THE USE OF ARTIFICIAL NEURAL NETWORKS AND OTHER APPROACHES TO THE CLASSIFICATION OF COMMON PATTERNS OF HUMAN MOVEMENT

by

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ABSTRACT

This thesis aims to apply neural networks in the classification of human patterns of movement and to compare the accuracy of this technique with existing methods (conventional statistics and clinical assessment).

Three different examples of human movement and one of posture were chosen for study and a variety of biomechanical parameters used to describe them. The temporal parameters of gait patterns, related to speed of walking and walking with splinted knee or weighted leg, were recorded. The angular displacement of both hips and knees was measured during stepping up or down steps of five different heights. Different standing postures were studied by measuring the disposition of body landmarks associated with imagined moods of human subjects. Finally, changes of the sit-stand-sit manoeuvre due to chronic low back pain, expressed as joint movement and forces exerted on the ground, were recorded.

Patterns were classified by neural networks, linear discriminant analysis and, in the case of sit-stand patterns, by qualified clinicians. By altering the number of variables to discriminate between patterns, benefits of the above classifiers were identified.

The success in classification of the measured patterns by neural networks was found to have an accuracy at least as high as that of linear discriminant analysis. A neural network is a useful tool for the discrimination of patterns of human movements; its main advantage is the ability to deal with a large number of predictor variables.

A successfully trained and tested neural networks can easily be set up in a computer and, on the evidence presented, could be used to help clinicians diagnose or assess pathological patterns of movement.

Γηράσκω δ' αεί διδασκόμενος
Σόλων 630-560 π.χ.

"As long as I live, I am ever learning"
Solon 630-560 B.C.

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CHAPTER ONE

INTRODUCTION

1.1 Introduction

Humans make conscious or unconscious decisions through their every day life to answer questions with various level of difficulty or importance. Under perfect circumstances, a decision making procedure should have well defined rules and lead to the same results independently of its user.

Decisions which carry consensus are often difficult to achieve either because the issue hinges on people's beliefs or because the decision making procedure is difficult and ill defined. Such situations are quite common in clinical environments. It is sometimes hard to diagnose a pathology from the patient's complaints or from clinical findings. In parallel, it is difficult to assess the patients' improvement as a result of a particular treatment.

Human movements are an essential part of living activities and are affected by diseases in various degrees. Clinicians use the alteration of the normal movements to diagnose pathologies or to assess the improvement on a patient's condition. Features of movements can be extracted and used to discriminate between different conditions.

The relative importance and the amount of the clinician's observations are based on his special training, experience and subjective judgements. Such observations do not allow the same decision to be made by all clinicians. When one clinician decides that a particular condition of a patient indicates improved status, another might not agree.

Work has been done in the past aiming to overcome problems concerning this decision making. Certain pathologies have been studied and described in sufficient detail to standardise. Two characteristic examples are the application of conventional statistics and expert systems to clinical problems in an effort to improve the classification of pathological patterns.

Although great progress has been made through the years, problems still exist. New improved techniques are required to help clinicians to classify different patterns of human movement. The technological development of high performance computers promise some welcome changes in the future.

Artificial intelligence deals with the improvement of the decision making procedure. Its latest "production" is the artificial Neural Networks (NNs) which are computer software that can mainly extract features from different patterns and define rules by which they can then recognise unknown patterns.

1.2 Literature review on neural networks

NNs have been around for about a century. For most of that time, they have been the domain of a small group of artificial intelligence experts, mathematicians, and neuroscientists. In the last few years, there has been an explosive growth in interest in NNs theory and application. This growth is largely due to the work of Rumelhart et al. in 1986, who introduced new ideas and new algorithms to overcome problems that had slowed down the development of NNs.

"Work in this area is now found routinely at international meetings on subjects as diverse as image processing, robotics, signal processing, optics, medical engineering, manufacturing systems and credit scoring, all in an attempt to set new standards of performance by looking at old problems in a new way" (Lisboa, 1992).

There is an enormous volume of research publications and a creation of at least four new journals (IJCNN Conf Proc, 1987; Neural Networks, 1988; IEEE tranc on Neural Networks, 1990 and Network Computation in Neural systems, 1991) as outlets for work specifically related to this new field.

Many texts have recently been published dealing with the history (Widrow & Lehr, 1990; Eberhart & Dobbins, 1990) or principles of NNs (Cowan & Sharp, 1988; Lippmann, 1987;

Kohonen, 1988). Introductory texts have also appeared in the medical bibliography (Boone et al., 1990; Astion & Wilding, 1992; Guerriere & Detsky, 1991; Scott, 1993) and in materials related to a wide range of sciences (Hinton, 1992; Crick, 1989; Anderson, 1986; Kinoshita, 1988; Camp, 1992).

Textbooks on NNs are available for both specialists (Rumelhart & McClelland, 1986; Aleksander & Morton, 1990) and new users of NNs (Beale & Jackson, 1990).

Backpropagation networks (Rumelhart et al., 1986) are the most widely used class of NNs and there are numerous published applications of them in both the basic science and clinical literature. Basic science applications include text to speech conversion (Sejnowski & Rosenberg, 1988), classification of handwritten characters (Weideman et al., 1989), interpretation of sonar signals (Gorman & Sejnowski, 1988), interpretation of proton-NMR spectra (Meyer et al., 1991), prediction of protein secondary structure from protein sequence (Holley & Karplus, 1989), classification of chromosomes (Graham et al., 1992), detection of DNA-binding sites (O'Neill, 1991) and many more.

Backpropagation networks have also been applied to a variety of clinical problems including diagnosis of low back pain (Mann & Brown, 1991), cardiac diseases from echocardiographic images (Cios et al., 1990), acute myocardial infarction (Furlong et al., 1991; Marshall et al., 1991), Alzheimer's disease (Kippenhan et al., 1992) cancer (Maclin et al., 1991; Dawson et al., 1991; Ravdin et al., 1992).

Clinical applications of NNs are particularly interesting when the NNs' ability to predict pathological patterns is compared with those of clinicians, conventional statistics or special designed expert systems.

Asada et al. (1990) distinguished between 9 interstitial lung diseases from a set of clinical information and radiographic findings. They found that the performance of NNs was as good as that of senior radiologists and they suggested that NNs will be useful in helping inexperienced clinicians.

Baxt (1991) used NNs to identify myocardial infarction in 356 patients presented to an emergency department with anterior chest pain. He concluded that clinicians are significantly less accurate than NNs.

Fujita et al. (1992) tried to diagnose, with the use of NNs, coronary artery diseases from myocardial SPECT Bull's-eye images. Their work showed that the recognition performance of the NNs is better than that of the radiology resident but worse than that of the experienced radiologist.

Gross et al. (1990) predicted 12 neonatal cardiopulmonary disorders based on radiographic findings and suggested that NNs have the potential to make this prediction with a consistency approximately equivalent to that of paediatric radiologists.

Wu et al. (1993) found that NNs can distinguish reliably between the patterns of mammographic image features that are associated with benign and malignant lesions. Their NNs performed at a level higher than averages achieved by attending radiologists or residents and better than an experienced mammographer.

Reibnegger et al. (1991) differentiated between three distinct liver diseases on the basis of several laboratory data. According to their conclusions, the ability of NNs to correctly predict a diagnosis is at least as high as that of linear discriminant analysis and as that of a special classification tree (expert system).

Bounds et al. (1988) diagnosed the cause of low back pain and sciatica, based on various clinical symptoms. Their results showed that the overall performance of NNs exceeds that of 3 groups of doctors and at its best is able to equal the performance of an expert system.

Astion and Wilding (1992) used NNs to categorize breast lesions as either malignant or benign on the basis of the pattern of laboratory data. They concluded that the accuracy of NNs is similar to the accuracy of discriminant function analysis and drew attention the limitations of such studies arising from the small sample size used to train as well as to test the classifier. These limitations are an important issue which has not been taken into account in most of the applications of NNs to clinical problems. Most of the existing studies are considered as demonstrations of NNs rather than real applications and this issue belongs to future rather than present work (Cicchetti, 1992).

Although there are many studies concerning the application of NNs to various clinical problems, only two studies have considered the recognition of human patterns of movement in Biomechanics.

Sepulveda et al. (1993) demonstrated successfully the use of NNs to model the relationship between the activity of 16 muscles and lower-limb dynamics (joint angles or moments) during human gait. The data used in this prediction, were obtained from the existing bibliography on gait.

Holzreiter and Kohle (1993) classified the ground reaction forces of 94 healthy persons and 131 patients with various problems of the lower limbs, in order to demonstrate the advantages of NNs.

In summary, NNs are an interesting and promising subject. Most of the published work, concerning their application to pattern recognition, showed satisfactory results and are expected to be particularly important in medicine. It is reasonable for researchers working on a wide range of subjects to apply NNs to the specific needs of their work.

1.3 General aims of the study

The main aims of the present thesis are to:

1. investigate the possibility of using neural networks to classify human patterns of movement;
2. find the predictive accuracy of neural networks to classify the above patterns;
3. compare NNs' performance with that of other pattern recognition techniques such as conventional statistics or subjective assessment by clinicians; and
4. identify advantages and disadvantages of NNs when they are applied to the classification of human patterns of movement.

More specific aims, such as to find the size of the NNs which performs a better classification or the kind of movement that can be classified by NNs, are described later in the thesis in each particular application.

1.4 Hypotheses

The main hypotheses that the experimental work aims to investigate are outlined below.

1. NNs can be used to classify human patterns of movement and can be used to help clinicians.
2. NNs have a acceptable predictive accuracy.

1.5 Summary

The present thesis approaches its aims in several stages. The first stage involves a review of the principles of patterns recognition, statistics and NNs. The second stage involves the experimental work and is comprised of four studies.

Each study is an effort to apply NNs to different areas of patterns of movement such as gait (study I) and stepping patterns (study II), changes of the standing posture (study III) and finally alteration of the sit-to-stand manoeuvres due to low back pain (study IV). The reasons for choosing these patterns and the specific aims of each experimental study, are presented in each particular chapter.

Problems and thoughts arising from each study are discussed at the end of each chapter and conclusions are obtained.

Finally, the last chapter discusses in general terms the application of NNs to the recognition of human patterns of movement and presents the general conclusions and suggestions for further studies.

CHAPTER TWO

PRINCIPLES OF

PATTERN RECOGNITION

STATISTICS AND NEURAL NETWORKS

2.1 Introduction

A significant proportion of the information that humans absorb is presented in the form of patterns. Text is presented for example with complex and varied patterns in the form of strings or letters and, before reaching cognitive levels of language processing, the visual system must first solve the pattern recognition problem. That is, recognising these patterns as alphabetic characters.

This example is considered an effortless task for the visual system. However, if this task is presented to a computer, it presents an enormous complexity which is further complicated for other tasks such as processing images or speech.

Pattern recognition problems are too diffuse in nature to allow the definition of the problem in formal terms. There is, however a deep underlying unity of purpose in pattern recognition research: to build machines or procedures that will perform those tasks which have been regarded as essentially "human" (Bachelor, 1978).

The fundamental objective for pattern recognition is classification : given a pattern of some form, can this pattern be analysed to provide a meaningful categorisation of its data content? A pattern recognition system can be considered as a two stage device. The first stage is feature extraction and the second, classification.

2.1.1 Feature extraction and discriminant function

If n features of a pattern are measured, each of which is a unique feature, then a feature vector can be created algebraically which is a combination of these features. The dimensionality of the vector (number of elements in it) creates an n dimensional feature space.

Consider a simple example which is intended to distinguish good from bad students. Suppose that there are two distinctive measurements that categorise each type, such as results from exams and attendance at lectures. After making a series of results and presence measurements on a few typical examples of each type, the measurements can be plotted in two-dimensional Euclidean plane (x_1,x_2) that defines the feature space (Figure 2.1).

The measured samples form two distinct clusters on the feature space. A dividing or decision boundary can be defined (Figure 2.1) which separates the two classes. This boundary is a line given by an equation called a discriminant function which maps the feature onto a classification space by defining a place that would separate the two clusters.

There is an infinite number of boundaries that can separate the two clusters and in more complicated problems there is more than one boundary.

It is obvious that the simplest function that would separate the above clusters, is a straight line which represents a very widely used category of classifiers known as linear classifiers.

The next step is to define a rule which will assign a class to these clusters, and also assign a new pattern to one of the classes. This procedure is known as a classification procedure and the rule is known as a classifier or decision maker (James, 1985).

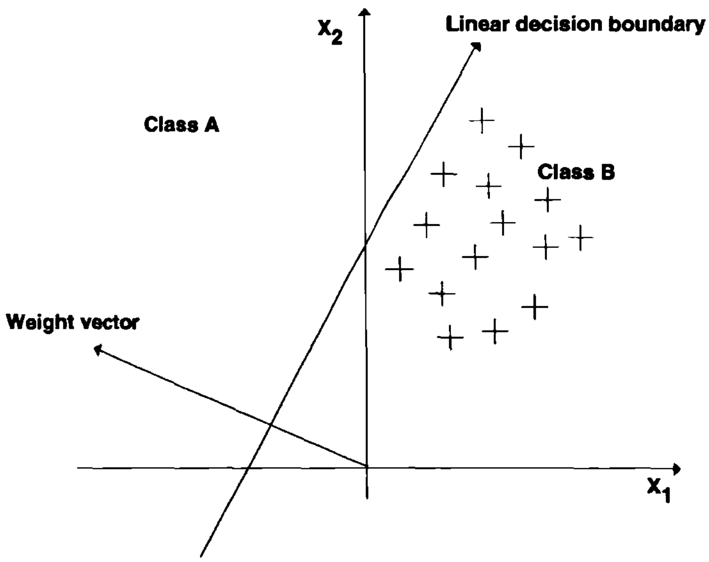

Figure 2.1

Discriminating classes with a linear decision boundary.

(adapted from Beale & Jackson, 1992)

2.1.2 Classification and linear classifiers

Classification analysis is a procedure that deals with the assignment of new unknown cases using a classification rule or classifier. The classifier uses information about the patterns that should have been already extracted from the analysis (discriminant analysis) of the structure of the groups (James, 1985).

Many classification schemes have been discussed in the literature, although two are more important: linear classifiers and nearest-neighbour classifier (Batchelor, 1978).

A nearest-neighbour classifier measures the distance on the feature space between an unclassified pattern and the closest patterns to it of each class. It assigns the unclassified patterns to whichever class it fits more closely.

As previously discussed, there are clusters that can be separated by a straight line. The orientation of the decision boundary on the feature space is found by adding a vector called weight vector W (Figure 2.1). The decision boundary defines a discriminant function f(x) of the form:

$$f(x)=\sum_{i=1}^{n} W_i X_i \tag{2.1}$$

where X : component of the pattern

W : component of the weight vector

n : dimensionality of the pattern

The output of the function for any pattern will be either a positive or negative value depending upon the value of the weight vector and the input vector. Supposing that the positive output indicates that the input vector belongs to class A and a negative output indicates class B, a decision mechanism, called a linear classifier, has been defined that simply looks for the sign of f(x) for the input value. The problem lies in actually finding a suitable weight vector that will give these results for all inputs from class A and class B (Beale & Jackson, 1990).

If a classifier is expected to be successful, it should have an effective procedure for estimating suitable values for its stored parameters. This procedure is called learning or training. Learning is central to all aspects of pattern recognition (Batchelor, 1978).

2.2 Statistical techniques

Multivariate statistics play an important role in the pattern recognition, approaching the recognition task in different ways to investigate:

1. the degree of relationship among variables
   (regression - correlation)
2. the significance of group differences
   (ANOVA - ANCOVA - MANOVA - MANCOVA)
3. the prediction of group membership
   (linear discriminant analysis)
4. the structure underlying a set of variables by assessing how the variables cluster together (Principal Components analysis) or when there are hypotheses about underlying structure, to develop this structure and to assess the fit between the data and the hypothetical structure (Factor Analysis). (Tabachnick & Fidell, 1989)

While all four above areas are overlapping, as far as feature detection is concerned, Linear Discriminant Analysis (LDA) deals with the task of classification. For the purpose of explaining the procedure of LDA, let us consider an example in which n patterns should be classified in c categories and there are p measurements from each pattern.

LDA was proposed by Fisher (1938) and forms a linear combination of the predictors to serve as the basis for assigning cases to groups. It first tests the overall relationship between groups and predictors to see if the different groups can be distinguished on the basis of the combination of the predictors. The next step is to examine the discriminant functions that compose the overall relationship.

A discriminant function score is predicted from the sum of the series of predictors, each weighted by a coefficient which maximizes differences between groups relative to differences within groups. There is one set of discriminant function coefficients for each discriminant function. This function is expressed as follows:

$$D = B_0 + B_1X_1 + B_2X_2 + \ldots\ldots + B_pX_p \qquad \textbf{(2.2)}$$

where $B_0, B_1, B_2, \ldots\ldots, B_p$: coefficients

D: discriminant score

$X_1, X_2, \ldots\ldots, X_p$: predictor variables

The maximum number of functions is limited by the number of groups or the number of predictors. It is either the number of predictors (p) or the degrees of freedom for groups (c-1), whichever is smaller. Patterns get separate discriminant function scores for each function when their own predictors are inserted into the equations.

Only a few of the functions usually carry worthwhile information. It is frequently the case that the first one or two discriminant functions account for the discriminating power, with no additional information forthcoming from the remaining functions. The contribution of each function to the discrimination is assessed and those that are not found to be reliable are omitted (Tabachnick & Fidell, 1989).

An important factor for the reliability of the classification is the number of patterns compared to the number of predictors. Lindeman et al. (1980) suggested that the total sample size should be at least 20 times the number of variables upon which the classification is to be based. When the patterns are described with a large number of predictors, a stepwise discriminant analysis is employed, which assesses each predictor individually by using a criterion (Wilk's lambda, Halal, etc). According to this criterion, each predictor is allowed or not allowed to enter the function. (Jonhson & Wichern, 1988)

At this stage, LDA describes either graphically or algebraically, the differential features of patterns from several known measurements. It tries to find "discriminants" whose numerical values are such that the predictors are separated as much as possible. This is called discrimination or separation. The next stage (classification or allocation) is to derive a rule that can be used to optimally assign a new pattern to the labelled groups. (Jonhson & Wichern, 1988)

The classification is performed by using Bayes's law (James, 1985). A pattern is classified, based on its discriminant score D, in the group for which the posterior probability is the largest. There is a simple relationship between posterior and conditions probability given by Bayes's law:

$$P(G_i \backslash D) = \frac{P(D \backslash G_i) \cdot P(G_i)}{\sum_{i=0}^{n} P(D \backslash G_i)\, P(G_i)} \qquad \textbf{(2)}$$

$P(G_i)$: prior probability, which is an estimate of the likelihood that a pattern belongs to a particular group when no information about it is available,

$P(D \backslash G_i)$: conditional probability, which estimates the probability of obtaining a particular discriminant score of D when the pattern is a member of a known group,

$P(G_i \backslash D)$: posterior probability, which is an estimate of how likely membership of a pattern in the various groups is, given the available information. (Norusis, 1988)

James (1985) stated that all the information that we have about possible group membership is contained in the set of conditional probabilities.

The following is an explanation of terms used in discriminant analysis (Norusis, 1988):

For tests concerning the predictor variables

The F values and their significance: are the same as those calculated from a one-way analysis of variance. When there are two groups, the F value is just the square of the t-value from the two-sample t-test. If the observed significance level is small, the hypothesis that all group means are equal is rejected.

Wilks' Lambda (Λ): is the ratio of the within-groups sum of squares to the total sum of squares. Large values of Lambda indicates that groups means do not appear to be different, while small values indicate the opposite.

Tests concerning the discriminant function

Eigenvalue (λ): is the ratio of the between-groups to within-groups sums of squares using the discriminant scores. Large eigenvalues are associated with "good" functions.

Canonical R: is the square root of the between-groups to total sums of squares. It is a measure of the degree of association between discriminant scores and groups.

Wilks' Lambda (Λ): is obtained as described above using the discriminant scores. This lambda is transformed to a variable which has approximately a chi-square distribution. This chi-square is used to assess the reliable discrimination of each discriminant function.

% of variance: is the % of the total between-groups variability.

Jackknifed classification: (or leaving-one-out method) involves leaving out each of the cases in turn, calculating the function based on the remaining n-1 cases, and then classifying the left-out case.

2.3 Neural networks

NNs are a class of learning systems that come under the broad classification of artificial intelligence. These computer programs make decisions based on the accumulated experience contained in successfully solved cases.

NNs go under many labels, including connectionist systems, parallel distributed processors, neurocomputers, adaptive networks, adaptive systems, collective decision circuits, natural intelligence, artificial neural systems and cognizers (Maclin et al., 1991).

They differ from the well known expert systems as far as leaning is concerned. An expert system requires an expert to find the characteristics that discriminate a pattern and to define the classification rule. However, NNs have the ability to learn from experience and to perform the feature detection as well as the classification when characteristic examples of each group of patterns are presented to them.

NNs originated from the study of the neurobiological systems but they are only loosely related to them. Although there have been major advances in the study of the neuron, NNs were developed based on the knowledge of the time. It is important, for the understanding of NNs, to refer to the neuron with particular attention to the important analogies that have been used for the development of the NNs.

2.3.1 The nervous system

The human brain is the most highly organized form of matter known with extremely developed mechanisms that are relatively poorly understood. The brain contains approximately ten thousand million (10^{10}) basic units, called neurons. Each of these neurons is connected to about ten thousand (10^4) others. (Hubel, 1979)

Neurons are cells specialized for the reception, integration and transmission of information. Each neuron has a body, or soma and processes, or neurites. Receptor neurites, known as dendrites, are usually numerous while each soma has only one efferent process, the axon. (Figure 2.2). Unidirectional communication occurs between neurons at the synapses, generally sited between the axon of one neuron and the cell surface of another. (Wilkinson, 1992)

The operation of the neuron is not a fully understood process at a molecular level, although the basic details are relatively clear. One of its main characteristic, known as the law of "all-or-none", can be summarised in few words. If enough active inputs are received by the neuron through the synapses and the resting potential within the neuron rises above a certain critical threshold, then the neuron will be activated and "fire" producing a voltage pulse called action potential; if not, then the neuron will remain in its inactive, quiet state. The threshold is always -70mV and the magnitude of the action potential is constant whatever is the rise of the resting potential. (Stevens, 1979)

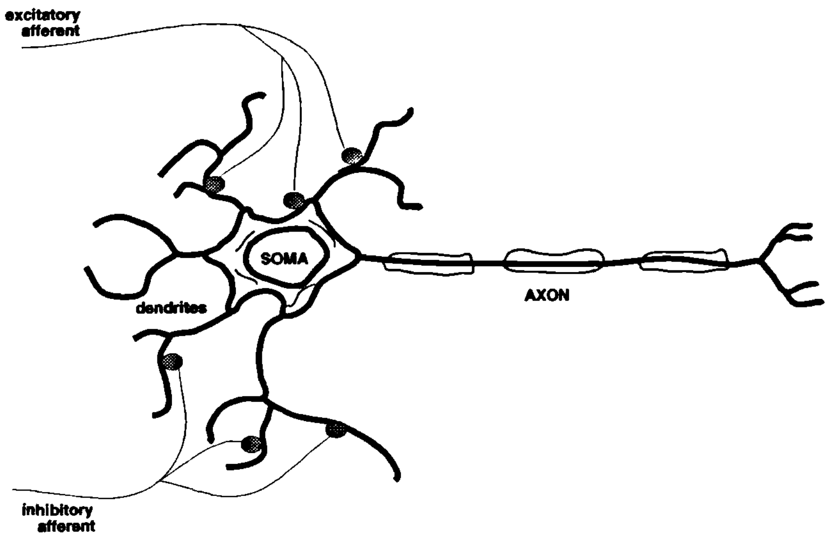

Figure 2.2

The basic neuron (multipolar).

Axons may have collateral branches and end by synapses either with other neurons or with effectors at neuromuscular or neuroglandular junctions. (Figure 2.3). When the potential of the presynaptic membrane is raised sufficiently by the action potential, chemicals (neurotransmitters or neuropeptides) are released by the presynaptic membrane and diffuse across the gap (synaptic cleft). These chemicals are received by the postsynaptic membrane. If the amount of neurotransmitters is sufficient, then a voltage pulse is produced. It may need more than one action potential before the presynaptic membrane is triggered or the postsynaptic membrane may need more neurotransmitters, in order to generate an action potential, than that already released by the presynaptic membrane.

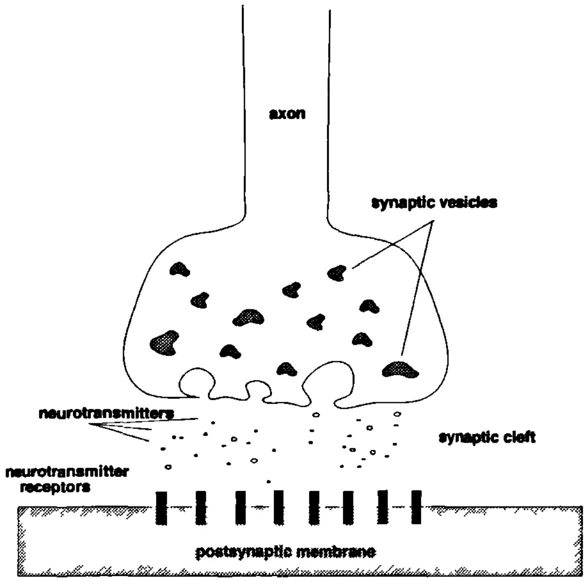

Figure 2.3

The synapse.

Some synapses excite the neuron they affect, whilst others serve to inhibit it. A single neuron may have many synaptic inputs (inhibitory or excitatory) and may send many synaptic outputs to other cells. (Eccles, 1965)

Hebb's theory, and so called Hebbian learning, is one of the fundamental principles governing learning procedure in biological systems. Desirable behaviour is reinforced while an undesirable one is discouraged. Learning is thought to occur when modifications are made to the effective coupling between one cell and another, at the synaptic junction. This seems to be achieved by facilitating the release of more neurotransmitters (Hebb, 1949).

2.3.2 Modelling the neuron

The main features of the neuron can be summarised as follows:

a. the output of a neuron is either "on" or "off" (step function)

b. the output of a neuron depends only on the inputs. A certain number of inputs must be "on" to make the neuron fire.

McCulloch and Pitts (1943) "translated" the above functions to mathematical equations and modelled the artificial neuron or unit. Much of today's research is based on this unit which is a model, and not a copy, of a real neuron because it only performs a few basic functions of it. In the artificial neural systems the word neuron is translated to a processing element or unit, dendrites to combining functions, soma to transfer function, axons to element output and synapses to weights. Combining functions and weights are referred as connections.

The processing element, shown in Figure 2.4, performs a weighted sum of its inputs, compares this to some internal threshold level, and turns "on" only if this level is exceeded. This can be expressed with equation 2.4. The internal threshold can be taken out of the body of the model and be connected to an extra input value that is fixed to be "on" all the time. The extra input of +1 is multiplied by a weight equal to minus the threshold value, $-\Theta$, and added in (this is known as biasing the neuron). In this case the equation 2.4 can be replaced by equation 2.5.

$$O=f_h\sum_{i=1}^{n} W_i X_i-\theta \tag{2.4}$$

$$O=f_h\sum_{i=0}^{n} W_i X_i \tag{2.5}$$

where O : output n : number of inputs

W : weights X : input

f_h : step function Θ : internal threshold

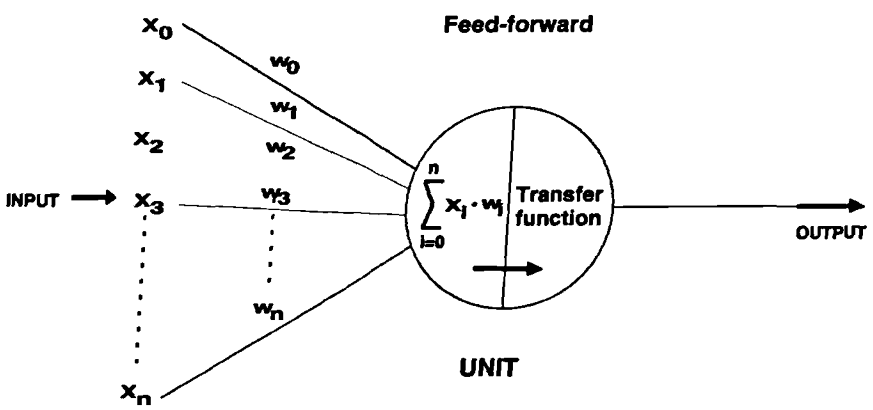

Figure 2.4

The artificial neuron (x: input variable, w: weight and n: number of features of the pattern)

Frank Rosenblatt (1962) connected up neurons in a simple fashion (in one layer) and named them as "perceptrons". He trained his perceptrons to perform different tasks using Hebbian learning. He forced them to learn from their mistakes by adjusting their weights. Whenever an input pattern is presented to a perceptron, an output is produced. If the output is correct, no adjustments is made on the weights. However, if it is incorrect, the weights of all activated synapses are increased, if the unit should be activated, and are decreased if the opposite obtains. Since the learning is guided by knowing what should be achieved, it is known as a supervised learning.

Widrow and Hoff (1962) proposed a learning rule known as the Widrow-Hoff or delta rule, which calculates the difference between the weighted sum and the required output, and calls that the error. Weights adjustment is then carried out in proportion to that error. Neurons using this learning algorithm are called adalines.

Perceptrons and adalines are linear classifiers that generate a line to partition the pattern space into two classes by adjusting the values of the element of the weight vector (Beal & Jackson, 1992).

Minsky and Papert (1969) stated the limitations to the capabilities of perceptrons. Any problem that is linearly inseparable cannot be solved by a single-layer perceptron.

An example of the latter, is the exclusive-or (XOR) problem where an output is produced only if either one or the other of the inputs is on, but not if both are off or both are on (parity problem).

2.3.3 The multilayer Perceptron

The parity problem can be overcome if several perceptrons are used, each set up to identify small, linearly separable sections of the inputs, then combining their output into another perceptron, which would finally indicate the class to which the input belongs. Figure 2.5 shows the solution of the parity problem.

Input	Output
0 0	0
0 1	1
1 0	1
1 1	0

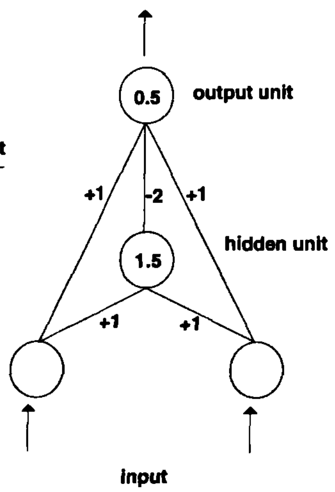

Figure 2.5

A solution to the XOR problem.

(adapted from Rumelhart et al., 1986)

Such an arrangement of perceptrons in layers, is called a multilayer perceptron neural network. Figure 2.6 shows a basic neural network which has three layers; an input layer, an output layer and a layer in between called the hidden layer. Each perceptron or unit is connected to all units of the next layer. A neural network may possess any number of layers and any number of units in each layer. Hidden layers are essential for solving most problems and may be seen as a place where the input data is partially labelled before the output layer needs to come to a final decision. Hence the hidden layers are said to be required to form internal representations of the training set which are not provided by the trainer. Usually, the input nodes do not process; they just serve to pass on the inputs to the hidden layer.

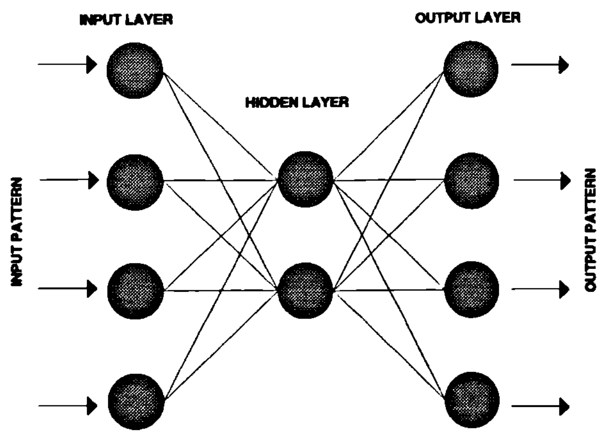

Figure 2.6

The multilayer perceptron.

There are two kinds of NNs according to their shape: feed-forward (or associative) and feedback (autoassociative or recurrent) networks. A feed-forward network is one which processes information in one direction, from the input to the output. That is, there are no closed loops. A feedback network is one where information can find its way around a loop from the output back to the input. Figure 2.7 shows some examples of NNs with different shapes. (Aleksander & Morton, 1990)

If feedback connections of a recurrent network act for a set number of training cycles, then the network can be replaced by a feed-forward one. Figure 2.8 shows how a recurrent network (Figure 2.8A) can be replaced by a feed-forward (Figure 2.8B) with identical behaviour over a set number of training cycles (Rumelhart et al., 1986).

Multilayer perceptron neural networks are unable to be trained. The perceptrons in the second layer do not know which of the real inputs were on or not. They are only aware of inputs from the first layer. This problem is known as the credit assignment problem or hard learning problem, since it means that the network cannot determine which of the weights should be increased and which should not, and so it cannot find out what changes should be made to produce a better solution. (Aleksander & Morton, 1990)

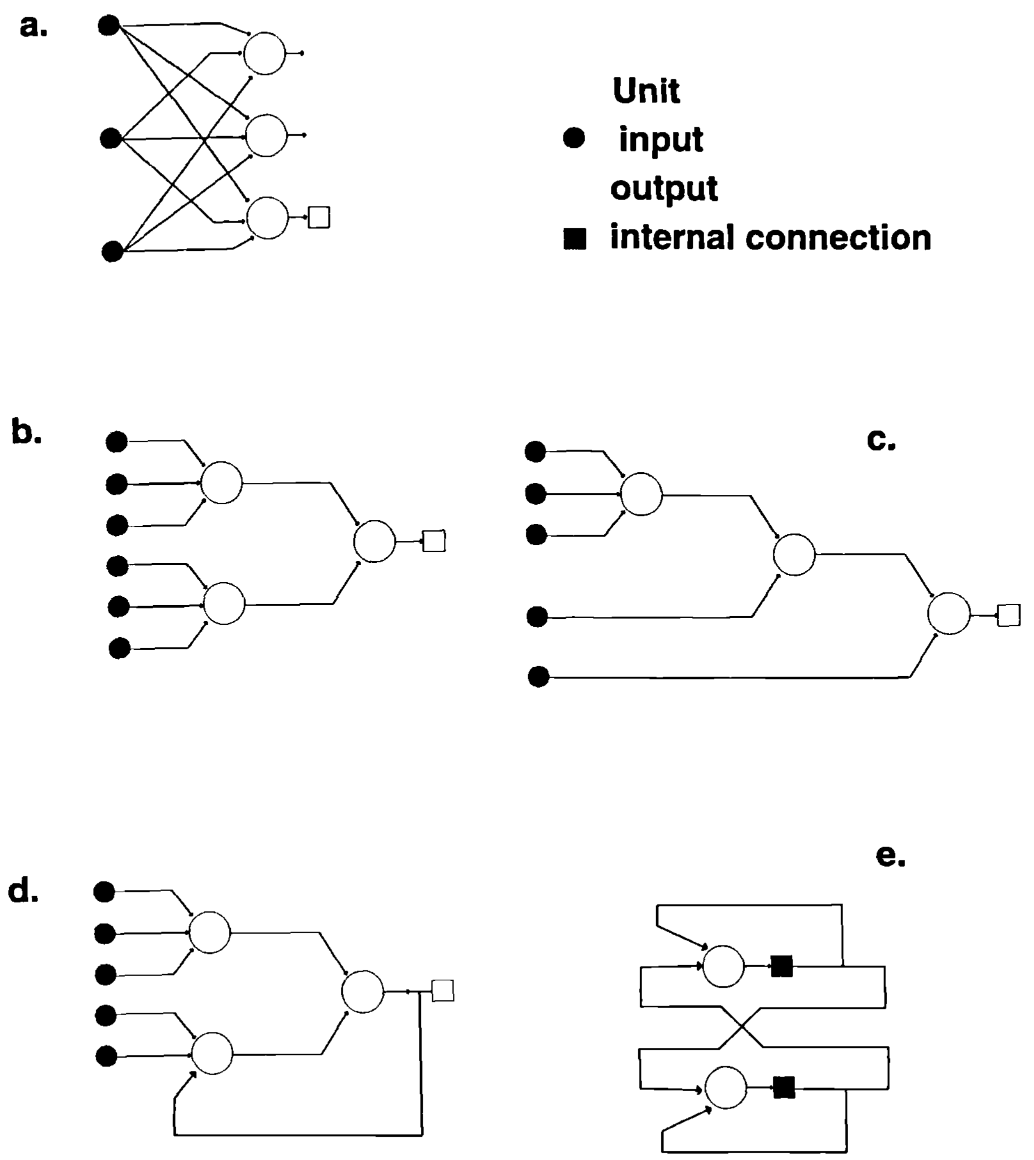

Figure 2.7

Examples of NNs with characteristic structures:

a. a single layer network (feed-forward),

b. & c. multilayer networks (feed-forward),

d. an autoassociative network (feedback),

e. a fully autoassociative network (feedback)

(adapted from Aleksander & Morton, 1990).

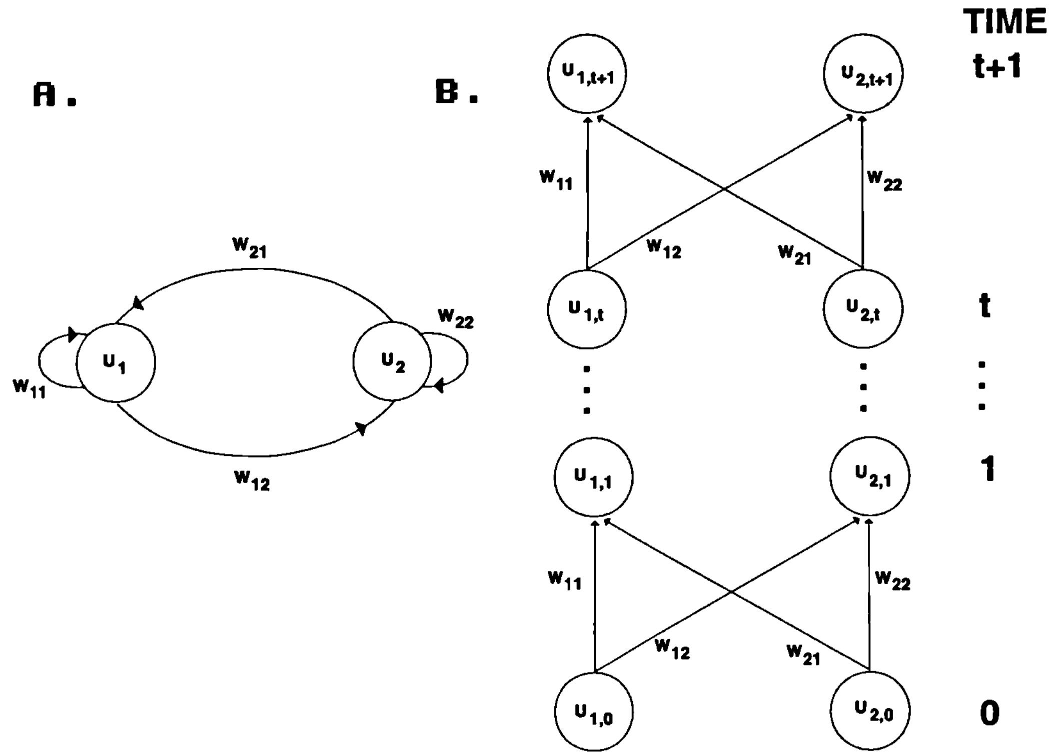

Figure 2.8

A comparison of a recurrent network and a feed-forward network with identical behavior. A: a completely connected recurrent network with two units. B: a feed-forward network which behaves the same as the recurrent network. In this case, there is a separate unit for each time step and all the weights are the same for all layers.

(adapted from Rumelhart et al., 1986)

The solution of the credit assignment problem was given by replacing the thresholding step function by a non-linear sigmoid function which is given by equation 2.6 (Rumelhart et al., 1986). This allows the output from the neuron to be related to its inputs in a more useful and informative way. Figure 2.9 shows the step as well as the sigmoid function.

$$O=\frac{1}{1+e^{-\sum_{i=0}^{n} w_i x_i}} \tag{2.6}$$

Where

W: weights O: output

X: input n: number of inputs

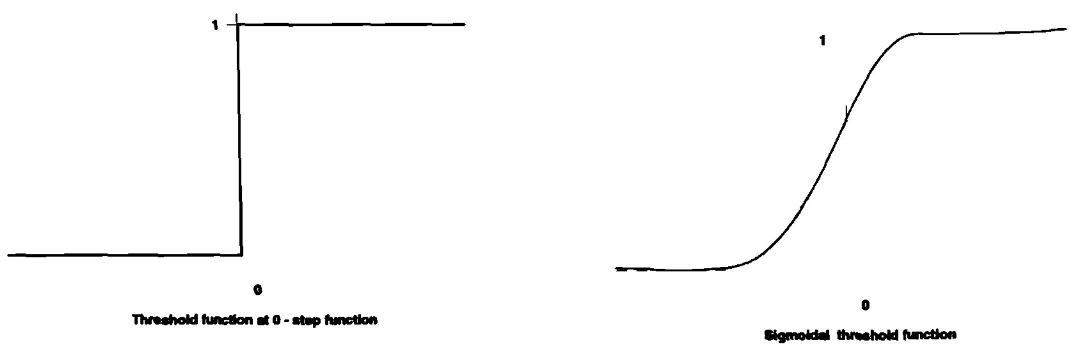

Figure 2.9

Two possible thresholding functions.

Because the single-layer perceptron has been modified by changing the step function and adding a hidden layer, the learning rule is forced to be altered. Rumelhart et al., (1986) suggested a new learning rule for neural networks called the "generalised delta rule" or "backpropagation rule" which is a steepest descent method of computing the weights that minimize the total Root Mean Squared (RMS) error over a set of training vectors. The total RMS error is given by equation 2.7. The introduction of this new learning rule signalled the renaissance of the whole subject.

$$RMS=\sqrt{\frac{\sum_{n}\sum_{i}(t_i-o_i)^2}{n\cdot i}} \qquad \textbf{(2.7)}$$

where o : output t : target output

i : number of output units

n : number of patterns

The error of a neural network was defined as the difference between the network's current output and the correct output that should be achieved. The generalised delta rule calculates the value of the error function for all the inputs, and then back-propagates the error from one layer to the previous one. Each unit has it's weights adjusted so that it reduces the value of the error function. The problem of adjusting the connections of the units in the hidden layer was solved by adjusting them in direct proportion to the error in the units to which it is connected.

The two important parameters during training is the momentum term (a) which determines what portion of the previous weight changes will be added to the current weight changes and the learning rate (n) which determines what percentage of dictated weight change will actually be made. The final adjustment of the weights is show by equation 2.8.

$$\Delta W_{ij}(t+1) = n(\delta_i o_j) + \alpha \Delta W_{ij}(t) \qquad \textbf{(2.8)}$$

where n : learning rate α : momentum term

$\delta_i o_j$: current weight change dictated by the Generalized Delta rule,

$\Delta W_{ij}(t)$: previous weight change.

2.3.4 Using neural networks

The first problem to be solved is to define the shape and size of the network. The size of the input layer (number of units) depends on the size of the input pattern (number of measured variables). The size of the output layer depends on the number of the classification categories in which the input patterns should be classified, as well as on how these categories will be expressed. If there are two categories, either one or two output units can be used. When one unit is used, its negative values represents one category and its positive the other one.

The hidden layer contributes significantly to the performance of the network and it was found that one hidden layer is sufficient to perform the pattern recognition task (Gorman & Sejnowski, 1988). Varying the number of hidden units creates a difference in the network's performance which tends to increase as the number of hidden units increases, until a limit is reached where performance decreases (Gorman & Sejnowski, 1988). According to Mirchandani (1989) the number of hidden units can be determined as a function of the number of separable regions in the input space and the dimension of the input space. In practice the size of the hidden layer is determined empirically. A random size is chosen and its performance is compared with that of increased or decreased sizes. (Astion & Wilding, 1992)

During the training of a network, a training file is required which must contain input patterns with known outputs. Input variables should be within a small range, usually of one unit and normalisation is applied to variables (offset the mean to zero and scale data within a specified range i.e. from 0 to 1 or from -5 to +5).

The network classifies all inputs of the training file and calculates its error. A pass of the whole training file through the network is called a training cycle. After each training cycle, the network adjusts its weights and another training cycle is initiated. This procedure continues until the error of the network approaches the zero value. Networks that are unable to correctly classify all input patterns continue to train indefinitely until training is terminated by the user. Any network is able to learn a training file with acceptable accuracy if it is left to be trained indefinitely but will then be unable to recognise unknown patterns. This is known as the overtraining problem (Astion et al., 1993).

Networks that can generalise are those which have as small number of hidden units as possible and are validated with a verification set as training progresses. The NNs are validated, like any other classification technique, using the cross-validation procedure or the jackknifed classification. (Astion et al., 1993)

During the cross-validation technique the accuracy of the classifier is tested by assigning new patterns which have not been used during training. During the jackknifed classification, one pattern is excluded from the sample and the classification function is defined on the remaining patterns. The excluded pattern is used to test the classification function and then is included in the sample while another pattern is excluded. This continues until all patterns have been used to test the classifier.

There are NNs like the Kohonen self-organising (Kohonen, 1984) and the Hopfield networks (Hopfield, 1982), which use unsupervised learning techniques. These NNs try to find characteristics of the patterns that separate them into classes without knowing the correct classes in a procedure. This is similar to Principal Component and Factor analysis. (Aleksander & Morton, 1990)

In the present study, NNs were constructed by using version 3.0 of the SAIC ANSim neural network software. The hardware was run on an IBM compatible PC with 8 Megabytes of RAM. Recurrent NNs of the above software, allow each unit of the hidden and the output layer to feedback to themselves and to other units of the same layer. These feedback connections act five time before the error of the network is calculated. That is, the feedback network is a feed-forward one.

CHAPTER THREE

STUDY I

The use of neural networks to distinguish patterns of human gait under normal and abnormal conditions

3.1 Introduction

"Human locomotion is a phenomenon of the most extraordinary complexity" (Saunders & Inman, 1953). Its primary objective can simply be stated as the translation of the body, from one point to another by means of a bipedal gait, along a pathway arguably requiring the least expenditure of energy. Gait is analysed for diagnostic purposes as well as to assess whether a patient has a reduced walking ability and whether a course of treatment has produced a real restoration of function.

Gait analysis is mainly comprised of the combination of three components, namely: visual observation, kinetic features (i.e. joint movements) and dynamic measurements (i.e. EMG).

Visual assessment is the assessment of the body's movements (pelvic sagittal rotation, pelvic coronal tilt, knee and hip flexion, knee and ankle interaction and lateral pelvic displacement), in three planes, during the gait cycle (Saunders & Inman, 1953).

Quantitative measurements of gait include the time-distance measurements and joint angles during the gait cycle. The time (T) between successive placements of the same foot is the cycle time (CT). The gait is in double-support phase (DSS) for a duration, tds, when both feet are touching the ground. Single support phase of one foot with a duration, tss, is the period of time when only one foot is in contact with the ground. For example, when the right foot is in contact with the ground (right stance phase) the left one is in the left swing phase moving forward to create the next step. Both of these phases are equal in terms of time. Two single support phases exist (SSP), the right (RSS) and left (LSS) single support phase for the right and left foot respectively. Figure 3.1 illustrates the relationship between the spatial-temporal components of the walking cycle (Murray, 1967).

When the gait is disturbed, the relationship between DSS and SSP's may differ. If the R. knee is fixed in an extended position, the range of the pelvic coronal tilt and R. hip abduction should be increased in order to move the R. lower limb forward. If a weight is strapped on the R. ankle then the muscular system should change its performance in order to control the limb during the right swing phase of walking. Both situations alter the normal walking cycle in a different way producing two abnormal gait patterns. The relationships between the temporal parameters are changed and these changes can be used to discriminate these two gait patterns.

While many parameters of gait can be measured, the temporal and spatial parameters have been shown to be of particular value as diagnostic indicators (Salem & Murdoch, 1985).

