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Artificial neural network simulation of lower limb joint angles in normal and impaired human gait

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Purpose: Simulating the complexities of lower limb motion can be useful for orthosis or rehabilitation planning. The aim of this study was to develop an artificial neural network (ANN) able to accurately simulate the changes in the angle of the ankle, knee and hip joints during the gait cycle, then to use it to simulate the impact of a restricted range of ankle and hip joint angle changes on the progression of the knee joint angle. *Methods*: Thirty four young healthy students participated in the study. Gait kinematics data were collected using the Vicon system, then analyzed with an ANN. *Results*: We developed an ANN able to accurately simulate the progression of joint angles of lower-limb motion; its simulation of the impact of restricted ankle and hip joint angular ranges in the on the knee joint indicate that the braking phase is critical. *Conclusions*: ANNs offer a useful research method in clinical biomechanics. Further research in this vein should expand our understanding of compensatory functions in the lower limbs.

Key words: *artificial neural network, joint angles, gait simulation*

1. Introduction

Advanced 3D motion capture systems have facilitated biomechanical research in recent decades, but due to their high cost such systems are still restricted to research environments. Data obtained by means of such technology can be used for direct analysis of kinematic and kinetic motion parameters. However, seeking to predict what will happen if certain parameters change, such as those of the muscles, or how changes to individual motion parameters will influence other joints, generally requires the use of advanced computer software, such as AnyBody (Aalborg, DF) or OpenSim [4], which require advanced programming skills.

However, artificial intelligence techniques are starting to be applied to simplify the above methods, though they have yet to become widely used for identifying defects in the movement of human lower limbs. These artificial intelligence techniques include artificial neural networks (ANNs), which are particularly useful for solving tasks where the structure or function of an observed system is complicated, as a result of which no straightforward algorithms are known to describe the particular phenomenon being studied.

ANNs, also known as connectionist systems or parallel distributed processing models, are computer-based, self-adaptive models that were first developed in the 1960s, but only gained wider popularity in the 1980s after the development of the back propagation algorithm by Rumelhart et al. [14]. ANNs, as simulations of the nervous system, are computational models 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 output signals as a response to previously unknown inputs. ANNs offer an extraordinarily flexible tool for inductive, nonlinear modeling of complex input-output relationships and finding complex patterns in data. The biggest advantage of ANNs is that they can process large numbers of data

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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.

To date, ANNs have been most often used in medical sciences to solve complex classification problems [17], but they have also been used to some extent in clinical biomechanics. One of the first and most important publications using ANNs in the analysis of human gait was [6], in which a neural network was trained to distinguish between healthy and pathological gait. Kaczmarczyk et al. [8] compared three methods for classifying the gait patterns of post-stroke patients into homogenous groups, concluding that ANNs could be successfully applied to such classification. Miller [11], in turn, used neural networks to determine the foot-strike and foot-off events. ANNs have also been used to better understand the properties of gait in people with disabilities [2], [12]. In general, such results have demonstrated the usefulness of ANNs in solving classification problems, attaining sensitivity on the level of 90%. Other applications include estimating joint kinetics and kinematics using electromyography [15]. Moreover, Kutilek et al. [9] developed an ANN system capable of predicting gait from a cyclogram, using information such as actual joint angles, angular acceleration, weight, and age of the individuals, in addition to elements based on linear regression and principal component analysis.

The aim of this study was to develop a neural network able to accurately simulate the course of changes in the angles of lower limb joints in the sagittal plane during the gait cycle. Provided that this was successful, we additionally sought to simulate the impact of changes in the angular range of the ankle and hip joints during gait on the progression of knee joint angle values.

2. Material and methods

2.1. Participants

Thirty-four (19 males and 15 females) young healthy students participated in the study, with mean age 21.71 ± 1.95 years old, height 1.76 ± 0.09 m and body mass 70.62 ± 11.39 kg. Ethical approval was sought and obtained from the local research ethics committee and all subjects provided full informed consent. The study was conducted according to the ethical principles of the Declaration of Helsinki.

