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Potential of the Genetic Algorithm Neural Network in the Assessment of Gait Patterns in Ankle Arthrodesis

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Abstract—The aim of this study was to develop an empirical model of parameter-based gait data, based on an artificial neural network and a genetic algorithm, for the assessment of patients after ankle arthrodesis. Ground reaction force vectors were measured by force platforms during level walking. Nine force parameters expressed in percentage of body weight and their chronologic incidence of occurrence expressed in percentage of stance phase period were used in modeling. Ten healthy persons and ten patients who had solid arthrodesis of the ankle were recruited in this study for developing the model. By applying the genetic algorithm neural network, the percentage of correct classification was 98.8% and the subset of discriminant parameters was be reduced to 9 out of 18. These key parameters were mainly related to the loading response and propulsive phase. This indicates that there was a reduction in the abilities in cushion impact and push off in the patients after ankle arthrodesis. Finally, the relative distance (D_r) was defined in this study and used in two new patients' examinations to demonstrate its clinical utility. © *2001 Biomedical Engineering Society.* [DOI: 10.1114/1.1342053]

Keywords—Genetic algorithm, Neural network, Gait, Pattern recognition, Ankle arthrodesis.

INTRODUCTION

Arthrodesis is the surgical procedure in which joints are removed, adjacent bones are repositioned and fusion of the bones is attempted. Arthrodesis of the hindfoot has been a common orthopedic procedure for over half a century. Originally, it was used to treat paralytic foot deformities caused by polio. While the specific indications for arthrodesis have expanded through the years, three general principles remain: correction of significant deformity, prevention of instability, and alleviation of pain. Ankle arthrodesis is still a treatment choice for most disabling arthritic ankles where conservative treatment fails.

Preoperative surgical planning is very important in minimizing the incidence of long-term problems associated with ankle fusion. The resulting alterations to gait can lead to residual pain and degenerative joint disease. Therefore, it is important to measure the changes of the gait pattern after arthrodesis to understand the clinical implication of the arthrodesis.

When a person walks, the ground generates a reaction force that is equal in magnitude and opposite in direction to the force applied to it by the foot. This ground reaction force (GRF) vector is readily determined with a force platform and can be decomposed into three orthogonal components: a vertical (compressive) component, and fore–aft and mediolateral (shear) components. Values can be identified from each of the three components that may be used for comparative purposes. Nine force parameters expressed in percentage of body weight (F1–F9) and their chronologic incidence of occurrence (T1–T9) expressed in percentage of stance-phase period have been defined by Chao *et al.*[3] These definitions are suitable for the investigation of foot mechanics during gait. While the individual parameters may be directly interpretable, the mixed set of significance results over all parameters is, however, difficult to interpret clinically.

Most studies of artificial neural networks (ANN) in musculoskeletal applications have focused on electromyography[4,8,9,17] and control of functional electrical stimulation.[7] Few have focused on gait pattern recognition. Sepulveda *et al.*[20] estimated limb joint angles and joint moments from electromyographic patterns. Barton and Lees[2] classified gait patterns by hip–knee angle diagrams. Holzreiter and Kohle[10] used an ANN model to assess gait patterns from ground reaction forces to classify ''healthy'' and ''pathological'' gait patterns. In their study, ground reaction forces used in the neural network were processed using a fast Fourier transform, not in time domain. However, the fast Fourier transform could not find obvious changes in peak force and chronologic incidence of their occurrence.

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There is increasing interest in mathematical methods for the prediction of medical outcomes.[1,5,11,13–15,19] Although supervised feed-forward backpropagation neural networks are very efficient in many pattern recognition tasks,[1,2,4,10,16,20] the genetic algorithm neural network (GANN), which can search in some appropriate space, has not been used for gait pattern recognition.

Genetic algorithms (GAs) are search algorithms based on the mechanics of natural selection. For a poorly understood and irregular space, GAs are an effective strategy for searching for the nearly optimal solution.[13,15,18] When a neural network uses a GA for training, there is an increase in computational time, but compared with simple gradient descent, the optimization process may be less likely to fall into local minima. Neural networks using GA may thus be more accurate in prediction. GAs can reduce the dimensionality of data used in a predictive process. They do so by emulating the selection process determining the survival or extinction of genes in biological systems. A potential predictor variable may be considered as analogous to a gene. In a GA the survival of that predictor variable, as an input of an ultimate information system, depends on how well it predicts the correct output.

