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An application of neural networks for distinguishing gait patterns on the basis of hip-knee joint angle diagrams

J.G. Barton*, A. Lees

Centre for Sport and Exercise Sciences, Liverpool John Moores University, Mountford Building, Byrom Street, Liverpool, L3 3AF, UK

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Abstract

In this study neural networks were applied to perform automated diagnosis of gait patterns. The three conditions of gait used were normal gait, a simulation of leg length difference, and a simulation of leg weight difference. Kinematic temporal changes were recorded by an on-line motion recording system. Hip-knee joint angle diagrams were obtained from eight subjects under the three conditions. After pre-processing, the hip-knee joint angle diagrams were presented to neural networks, which learned to distinguish the three conditions. Subsequent to training, unknown gait patterns were presented to the neural networks, which assigned those patterns into the right class with a correct assignment ratio of 83.3%. The results suggest that neural networks could be applied successfully in the automated diagnosis of gait disorders in a clinical context.

Keywords: Gait analysis; Neural network; Automated diagnosis; Angle-angle diagram

1. Introduction

The diagnosis and rehabilitation of locomotor disorders is increasingly supported by kinematic analysis. According to Rose [1], conditions of cerebral palsy may be strongly influenced by the results of clinical gait analysis, making this one of the most important practical applications of the methodology. Gage [2] studied the variations in outcome of the surgical treatment of spastic diplegia, and ascribed these to the fact that the spectrum of neurological pathology cannot be differentiated by clinical evaluation alone. Hicks et al. [3] found that idiopathic toe walking and cerebral palsy could easily be differentiated by sagittal plane kinematic analysis as opposed to using electromyography only.

Hip-knee joint angle diagrams show the changes in the knee-joint angle as a function of the hip-joint angle. These unusual 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 movements of nearly the entire body (trunk, thigh and lower leg), and so could be representative of the subject's gait pattern and serve as a basis for separating different gait patterns.

The traditional interpretation of these diagrams is partly quantitative, but the use of qualitative and subjective terms is also common referring to the shape or slope of the loop. Milliron and Cavanagh [4] provided data to document lower extremity kinematic changes during varied grade and varied speed running. Their interpretation of the diagrams was that as speed increased, 'the main visual impression of the hip-knee joint angle diagrams was that they simply got larger in all directions except knee extension'. This was confirmed by the numerical values for maximum flexion and extension of the hip and knee angles. In the progression from uphill to downhill running the addition of 'a major new lobe' was the most notable change to the curve in the region

* Corresponding author.

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of knee extension and hip extension. Numerical data were also presented to support the qualitative data. In these descriptions the quantitative results could be derived from the isolated pieces of data, and the qualitative statements could be regarded as attempts to capture the contextuality of the pattern. The automation of gait pattern recognition should be able to handle both the quantitative and the qualitative information contents of the hip-knee joint angle diagrams. The complexity of this separation task based on hip-knee joint angle diagrams requires the contextual and simultaneous data handling of neural networks (NN).

The aim of this study was to investigate whether a NN can be used in the automated recognition of gait patterns, which were represented by extensively pre-processed hip-knee joint angle diagrams.

2. Methods

Five male and three female subjects (mean ± S.D. age: 27 ± 9.2 years; mass: 71 ± 16.4 kg) walked on a motorised treadmill at a speed of 1.1 $m \cdot s^{-1}$, at self chosen step frequency in their own shoes. Prior to data collection four reflective markers were attached at four anatomical landmarks on the left side of the body: chin-neck intersect, the superior border of the greater trochanter, the middle of the knee joint line, and on the lateral malleolus. In order to see the hip marker continuously, the subjects were asked to walk with their arms crossed. Data were recorded by the Mac Reflex system at a sampling rate of 120 Hz. Three experimental conditions were used. First the subjects walked freely, then with a 20 mm thick sole attached to their left shoe, and finally with 3.5 kg mass attached to the left lower leg. The subjects were given approximately 30 s to become familiar with each of the new walking conditions on the treadmill, and then 10 s periods of data were recorded. These conditions were used to perturbate gait styles with similar effects to that observed in clinical patients.

Hip and knee angles against time were calculated as the angles between the relevant markers. One stride was analysed, the start of the stride being defined as the point in time when the left ankle marker stopped moving forward. The end of the stride was the next such point in time. These points were identified on the horizontal velocity component curve of the ankle marker.