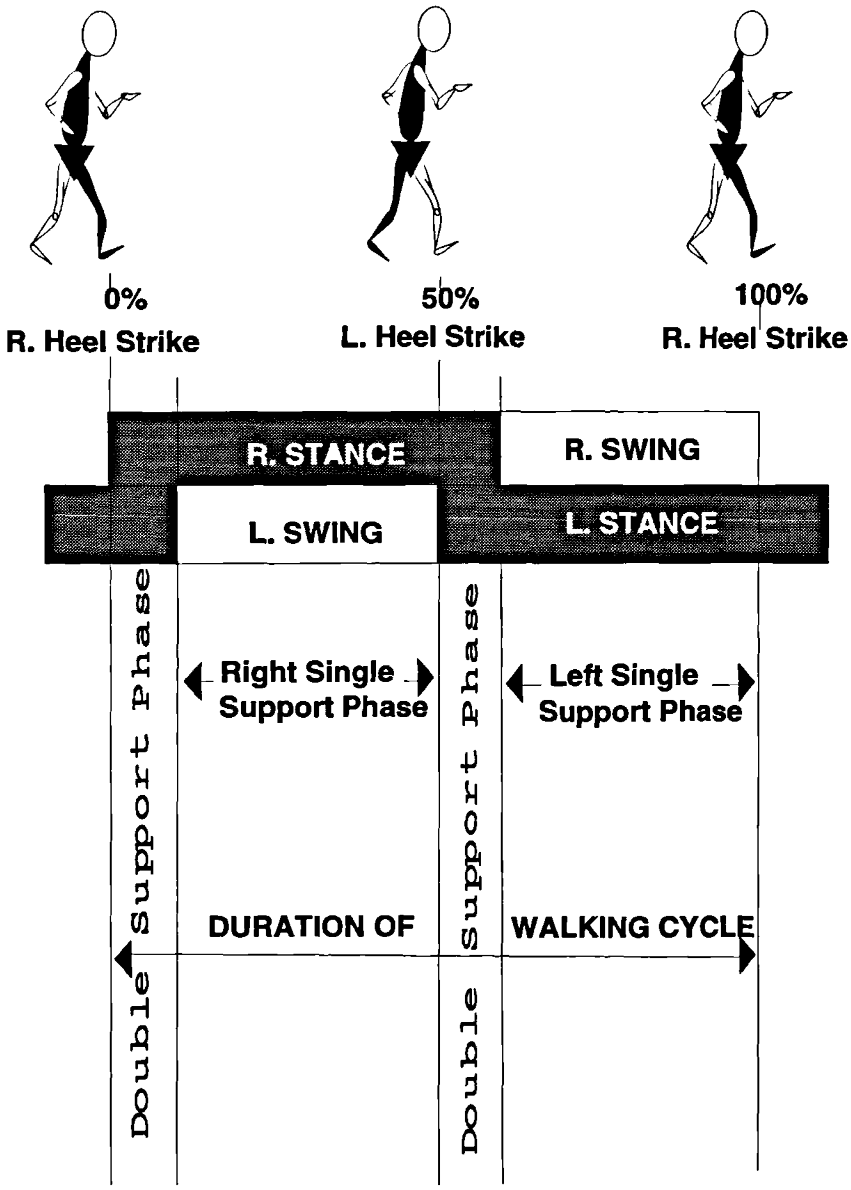

Figure 3.1

The relationship between spatial and temporal components of the walking cycle.

(adapted from Murray, 1967)

3.1.1 Statement of problem

As explained by Grieve (1969), there is a communication problem concerning gait assessment. This problem may not affect the diagnosis or the treatment but it allows only a subjective impression of progress which is used to prescribe a correct course of treatment. The comparison of gait charts before and after therapy to evaluate progress, or comparison between the subject's gait charts and the gait chart of normal walking, are possible approaches to this problem.

The ability to discriminate gait patterns as accurately as possible, is of interest if it obviates the use of subjective judgements and allows a better reporting of gait assessment.

3.1.2 Research outline: aims and objectives

The present study aims to :

a. discriminate gait patterns with the use of NNs;

b. apply NNs to the classification of patterns of movements which are described with the use of their temporal parameters and with a small number of variables;

c. compare the performance of NNs with that of LDA;

d. investigate the performance of NNs in which the number of the classifying categories is greater or almost equal to the number of the predicted variables.

3.2 Materials and method

An experiment was designed and carried out to measure the temporal parameters of gait (DSS, RSS and LSS) during walking with seven different speeds, under three different conditions.

3.2.1 Subjects

Twenty unpaid volunteers, ten male and ten female, staff or students of this institute, took part in the experiment. None had an history of locomotor disturbance. The physical characteristics of subjects are summarized in Table 3.1 and more details are included in Appendix A: Table A1.

Table 3.1: Physical characteristics of subjects.

		Males	**Females**	**Overall**
N		10	10	20
Age (years):	**Mean**	24.7	26.7	25.7
	SD	3.6	6.6	5.3
	Max	32	43	43
	Min	19	21	19
Weight (Kg):	**Mean**	73.8	66.3	70.1
	SD	9.4	10.8	10.6
	Max	93	85	93
	Min	60	51	51
Stature (m):	**Mean**	1.76	1.69	1.72
	SD	0.05	0.06	0.07
	Max	1.87	1.78	1.87
	Min	1.69	1.62	1.62

3.2.2 Experimental equipment

The equipment used consisted of a BBC microcomputer, an A/D converter (CED 1401, Intelligent Interface, Cambridge Electronic Design Ltd), two light-sensors, one metal walkway (5.45m long) and different sized pairs of shoes with electrodes attached.

An optical sensor was placed at each end of the metal walkway at shoulder height to measure the time taken to traverse the distance after a steady speed had been reached. Speeds of walking were calculated in units of statures per second.

The sole and heel of each shoe were covered with aluminium foil. The shoes and the walkway were connected to a network of resistors and a power supply. The double support, single support and swing phases of each limb generated different voltages in the circuit which were fed to an A/D converter of a BBC microcomputer.

Software (BBC Basic) was written to control the acquisition of the experimental data (e.g. subject's name, weight, height, speed of walking and temporal parameters of walking). A diagram of the experimental apparatus is shown in Figure 3.2.

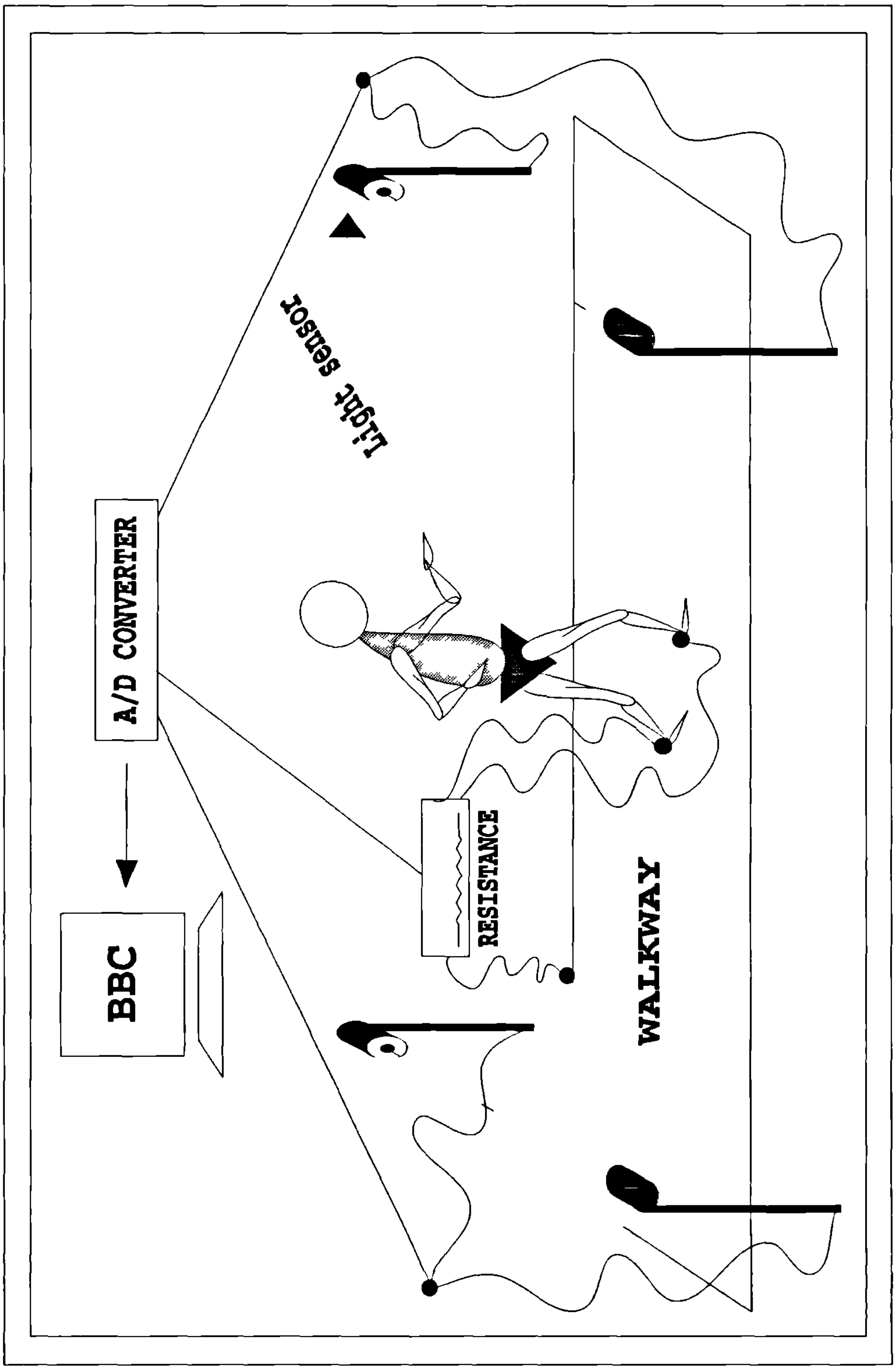

Figure 3.2
The experimental apparatus

3.2.3 Experimental procedure

Stature and weight were measured at the beginning of the test after explaining the experiment to the subject and obtaining informed consent. The subject wore a pair of suitably sized shoes fitted with foil contacts.

The experiment was divided into three parts according to the different conditions (CD) of walking:

CD1 : normal walking,

CD2 : walking with a 3.5 Kg mass strapped securely and comfortably to the right ankle and

CD3 : walking with the right knee fixed in an extended position by means of a knee brace.

For each of these conditions the subject was asked to walk at seven different speeds (0.30, 0.45, 0.60, 0.75, 0.90, 1.05, 1.20 statures/sec), each within an acceptable range of ±0.05. Walking commenced 7m from the beginning of the metal walkway so that a steady state of rhythm and speed existed during data collection. A period of five minutes was given for the subject to become familiar with a new walking condition before data collection.

The subject had to walk as many times as was necessary in order to achieve a desired speed. The same procedure was carried out for all the selected speeds and all the conditions of walking. The procedure for each subject took approximately one hour. The mean value of the obtained speeds are summarised in Table 3.2.

Table 3.2: The obtained speeds of walking in statures/sec

	MALES				FEMALES			
	Mean	**SD**	**Max**	**Min**	**Mean**	**SD**	**Max**	**Min**
Condition 1:								
spd 0.30:	0.32	0.03	0.35	0.26	0.30	0.02	0.35	0.28
spd 0.45:	0.43	0.01	0.46	0.41	0.44	0.02	0.49	0.40
spd 0.60:	0.60	0.03	0.64	0.56	0.61	0.03	0.65	0.56
spd 0.75:	0.74	0.01	0.76	0.71	0.75	0.02	0.79	0.70
spd 0.90:	0.90	0.01	0.93	0.88	0.88	0.02	0.93	0.85
spd 1.05:	1.03	0.01	1.05	1.01	1.05	0.03	1.09	1.00
spd 1.20:	1.19	0.02	1.23	1.16	1.20	0.03	1.25	1.16
Condition 2:								
spd 0.30:	0.32	0.03	0.35	0.25	0.32	0.01	0.35	0.29
spd 0.45:	0.44	0.01	0.47	0.41	0.43	0.03	0.48	0.40
spd 0.60:	0.60	0.02	0.64	0.56	0.59	0.02	0.63	0.55
spd 0.75:	0.75	0.02	0.79	0.72	0.74	0.03	0.80	0.70
spd 0.90:	0.89	0.02	0.92	0.86	0.90	0.03	0.95	0.86
spd 1.05:	1.05	0.02	1.10	1.02	1.03	0.03	1.08	1.00
spd 1.20:	1.19	0.02	1.24	1.16	1.19	0.04	1.25	1.15
Condition 3:								
spd 0.30:	0.31	0.01	0.34	0.27	0.31	0.02	0.34	0.28
spd 0.45:	0.44	0.02	0.49	0.43	0.45	0.02	0.49	0.41
spd 0.60:	0.62	0.01	0.65	0.60	0.61	0.02	0.65	0.56
spd 0.75:	0.75	0.02	0.79	0.72	0.76	0.02	0.79	0.71
spd 0.90:	0.92	0.01	0.94	0.89	0.88	0.03	0.95	0.85
spd 1.05:	1.03	0.02	1.07	1.00	1.05	0.03	1.10	1.01
spd 1.20:	1.19	0.03	1.23	1.16	1.17	0.01	1.21	1.15

*spd : speed

The actual speeds of walking observed for each subject, are included in Appendix A: Table A2a and A2b.

3.2.4 Data presentation

The data obtained, which are included in Appendix A: Table A3, were used for graphical representation of the speed or conditions of walking.

Figure 3.3 shows the relationship between the DSS and the average value of the SSPs for seven walking speeds under CD1. Figure 3.4 shows the relationship between the mean value of DSS ±SD and the SSPs ±SD for seven walking speeds under CD1. For Figure 3.3 and 3.4 the average value of RSS and LSS have been used because the walking is normal and it is supposed to be symmetrical (RSS≈LSS). These Figures show that as the values of DSS and SSPs increase, the speed of walking decreases.

Figure 3.5 shows the duration of walking cycle in relationship to seven walking speeds under three walking conditions. Figure 3.6 shows the mean value of the walking cycle ±SD for seven walking speeds under three walking conditions. Figure 3.5 and 3.6 show that as the speed of walking increases the cycle time decreases for all the walking conditions.

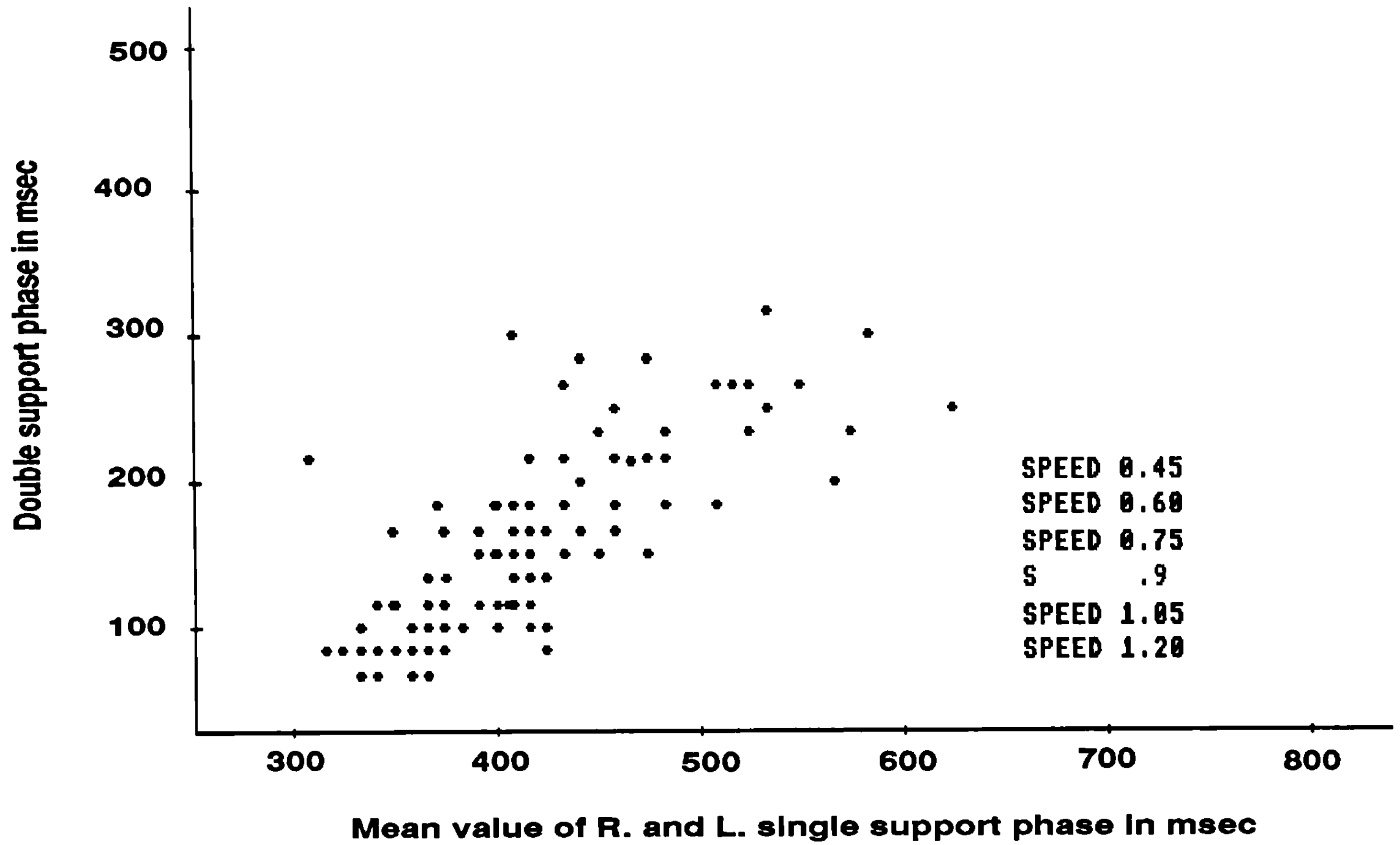

Figure 3.3

The relationship between DSS and the average value of the SSPs for the seven walking speeds under CD1 (data collected from 20 subjects).

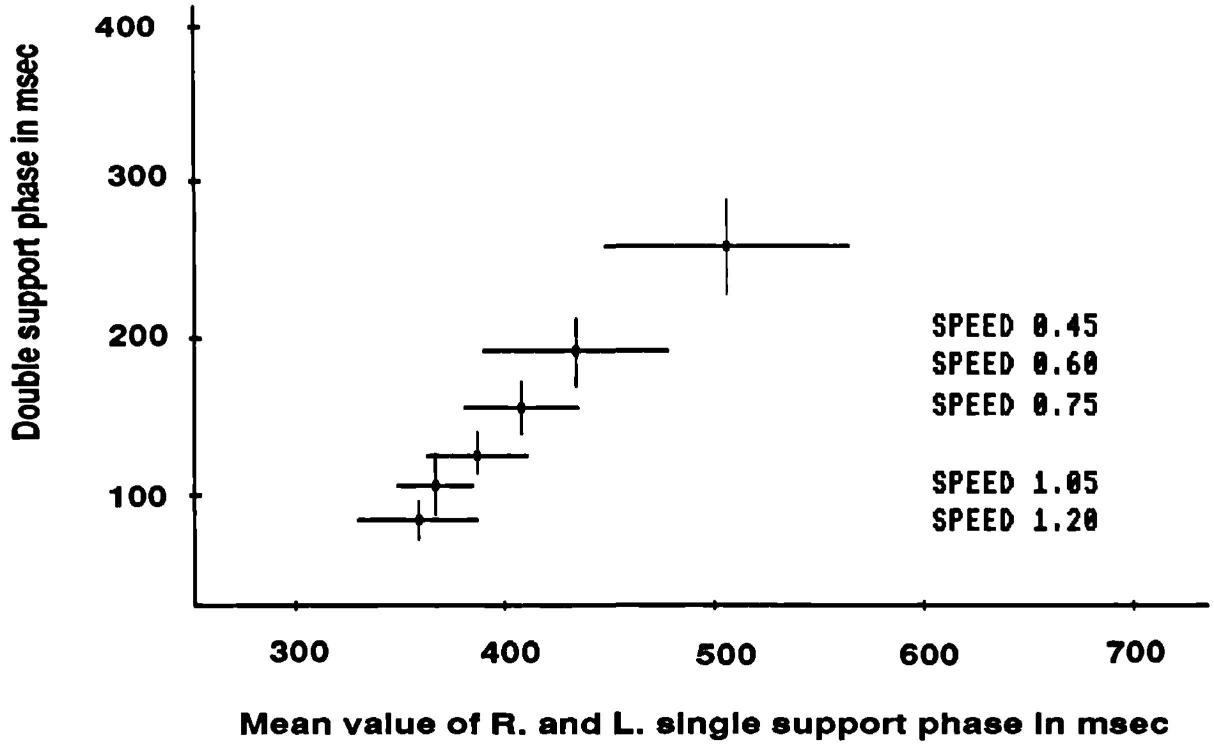

Figure 3.4

The relationship between the mean values of DSS ±SD and the SSPs ±SD for seven walking speeds under CD1 (data collected from 20 subjects).

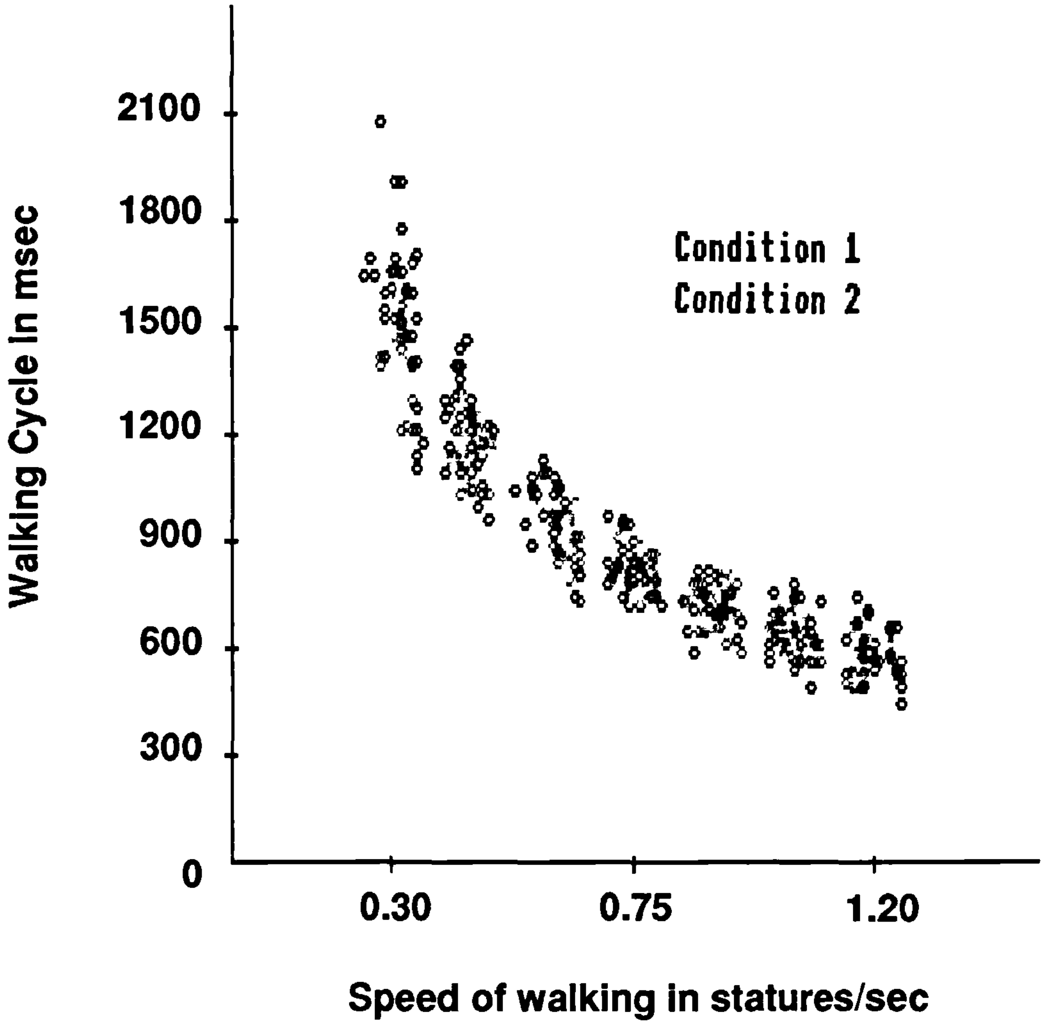

Figure 3.5

The duration of walking cycle in relationship to seven walking speeds under three walking conditions (data collected from 20 subjects).

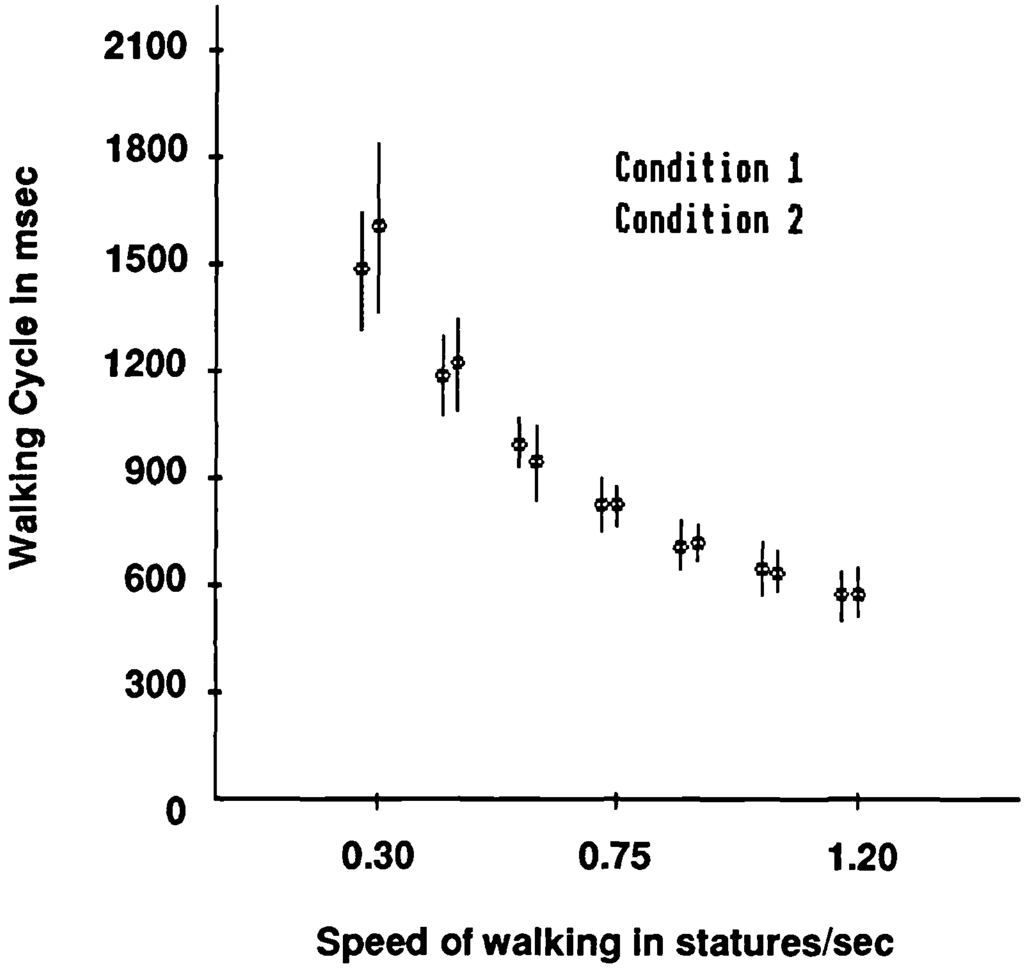

Figure 3.6

The mean value of the walking cycle ±SD for seven walking speeds under three walking conditions (data collected from 20 subjects).

3.2.5 Data analysis using NNs and LDA

Data from group 1 of five men and five women (DG1) was used for classification (training) and that of the remainder (DG2) for recognition (testing). The procedure was reversed and the results pooled in order to test all subjects. Successful pattern recognition either correctly identified the speed in a selected walking condition (Case 3.1) or the walking condition at a selected walking speed (Case 3.2). The classification techniques used were NNs and LDA.

Direct LDA was performed using Minitab (statistical software, release 7). Sample sizes were used to estimate prior probabilities of group membership.

Normalization was applied to all data within a specific range of ± 0.5 prior to analysis by the NNs. The positive answer of the network was +0.5 and the negative was -0.5. The learning rate for each NN was 0.02 and its momentum factor was 0.9. All the weights of the NNs were initialised to ±0.1. Several NNs were constructed in which the size of the hidden and the input layer was varied. The two NNs finally selected were as follows:

3.2.5.1 Case 3.1

A three layered recurrent NN (Figure 3.7) was constructed with 3 input, 9 hidden and 7 output units. The input was

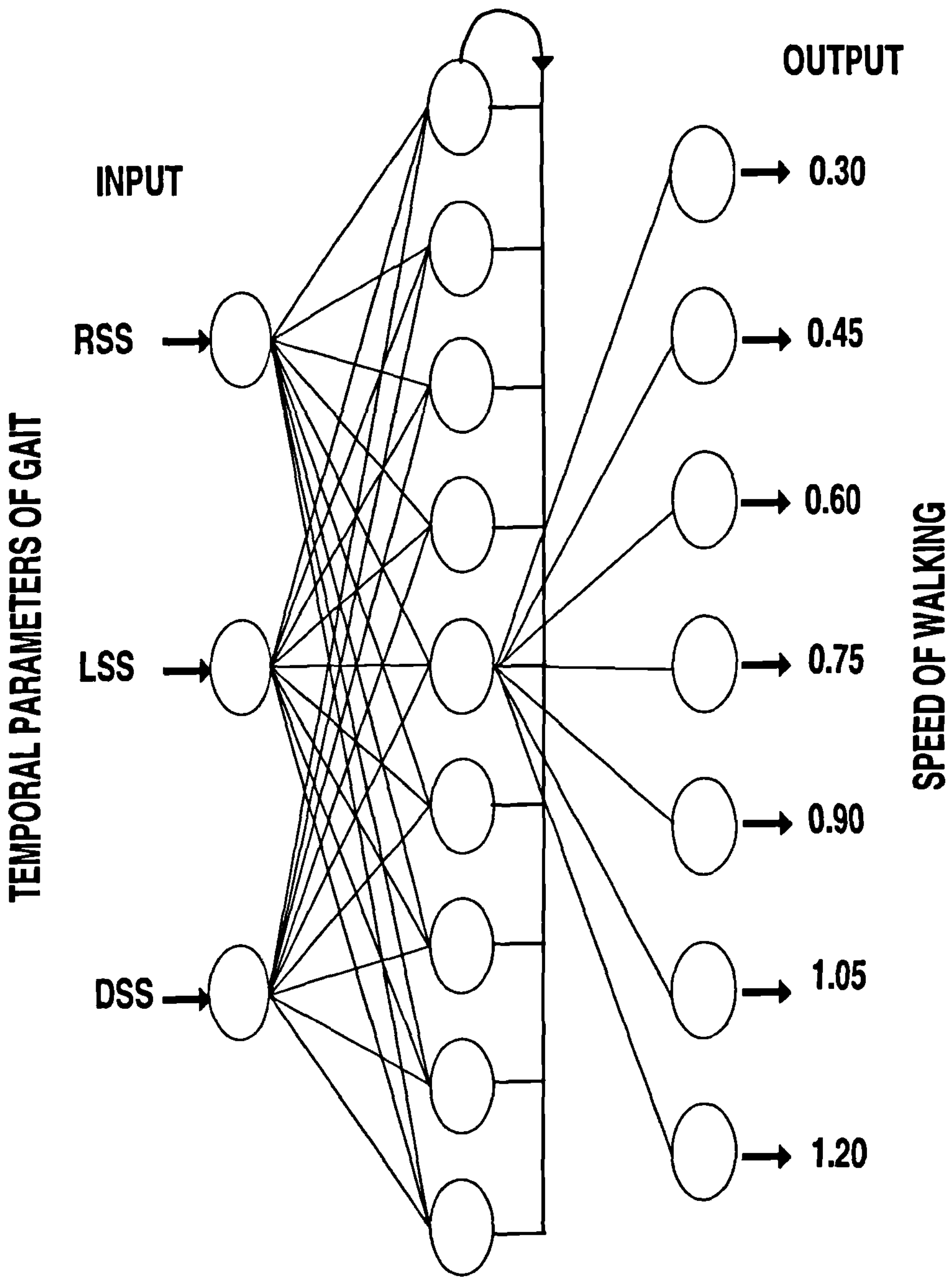

Figure 3.7

A three layered recurrent network with 3 input, 9 hidden and 7 output units (not all connections are shown). It was constructed and trained to recognise the speed of walking (in statures/sec) using as input the temporal parameters of gait (in msec).

consisted of the DSS, RSS and LSS in msec. The DG1 from CD1 was used to train the NN and the DG2 from CD1 was used to test it and vice versa. The process was also repeated for CD2 and CD3. As a result, six NNs were trained (NN 3.1 - NN 3.6) and Table 3.3 summarises their characteristics. The same procedure was carried out using LDA.

3.2.5.2 Case 3.2

A three layered recurrent network was constructed with 4 input, 9 hidden and 3 output units (Figure 3.8). Each input consisted of the walking speed in m/sec, the DSS, the ratio and the sum of the single support phases during a particular walking speed. The DG1 for each speed was used for the training of the network and the DG2 at the same speed was used to test the network and vice versa. As a result 14 NNs were trained (NN 3.7 - NN 3.20) and their characteristics are summarised in Table 3.3. The same procedure was carried out using LDA.

All temporal parameters collected during walking with seven speeds were used to define the walking condition. A three layered recurrent network was constructed with 21 input (7 speeds x 3 temporal parameters of gait), 9 hidden and 3 output units. Data from DG1 were used to train the network and the DG2 to test it and vice versa. As a result 2 NNs were trained (NN 3.21 and NN 3.22) and their characteristics are included in Table 3.3.

Table 3.3 : The results of the models studied with the characteristics of the trained networks.

Models studied		WS[+]	TrF[‡]	RcF[¶]	TrC[*]	tRMS[§]	mUE[**]
CASE 3.1							
	NN 3.1	CD1	DG1	DG2	2228	0.099	0.743
	NN 3.2	CD1	DG2	DG1	3006	0.096	0.992
	NN 3.3	CD2	DG1	DG2	1430	0.078	0.516
	NN 3.4	CD2	DG2	DG1	1864	0.090	0.635
	NN 3.5	CD3	DG1	DG2	3071	0.091	0.971
	NN 3.6	CD3	DG2	DG1	2420	0.080	0.537
CASE 3.2							
	NN 3.7	SP1	DG1	DG2	1072	0.045	0.239
	NN 3.8	SP1	DG2	DG1	1130	0.097	0.518
	NN 3.9	SP2	DG1	DG2	628	0.083	0.364
	NN 3.10	SP2	DG2	DG1	1778	0.091	0.399
	NN 3.11	SP3	DG1	DG2	1232	0.052	0.248
	NN 3.12	SP3	DG2	DG1	950	0.093	0.469
	NN 3.13	SP4	DG1	DG2	920	0.072	0.363
	NN 3.14	SP4	DG2	DG1	610	0.095	0.424
	NN 3.15	SP5	DG1	DG2	705	0.096	0.432
	NN 3.16	SP5	DG2	DG1	1176	0.096	0.489
	NN 3.17	SP6	DG1	DG2	637	0.080	0.499
	NN 3.18	SP6	DG2	DG1	1795	0.127	0.812
	NN 3.19	SP7	DG1	DG2	850	0.079	0.326
	NN 3.20	SP7	DG2	DG1	620	0.068	0.279
	NN 3.21	--	DG1	DG2	430	0.031	0.111
	NN 3.22	--	DG2	DG1	430	0.035	0.127

[+] Ws : walking condition for Case 3.1 and walking speed for Case 3.2

[‡] TrF : data set used for the training (classification)

[¶] RcF : data set used for the testing (recognition)

[*] TrC : training cycles

[§] tRMS : total RMS (root mean square) error

[**] mUE : maximum output unit error

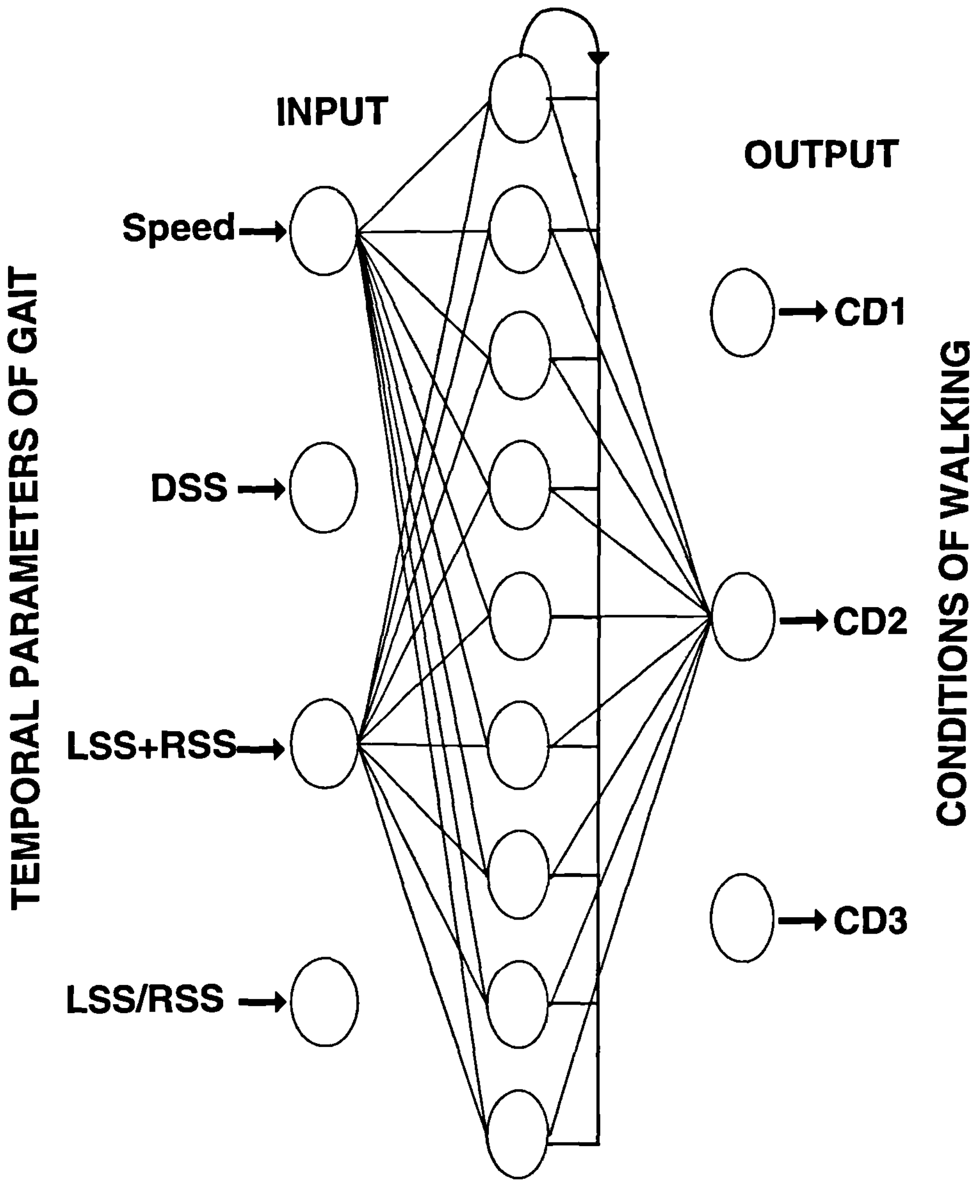

Figure 3.8

A three layered recurrent network with 4 input, 9 hidden and 3 output units (not all connections are shown). It was constructed and trained to recognise the conditions of walking using as input the temporal parameters of gait (in msec) and the speed of walking (in m/sec).

3.3 Results

The results from classification and recognition, using NNs and LDA, for all the studied models are included in Table 3.4. Table 3.5 includes the overall results.

The McNemar's χ^2 test shows a statistically significant difference between NNs and LDA (Case 3.1) for the overall results during classification using the training file ($\chi^2(1)=86$, $P<0.001$) and no statistically significant difference for the recognition of the testing file ($\chi^2(1)=2.29$, $P>0.05$). NNs and LDA correctly classify 98% and 77% of the training file respectively. The ability of NNs and LDA to recognise unknown patterns is 73% and 68% respectively.

McNemar's χ^2 test shows statistically significant difference between NNs and LDA (Case 3.2 excluding NN 3.21 and NN 3.22) for the overall results during classification using the training file ($\chi^2(1)=114$, $P<0.001$) as well as during recognition using the testing file ($\chi^2(1)=8.3$, $P<0.01$). NNs correctly classified 99% of the training file and recognised 64% of the testing file. The results from the use of LDA were 70% during classification and 55% during recognition. The inputs of the studied models NN 3.21 and NN 3.22 consisted of 21 variables; such large inputs cannot be used for direct LDA. These NNs recognised 92% of the unknown patterns.

Table 3.4 : Detailed results of the models studied. In case 3.1 the number of patterns was 70 and in case 3.2, 30.

Models studied		Number of successfully recognised patterns			
		LDA		**NNs**	
		tr*	rc*	tr	rc
CASE 3.1:	NN 3.1	51	52	68	61
	NN 3.2	61	50	69	50
	NN 3.3	54	47	69	50
	NN 3.4	54	49	68	52
	NN 3.5	49	47	68	47
	NN 3.6	54	39	69	45
	OVERALL :	**323**	**284**	**411**	**305**
CASE 3.2:	NN 3.7	24	12	30	21
	NN 3.8	21	20	29	26
	NN 3.9	22	18	30	22
	NN 3.10	21	22	30	20
	NN 3.11	24	19	30	26
	NN 3.12	25	20	30	22
	NN 3.13	21	16	30	12
	NN 3.14	21	12	30	15
	NN 3.15	18	16	30	20
	NN 3.16	21	19	29	12
	NN 3.17	17	14	29	14
	NN 3.18	19	11	29	15
	NN 3.19	17	19	30	22
	NN 3.20	23	14	30	22
	OVERALL :	**294**	**232**	**416**	**269**
	NN 3.21	--	--	30	26
	NN 3.22	--	--	30	29

* tr : classification results using the training file,
rc : results from the recognition using the testing file.

Table 3.5 : Overall results of the models studied. In case 3.1 the number of patterns was 70 and in case 3.2 was 30 per studied model. Six models were studied in Case 3.1 and 14 models in Case 3.2.

	Training*		Testing**	
	LDA	**NNs**	**LDA**	**NNs**
CASE 3.1				
Mean	54	68.5	47	51
SD	4	0.5	4	5.5
Overall	323	411	284	305
%	77	98	68	73
	($p<0.001$)		($p>0.05$)	
CASE 3.2				
Mean	21	29.7	16.6	19.2
SD	2.5	0.5	3.5	4.7
Overall	294	416	232	269
%	70	99	55	64
	($p<0.001$)		($p<0.01$)	

* training: results obtained from the training file,

** testing: results obtained from the testing file.

3.4 Discussion

A major problem in gait analysis is how to maximize the usefulness of laboratory data. The most common approach to the interpretation of such data is to apply standard statistical methods by which each pattern can be described and the relationship between different patterns identified. The difficulty appears during classification of different patterns and recognition of a new one.

The recognition of the speed or the condition of walking is not important. The aim of the present study is to investigate the ability of NNs to discriminate patterns of human gait and the present selected example allowed the collection of data from many different patterns (21 patterns from each subject, 7 speeds x 3 conditions).

The performance of the two multivariate techniques (NNs and LDA) cannot be compared in each of the studied models due to small samples sizes in both testing and training file. This comparison requires at least 10 patterns that have been classified differently by both classification techniques (Siegel & Castellan, 1988).

All NNs in both Cases (3.1 and 3.2) have the same structure and the same patterns have been analysed under different conditions. In this study the same data from the same subjects have been handled in different ways. So it can be assumed that the results in Table 3.4 come from one network for Case 3.1 and from another one for Case 3.2 and the overall performance of these NNs can be compared with that of LDA.

The shrinkage (decrease in classification rates when the discriminant function applied to testing patterns) is 25% for NNs in both Cases while LDA's shrinkage is 9% in Case 1 and 15% in Case 2. Considering subject-to-variable rations almost equal to 3.3:1 for case 1 and 2.5:1 for case 2, NNs observed high shrinkages (Fletcher et al., 1978). These shrinkages and the results from McNemar's test suggest a possible overtraining of the NNs. When small sample sizes are used, it is difficult to decide where to stop the training of NNs and the only measure is to get the highest success rate with both the training and the testing file.

On the above evidence, it cannot be concluded that NNs are better than LDA but it can be stated that NNs are a useful technique for multivariate analysis with a predictive accuracy at least as high as that of LDA.

In the studied models NN 3.21 and NN 3.22, twenty one variables are used to predict the conditions of walking. The network has a mean accuracy of 92% in correctly recognising the unknown patterns while LDA cannot be applied without pre-evaluation of the predicted variables.

During this pre-evaluation the variables are evaluated for their contribution to the solution of the discrimination and only those that found to play an important role, are used (Tabachnick & Fidell, 1989).

3.5 Conclusions

It can be concluded that :

a. NNs can be used to discriminate gait patterns;

b. NNs can assess and classify patterns which are described with the use of their temporal parameters and with a small number of variables;

c. the accuracy of NNs is at least as high as that of LDA;

d. the structure of NNs in which the number of the classifying categories is greater or almost equals to the number of the predicted variables, has an acceptable accuracy;

e. NNs are expected to be particularly useful for solving problems which can not be solved by direct LDA because of the large number of the predicted variables.

CHAPTER FOUR

STUDY II

The use of neural networks to distinguish stepping patterns

4.1 Introduction

Going up and down stairs is a common activity of daily living which is as important as walking. The capacity to do both is assessed subjectively in physical medicine and orthopaedics. The monitoring of stepping requires less space than that for walking. Stepping action has been the subject of biomechanical analysis.

"An understanding of the mechanics of stair-climbing is an important step toward greater knowledge of the function of the lower-extremity disorders. This information is also needed to improve patient management..." (Andriacchi et al., 1980).

A larger range of knee motion was shown by kinematic studies to be required during stepping than during level walking. Laubenthal et al. (1972) observed that about 83 degrees of knee flexion is required to climb up or down stairs and Hoffman et al. (1977) found that approximately 12 degrees more knee flexion is required during stair-climbing than during level walking. Andriacchi et al. (1980) found that going up or down stairs results in higher joint moments at the hip and knee than during level walking.

When a lower extremity leads upwards and forwards or downwards and forwards in a stepping action, movements in the gravity field are performed which are similar amongst normal subjects (Grieve et al., 1978). If the subjects' performance is disturbed either by the same neuromuscular disorder or by changing the height of the step, similarities of performance of a certain degree still exist between subjects. It is possible to assess performance and identify the cause or the level of disturbance by making comparisons between subjects.

Grieve et al. (1978) described stepping, selecting similarities and critical points, in order to establish a norm. The stepping pattern was represented and studied with the use of the angle-angle or thigh-knee diagram. Figure 4.1 illustrates the stepping forward and upward of the lead leg with the use of the angle-angle diagram. The critical points selected were the co-ordinates of the starting (point 1) and finishing position (point 7), the minimum hip excursion (point 3), the least leg excursion (point 2), the greatest leg excursion (point 4), the tip (point 5) and notch of the curve (point 6). The events that occurred in the stepping movements, which are presented in this curve, have been investigated as well as the size of the curve at different heights of the step i.e. at high steps, the curve becomes more extended.