A GANN, like a traditional neural network (NN) can be considered a ''black box'' system with a definite but unknown relationship between the inputs and outputs. There is, however, an important difference between the NN and GANN. In a GANN only those items of data, which have value in predicting the outputs, are retained as inputs to the system. A neural network, on the other hand, does not exclude irrelevant data inputs to the system. A neural network, on the other hand, does not exclude irrelevant data inputs from the final system. It nullifies the effects of such data inputs by assigning a low weight to them in the decision process.

The design of a classifier is characterized by a so-called design bias, which implies an unavoidable loss of prediction capability due to the need of determining its degrees of freedom from a finite set of training samples. The design of a classifier is a demanding task involving several aspects. One task, choosing the type and number of input features, significantly influences discrimination results. Several multivariate statistical methods, such as Fisher's discriminant analysis, can help evaluate the discrimination potential of the parameters included in the input feature vector.[12] In this study, we proposed a new approach using the GA (Ref. 6) to choose the input feature vector for gait parameters. The selection process was done by means of a GA, which selected predictor variables based on their contribution to the predictive process. Therefore, we combined the GA and NN in this study to select an optimal subset of predictor variables in a neural network.

Although many researchers have developed neural networks and declared them to be accurate enough under

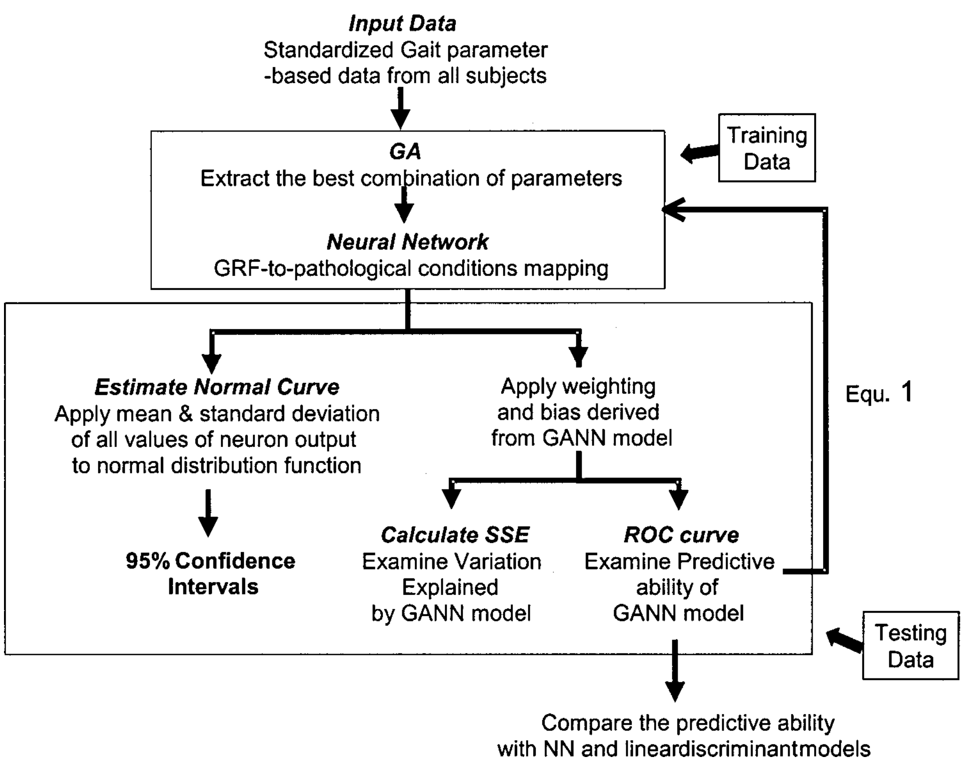

FIGURE 1. Flow chart describing the development of the GANN model.

specific circumstances, many have not performed the necessary statistical verification to support those claims.[2,10] Furthermore, these studies have only addressed differences that are easily discernible. There are only a few analysis techniques developed for interpretation of clinical results. Therefore, the main purposes of this study were: (1) to develop a GA-based network model in the assessment of gait patterns in ankle arthrodesis; (2) to investigate the model accuracy in categorizing different gait patterns; (3) to compare the prediction ability of the GA-based model with that of the stepwise variant of the linear discriminant method; and (4) to interpret the clinical implications of the results.

