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# ASSESSMENT OF GAIT PATTERNS USING NEURAL NETWORKS

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**Abstract**—A new approach for the assessment of gait patterns is presented. The use of neural network techniques for decision making in gait analysis is for some purposes more effective than biomechanical methods or conventional statistics. To demonstrate this, a neural network was trained to distinguish 'healthy' from 'pathological' gait. The algorithm presented here can be used for several purposes because it learns from examples of diagnosed gait patterns without having any built-in model of gait.

## NOMENCLATURE

| | |
|---|---|
| $o_n$ | output of unit $n$ |
| $\mathrm{net}_n$ | net input (sum of the weighted inputs) of unit $n$ |
| $w_{nm}$ | weight of connection between unit $n$ and unit $m$ |
| $i_m$ | $m$th input of a unit |
| $s_n$ | number of inputs to unit $n$ |
| $c$ | constant for initialization range of random weights |
| $\delta_n$ | error signal for unit $n$ |
| $t_n$ | target value for unit $n$ |
| $\eta$ | learning rate |
| $a_i$, $b_i$ | Fourier coefficients |
| $a_{ij}$, $b_{ij}$ | Fourier coefficients of footstrike pair $j$ |

## INTRODUCTION

Some difficulties in finding general rules for the assessment of gait may be caused by an effect which is well known in cognitive science, pattern recognition, and artificial intelligence research: extractable information of patterns depends on what type of view is used (Hofstadter, 1985; Koffka, 1936; Marr, 1982). For example, separated observation of pixels of a TV screen may lead to completely different information than the observation of the whole screen. Similarly, details of gait seem to be more individual than global patterns.

Most common methods using mechanics and statistics basically focus on details of gait compared to what the human observer perceives. Although new information can be gathered with this kind of focusing, some information will be lost. The application of neural networks as presented here lies in between the kind of observation by humans and the one of mechanics or statistics.

## BASIC CONSIDERATIONS

The introduction of new methods like neural networks is closely coupled with the analysis of commonly used methods. As a result of this, some weak points in the application of the latter methods become obvious.

Every natural science consists of a set of rules and a set of explanations under which a specific rule is applicable. Discovery of a rule may arise from theoretical considerations or practical observations. In any case, a rule is accepted only if it is reproducible in accordance with experimental results. The verification of correctness of a rule is done by repeated comparison between the calculated and the observed results, and the development of a new basic rule can be done only by searching the best-fitting model for the experiment.

In most cases in gait analysis the application of both mechanical and statistical rules lacks the satisfaction of some required conditions. In the case of biomechanics some values cannot be measured (e.g. inner forces can only be estimated), set aside the fact that human bodies are not rigid, which usually is the assumption. As for statistics, each method was developed for a specific experiment under certain conditions. The correctness of results is guaranteed only if the required conditions are given according to a model of how the data were generated. In gait analysis this model is a controversial point. Application of a statistical test on many different parameters without having any model is incorrect because the results of the tests are random values and some of them may be significant by accident.

The above-mentioned lack can be overcome by verifying the results, as is usually done for basic rules in natural science. Verification ensures the correctness of any algorithm, regardless of it being statistical, mechanical or something else. This offers the opportunity to use even completely new algorithms.

## NEW WAYS IN GAIT ANALYSIS

To demonstrate the advantages of neural networks in gait analysis, a well-known, complicated task, the classification of 'healthy' and 'pathological' gait, was chosen. It is not the primary purpose of this paper to

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elaborate on this particular application; rather, the application is taken as an example in a field where statistics and mechanics are not efficient.

Assessment of 'gait quality' is legitimately a controversial issue, not the least because the definition of quality in gait is highly subjective and dependent on the context and target of assessment. Especially, concerning rehabilitation the definition of an 'ideal' gait pattern could vary markedly with respect to diverse groups of patients. For example, a patient with an artificial limb will definitely have to learn a different style of gait compared to a patient with calcaneus fracture. This, indeed, indicates why the definition of a generally usable gait quality parameter is impossible to find. However, in many cases of gait analysis such a parameter is needed to provide a means for clinical diagnosis and scientific decision making.