A locomotor assessment takes place for diagnostic purposes or in order to assess the patient's progress as a result of treatment. A clinician can assess the ability of a patient

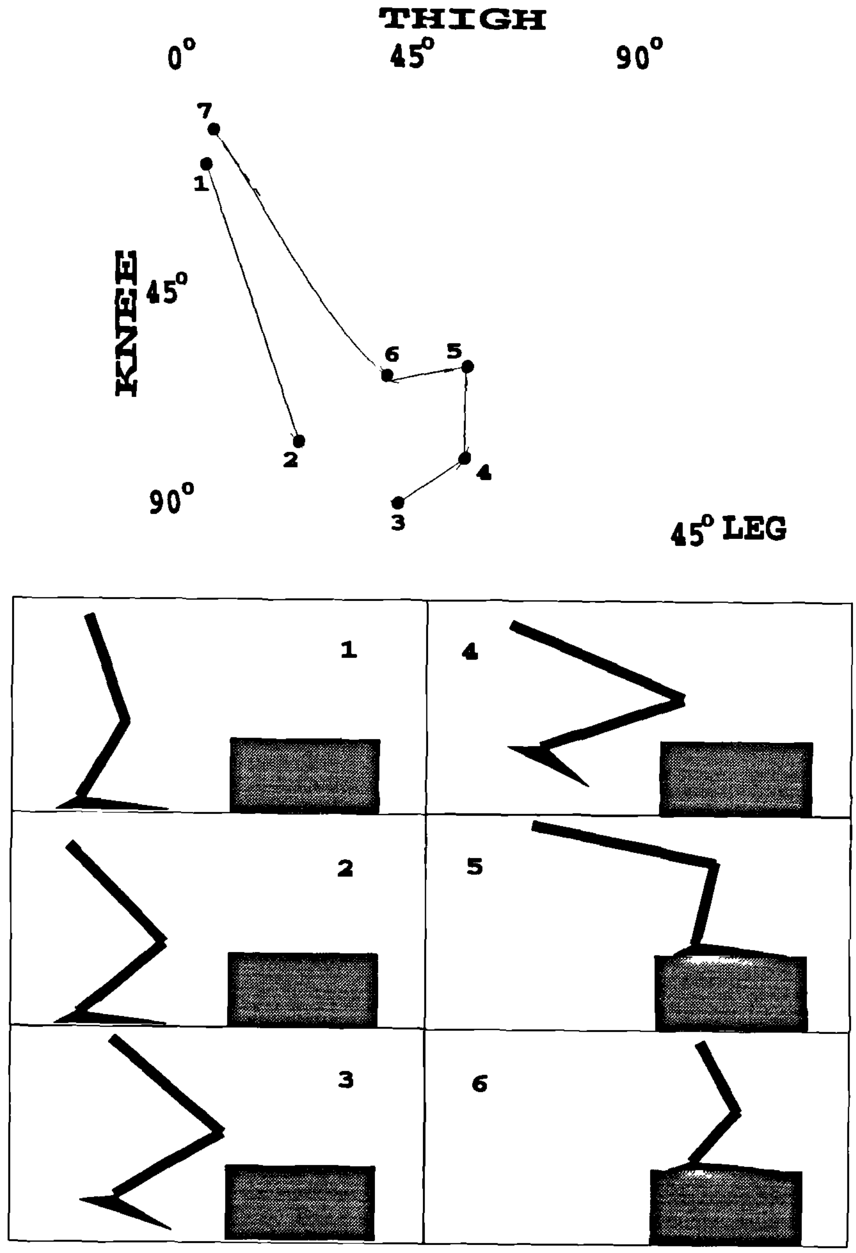

Figure 4.1

The thigh-knee or angle-angle diagram of the lead leg during stepping forward-up. The 7 points represent characteristic events (P1: starting position, P2: the least leg excursion, P3: the minimum hip excursion, P4: the greatest leg excursion, P5: the tip, P6: the notch of the curve and P7: finishing position). (adapted from Weatherston, 1975) to step and can compare his performance with a "norm" or a previous performance. This assessment is an subjective one and allows a subjective communication between clinicians.

If stepping movements are to be used as a clinical test, the knowledge of standard patterns only is not enough. The patient's pattern can be compared with norms in order to gain useful information, but the exact category to which each pattern belongs can not be found and it is difficult to demonstrate the method of categorisation of patterns. To avoid subjective problems, standard techniques are needed to evaluate and discriminate between stepping patterns.

4.1.1 Research outline: aims and objectives

The present study aims to:

a. distinguish stepping patterns with the use of NNs;

b. apply NNs to the recognition of patterns of human movements which are described with the use of the angular displacement of different joints and with a large number of variables;

c. compare the performance of NNs with that of LDA;

d. investigate the performance of NNs in which the number of the classifying categories is smaller than the number of the predicted variables.

4.2 Materials and method

An experiment was designed and carried out to measure the angular displacement of both hips and knees during stepping forward-up and forward-down at five different step heights.

4.2.1 Subjects

Eighteen healthy subjects volunteered for this experiment (11 males and 7 females). All were students or academic staff with no history of locomotor disturbance. Table 4.1 summarizes the physical characteristics of subjects and more details are included in Appendix B: Table B1.

Table 4.1 : Physical characteristics of subjects

		MALES	FEMALES	OVERALL
N		11	7	18
Age (years):	**Mean**	25.6	25.5	25.6
	SD	4.8	3.5	4.2
	Max	35	30	35
	Min	20	21	20
Weight (Kg):	**Mean**	73.7	60.4	68.5
	SD	7.3	12.2	11.3
	Max	88	85	88
	Min	64	49	49
Stature (m):	**Mean**	1.75	1.69	1.73
	SD	0.04	0.06	0.06
	Max	1.81	1.77	1.81
	Min	1.68	1.63	1.63

4.2.2 Experimental equipment.

The equipment used consisted of a BBC microcomputer, an A/D converter (CED 1401 Intelligent Interface, Cambridge Electronic Design Ltd), pairs of shoes with metallised soles, a metal bench with adjustable height and 3 wooden benches with heights of 0.1, 0.2 and 0.3m respectively.

Four flexible electrogoniometers (Penny & Giles Blackwood Ltd, Gwent, UK) were used to measure the flexion-extension angles of both hips and both knees. Each electrogoniometer consists of a flexible strain gauge strip surrounded by a protective helical spring. The two ends are embedded in blocks for attachment to the subject. They are light, flexible devices and do not require the identification of the centre of joint rotation. Therefore, they can be attached in a relatively uncritical manner to the surface of limb segments on either side of an articulation without restricting motion. These goniometers have been used successfully in many studies (Goodwin et al., 1992; Ojima et al., 1991; and Rowe et al., 1989). Figure 4.2 shows the placement of the goniometers on both hips and both knees. The goniometers were connected via a cable to battery powered pre-amplifiers whose outputs were fed to the A/D converter after further amplification.

The wooden benches and the metal bench with the adjustable height were used to obtain the desired heights of the step.

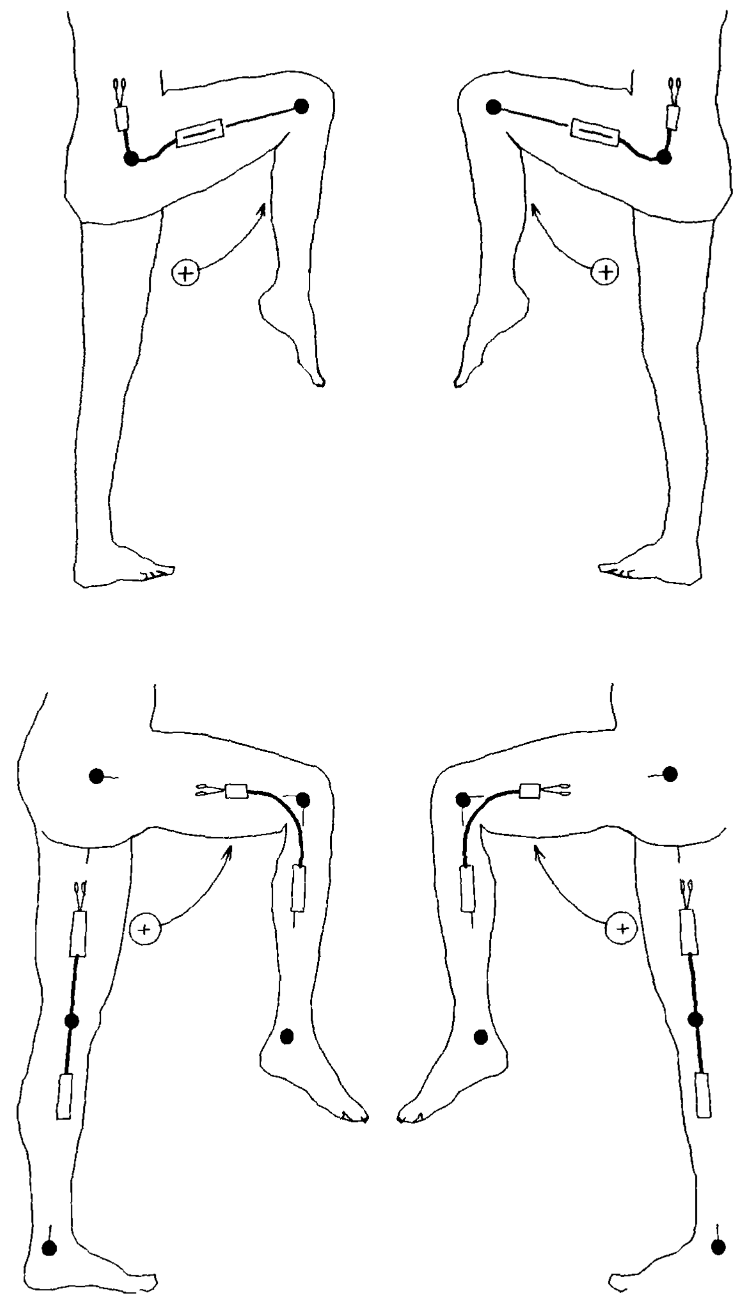

Figure 4.2

The placement of 4 electrogoniometers on both hips and both knees.

Aluminium foil was placed on the top of the benches, as well as under the shoes. Both the shoes and the benches were connected to a network of resistors and a power pack. The voltage output of the network was uniquely determined according to whether either or both feet were in contact with either the upper or lower step. These signals were digitized.

The A/D converter was controlled by a BBC host microcomputer using software written in BBC Basic. The electrical signals were amplified, digitized and sampled by the computer at 800Hz for 5sec. The results were displayed on the computer monitor and then saved on disk for further processing and analysis.

Prior to the measurements, all electrogoniometers were calibrated by fixing on a stable and accurate universal goniometer. Six measurements took place at twenty different placements of the universal goniometer with the end plates of the electrogoniometers at the same level and at two different levels. Actual and observed values for all the electrogoniometers were highly correlated (root mean square error (RMS)=0.7°, RMS=0.6°, RMS=0.9°, RMS=0.9° and R^2=0.999 for each electrogoniometer respectively). One-way ANOVA analysis showed no statistical significant difference between the 6 set of readings for all electrogoniometers ($F(5,114)=0.01$, $F(5,114)=0.02$, $F(5,114)=0.00$, $F(5,114)=0.00$ and $p>0.1$ for each electrogoniometer respectively).

4.2.3 Experimental procedure

Stature and weight were measured at the beginning of the test after explaining the experiment to the subject and obtaining informed consent. The subject's stature was used to define the height of the five different steps (5%, 10%, 15%, 20%, and 25% of his stature). Table 4.2 summarises the height of the 5 steps for the 18 subjects.

Each subject wore briefs which facilitated the location of necessary anatomical landmarks and gave the subject unrestricted leg movement. The four electrogoniometers were placed at both hips and knees with the use of double-sided adhesive tape. The pre-amplifier was attached to a waist belt and shoes suited to the subject's foot size were used. All the cables were fixed on the skin with micropore and the pre-amplifier was connected via a long cable to an equipment trolley. The subject was asked to stand on the lower bench, in a relaxed upright position. In this position, all the goniometers were set to zero. The subject then stepped forward-up using the right leg first at a step with a height equal to 5% of his stature. The data were saved and the subject stepped forward-down, again using the right leg first. The same procedure was repeated for the five different step heights. The subject was allowed to practice beforehand in order to familiarize himself with each task. The total number of unique movement patterns for each individual was ten and

Table 4.2: The height of the used steps in mm.

		MALES	FEMALES	OVERALL
N of subjects		11	7	18
5% of stature:	**Mean**	87.6	84.2	86.3
	SD	1.76	2.89	2.76
	Max	90.0	88.5	90.0
	Min	84.0	81.0	81.0
10% of stature:	**Mean**	175.4	168.64	172.7
	SD	3.66	5.70	5.56
	Max	181.0	177.0	181.0
	Min	168.0	162.5	162.5
15% of stature:	**Mean**	263.0	252.9	259.1
	SD	5.42	8.55	8.29
	Max	271.0	265.5	271.0
	Min	252.0	243.7	243.7
20% of stature:	**Mean**	351.0	337.2	345.6
	SD	7.38	11.41	11.19
	Max	362.0	354.0	362.0
	Min	336	325.0	325.0
25% of stature:	**Mean**	438.6	421.6	432.0
	SD	9.13	14.26	13.93
	Max	452.0	442.5	452.0
	Min	420.0	406.2	406.2

the approximate amount of time needed for the whole experiment was thirty minutes. Figure 4.3 shows a general set-up of the equipment during data collection.

4.2.4 Data presentation

The beginning of stepping forward-up (or forward-down) was taken to be the moment when the right foot lost contact with the lower step (upper step for forward-down), and its end was taken to be when the left foot made contact with the upper step (lower step for forward-down). The digitised outputs of the resistor network were used to recognise the beginning and the end of the task.

The data were represented in two different ways: a. the range of each motion was plotted against time (first data set: DS1) during stepping forward-up and forward-down and b. the range of motion of the hip plotted against the range of the knee motion (angle-angle diagram) for both lower extremities (second data set: DS2) during stepping forward up. Figure 4.4 shows the angular displacement of both knees and both hips of a subject during stepping forward-up to a step with height equal to 25% of his stature. All data collected during stepping forward-up are included in Appendix B (Figure B1 to B6), providing a graphical representation similar to Figure 4.4. Figure 4.5 is a plot of the hip motion against the knee motion (angle-angle diagram) of the same data which were used in Figure 4.4.

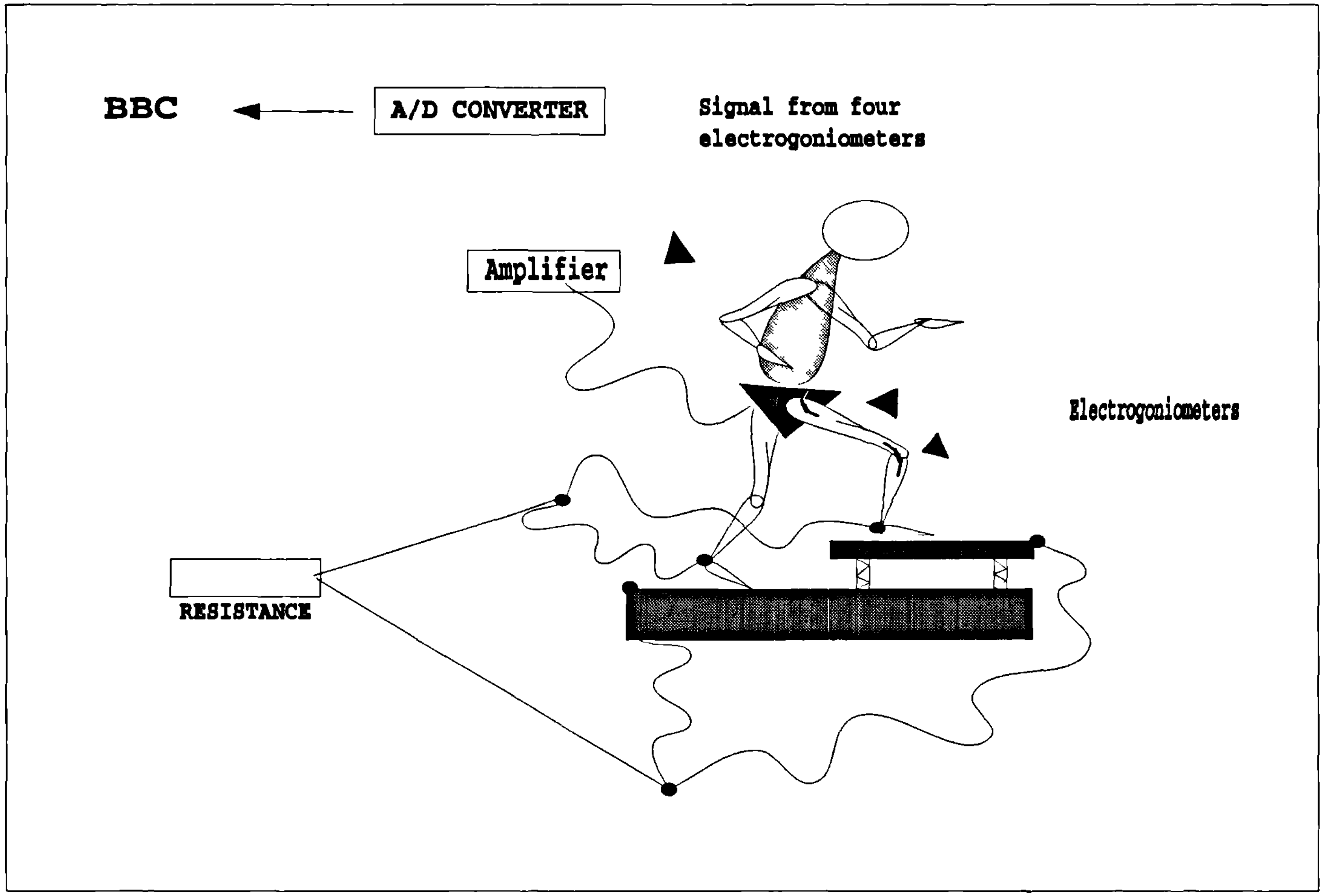

Figure 4.3

A general set-up of the equipment during data collection

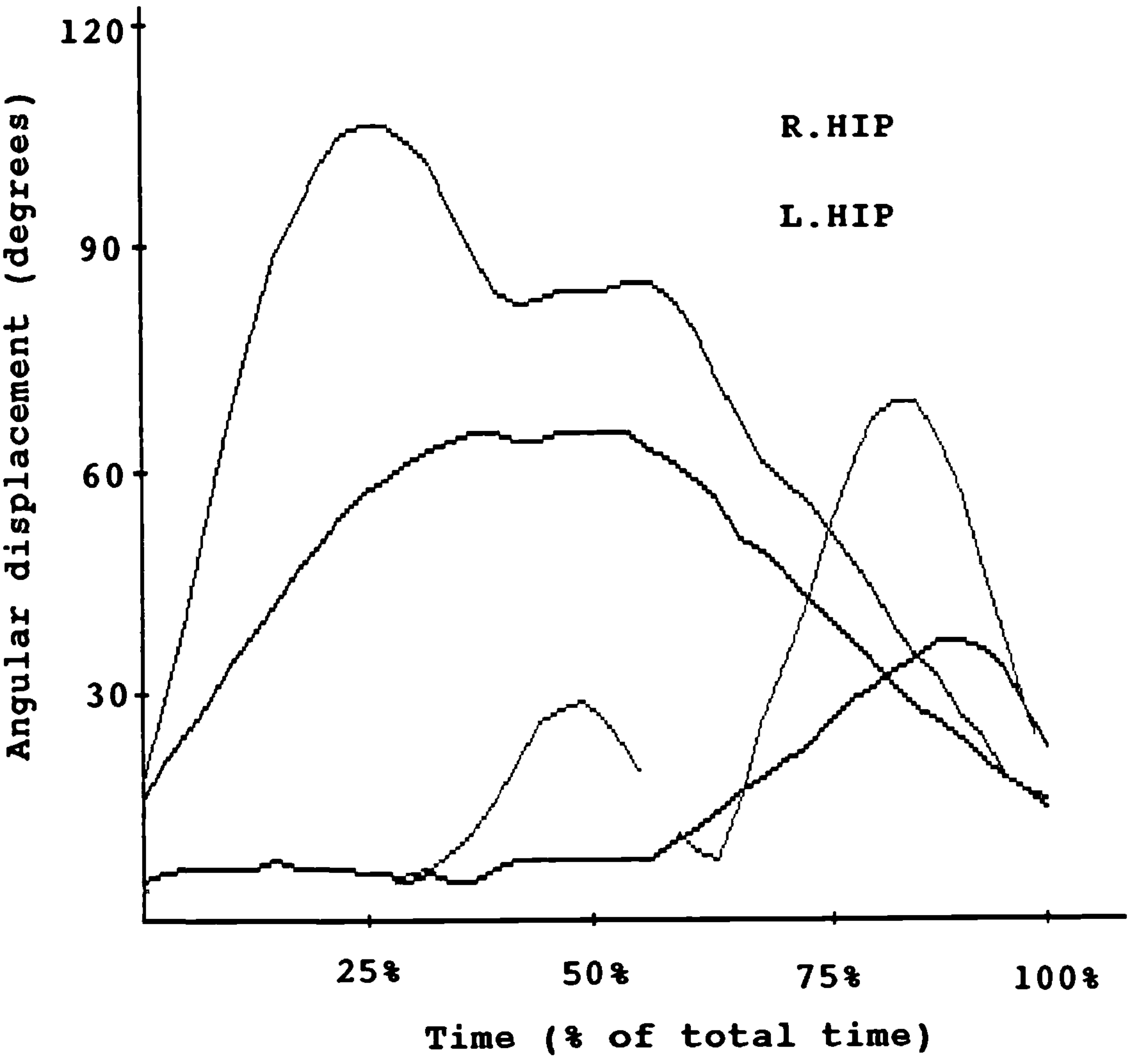

Figure 4.4

Graphical representation of the angular displacement of both hips and knees during stepping forward-up. (Data from subject M01 and step height 25%).

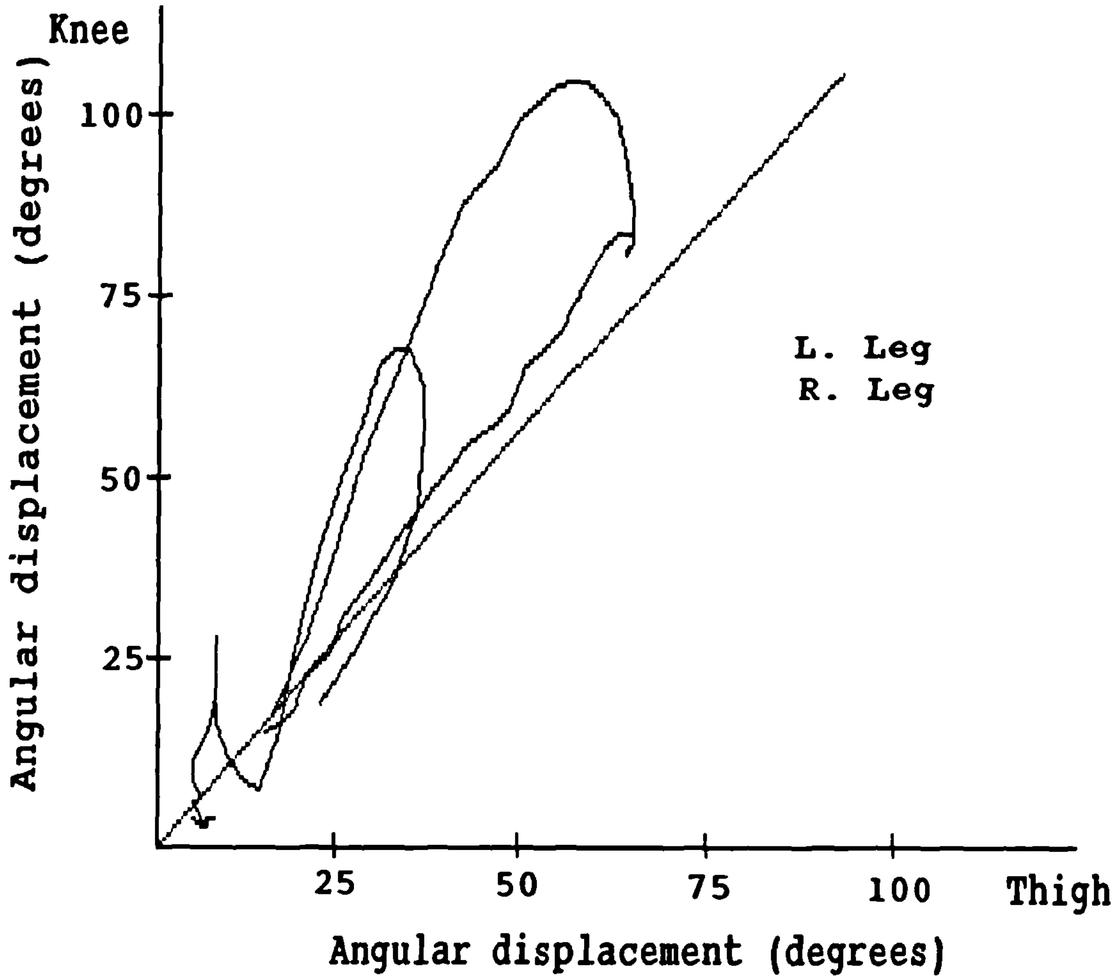

Figure 4.5

The angle-angle diagram for both lower extremities during stepping forward-up. (Data from subject M01 and step height 25%).

The data of DS1 were normalized by time and the values obtained every 10% of the total time were noted. Figure 4.6 is a graphical representation of the data set used in Figure 4.4 after the applied normalization. Each variable in this data set, was given a name which consists of two characters and one number. The first character (R or L) symbolises the left or right lower extremity and the second character (H or K) symbolises a joint (hip or knee). The number (from 0 to 100) represents the % time at which this variable was collected. For example, a variable with name RK05 is the range of motion of the right knee at 5% of the total time.

From DS2 seven points were selected (Grieve et al., 1978) on the angle-angle diagram for each lower extremity, which leads to 28 variables (7 points x 2 co-ordinates x 2 lower extremities). These points for the lead leg are the points described by Grieve et al. (1978). For the other leg they are the starting (point 1) and finishing (point 7) position, the three tops of the curve (points 2, 3 and 5) the least leg excursion (point 4)and the greatest leg excursion (point 6). Figure 4.7 is a graphical representation of the data set used in Figure 4.5 after the collection of seven points. Each variable in this data set was given a name which consists again of two characters and a number. The two characters, R or L and H or K, have the same meaning as those in DS1. The number represents the point on the angle-angle diagram (from 1 to 7).

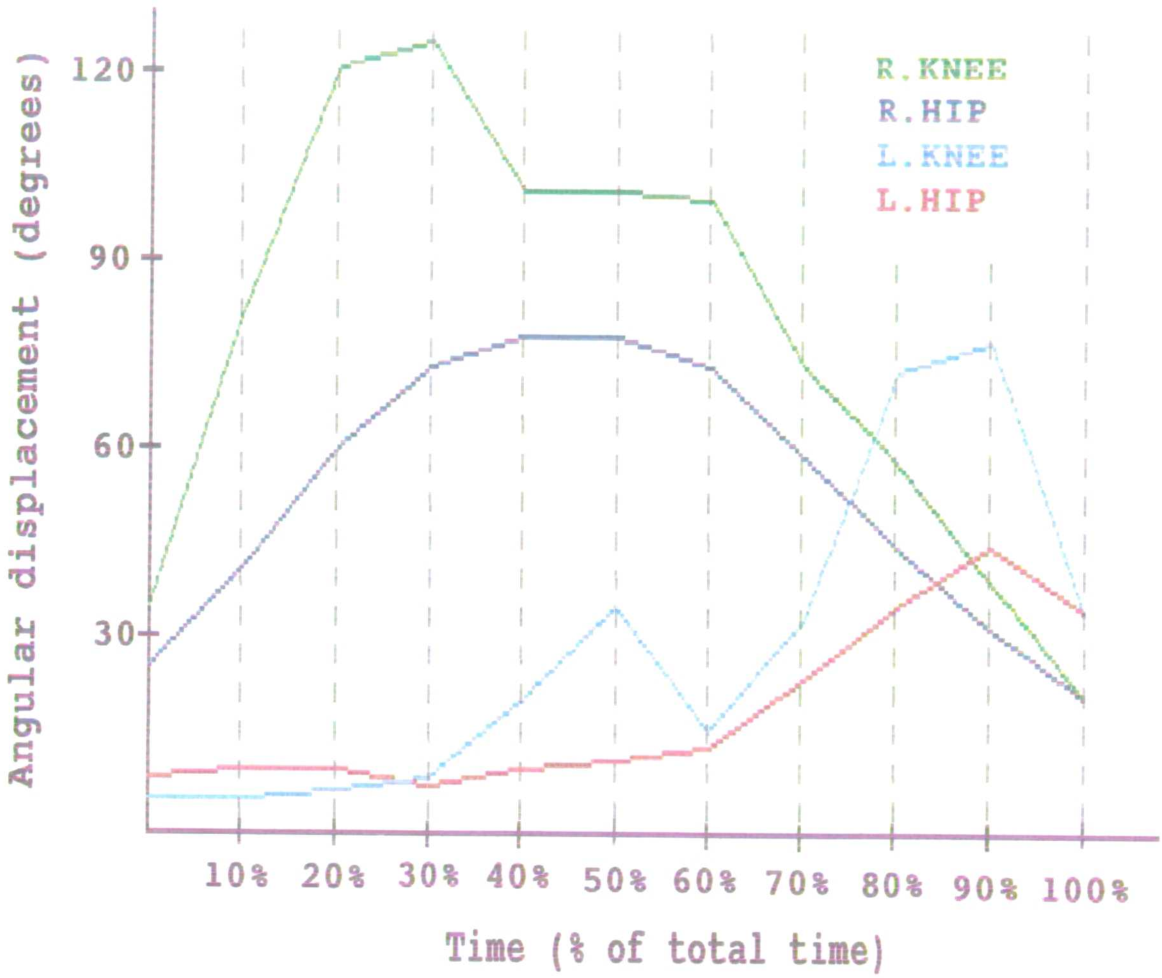

Figure 4.6

Graphical presentation of the angular displacement of both hips and knees during stepping forward-up. (Data from subject M01 after the applied normalisation on the data set. Step height is equal to 25% of the subject's stature)

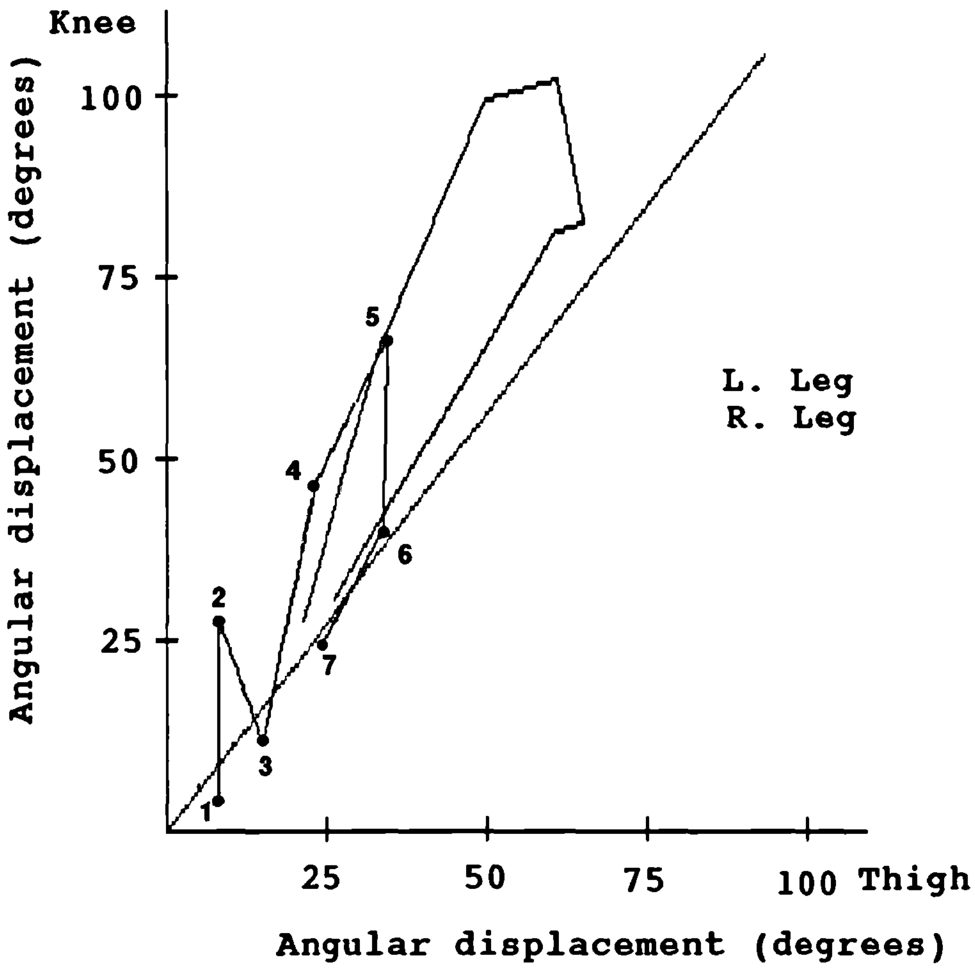

Figure 4.7

The angle-angle diagram for both legs during stepping forward-up, after the collection of the seven critical points from each lower extremity. (Data from subject M01 and step height equals to 25% of subject's stature).

4.3 Data analysis and results

Each of the data sets were separated into two groups. One group of data (data from 8 men and 5 women, 65 patterns) was used in the training procedure for prediction of the height of the step from the range of motion of both hips and both knees (training data). The rest of the data (25 patterns) were used to test the success of the classification procedure (testing data). NNs as well as Linear Discriminant Analysis was used.

4.3.1 Discriminant analysis.

A discriminant function analysis (LDA 4.1) was performed using SPSS/PC+ V2.0 (Norusis, 1988) to assess prediction of step height during stepping forward-up from the range of motion of both hips and both knees (DS2). Due to the large number of predictor variables (28), compared to the available number of patterns (65), the stepwise discriminant function analysis employing the Wilks' Lambda criterion, was chosen, in order to minimize the number of predictor variables.

For classification, sample sizes were used to estimate prior probabilities of group membership. Table 4.3 shows the variables included in the model in each step with the associated Wilks' Lambda, F-statistic and the statistically significant level.

Table 4.3: Results of the first discriminant function analysis (LDA 4.1) with the variables included in the model at each step and the associated Wilk's Lambda. The correlation between discriminant functions and predictor variables are shown.

Variables				**Correlation of predictors with discriminant functions**	
	WL*	**F(4,60)**	**p**	**funct* 1**	**funct 2**
RK5	0.164	76.6	0.000	**0.58**	-0.13
LK2	0.112	28.0	0.000	0.20	**0.53**
LK4	0.800	20.4	0.000	-0.25	0.12
LK5	0.053	17.7	0.000	0.18	-0.10
LK3	0.042	15.0	0.000	0.15	0.14
RK4	0.036	12.9	0.000	0.31	-0.22
RH2	0.032	11.3	0.000	0.24	-0.11
RH3	0.027	10.3	0.000	0.31	-0.12
Canonical R				0.97	0.72
Eigenvalue				15.2	1.1
% of variance				92.7%	6.6%

* funct: function

WL: Wilks' Lambda

Four discriminant functions were calculated, with a combined $\chi^2(32)=208$, $p<0.001$. After removal of the first function, there was still a strong association between groups and predictors, $\chi^2(21)=48$, $p<0.001$. After additional removal of the second function, there was a very small association between groups and predictors, $\chi^2=(12)=6$ $p>0.1$, resulting in the omission of the third and fourth function from further analysis. Figure 4.8 shows the relationship between function one and two as well as their contribution to the separation of the 5 groups. Figure 4.9 is the territorial map showing which region belongs to each predicted category.

The loading matrix of correlations between the 8 predictor variables and the 2 discriminant functions as seen in Table 4.3, shows that the primary predictor (loadings of 0.50 and above) for the first discriminant function is RK5 and for the second one is LK2.

During the classification procedure for the total useable sample of 65 patterns, 58 (89%) were classified correctly, compared to 13 (20%) that would be correctly classified by chance alone. The correctly classified patterns for each group (step height from 25% of stature to 5%) were as follows: 12 (92%), 8 (61.5%), 13 (100%), 12 (92%) and 13 (100%).

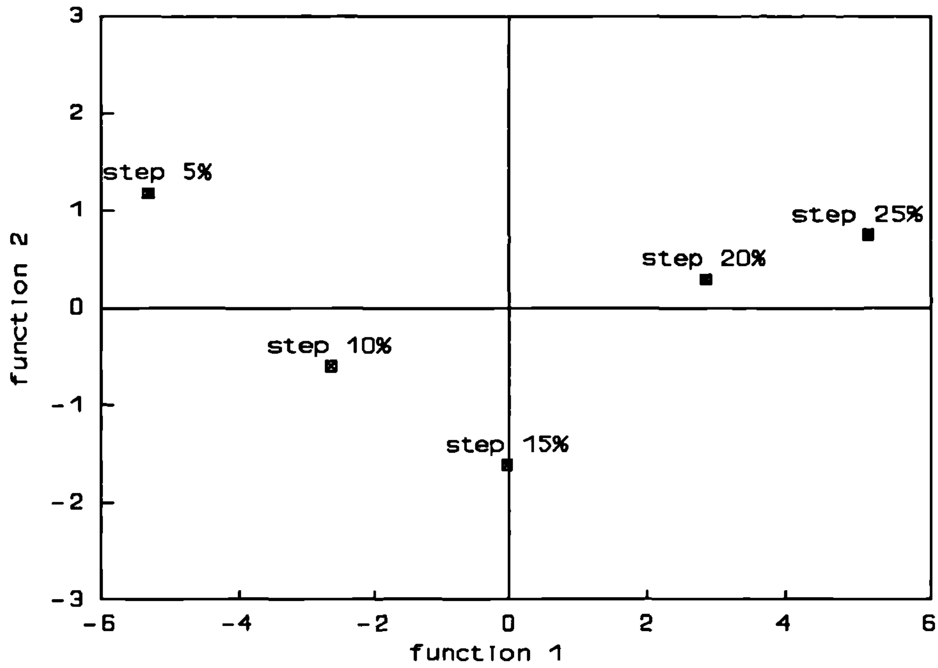

Figure 4.8

Plot of group centroids of the discriminant scores obtained by two discriminant functions (LDA 4.1) derived from 8 variable predictors. The horizontal axis represents the scores of first discriminant function and the vertical axis represents the scores of the second function. Each group is a step with height expressed as a percentage of the subjects' stature (from 5% to 25%) as seen on the plot.

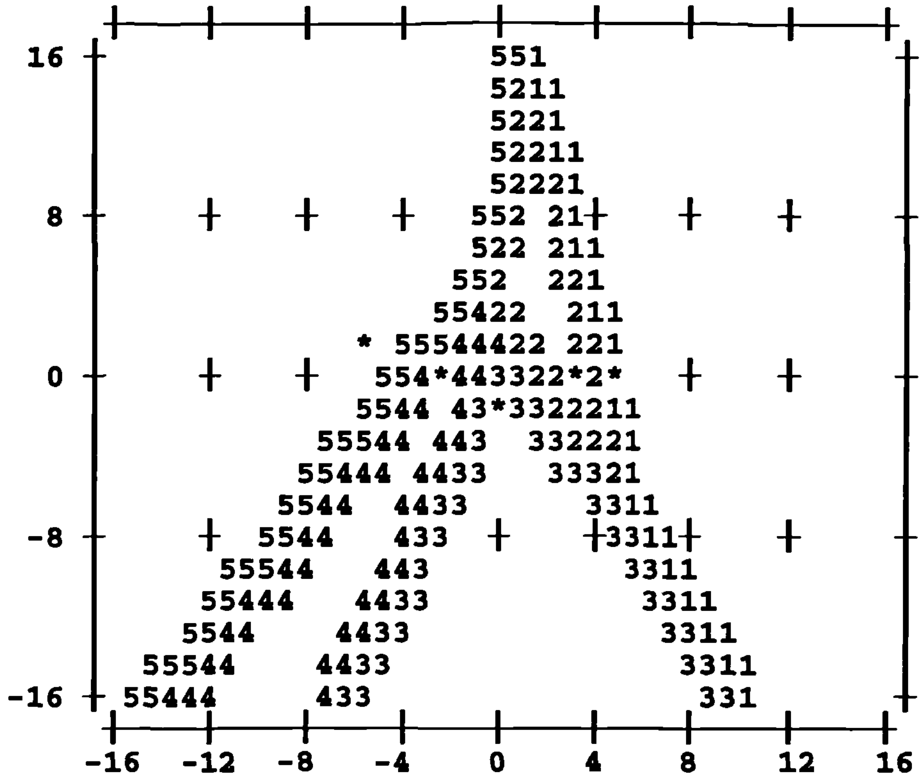

Figure 4.9

The territorial map for the five groups (step height) on the two discriminant functions (LDA 4.1). The horizontal axis represents the scores of first discriminant function and the vertical axis represents the scores of the second function. The mean of each group is indicated by an asterisk (*). The numbered boundaries mark off the combination of function values that result in the classification of the cases into the five groups. The numbers 1, 2, 3, 4 and 5 symbolise the height of the step, 25%, 20%, 15%, 10% and 5% of the subjects stature respectively.

The stability of the classification procedure was checked by a cross-validation run using the testing data. From the 25 patterns, 21 (84%) were correctly classified, compared again to 5 (20%) that would be correctly classified by chance alone.

A second discriminant function analysis (LDA 4.2) was performed to assess prediction of step height during stepping forward up from the range of motion of the right knee (DS1). The stepwise method was employed using the Wilks' Lambda criterion and sample sizes were used to estimate prior probabilities of group membership. Table 4.4 shows the variables included in the model in each step with the associated Wilks' Lambda, F-statistic and the statistically significant level.

Four discriminant functions were calculated with a combined $\chi^2(20)=139$, $p<0.001$. After removal of the first function, there was a small association between groups and predictors, $\chi^2(12)=15$ $p>0.1$. As a result, only the first function was used.

Figure 4.10 is a histogram (from SPSS/PC+ V2.0) of the scores obtained for each case by the discriminant function. The loading matrix of correlations between the 5 predictors and the discriminant function as seen in Table 4.4 shows that the primary predictor is RK60.

Table 4.4: Results of the second discriminant function analysis (LDA 4.2) with the variables included in the model at each step and the associated Wilk's Lambda. The correlation between discriminant function and predictor variables are shown.

Variables	**WL***	**F(4,60)**	**p**	**Correlation of predictors with discriminant function**
RK60	0.16	79	0.000	**0.86**
RK30	0.14	24	0.000	0.22
RK40	0.12	16	0.000	0.53
RK50	0.10	12	0.000	0.75
RK70	0.10	9.7	0.000	0.77
Canonical R				0.94
Eigenvalue				7.2
% of variance				96%

* WL: Wilks' Lambda

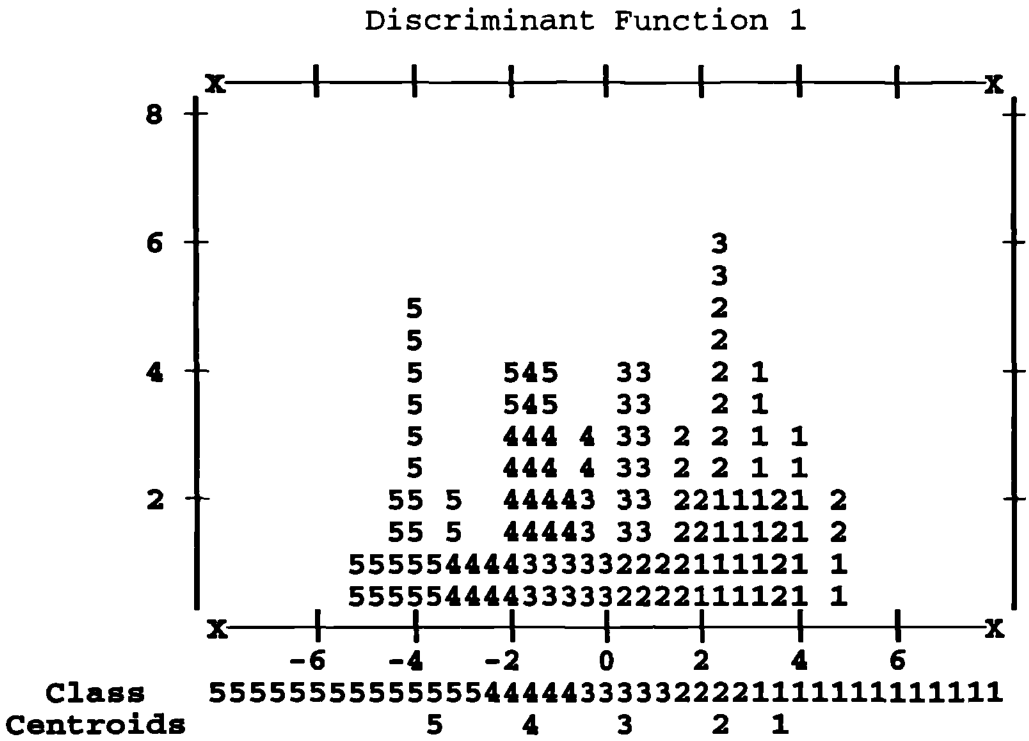

Figure 4.10

Histogram of the scores obtained by the discriminant function (LDA 4.2) for all groups (step height). Two symbols (1's, 2's, 3's 4's or 5's) represent one case. The row of those symbols underneath the plot denote to which group scores are assigned. The last row of numbers represents the group centroid. The vertical axis represents number of cases. The numbers 1, 2, 3, 4 and 5 symbolise the height of the step, 25%, 20%, 15%, 10% and 5% of the subjects' stature respectively.

During the classification procedure of the 65 patterns, 48 (74%) were correctly classified compared to 13 (20%) that would be correctly classified by chance alone. The correctly classified patterns for each group (step height from 25% of stature to 5%) were as follows: 10 (77%), 8 (62%), 10 (77%), 9 (69%) and 11 (85%).

The stability of the classification procedure was checked by a cross-validation run using the testing data. From the 25 patterns 18 (72%) were correctly classified, compared to 5 (20%) that would be correctly classified by chance alone.

4.3.2 Neural networks

Normalization was applied to all data within a specific range of ±0.5 prior to analysis by the network. The positive answer of the network was +0.5 and the negative was -0.5. The learning rate of all NNs was 0.02 and their momentum factor was 0.9. The weights of the NNs were initialised to ±0.1 Several recurrent networks were constructed in which the size of the hidden layer and the input layer was varied. The networks finally selected were as follows:

4.3.2.1 Case 4.1 using DS1

A three layered recurrent network (NN 4.1) was constructed with 44 input, 12 hidden and 6 output units (Figure 4.11). Each input consisted of the angular displacement of both knees and hips. Successful pattern recognition correctly identified the height of the step as well as the direction of the movement (up or down). This network was trained after 90 cycles. Its total RMS error was 0.039 and its maximum unit error was 0.175.

Another three layered recurrent network (NN 4.2) was constructed with 11 input, 9 hidden and 5 output units (Figure 4.12). Each input consisted of the angular displacement of the right knee during stepping forward-up to five step heights. Successful pattern recognition correctly identified the height of the step. NN 4.2 was trained after 140 cycles with a total RMS error of 0.031 and a maximum unit error of 0.139.