The data processing steps were:

(1) Normalisation in time. This yielded 128 angle values with constant time intervals for the hip and knee angles, respectively.

(2) Fast Fourier-transformation (FFT). This procedure resulted in a set of coefficients, which reflected the frequency distribution of the temporal signal, and is used widely in pre-processing waveforms [5,6]. In case of temporal curves with mainly low frequency content (like temporal hip and knee angles) the coefficients of those lower frequencies can be used to represent the curves. In this way the FFT can be regarded as a feature extracting function, which reduces the size of the pattern, but still preserves the features of the curves. Fast Fourier-transformation of the 128 values was performed, yielding 64 real coefficients and 64 imaginary coefficients for both angles. The coefficients of only the lower frequencies were necessary to define essential characteristics of the cycle, and so eight real and eight imaginary numbers were used to represent the hip temporal angle graph and another eight real and eight imaginary numbers to represent the knee temporal angle graph. The first imaginary coefficient representing the constant in the FFT of the hip angle curve and the knee angle curve was always 0, therefore this was excluded from the data set. In the end, 30 pieces of data (2*8 real and 2*7 imaginary coefficients) were assigned to three conditions for eight subjects.

(3) Linear transformation of the 30 coefficients. This was achieved by taking a FFT coefficient of each subject/condition and establishing the 90% confidence limits (equal to ±1.67 S.D.). Data were scaled between the lower limit (0) and the higher limit (1). Data outside this range were assigned equal to 0 or 1 as appropriate. This was repeated for each coefficient.

The Mac Reflex motion recording system (Qualisys AB, Partille, Sweden) can automatically identify the three-dimensional position of up to 40 markers placed on the body at a sampling frequency of 120 Hz. Various physical parameters (displacement, velocity, angles, etc.) can be derived, which provide a wealth of kinematic information about the observed movement. Such a complex dynamic activity as human gait cannot be described entirely by a set of individual parameters, but must be perceived by using all the pieces of data simultaneously, together with the interdependencies amongst the pieces of data. The inclusion of contextuality into perception is an obvious part of the human mental process. For example a series of letters may have the meaning of a word instead of merely the individual vocals represented by the letters. Computer-based systems such as the Mac Reflex supply the user with sufficient information, but the interpretation of the results still needs the resources of a human expert.

Artificial neural networks (NN) are simulations of the nerve system, and so are able to simulate the performance of a human expert. A NN is a group of highly interconnected neurons, arranged in layers. The operation of a NN can be divided into two phases. First, as a response to presented inputs the synaptic weights change, until the NN learns to associate the inputs with the expected outputs. This process is called 'learning'. The second mode of a NN is called 'testing', when it generates an output signal as a response to previously unknown inputs, i.e. it generalises. The effectiveness of generalisation can be expressed as the ratio of correctly recognised input patterns to all of the presented patterns in the test phase. Detailed information on NNs can be found elsewhere [7–13].

The advantages of a NN is that it can receive large numbers of data simultaneously and because of its 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 NNs potentially useful tools in the automated recognition of various gait patterns. Holzreiter and Köhle [14] have introduced a NN which was trained to distinguish 'healthy' from 'pathological' gait. These gait patterns were represented by the vertical forces of two subsequent left and right footstrikes. The trained NN could assign previously unknown gait patterns into the right class at a success rate in the range 75–95%. The review of Miller et al. [15] describes other neural networks applied in different areas of investigation, with similar results. Recently Aminian et al. [16] used accelerometer data to recognise the incline, speed and covered distance of walking by training NNs. The results showed good agreement between actual and predicted variables.

Unfortunately the optimal structure of a NN changes from application to application [10,11], therefore in the construction of the NN the general guidelines suggested by Lawrence [17] have been followed. A four-layer, back-propagation neural network [18] was constructed by a NN simulation software [19] (Brainmaker Professional v3.11 for Windows, California Scientific Software, CA). The input layer and the output layer consisted of 30 and three neurons, respectively, corresponding to the number of input data (30) and the number of gait classes (3). Two hidden layers were defined, with five and four neurons, respectively (Fig. 1).