METHODS

Data from normal subjects and patients with ankle arthrodesis were used to construct the GANN model for parameter-based gait measures. A flow chart describing the process of developing a GANN model is shown in Fig. 1. This study is meant to provide an overview of the GANN applied in the analysis of gait parameter-based data.

Once a GANN model has been developed to describe the gait parameter-based pattern, it can be used to assess the gait data of new subjects. The process of the assessment of patient gait wave forms is illustrated in Fig. 2. Detection of the difference is performed using the relative distance from the value of the output neuron to the position of 95% confidence interval estimated by the normal distribution function of normal subjects. The interpretation (clinical meaning) follows the identification.

Standardized Gait Parameter-Based Input Data

To distinguish differences between healthy and pathological gait, the input patterns used to train the network were based on the ground reaction force vectors. Ground reaction forces measured by Kistler force platforms (Amherst, NY) were used for gait pattern recognition. Signals from the force plate was recorded with a sampling rate of 1000 Hz and postprocessed with a low-pass filter at 10 Hz, and used as classifier input data. A total of nine force parameters expressed in percentage of body weight, F1–F9, and their chronologic incidence of occurrence, T1–T9, expressed in percentage of stance-phase period were used (Fig. 3). The variables were then normalized to percentage of gait cycle and percentage of body weight, and then linearly transformed into the interval [0,1].

The data set is comprised of 99 pairs of foot strikes of ten healthy persons (age 28.8±3.8 years, body weight 61.2±11.2 kg) and ten patients (age 39.6±15.3 years, body weight 61.5±9.9 kg) who had solid arthrodesis of the ankle because of trauma, degenerative osteoarthritis, or rheumatic arthritis. Subjects have been informed of the experimental methods and all have given their consents prior to their participation. In patients, only the affected side was introduced in each trial. 40 control trials and 23 patient trials were employed for training and 17 control trials and 19 patient trials for testing. Learning repetitions were performed with different training and validation data sets.

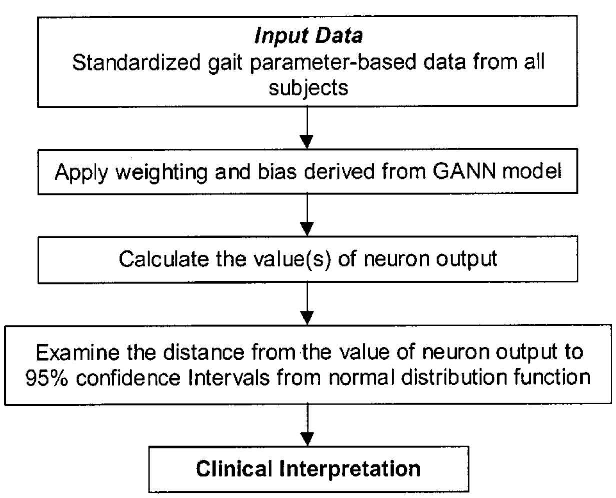

FIGURE 2. Flow chart of the assessment of patient data.

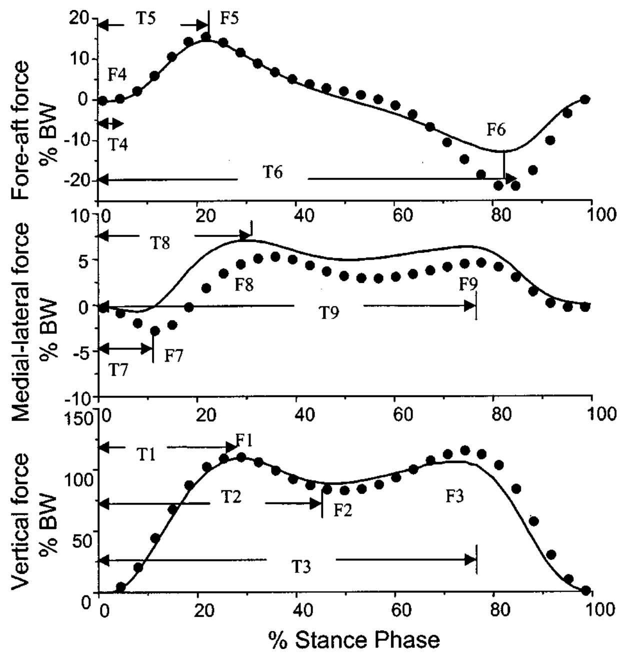

FIGURE 3. Graphs showing ground reaction force (lower graph: vertical; upper graph: fore–aft, middle graph: medial–lateral force) for the patients who had received ankle arthrodesis (solid curve) compared with that for the normal subjects (broken curve).