2.2. Instrumentation and data collection

First, anthropometric measurements were taken for each person. Next, thirty four spherical markers were placed at anatomical landmarks, according to the biomechanical model PlugInGait standards available within the motion capture system (Vicon Motion Systems Ltd, UK). A motion capture system, consisting of nine infra-red cameras, was employed to collect kinematic data at a sampling rate of 100 Hz. The system was calibrated according to the manufacturers' recommendations before the trials were conducted. Each subject performed three trials at their preferred walking speed along a 10-meter walkway. Further analysis was carried out based only on attempts made without any random mistakes, with the individual performing the task naturally.

2.3. Data reduction

The kinematic parameters of the gait cycle for each person tested were exported to the MatLab program (MathWorks, USA). In order to limit the size of the input neurons and perform further ANN analysis, the data was tested at 50 Hz. Next, the kinematic curves were filtered with a 4th order Butterworth filter with a low-pass frequency of 20 Hz. This data was then imported into the Statistica program (StatSoft, PL).

2.4. ANN classification and simulation

This part has been divided into two stages. In the first stage (classification), it was checked whether it was possible to build a network that correctly assigns the given curves to the appropriate joints. In the second stage (simulation), we made simulation of the impact of changes in the angular range of the ankle and hip joints during gait on the progression of knee joint angle values. Classification was based on full angular changes in the gait cycle domain. The ANN was used to analyze the time-series data. In the matrix created for entering the data, the rows represented the events (34 subjects). For each subject we had facts, what was represented by joint angles values in sequence 50 values for ankle, 50 points for knee and 50 values for hip. The quantitative data input layer included 150 neurons containing angular values, separately for each of the 3 joints in all subjects. The entry neuron

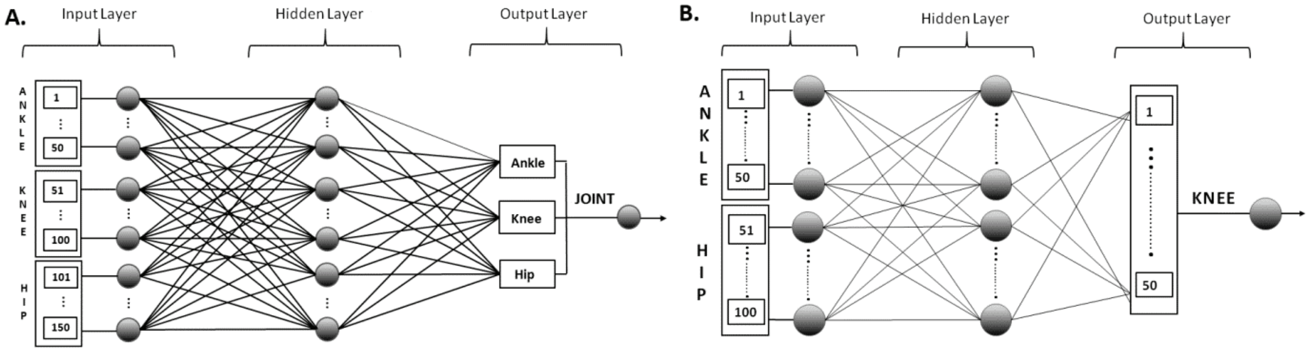

Fig. 1. Block diagram of Artificial Neural Network for: A – classification, B – simulation

matrix was therefore 50 × 3 × 34. Classification was performed automatically using the Multi-Layer-Perceptron (MLP) network with 34 input neurons, one hidden layer of 18 neurons and one output neuron for 3 joints (Fig. 1A). Next, at simulation stage, we recognized that the number of events was likely insufficient in relation to the number of facts. While there are no clear-cut rules for the ratio between facts and events, as this depends on the type of network and the subject of the study, it is generally assumed that this ratio should be around 1 or more. In our study the fact-event ratio was initially 0.22, which could hinder the construction of a properly functioning network. For this reason, the number of events observed was doubled (68 subjects), obtaining a ratio of 0.45. Next, using the MLP network for time-series data, a network with 100 input neurons was constructed: for ankle and hip angles, 20 neurons in the hidden layer and 50 exit neurons for the knee joint (Fig. 1B).