We feel that employing biomechanically derived loads of joints or tendons in accomplishing this purpose (Denoth, 1987) does not meet the actual requirements. Gait is not merely a mechanical problem, it is also a personal expression. Horvath (1990) selected 71 terms (in the German language) to describe gait patterns, and most of them are more psychological than mechanical in nature. In addition, internal loads cannot be calculated precisely, and even knowing them would not give rise to straightforward assessments. Since gait analysis is highly interdisciplinary, algorithms have to take into account knowledge from diverse fields which, using conventional methods, is difficult to achieve.

A convenient strategy is training neural networks by using examples of gait patterns with known diagnosis. Having set up the network's architecture, it can easily be adopted to perform different tasks by training it with different examples (Köhle and Holzreiter, 1991). The algorithm presented here makes use of a so-called supervised learning strategy. This means that during learning the corresponding quality parameter (the so-called target) for each gait pattern is provided. The training adjusts a set of internal parameters in such a way that for each presented gait pattern the system's response correlates with the target. As an intrinsic feature of neural networks, they usually produce correct answers even for samples which they were not trained on. This effect is called 'generalization'.

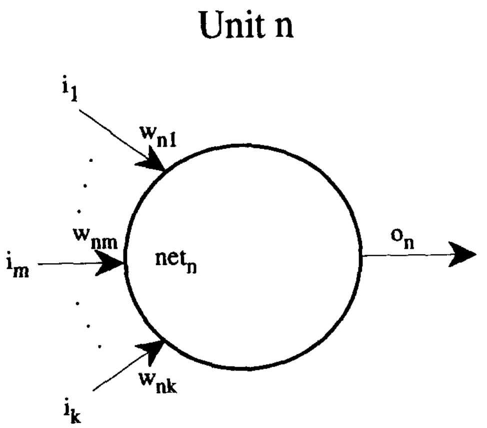


Fig. 1. Schematic structure of a unit in a neural network

## ARCHITECTURE OF THE SYSTEM

Typically, neural networks consist of interconnected processing elements (the so-called units), a mechanism for producing the network's response, and a method of encoding information. Detailed information on neural networks can be found elsewhere (Köhle, 1990). For the presented algorithm, we confined ourselves to sigmoidal units, with each unit $n$ having input values $i_m$, a single output value $o_n$ (Fig. 1), which is calculated by

$$o_n = \frac{1}{1+e^{-\mathrm{net}_n}}, \tag{1}$$

where

$$\mathrm{net}_n = \sum_m w_{nm} i_m \tag{2}$$

and $w_{nm}$ are the so-called weights, determining the connection strength between the two units. These weights are to be adjusted during training. They are initialized with an evenly distributed random value in the range of

$$\pm \frac{c}{\sqrt{s_n}}, \tag{3}$$

where $s_n$ is the number of inputs to unit $n$, and $c$ is a constant ($c = 0.25$ was used).

The topology of a neural network is the organization of units into groups and the connections between them. For the experiments a three-layer feed-forward topology was used (Fig. 2).

## TRAINING

For training purposes we used the back propagation algorithm (Rumelhart *et al.*, 1986). Applying equations (1) and (2) to each unit of the network in feed-forward direction, for a specific pattern of input values one will get a corresponding output pattern depending upon the actual values of the weights. Since the initial weights are randomly selected, the network will not produce the desired output pattern. To determine how the weights should change, a two phase procedure is applied.