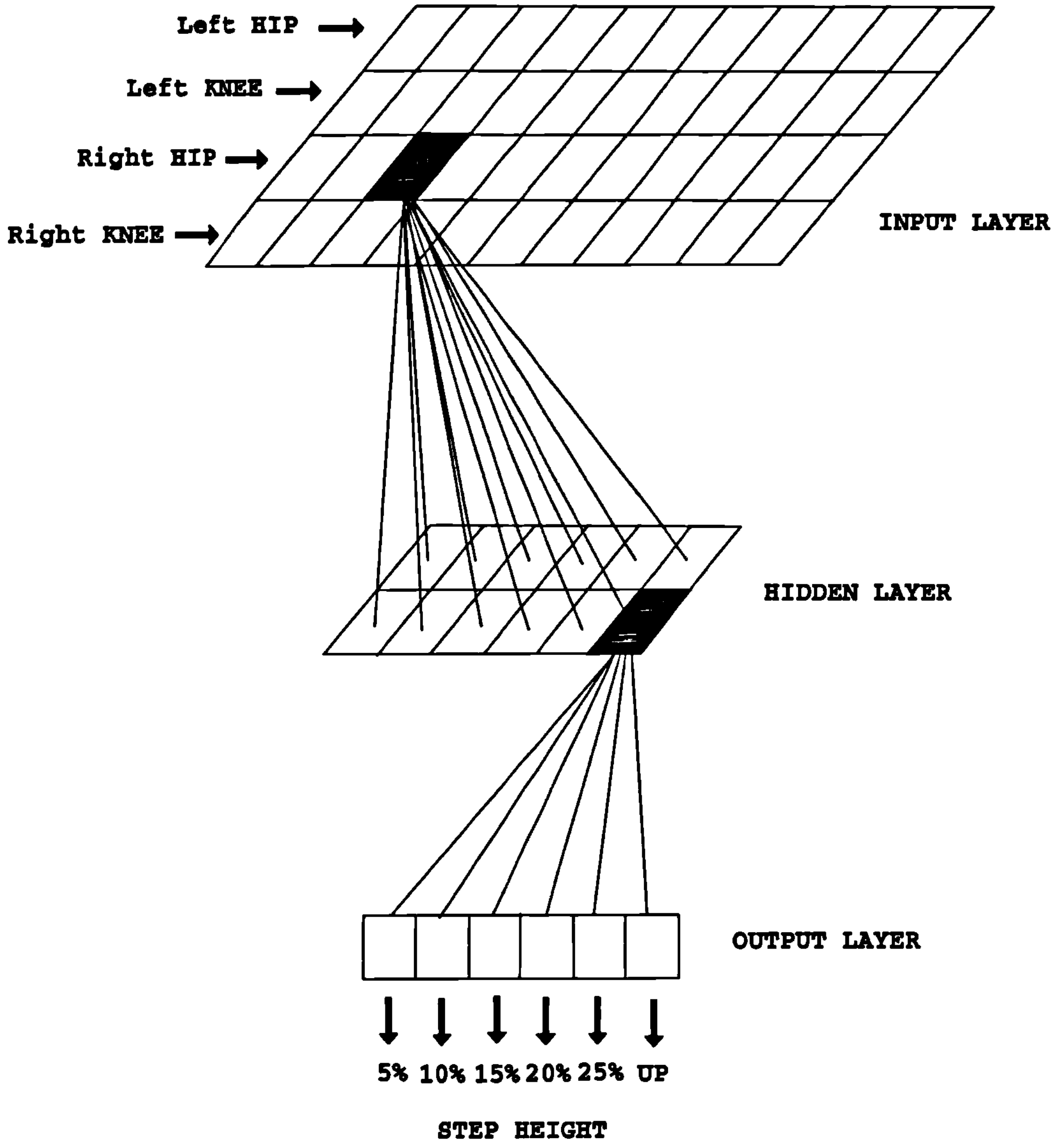

Figure 4.11

A three layered recurrent network (NN 4.1) with 44 input, 12 hidden and 6 output units (not all connections are shown). It was trained to recognise the height of the step and the direction of the movement (up or down) using as input the angular displacement of both hips and both knees.

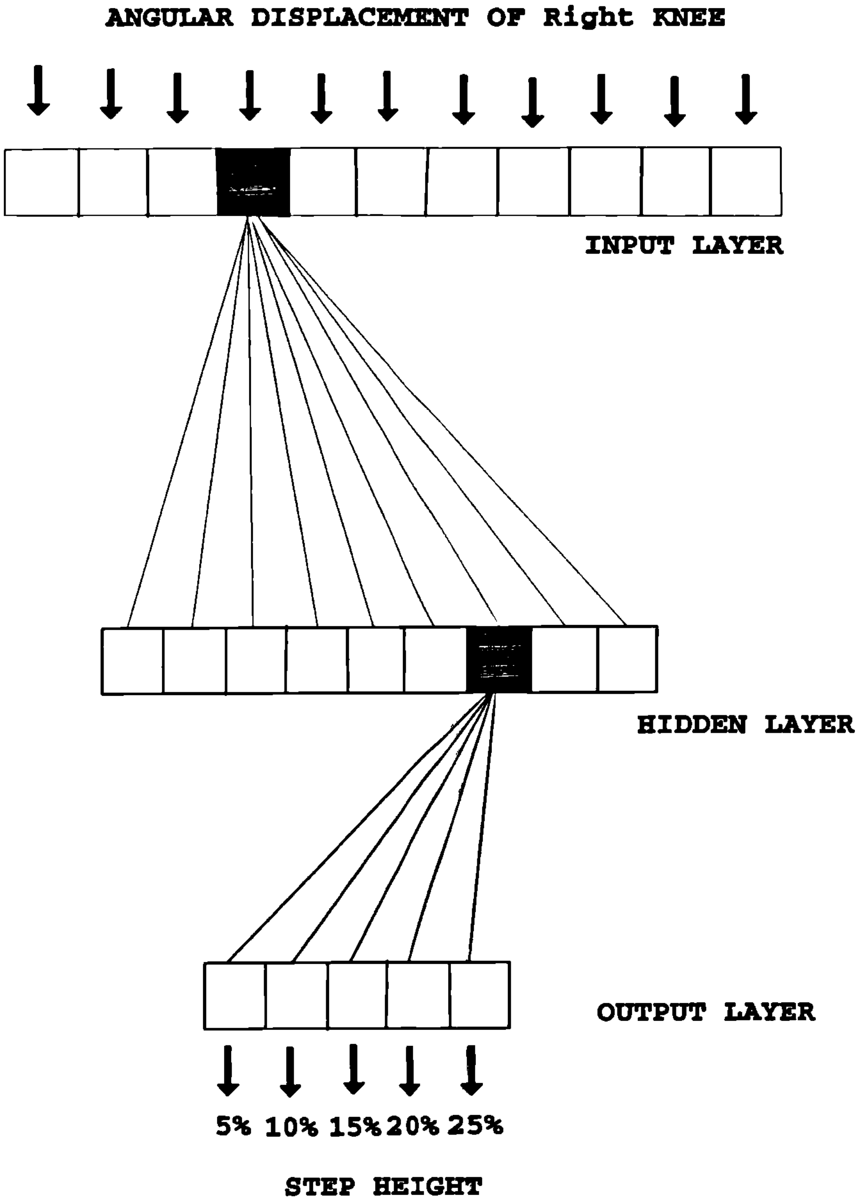

Figure 4.12

A three layered recurrent network (NN 4.2) with 11 input, 9 hidden and 5 output units (not all connections are shown). It was constructed and trained to recognise the height of the step using as input the angular displacement of the right knee.

4.3.2.2 Case 4.2 using DS2

A three layered recurrent network (NN 4.3) was constructed with 28 input, 10 hidden and 5 output units. Each input pattern consisted of the X and Y co-ordinates of the 7 points from the angle-angle diagram. This network was trained after 110 cycles. Its total RMS error was 0.048 and its maximum unit error was 0.072.

Another three layered recurrent network (NN 4.4) was constructed with 8 input, 7 hidden and 5 output units. Each pattern consisted of the 8 variables which were obtained in the first discriminant analysis in Table 4.3. This network was trained after 136 cycles. Its total RMS error was 0.039 and its maximum unit error was 0.098.

All NNs classified correctly all patterns in both training and testing data.

4.4 Discussion

The ability to discriminate stepping patterns is an important tool in the assessment of the performance of the musculoskeletal system. As this ability improves, the possibility of recognition of pathologies is enhanced. The possibility of using NNs to achieve this improvement is of interest.

In the present study, the stepping pattern was altered by changing the step height, which was then predicted from the range of motion of both hips and both knees. The step height was not the subject of investigation but this experiment produced a set of stepping patterns and the interest was focused on their classification.

The stepping patterns were presented in two different ways (DS1 and DS2) aiming to investigate different approaches which might lead to better classification.

NNs discriminated all patterns correctly in all studied models. The results are the same either with a large number of variables (NN 4.1) or with a small one (NN 4.4). It can be concluded that all variables are not needed to discriminate the patterns but no information can easily be extracted from the NNs about the contribution of each particular variable to the solution of the problem. Even if the values of each weight of the NN are known, little can be concluded about the importance of each variable due to the large number of weights from the input to the hidden layer, as well as due to the "transformation" of the input variables to new ones at the hidden units.

Evaluation of each variable might be achieved only if all possible combinations of the variables were used as an input to the NN. If there are n combinations, then n NNs need to be trained, which is a time-consuming procedure.

In addition, LDA can give significant information about each variable as is seen in Table 4.3 and 4.4. This information is given after pre-evaluation, which is necessary when LDA is performed. Large numbers of predictor variables, compared to the number of patterns, can not be used directly and a stepwise discriminant function analysis must be employed. This is not the case for NNs, whose ability to back-propagate the error and adjust their weights, maximizes the contribution of some variables and minimizes the contribution of some others, performing a kind of "secret" pre-evaluation.

Whenever the number of variables needs to be reduced, some reduction of information about the studied patterns occurs which affects the results of the discrimination procedure. The ability of NNs to use any number of variables is a great advantage.

When new patterns are studied, for which no previous information is available, as many parameters as possible should be measured, leading to a large number of variables and to a vast amount of data. Such situations are quite common in areas which deal with the study of human patterns of movement and the researcher is often in a difficult position when he wants to analyse the data. NNs might be a possible new approach.

The success of NNs in discriminating the stepping patterns (100%) is greater than both LDAs (89% and 74% respectively) but it is not known if this difference is statistically significant due to the small number of patterns in both training and testing data (65 and 25 respectively). Even if this difference is not significant, it is an important finding. Whenever pathological patterns are assessed and one more subject can be assessed with greater confidence, the service to this subject is invaluable.

When the same variables were analysed by both LDA and NNs, the latter gave better results (second LDA and NN 4.4). This suggests that NNs are more sensitive to changes of a pattern than LDA. Their feed-back connections might have better success in minimizing the within-group and maximizing the between-group differences.

4.5 Conclusions

It can be concluded that:

a. NNs can distinguish stepping patterns associated with step height;

b. NNs can recognise patterns of human movements which are presented by the angular displacement of different joints and consist of a large number of variables;

c. NNs recognised correctly more patterns than LDA;

d. no information is available from the NNs about the contribution of each predictor variable to the discrimination of pattern; and

e. LDA provides significant information concerning the above contribution.

CHAPTER FIVE

STUDY III

The use of neural networks to recognise standing postures associated with imagined moods of human subjects.

5.1 Introduction

Posture, which is the relative disposition of the body at any one moment, is a composite of the positions of different joints of the body at that time. Thus, the position of one joint has an effect on the position of the other joints (Maggee, 1992).

While standing posture is not a movement, it is still of great interest because it is achieved by the cooperation of the musculoskeletal and the nervous system. The assessment of the standing posture is a common procedure for the diagnosis or the assessment of pathological problems. Problems like back pain or scoliosis are due to abnormal posture or result in it and they are mainly diagnosed or assessed on the bases of postural changes.

Any clinician knows how important, as well as difficult, it is to distinguish different postures, based on subjective observations. New techniques are required to improve the discrimination of different postures.

In study I and II, the studied patterns were produced by artificially altering the normal pattern of gait and stepping respectively. A procedure that leads to subtle changes of standing posture is more problematical. A data set was available in the laboratory which was describing different standing postures associated with imagined moods of human subjects.

It is noteworthy that we can often recognise the mood that a person is in from his/her stance and from the way that he/she walks. The idea of a minimally clad person, being photographed in a brightly lit laboratory, pretending to be happy, relaxed or depressed (regardless of how they felt when they arrived) is faintly ridiculous. Nevertheless, mood is not the subject of this study and the procedure did give rise to subtle and repeatable changes of standing posture and a data set which was suitable for testing the ability of the neural networks to detect the subjects' pretences.

5.1.1 Research outline: aims and objectives

The present study aims to:

a. distinguish patterns of posture with the use of NNs;
b. apply NNs to the discrimination of patterns that are described with the co-ordinates of some anatomical landmarks; and
c. compare the performance of NNs with that of LDA.

5.2 Materials and method

Standing postures were recorded in three different moods imagined by the subjects: depressed (D), happy (H) and relaxed (R). Twelve volunteers (6 men and 6 women) acted as subjects. They were free from musculoskeletal disorders. No other selection criteria were applied. Table 5.1 summarises their stature.

Each subject was barefoot and wore briefs (and bra if female). Markers (consisting of rubber grommets) were attached to the skin with double sided adhesive tape over the glabella, sternal angle, right (R) acromium, R. anterior superior iliac spine, superior border of the R. greater trochanter, R. knee joint line midway between the patella and the popliteal fossa and the inferior margin of the R. lateral malleolus. Straws (120 mm long, and painted black over half their length) were fitted into the grommets at the glabella, sternum and anterior superior iliac spine. The straws greatly increased the chance of determining a landmark's location by compact during digitisation of the photographs if a grommet was obscured. A flexible plastic tape was attached to the back overlying the spinous processes. It carried studs, 40 mm apart, to which black and white straws were fitted. The upper stud was located over the vertebra prominens. Figure 5.1 is a line drawing of a human subject in a standing posture with the measured anatomical landmarks superimposed.

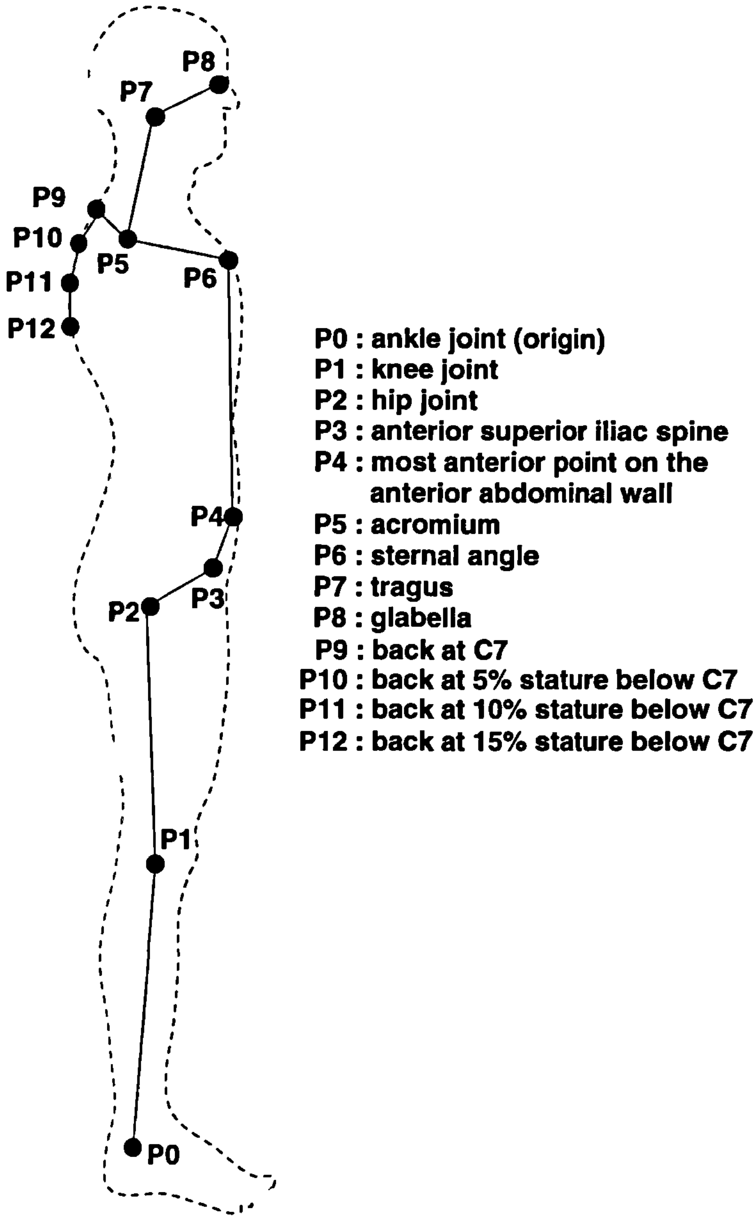

Figure 5.1

Right view of a human standing posture, indicating the set of the measured anatomical landmarks (P0-P9) and computed landmarks (P10-P12).

A Canon F camera (200 mm lens, Ilford HP4 film) was located 18 m from the mid-sagittal plane of the subject with the optical axis horizontal and perpendicular to the plane. A plumb line was suspended behind the subject in the mid-sagittal plane and carried two marker balls 1m apart. The right side of the subject was photographed.

The subject was asked to adopt a symmetrical stance with feet comfortably apart and that foot placement was maintained during the experiment. The subject faced a large black and featureless cloth screen. One experimenter stood behind the subject to give instructions while another operated the camera. The same person gave the instructions to each subject and spoke quietly. Using a randomised order of requests, different for each subject, he asked the subject to imagine that he/she was in a particular mood e.g. 'you are very relaxed ... extremely calm ... very relaxed', repeating the suggestion at intervals until the subject grunted to indicate that he/she was in that frame of mind. The instructor then gave a signal for the photograph to be taken. The three moods were requested in random order, and repeated eight times in different random orders restricted only by the condition that no mood was requested twice in succession.

The photographs were back projected orthogonally onto a screen and the images of the landmarks and the plumb line markers digitised by means of a Grafbar 7 sonic digitiser linked to an Apple IIe microcomputer. Basic software was used to rotate the digitised data to correspond to the vertical and horizontal axes in the sagittal plane and scaled to millimetres. No parallax corrections were made because of the long camera distance. Subsequent processing was done with an Elonex 486 PC.

The data set associated with each photograph contained horizontal (x) and vertical (y) coordinates (in mm) in the sagittal plane, referred to the ankle as origin. Linear interpolations were applied to the back landmarks to give the coordinates of C7 and the skin at points 5, 10 and 15% of stature inferior to it. The coordinates of all landmarks were finally computed as fractions of stature.

Table 5.1: The subjects' stature in m.

	MALES	**FEMALES**	**OVERALL**
N	6	6	12
Mean	1.79	1.66	1.73
SD	0.04	0.07	0.09
Max	1.85	1.76	1.85
Min	1.76	1.55	1.55

5.3 Data presentation and analysis

Each recorded variable was given a name which consists of a character (x or y) and a number (from 0 to 12) . The number represents the corresponding anatomical landmark (as seen in Figure 5.1) and the character represents the vertical (y) or the horizontal (x) axis.

The studied patterns were presented in three different models. In the first model (MD1) the coordinates of 12 anatomical landmarks (excluding the ankle which is the origin) were used to describe each posture which leads to 24 variables per pattern. The data of MD1 were separated into two files. One file of data (data from 3 men and 3 women) was used for training or classification (training file) and the other (data for the remaining subjects) was used for testing or prediction (testing file). Both the training and the testing file contained all of the eight trials of the subjects in each of the three postures, that is, no averaging was performed. As a result, both of these files contained 144 inputs (6 subjects x 3 moods x 8 repetitions).

For the second model (MD2) the variables of the MD1 were used but averaging was performed for each subject between the eight recording postures of the same mood which gave three patterns per subject. In the third model (MD3) the coordinates of 6 landmarks from MD2 (P5, P7, P8, P9, P10 and P6 as origin) used to describe each posture leading to 10 variables per pattern (excluding P6). Figure 5.2 illustrates the postures associated with the three imagined moods of MD3 after averaging was performed. The graphical presentation of all patterns are included in Appendix C: Figure C1 to C4. MD2 and MD3 contained 36 inputs (12 subjects x 3 moods).

5.3.1 Discriminant analysis

Three stepwise discriminant function analyses were performed (LDA 5.1, LDA 5.2 and LDA 5.3 for MD1, MD2 and MD3 respectively) using SPSS/PC+ V2.0 (Norusis, 1988) to classify the standing postures associated with imagined moods. The Wilks' Lambda criterion was employed and sample sizes were used in the estimation of prior probabilities of group membership. Table 5.2 shows the variables included in each LDA at each step with the associated significant level.

Two discriminant functions were calculated with a combined $\chi^2(20)=183$ $p<0.001$, $\chi^2(8)=28.6$ $p<0.001$ and $\chi^2(8)=36.6$ $p<0.001$ for LDA 5.1, LDA 5.2 and LDA 5.3 respectively. After removal of the first function, there was a very small association between groups and predictors (for LDA 5.1: $\chi^2(9)=14$ $p>0.1$, for LDA 5.2: $\chi^2(3)=0.2$ $p>0.1$ and for LDA 5.3: $\chi^2(3)=1.13$ $p>0.1$).

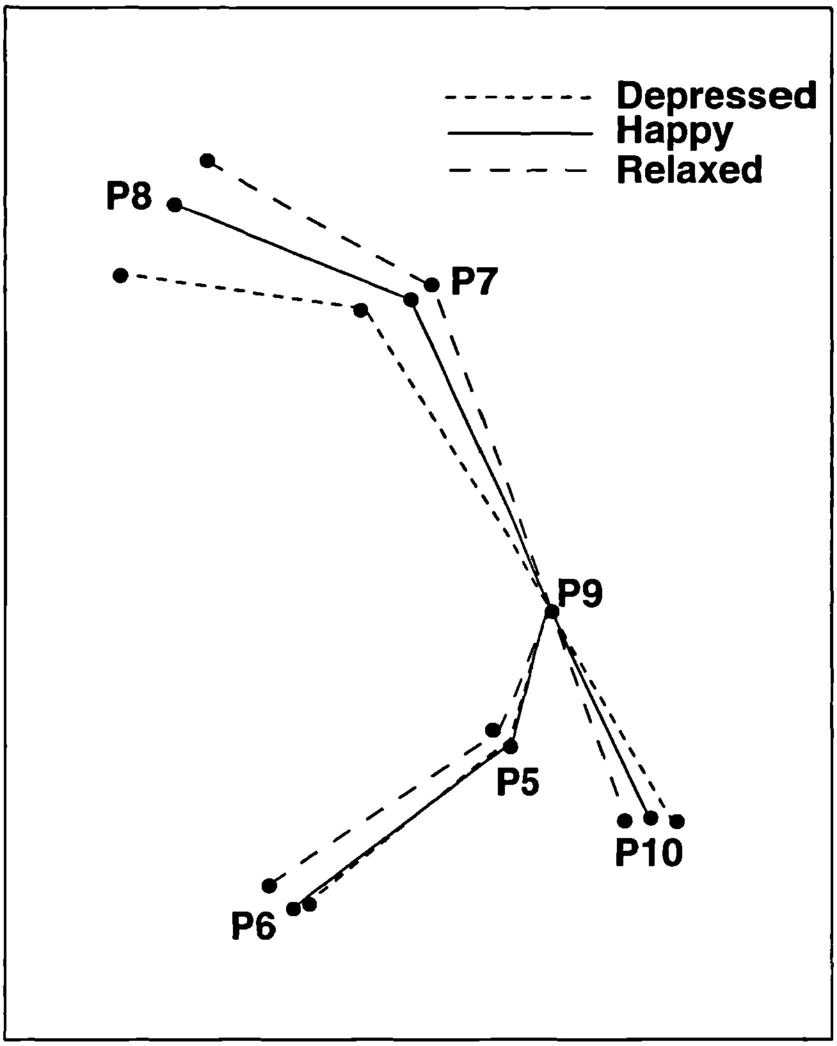

Figure 5.2

Graphical representation of three human standing postures (left view) based on 6 anatomical landmarks of the upper body. Mean data obtained from 12 subjects after averaging performed for the eight trials of each mood.

Table 5.2: Results of the three discriminant function analysis (LDA 5.1, LDA 5.2 and LDA 5.3) with the variables included in the model at each step and the associated Wilk's Lambda. The correlation between discriminant functions and predictor variables are shown.

LDA 5.1	VR[$]	WL[£]	p	F(2,141)	CORR[@]
	X8	0.73	0.000	25.9	-0.390
	X7	0.41	0.000	39.8	0.012
	Y4	0.34	0.000	33.1	0.006
	X6	0.30	0.000	28.6	-0.058
	X4	0.29	0.000	23.2	-0.140
	X3	0.28	0.000	19.7	0.048
	X7	0.28	0.000	17.1	-0.078
	Y8	0.27	0.000	15.5	-0.308
	Y5	0.26	0.000	13.9	-0.045
	X5	0.26	0.000	12.7	-0.060
	Canonical R				0.843
	Eigenvalue				2.46
	% of variance				95.8%

LDA 5.2	VR[$]	WL[£]	p	F(2,33)	CORR[@]
	X1	0.72	0.040	6.5	0.520
	X3	0.49	0.000	6.9	0.067
	X6	0.45	0.000	5.0	0.006
	X7	0.40	0.000	4.3	0.014
	Canonical R				0.77
	Eigenvalue				1.46
	% of variance				99.5%

LDA 5.3	VR[$]	WL[£]	p	F(2,33)	CORR[@]
	X5	0.56	0.000	12.0	0.621
	X10	0.47	0.000	7.4	0.112
	Y5	0.43	0.000	5.3	-0.471
	Y7	0.38	0.000	4.7	-0.070
	X9	0.31	0.000	4.6	0.492
	Canonical R				0.82
	Eigenvalue				2.08
	% of variance				98.3%

[$] VR: variables
[£] WL: Wilk's Lambda
[@] CORR: correlation of predictors with discriminant function

Figures 5.3, 5.4 and 5.5 are histograms of the scores obtained for each case by the discriminant function for each LDA. Table 5.2 shows the loading matrix of correlations between the predictors and the discriminant functions.

During the classification procedure of all patterns, 110 out of 144 (81%) correctly classified by LDA 5.1, 27 out of 38 (75%) by LDA 5.2 and 24 out of 38 (67%) by LDA 5.3 (compared to 33% that would be correctly classified by chance alone). The stability of LDA 5.1 was checked by a cross-validation run using the testing file. The stability of LDA 5.2 and LDA 5.3 was checked by a jackknifed classification run.

5.3.2 Neural Networks

A recurrent network (NN 5.1) was constructed with 24 input, 6 hidden and 3 output units (Figure 5.6). Each input pattern consisted of the X and Y co-ordinates of the 12 anatomical landmarks from MD1. The training file was used during the training procedure and the testing file was used to check the ability of the network to generalize. NN 5.1 was trained after 475 cycles. Its total RMS error was 0.10 and its maximum unit error was 0.60.

Figures 5.3 to 5.5

Histograms of the scores obtained by the discriminant functions (LDA 5.1, LDA 5.2 and LDA 5.3) for all groups (3 moods). Two symbols (1's, 2's and 3's) represents one case in Figure 5.3 and Figure 5.5. Only one symbol represent one case in Figure 5.2. The row of those symbols underneath the plot denote to which group scores are assigned. The last row of numbers represents the group centroid. The vertical axis represents number of cases. The numbers 1, 2 and 3 symbolise Depressed, Happy and Relaxed mood respectively.

Figure 5.3: Histogram of the scores obtained by the discriminant function (LDA 5.1).

```
       X----+----+----+----+----+----+----+----X
  16  +                                         +
      |                         2               |
      |                3        32              |
  12  +                3   3   332              +
      |                1   3 33332              |
      |                1   3333332              |
      |                1  333333222             |
   8  +                1  333333222             +
      |                13 333332222             |
      |                11 323332222             |
      |                11 113332222             |
   4  +             1111 113332222 2            +
      |         1   11111113332222 2            |
      |        11  111111112222222 2            |
      |       111  111111111122222 2            |
       X----+----+----+----+----+----+----+----X
           -6   -4   -2    0    2    4    6
Class 11111111111111111111333332222222222222222
Centroids             1     3   2
```

Figure 5.4: Histogram of the scores obtained by the discriminant function (LDA 5.2).

```
       x----+----+----+----+----+----+----+----x
    8 +                   3                     +
      |                   3                     |
      |                   3                     |
      |                   3                     |
    6 +                   3                     +
      |                   3                     |
      |                   3     1               |
      |                   3     1               |
    4 +                   2     1               +
      |                   2     1               |
      |                3  2  2  1               |
      |                3  2  2  1               |
    2 +               22332331 311              +
      |               22332331 311              |
      |          2  2 222312311111              |
      |          2  2 222312311111              |
       x----+----+----+----+----+----+----+----x
           -6   -4   -2    0    2    4    6
 Class 22222222222222222223333111111111111111111
 Centroids                2  3   1
```

Figure 5.5: Histogram of the scores obtained by the discriminant function (LDA 5.3).

```
       x----+----+----+----+----+----+----+----x
    8 +                  3                      +
      |                  3                      |
      |                  3                      |
      |                  3                      |
    6 +                  3                      +
      |                  3                      |
      |                  3     1                |
      |                  3     1                |
    4 +               2  2     1                +
      |               2  2     1                |
      |               23 2     1                |
      |               23 2     1                |
    2 +               23 23 33 1 1 1            +
      |               23 23 33 1 1 1            |
      |             222231223311 1 11           |
      |             222231223311 1 11           |
       x----+----+----+----+----+----+----+----x
           -6   -4   -2    0    2    4    6
 Class 22222222222222222233331111111111111111111
 Centroids                2 3     1
```

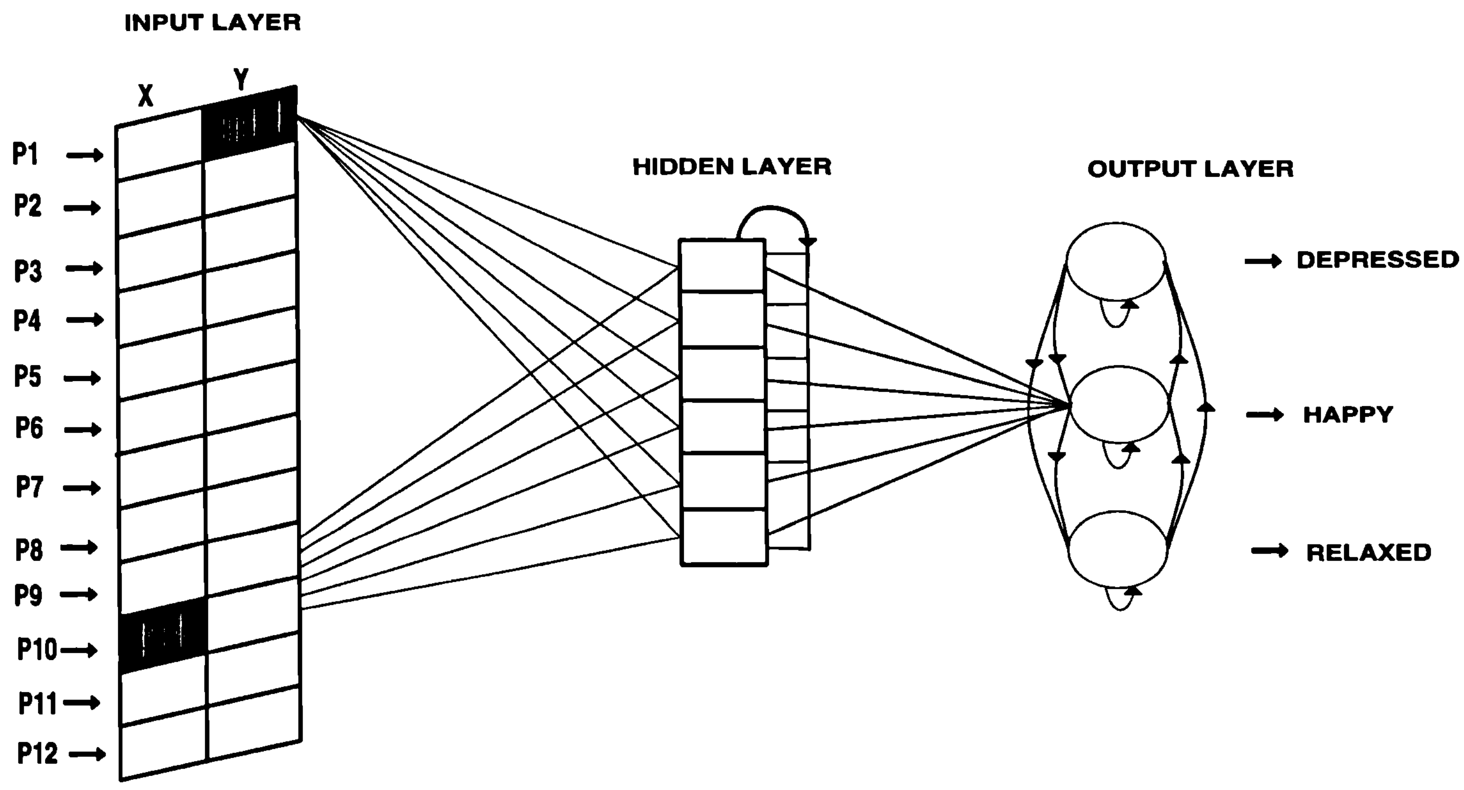

Figure 5.6

A three layered recurrent neural network (NN 5.1) with 24 input, 6 hidden and 3 output units (not all connections are shown). It was constructed and trained to recognise the human standing posture using an input the X & Y coordinates of 12 anatomical landmarks.

A second recurrent network (NN 5.2) was constructed with 24 input, 9 hidden and 3 output units. Each input pattern consisted of the X and Y co-ordinates of the 12 anatomical landmarks from MD2. All patterns were used during the training procedure which was applied for 950 cycles. NN 5.2's total RMS error was 0.06 and its maximum unit error was 0.28. The network was checked with a jackknifed classification run. Table 5.3 shows the number of training cycles, the total RMS error and the maximum unit error of the network after each step during the jackknifed classification of the patterns.

A third recurrent network (NN 5.3) was constructed (Figure 5.7) with 10 input, 6 hidden and 3 output units. Each input pattern consisted of the X and Y co-ordinates of the 5 anatomical landmarks from MD3. All patterns were used during the training procedure which last 823 cycles. NN 5.3's total RMS error was 0.10 and its maximum unit error was 0.64. The network was checked with a jackknifed classification run. Table 5.3 shows the number of training cycles, the total RMS error and the maximum unit error of the network after each step during the jackknifed classification of the patterns.

Table 5.3: The characteristics of NN 5.2 and NN 5.3 during the jackknifed procedure. The pattern which was excluded from the training file is shown.

	NN 5.2				**NN 5.3**			
No	**TC**	**tRMS**	**mUR**	**R**	**TC**	**tRMS**	**mUR**	**R**
1	657	0.08	0.46	N	671	0.09	0.33	Y
2	610	0.09	0.49	Y	769	0.14	0.97	Y
3	630	0.09	0.39	Y	775	0.15	0.99	Y
4	690	0.09	0.38	Y	1016	0.07	0.31	Y
5	750	0.08	0.36	Y	1310	0.10	0.99	Y
6	720	0.09	0.38	Y	1179	0.09	0.47	Y
7	570	0.09	0.36	Y	934	0.14	0.99	Y
8	620	0.08	0.33	Y	447	0.14	0.99	N
9	591	0.10	0.29	Y	518	0.15	0.99	Y
10	571	0.09	0.36	Y	632	0.14	0.99	Y
11	610	0.09	0.32	N	854	0.14	0.99	Y
12	594	0.09	0.36	N	682	0.14	0.99	Y
13	660	0.09	0.38	Y	559	0.14	0.99	N
14	565	0.09	0.38	Y	619	0.14	0.99	Y
15	561	0.09	0.32	Y	609	0.14	0.99	Y
16	640	0.09	0.34	N	457	0.15	0.99	Y
17	559	0.09	0.40	Y	690	0.14	0.99	Y
18	579	0.09	0.33	Y	782	0.14	0.99	Y
19	670	0.08	0.29	Y	556	0.14	0.99	Y
20	569	0.09	0.34	Y	654	0.14	0.99	Y
21	561	0.09	0.29	Y	696	0.14	0.99	Y
22	503	0.09	0.37	N	841	0.14	0.99	N
23	522	0.09	0.29	Y	664	0.14	0.99	Y
24	612	0.08	0.27	N	950	0.14	0.99	Y
25	486	0.09	0.35	N	299	0.09	0.55	N
26	533	0.09	0.32	N	428	0.09	0.47	N
27	710	0.09	0.44	N	429	0.09	0.47	Y
28	965	0.15	0.99	N	432	0.09	0.51	Y
29	862	0.09	0.31	Y	461	0.09	0.50	Y
30	787	0.09	0.29	Y	385	0.09	0.48	Y
31	721	0.09	0.34	N	369	0.09	0.54	N
32	584	0.09	0.41	Y	367	0.09	0.55	N
33	535	0.13	0.55	Y	387	0.09	0.51	N
34	809	0.09	0.41	Y	378	0.09	0.51	N
35	511	0.08	0.34	Y	408	0.08	0.46	N
36	642	0.09	0.40	Y	319	0.11	0.59	N

No : pattern excluded from the training file,
TC : number of training cycles,
tRMS: total RMS error,
mUR : maximum unit error and
R : results of the classification of the pattern which was excluded from the training file, N=wrong and Y=correct.

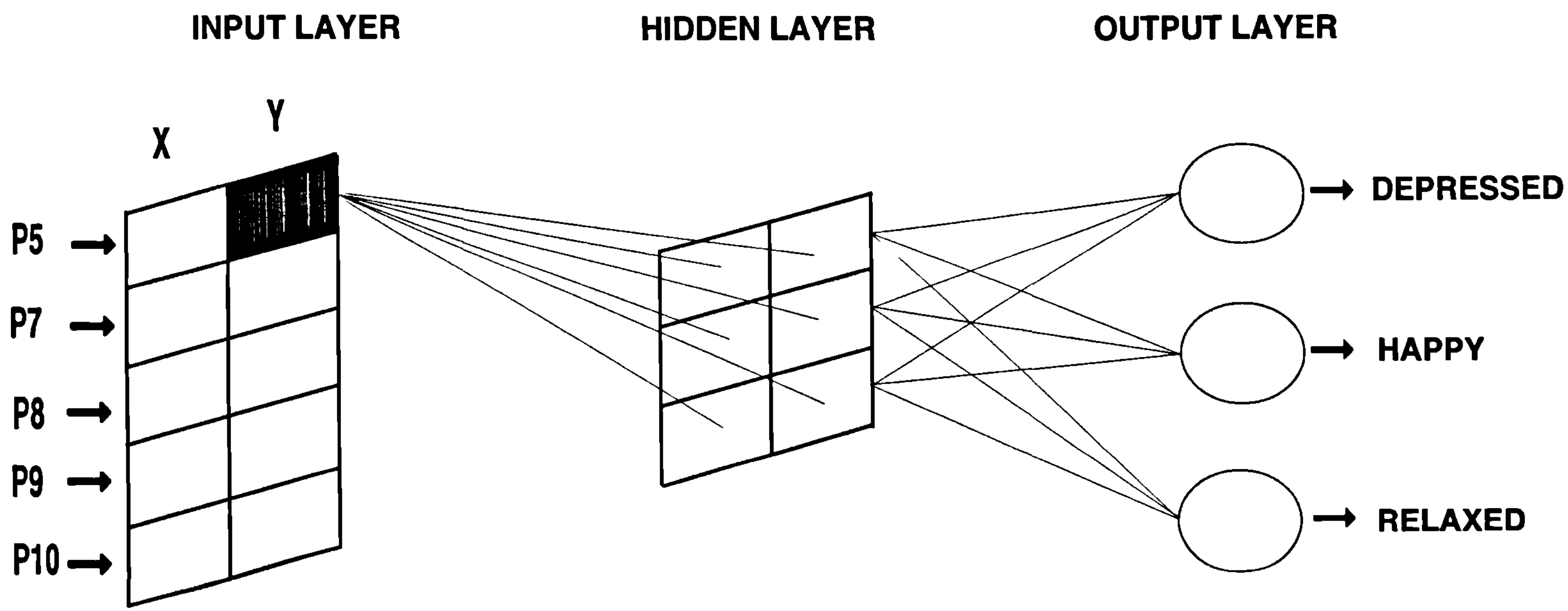

Figure 5.7

A three layered recurrent neural network (NN 5.2) with 10 input, 6 hidden and 3 output units (not all connections are shown). It was constructed and trained to recognise the human standing posture on the basis of X and Y coordinates of 5 anatomical landmarks.

5.4 Results

Table 5.4 shows the correctly classified patterns of MD1, MD2 and MD3 by LDA as well as by NNs. These results are from the classification procedure of the patterns and the procedure by which the classification was checked either with a cross-validation or a jackknifed run.

McNemar's χ^2 test was used to compare the performance of NN 5.1 and LDA 5.1. A statistically significant difference exists ($\chi^2(1)=4.02$, $p<0.05$) between the performance of NN 5.1 and that of LDA 5.1.

Table 5.4: The number of correctly classified patterns by NNs and LDA using MD1, MD2 and MD3. The results are obtained during the classification procedure as well as during the procedure by which the classification was checked (cross-validation run for LDA 5.1-NN 5.1 and jackknifed classification for LDA 5.2 - NN 5.2 - LDA 5.3 - NN 5.3). In MD1, there are 48 patterns from each mood and 144 as a total. In MD2 and MD3, there are 12 patterns from each mood and 36 as a total.

Model	Method	Depressed	Happy	Relaxed	Total
MD1:					
	LDA 5.1:				
	CL	32 (79%)	43 (90%)	35 (73%)	110 (81%)
	CV	34 (71%)	24 (50%)	16 (33%)	74 (51%)
	NN 5.1:				
	CL	48 (100%)	48 (100%)	47 (98%)	143 (99%)
	CV	32 (67%)	24 (50%)	32 (67%)	88 (61%)
MD2:					
	LDA 5.2:				
	CL	11 (92%)	7 (58%)	9 (75%)	27 (75%)
	JF	10 (83%)	7 (58%)	7 (58%)	24 (67%)
	NN 5.2:				
	CL	12 (100%)	12 (100%)	11 (92%)	35 (97%)
	JF	9 (75%)	6 (50%)	10 (83%)	25 (69%)
MD3:					
	LDA 5.3:				
	CL	11 (92%)	7 (58%)	6 (50%)	24 (67%)
	JF	10 (83%)	7 (58%)	4 (33%)	21 (58%)
	NN 5.3:				
	CL	12 (100%)	12 (100%)	11 (92%)	35 (97%)
	JF	11 (92%)	9 (75%)	5 (42%)	25 (69%)

CL: results obtained by the classification procedure,
CV: results obtained when the classification was checked by cross-validation and
JF: results obtained when the classification was checked by jackknifed classification.

5.5 Discussion

The present study deals with the prediction of the mood that a person pretends or assumes under these artificial circumstances, from the changes of his/her standing posture. This prediction was not the aim but it was used as an example where discrimination of different postures can be done and NNs can be used. The studied postures were presented and analysed in three different models aiming to see how NNs and LDA behave when the same patterns are presented in a different way.

MD1 offered the opportunity to compare statistically NNs with LDA due to the large number of patterns used and NNs were found to be better than LDA. Treating the eight trials of each subject as independent patterns, the within-groups variation increases compared to the between-groups variation.

A true statistical comparison between NNs and LDA cannot be made for the discrimination of patterns of MD2 and MD3 because of the small number of patterns (36) of these models. However, it should be noted that NNs recognised correctly more patterns (from MD2 and MD3) than LDA. Both classification techniques demonstrated a better success rate in MD2 than in MD1, probably due the decrease of the within-group variation.

As has been discussed in study II, no information about the predictor variables is available from NNs. Table 5.1 shows information about these variables which are produced by LDA. It should be noted that LDA selected 10 variables in MD1 and 4 in MD2. The variables selected in MD1 are the x and y co-ordinates of anatomical landmarks of the trunk and upper body. The variables selected in MD2 are only the x co-ordinates of the anatomical landmarks of all levels of the body. The patterns used by either LDA 5.1 or LDA 5.2 are the same. Why are the variables used by these LDAs not the same? Is it because of the decrease of the within-group variation or is it due to the decrease of sample size? No answer can be given by the present study and further investigation is needed.

Moving from MD2 to MD3, there is a decrease of the available variables which are describing each pattern. The success rate for NNs is the same in MD2 as well as in MD3 (69%). The LDA's success rate decreased from 67% for MD2 to 58% for MD3 and at the same time the number of variables selected by LDA increased. It seems as though there is a relationship between the patterns of MD3 which is more difficult to identify using LDA than the relationship within the patterns of MD2.

LDA probably performs in a different way to NNs and it uses different characteristics to discriminate the patterns. It seems likely that the training procedure is an important parameter, as it is guided by the user and the NNs are "forced" to learn the relationship between the patterns. The small sample size and the fact that the patterns are artificial do not allow the above findings to be generalized. The present work should be repeated with a large number of natural patterns.

An advantage of the use of NNs in the assessment of patterns of posture is their ability to deal with an unlimited number of variables. Supposing that a clinician wants to assess neck pain from postural changes. The lower body is not included in his assessment because it is not considered important and at the same time its consideration increases the number of variables and makes the diagnosis difficult, if not impossible. But who can say that the assessment of this part of the body is unimportant? The answer to this question might be provided by the use of NNs.

5.6 Conclusions

It can be concluded that:

a. NNs can be used to distinguish patterns of human posture;
b. NNs can be used to discriminate patterns that are presented with the co-ordinates of some anatomical landmarks;
c. NNs can deal better than LDA with problems that have high within-groups variation.

CHAPTER SIX

STUDY IV

The use of neural networks to identify the existence of low back pain problem from the patterns of the sit-to-stand manoeuvres.

6.1 Introduction

Low back pain is a pain that almost everyone experiences in his/her life with various levels of intensity and frequency. As a term, low back pain describes the patient's symptoms which are pain on the low back and covers a wide range of problems with various aetiologies. The diagnosis as well as the treatment of a problem which causes low back pain is a difficult task and has generated a great research interest (Cailliet, 1991).

Low back pain affects the daily life of the patients and their patterns of movement. Particularly when the pain is chronic, this introduces problems to society of socio-psychological and economical importance. One characteristic example is the absence of the sufferer from his work for a few days to a few months per year and the enormous amount of money needed for health care of the low back patients. Consequently, the identification of the real low back pain patient is important.

Sitting down and standing up from a chair, like walking, are common human activities and have been the subject of investigation in order to be standardised (Kralj et al., 1990; Roebroeck et al., 1994; Riley et al., 1991; Schultz et al., 1992). The sit-stand manoeuvre is one of the patterns of human movement that is found to be altered by low back pain problems (Coghlin & McFadyen, 1994).

There are at least two strategies employed by normal people to perform the task of transferring from a sitting to a standing position. Chronic low back pain patients use modified strategies which cannot be grouped into either of the normal strategies (Coghlin & McFadyen, 1994).

Although low back pain patients may be use different strategies during the sit-stand-sit transfer, it is difficult to identify changes in these performances due to their small amplitude and to the large number of descriptive variables. New techniques are required to identify changes of the sit-stand manoeuvres and help clinicians to identify low back pain problems.

6.1.1 Research outline: aims and objectives

The present study aims to:

a. identify the existence of low back pain problem from the patterns of the sit-to-stand manoeuvres using NNs;

b. apply NNs to the recognition of patterns of human movement based upon the range of motion of various joints and the forces exerted on the ground by both feet;

c. compare the performance of NNs to identify pathological patterns of human movement with that of LDA and that of clinicians.

6.2 Materials and method

An experiment was designed and carried out to measure the horizontal and vertical forces exerted on the ground by both feet as well as the range of motion of the right knee, right hip and lumbar spine during the sit-stand and stand-sit manoeuvres of healthy volunteers, back pain patients and subjects pretending to have back pain problems.

6.2.1 Subjects

Three groups of unpaid volunteers (23 males and 13 females) participated in the present study. The first group (H) consisted of fourteen healthy subject (9 males and 5 females) with no history of locomotor disturbance. The second group (M) consisted of twelve subjects (9 males and 3 females) whose only history of locomotor disturbance was one previous back pain episode at least one year before the experiment. Subjects of the first and second group were students or academic staff.

The third group (P) consisted of ten persons suffering from non specific, chronic low back problem (5 males and 5 females) recruited from the physiotherapy department of the Royal Free Hospital. These patients had no history of any other locomotor disturbance, including sciatica, and they had a low back pain history of more than a year. They also scored between 20 and 40% on the Oswestry Back Disability

Index (OBDI) indicating moderate disability (Fairbank et al., 1980) and they were free of any pain during the experiment. Table 6.1 summarises the physical characteristics of the subjects and more details are included in Appendix D: Table D1.

All subjects received an information package describing the purpose of the experiment and the procedures involved. They also received a health questionnaire (Dickinson et al., 1992; Kuorinka et al., 1987), the OBDI and informed consent. These leaflets provided the information to identify the volunteers to be included in the study and to allocate them to the appropriate group.

The present study was approved by the Ethical practices Sub Committee of the Royal Free Hampstead NHS Trust. Appendix D includes the ethics clearance, the letter to the subjects, the volunteers information package, the health questionnaire, the OBDI and the informed consent.

Table 6.1: Physical characteristics of subjects.