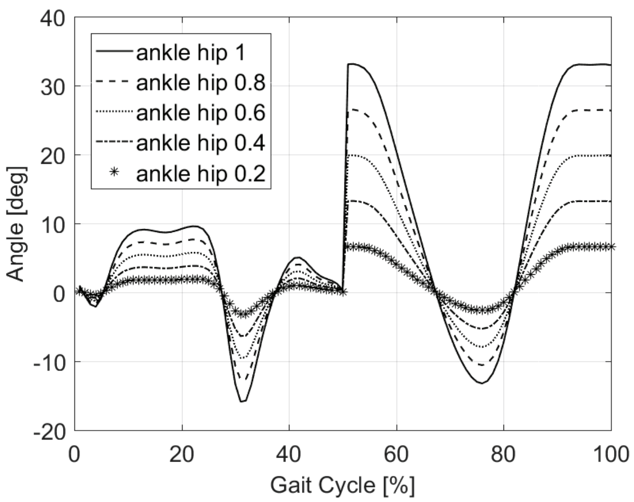

Fig. 2. The input data for simulation in ANN.
The values of angular changes in the ankle and hip joints
at 80%, 60%, 40% and 20% of the real angle values

The following procedures were used in the learning algorithm in both networks: i) to train the neural networks, we used the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm, which is a quasi-Newton optimization method; ii) a logistic function was used to activate all of the neurons in the hidden layer; iii) the Tanh function was used at the output layer. Training, validation and testing were performed by randomly dividing all 68 events into three equal subsets. Simulations of the interaction between the joint angles of the lower limb during gait were performed based on the influence of the angular changes in the ankle and hip joint on the angle of the knee joint. Figure 2 shows the angular changes of the ankle and hip joints at 100%, 80%, 60%, 40% and 20% of the real values obtain from Vicon system. Therefore, the range of angular movement was gradually reduced by 20%.

Note that the correlation coefficients in each curve combination from Fig. 2 are always 1. To compare output from the simulation curves in the knee joint, the correlation coefficients [3] were calculated for all these curves combinations. We used MatLab (MathWorks, USA) function: corrcoef (X, Y). The general formula to compute correlation coefficient for two signals X and Y and N samples is as follows:

$$r = \frac{N\Sigma XY - (\Sigma(X)(\Sigma(Y))}{\sqrt{[N\Sigma X^2 - (\Sigma X)^2][N\Sigma Y^2 - (\Sigma Y)^2]}}$$

3. Results

3.1. ANN training and classification

We tested whether an ANN time-series classification network correctly assigned changes in angle values to the individual joints. As the data in Table 1 show, the percentage of correctly assigned changes to individual joints is high.

Table 1. Results of ANN classification of changes in angle values to specific lower limb joints in gait of healthy persons

	Ankle Angle	Hip Angle	Knee Angle
Total	49	50	50
Correct	49	49	49
Incorrect	0	1	1
Correct [%]	100	98	98
Incorrect [%]	0	2	2

These results indicate that homogeneity of lower limb joint angles during gait is preserved by the ANN. They also give grounds to assume that an ANN may be further used to simulate the interaction of the angles between lower limb joints during gait in healthy subjects.

3.2. Teaching, testing and validation of ANN

In the next step of the analysis, a second network was built to record the full course of changes in joint angles of the lower limb during one gait cycle. The learning quality, which ranges between 0 to 1, was found to be 0.9852 for the teaching subset, 0.9047 for the testing subset, and 0.9388 for the validation subset, thus leading us to conclude that this network correctly reflected the observed changes. Figure 3 presents the average course of the true (experimentally recorded) values of knee joint angle changes (Exp) in the group of 34 subjects, as compared to the knee joint angle value for an average of 68 cases generated by ANN.