For the output units $o_n$ an error signal $\delta_n$ is derived as a function of the difference between the network's output and the target $t_n$:

$$\delta_n = o_n(1-o_n)(t_n - o_n). \tag{4}$$

This error signal $\delta_n$ can be used for adjusting the weights of the output units $n$ by adding the weight

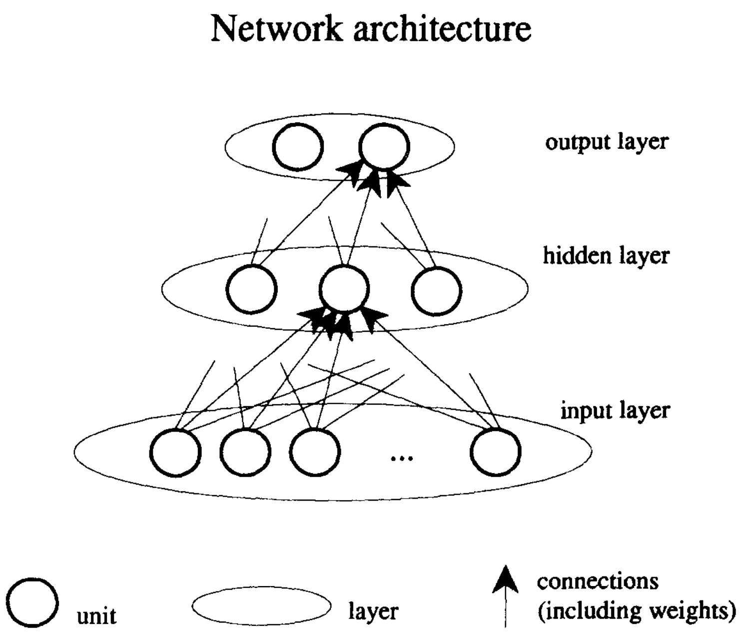


Fig. 2. Architecture of a three-layer neural network

change $\Delta w_{nm}$ to the weight $w_{nm}$:

$$\Delta w_{nm} = \eta\, \delta_n\, o_m, \tag{5}$$

where $\eta$ is the learning rate ($\eta = 0.2$ was used).

For hidden units $o_n$ where there is no target output available the error signal $\delta_n$ is calculated by

$$\delta_n = o_n(1 - o_n) \sum_{j=1}^{k} \delta_j w_{jn}, \tag{6}$$

where $k$ is the number of output units. The weights are corrected by applying equation (5). The training of the network is an iterative process of correcting weights according to the errors produced by the example gait patterns.

In order to classify 'healthy' and 'pathological' gait patterns, the network was trained using 200,000 iterations where the patterns of the so-called training set were presented several times in random order. The training set is a subset of all measured pairs of footstrikes.

## METHOD

The gait patterns were measured using two ground reaction force measurement platforms (Kistler 9281 B), mounted in a way that pairs of two subsequent left and right footstrikes could be observed. For the purpose of distinguishing between 'healthy' and 'pathological' gait, left/right and right/left strike combinations were treated as equal. The input patterns used to train the network were based solely on the vertical force components of the measured gait patterns, which were then normalized, fast-Fourier-transformed and linearly transformed.

Evaluation steps for the network input:

(1) Measurements were made at a sampling frequency of 250 Hz. Data from before and after the stance phase were not included in further calculations.

(2) Normalization in time, yielding 128 values in constant time intervals.

(3) Normalization by dividing the vertical force values by the person's weight.

(4) Fast Fourier-transformation of the 128 values, yielding 64 real coefficients ($a_0$–$a_{63}$) and 64 imaginary coefficients ($b_0$–$b_{63}$). For further calculations, only the coefficients of the lower frequencies ($a_0$–$a_{14}$, $b_0$–$b_{14}$) were used.

(5) Linear transformation of the resulting coefficients ($a_0$–$a_{14}$, $b_0$–$b_{14}$) into the interval [0, 1] by

$$a_{ij\text{new}} = \frac{a_{ij} - \min A_i}{\max A_i - \min A_i},$$

$$b_{ij\text{new}} = \frac{b_{ij} - \min B_i}{\max B_i - \min B_i}, \tag{7}$$

where $i = 0, \ldots, 14$, $j$ is the number of pairs of footstrikes, and

$$A_i = \{a_{ij} \mid j \in N\}, \quad B_i = \{b_{ij} \mid j \in N\}.$$

The data set comprises 8173 pairs of footstrikes of 94 'healthy' persons and 131 patients of the rehabilitation center 'Weißer Hof' (Rehabilitationszentrum 'Weißer Hof' der Allgemeinen Unfallversicherungsanstalt, 3400 Klosterneuburg, Austria); 71 of the patients had a calcaneus fracture, 12 had artificial limbs, and the rest had various diseases.