The data set was split into a training and a test set. The data from six subjects (18 patterns) were assigned to the training set, and the data from two subjects (six patterns) were included in the test set. The data in the training set were presented one after the other to the NN, which learned to associate all the training patterns to their corresponding classes, by dynamically changing its internal weights. Subsequent to training the test patterns were presented, which were unknown to the trained NN. The ratio of good recognitions to the number of all test patterns gives the ratio of correct assignment, which indicates the generalisation capability of the NN.

Because of the limited number of subjects used in this study the data was split into training and test sets in three further ways, in order to cover the whole data range by systematically assigning a different 25% of the total data to the test set, as illustrated in Fig. 2.

When a NN is trained, it starts up with randomised weights, and progresses to the global solution of the separation task. Every time it is retrained the weights are randomised again, which means that the NN can get to a different solution with a different correct assignment ratio. The most successful NN has to be selected from several trials. Training and testing was repeated four times for all four training-testing sets (16 NNs), and the four NN configurations with the best correct assignment ratios were kept.

3. Results

Fig. 3 shows the conventions used for the hip and knee joint angles. The hip-knee joint angle diagrams obtained from one of the subjects walking on a treadmill

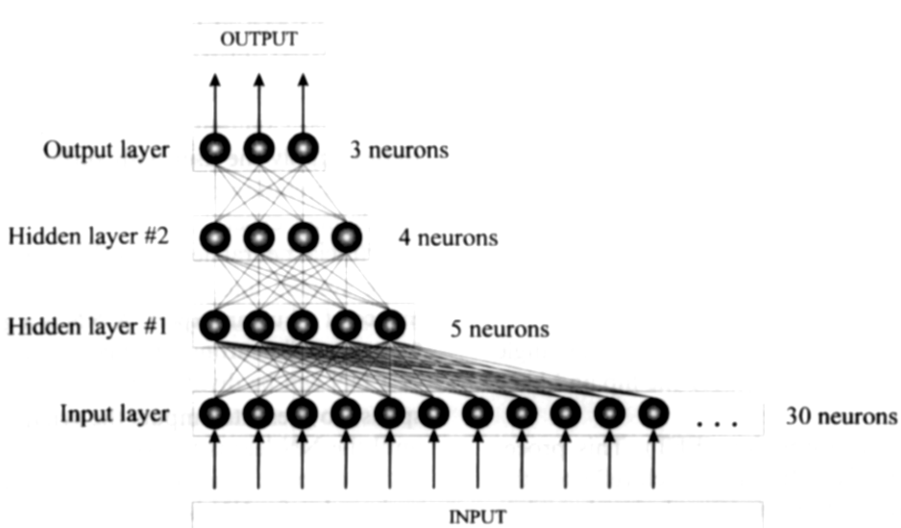

Fig. 1. The structure of the neural network to distinguish the three conditions.

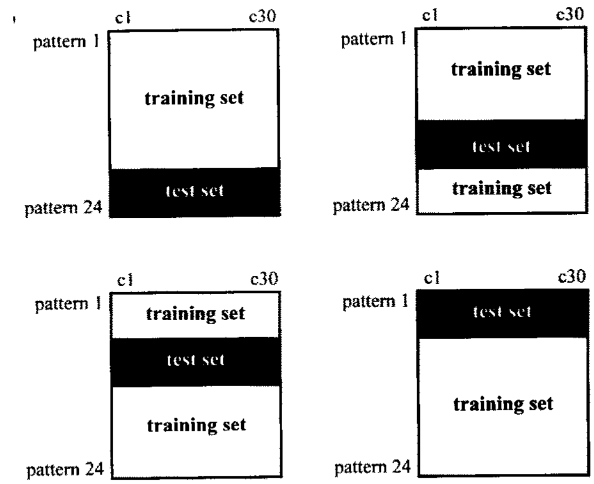

Fig. 2. The four ways the data were split into training and test sets.