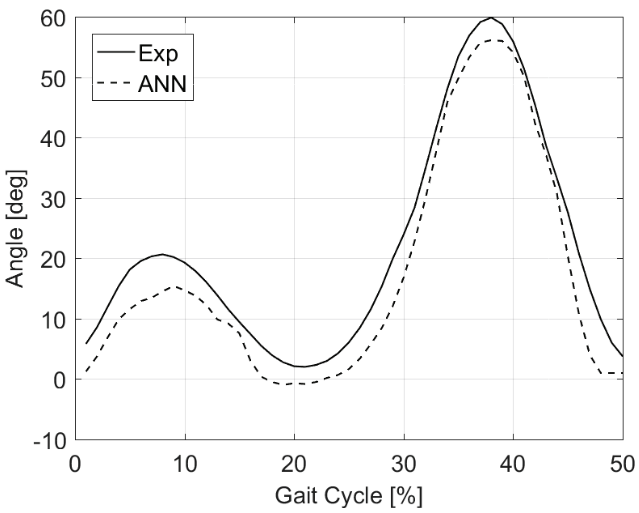

Fig. 3. The average progression of the true (experimentally recorded) values of knee joint angle changes (Exp) *vs.* the knee joint angle progression as generated by the neural network (AAN)

The obtained curves are not shifted in time, so it was possible to verify them using the correlation coefficient, which was high and amounted to $r = 0.9940$.

3.3. Simulation of interaction between joint angles

Next, we performed a computer simulation of the effect of various degrees of reduction of the angular ranges in the ankle and hip joints (Fig. 2) on the progression of the knee joint angle. Figure 4 shows the result of the simulation.

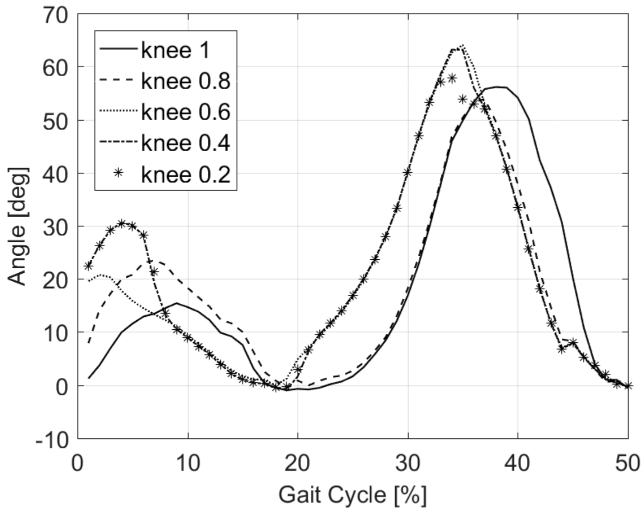

Fig. 4. Simulation of the impact of various degrees of restriction in the angular range of the ankle and hip joints on the progression of the knee joint angle during gait

The simulation results showed the greatest changes in knee angle progression joint in the braking phase and in the transfer phase. There are significant differences in local extremes in the range from 15.41 to 30.55 degrees in the support phase and 53.88 to 64.03 in the transfer phase. In addition, the appearance of extremes is random, meaning the systematic reduction in the value of the ranges of motion in the ankle and hip joints did not affect the algorithmic changes in the maximum results achieved for the knee joint. Also, the correlation coefficients between the curves are high and are presented in different combinations in Table 2.

The lowest correlation value of 0.7021 was calculated between the knee joint curves at the near-limits of the simulation, i.e., between 100% and 20% of true values.

Table 2. Correlation coefficients (r) for various combinations of the impact of weakening the remaining joints on the simulation results for the knee joint

Combinations	r	Combinations	r	Combinations	r	Combinations	r
1–0.8	0.9041						
1–0.6	0.7458	0.8–0.6	0.8458				
1–0.4	0.7076	0.8–04	0.8455	0.6–0.4	0.9803		
1–0.2	0.7021	0.8–0.2	0.8397	0.6–0.2	0.9740	0.4–0.2	0.9972

4. Discussion

The aim of this study was to use an Artificial Neural Network (ANN) to simulate the progression of angle values in the lower limb joints during gait, and also to simulate the impact of changes in positioning of the ankle and hip joints during the gait cycle on changes in the angle of the knee joint.

Skilled locomotor behavior is known to require information from various levels within the central nervous system (CNS). Mathematical models have allowed researchers to simulate various mechanisms in order to understand the organization of the locomotor control system. While it is difficult to adequately characterize the numerous inputs, an alternative strategy may be to use a kinematic movement plan to represent the complex inputs based on the possibility that the CNS may plan movements at a kinematic level. In this study, we have demonstrated the viability of using ANN models to represent the transformation of a kinematic plan into the motor patterns in the knee joint.