Group	N	Stature (m)	Weight (Kg)	Age (years)
(H)	14			
Mean		1.74	71	34.8
SD		0.05	10.8	5.5
Max		1.86	83	48
Min		1.65	58	28
(M)	12			
Mean		1.75	72	24.9
SD		0.06	12	1.8
Max		1.88	92	28
Min		1.68	59	21
(P)	10			
Mean		1.71	72.9	41.4
SD		0.09	12	9.7
Max		1.87	90	54
Min		1.55	55	24
Overall	36			
Mean		1.73	71.9	33.4
SD		0.07	11.3	8.9
Max		1.88	92	54
Min		1.55	55	21

6.2.2 Experimental equipment

The equipment used consisted of :

1. a host computer (BBC B computer with a 6502 second processor, Acorn Ltd);
2. an A/D converter (CED 1401 Intelligent Interface, Cambridge Electronic Design Ltd);
3. a Panasonic video camera (F15 CCD) with matching monitor and video recorder (AG 6200);
4. two biomechanical force plates;
5. an armless, adjustable seat which was equipped with an adjustable backrest;
6. three flexible electrogoniometers (Penny and Giles Blackwood Ltd, Gwent, UK); and
7. a network of resistors and a power supply.

The electrogoniometers were used to measure the flexion-extension angles of right knee, right hip and lumbar spine (from sacrum to the T12). They were connected to pre-amplifiers whose output was fed to the A/D converter after further amplification. Their reliability was checked with the procedure described in section 4.2.2. Actual and observed values for the three electrogoniometers were highly correlated (R^2=1.000 & RMS=1°, R^2=0.999 & RMS=1.2° and R^2=1.000 & RMS=1.1° respectively).

Two pieces of aluminium, separated by 4 springs, were placed on the seat as well as on the front area of the backrest and were connected to the network of resistors. The voltage output of the network was uniquely determined according to whether the subject's body was in contact with the chair and whether to the seat or backrest. These signals were also digitized. The force sensitivity of this structure was measured to be 10N for the seat and 5N for the backrest.

The video camera was placed 3m away from the seat and it was used to videotape the subjects from the right side, in the sagittal plane, as they performed the stand-sit and sit-stand movements.

The force plates were placed in front of the seat, 10cm apart and used to measure horizontal and vertical forces of both feet as well as their centre of foot pressure. The signals from the force plates were also digitized. Section 6.2.2.1 includes information about the force plates.

The A/D converter was controlled by the host computer using software written in BBC Basic. Each electrical signal was amplified, digitized and sampled by the computer at 100Hz for 5sec. Horizontal as well as vertical forces and centres of foot pressure were calculated. All data were displayed on the computer monitor and then saved for further processing and analysis. Figure 6.1 is a block diagram of the experimental equipment and Appendix E includes the software written to control this equipment.

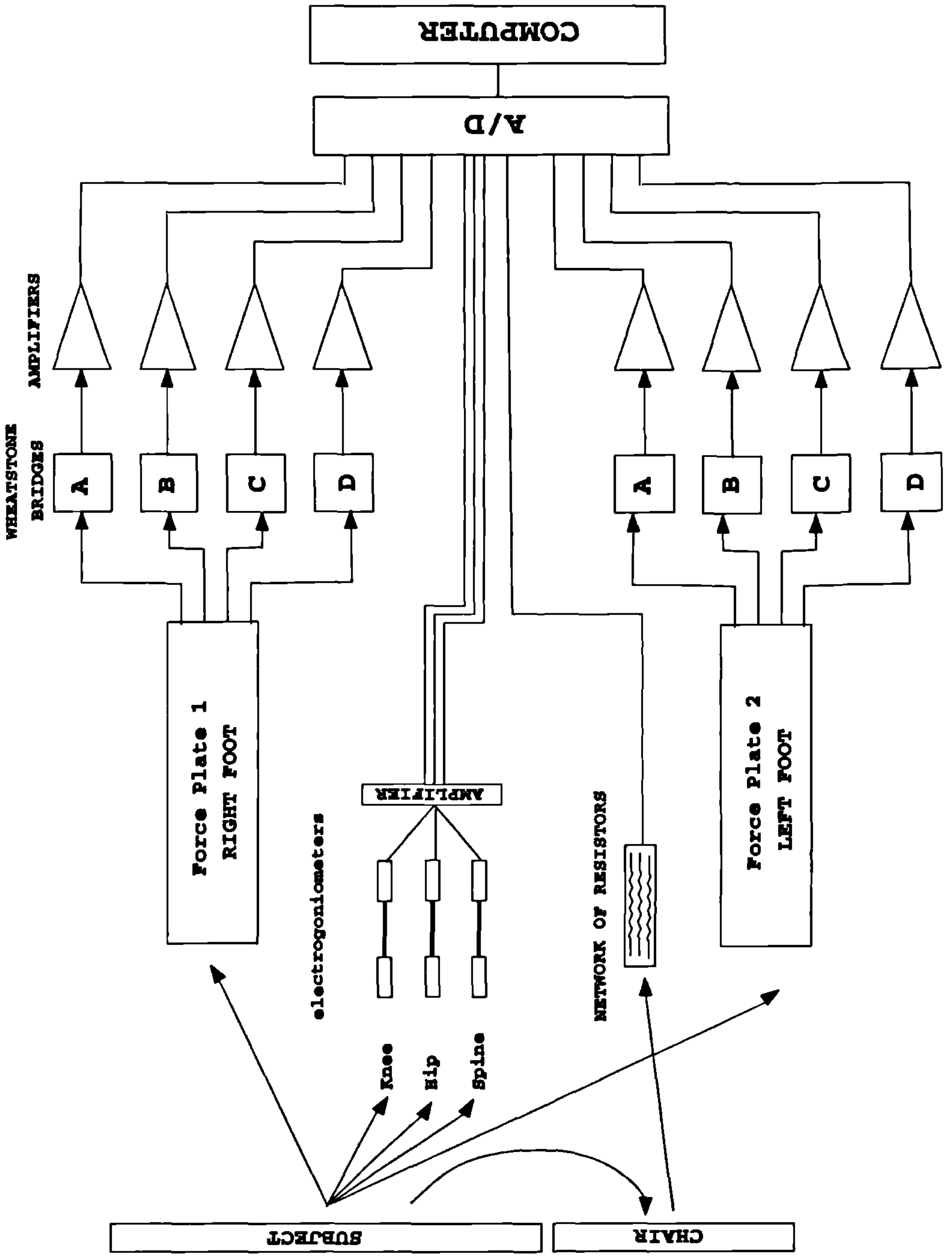

Figure 6.1: Block diagram of the experimental equipment

6.2.2.1 Force plates

Force plates were required to measure forces exerted on the ground by each foot of the subject during the sit to stand manoeuvre. Two force plates were designed and manufactured for this purpose.

6.2.2.1.1 The design of the force plates

According to the criteria defined, the force plates should:

1. be built in the laboratory at low cost;
2. produce accurate and reliable measurements;
3. measure the horizontal force (F_H) which was expected to be less than 40Kg, identifying the direction of this force, forward as positive (+) and backwards as negative (-);
4. be able to accept a maximum total vertical force (F_V) up to 80Kg;
5. measure the anterior-posterior location of the centre of foot pressure (CFP).

Figure 6.2 and 6.3 are line drawings of one of the force plates. In this Figures, each component of the force plate is given a name and detail drawings of each particular component are presented in Appendix E: Figure E1 to E5.

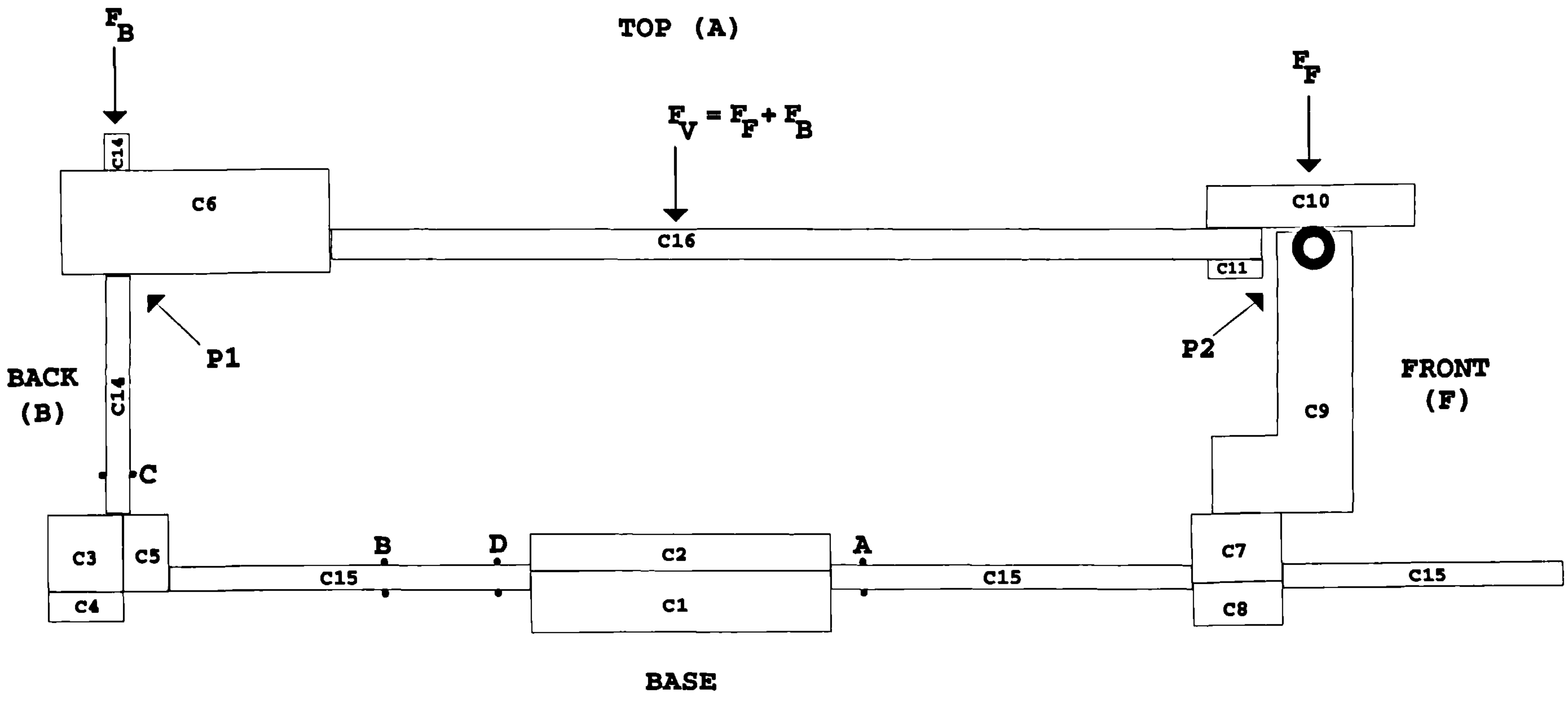

Figure 6.2: Line drawing of the force plate (lateral view and scale 1:3)

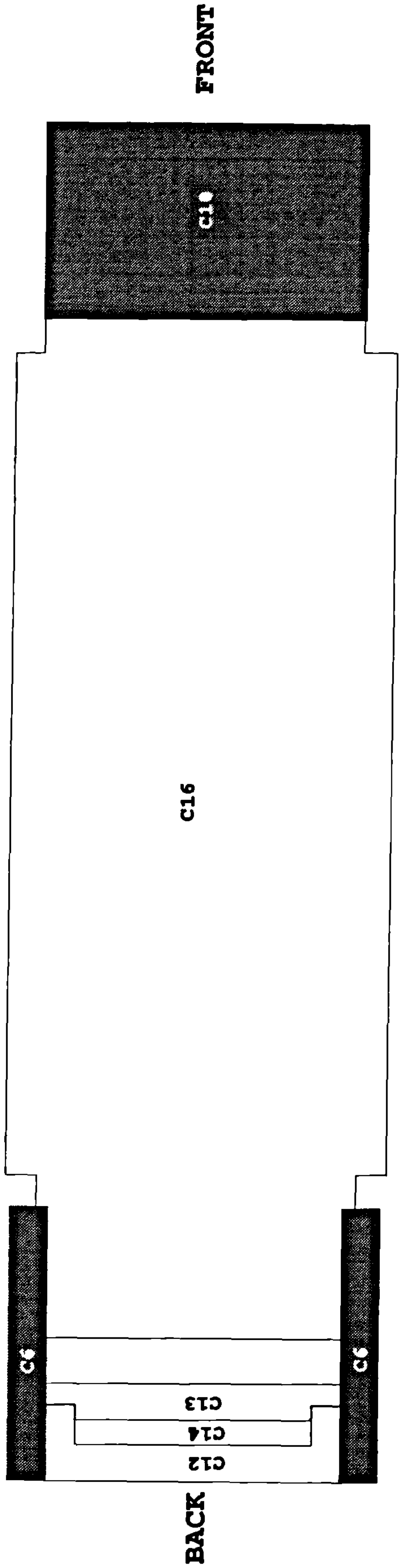

Figure 6.3: Line drawing of the force plate (view from above and scale 1:3)

As it can be seen in Figure 6.2, the top of the force plate (C16 plus C6 component) was free to rotate about the point P1 which acts as a hinge between the top surface and component C14. Horizontal forces are transmitted to the lower part of the force plate only through point P1 and are producing a bending moment of component C14. Vertical forces are transmitted to the lower part of the force plate through both points, P1 and P2, and are producing bending moments of component C15. The assumption was made that any force should produce bending moments of components C14 and C15 due to the deformation of the force plate.

6.2.2.1.2 Force measurement

Compressive and tensile forces produced at each component of the force plate (C14 and C15) were measured at points A, B, C and D (Figure 6.2) using four foil strain gauges (compensated for use on steel) for each point bonded to the metal and connected in a Wheatstone Bridge configuration.

Outputs from the eight Wheatstone Bridge circuits (two force plates with four bridges each) were connected to separate amplification circuits (eight RS components strain gauge amplifiers 308-815 and PCB 435-692) before being passed to the analogue inputs of a CED 1401 Intelligent Interface (Cambridge Electronic Design Ltd). Figure 6.4 is a photograph of one of the force plates with the strain gauges attached and Figure 6.5 is a photograph of the amplification circuits.

The CED 1401 converted the analogue voltage signals from the 8 amplifiers into 12 bit digital format. Each amplifier was sampled at 100Hz over 5sec time intervals which was sufficient to capture a sit-stand or stand-sit manoeuvre. The digital values from each channel were passed to the host computer for processing and display.

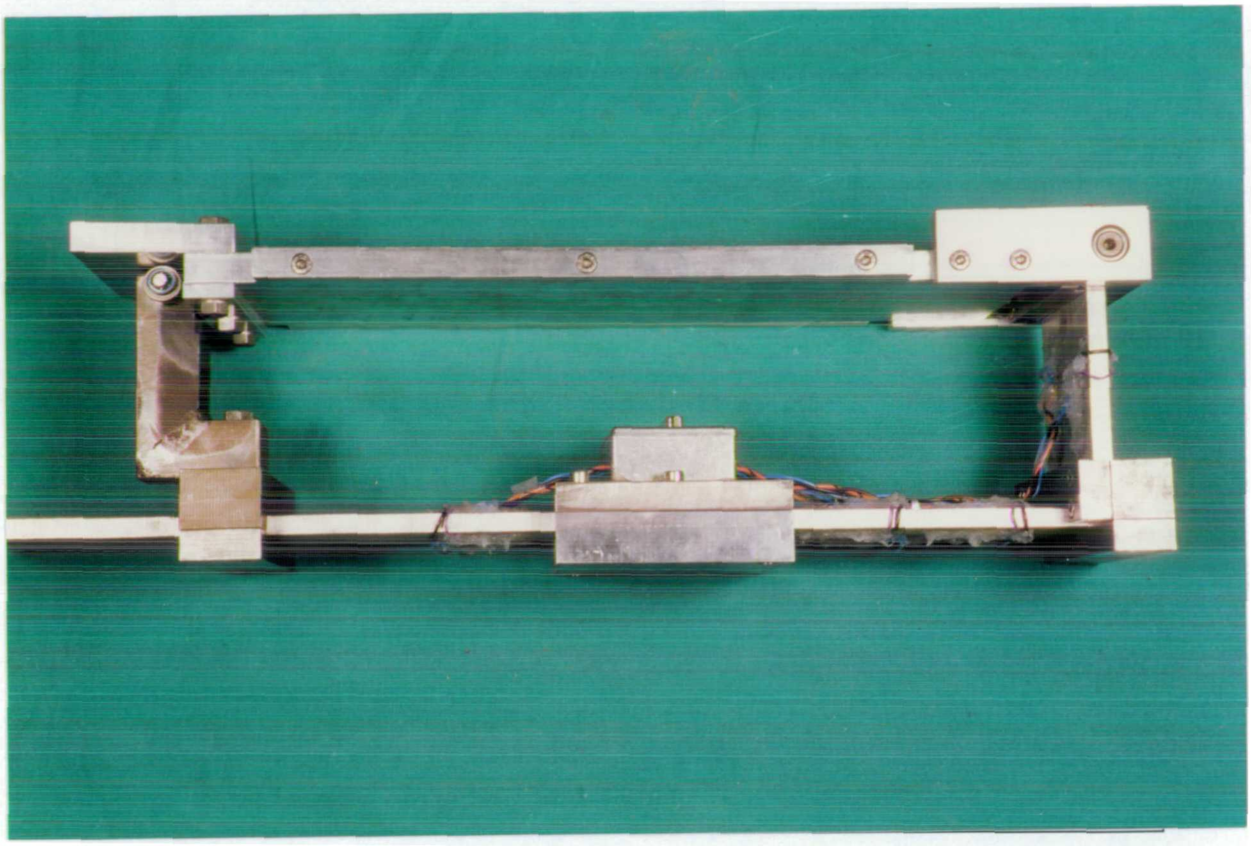

Figure 6.4

A photograph of the force plate (lateral view) with the strain gauges on it.

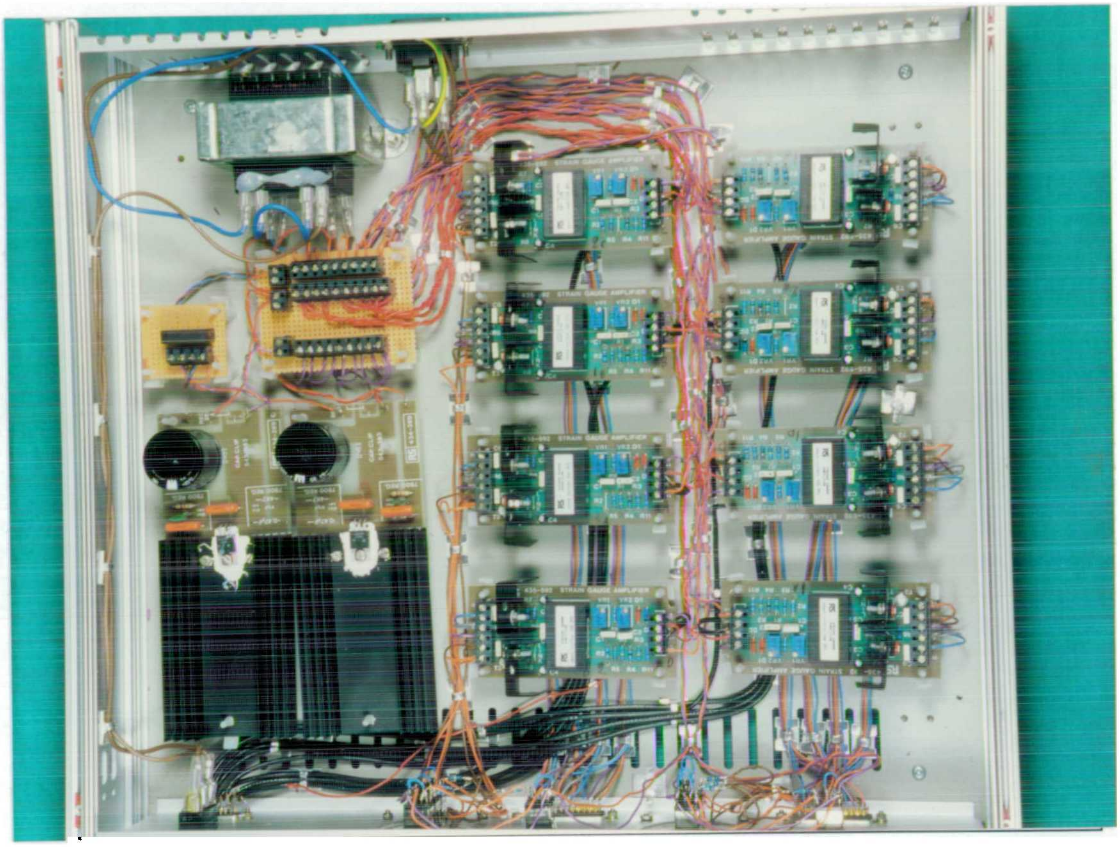

Figure 6.5

A photograph of the amplification circuits
(strain gauge amplifiers 308-815 and PCB 435-692).

6.2.2.1.3 Force plate calibration

The assumptions were made that any applied force on the force plate would produce outputs in all four Wheatstone Bridges and that:

1. bridge A is more sensitive to the F_F component of the vertical force;
2. bridge C is more sensitive to horizontal force; and
3. bridges B and D are more sensitive to horizontal force and to the F_B component of the vertical force but their difference (output of B minus output of D) is more sensitive to F_B.

Each force should be equal to the sum of the outputs of the above bridges multiplied by appropriate constants. This was expressed by the following set of simultaneous equations :

$$F_H = \alpha V_A + \beta V_C + \gamma (V_B - V_D) \tag{6.1}$$

$$F_F = \delta V_A + \varepsilon V_C + \zeta (V_B - V_D) \tag{6.2}$$

$$F_B = \theta V_A + \kappa V_C + \lambda (V_B - V_D) \tag{6.3}$$

F_H = horizontal force

F_F = component of the vertical force at P1

F_B = component of the vertical force at P2

α, β, γ, δ, ε, ζ, θ, κ, λ = calibration constants

V_A = voltage change at A / calibration deflection of A

V_B = voltage change at B / calibration deflection of B

V_C = voltage change at C / calibration deflection of C

V_D = voltage change at D / calibration deflection of D

Calibration deflections for the CED were obtained by activating a calibration resistor which was in parallel with one arm of each Wheatstone Bridge circuit.

The nine calibration constants of the above equations were obtained by solving a set of three simultaneous equations for each force. Data for these equations were collected by applying known forces in known direction and with known points of application.

Figure 6.6 shows the experimental set up used to calibrate the force plates. A total of 5 loads, between 0 to 40 Kg, were applied horizontally in a positive as well as negative direction. A total of 8 loads, between 0 and 70Kg, were applied vertically at 6 different points. Four hundred and twenty readings were finally collected and multiple regression analyses was used to find the best-fit values for the nine constants. Table 6.2 summarises the results of the multiple regression analysis for both force plates.

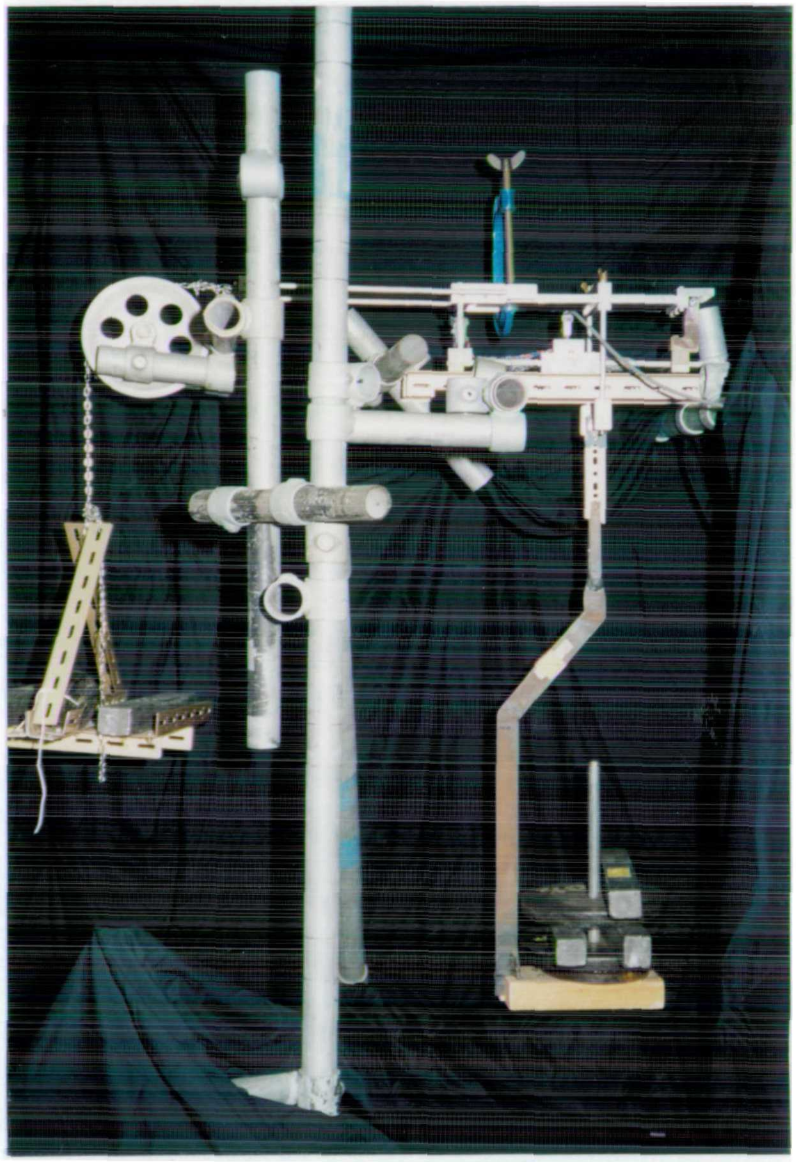

Figure 6.6

A photograph of the experimental set up used to calibrate the force plates.

Table 6.2: Summary of multiple regression analysis for determination of the F_H, F_B and F_F forces following calibration of the force plates (all units are in Newtons)

	Force	Calibration constant	Value of calibration constant	Standard error	R^2	RMS error (N)
FORCE PLATE 1	F_H	constant	7.12	0.87	0.998	10.3
		α	6.83	0.68		
		β	451.40	0.92		
		γ	6.23	2.07		
	F_F	constant	-1.57	0.37	0.999	4.4
		δ	-194.36	0.29		
		ε	-1.09	0.39		
		ζ	3.42	0.88		
	F_B	constant	8.84	0.57	0.997	6.8
		θ	5.44	0.45		
		κ	17.64	0.61		
		λ	545.58	1.37		
FORCE PLATE 2	F_H	constant	2.10	0.47	0.999	5.8
		α	1.75	0.39		
		β	367.68	0.51		
		γ	6.05	1.31		
	F_F	constant	9.92	0.55	0.998	6.8
		δ	-197.32	0.46		
		ε	32.95	0.59		
		ζ	-13.25	1.52		
	F_B	constant	17.08	0.76	0.995	9.4
		θ	4.43	0.64		
		κ	-86.51	0.82		
		λ	604.39	2.11		

One hundred and five new readings were collected, applying the vertical force at 5 new points, to test the reliability of these calibration constants. Table 6.3 summarises the relationship between actual and observed values of the forces and centre of foot pressure for both force plates.

It was concluded that these results provided an acceptable level of measurement error and therefore the calibration constants in Table 6.2 were used to convert digital values from the CED into forces in Newtons.

Table 6.3: Correlation between actual and observed values of F_H, F_F, F_B (in Newtons) and CFP (in mm) for both feet.

	FORCE PLATE 1				**FORCE PLATE 2**			
	F_H	**F_F**	**F_B**	**CFP**	**F_H**	**F_F**	**F_B**	**CFP**
R^2	0.998	0.999	0.997	0.992	1.00	0.998	0.994	0.992
RMS error	8.3	4.7	6.4	7.1	3.3	6.2	9.6	7.1

6.2.3 Experimental procedure

The subjects were asked to first read carefully the volunteers' information package and to sign the informed consent. Afterwards, their anthropometric characteristics (age, height and weight) as well as their shoe size, were recorded.

Each subject was tested while wearing briefs and flat shoes. The three electrogoniometers placed at the right knee, right hip and lumbar spine, with the use of double-sided adhesive tape. The pre-amplifier of the electrogoniometers was attached to a waist belt located the level of the chest.

The height of the seat was adjusted to ensure that the subject's thighs were parallel to the ground and the lower part of the backrest was adjusted to the level of the inferior angle of the scapula. The back of each shoe was positioned on a point of the force plate (left edge of C16, Figure 6.3) which was kept the same for all subjects.

The subjects stood on the force plates in a relaxed position and the total vertical force applied on each force plate was recorded. They then sat on the seat in a passive sitting posture with neutral or slight kyphosis, holding their arms across the chest. They were also instructed to touch but not exert significant force on the backrest. If force was applied to the backrest, the latter was free to move backwards until checked by a stop.

The subjects were asked to stand-up in a comfortable and natural manner at a preferred speed. This procedure was repeated five times and then the subjects held a relaxed standing position with the arms again across the chest. From this starting position they sat down and touched the backrest without looking behind them.

The total number of unique movement patterns for each individual was ten (5 for standing up and 5 for sitting down). The approximate amount of time needed for the whole experiment was thirty minutes. The subjects were allowed to practice beforehand to familiarize themselves with the task.

The subjects of group (M) were asked to imagine that this was part of a medical assessment. They had to pretend that they were back pain patients and as a result to have some possibility of benefit from their insurance company. They were allowed to think about the task and practice the sit-stand and stand sit manoeuvres before the experiment as many times as they wanted.

6.2.4 Data presentation

The beginning of the stand-up manoeuvre was defined as the moment when the total vertical force, applied on the force plates, changed by 2.5% of its value during relaxed sitting. It's end was defined as the moment when the total vertical force was greater than 97.5% of its value during relaxed standing. The procedure was reversed for the sitting down manoeuvre.

Each manoeuvre was separated into two phases according to whether the subject's body was in contact with the seat (phase 1) or not (phase 2). The duration of these phases was calculated with the use of the signal produced by the network of resistors. Figure 6.7 shows the duration of both phases during the sit-stand-sit manoeuvre of the subjects.

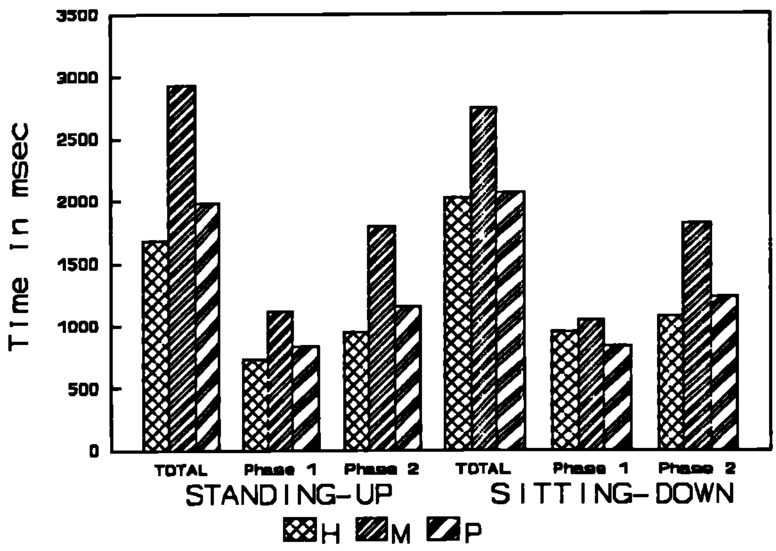

Figure 6.7: The time (total, phase 1 and phase 2) taken by the three groups to stand up and to sit down.

Forces were computed as fractions of body weight while the CFP was expressed as percentage of foot length using as origin the heel. Whenever the range of motion is expressed in relative angles, it is referred to relaxed sitting position (SP). All measurements were normalized by time and averaging was performed over the 5 trials.

The two manoeuvres, stand up and sit down, were treated as one continuous task for the purpose of analysis. Each variable was given a name consisting of the name of the appropriate parameter i.e. F_F and a number which represents the stand-up (1) or sit-down (2) manoeuvre and the % of time at which this variable was obtained.

A healthy male (S1) subject (age 23 years, weight: 58Kg and height: 1.73m) volunteered to repeat the sit-stand manoeuvre 10 times (5 times in one day and the rest in the next day). Figure 6.8 shows the F_H, F_V and CFP from both legs, and the relative angles of R. knee and hip of the ten trials. Measurements of the range of motion between the 10 trials had an average standard deviation equals to 1.31° (range from 1.62° to 6.19°). Force measurements had an average standard deviation equals to 1.6%BW (range from 0.18 to 5.07%BW). Finally the centre of foot pressure measurements had an average standard deviation equals to 1.52% of foot length (range from 1.98 to 7.19% of foot length). Figure 6.9 to 6.14 are presenting graphically the data collected from all subjects.

Figure 6.8 to 6.14

Graphical representation of data collected from all subjects. Different colours represent different subjects and Figure 6.8 represents the 10 trials of the same subject. The symbols used, have the following meaning:

R: right foot **L:** left foot

F_V: total vertical force of one foot

F_H: horizontal force **SP:** sitting position

CFP: centre of foot pressure

Figure 6.8: Subject (S) during standing up.

Figure 6.9: Group (H) during standing up.

Figure 6.10: Group (M) during standing up.

Figure 6.11: Group (P) during standing up.

Figure 6.12: Group (H) during sitting down.

Figure 6.13: Group (M) during sitting down.

Figure 6.14: Group (P) during sitting down.

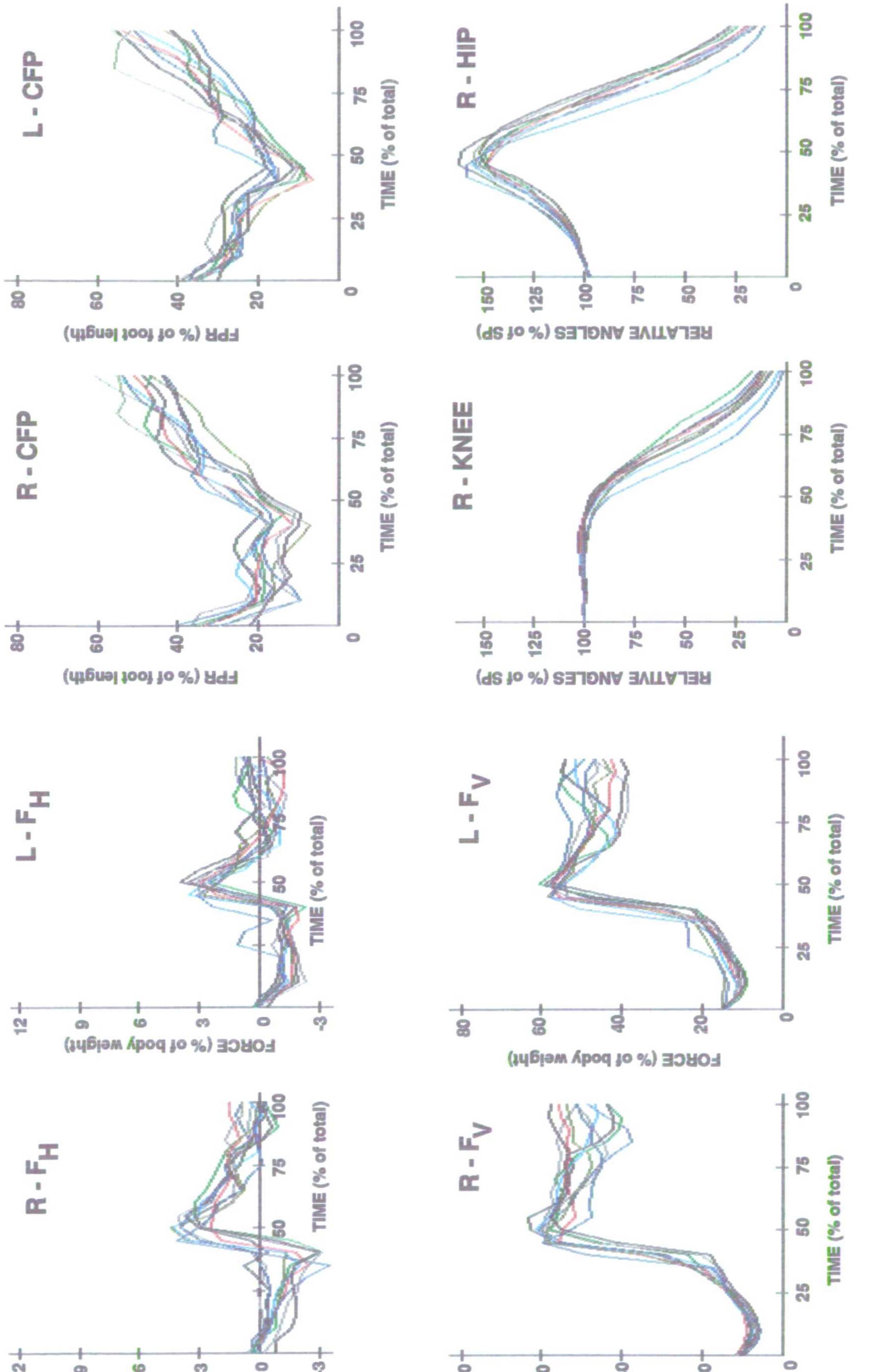

Figure 6.8: Subject (S) during standing up.

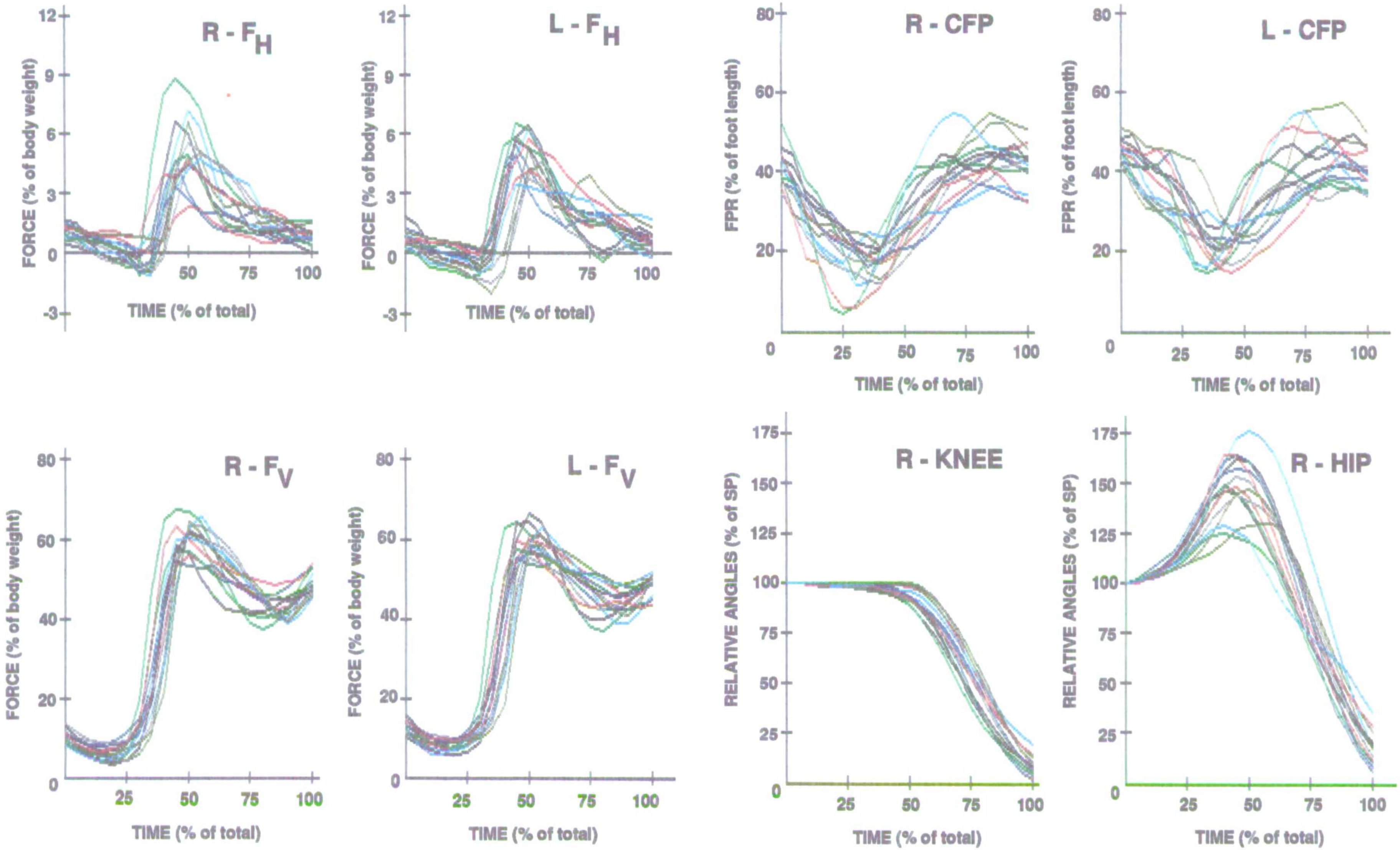

Figure 6.9: Group (H) during standing up.

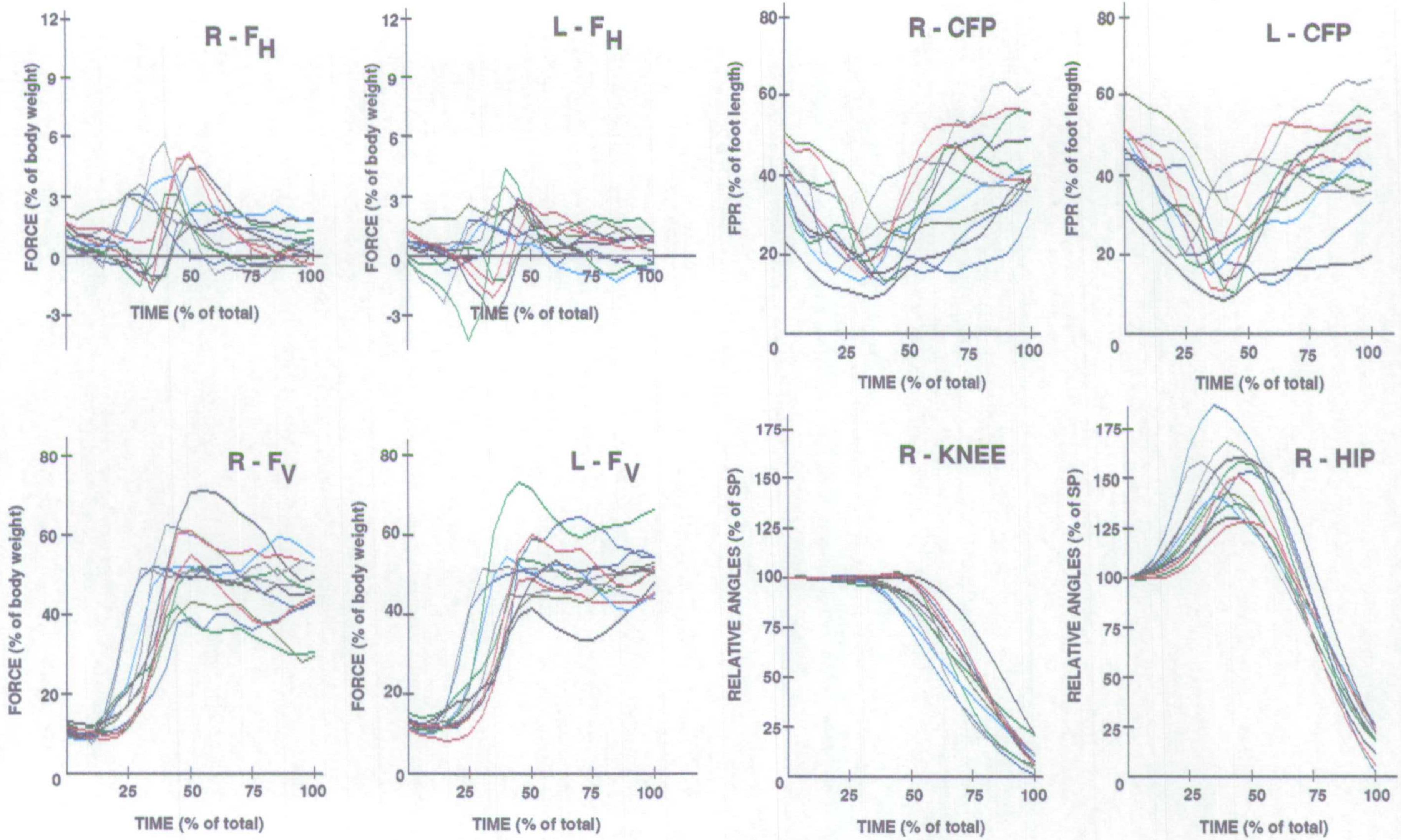

Figure 6.10: Group (M) during standing up.

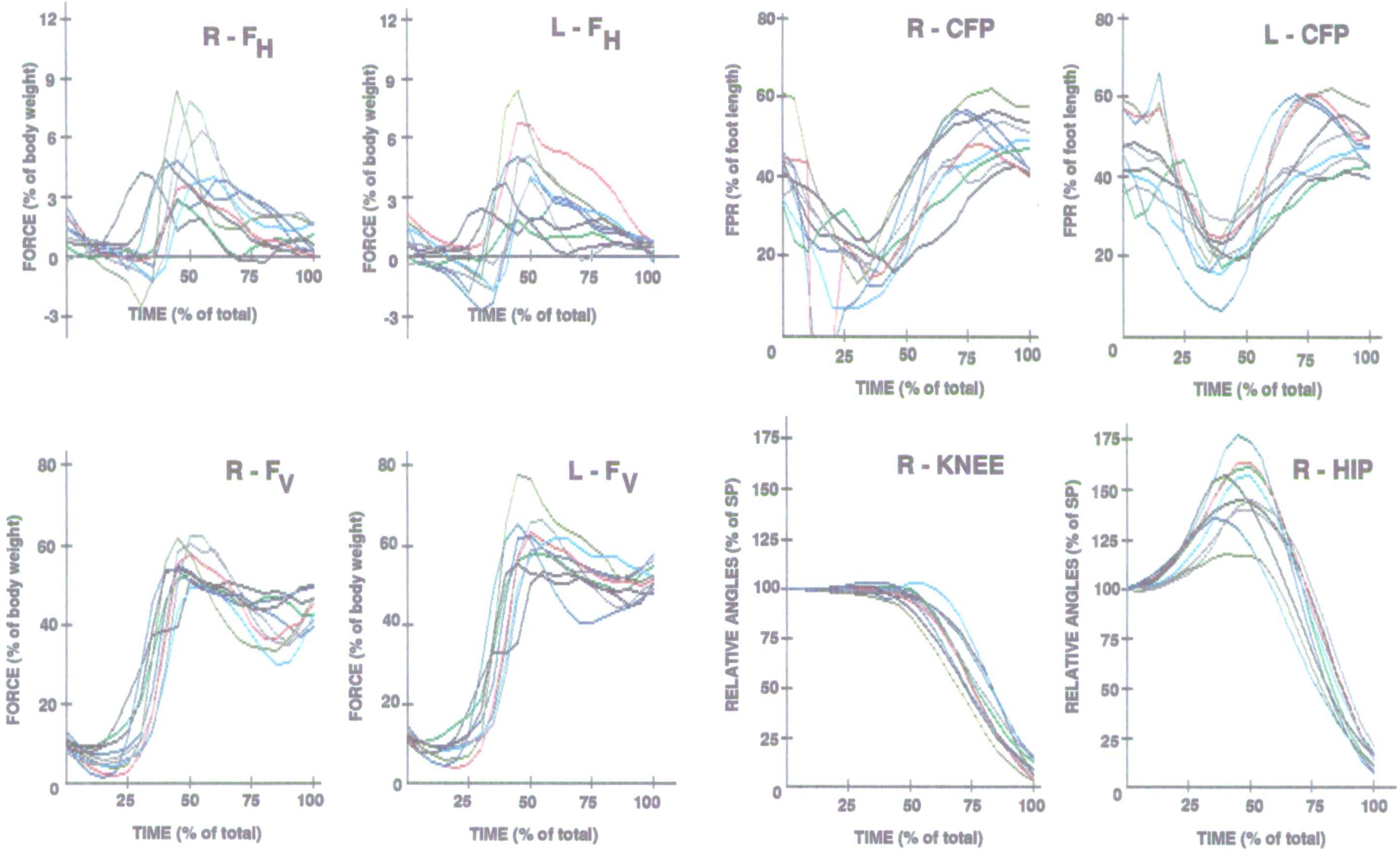

Figure 6.11: Group (P) during standing up.

