterns, which were normal walking, a simulation of lower limb length and a simulation of lower limb weight asymmetry. The angles were normalized in time, fast –Fourier transformed and normalized to the interval [0, 1]. As in their previous work, Barton & Lees again used a two-hidden-layer neural network. The average accuracy of classification rate among the three walking conditions was 83.3%.

Lafuente et al. (1998) reverted to the standard network structure (i.e. with one hidden layer), utilized likewise by Holzreiter and Kohle (1993) when attempting a classification into four gait categories. 148 subjects with ankle, knee or hip arthrosis and 88 control subjects without lower limb pathology participated in the study. 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 authors obtained 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 & Lees (1997) utilized kinematic parameters similar to those we used in our 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 analyzed (n = 8).

Our study, as reported in Kaczmarczyk et al. (2009), found ANN analysis to be superior to qualitative variable analysis for classifying post stroke patients' gait patterns into three gait types, as well as superior to the analysis of min/max joint angle values. Moreover, it substantially decreases data processing time for clinical gait labs (Miller 2009). The detection of gait events is essentially a classification problem; an application for which artificial neural networks are well suited. Miller (2009) used a single-hidden-layer, feedforward network for the purpose of classifying foot-contact and foot-off events using the sagittal plane coordinates of heel and toe markers. The timing of events detected using this method was

compared to the timing of events detected by measuring the ground reaction force using a force plate for a total of 40 pathologic subjects divided into two groups: barefoot and shod/braced. On average, the neural network detected foot-contact events 7.1 ms and 0.8 ms earlier than the force plate for the barefoot and shod/braced groups respectively. The average difference for foot-off events was 8.8 ms and 3.3 ms. Given that motion capture data were collected at 120 Hz, this implies that the force plate method and neural network method generally agreed within 1–2 frames of data.

There are currently no robust methods available for the identification of gait events in pathologic gait, although several methods of identifying gait events based on kinematic data have been developed and successfully validated in normal walking (Hreljac & Marshall 2000, Zeni et al., 2008, O'Connor et al., 2007, Ghoussayni et al., 2004). For example, the maximum vertical and horizontal components of the acceleration of foot markers can be used to identify foot contact and foot-off events (Hreljac & Marshall 2000). However, this method has been invalidated for toe walkers (Hsue et al., 2009). In addition, others have used accelerometers to identify gait events (Lau & Tong 2008). Even though these methods have shown reasonable accuracy when used on normal subjects, none have been validated for use in pathologic gait. Consequently, ANNs have been shown to be an accurate, autonomous method for detecting gait events in pathologic gait. More generally, our study has helped confirm the appropriateness of using neural networks in gait research.

Aside from gait classification, early prediction of functional outcome and motor recovery remains a crucial factor in client-centred practice, discharge planning, and utilization of rehabilitation resources. According to Oczkowski & Barreca (1999) traditional predictive models, utilizing standard population statistics, appeared unable to predict the degree of disability or place of discharge for individual stroke survivors. These statistical methods of prediction incorporated the most recurrent or powerful variables so that some specific patient information was inevitably lost. ANNs modelling offers another methodologic approach to predicting outcome. It has been successfully used to determine outcome, length of stay, disease reoccurrence, and costs in other medical conditions by identifying patterns based on a group of input variables and their resultant outcomes. The patterns are not preconceived but learned from experience. After learning occurs, the neural network can then classify new cases having the same or similar defining characteristics.

Furthermore, neural network modelling differs from standard regression analysis by maintaining and processing all available information in the clinical data base. This method does not discard variables that may be critical in determining outcome for an individual stroke survivor. Consequently, neural network modelling better handles the heterogeneity found in the stroke population. Neural network modelling imitates the brain's biological features of learning, association, and memory without the addition of human judgment errors.