Extract The Best Combination of Parameters by GA

The GA randomly selects data containing information about the patient as inputs to the system. This information is used by the neural network to predict the gait patterns for the individual patient. The efficiency of the predictive process is then returned to the genetic algorithm to determine the probability that these items are used as predictor variables in the final system. The flow chart of the genetic algorithm-based neural network is shown in Fig. 4. In this study, the force plate data set originally contained 18 possible predictor variables. The parameter options presented to the GA were: population size (g): 200, crossover probability (p_c): 0.8, and basic mutation probability (p_m): 0.001. The predictive efficiency was defined as follows:

Fitness Function. The initial population was generated by randomly forming g training patterns. Each pattern contained r variables. The optimal classifier in the classification problem of gait patterns was obtained by maximum fitness values in different conditions (1–18 variables used in NN training). The fitness functions (F_g) were calculated using the ''relative operating characteristic'' (ROC) method to calculate the accuracy of cases of the target t classified as output j. The details of the ROC method are described below in the section on statistical methods.

The probability that a pattern would be selected was recalculated after each generation by the following method. If there were g patterns in which r variables were selected at a time by a random process, then the reproduction probability of this pattern was given by rounding p_{selg} towards the nearest integer lower than the original p_{selg} value:

$$p_{selg}=\frac{F_g}{\sum_{i=1}^{g} F_g}\times g. \tag{1}$$

The new patterns were created to let the sum of p_{selg} just equal g. These weights were used in the selection process of each pattern for an information genome at the next stage. Finally, the maximum value of the fitness function (F_g) was reached. The process was controlled by a 18×1 matrix holding the predictive efficiency for each size of the variables used in the NN training (1–18 variables). The efficiencies were compared after each cycle was finished. The selection process continued at each stage until all patterns converged to one pattern. The process continued until all variables used in the ANN training were completed. The stored optimal variable references and the stored efficiency then constitute the solution to the problem.

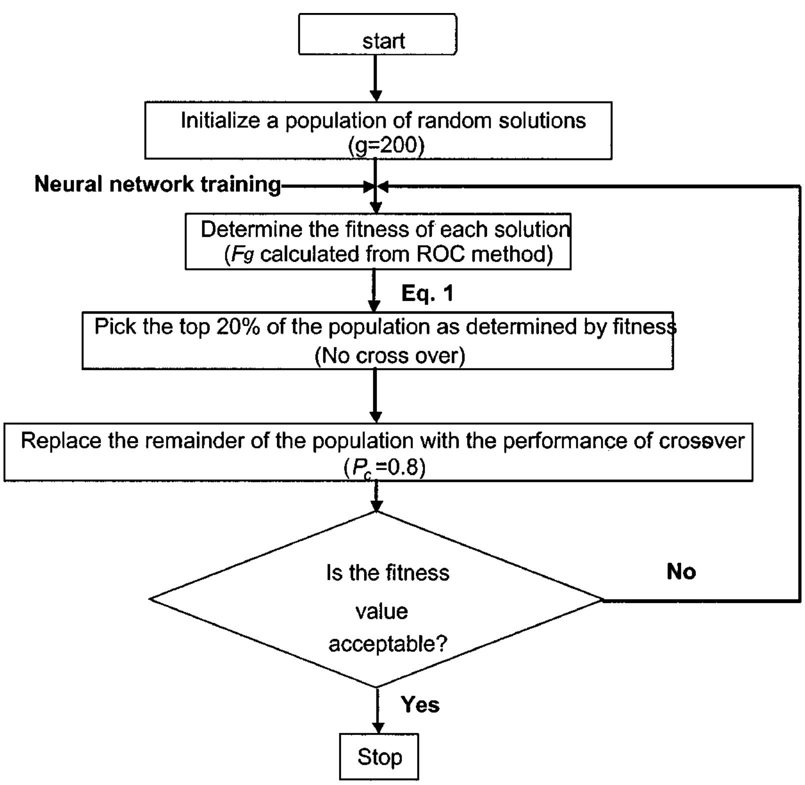

FIGURE 4. Flow chart of a genetic algorithm-based neural network.

TABLE 1. Variables selected by the GANN for prediction of the gait pattern for ankle arthrodesis patients in their optimal models and compared with the percentage of ''group cases'' correctly classified in each parameter by the linear discriminant.