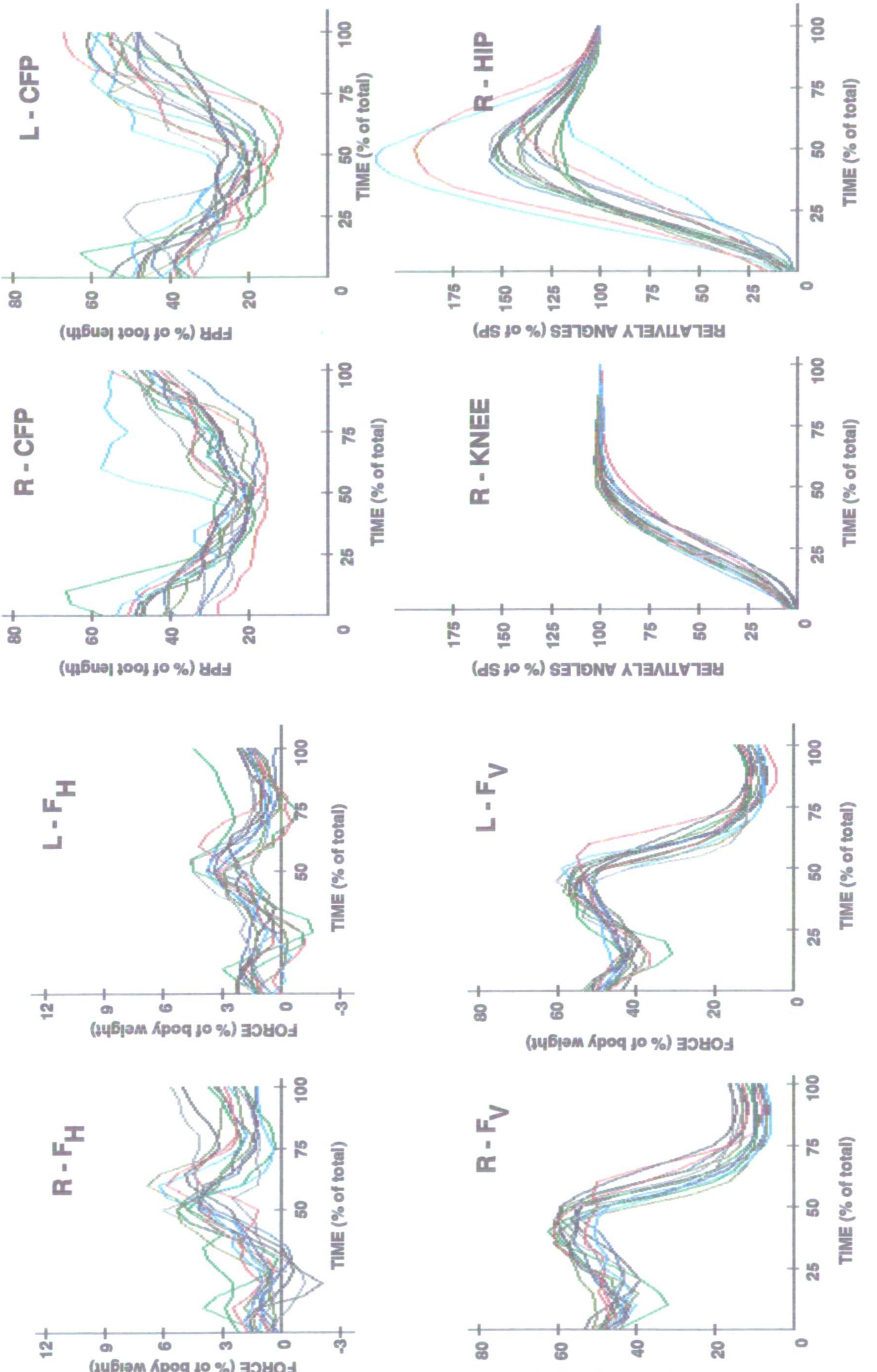

Figure 6.12: Group (H) during sitting down.

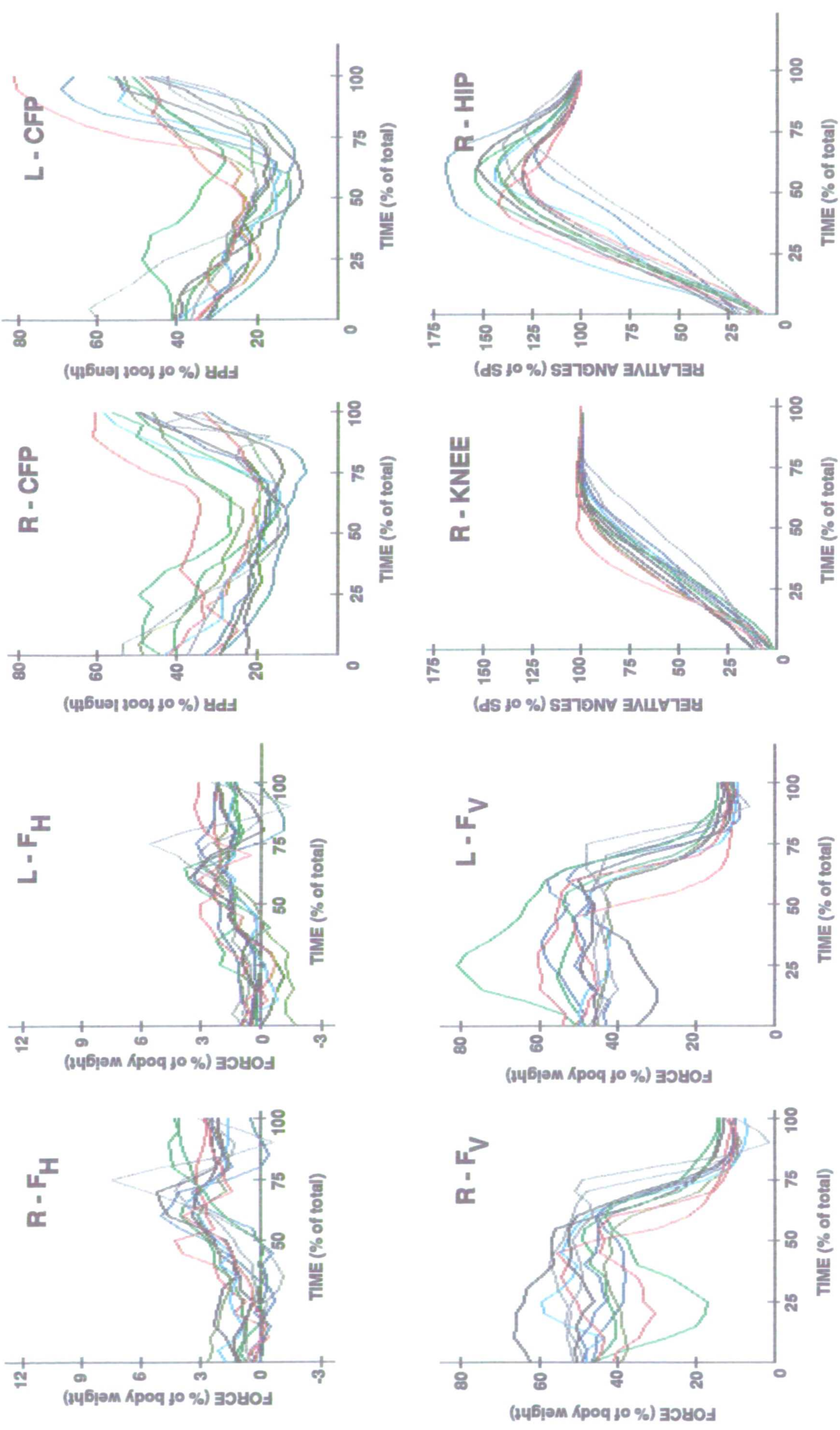

Figure 6.13: Group (M) during sitting down.

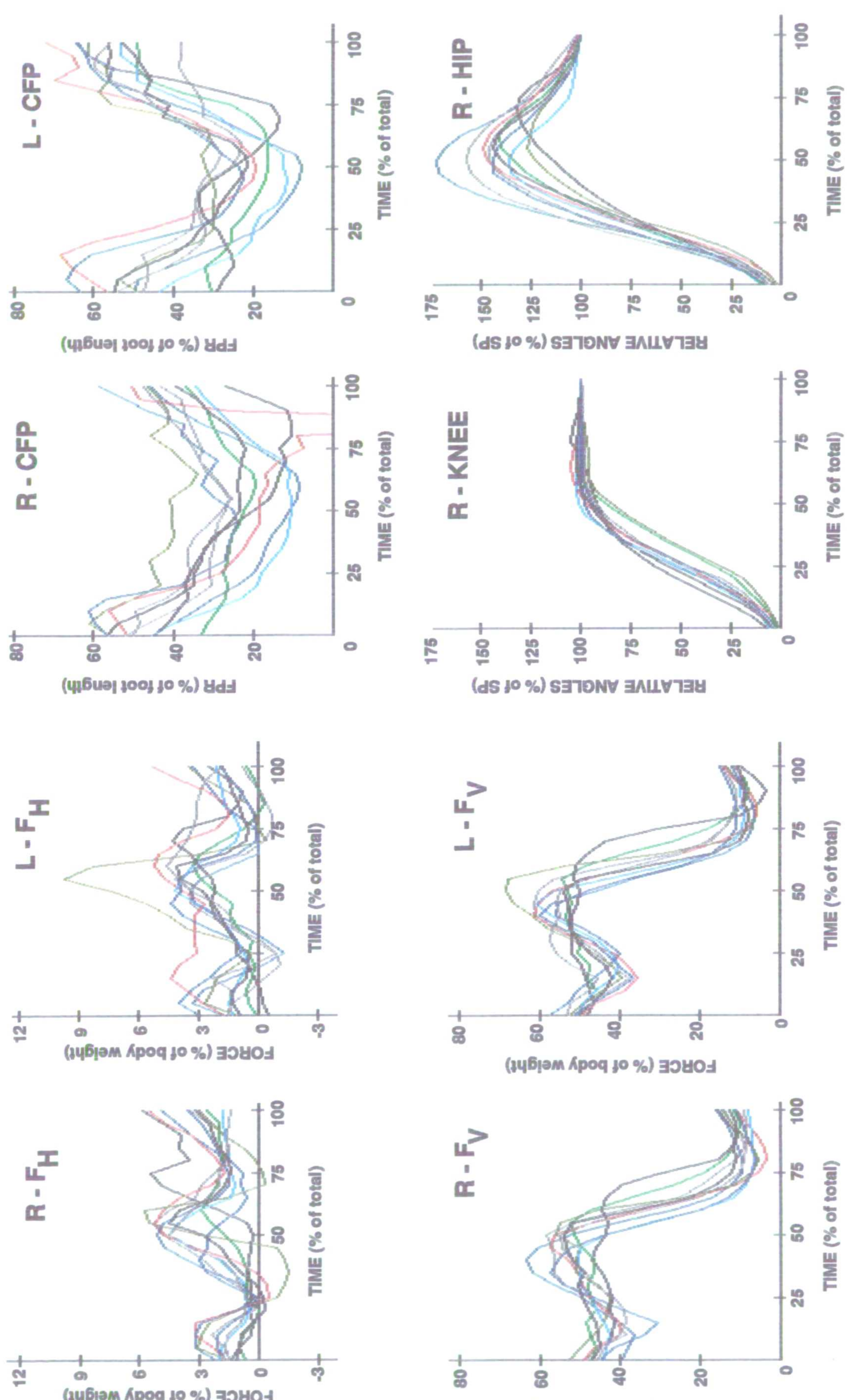

Figure 6.14: Group (P) during sitting down.

6.3 Data analysis

The thirty six subjects were classified into the three different groups (H-M-P) using NNs, LDA and physiotherapists' clinical assessment.

6.3.1 Discriminant analysis

A discriminant function analysis was performed using SPSS/PC+ V2.0 (Norusis, 1988) to predict the group in which each person belongs from the range of motion of R. knee, R. hip and lumbar spine (relative angles during sit-stand manoeuvre), and from the changes of the horizontal force as well as the centre of foot pressure of both feet (during the sit-stand-sit manoeuvre). Due to the large number of predictor variables (154), the stepwise discriminant function analysis employing the Wilks' Lambda criterion, was chosen.

For classification, equal sample sizes were used to estimate prior probabilities of group membership. Table 6.4 shows the variables included in the model in each step with the associated Wilks' Lambda, F-statistic and the statistically significant level. Two discriminant functions were calculated, with a combined $\chi^2(50)=183$, $p<0.001$. After removal of the first function, there was still a strong association between groups and predictors, $\chi^2(24)=82$, $p<0.001$. Figure 6.15 is the territorial map showing which region belongs to each predicted group and the relationship between function one and two.

The loading matrix of correlations between the 25 predictor variables, selected by LDA, and the two discriminant function as seen in Table 6.4, shows that there is no primary predictor either for the first function or for the second one.

All subjects were correctly classified by the above two discriminant functions. The stability of the classification procedure was checked by a jackknifed classification using the same predictor variables as shown in Table 6.4. Jackknifed classification classified correctly 24 subjects out of 36 (67%). The correctly classified subjects from each group were 9 for group (H) out of 14 (64%), 9 for group (M) out of 12 (75%) and 6 for group (P) out of 10 (60%). The procedure was accepted as successful, compared to 33% that would be correctly classified by chance alone.

Table 6.4: Results of the discriminant function with the variables included in the model at each step and the associated Wilk's Lambda. The correlation between functions and predictor variables are shown.

				Correlation of predictors with	
Variables	**WL***	**F(2,33)**	**p**	**f1***	**f2***
F_H2 06	0.474	18.3	*	-0.064	-0.109
F_H2 13	0.000	25.9	*	-0.018	-0.099
F_H2 14	0.012	12.8	*	-0.000	-0.032
F_H2 15	0.018	11.5	*	-0.002	-0.031
F_H2 16	0.022	11.9	*	0.004	-0.100
F_H2 18	0.301	13.2	*	0.040	-0.053
F_H1 06	0.000	25.1	*	-0.039	-0.069
F_H1 12	0.006	14.5	*	0.018	-0.062
F_H1 16	0.049	11.4	*	-0.035	-0.038
F_H1 19	0.001	23.1	*	-0.004	0.064
CFP2 08	0.003	17.1	*	0.017	-0.046
CFP2 12	0.002	20.5	*	0.006	-0.064
CFP1 06	0.001	21.7	*	0.003	-0.005
CFP1 07	0.000	28.1	*	0.014	-0.037
CFP1 13	0.038	11.4	*	0.000	-0.056
CFP1 22	0.066	11.1	*	-0.016	0.014
K12	0.000	27.9	*	0.022	0.048
K20	0.000	24.2	*	0.000	-0.038
K21	0.009	13.4	*	-0.000	-0.037
H4	0.000	29.2	*	-0.012	0.041
H5	0.026	12.4	*	-0.027	0.029
H12	0.109	11.8	*	0.014	0.104
H19	0.210	12.2	*	-0.023	0.049
S10	0.143	12.3	*	0.036	0.076
S19	0.004	15.8	*	0.019	0.045
Canonical R				0.996	0.990
Eigenvalue				122.9	49.6
% of Variance				71.3%	28.7%

* p<0.001, f1 & f2: function 1 & 2, WL: Wilk's Lambda

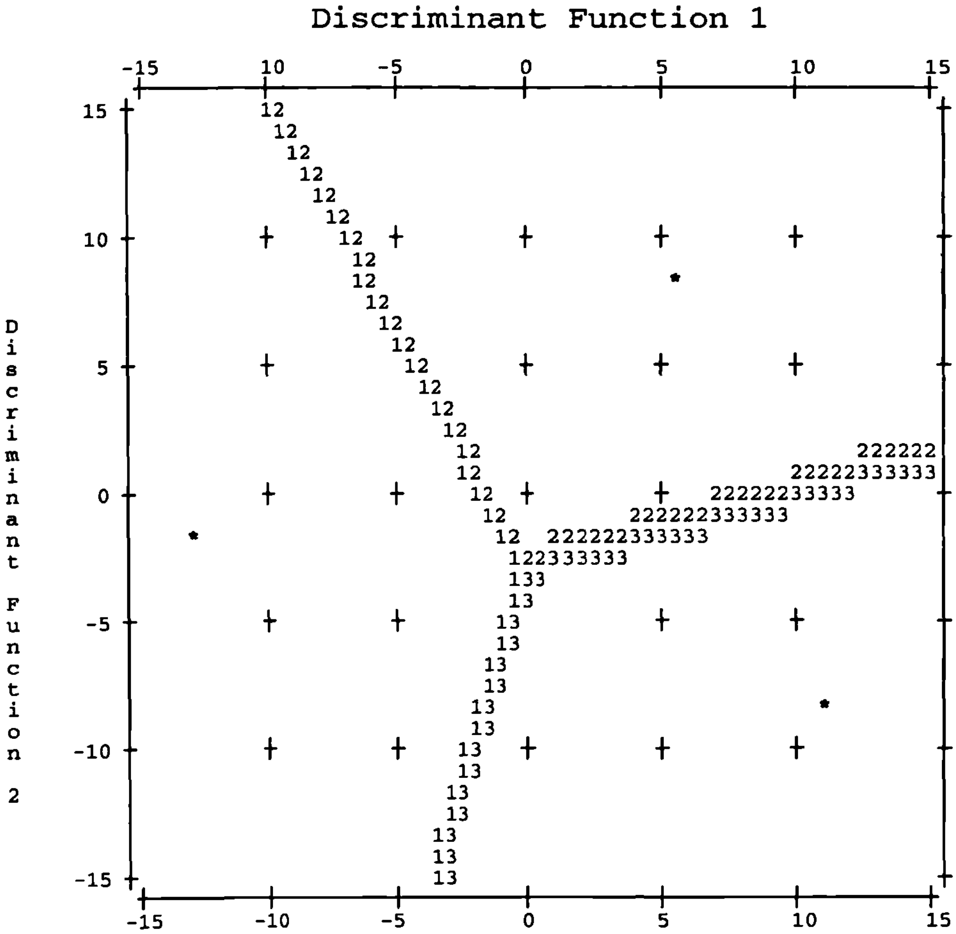

Figure 6.15

The territorial map for the three groups (1: healthy, 2: pretending to have back problems and 3: back pain patients) on the two discriminant functions. The mean of each group is indicated by an asterisk (*). The numbered boundaries mark off the combination of function values that result in the classification of the cases into the three groups.

6.3.2 Neural networks

Normalization was applied to all data within a specific range of ±0.5 to be analysed by the network. The positive answer of the network was +0.5 and the negative was -0.5. The learning rate was 0.02 and the momentum factor was 0.9. The weights of the NNs were initialised to ±0.1. Several recurrent networks were constructed in which the size of the hidden layer was varied.

The network finally selected was a three layered recurrent one (NN 6.1) with 242 input, 20 hidden and 3 output units (Figure 6.16). Each input consisted of the angular displacement of right knee, right hip and lumbar spine, and of the F_H, F_F, F_B and CFP of both feet. This network was trained after 70 cycles. Its total RMS error was 0.093 and its max unit error 0.29. The network was correctly classified 35 out of 36 subjects (97%). The stability of the network was checked by a jackknifed training. Table 6.5 shows the number of training cycles, the total RMS error and the maximum unit error of the network after each step of the jackknifed training. The network classified correctly 31 subjects out of 36 (86%). The correctly classified subjects from each group were 13 for group (H) out of 14 (93%), 10 for group (M) out of 12 (83%) and 8 for group (P) out of 10 (80%). The procedure was accepted as successful, compared to 33% that would be correctly classified by chance alone.

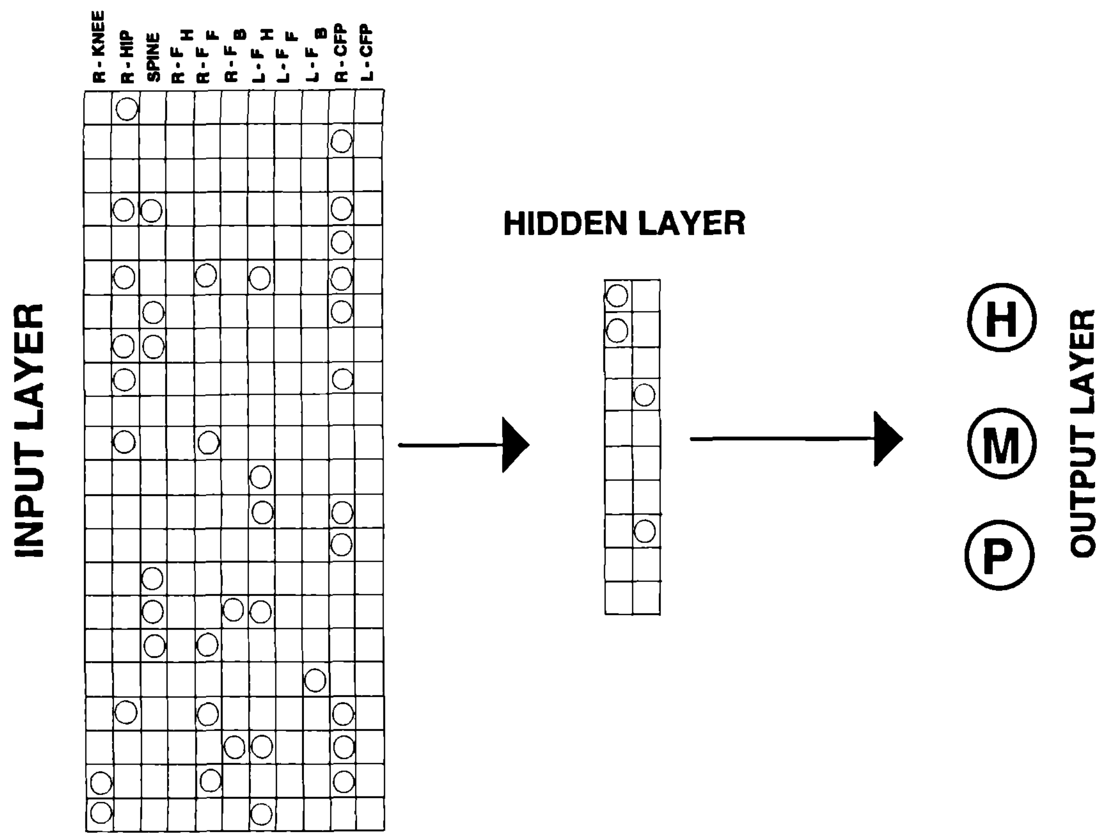

Figure 6.16

A three layered recurrent network (NN6.1) with 242 input, 20 hidden and 3 output units. It was trained to recognise if a person is healthy, low back pain patient or someone who is pretending to have a back pain based on the changes of the sit-stand-sit manoeuvres.

Table 6.5: The characteristics of the NN 6.1 during the jackknifed training. The pattern which was excluded from the training file is shown with its prediction.

No	**TC**	**tRMS**	**mUE**	**G**	**R**
1	63	0.095	0.48	H	Y
2	65	0.082	0.42	H	Y
3	68	0.096	0.32	H	Y
4	73	0.076	0.27	H	Y
5	73	0.068	0.17	H	Y
6	62	0.155	0.59	H	Y
7	75	0.096	0.45	H	Y
8	73	0.096	0.49	H	Y
9	72	0.095	0.34	H	Y
10	68	0.096	0.36	H	Y
11	73	0.084	0.34	H	Y
12	70	0.098	0.38	H	Y
13	69	0.094	0.35	H	Y
14	66	0.093	0.37	H	**N**
15	56	0.196	0.74	M	Y
16	73	0.096	0.49	M	**N**
17	65	0.097	0.49	M	Y
18	66	0.094	0.43	M	Y
19	73	0.099	0.36	M	Y
20	59	0.099	0.46	M	Y
21	70	0.099	0.35	M	Y
22	70	0.097	0.43	M	Y
23	73	0.067	0.27	M	Y
24	70	0.090	0.38	M	Y
25	72	0.091	0.31	M	Y
26	70	0.097	0.38	M	**N**
27	84	0.051	0.17	P	**N**
28	91	0.019	0.06	P	Y
29	77	0.075	0.22	P	Y
30	80	0.061	0.21	P	Y
31	76	0.081	0.25	P	Y
32	92	0.049	0.17	P	Y
33	80	0.081	0.22	P	Y
34	98	0.046	0.15	P	Y
35	67	0.098	0.36	P	Y
36	71	0.084	0.29	P	**N**

* **No:** pattern excluded from the training file,
TC: number of training cycles,
tRMS: total RMS error,
mUE: maximum unit error,
G: real group **R:** predicted group
Y: correct prediction **N:** wrong prediction.

6.3.3 Clinical assessment

Nine physiotherapists (PH1-PH9) assessed the patterns of movement of the 36 volunteers by watching the videotaped sit-stand and stand-sit manoeuvres. Figure 6.17 is a frozen image of one of the videotaped subjects performing the standing up.

The physiotherapists were state registered and members of the Chartered Society of Physiotherapy, working in different hospitals in London. They had an average of 7±3.5 years (range from 2 to 11 years) of clinical experience.

Physiotherapists were asked to decide if the patterns of movement of each particular subject are normal or not and if not, to decide if this particular person had a back pain problem or he was pretending to have one.

All physiotherapists stated at the end that it was relatively easy to discriminate between normal and abnormal but it was almost impossible to separate the abnormal patterns into pathological and malinger.

Cochran's Q test (Siegel & Castellan, 1988) showed a statistical significant difference ($Q(8)=17.9$, $p<0.001$) between the performance of the 9 physiotherapists to discriminate the three patterns of movement.

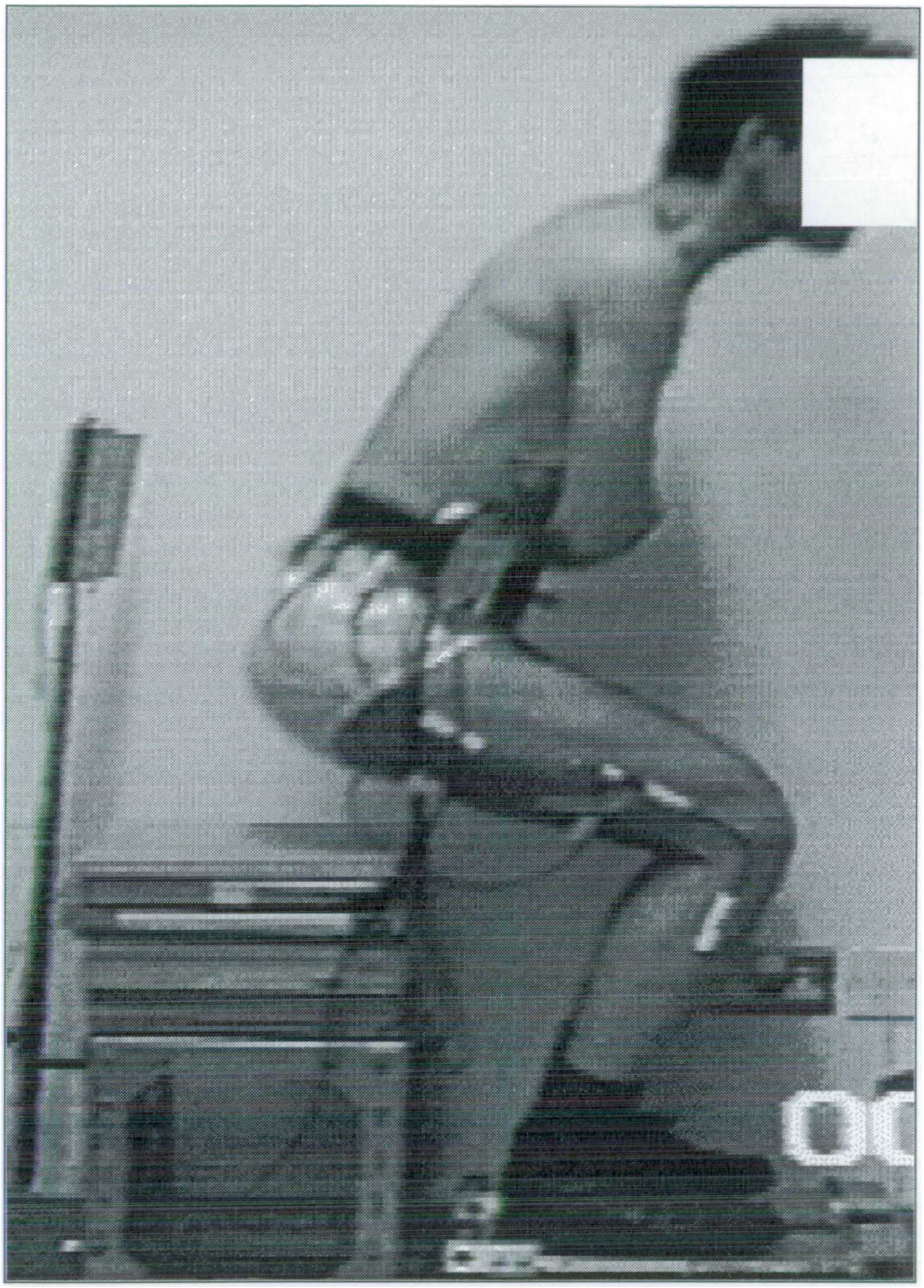

Figure 6.17

A frozen image of one of the videotaped subjects performing the standing up.

6.4 Results

Figure 6.18 shows the success rate of NNs, LDA and physiotherapists to discriminate the three different groups of subjects. Figure 6.19 shows their sensitivity and specificity to discriminate between normal and abnormal patterns of movement. Figure 6.20 shows their sensitivity and specificity to discriminate between back pain patients and non back pain subjects.

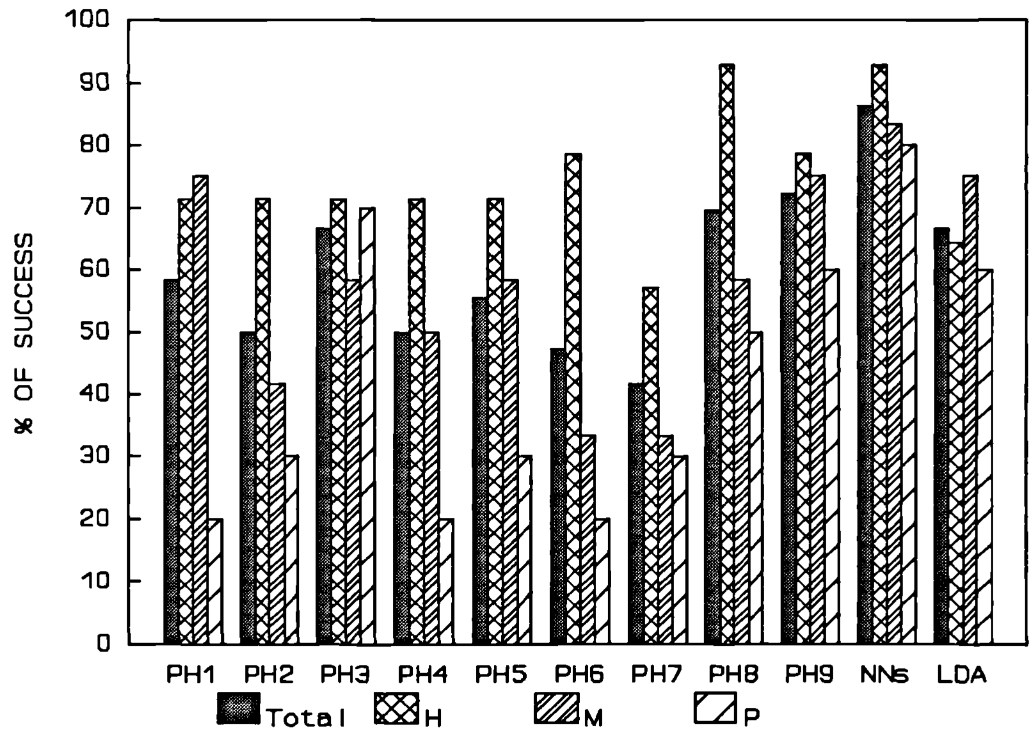

Figure 6.18

The success rate of NNs, LDA and physiotherapists to discriminate the three groups of subjects.

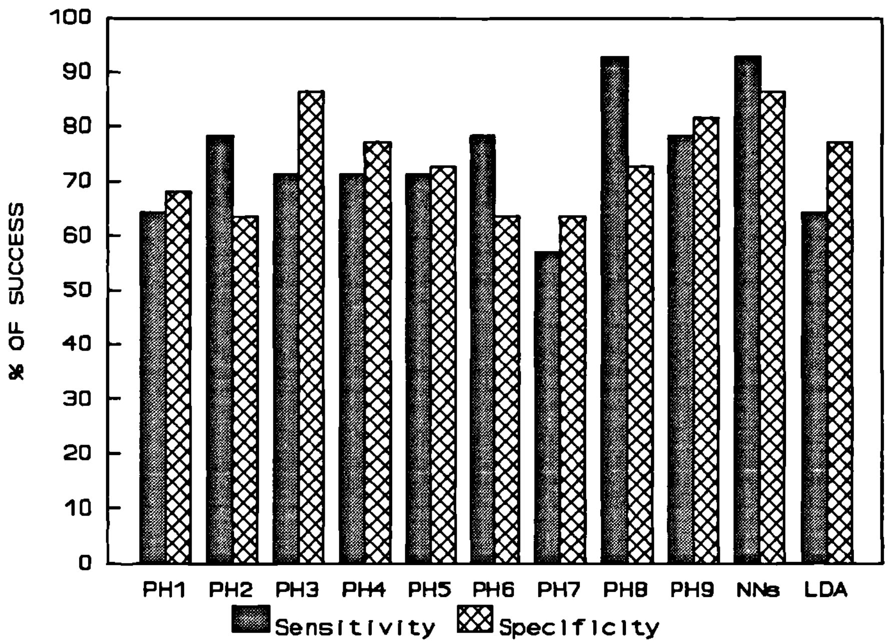

Figure 6.19: The sensitivity-specificity of NNs, LDA and physiotherapists to discriminate between normal and abnormal patterns of movement.

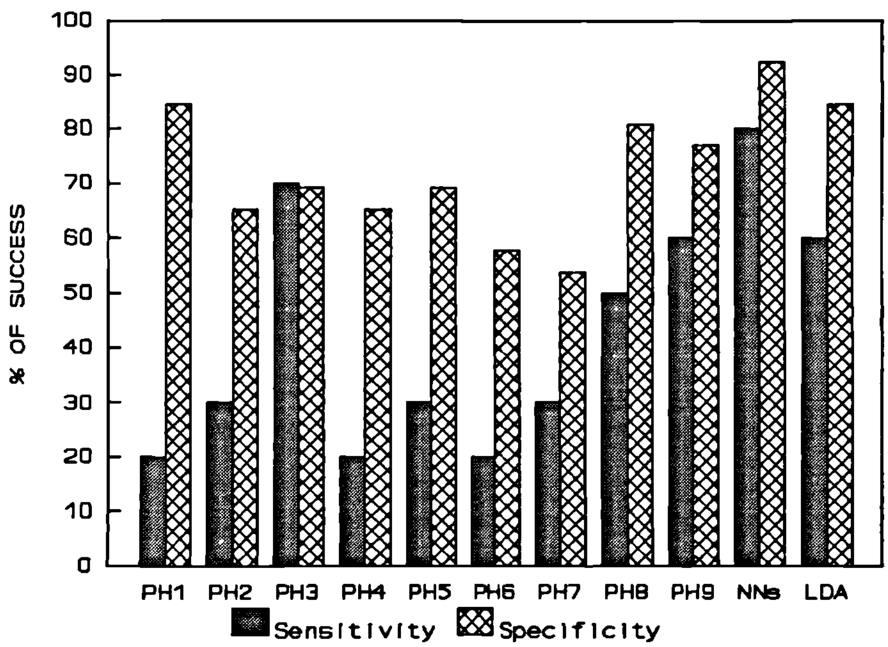

Figure 6.20: The sensitivity and specificity of NNs, LDA and physiotherapists to discriminate between back pain patients and no back pain people.

6.5 Discussion

The recognition of pathological patterns of movement is a daily task performed by medical doctors or physiotherapists in order to diagnose or assess a pathology respectively. The identification of the real low back pain patient is such an example and it has been used in the present study aiming to investigate the possibility of using NNs as a diagnostic or assessment tool.

The aim of the study was focused on the identification of the abnormal patterns of movement due to low back pain and not on the diagnosis of back pain problems. Consequently, the judgement of a physiotherapist was regarded as equally acceptable to a medical doctor.

Subjects pretending to have a back pain problem were included in an effort to make the classification task more complicated by introducing a third category of patterns. These subjects have been used instead of real malingerers. It is difficult to identify real malingerers and include them in a study. It is also impossible to find if the patients of the present study are real patients and not malingerers. The use of malingerers belongs to future rather than present work.

It is important to note that physiotherapists, by their own account, have not trained to assess patients by watching them on monitors and that they usually assess patients by many more tests rather than look at them only from the right view in the sagittal plane as they perform the sit-stand-sit transfer. Although such statements should be taken into account, the comparison between the performance of the physiotherapists showed that their discriminatory power differs significantly from each other. Their sensitivity-specificity to discriminate between normal and abnormal performance (Figure 6.19) is quite high and similar for all of them. In addition, their sensitivity-specificity to separate the low back pain patients from the non back pain subjects (Figure 6.20) is low and varies from one physiotherapist to another.

These results were expected to be observed. Clinicians can easily discriminate normal from abnormal patterns of movement. The normal patterns are part of the daily life and are familiar particularly to physiotherapists. Pathological problems affect these patterns and alter them in various levels. Consequently any deviation from the normal performance can be identified, relatively easily, resulting in an acceptable success rate for this pattern recognition problem.

The discrimination of different pathological problems is more difficult than the discrimination between normal and abnormal patterns. When pathologies produce abnormal patterns of movement, there is usually an overlapping between the characteristics of these patterns. The discrimination becomes difficult and the clinician is expected to make a decision. Like any classifier, the physiotherapists make such a decision based on previous knowledge obtained by training and experience. That explains the fact that someone needs a study period before he/she becomes a clinician and experience before he/she obtains a fully qualified position.

Physiotherapists with different levels of experience have been used to demonstrate the problems concerning the personal judgements of clinicians and the need for a method which will help to improve the clinical assessment.

NNs achieved the highest success rate (Figure 6.18) although it is not known if they are statistically better than physiotherapists and LDA due to the small sample size. NNs also achieved high sensitivity-specificity rates to discriminate normal from abnormal movements as well as back pain patients from no back pain subjects.

NNs were found to have an predictive accuracy at least as high as that of the best physiotherapist and this is an important finding. They will be a very useful tool helping physiotherapists to make decisions. As soon as they are trained and validated by the appropriate data, they can be used to advise particularly the new and inexperienced physiotherapists.

6.6 Conclusions

It can be concluded that:

a. NNs can identify the existence of low back pain problems from the patterns of the sit-stand manoeuvres;

b. NNs can discriminate patterns of human movement described with the use of the range of motion of different joints as well as with the forces exerted on the ground by both feet and with a large number of variables;

c. the performance of NNs to identify pathological patterns of human movement is at least as high as that of LDA and higher than that of physiotherapists;

d. NNs will be useful in helping clinicians to diagnose or assess pathologies.

CHAPTER SEVEN

GENERAL DISCUSSION

AND

CONCLUSIONS

7.1 General discussion

The present thesis aims to investigate the possibility of using NNs as an alternative approach in the discrimination of patterns of human movement. Primary objectives are the investigation of the accuracy of NNs and the identification of their advantages and disadvantages. There is also an interesting question concerning the nature of the patterns that can be discriminated by NNs. The design of NNs that can be used in a clinic belongs to future rather than present work.

Artificially altered patterns of human movement have mainly be used. It is more convenient to work with normal subjects and alter their movements rather than using patients. The participation of patients in a experiment which do not provide new aspects of a disease or a treatment that can be used to improve patients' health care, is not ethically acceptable.

LDA is a standard statistical method for pattern recognition and it has been alongside NNs. Comparison between LDA and NNs was allowed conclusions to be obtained.

When one classification technique performs better than another in a particular task, it is difficult to generalize this finding and accept that this technique is better than the other in any other task.

An important parameter in the pattern recognition task is the sample size for both training and testing data. As the subject-to-variables ratio decreases, the probability increases that one will observe a chance relationship between a predictor variable and an output category (Cicchetti, 1992). In the present work, the sample size problem has been faced by using artificial altered patterns which allowed the production of many patterns from a small number of subjects and "artificially" increases the sample size. The application of two or three techniques at the same time allowed the comparison between them to be made while facing the same sample size problem. In the present study, it has proved possible to find how well some particular problems are solved by NNs in comparison with traditional classifiers but not possible to establish whether the difference between the success rates of NNs and another classifier is significant.

There are two main differences between NNs and LDA concerning the selection of variables and the training procedure. When there is a large number of variables, this number must be reduced before LDA can be applied. Such a reduction requires familiarity either with statistics or with the measured variables in order to achieve the best possible reduction. In contrast NNs have the ability to deal with a large number of variables and to perform this reduction by adjusting their connections.

The training procedure of NNs is guided and terminated by the user and consequently requires an experienced user. In contrast LDA's user do not have any control over training. LDA's and NNs' common characteristic is the use of classification rules based on probabilities.

It is difficult, if not meaningless to suggest that the user should always resort to one or other classification technique. The choice is linked to the user's specific knowledge and needs. If someone is interested just on the better rate of the prediction then the NNs solution is more convenient. In addition, when someone wants to find the importance of each particular variable to the separation of the patterns then the LDA is the appropriate technique. Obviously the user of any of these techniques should be familiar with computers and with statistical procedure if LDA is going to be used or with NNs' principles and applications if NNs are used.

The application of NNs requires experience in order to define the size of the network and perform the training. Such experience will allow the user to have control over the training procedure and avoid overtraining problems or insufficient trained situations.

There is no need for the user of NNs to have any knowledge on the separation of the patterns or the contribution of each particular measured parameter to the solution of the discrimination problem. The user simply needs to include in the training and testing data enough patterns from all possible existing categories. Familiarity is needed with the problem rather with it's solution.

The training procedure is usually time-consuming. It can last from a few minutes to a few hours or days. The time required by training depends on the number of the NNs' connections, on the number of patterns, on the number of predictive variables and on the level of the difficulty that the separation of the different groups have. The more connections, or patterns, or variables there are, the longer the time required for the training. If the relationship between the patterns that separate them, is difficult to identify then the NNs' training lasts longer.

When the NNs' ability to generalize is tested by cross-validation then it lasts for a few seconds. As soon as a pattern is presented to the NNs, it is classified to the appropriate group. The problem arises when the jackknifed classification is used. If the training of a particular network requires time T, and their are N patterns in the training data, then the jackknifed classification requires time T*N to be performed. For example, the jackknifed classification for NN 5.3 was performed in about 7-8 hours while for NN 6.1 was performed in about 72 hours.

A successfully trained and tested NN can be easily set up in a pocket microcomputer and used in a clinical environment. The clinician will have to type the input or connect the microprocessor with the equipment that collects the data. As soon as the NNs have the variables that present the pattern, they will classify this pattern. Such a network does not require either retraining or revalidation and the clinician does not need to have any knowledge either about NNs or about the training procedure.

7.2 General conclusions

The main conclusions obtained from the present thesis are outlined below.

1. Neural networks can be used to classify patterns of human movement such as gait and stepping patterns, alterations of the standing posture and changes of the sit-stand manoeuvres. These patterns are presented with the use of their temporal parameters, the angular displacement of some joints, the co-ordinates of some anatomical landmarks or with the forces exerted on the ground by the human body.

2. Neural networks have a predictive accuracy which is as high as that of linear discriminant analysis.

3. Neural networks have the advantage to deal with a large number of predictor variables.

4. Neural networks can discriminate pathological patterns of human movement and can be used to help clinicians in order to diagnose or assess pathologies.

7.3 Suggestions for further studies

Further studies should be focused on the solution of clinical problems. A particular problem, whose solution is important, must be chosen and approached by NNs. Data must be collected from large sample sizes and used for the training as well as the testing of NNs. Comparison should be made between the performance of NNs and that of clinicians or other pattern recognition techniques before NNs can be used as a diagnostic or assessment tool.

Further studies should also investigate the possibility of using other kinds of NNs such as those employing unsupervised learning techniques. These application will be particularly important because they will define the different categories of patterns that can then be used to assess a patients' condition or the improvement of their functional status.

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APPENDIX A

corresponds to chapter three and includes:

Table A1: Physical characteristics of subjects

Table A2a: Obtained speeds of walking (females) in statures/sec.

Table A2b: Obtained speeds of walking (males) in statures/sec.

Table A3: Data collected from 10 males and 10 females in msec.

Table A1: Physical characteristics of subjects.

	MALES			FEMALES		
Subject's No	**Age (years)**	**Weight (Kg)**	**Stature (m)**	**Age (years)**	**Weight (Kg)**	**Stature (m)**
1	25	74	1.74	30	63	1.75
2	22	67	1.73	31	57	1.63
3	22	74	1.77	22	60	1.70
4	24	69	1.77	23	85	1.65
5	19	60	1.71	21	67	1.62
6	25	83	1.78	26	51	1.62
7	32	93	1.87	25	74	1.76
8	29	78	1.77	43	56	1.64
9	24	65	1.69	23	72	1.71
10	25	75	1.75	23	78	1.78

Table A2a: obtained speeds of walking (females) in statures/sec.

	F01	F02	F03	F04	F05	F06	F07	F08	F09	F10
Condition 1:										
Spd 0.30:	0.32	0.28	0.35	0.31	0.32	0.32	0.31	0.30	0.29	0.29
Spd 0.45:	0.45	0.43	0.47	0.49	0.43	0.48	0.45	0.45	0.43	0.40
Spd 0.60:	0.60	0.58	0.63	0.64	0.65	0.60	0.60	0.65	0.56	0.61
Spd 0.75:	0.74	0.78	0.70	0.79	0.74	0.74	0.76	0.76	0.74	0.76
Spd 0.90:	0.88	0.93	0.91	0.86	0.89	0.89	0.85	0.90	0.88	0.85
Spd 1.05:	1.09	1.08	1.09	1.04	1.06	1.03	1.05	1.00	1.03	1.08
Spd 1.20:	1.16	1.21	1.20	1.20	1.22	1.18	1.25	1.24	1.16	1.18
Condition 2:										
Spd 0.30:	0.31	0.32	0.34	0.33	0.34	0.34	0.29	0.30	0.34	0.35
Spd 0.45:	0.42	0.47	0.40	0.40	0.46	0.43	0.45	0.47	0.48	0.40
Spd 0.60:	0.62	0.58	0.56	0.60	0.63	0.60	0.58	0.63	0.55	0.57
Spd 0.75:	0.77	0.75	0.70	0.77	0.79	0.70	0.73	0.80	0.74	0.70
Spd 0.90:	0.86	0.93	0.95	0.88	0.89	0.91	0.94	0.88	0.91	0.89
Spd 1.05:	1.01	1.02	1.01	1.07	1.06	1.06	1.08	1.00	1.00	1.02
Spd 1.20:	1.24	1.18	1.25	1.16	1.18	1.15	1.25	1.15	1.16	1.25
Condition 3:										
Spd 0.30:	0.34	0.34	0.28	0.32	0.32	0.31	0.31	0.28	0.31	0.33
Spd 0.45:	0.44	0.46	0.45	0.42	0.41	0.46	0.48	0.48	0.41	0.49
Spd 0.60:	0.63	0.56	0.59	0.59	0.63	0.63	0.65	0.65	0.61	0.63
Spd 0.75:	0.79	0.71	0.75	0.79	0.77	0.74	0.76	0.73	0.79	0.78
Spd 0.90:	0.86	0.89	0.93	0.88	0.86	0.87	0.85	0.95	0.88	0.89
Spd 1.05:	1.01	1.08	1.03	1.07	1.09	1.03	1.05	1.10	1.03	1.10
Spd 1.20:	1.16	1.21	1.16	1.16	1.18	1.18	1.17	1.16	1.15	1.18

*spd : speed

Table A2b: obtained speeds of walking (males) in statures/sec.