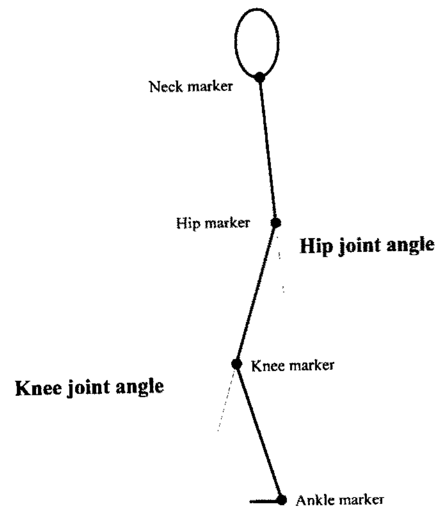

Fig. 3. The conventions used for the hip and knee angles.

at 1.1 $m \cdot s^{-1}$ under the three conditions are shown on Fig. 4a–c.

Fig. 5 illustrates the average and S.D. of the real and imaginary FFT coefficients for the hip and knee angles under the three experimental conditions. In order to visualise the FFT coefficients the cubic roots of the coefficients were taken, to compensate for the large differences among the coefficients (for example 2893, 578.31, 23.14, −124.91, −12.47, −11.26, 1.13, 6.85).

All four NNs could successfully learn to associate the inputs to the outputs in the training sessions, which proved that the NNs could find the relationships which enable the separation of three different types of gait patterns (represented by FFT coefficients of the hip-knee joint angle diagrams).

The proportion of the correctly recognised patterns relative to the number of all patterns through the 16 trained NNs are shown in Table 1. Taking the average of those figures an overall correct assignment ratio of 75% was found (72 correct recognitions out of 96 patterns), but this included those NNs which could not arrive at the optimal solution. The correct assignment ratios of the four best NNs were 4/6, 5/6, 5/6, and 6/6, respectively. The average of these ratios gives 83.3% (20 correct recognitions out of 24 patterns), which means that 83.3% of the unknown gait patterns were assigned into the right category.

4. Discussion

The FFT coefficients in Fig. 5 show a highly similar pattern across the three gait conditions. The differences

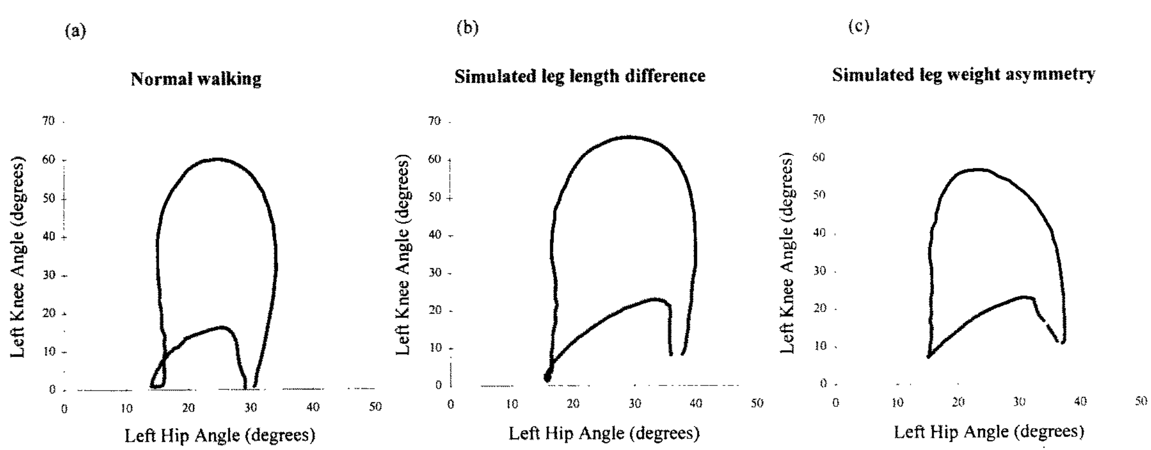

Fig. 4. The hip-knee joint angle diagrams of a healthy subject walking at 1.1 $m \cdot s^{-1}$ under three experimental conditions.