Numerous studies seem to confirm the superiority of ANNS over traditional statistical methods like regression analysis and rough sets (Edwards, et al.; 1999, Rowland et al., 1998). Edwards et al. (1999) showed that the ANN was superior to the logistic regression model and correctly classified all patients (100%) as alive or dead compared with 85% correct classification for the logistic regression model. ANN analysis seems to use information for prediction of mortality more effectively in this sample of patients with ICH. Rowland et al. (1998), in turn, developed and compared 3 models (logistic regression, neural networks, and rough sets) in the in prediction of ambulation at hospital discharge following spinal cord injury. All models had sensitivity, specificity, and accuracy greater than 80% at ideal

thresholds; however, the ANNs performed better than the other traditional methods. Similar results were obtained by Li et al. (2000), who compared three different mathematical models for building a traumatic brain injury (TBI) medical decision support system (MDSS). The results showed that, assuming equal importance of sensitivity and specificity, the logistic regression model had a (sensitivity, specificity) of (73%, 68%), compared to (80%, 80%) from the RBF model and (88%, 80%) from the MLP model. This study demonstrated the feasibility of applying neural networks as the mechanism for TBI decision support systems based on clinical databases. The results also suggest that ANNs may be a better solution for complex, non-linear medical decision support systems than conventional statistical techniques such as logistic regression.

One important aspect of our research, as profiled above, is the relationship between CT scan results and the pathological gait pattern in post stroke patients. A better awareness of these interdependencies, gleaned through the use ANNs, will enable the identification of CT scan criteria to be used in strategies for early rehabilitation of post stroke patients.

The post stroke patients were classified into three groups according to pathological gait patterns rather than brain lesion parameters and showed similar levels of correct classification based on CT scan parameters, with the overall average result of 71.3% correct classification for all patients – a result that may be described as relatively good.

Our study, as reported in Kaczmarczyk et al. (in preparation), showed that the weight of the individual parameters depends on the configuration (accompanying parameter), and thus does not have a fixed effect on the classification. In specific, we found that of the four lesion geometry factors considered, lesion size and location are the most dominant factors. Evidence from previous studies lends support to the importance of these factors. Alexander et al. (2009) identified an association between a focal subcortical structure and gait asymmetry. This finding is similar to that of Miyai et al. (2000), who proved that injury to the putamen was associated with poor functional outcome in chronic stroke patients. In contrast, Dominkus et al. (1990) showed that better results were observed in those with subcortical than with cortical lesions. Perennou et al. (1999), in turn, found that lesion size has the greatest influence on motor recovery. However, Binkofski et al. (2001) showed no significant correlation between initial lesion size and recovery of upper-limb motor function. There was also no significant correlation between motor recovery and functional outcome with stroke pathology (infarction or hemorrhage) in the study of Chen et al. (2000). This result was compatible with the report of Nakayama et al. (1994), although Allen (1984) reported that patients with intracerebral hemorrhage have a worse outcome in the acute stage. Some studies reported there was no link between walking recovery and the hemiplegic side (Viosca et al., 2005, Laufer et al., 2003, Chen et al., 2000) while other studies found such association (Kwolek & Spławiński 1996, Mcciocchi et al., 1998). The reason for the disparity of findings may lie in the application of only one parameter describing stroke in the analysis.

Our work studied the effect of simultaneous impact of four brain lesion factors on gait patterns in post stroke patients. This concept is supported by the findings of several previous studies (Chen et al., 2000, Fries et al., 1993). According to Chen et al. (2000) motor recovery and functional outcome after stroke correlate with "brain lesion profiles" that combined the delimiting size and location of lesions, rather than the absolute or relative lesion size only. When the delimiting sizes were set at 75cm^3 for cortical, 4cm^3 for CR, 0.75cm^3 for IC, 22cm^3 for putaminal, and 12cm^3 for thalamic lesions, BLPs could determine motor and functional outcomes. Fries et al. (1993) did not identify the delimiting size,

although they demonstrated that small capsular lesions can selectively disrupt the output of distinct motor areas, while large capsular lesions cause more severe deficits. These authors analyzed two factors simultaneously: size and location. However, because numerous studies have confirmed the influence of side of stroke and type of stroke, in our analysis we also took those factors into account.