	Predictive variables																	
Predictive method	T1	T2	T3	T4	T5	T6	T7	T8	T9	F1	F2	F3	F4	F5	F6	F7	F8	F9
% correct classification	61	38	55	60	55	34	63	56	33	55	54	63	66	50	76	57	72	66
GANN		+		+				+		+			+	+	+	+	+	
Linear discriminant		3	6		5							4			1		2	

GRF-to-Pathological Conditions Mapping Using the Neural Network

A three-layer neural network that used the backpropagation learning algorithm was used in this study. In the GRF-to-pathological conditions mapping, the input signals were the peak values of the GRF. The mean-square error between the network outputs and the expected values was set to 0.01. The learning rate was varied dynamically to accelerate convergence. The logistic sigmoid activation transfer function was used in both hidden (5 neurons) and output layers. Output from the output-layer neuron was only one value (between 0 and 1). The number ''0'' corresponded to the normal condition and the number ''1'' corresponded to the pathological condition.

Examine the Predictive Ability of the GANN Model

After training the network, a test of its ability to generalize was performed. To illustrate the accuracy of the classification methods, the ROC curves were used.[21] In these graphs, the true-positive proportion (sensitivity) is plotted against the false-positive proportion (complement of specificity for various possible settings of the decision criterion). The area under the ROC curve was used to measure the classification performance. By calculating these areas for different classification methods, the methods can be compared along the full range of specificities to determine which has the better overall discriminability. Finally, three models were tested:

(1) A NN model based on the entire 18 variable set, with no restrictions on the number of variables in the final model to develop an optimal unrestricted model.
(2) A GANN model that was allowed to use its own ''best'' predictor variables from the original 18 (acquired by the GANN method).
(3) Linear discriminant classifier based on traditional statistical theory that was allowed to use its own ''best'' predictor variables from the original 18.

The first two models were implemented by custom software coding in MATLAB and the last one was implemented by SPSS software.

Examine the Variation Explained by the GANN Model

If the residual was significant, it indicated that the model established in this study does not fit the patient data. A sum of squares of residuals outside the 95% confidence interval established from normal subjects indicated that the subject was an outlier from the model and that this subject may belong to a population with a different underlying structure from the data used in this model.

Estimate the Normal Curve

The normal function $f(x)$ fitted to histograms is defined as

$$f(x) = \mathrm{NC}^*\mathrm{step}^*\mathrm{normal}(x,\mathrm{mean},\mathrm{std\_dev.}), \tag{2}$$

where NC; the number of cases, step: the categorization step size (e.g., the integral categorization step size is 1), and normal: the normal distribution function.

RESULTS

Selection of the Most Discriminating Input Features

Predictor variables selected by the GANN, stepwise linear discriminant, and the percentage of the ''group case'' correctly classified in each parameter by the linear discriminant are shown in Table I. The classification outcome was worse when only a subset of the variables was introduced in the model (all lesser than 72%). A

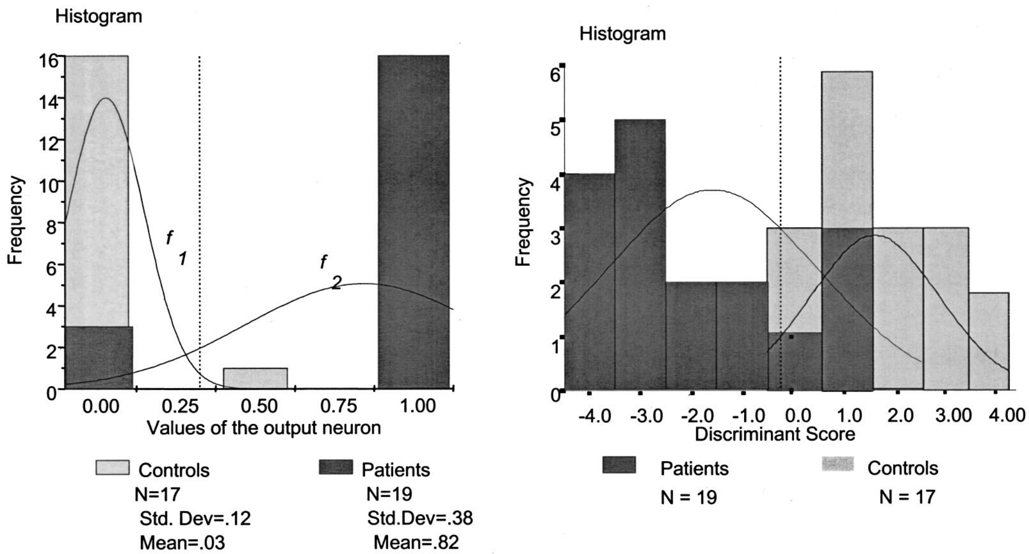

FIGURE 5. Frequency histogram comparing the different analysis methods. Subjects (control trials=17, patient trials=19) were separated based on their value of the output neuron (neural network classifier; left graph) and discriminant score (discriminant analysis; right graph). The less overlap between the groups, the better the diagnostic performance.