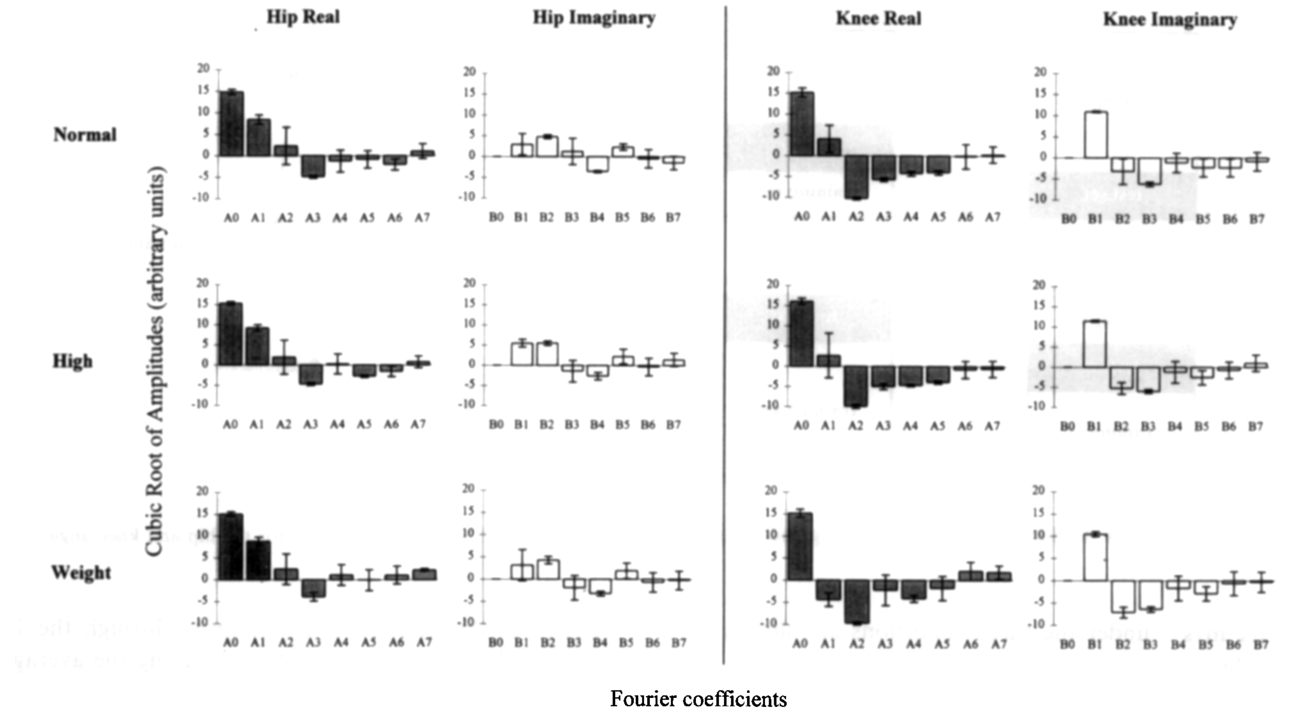

Fig. 5. The averages and S.D. of the cubic roots of the eight FFT coefficients for the hip and knee angles under the three conditions of normal walking (Normal), leg length difference (High) and leg weight asymmetry (Weight).

among conditions are less than the S.D., which suggests that an isolated coefficient would not be sufficient to separate the conditions on a statistical basis should that be used. However, handling all the coefficients together by the NN resulted in a successful separation.

The FFT resulted in 30 numbers representing the hip-knee joint angle diagrams. A set of FFT coefficients represents one and only one curve as it evolves in time, and so is more complete than the graphical plot, because inherently it contains the time dimension of the data, which was missing from the loops. Furthermore, breaking down the curves into frequency components (by FFT) enabled the NN to 'see' the patterns through frequency windows. This approach would make it possible to evaluate the importance of the various frequencies, by observing the weights belonging to each frequency. The operation of the NN ensured that the context of each frequency was preserved, so it handled the information in its complexity.

Table 1
The correctly recognised patterns of all 16 NNs trained

Test set	No. of NN	Correctly recognised patterns/all patterns
4th quarter	1a	5/6[a]
	1b	5/6
	1c	5/6
	1d	5/6
3rd quarter	2a	4/6
	2b	5/6[a]
	2c	4/6
	2d	4/6
2nd quarter	3a	4/6[a]
	3b	4/6
	3c	4/6
	3d	4/6
1st quarter	4a	5/6
	4b	4/6
	4c	6/6[a]
	4d	4/6

[a]The average of the best results which gave the overall correct assignment ratio of 83.3% (20/24).

The 83.3% correct assignment ratio was similar to the results of other NN applications [12,13], which verifies the use of NNs in processing kinematic information of gait in order to distinguish various gait patterns. The simulated pathological conditions were exaggerated in this study. A 3.5 kg leg mass difference is quite rare (for example lymphoedema), although a 20 mm leg length difference is not unusual. The number of categories was also limited, but the potential of NNs and the results presented here suggest that NNs could differentiate among smaller, less visually obvious differences in gait.