Although many studies have assessed the influence of brain lesion parameters on motor and functional outcomes, to the best of our knowledge, none so far has investigated the association between lesion parameters and pathological gait patterns in hemiplegic stroke patients. Only Giroud and Dumas (1995) have attempted, as we have, to identify a link between stroke location and gait disturbances. These authors described a characteristic type of gait in patients with lesions near the corpus callosum. The patients used a wide base, with feet rooted to the ground. Gait consisted of shuffling with short steps, without upper limb movement and slight extension of the trunk. These authors used evaluative scales in quantifying neurological deficit and improvement in locomotive function that involves a subjective element. Clinical practice thus has a need for objective gait classification in post stroke patients, as a basis for predicting the degree of rehabilitation progress that is achievable within a specific timeframe, in each of the gait type groups distinguished.

Our observations indicate that finding the relationship between an objective patient classification based on ANN technique into a specific subgroup of pathological gait and CT scan parameters may serve as a relatively good predictor of future functional condition and degree of improvement. Given that CT data are beginning to have more influence on rehabilitation practices (Boyd et al., 2007), our results may have considerable clinical implications. For instance, during the early stages after stroke when the most recovery may be possible (Jørgensen et al., 1995) long before kinematic gait tests may be performed, the results presented herein may lay the groundwork for implementing an early diagnostic and therapeutic procedure by providing an early prediction of pathological gait classification. This procedure would moreover provide predictions about prospects for gait improvement, but would be subject to further verification by other gait analysis methods as patient motor function returns.

The results of our study may provide the basis for implementing diagnostic and therapeutic procedures that take account of predictions concerning future gait pattern, which would then be gradually verified as locomotive function returns. Future research in this direction should concentrate on the more precise specification of the distinguished gait patterns and on the development of effective programs of procedure in individual cases.

The ANN methodology, here used successfully for classifying gait types in post stroke patients, seems to have the potential to distinguish pathological gait types stemming from other disorders. The scheme followed by our research, as described in detail in the previous section, could be productively applied in such cases for developing an objective diagnostic method based on quantitative data, associating symptoms with therapeutic procedures and predicted rehabilitative effects.

4. Conclusions

The work by various authors reviewed in this chapter, including our own, has shown that ANNs are very promising as a potential tool for use in gait classification in various types of disabilities, offering numerous advantages over other methods. ANN classification may allow for more effective treatment with appropriately targeted, early intervention.

Moreover, ANNs are also proving useful as a state-of-the-art tool in the monitoring and planning of rehabilitation strategies. In general, the various studies described in this chapter have helped confirm the appropriate use of neural networks in gait classification, and so ANNs can be expected to continue to be a productive field in physiotherapy research.

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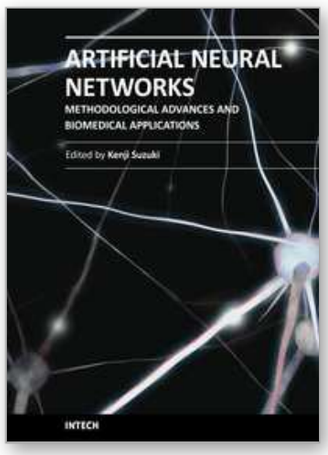

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Artificial neural networks may probably be the single most successful technology in the last two decades which has been widely used in a large variety of applications in various areas. The purpose of this book is to provide recent advances of artificial neural networks in biomedical applications. The book begins with fundamentals of artificial neural networks, which cover an introduction, design, and optimization. Advanced architectures for biomedical applications, which offer improved performance and desirable properties, follow. Parts continue with biological applications such as gene, plant biology, and stem cell, medical applications such as skin diseases, sclerosis, anesthesia, and physiotherapy, and clinical and other applications such as clinical outcome, telecare, and pre-med student failure prediction. Thus, this book will be a fundamental source of recent advances and applications of artificial neural networks in biomedical areas. The target audience includes professors and students in engineering and medical schools, researchers and engineers in biomedical industries, medical doctors, and healthcare professionals.

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