single parameter may not be sufficient to distinguish between two groups. In order to find a suitable parameter, a combination of several force and time parameters is needed.

By applying the GANN and a stepwise variant of the linear discriminant algorithm, the subset of discriminant parameters can be reduced to 9 and 6, respectively. The reduce subset of discriminant parameters by the linear discriminant algorithm can be ranked in order.

Prediction Ability Comparison

The frequency histograms in Fig. 5 show the distribution of ankle arthrodesis patients and controls to be separated based on values of the output neuron and discriminant scores. The cutoff points were chosen so that the false-positive ratios (the area under the frequency histogram to the right (classified by the GANN) or left (classified by the discriminant analysis) of the cutoff point divided by the total area under the frequency histogram in the control group) were the same for both methods. As can be seen, the true-positive ratio [the area under the frequency histogram to the right (classified by the GANN) or left (classified by the discriminant analysis) of the cutoff point divided by the total area under the frequency histogram in the patient group] was higher for the GANN classifier.

The vertical line displays the cutoff point. If the cutoff point separating the groups is changed, the true-positive and the false-positive ratios are changed as well. The ROC curves shown in Fig. 6 were obtained by plotting the true-positive ratio versus the false-positive ratio for different cutoff points. The distance between each point is 1/17 and the cutoff points were decided by the values of the output neuron of the controls. The true-positive ratio corresponds to the sensitivity, and the false-positive ratio is the complement of the specificity of the diagnostic system. The percentage of correct classification measured by the area under the ROC curve (ROC area) for the GANN method was 98.8%. In contrast, the percentages of correct classification for the statistical method and the ANN (using all possible predictor variables) were only 91.5% and 89.7%. The GANN and linear discriminant produced an improvement in accuracy when compared to the NN. Improvement with the GANN was significantly higher than that with the linear discriminant.

Estimate Variation Explained by the GANN Model

In this study, the sum of the squared error was calculated by applying the weight and bias established by the model to the output of the neuron from the test data

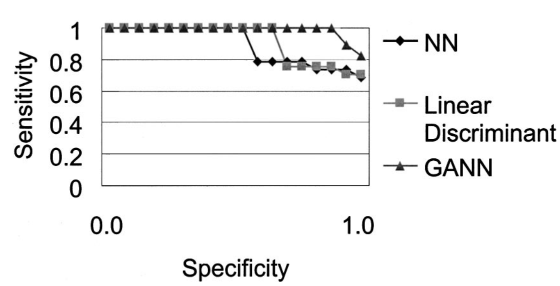

FIGURE 6. Relative operating characteristic (ROC) curves for three models on classifying the outcomes of cases for ankle arthrodesis patients.

(six parameters were used). To integrate the units (the percentage of gait cycle and the percentage of body weight), the normalized data (from 0 to 1) were compared with our estimated result. After being operated by the logistic sigmoid activation transfer function, it showed that 15 out of 17 patient testing data fell within the 95% confidence interval established by normal testing data. A sum of squares of residuals outside the 95% confidence interval established from normal subjects indicated that the subject was an outlier from the model and that this subject may belong to a population with a different underlying structure from the data used in this model. It is said that the model is suitable to exploit the variable patient's gait pattern.

Estimate the Normal Curve and Interpret the Value of the Neuron Output

The two normal curves (f_1 and f_2) superimposed onto each histogram were derived from Eq. (2) and are plotted in Fig. 5. The position of the 95% confidence interval (x_0) estimated by the normal distribution function established by the normal group is a value nearly 0.23.