After having trained the network, a test of its generalization ability must be performed. This requires splitting up the set of input patterns into a training set

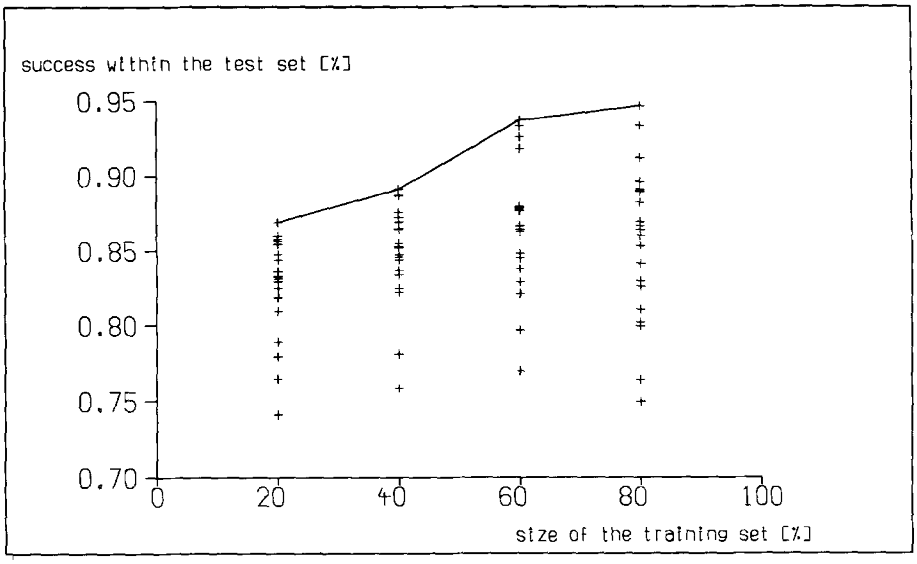


Fig. 3. Dependence of the generalization ability from the size of the training set. The subjects were randomly split up into 20% test set and 80% training set, 40% test set and 60% training set, and so on. The ordinate shows the quotient of correct group assignment in the test set.

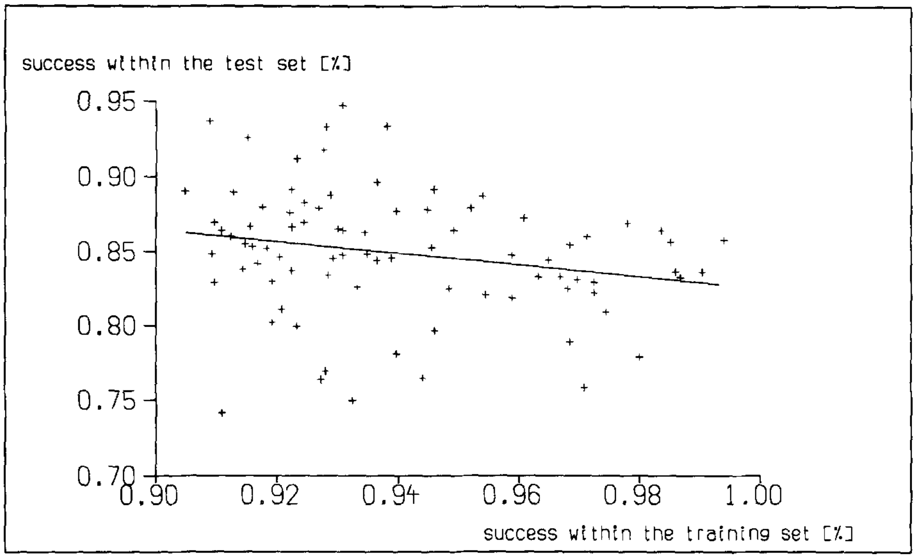


Fig. 4. Correlation between the quotas of correct assignment within the test set (ordinate) and the training set (abscissa). The lack of a correlation indicates that the prediction ability cannot be estimated by the success within the training set.

and a test set. The complete data set of a single person was randomly assigned to one set only. The training set is used for the adjustment of the weights, while the test set serves to evaluate the generalization ability of the network.