	M01	M02	M03	M04	M05	M06	M07	M08	M09	M10
Condition 1:										
Spd 0.30:	0.33	0.34	0.34	0.35	0.35	0.32	0.35	0.32	0.27	0.26
Spd 0.45:	0.44	0.44	0.42	0.43	0.46	0.45	0.41	0.46	0.43	0.44
Spd 0.60:	0.61	0.60	0.60	0.56	0.61	0.61	0.61	0.63	0.58	0.64
Spd 0.75:	0.76	0.74	0.75	0.73	0.72	0.76	0.76	0.76	0.73	0.71
Spd 0.90:	0.89	0.90	0.92	0.92	0.88	0.89	0.92	0.92	0.89	0.93
Spd 1.05:	1.01	1.02	1.05	1.05	1.03	1.04	1.02	1.05	1.04	1.01
Spd 1.20:	1.17	1.18	1.23	1.19	1.23	1.18	1.20	1.23	1.20	1.16
Condition 2:										
Spd 0.30:	0.25	0.35	0.33	0.33	0.35	0.31	0.32	0.29	0.32	0.35
Spd 0.45:	0.42	0.45	0.45	0.45	0.45	0.47	0.45	0.46	0.41	0.43
Spd 0.60:	0.61	0.64	0.59	0.62	0.62	0.61	0.56	0.61	0.56	0.60
Spd 0.75:	0.78	0.78	0.76	0.73	0.74	0.76	0.74	0.72	0.75	0.79
Spd 0.90:	0.91	0.90	0.90	0.92	0.88	0.87	0.87	0.92	0.87	0.86
Spd 1.05:	1.10	1.05	1.05	1.05	1.06	1.08	1.02	1.02	1.07	1.03
Spd 1.20:	1.17	1.18	1.23	1.19	1.19	1.18	1.24	1.19	1.17	1.16
Condition 3:										
Spd 0.30:	0.32	0.31	0.34	0.32	0.30	0.32	0.27	0.31	0.31	0.33
Spd 0.45:	0.47	0.44	0.49	0.45	0.43	0.46	0.43	0.43	0.43	0.44
Spd 0.60:	0.62	0.60	0.63	0.62	0.65	0.64	0.64	0.62	0.62	0.60
Spd 0.75:	0.79	0.72	0.72	0.75	0.79	0.73	0.76	0.75	0.78	0.76
Spd 0.90:	0.91	0.92	0.92	0.90	0.93	0.94	0.94	0.92	0.89	0.93
Spd 1.05:	1.07	1.02	1.05	1.05	1.00	1.02	1.02	1.02	1.04	1.06
Spd 1.20:	1.17	1.18	1.23	1.23	1.19	1.22	1.16	1.23	1.17	1.16

*spd : speed

Table A3: Data collected from 10 males and 10 females in msec.

	Speed	Condition 1 RSS	Condition 1 LSS	Condition 1 DSS	Condition 2 RSS	Condition 2 LSS	Condition 2 DSS	Condition 3 RSS	Condition 3 LSS	Condition 3 DSS
M01										
	0.30	583	516	400	566	616	383	550	666	283
	0.45	583	583	300	533	550	216	466	566	216
	0.60	483	450	213	466	483	200	450	500	150
	0.75	416	416	183	416	450	150	433	466	133
	0.90	416	400	150	416	450	116	400	433	113
	1.05	400	400	100	383	450	100	366	400	116
	1.20	466	383	100	383	433	83	366	366	116
M02										
	0.30	583	616	350	433	550	266	416	666	250
	0.45	500	533	266	383	550	233	416	650	216
	0.60	433	433	183	366	433	166	383	483	166
	0.75	383	400	150	366	416	133	350	416	116
	0.90	366	400	113	366	400	100	333	383	100
	1.05	350	383	100	350	333	83	333	383	66
	1.20	333	350	66	316	383	66	333	350	66
M03										
	0.30	533	550	350	566	616	366	533	650	233
	0.45	566	583	233	550	583	216	483	600	200
	0.60	433	450	200	483	483	216	433	466	183
	0.75	450	450	150	416	466	116	433	483	150
	0.90	400	400	133	416	433	133	400	450	133
	1.05	383	366	166	416	433	100	400	433	100
	1.20	383	383	100	383	383	66	383	400	66
M04										
	0.30	649	666	350	566	616	300	400	616	250
	0.45	616	633	250	483	533	266	333	550	183
	0.60	483	466	216	450	500	183	416	516	166
	0.75	483	466	150	450	483	166	383	450	150
	0.90	416	416	116	400	366	116	350	416	100
	1.05	416	400	116	400	433	100	350	400	83
	1.20	416	433	83	400	433	83	366	450	66
M05										
	0.30	433	416	299	433	516	266	316	600	233
	0.45	433	433	216	466	500	250	350	550	216
	0.60	400	416	183	433	483	183	366	450	166
	0.75	400	416	166	366	450	150	350	433	150
	0.90	366	366	133	366	416	133	400	416	116
	1.05	366	366	116	383	433	116	366	400	100
	1.20	366	366	83	350	383	100	383	416	66
M06										
	0.30	516	533	350	550	616	333	550	650	300
	0.45	483	466	283	466	516	250	466	500	250
	0.60	416	416	216	416	466	200	400	450	166
	0.75	416	400	166	383	433	166	416	416	133
	0.90	400	400	150	383	433	150	365	433	100
	1.05	366	366	133	350	400	116	350	383	100
	1.20	333	350	116	350	383	100	316	333	83
M07										
	0.30	583	583	333	566	616	316	566	750	416
	0.45	533	516	266	516	583	250	500	633	233
	0.60	466	450	166	466	450	216	450	533	166
	0.75	416	416	150	450	500	150	450	483	133
	0.90	416	400	116	383	416	133	400	450	116
	1.05	383	366	100	383	416	83	400	416	66
	1.20	366	366	66	350	383	50	383	416	83

(continued over ...)

(Table A3 continued ...)

M08

0.30	533	600	333	533	666	316	483	600	300
0.45	450	466	250	450	566	250	400	616	250
0.60	416	450	183	416	500	183	400	500	166
0.75	433	433	150	400	433	150	350	433	150
0.90	433	400	100	400	450	116	350	400	166
1.05	366	400	100	350	433	100	366	383	133
1.20	350	366	83	333	400	83	300	350	100

M09

0.30	600	616	366	533	583	300	483	650	250
0.45	516	500	266	500	533	216	483	566	200
0.60	466	450	216	433	483	200	433	466	133
0.75	433	416	166	383	433	166	400	466	116
0.90	400	383	133	400	450	116	366	416	100
1.05	366	383	116	350	416	83	383	433	83
1.20	366	383	83	350	416	66	366	416	50

M10

0.30	550	550	450	450	500	316	416	550	283
0.45	416	400	300	433	500	250	416	516	216
0.60	283	333	216	383	433	216	383	483	166
0.75	359	383	183	333	400	183	383	416	133
0.90	366	349	133	333	300	133	366	382	116
1.05	349	350	116	333	383	100	350	366	83
1.20	350	350	83	333	366	83	316	350	66

F01

0.30	633	600	366	533	600	416	366	816	266
0.45	533	500	266	500	533	333	366	650	216
0.60	450	466	183	433	483	200	350	516	183
0.75	400	400	183	400	433	150	350	450	166
0.90	383	416	133	400	450	116	365	433	133
1.05	350	350	116	400	433	116	333	416	116
1.20	383	383	100	383	416	83	316	366	100

F02

0.30	716	733	466	533	666	333	466	600	266
0.45	516	550	316	450	566	216	516	600	216
0.60	483	483	233	416	466	300	400	516	200
0.75	400	416	166	400	450	133	383	416	150
0.90	416	416	116	366	400	116	366	433	116
1.05	366	383	100	383	416	100	366	383	83
1.20	350	350	83	316	333	100	300	333	66

F03

0.30	433	450	266	516	550	316	433	583	350
0.45	450	450	233	500	516	266	450	466	250
0.60	416	416	166	450	483	216	450	483	183
0.75	400	416	133	416	466	133	416	400	133
0.90	400	400	116	366	416	100	400	416	100
1.05	366	383	83	383	416	83	400	383	83
1.20	350	366	83	350	383	50	383	383	66

F04

0.30	600	633	383	566	666	333	533	633	333
0.45	516	533	233	466	550	266	416	600	216
0.60	433	450	166	433	533	183	416	516	183
0.75	400	433	133	383	450	133	366	433	133
0.90	350	400	133	366	400	116	350	400	116
1.05	316	400	83	366	383	100	333	366	100
1.20	350	366	66	333	333	66	333	366	83

(continued over ...)

(Table A3 continued ...)

F05				
	0.30	716 666 350	616 650 316	516 700 250
	0.45	566 533 266	500 533 233	450 583 200
	0.60	416 383 183	416 433 200	350 416 166
	0.75	366 383 166	366 416 133	316 433 116
	0.90	366 333 133	366 383 116	333 433 100
	1.05	333 333 100	333 383 100	316 383 83
	1.20	316 333 83	333 366 83	333 350 83
F06				
	0.30	766 750 350	683 700 300	550 733 300
	0.45	566 566 200	583 583 250	500 566 216
	0.60	483 483 183	500 483 200	433 483 150
	0.75	416 433 133	400 450 150	366 416 133
	0.90	400 383 116	366 400 116	350 366 116
	1.05	350 383 83	350 366 100	333 350 100
	1.20	366 350 83	333 366 66	283 316 66
F07				
	0.30	666 682 433	516 583 400	383 566 416
	0.45	516 550 250	383 533 216	433 550 250
	0.60	516 500 183	466 566 183	400 483 166
	0.75	400 416 133	350 433 133	366 450 116
	0.90	400 410 116	350 383 100	350 416 133
	1.05	366 383 100	300 366 66	333 383 100
	1.20	316 316 83	300 350 50	316 383 50
F08				
	0.30	566 566 416	483 533 450	416 616 333
	0.45	433 450 283	383 383 283	416 450 233
	0.60	400 383 166	383 366 233	383 350 150
	0.75	383 400 150	366 333 166	350 350 133
	0.90	366 366 133	350 333 133	333 366 100
	1.05	350 366 100	333 300 116	333 366 83
	1.20	333 350 83	350 383 100	333 350 66
F09				
	0.30	533 583 300	450 633 216	466 600 250
	0.45	500 466 216	433 466 183	416 500 200
	0.60	400 433 183	450 466 166	366 483 150
	0.75	383 416 150	366 399 133	383 450 116
	0.90	350 350 133	400 366 100	366 400 100
	1.05	366 366 100	366 333 100	333 366 83
	1.20	333 333 83	333 316 83	316 366 66
F10				
	0.30	533 583 366	483 566 333	483 566 300
	0.45	433 433 266	433 566 300	400 516 250
	0.60	400 400 183	400 433 250	416 533 166
	0.75	333 366 166	416 433 216	366 433 133
	0.90	350 333 133	366 433 116	366 400 100
	1.05	333 333 100	350 416 100	366 383 83
	1.20	350 316 66	316 382 83	366 383 50

* RSS : right single support phase
LSS : left single support phase
DSS : double support phase
Speed: in statures/sec

APPENDIX B

corresponds to chapter four and includes:

Table B1: Physical characteristics of subjects.

Figures B1 to B6: include the graphical presentation of angular displacement (in degrees) of both knees and both hips from 18 subjects during stepping forward up at 5 different steps. Each graph has a symbol which represents the sex of the subject (M or F), his or her number and the height of the step expressed as a percentage of the subject's height (from 5% to 25%).

Figure B1: Graphs from subject M01, M02 and M03

Figure B2: Graphs from subject M04, M05 and M06

Figure B3: Graphs from subject M07, M08 and M09

Figure B4: Graphs from subject M10, M11 and F01

Figure B5: Graphs from subject F02, F03 and F04

Figure B6: Graphs from subject F05, F06 and F07

Table B1: Physical characteristics of subjects.

	MALES			FEMALES		
Subject's No	**Age (years)**	**Weight (Kg)**	**Stature (m)**	**Age (years)**	**Weight (Kg)**	**Stature (m)**
1	21	70	1.76	30	61	1.75
2	22	65	1.71	23	85	1.65
3	24	83	1.78	30	49	1.63
4	25	70	1.72	21	64	1.70
5	25	72	1.81	26	52	1.68
6	20	64	1.76	23	52	1.62
7	35	75	1.76	26	60	1.77
8	33	88	1.68			
9	29	78	1.77			
10	24	76	1.77			
11	24	70	1.77			

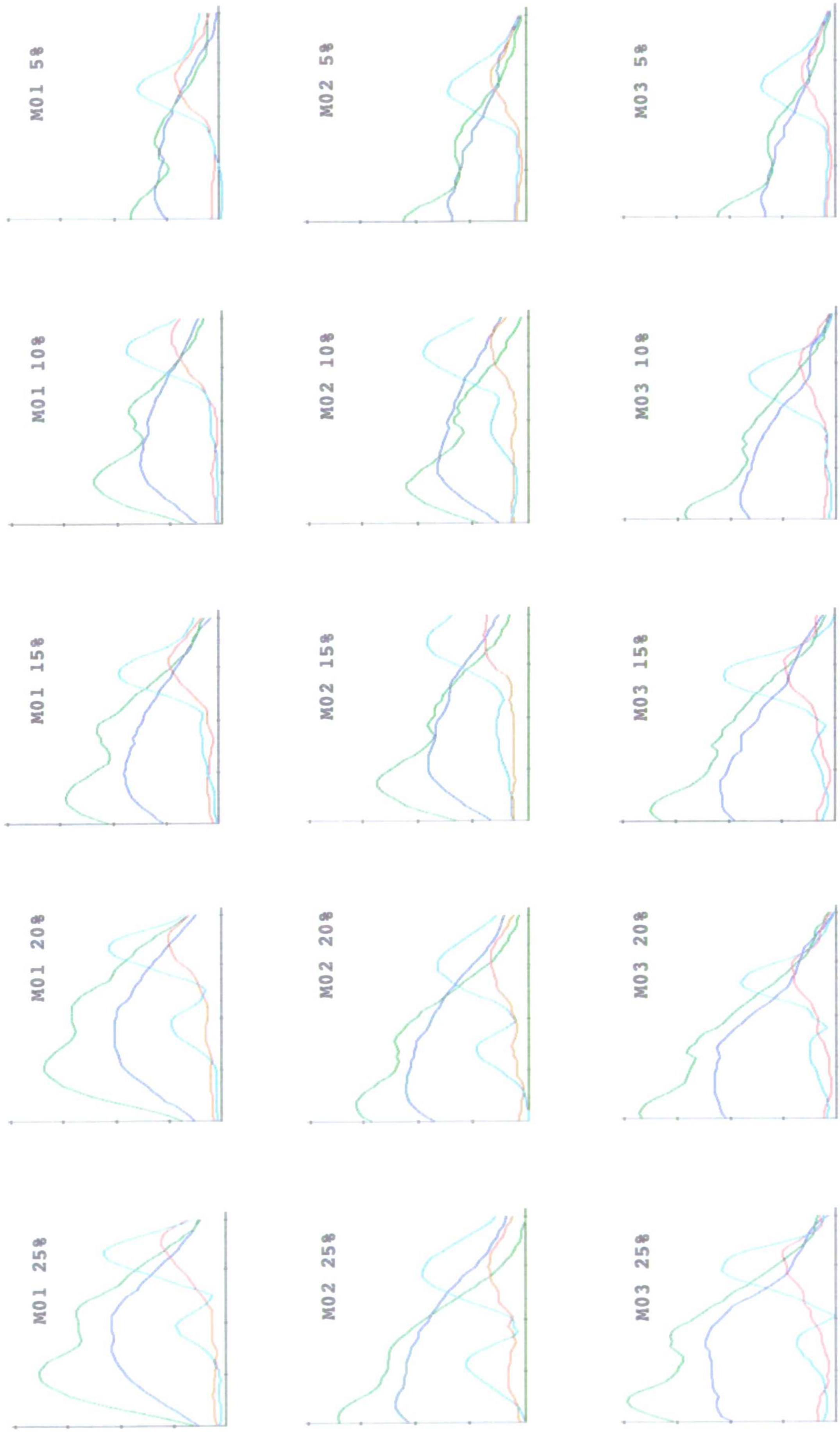
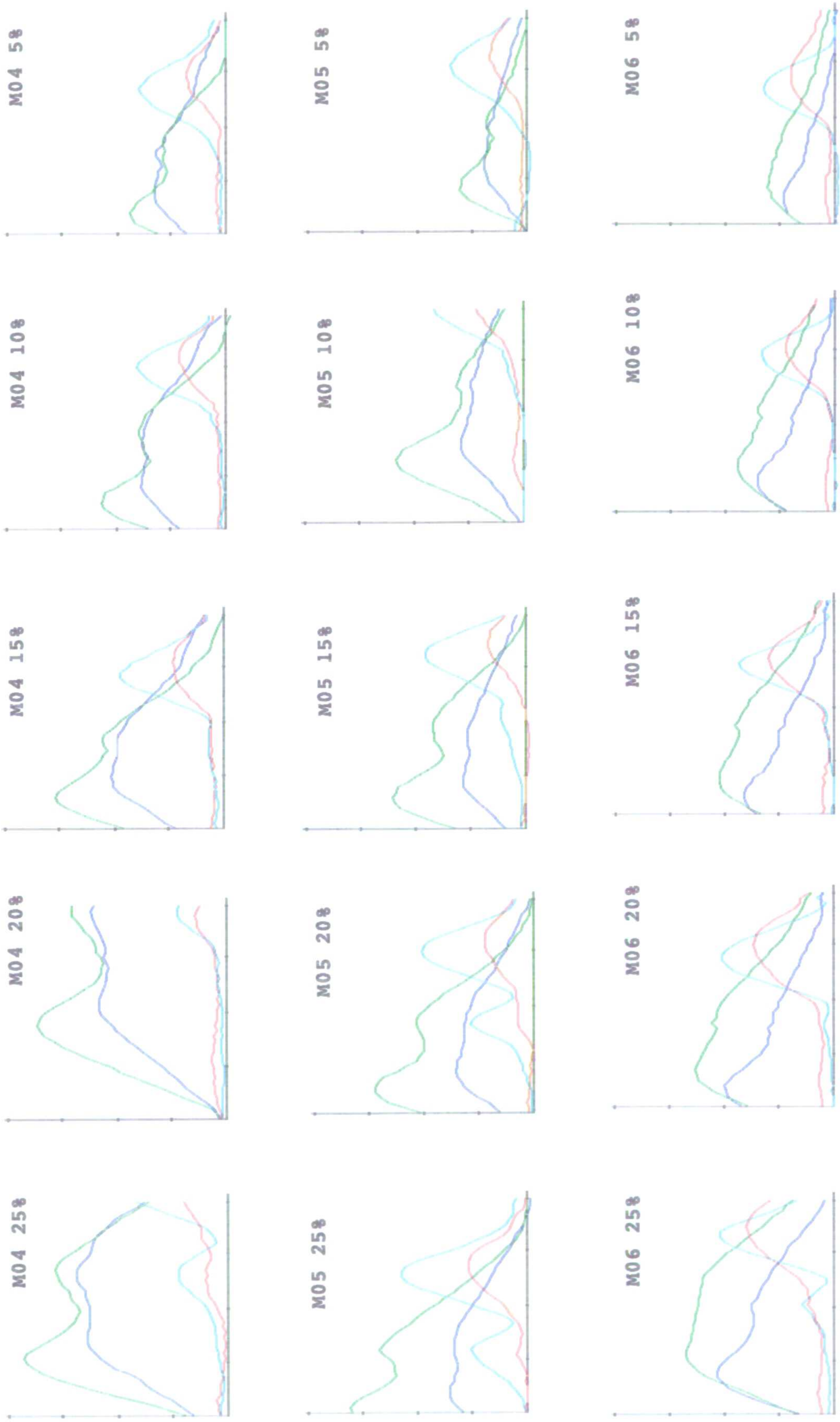

M01 5%
M02 5%
M03 5%
M01 10%
M02 10%
M03 10%
M01 15%
M02 15%
M03 15%
M01 20%
M02 20%
M03 20%
M01 25%
M02 25%
M03 25%

Figure B1



M04 5%
M04 10%
M04 15%
M04 20%
M04 25%
M05 5%
M05 10%
M05 15%
M05 20%
M05 25%
M06 5%
M06 10%
M06 15%
M06 20%
M06 25%

Figure B2

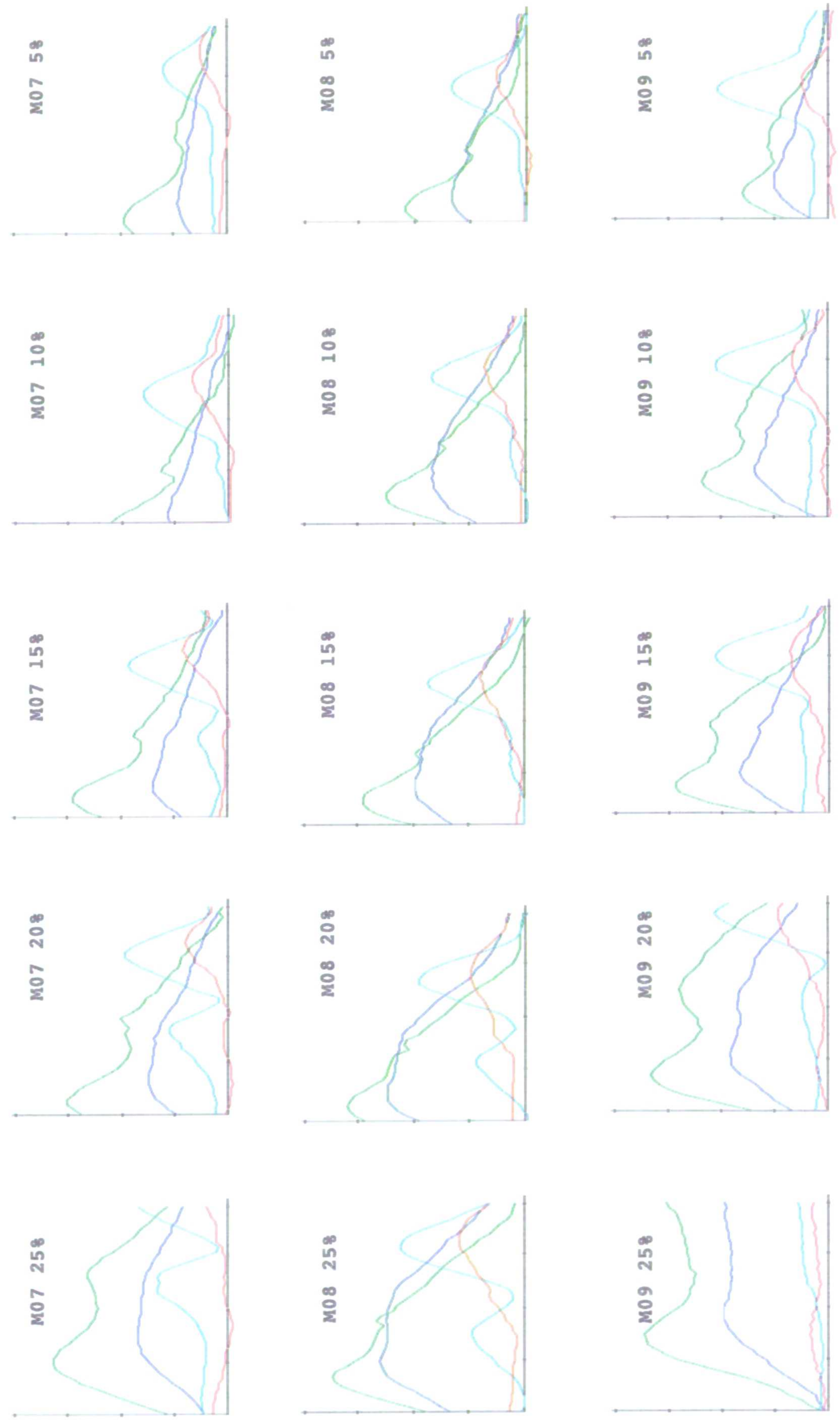

M07 5%
M07 10%
M07 15%
M07 20%
M07 25%
M08 5%
M08 10%
M08 15%
M08 20%
M08 25%
M09 5%
M09 10%
M09 15%
M09 20%
M09 25%

Figure B3

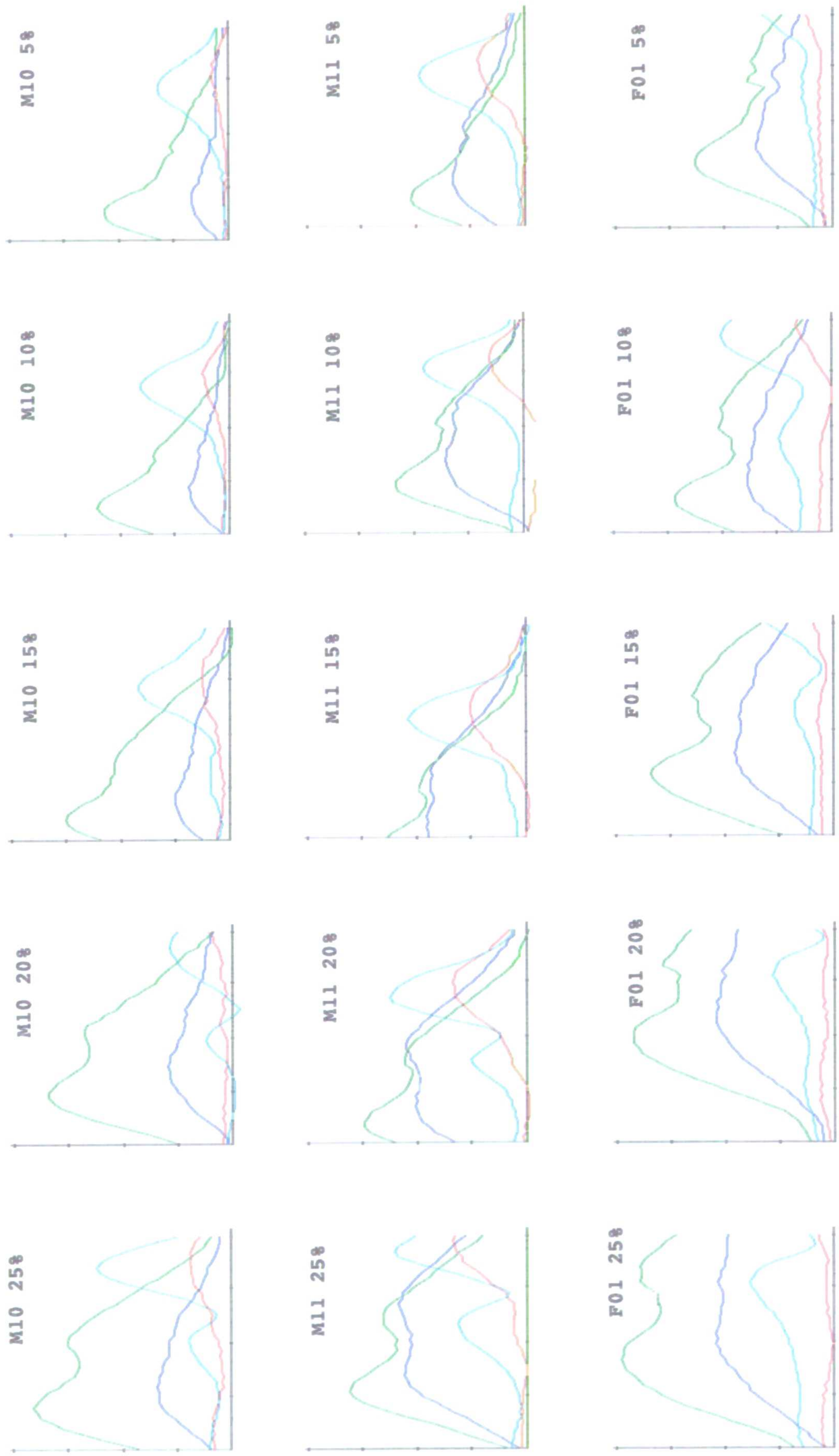

M10 5%
M10 10%
M10 15%
M10 20%
M10 25%
M11 5%
M11 10%
M11 15%
M11 20%
M11 25%
F01 5%
F01 10%
F01 15%
F01 20%
F01 25%

Figure B4

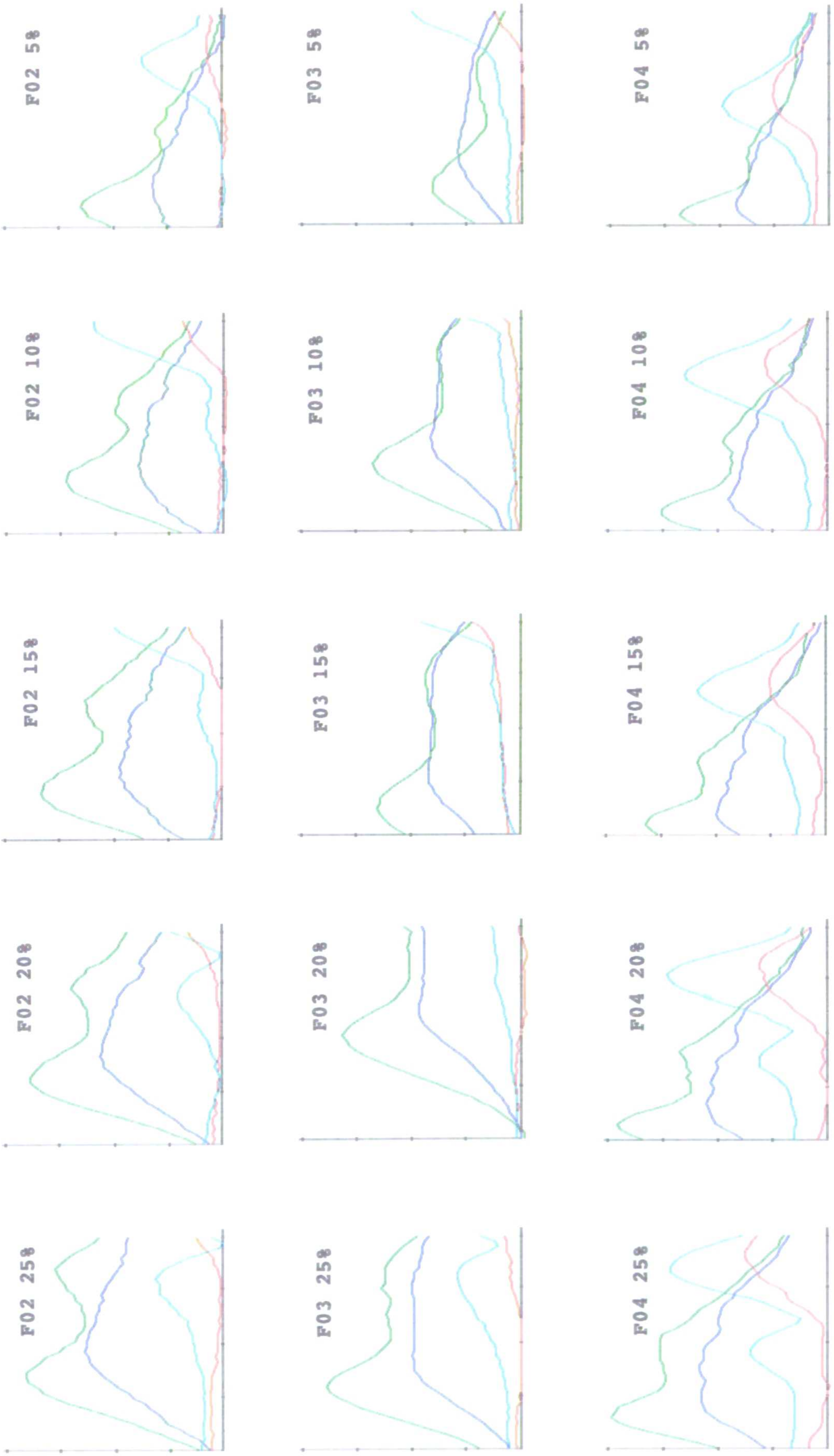

F02 5%
F02 10%
F02 15%
F02 20%
F02 25%
F03 5%
F03 10%
F03 15%
F03 20%
F03 25%
F04 5%
F04 10%
F04 15%
F04 20%
F04 25%

Figure B5

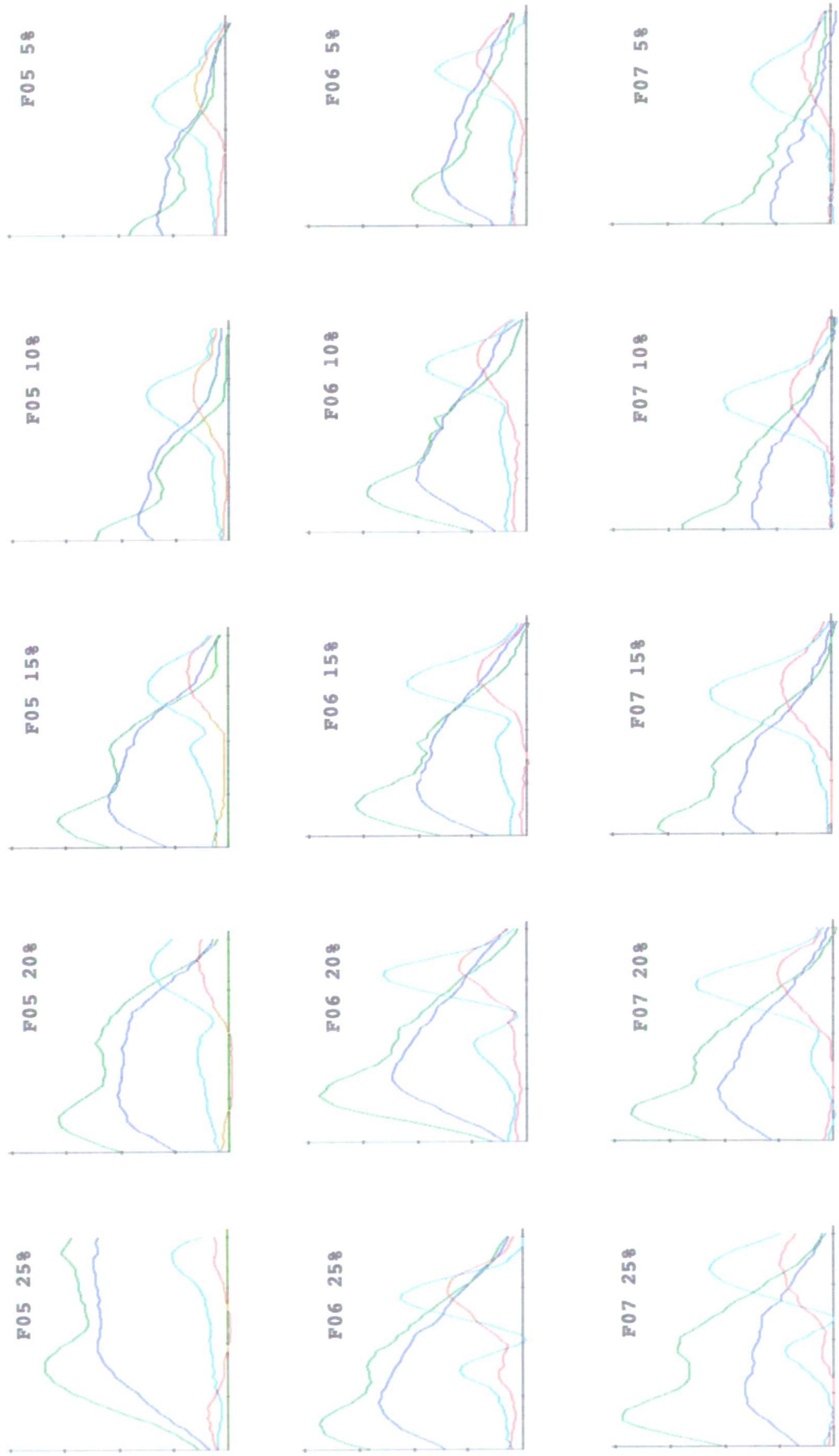

F05 5%
F05 10%
F05 15%
F05 20%
F05 25%
F06 5%
F06 10%
F06 15%
F06 20%
F06 25%
F07 5%
F07 10%
F07 15%
F07 20%
F07 25%

Figure B6

APPENDIX C

corresponds to chapter five and includes:

Figures C1 to C4: are the graphical presentation of the posture (upper body) from 12 subjects under three imagined moods, depressed (D), happy (H) and relaxed (R). Each graph has a symbol which represents the number of the subject (from 1 to 12) and his or her mood. All graphs have the same scale and the different plotted points are those shown in Figure 5.2.

Figure C1: Graphs from subject S01, S02 and S03
Figure C2: Graphs from subject S04, S05 and S06
Figure C3: Graphs from subject S07, S08 and S09
Figure C4: Graphs from subject S10, S11 and S12

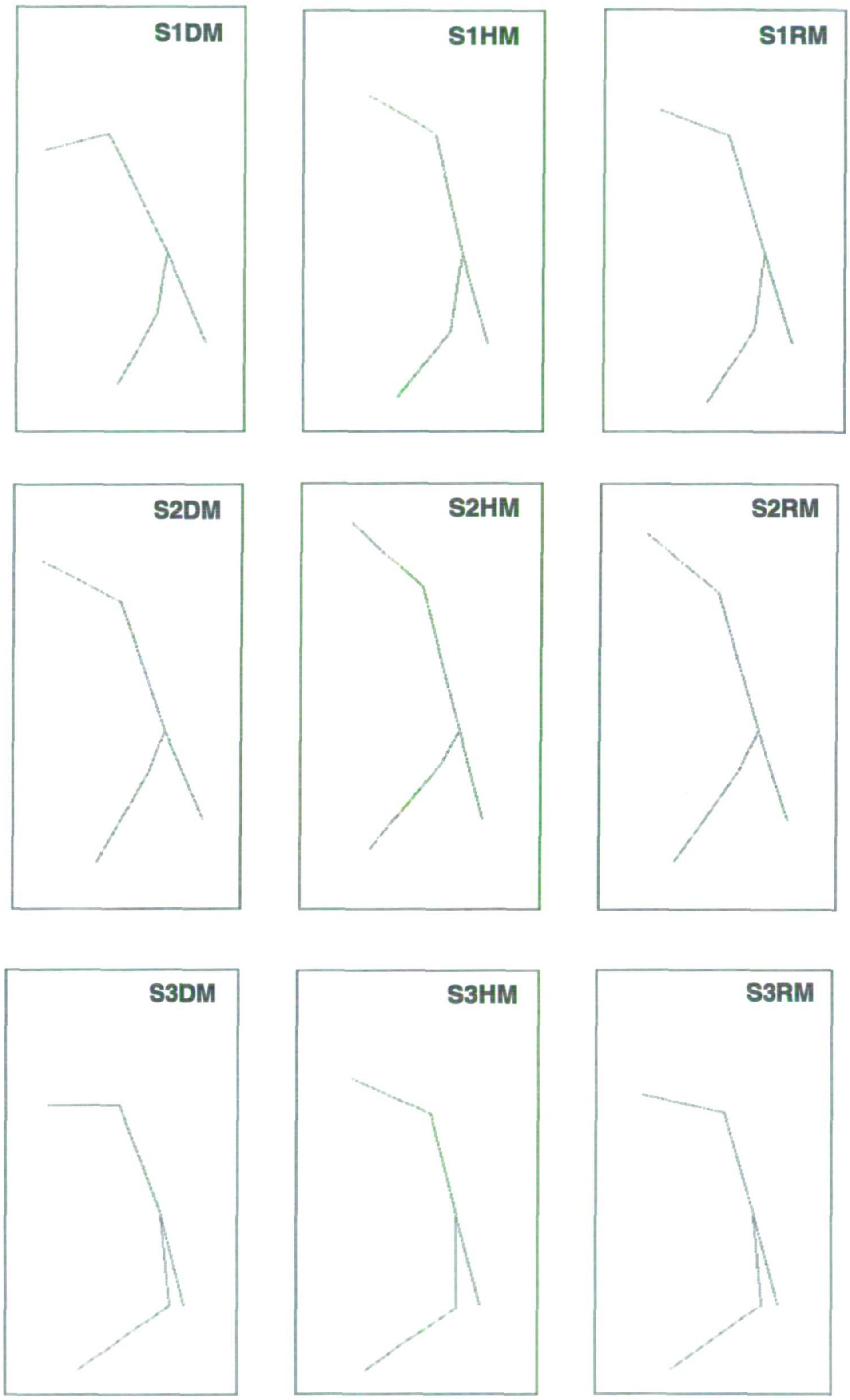


Figure C1: Graphs from subject S01, S02 and S03.

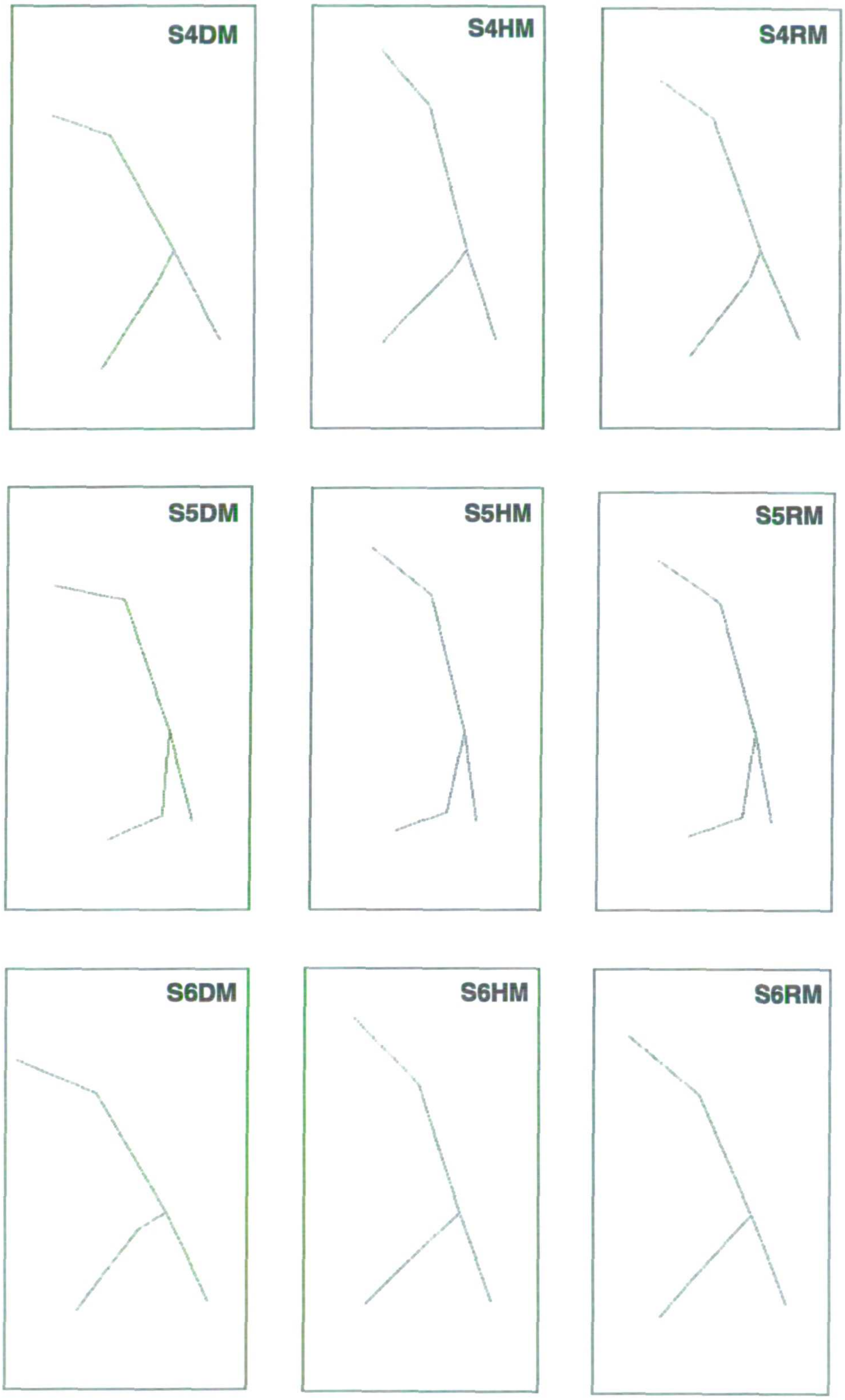


Figure C2: Graphs from subject S04, S05 and S06.

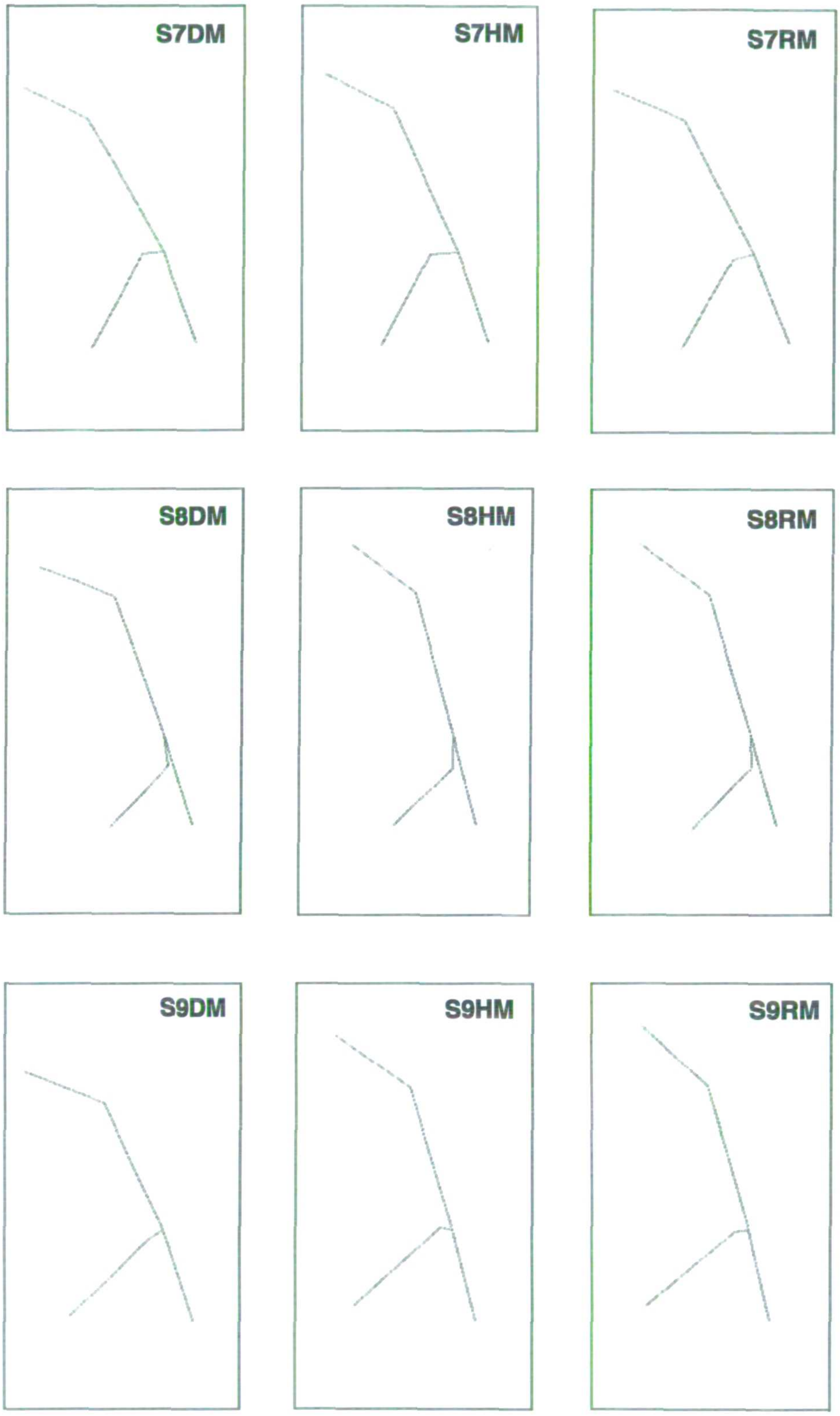


Figure C3: Graphs from subject S07, S08 and S09.