To evaluate a new case, the weight and bias established by the model are applied to the new data. If the output of the neuron from the new data is lower than x_0, it is inferred that the gait pattern in these new data is similar to the normal gift data. If the output of the neuron (x_1) from the new data is higher than x_0, the relative distance (D_r) from the output of the neuron calculated by the new data to x_0 is used as an index which means that there is a similarity between the new data and the normal subjects. The D_r is defined as follows:

$$D_r = \frac{1 - x_1}{1 - x_0}.$$

The relative distance (D_r) is a measure of the difference from the normal. Thus, the D_r value defined in this study near 1 is interpreted as a gait pattern similar to that of normal subjects. Similarly, any other pathological gait patterns could be quantitatively presented.

Case Examination

In clinical applications, the ground reaction forces (the average of three trials) of two new subjects A and B were tested by using this model. The results are shown in Fig. 7. Both subjects suffered traffic accidents and had undergone modified Blair's ankle arthrodesis. The results show that the force patterns of subject A were almost within the normal ranges, while the force patterns of subject B appeared to be abnormal. The main features selected by the GANN model were related to the loading response and propulsive phase. It means that these patients exhibited a loss of the abilities to cushion impact and to push off after ankle arthrodesis.

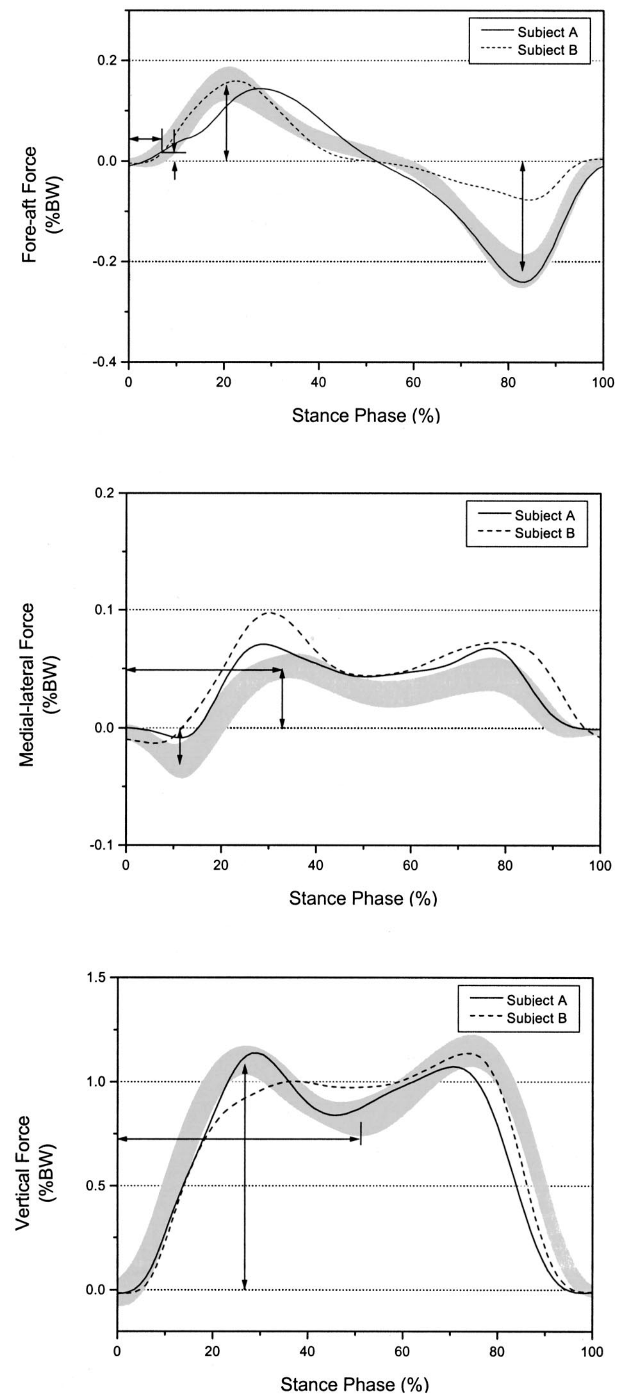

FIGURE 7. Ground reaction force wave-form data are shown from initial contact to push off. The range of the normal subjects is shown with the baded area. Ground reaction forces (four features for fore–aft force, three features for medial–lateral force, and two features for vertical force) were used in the GANN model assessment for subjects A and B, respectively.

The value of the neuron output from the GANN model assessment was 0.43 for subject A and 0.88 for subject B. The value of the neuron output in subject A was more close to zero and fell well within the cluster of normals. It means that case A could be well identified as a case which had a more normal gait pattern than subject B. The relative distance (D_r) from the normals in these two cases could be quantitatively presented as 0.72 and 0.15 for subjects A and B, respectively.