## RESULTS

Figure 3 shows the dependence of generalization ability from the size of the training set. The subjects were randomly split up into 20% test set and 80% training set, 40% test set and 60% training set, and so on. The ordinate shows the quotient of correct group assignment in the test set. Considering a complete set of 225 individuals, this gives an *estimate of how many persons are needed to achieve satisfactory results.* The best rate of correct assignment (success) within the test set comes close to 95%. Furthermore, it can be seen that, using the same training set and the same amount of training for different runs of the network, not every run is equally successful. This is due to the randomly initialized weights. Hence, for each size of the training set the network was trained 20 times.

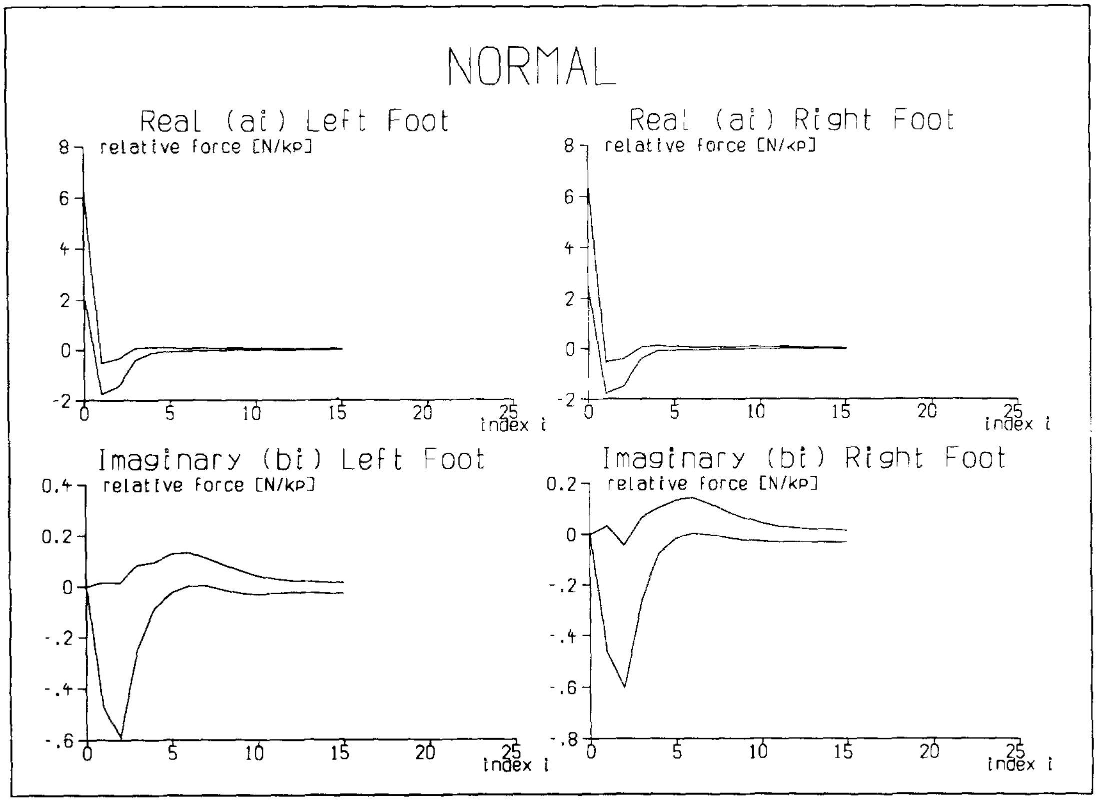


Fig. 5. Standard deviation range of the normalized Fourier coefficients of the 'healthy' group.