First, we have shown that it is possible to construct an ANN that almost flawlessly classifies data on the progression of angular changes during gait in a given lower-limb joint to the correct joint (ankle, hip, knee) (Table 1). Secondly, we have shown that it is possible to build an ANN that accurately reflects the course of changes in the ankle and hip joints during a single step in human gait (Fig. 3). Thirdly, we have demonstrated that simultaneous weakening of the range of angle in the ankle and hip joint to the level of 80%, 60%, 40% and 20% of the real angle values causes uneven and irregular changes in angular values for the knee joint during gait cycle (Fig. 4). The observed changes mainly involved the sporadic appearance of maxima in the support phase. The order of their occurrence did not point to any algorithm: the knee joint maxima were 15.4° and 56.12° for 100% of the values in the neighboring joints, 23.4° and 53.8° for a weakening of 80%, 20.7° and 64° for 60%, 30.5° and 63.1° for 40%, and 30.4° and 57.7° for 20%. Moreover, as indicated in Fig. 4, the trajectories obtained by the ANN are not so smooth as the original one. At this stage of the research it is difficult to give a binding interpretation. We hypothesize that this may be related to the phenomenon of compensation that awaits an experimental explanation, but also on the errors that always appear during simulations. The correlation results (Table 3) indicate that the differences between the curves were not significant. This suggests that the ANNs work in a manner very similar to the human body.

Pathologies that lead to joint deformities, muscle weakness, sensory loss, impaired motor control or pain interfere with the tightly regulated patterns of the motor system, and so compensatory strategies might be required in order to maintain proper function. Therefore, when there is restriction of movement in a given joint, then at some point there will be changes in the functioning of the muscles. As Liu et al. [10] point out, if any muscle force development capacity is impaired, it is usually possible either (1) to compensate for the damage to the muscle by modifying the efforts of other muscles, while still performing the same or very similar motion as a whole, or (2) to significantly modify the motion into another movement that naturally results in a lower mechanical load being imposed on the damaged muscle [7]. In our study, we can see that neural networks tend to favor the former, which is confirmed by high correlation coefficients (Table 2) and is in line with research [1], [5].

In recent years, apart from research using ANN for classification purposes, there have been several studies using ANN to predict or measure different gait parameters based on other data [16]. Sepulveda et al. [15] introduced an approach, based on ANN with the back-propagation algorithm, to map two different transformations: (1) EMG → joint angles; and (2) EMG → joint moments. Both networks were successfully trained to map the input vector onto the output vector. The models were tested by feeding in an input vector where all 16 muscles were slightly different (20%) from the training data, and the predicted output vectors suggested that the models were valid. The trained networks were then used to perform two separate simulations: for 30% reduction in soleus activity and for removal of rectus femoris. Their net 2, in which electromyography was mapped onto joint moments, provided the most reasonable results, suggesting that neural networks can provide a successful platform for both biomechanical modeling and simulation and demonstrating the potential of ANNs.

Prentice et al. [13], in turn, used ANN for the kinematic representation of the limb movement. The constructed ANN model generated the EMG activity of 8 muscles of the lower limb and trunk. A total of 120 walking strides represented normal walking and ten conditions where the normal gait was modified in terms of cadence, stride length, stance width or required foot clearance. The final network was assessed on its ability to predict the EMG activity on individual walking trials as well as its ability to represent the general activation pattern of a particular gait condition. These results indicated the ability of single network ANNs to represent the transformation between a kinematic movement plan and the necessary muscle activations for normal steady state locomotion, but they were also able to generate muscle activation patterns for conditions requiring changes in walking speed, foot placement and foot clearance.

5. Conclusions

These and other studies illustrate that neural networks are mainly used for classifying purposes and predicting movement based on EMG signals. Our work, in turn, appears to be the first to report the use of ANN in order to predict the behavior of a single joint under the influence of changes occurring in the neighboring joints. We conclude that the specific properties of ANNs made them useful in clinical biomechanics, the most important such feature being the ability to solve non-linear problems intractable by statistical analysis methods. The potential applications of ANNs have implications for both the fundamental understanding of the control of locomotion, as well as practical use of artificial control systems in rehabilitation medicine. Further efforts should be focused on the development of larger training sets based on normal and pathological data.

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