DISCUSSION

From the case examination, it appears that the time interval between the data of fusion and the date of follow-up examination may be an important issue of gait accommodation and contribute to the gap in their D_r values. The time interval was 3 years for case A and 1 year for case B. Some patients can utilize several specific mechanisms to allow themselves to have a reasonable normal gait, but the compensatory movements may be absent in the other cases. For the latter cases, the improvement of gait may be suggested by the use of a cushioned heel and rocker-bottom sole. Considering this requirement, the quantitative D_r value can help clinicians in objective decision making.

To characterize the patients' gait patterns, many steps must be performed. These include: reduction in the dimension of the raw data, training and testing the model, the accuracy evaluation (discriminate rate and sum of square error), practicability evaluation and discussion about the relationship between the gait score (output of the neuron) and the grading score.

A simpler exploratory analysis disclosed an important overlap between the classes, so that a multidimensional approach was suggested as the most feasible way of classifying subjects. Difficulties in identifying general rules for the assessment of gait have led to the development of artificial intelligence research that could extract information from patterns depending on the type of view used. The patterns of the gait seem to be more individual than global. Most common methods using mechanics and statistics basically focus on the details of the gait similar to the perception of the human observer. Although new information can be gathered with this kind of focus, some information will be lost. Therefore, the alternative approach developed here using the GANN seems to be suitable.

The variables selected by both predictive methods demonstrated that the ground reaction force was suitable. This is consistent with the clinical impression that ankle arthrodesis will affect the gait pattern. The results of this study also suggest that measures of the ground reaction force carry important prognostic information, because inclusion of this measure allowed for prediction of the gait pattern with greater accuracy. The factors determining the recovery conditions of ankle arthrodesis patients are poorly understood. It has been shown in Fig. 3 that the temporal force factor (T2) was different from those in normal subjects ($p=0.01$). This difference with regard to T2 is related to the decreased loading rate of patients who have ankle arthrodesis (the body center of mass peaks later in the stance phase because the foot is loaded more slowly). The fore–aft component of the GRF (F6) was significantly lower after ankle arthrodesis compared with the values for the normal subjects ($p=0.01$). This indicated the cyclic accelerations and decelerations of GRF occurred with a gentle slope after ankle arthrodesis. In the mediolateral component, the ground reaction forces (F8) were different from those in normal subjects ($p=0.01$). This indicated abnormally high lateral shear sources during walking by the patients who had undergone ankle arthrodesis. This alteration in force vector appeared to be explained by the pronation gait of these patients, since it showed that during stance the hindfoot maintained an everted position instead of the normal inverted position.

Furthermore, breaking down the vertical force component curves of the measured gait patterns into frequency components by fast Fourier transform 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 component.[10] In contrast, the peak force and time components used in our study could enable the NN to find the patterns in the time domain. The NN could also find obvious changes in peak force and chronologic incidence of their occurrence and had better discrimination ability in the time domain (98.7%) that observation in the frequency domain (95%). Therefore, it is believed that applying the three components of the GRF in the time domain as input information to the NN is suitable, and may contain more information than using only the vertical force in the frequency domain. The results of this study also show better performance at distinguishing gait patterns than a previous study (applied hip–knee angle diagrams as inputs) by Barton[2] (83.3%).

In addition to creating a NN model to classify the ''healthy'' and ''pathological'' gait patterns, we also compared our method with another modeling technique. This has not been done previously. Although there are differences in performance between the statistical method (91.5%) and the GANN method (98.7%), each has excellent predictive capabilities. Choices between them will likely be made based on the needs of special applications, rather than one being intrinsically more powerful. Although the statistical method requires less training and classification time than the neural network, the NN method has better accuracy than the statistical method in discriminating between groups.

Because fore-plate measures are readily calculated and require standard equipment, prospective evaluation of their use in a routine postoperative workup may be warranted. The authors conclude that, for these ankle arthrodesis patients, a neural network method may classify the gait pattern with a high degree of accuracy that is considerably better than linear discriminant classification. We suggest that the implementation of the GANN in clinical practice deserves further investigation. In addition, it can also be easily modified for other types of parameter-based data.

One potential limitation to this study is that the two groups have very large differences in the range of ages; the possible implications of these differences have been combined with the effects of arthrodesis in the GANN model. Therefore, the age factor must be considered in the future.

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