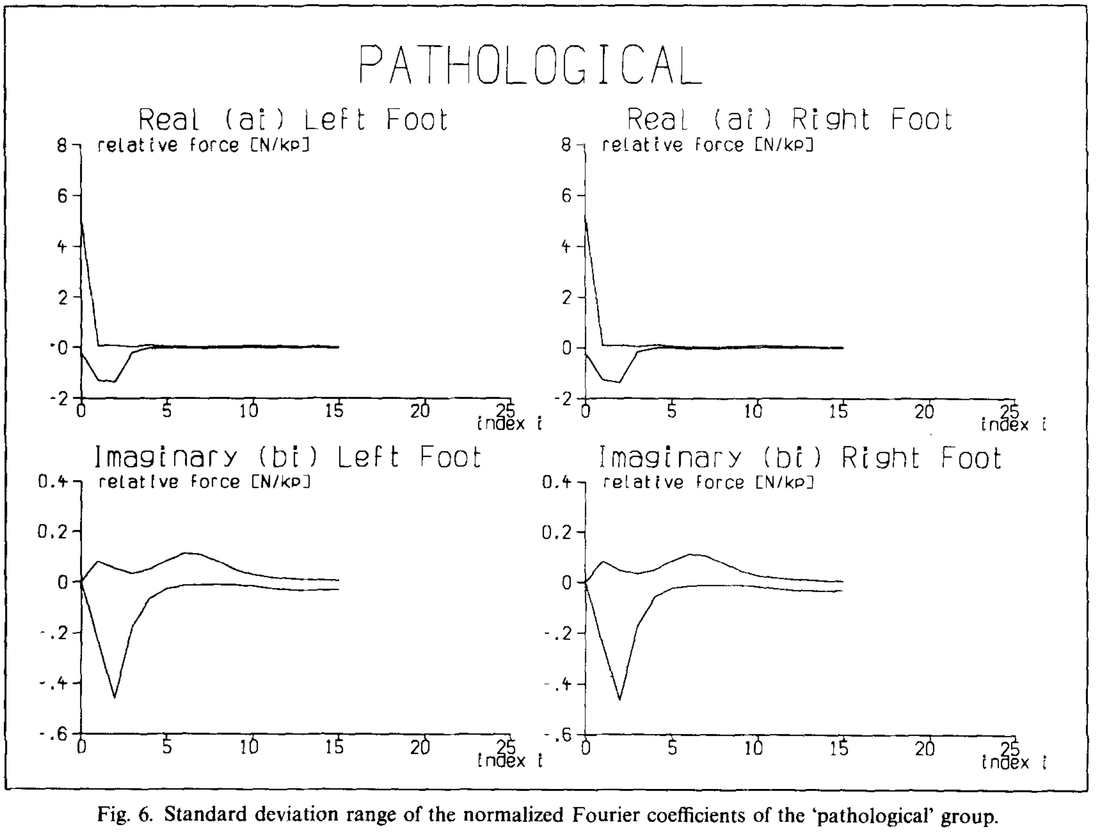


Fig. 6. Standard deviation range of the normalized Fourier coefficients of the 'pathological' group.