The interpretation of hip-knee joint angle diagrams by human experts is possible. However including the angular changes of all major joints in the leg (hip, knee, ankle joints) would result in a four-dimensional curve if the time dimension was included too. Such complexity would seem to be necessary in order to distinguish minor differences in gait, but the interpretation of such complex patterns exceeds the capabilities of humans. The more contextual information that is included, the less likely it is that a human can cope with the increasing complexity of the pattern. Neural networks can still handle these highly complicated patterns, which is another argument supporting the use of neural networks in automated gait pattern recognition.

5. Conclusion

Neural networks were trained to distinguish three gait patterns, which were normal walking, a simulation of leg length difference and a simulation of leg weight asymmetry. Subsequent to training the NNs could recognise unknown gait patterns at a correct assignment ratio of 83.3%. The gait patterns were represented by fast Fourier-transformation coefficients of the temporal patterns of hip-joint angle and knee-joint angle curves of a single step. The results suggest that it is worth investigating a more general automated gait pattern recognition neural network, which could handle gait patterns of actual pathological subjects. Such a system could be linked to the kinematic analysis system, providing prompt evaluation of gait.

References

[1] Rose G K. Clinical gait assessment: a personal view. *J Med Eng Technol* 1983; 7: 273–279.

[2] Gage J R. Gait analysis for decision-making in cerebral palsy. *Bull Hosp Jt Dis Orthop Inst* 1983; 43: 147–163.

[3] Hicks R, Durinick N, Gage J R. Differentiation of idiopathic toe-walking and cerebral palsy. *J Pediatr Orthop* 1988; 8: 160–163.

[4] Milliron M J, Cavanagh P R. Sagittal plane kinematics of the lower extremity during distance running. In: Cavanagh P R, ed. *Biomechanics of Distance Running*. Champaign, IL: Human Kinetics, 1990.

[5] Granlund G H. Fourier preprocessing for hand print character recognition. *IEEE Trans Comput* 1972; 21: 195–201.

[6] Schneider E, Chao E Y. Fourier analysis of ground reaction forces in normals and patients with knee joint disease. *J Biomech* 1983; 16(8): 591–601.

[7] Lisboa P G J (ed.). *Neural Networks, Current Applications*. London: Chapman and Hall, 1992.

[8] Hecht-Nielsen R. *Neurocomputing*. Reading, MA: Addison-Wesley, 1990.

[9] Davalo E, Naïm P. *Neural Networks*. London: Macmillan, 1991.

[10] Eberhart R C, Dobbins R W. *Neural Network PC Tools, A Practical Guide*. San Diego: Academic Press, 1990.

[11] Zurada J M. *Introduction to Artificial Neural Systems*. St. Paul: West Publishing Company, 1992.

[12] Sepuldeva F, Wells D M, Vaughan C L. A neural network representation of electromyography and joint dynamics in human gait. *J. Biomech* 1993; 26: 101–109.

[13] Aminian K, Robert P, Jequier E, Schultz Y. Level, downhill and uphill walking identification using neural networks. *Electron Lett* 29: 1563–1565.

[14] Holzreiter S H, Köhle M E. Assessment of gait patterns using neural networks. *J Biomech* 1993; 26: 645–651.

[15] Miller A S, Blott B H, Hames T K. Review of neural network applications in medical imaging and signal processing. *Med Biol Eng Comput* 1992; 30: 449–464.

[16] Aminian K, Robert P, Jéquier E. Incline, speed, and distance assessment during unconstrained walking. *Med Sci Sports Exerc* 1995; 27: 226–234.

[17] Lawrence J. *Introduction to Neural Networks*. California Scientific Software, CA, 1993.

[18] Rumelhart D E, Hinton G E, Williams R J. Learning internal representations by error propagation. In: Rumelhart D E and McClelland J L, eds. *Parallel Distributed Processing*. Cambridge, MA: MIT Press, 1986: 318–362.

[19] Lawrence J, Fredrickson J. *BrainMaker Professional User's Guide and Reference Manual*. California Scientific Software, CA, 1993.