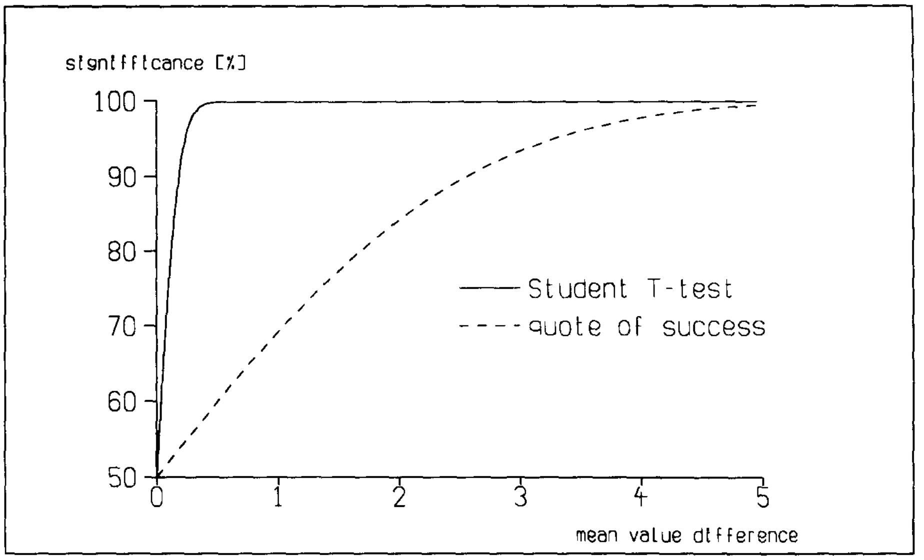


Fig. 7. Comparison of the Student $t$-test with the probability of a correct classification depending upon the difference of the mean values. Both samples comprise 100 normally distributed values with a variance of 1. A Student $t$-test detects only the probability of a difference. Decision making needs at least a difference of the mean values of four standard deviations to reach a probability of 95%.

It is important to note the absence of a correlation between the generalization ability of the network and the success within the training set, as shown in Fig. 4. This points out the necessity of testing the system's performance according to the data the network has not been trained on (i.e. its prediction abilities). The technique of splitting the data set into training and test data is similar to cross-validation known from statistics.

The standard deviation range of the Fourier coefficients of the 'healthy' and 'pathological' groups are shown in Figs 5 and 6, respectively. The data presented were preprocessed according to evaluation steps (1–4). It can be seen that *a single coefficient is not sufficient to distinguish between the two groups.* It is important to note that a difference with a statistical significance of 95% is not sufficient for the assignment of elements to a specific class. Figure 7 compares the response of a Student $t$-test with the probability of a correct classification depending upon the difference of the mean values. Both samples comprise 100 normally distributed values with a variance of 1. Decision making needs at least a difference of the mean values of four standard deviations to reach a probability of 95%. *In order to find a fairly sensible parameter, a combination of several Fourier coefficients is needed, which is exactly what the neural network does.*

The interpretation of the network output is not merely a classification of the input pattern, it includes an *estimate of how well a pattern fits into the assigned class.* Thus, an output value of 0.9 indicates a 'more pathological' pattern than the one which yields 0.6 (where 0 is considered to be 'healthy' and 1 is 'pathological'). Using this feature for more subtle classification and combining it with speech output brings about a convenient feedback utility by providing immediate answers when walking over the platforms.

## DISCUSSION

The present way of using neural networks for the classification of gait patterns comes close to statistical methods as both of them deal with probabilities. However, when using a statistical algorithm outside its defined range of applicability, a verification of the results is required.

Neural networks provide means (Le Cun, 1990) to determine which parameters are more relevant than others for a specific classification task by examining the size of the internal weights.

Besides the application for classification, neural networks can be used as multi-dimensional nonlinear transformation algorithms. This can be useful for the design of mathematical models of complex dependencies, like for simulations of how different walking speeds, different treatments, and so on, affect the shape of a specific gait pattern. Especially, for the handling of huge data sets neural networks are more convenient to apply than statistical methods. Furthermore, neural network techniques are available in hardware (e.g. Touretzky, 1990).

In clinical gait analysis there are often conflicting demands regarding engineers on the one hand and doctors or therapists on the other. Engineers would emphasize physical/technical aspects, whereas doctors have to take into account less precise, qualitative factors in order to make a diagnosis. Doctors may tend to make use of an analysis based on a simplified mechanical model of the complex biological structure. However, this may be misleading as biomechanical calculations are often determined by what is easily defined in mechanical terms rather than what is relevant for the patient.

The advantage of using neural network techniques is that the definition of the target (the state of health determined by the doctor) is clearly separated from the selection of the algorithm which operates on the data.

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