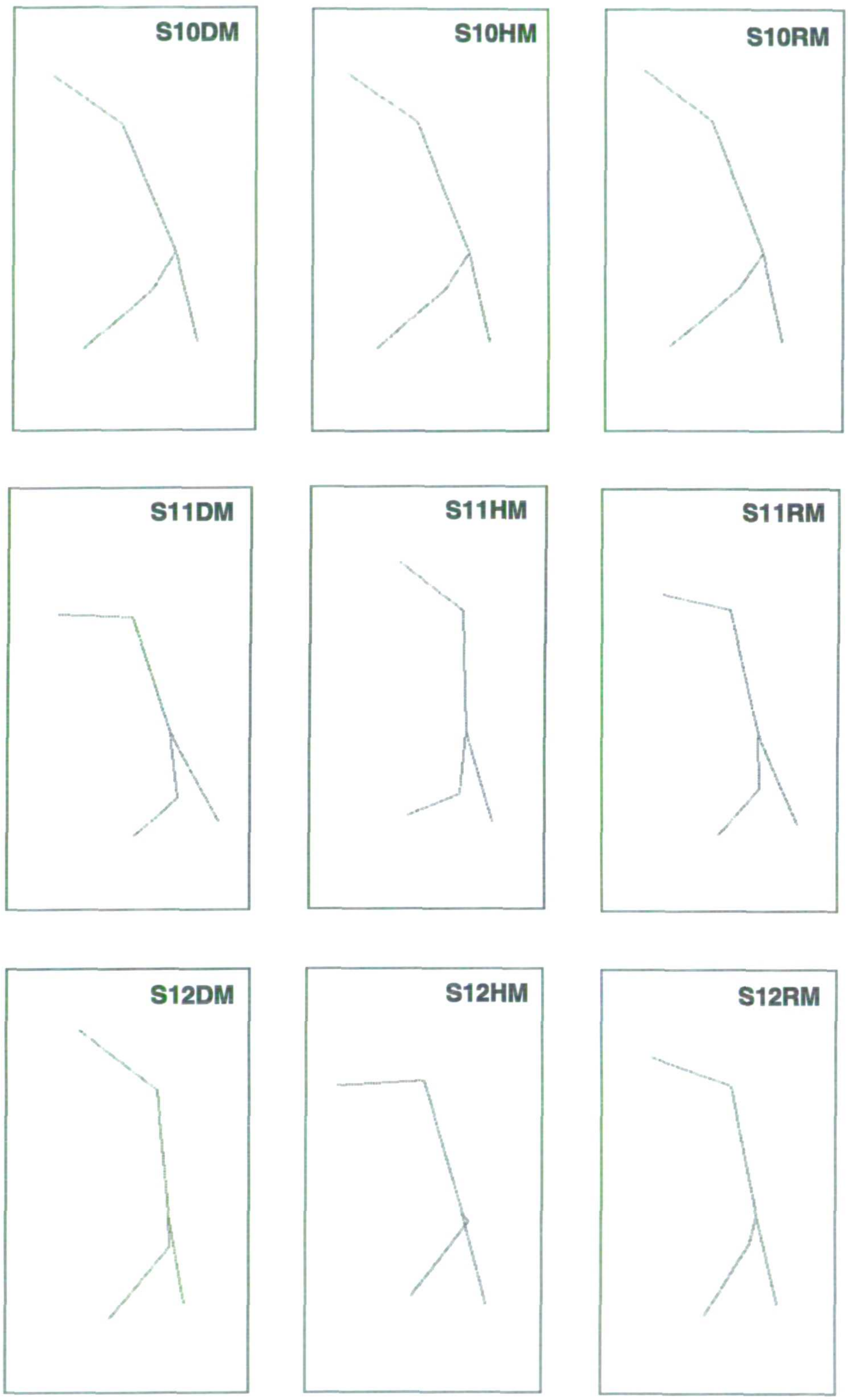


Figure C4: Graphs from subject S10, S11 and S12.

APPENDIX D

corresponds to chapter six and includes:

Table D1: Physical characteristics of subjects

Ethics clearance

Letter to volunteers

Volunteer's information package

Health questionnaire

Oswestry Back Disability Index

Informed consent

	GROUP (H)				GROUP (M)				GROUP (P)			
No	**sex**	**weight (kg)**	**height (m)**	**age years**	**sex**	**weight (Kg)**	**height (m)**	**age years**	**sex**	**weight (Kg)**	**height (m)**	**age years**
1	M	63	1.79	37	M	95	1.76	28	M	85	1.85	54
2	M	97	1.67	37	M	75	1.79	24	F	80	1.55	50
3	M	75	1.75	30	M	68	1.72	25	F	58	1.64	34
4	M	80	1.86	35	M	63	1.78	25	M	72	1.75	49
5	M	83	1.77	32	F	69	1.65	25	M	81	1.70	39
6	M	75	1.70	40	F	59	1.70	24	M	90	1.87	45
7	M	70	1.71	34	M	62	1.68	27	F	60	1.67	29
8	M	75	1.75	30	M	79	1.74	27	M	70	1.70	43
9	M	72	1.81	34	F	57	1.73	24	F	78	1.77	47
10	F	63	1.75	33	M	70	1.79	25	F	55	1.64	24
11	F	60	1.65	29	M	75	1.83	21	*	**	**	**
12	F	58	1.74	41	M	92	1.88	24	*	**	**	**
13	F	60	1.71	28	*	**	**	**	*	**	**	**
14	F	65	1.73	48	*	**	**	**	*	**	**	**

Table D1: Physical characteristics of subjects.

THE ROYAL FREE HAMPSTEAD NHS TRUST

ROYAL FREE HOSPITAL
POND STREET
LONDON NW3 2QG

TELEPHONE 071 794 0500

MED A D E RS OFF E

REPLY TO EXTENSION 4701

10 November 1993

Prof D Grieve
Dept of Anatomy
& Developmental Biology

Dear Professor Grieve

Re: 143-93

THE USE OF ARTIFICIAL NEURAL NETWORKS TO ASSESS PATHOLOGICAL PATTERNS OF THE SIT-TO-STAND MANOEUVRE

I am pleased to be able to inform you that your recent submission to the Ethical Practices Sub Committee has now received approval by the majority of Members, with no outstanding adverse comments, and is thus <u>approved</u>.

This approval will be formally ratified when the Committee next meets and meanwhile you are free to go ahead with your project.

Yours sincerely,

J Sinclair

Julie Sinclair
Secretary
Ethical Practices Sub Committee

Royal Free Hospital School of Medicine
University of London

Division of Basic Medical Sciences
Rowland Hill Street London NW3 2PF
Tel: 071-794 0500
Fax: 071-794 1248

Department of Anatomy and Developmental Biology

Professor Geoffrey Goldspink, PhD, ScD, FRSC (Head of Department) Ext. 4355
Professor Don Grieve, MSc, PhD, FErgs (Professor of Biomechanics) Ext. 4383
Professor Eric A. Barnard, PhD, FRS (Director of Molecular Neurobiology Unit) Ext. 4211

1 December 1993

Dear Sir,
In our department we are trying to detect the existence of low back pain problems applying new techniques. At the moment we need to measure the movements of the body during the sit-to-stand manoeuvre from healthy, as well as back pain, patients.

These measurements are done at the Human Performance Laboratory of the Royal Free Hospital School of Medicine and take about an hour. Your participation in this study will not affect any other services you receive from this hospital.

If you are interested in taking part in this study, please read the volunteer's information package and answer the health questionnaire. We will contact you to make an appointment.
Thank you for you co-operation

Yours sincerely

Mr. George Gioftsos
Physiotherapist, Ph.D student

Volunteer's information package

Sit-to-stand manoeuvre test

1. Project objectives

The purpose of this study is to investigate whether artificial neural networks can detect the existence of low-back problems from the patterns of movement encountered in sit-stand manoeuvres.

2. Test procedures

Volunteers who participate in this study must either

a. meet minimal standards of good health and be currently free of any musculoskeletal injury or

b. be low back patients.

Selection of subjects will be done after evaluation of their answers to the health questionnaires and the following steps will then take place:

a. the test will be explained and the informed consent will be signed,

b. anthropometric measures such as height and weight will be taken,

c. electrogoniometers will be fixed to the right ankle, hip and the back with double sided sellotape and will be connected.

You will then be asked to:

1. stand on two force-plates in front of a chair,
2. sit-down and then stand up in a normal slow pace and
3. repeat the sit-to-stand manoeuvre ten times.

3. Risks and discomfort

The same experiment has been repeated previously by healthy volunteers many times without any problem or discomfort. To the best of our knowledge, it is the first time that back pain patients will take part in this kind of study.

If any discomfort occurs during the test, it will be terminated.

4. Inquiries

Questions concerning the procedures used are welcome. If you have any doubts please ask for further explanation.

5. Freedom of consent

Participation is on a voluntary basis. You are free to deny consent, if you so desire, at any time during or between trials.

6. Confidentiality

All questions, answers and results from this study will be treated with absolute confidentiality. Subjects will be identified in the resultant manuscript and/or publications by use of subject codes only.

Surname: **No:**

Name:

The date of inquiry ___ ___ ___
day month year

Sex **1 Female 2 Male**

What year were you born?

How many years and months have you been doing your present type of work?
_____years+_____months

On average, how many hours a week do you work? ______ hours a week

How much do you weight? ______Kg

How tall are you? ______cm

Are you right-handed or left-handed?
1 right-handed
2 left-handed

Address and telephone number:

How to answer the questionnaire:

Please answer by putting a cross in the appropriate box-one cross for each question. You may be in doubt as to how to answer, but please do your best anyway. Please answer every question, even if you have never had trouble in any part of your body.

Trouble with the locomotive organs

Have you at any time during the last 12 months had trouble (ache, pain, discomfort) in:	To be answered only by those who have had trouble	
	Have you at any time during the last 12 months been prevented from doing your normal work (at home or away from home) because of the trouble?	Have you had trouble at any time during the last 7 days?
Neck 1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes
Shoulders 1 ☐ No 2 ☐ Yes, in the right shoulder 3 ☐ Yes, in the left shoulder 4 ☐ Yes, in both shoulders	1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes
Elbows 1 ☐ No 2 ☐ Yes, in the right elbow 3 ☐ Yes, in the left elbow 4 ☐ Yes, in both elbows	1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes
Wrists/hands 1 ☐ No 2 ☐ Yes, in the right wrist/hand 3 ☐ Yes, in the left wrist/hand 4 ☐ Yes, in both wists/hands	1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes
Upper back 1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes
Low back (small of the back) 1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes
One or both hips/thighs 1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes
One or both knees 1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes
One or both ankles/feet 1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes	1 ☐ No 2 ☐ Yes

LOW BACK

How to answer the questionnaire:

In this picture you can see the approximate of the part of the body reffered to in the questionaire. By low back trouble is meant ache, pain or discomfort in the shaded area whether or not it extends from there to one or both legs (sciatica).

Please answer by putting a cross in the appropriate box-one cross for each question. You may be in doubt to answer, but please do your best anyway.

1 Have you had low back trouble (ache, pain or discomfort)?

1☐ No 2☐ Yes

If you answered No to Question 1, do not answer question 2-8.

2 Have you ever been hospitalized because of low back trouble?

1☐ No 2☐ Yes

3 Have you ever had to change jobs or duties because of low back trouble?

1☐ No 2☐ Yes

4 What is the total length of time that you have had low back trouble during the last 12 12 months?

1☐ 0 days
2☐ 1-7 days
3☐ 8-30 days
4☐ More than 30 days, but not every day
5☐ Every day

If you answered 0 days to Question 4, do not answer question 5-8.

5 Has low back trouble caused you to reduce your activity during the last 12 months?

a. Work activity (at Home or away from home)?

1☐ No 2☐ Yes

b. Leisure activity?

1☐ No 2☐ Yes

6 What is the total length of time that low back trouble has prevented you from doing your normal work (at home or away from home) during the last 12 months?

1☐ 0 days
2☐ 1-7 days
3☐ 8-30 days
4☐ More than 30 days

7 Have you been seen by a doctor, physiotherapist or other such person because of low trouble during the last 12 months?

1☐ No 2☐ Yes

8 Have you had low back trouble at any time during the last 7 days?

1☐ No 2☐ Yes

The Oswestry Back Disability Index

Name:

How long have you had back pain ...Years...Months...Weeks
How long have you had leg pain ...Years...Months...Weeks

Please read: This questionnaire has been designed to give information as to how your back pain has affected your ability to manage in every day life. Please answer every section, and mark in each section only the one statement which applies to you. We realise you may consider that two of the statements in any one section relate to you, but please just mark the one which most closely describes your problem.

Section 1 - Pain Intensity

..... I can tolerate the pain I have without having to use pain killers.
..... The pain is bad but I manage without taking pain killers.
..... Pain killers give complete relief from pain.
..... Pain killers give moderate relief from pain.
..... Pain killers give very little relief from pain.
..... Pain killers have no effect on the pain and I do not use them.

Section 2 - Personal Care (washing, dressing, etc)

..... I can look after myself normally without causing extra pain.
..... I can look after myself normally but it causes extra pain.
..... It is painful to look after myself and I am slow and careful.
..... I need some help but manage most of my personal care.
..... I do not get dressed, wash with difficulty and stay in bed.

Section 3 - Lifting

..... I can lift heavy weights without extra pain.
..... I can lift heavy weights but it gives extra pain.
..... Pain prevents me from lifting heavy weights off the floor, but I can manage if they are conveniently positioned, eg on a table.
..... Pain prevents me from lifting heavy weights but I can manage light to medium weights if they are conveniently positioned.
..... I can lift only very light weights.
..... I cannot lift or carry anything at all.

Section 4 - Walking

..... Pain does not prevent me walking any distance.
..... Pain prevents me walking more than 1 mile.
..... Pain prevents me walking more than 1/2 mile.
..... Pain prevents me walking more than 1/4 mile.
..... I can only using a stick or crutches.
..... I am in bed most of the time and have to crawl to the toilet.

Section 5 - Sitting
..... I can sit in any chair as long as I like.
..... I can only sit in my favourite chair as long as I like.
..... Pain prevents me sitting more than 1 hour.
..... Pain prevents me from sitting more than 1/2 hour.
..... Pain prevents me from sitting more than 10 min.
..... pain prevents me from sitting at all.

Section 6 - Standing
..... I can stand as long as I want without extra pain.
..... I can stand as long as I want but it gives me extra pain.
..... Pain prevents me from standing for more than 1 hour.
..... Pain prevents me from standing for more than 30 min.
..... Pain prevents me from standing for more than 10 min.
..... Pain prevents me from standing at all.

Section 7 - Sleeping
..... Pain does not prevent me from sleeping well.
..... I can sleep well only by using tablets.
..... Even when I take tablets I have less than six hours sleep.
..... Even when I take tablets I have less than four hours sleep.
..... Even when I take tablets I have less than two hours sleep.
..... Pain prevents me from sleeping at all.

Section 8 - Social life
..... My social life is normal and gives me no extra pain.
..... My social life is normal but increases the degree of pain.
..... Pain has no significant effect on my social life apart from limiting my more energetic interest, eg dancing etc.
..... Pain has restricted my social life and I do not go out as often.
..... I have no social life because of pain.

Section 9 - Travelling
..... I can travel anywhere without extra pain.
..... I can travel anywhere but it gives me extra pain.
..... Pain is bad but I manage journeys over two hours.
..... Pain restricts me to journeys of less than one hour.
..... Pain restricts me to short necessary journeys under 30 minutes.
..... Pain prevents me from travelling except to the doctor or hospital.

Royal Free Hospital School of Medicine
University of London

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Department of Anatomy and Developmental Biology

Professor Geoffrey Goldspink, PhD, ScD, FRSC (Head of Department) Ext. 4355
Professor Don Grieve, MSc, PhD, FErgs (Professor of Biomechanics) Ext. 4383
Professor Eric A. Barnard, PhD, FRS (Director of Molecular Neurobiology Unit) Ext. 4211

INFORMED CONSENT

The university and those conducting this project subscribe to the ethical conduct of research and to the protection at all times of the interests, comfort and safety of subjects. This form and the information it contains are given to you for your own protection and full understanding of the procedures, risks and benefits involved. Your signature on this form will signify that you have received the adequate opportunity to consider the information in the document, and that you voluntarily agree to participate in the project.

Having been asked by Mr. G. Gioftsos of the Dept. of Anatomy & Developmental Biology of The Royal Free Hospital School of Medicine, University of London, to participate in a research project experiment, I have read the procedures specified in the document entitled:

Subject information package: Sit-to-Stand manoeuvre test.

I understand the procedures to be used in this experiment and the personal risks to me in taking part.

I understand that I may withdraw my participation in this experiment at any time. I also understand that I may register any complaint I might have about the experiment with the chief researcher named above or with Prof. D.W. Grieve, in the Dept. of Anatomy, Royal Free Hospital.

I may obtain a copy of the results of this study, upon its completion, by contacting Prof. D.W. Grieve or Mr. G. Gioftsos.

I agree to participate by performing the sit-to-stand manoeuvre test (as explained to me by the principle investigator and referred to in the document named above).

SURNAME______________________________________

FIRST NAME___________________________________

DATE OF BIRTH________________________________

ADDRESS______________________________________

____

SIGNATURE____________________________________

DATE____

SIGNATURE OF WITNESS_________________________

APPENDIX E

corresponds to chapter six and includes:

Software written to control the equipment

Figures E1 to E5: line drawings of the different components of the force plate (all measurements are in mm). Each component has a symbol which corresponds to Figure 6.2. The symbols A, L and F mean view from above, lateral view and view from in front respectively.

Figure E1: Components C1, C2 and C6.

Figure E2: Components C7, C8 and C9.

Figure E3: Components C12 and C13.

Figure E4: Components C3, C4 and C5.

Figure E5: Components C10, C15 and C16.

```
10 REM*****************PROGRAM "BACK"***************
20 REM Author: GEORGE GIOFTSOS      21 DEC 1993
30 REM This prog sellects data during the sit-stand experiment
40 REM It's doing the following: sets zero in 8 amplifiers, records
50 REM baselines and calibration values of 8 ampl, records
60 REM baselines for 4 goniometers, samples for 5sec with 100Hz
70 REM 13 channels,takes of baselines,divides by calibration values
80 REM gives range of motion for hip-knee-spine, three forces for
90 REM each leg (horiz-vert front-vert back) and temporal par.
100 MODE12:REM @%=&00006
110 *RMEnsure CEDDRV 0.00 RMLoad System:Modules.CEDDRV
120 *Set CED$ON 1
130 *Set CED$Dir adfs::4.$.CED1401
140 *Set CEDCommands$Path adfs::4.$.CED1401.b.
150 LIBRARY "Lib:Error"
160 ON ERROR PROCerror(REPORT$,ERL):END
170 DIM Command$(40)
180 FOR J= 0 TO 4: READ Command$(J):NEXT
190 DATA "ADCMEMI","SN2","SS2","ADCMEMF","END"
200 PROCLoad1401Commands(Command$())
210 PROCDEFINE:CLS:PROCSUBJECT
220 MODE12:PRINTTAB(5,50)"ADJUST VOLTAGES (y/n)?";:REPEAT
230 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 250
240 PROCVOLTAGES
250 CLS:PRINTTAB(5,10)"RECORD BASELINE VALUES(y/n)?";: REPEAT
260 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 300
270 PROCBASELINE:CLS:PROCLEGENTS1
280 PRINTTAB(15,25)"ARE YOU HAPPY WITH THESE VALUES (Y/N)?";:REPEAT
290 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 270
300 CLS
310 PRINTTAB(5,15)"WANT TO RECORD CALIBRATION VALUES (y/n)?";:REPEAT
320 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 370
330 PROCCALIBRATION:FOR J=1 TO 8:CAL(J)=CAL(J)-BLF(J):NEXT
340 CLS:PROCLEGENTS2
350 PRINTTAB(5,25)"ARE YOU HAPPY WITH THESE VALUES (Y/N)?";:REPEAT
360 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 330
370 CLS:PRINTTAB(5,10)"RECORD THE WEIGHT (y/n)?";:REPEAT
380 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 420
390 @%=&20806:CLS:PROCWEIGHT
400 PRINTTAB(5,15)"ARE YOU HAPPY WITH THESE VALUES (y/n)?";:REPEAT
410 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 390
420 CLS:PRINTTAB(15,25)"HIT A KEY TO START":VDU4:Y$=GET$
430 PROCSAMPLING
440 CLS:PRINTTAB(5,15)"HAPPY WITH DATA COLLECTION (y/n)?";:REPEAT
450 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 420
460 CLS:@%=&20306:PROCTRANSFER1:CLS:PRINT" HIT A KEY":CLS
470 PROCMINUS:REM***(READINDS FROM FORCES-BASELINE)/CALIBRATION****
480 PROCSMOOTH:PROCCHANGE
490 PROCDRAWX:PROCDRAWFORCESVER:PROCDRAWFORCESALL:PROCDRAWFORCESHOR
500 PROCDRAWGONIO:PROCEPILOG
510 MODE3:PROCSAVE
520 PRINTTAB(0,20)CHR$(136)"Did you finish the test(y/n)?";:REPEAT
530 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 220
540 STOP
550 REM MMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMMM
570 DEFPROCLoad1401Commands(Command$()):REM *LOADS 1401 COMMANDS***
580 REM - LOADS COMMANDS INTO 1401
590 LOCAL buffer%, lengthBuffer%, halfBuffer%
600 lengthBuffer%=6144       :REM the size of memory for work space
610 halfBuffer%=lengthBuffer% DIV 2
620 DIM buffer% lengthBuffer%+2
630 OSCLI "CED I"
640 LOCAL N$,n
650 WHILE Command$(n)<>"END":N$=Command$(n)
660 *CED WR
670 PRINT";";N$:INPUT";ERR;"E1,E2:*CED
680 IF E1=255 THEN
```

```
690     PRINT"Loading ";N$
700     N$="CEDCommands:"+N$
710     X=OPENINN$
720     Y=EXT#(X)
730     CLOSE#X
740     IF Y=0 PRINT"Can't load ";N$'"Load via USEFUL":END
750   OSCLI"LOAD "+N$+" "+STR$~(buffer%)
760  *CED RW
770   SYS "CED_SetTransfer",0,buffer%,0
780   PRINT"CLOAD,0,";Y
790   *CED
800 ENDIF
810 n+=1
820 ENDWHILE
830 ENDPROC:REM**************************************************
850 DEFPROCDEFINE:REM*********DEFINES ARRAYS****************
860 DIM GAP% 25999:DIM BLF(8):DIM CAL(8):DIM W(8):DIM BLG(4)
870 DIM A(12,499):DIM B(12,499):DIM C(12,499)
880 ENDPROC:REM*********************************************
900 DEFPROCERROR:REM**CHECKS 1401 FOR ERROR***
910 CLS:*CED I
920 *CED WR
930 INPUT"ERR;"E1,E2
940 *CED
950 PRINT "ERROR REPORT WAS ";E1;",";E2:PRINT
960 IF E1<>0 OR E2<>0 THEN GOTO 910
970 *CED
980 ENDPROC:REM*******************************
1000 DEFPROCSUBJECT:REM********SUBJECTS'S DETAILS***********
1010 PRINTTAB(0,20)"record SUBJECTS'S NAME (y/n)?";:REPEAT
1020 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 1240
1030 CLS:VDU5:GCOL1:PRINTTAB(10,2)"STUDY OF SIT-TO-STAND":VDU4
1040 INPUTTAB(0,6)"What is the subject's NUMBER",No$
1050 INPUTTAB(0,8)"What is the subject's NAME",A$
1060 INPUTTAB(0,10)"What is his AGE (years)",B
1070 IF B<10 OR B>100 THEN GOTO 1060
1080 INPUTTAB(0,12)"What is his STATURE (cm)",C
1090 IF C<100 OR C>220 THEN GOTO 1080
1100 INPUTTAB(0,14)"What is his WEIGHT (Kg)",D
1110 IF D<40 OR D>120 THEN GOTO 1100
1120 INPUTTAB(0,16)"What is his FOOT LENGTH (mm)",FPR
1130 IF FPR<100 OR FPR>400 THEN GOTO 1120
1140 PRINTTAB(0,20)"Do you want to PRINT DATA (y/n)?";:REPEAT
1150 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 1230
1160 CLS:VDU2:PRINT:PRINT:PRINT
1170 PRINT "NAME",A$,"No:",No$:PRINT
1180 PRINT "AGE",B;"YEARS":PRINT
1190 PRINT "WEIGHT",D;"Kg":PRINT
1200 PRINT "STATURE",C;"cm":PRINT
1210 PRINT "FOOT LENGTH",FPR;"mm":PRINT
1220 VDU3
1230 PRINTTAB(0,20)"HIT A KEY, IF YOU WISH TO CONTINUE":Y$=GET$
1240 CLS:ENDPROC:REM********************************
1260 DEFPROCVOLTAGES:CLS:REM*********ADJUST VOLTAGES****************
1270 VDU5:GCOL3:PRINTTAB(23,0)"ADJUST VOLTAGE OF THE BRIDJES":VDU4
1280 PROCLEGENTS
1290 FOR J=0 TO 100
1300 *CED WR
1310 INPUT"ADC,8 9 10 11 12 13 14 15;"A8,A9,A10,A11,A12,A13,A14,A15
1320 *CED
1330 PRINTTAB(18,8) A8/16,A9/16,A10/16,A11/16
1340 PRINTTAB(18,18) A12/16,A13/16,A14/16,A15/16
1350 NEXT
1360 PRINTTAB(25,25)"Have you FINISHED (y/n)?";:REPEAT
1370 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 1270
1380 ENDPROC:REM************************************************
1400 DEFPROCLEGENTS:REM***********SETS SCREEN**********
```

```
1410 VDU5:GCOL2
1420 PRINTTAB(5,5)"FPLATE 1:":GCOL4:PRINTTAB(25,5)"Va","Vb","Vc","Vd"
1430 GCOL1
1440 PRINTTAB(5,15)"FPLATE 2:":GCOL4:PRINTTAB(2,1)"Va","Vb","Vc","Vd"
1450 VDU4
1460 ENDPROC:REM***************************************
1480 DEFPROCLEGENTS1:REM********SETS SCREEN 1****************
1490 VDU5:GCOL3:PRINTTAB(25,0)"BASELINE'S VOLTAGES":GCOL2
1500 PRINTTAB(5,5)"F PLATE 1:":GCOL4:PRINTTAB(2,5)"Va","Vb","Vc","Vd"
1510 GCOL7:PRINTTAB(20,8) BLF(1),BLF(2),BLF(3),BLF(4):GCOL1
1520 PRINTTAB(5,15)"FPLATE 2:":GCOL4:PRINTTAB(5,5)"Va","Vb","Vc","Vd"
1530 GCOL7:PRINTTAB(20,18)BLF(5),BLF(6),BLF(7),BLF(8):VDU4
1540 ENDPROC:REM*******************************
1560 DEFPROCLEGENTS2:REM*********SETS SCREEEN2***************
1570 VDU5:GCOL3:PRINTTAB(25,0)"CALIBRATION VALUES"
1580 GCOL2
1590 PRINTTAB(5,5)"FPLATE 1:":GCOL4:PRINTTAB(25,5)"Va","Vb","Vc","Vd"
1600 GCOL7:PRINTTAB(20,8) CAL(1),CAL(2),CAL(3),CAL(4)
1610 GCOL1
1620 PRINTTAB(5,15)"FPLATE 2:":GCOL4:PRINT"Va","Vb","Vc","Vd"
1630 GCOL7:PRINTTAB(20,18)CAL(5),CAL(6),CAL(7),CAL(8)
1640 VDU4
1650 ENDPROC:REM********************************************
1670 DEFPROCBASELINE:REM **************RECORDS BASELINE*********
1680 CLS:PRINT:PRINT
1690 PRINT "PRESS SPACEBAR TO OBTAIN BASELINE VALUES":PRINT:A$=GET$
1700 CLS:PRINTTAB(10,10)"PLEASE WAIT... SAMPLING IN PROGRESS"
1710 *CED I
1720 *CED WR
1730 PRINT "ADCMEMI,2,0,8000,8 9 10 11 12 13 14 15,1,C,100,10"
1740 REPEAT : INPUT"ADCMEMI,?;"A% : UNTIL A%=0
1750 *CED
1760 CLS:PRINT "SAMPLING HAS BEEN DONE"
1770 *CED WR
1780 PRINT "SN2,S,8000,0,8000,8"
1790 *CED
1800 PRINT "SEPARATION HAS BEEN DONE"
1810 *CED WR
1820 PRINT "SS2,A,8000,1000" : INPUT""A% : BLF(1)=A%DIV16
1830 PRINT "SS2,A,9000,1000" : INPUT""A% : BLF(2)=A%DIV16
1840 PRINT "SS2,A,10000,1000" : INPUT""A% : BLF(3)=A%DIV16
1850 PRINT "SS2,A,11000,1000" : INPUT""A% : BLF(4)=A%DIV16
1860 PRINT "SS2,A,12000,1000" : INPUT""A% : BLF(5)=A%DIV16
1870 PRINT "SS2,A,13000,1000" : INPUT""A% : BLF(6)=A%DIV16
1880 PRINT "SS2,A,14000,1000" : INPUT""A% : BLF(7)=A%DIV16
1890 PRINT "SS2,A,15000,1000" : INPUT""A% : BLF(8)=A%DIV16
1900 *CED
1910 CLS:PRINTTAB(10,5)"RECORDING OF BASELINES HAS BEEN DONE"
1920 REM PRINTTAB(10,15) "PRESS SPACE BAR FOR THE BASELINES":Y$=GET$
1930 ENDPROC:REM*************************************************
1950 DEFPROCCALIBRATION:REM ****************************************
1960 REM - RECORDS CALIBRATION VALUES FOR ALL 8 BRIDGES
1970 CLS:PRINT:PRINT
1980 PRINT"SWITCH ON CAL RESISTORS, PRESS SPACEBAR":PRINT:A$=GET$
1990 CLS:PRINTTAB(10,10)"Did you SWITCH ON RESISTORS (y/n)?";:REPEAT
2000 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 1970
2010 CLS:PRINTTAB(10,10)"PLEASE WAIT...SAMPLING IN PROGRESS"
2020 *CED I
2030 *CED WR
2040 PRINT "ADCMEMI,2,0,8000,8 9 10 11 12 13 14 15,1,C,100,10"
2050 REPEAT : INPUT"ADCMEMI,?;"A% : UNTIL A%=0
2060 *CED
2070 CLS:PRINT "SAMPLING HAS BEEN DONE"
2080 *CED WR
2090 PRINT "SN2,S,8000,0,8000,8"
2100 *CED
2110 PRINT "SEPARATION HAS BEEN DONE"
```

```
2120 *CED WR
2130 PRINT "SS2,A,8000,1000" : INPUT""A% : CAL(1)=A%DIV16
2140 PRINT "SS2,A,9000,1000" : INPUT""A% : CAL(2)=A%DIV16
2150 PRINT "SS2,A,10000,1000" : INPUT""A% : CAL(3)=A%DIV16
2160 PRINT "SS2,A,11000,1000" : INPUT""A% : CAL(4)=A%DIV16
2170 PRINT "SS2,A,12000,1000" : INPUT""A% : CAL(5)=A%DIV16
2180 PRINT "SS2,A,13000,1000" : INPUT""A% : CAL(6)=A%DIV16
2190 PRINT "SS2,A,14000,1000" : INPUT""A% : CAL(7)=A%DIV16
2200 PRINT "SS2,A,15000,1000" : INPUT""A% : CAL(8)=A%DIV16
2210 *CED
2220 ENDPROC:REM*****************************************
2240 DEFPROCWEIGHT:REM *****************************************
2250 REM - RECORDS WEIGHT
2260 CLS:PRINTTAB(10,10)"READY (y/n)?";:REPEAT
2270 A%=GET:UNTIL A%=78 OR A%=89:IF A%=78 GOTO 2260
2280 CLS:PRINTTAB(10,10)"PLEASE WAIT...SAMPLING IN PROGRESS"
2290 *CED I
2300 *CED WR
2310 PRINT "ADCMEMI,2,0,8000,8 9 10 11 12 13 14 15,1,C,100,10"
2320 REPEAT : INPUT"ADCMEMI,?;"A% : UNTIL A%=0
2330 *CED
2340 CLS:PRINT "SAMPLING HAS BEEN DONE"
2350 *CED WR
2360 PRINT "SN2,S,8000,0,8000,8"
2370 *CED
2380 PRINT "SEPARATION HAS BEEN DONE"
2390 *CED WR
2400 PRINT "SS2,A,8000,1000" : INPUT""A% : W(1)=A%DIV16
2410 PRINT "SS2,A,9000,1000" : INPUT""A% : W(2)=A%DIV16
2420 PRINT "SS2,A,10000,1000" : INPUT""A% : W(3)=A%DIV16
2430 PRINT "SS2,A,11000,1000" : INPUT""A% : W(4)=A%DIV16
2440 PRINT "SS2,A,12000,1000" : INPUT""A% : W(5)=A%DIV16
2450 PRINT "SS2,A,13000,1000" : INPUT""A% : W(6)=A%DIV16
2460 PRINT "SS2,A,14000,1000" : INPUT""A% : W(7)=A%DIV16
2470 PRINT "SS2,A,15000,1000" : INPUT""A% : W(8)=A%DIV16
2480 *CED
2490 FOR J=1 TO 8:W(J)=((W(J)-BLF(J))/CAL(J)):NEXT
2500 FH1=7.13+6.84*W(1)+451*W(3)+6.24*(W(2)-W(4))
2510 FF1=-1.58-194*W(1)-1.09*W(3)+3.43*(W(2)-W(4))
2520 FB1=8.85+5.44*W(1)+17.6*W(3)+546*(W(2)-W(4))
2530 FH2=2.1+1.76*W(5)+368*W(7)+6.05*(W(6)-W(8))
2540 FF2=9.92-197*W(5)+33*W(7)-13.3*(W(6)-W(8))
2550 FB2=17.1+4.44*W(5)-86.5*W(7)+604*(W(6)-W(8))
2560 FVALL=FF1+FB1+FF2+FB2:CLS:VDU2
2570 PRINT "FVALL",FVALL:PRINT "FV1",FF1+FB1:PRINT "FV2",FF2+FB2
2580 PRINT:PRINT "FH1",FH1:PRINT:PRINT "FH2",FH2:VDU3
2590 Y$=GET$
2600 ENDPROC:REM*****************************************
2620 DEFPROCSAMPLING:REM*********COLLECTS DATA****************
2630 REM SAMPLING FOR 5SEC WITH 100HZ ALL 13 CHANNELS
2640 CLS:PRINTTAB(10,10)"PLEASE WAIT...SAMPLING IN PROGRESS"
2650 *CED I
2660 *CED WR
2670PRINT"ADCMEMI,2,0,13000,01 2 3 4 8 9 10 11 12 13 14 15,1,C,77,10"
2680 REPEAT : INPUT"ADCMEMI,?;"A% : UNTIL A%=0
2690 *CED
2700 CLS:PRINT "SAMPLING HAS BEEN DONE":VDU7
2710 *CED WR
2720 PRINT "SN2,S,13000,0,13000,13"
2730 *CED
2740 CLS:PRINT "SEPARATION HAS BEEN DONE":CLS
2750 *CED WR
2760 SYS "CED_SetTransfer",1,GAP%,0
2770 PRINT "TOHOST,13000,13000,1"
2780 TIME=0:REPEAT UNTIL TIME>300
2790 *CED
2800 PRINT "DATA HAVE BEEN SENDED TO HOST"
```

```
2810 ENDPROC:REM************************************************
2830 DEFPROCTRANSFER1:REM******TAKE DATA FROM 1401*******
2840 FOR K=0 TO 12:FOR J=0 TO 499
2850 A(K,J)=?(GAP%+K*1000+J*2)+?(GAP%+K*1000+J*2+1)*256
2860 IF A(K,J) > 32767 THEN A(K,J) = A(K,J) - 65536
2870 REM PRINT A(K,J);
2880 NEXT:PRINT:NEXT
2890 ENDPROC:REM****************************************
2910 DEFPROCMINUS:REM********************
2920 FOR J=0 TO 499
2930 A(5,J)=((A(5,J)/16)-BLF1)/CL(1):A(6,J)=((A(6,J)/16)-BLF2)/CL(2)
2940 A(6,J)=((A(6,J)/16)-BLF(2))/CAL(2)
2950 A(7,J)=((A(7,J)/16)-BLF(3))/CAL(3)
2960 A(8,J)=((A(8,J)/16)-BLF(4))/CAL(4)
2970 A(9,J)=((A(9,J)/16)-BLF(5))/CAL(5)
2980 A(10,J)=((A(10,J)/16)-BLF(6))/CAL(6)
2990 A(11,J)=((A(11,J)/16)-BLF(7))/CAL(7)
3000 A(12,J)=((A(12,J)/16)-BLF(8))/CAL(8)
3010 NEXT
3020 ENDPROC:REM*** **********************
3040 DEFPROCSMOOTH:REM******SMOOTHS DATA**********************
3050 FOR K=0 TO 12
3060 C(K,0)=(A(K,0)+A(K,1))/2:C(K,499)=(A(K,498)+A(K,499))/2:NEXT
3070 FOR J=1 TO 498:FOR K=0 TO 12
3080 C(K,J)=(A(K,J-1)+A(K,J)+A(K,J+1))/3
3090 NEXT:NEXT
3100 FOR J=0 TO 499:FOR K=0 TO 12:A(K,J)=C(K,J):NEXT:NEXT
3110 ENDPROC:REM*******************************************
3130 DEFPROCCHANGE:REM*********CALCULATES FORCES-DISTANCE*****
3140 FOR J=0 TO 499
3150 B(1,J)=((A(1,J)-3276.5)/72)-180:B(3,J)=((A(3,J)-3276.5)/72)-180
3160 B(2,J)=(((A(2,J)-3276.5)/72.8)-180)*-1
3170 NEXT
3180 FOR J=0 TO 499
3190 B(5,J)=7.13+6.84*A(5,J)+451*A(7,J)+6.24*(A(6,J)-A(8,J))
3200 B(6,J)=-1.58-194*A(5,J)-1.09*A(7,J)+3.43*(A(6,J)-A(8,J))
3210 B(7,J)=8.85+5.44*A(5,J)+17.6*A(7,J)+546*(A(6,J)-A(8,J))
3220 B(8,J)=2.1+1.76*A(9,J)+368*A(11,J)+6.05*(A(10,J)-A(12,J))
3230 B(9,J)=9.92-197*A(9,J)+33*A(11,J)-13.3*(A(10,J)-A(12,J))
3240 B(10,J)=17.1+4.44*A(9,J)-86.5*A(11,J)+604*(A(10,J)-A(12,J))
3250 NEXT
3260 FOR J=0 TO 499
3270 B(11,J)=3.27+0.989*((B(6,J)/(B(6,J)+B(7,J)))*400)
3280 B(12,J)=-3.11+1.02*((B(9,J)/(B(9,J)+B(10,J)))*400)
3290 NEXT
3300 FOR J=0 TO 499
3310 IF A(0,J)>8000 THEN B(0,J)=1
3320 IF A(0,J)<1000 THEN B(0,J)=3
3330 IF A(0,J)<8000 AND A(0,J)>1000 THEN  B(0,J)=2
3340 NEXT
3350 ENDPROC:REM**********************************************
3370 DEFPROCSAVE:REM***************SAVE DATA***************
3380 CLS:PRINT:PRINTTAB(20,30) "SAVE DATA? (Y/N  ";:REPEAT
3390 A%=GET:UNTIL A%=89 OR A%=78:IF A%=78 THEN ENDPROC
3400 CLS:PRINT:INPUT "WHAT IS THE FILES NAME? ";FIL$
3410 OSCLI "DIR $.GEORGE.G/BACK.DATA"
3420 F = OPENOUT FIL$
3430 FOR J=0 TO 499
3440    FOR K=0 TO 12
3450      PRINT# F, B(K,J)
3460    NEXT
3470    PRINT
3480 NEXT
3490 CLOSE#F
3500 CLS:PRINT:PRINT
3510 *CAT
3520 ENDPROC:REM***********************************
```

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3540 DEFPROCEPILOG:REM*********CHOOSE PLOTS************************
3550 MODE12:INPUTTAB(10,20)"DO YOU WANT DATA OR PLOTS (D/P/Q)?",DY$
3560 IF DY$="D" THEN GOTO 3590
3570 IF DY$="P" THEN GOTO 3600
3580 IF DY$="Q" THEN ENDPROC
3590 PROCPRINT1:GOTO 3550
3600 CLS:INPUTTAB(10,10)"PLOT: DISTANCE ANKLES FORCES (D/A/F/Q)?",Y$
3610 IF Y$="D" THEN PROCDRAWX
3620 IF Y$="A" THEN PROCDRAWGONIO
3630 IF Y$="F" THEN GOTO 3660
3640 IF Y$="Q" THEN ENDPROC
3650 GOTO 3550
3660 CLS:INPUTTAB(10,10)"WHICH FORCES: ALL-HOR-VER  A/H/V/Q)?",G$
3670 IF G$="A" THEN PROCDRAWFORCESALL
3680 IF G$="H" THEN PROCDRAWFORCESHOR
3690 IF G$="V" THEN PROCDRAWFORCESVER
3700 GOTO 3550
3710 ENDPROC:REM************************************************
3730 DEFPROCDRAWX:REM**********PLOTS X DISTANCES*******************
3740 MODE12
3750 VDU 28,0,3,79,0:VDU 24,0;0;1279;955;:VDU29,100;100;:COLOUR 3
3760 GCOL7:MOVE 10,10:DRAW 10,825:MOVE 10,10:DRAW 1279,10
3770 VDU5
3780 MOVE 20,210:DRAW 0,210:MOVE 20,410:DRAW 0,410:
3790 MOVE 20,610:DRAW 0,610:MOVE 20,810:DRAW 0,810
3800 MOVE 630,20:DRAW 630,0:MOVE 1260,20:DRAW 1260,0
3810 MOVE 30,830:PRINT "400mm"
3820 MOVE 1120,60:PRINT "TIME"
3830 MOVE 610,60:PRINT "50%"
3840 VDU4:GCOL3
3850 MOVE 10,760:FOR J=0 TO 499:DRAW (J*2.5)+10,(B(0,J)*20)+760:NEXT
3860 GCOL1:MOVE 10,(B(11,0)*2)+10
3870 FOR J=1 TO 499:DRAW (J*2.5)+10,(B(11,J)*2)+10:NEXT
3880 VDU5:MOVE 920,740:PRINT "R Foot PRESSURE":VDU4
3890 GCOL2:MOVE 10,(B(12,1)*2)+10
3900 FOR J=1 TO 499:DRAW (J*2.5)+10,(B(12,J)*2)+10:NEXT
3910 VDU5:MOVE 920,700 :PRINT "L Foot PRESSURE":VDU4
3920 Y$=GET$:MODE12:REM************************
3930 VDU 28,0,3,79,0:VDU 24,0;0;1279;955;:VDU29,100;100;:COLOUR 3
3940 GCOL7:MOVE 10,10:DRAW 10,825:MOVE 10,10:DRAW 1279,10
3950 MOVE 10,(FPR*2)+10:DRAW 1279,(FPR*2)+10
3960 VDU5
3970 MOVE 20,210:DRAW 0,210:MOVE 20,410:DRAW 0,410:
3980 MOVE 20,610:DRAW 0,610:MOVE 20,810:DRAW 0,810
3990 MOVE 630,20:DRAW 630,0:MOVE 1260,20:DRAW 1260,0
4000 MOVE 30,(FPR*2)+30:PRINT "TOES"
4010 MOVE 1120,60:PRINT "TIME"
4020 MOVE 610,60:PRINT "50%"
4030 VDU4:GCOL3
4040 MOVE 10,760:FOR J=0 TO 499:DRAW (J*2.5)+10,(B(0,J)*20)+760:NEXT
4050 GCOL1:MOVE 10,((B(11,0)-27)*2)+10
4060 FOR J=1 TO 499:DRAW (J*2.5)+10,((B(11,J)-27)*2)+10:NEXT
4070 VDU5:MOVE 920,740:PRINT "R Foot PRESSURE":VDU4
4080 GCOL2:MOVE 10,((B(12,0)-27)*2)+10
4090 FOR J=1 TO 499:DRAW (J*2.5)+10,(B(12,J)-27)*2+10:NEXT
4100 VDU5:MOVE 920,700 :PRINT "L Foot PRESSURE":VDU4
4110 Y$=GET$
4120 ENDPROC:REM************************************************
4140 DEFPROCDRAWFORCESVER:REM**********PLOTS F-VERTICAL***********
4150 MODE12
4160 VDU 28,0,3,79,0:VDU 24,0;0;1279;955;:VDU29,100;100;:COLOUR 3 128
4170 GCOL7:MOVE 10,10:DRAW 10,825:MOVE 10,10:DRAW 1279,10
4180 VDU5
4190 MOVE 20,210:DRAW 0,210:MOVE 20,410:DRAW 0,410:
4200 MOVE 20,610:DRAW 0,610:MOVE 20,810:DRAW 0,810
4210 MOVE 630,20:DRAW 630,0:MOVE 1260,20:DRAW 1260,0
4220 MOVE 30,830:PRINT "800N"
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4230 MOVE 1120,60:PRINT "TIME"
4240 MOVE 630,60:PRINT "50%"
4250 VDU4:GCOL3
4260 MOVE 10,760:FOR J=0 TO 499:DRAW (J*2.5)+10,(B(0,J)*20)+760:NEXT
4270 GCOL1:MOVE 10,B(7,0)+B(6,0)+10
4280 FOR J=1 TO 499:DRAW (J*2.5)+10,B(7,J)+B(6,J)+10:NEXT
4290 VDU5:MOVE 920,740:PRINT "R VER FORCE":VDU4
4300 GCOL2:MOVE 10,B(10,0)+B(9,0)+10
4310 FOR J=1 TO 499:DRAW (J*2.5)+10,B(10,J)+B(9,J)+10:NEXT
4320 VDU5:MOVE 920,700 :PRINT "L VER FORCE":VDU4
4330 Y$=GET$
4340 ENDPROC:REM**************************************************
4360 DEFPROCDRAWGONIO:REM**********PLOTS ANGLES-JOINTS*************
4370 MODE12
4380 VDU 28,0,3,79,0:VDU 24,0;0;1279;955;:VDU29,100;100;:COLOUR 3
4390 GCOL7:MOVE 10,10:DRAW 10,825:MOVE 10,10:DRAW 1279,10
4400 VDU5
4410 MOVE 20,210:DRAW 0,210:MOVE 20,410:DRAW 0,410:
4420 MOVE 20,610:DRAW 0,610:MOVE 20,810:DRAW 0,810
4430 MOVE 530,20:DRAW 530,0:MOVE 1060,20:DRAW 1060,0
4440 MOVE 30,830:PRINT "140 degrees"
4450 MOVE 1120,60:PRINT "TIME":MOVE 1030,60:PRINT "100%"
4460 MOVE 500,60:PRINT "50%"
4470 VDU4:GCOL3
4480 MOVE 10,760:FOR J=0 TO 499:DRAW (J*2.5)+10,(B(0,J)*20)+760:NEXT
4490 GCOL1:MOVE 10,(B(1,0)*5.7)+10
4500 FOR J=1 TO 499:DRAW (J*2.5)+10,(B(1,J)*5.7)+10:NEXT
4510 VDU5:MOVE 1000,740:PRINT "R KNEE":VDU4
4520 GCOL2:MOVE 10,(B(2,1)*5.7)+10
4530 FOR J=1 TO 499:DRAW (J*2.5)+10,(B(2,J)*5.7)+10:NEXT
4540 VDU5:MOVE 1000,700 :PRINT "R HIP":VDU4
4550 GCOL7:MOVE 10,(B(3,0)*5.7)+10
4560 FOR J=1 TO 499:DRAW (J*2.5)+10,(B(3,J)*5.7)+10:NEXT
4570 VDU5:MOVE 1000,660:PRINT "SPINE":VDU4
4580 Y$=GET$
4590 ENDPROC:REM**************************************************
4610 DEFPROCDRAWFORCESALL:REM**********PLOTS ALL FORCES********
4620 MODE12
4630 VDU 28,0,3,79,0:VDU 24,0;0;1279;955;:VDU29,100;100;:COLOUR 3
4640 GCOL7:MOVE 10,10:DRAW 10,825:MOVE 10,10:DRAW 1279,10
4650 VDU5
4660 MOVE 20,210:DRAW 0,210:MOVE 20,410:DRAW 0,410:
4670 MOVE 20,610:DRAW 0,610:MOVE 20,810:DRAW 0,810
4680 MOVE 630,20:DRAW 630,0:MOVE 1260,20:DRAW 1260,0
4690 MOVE 30,830:PRINT "500N"
4700 MOVE 1120,60:PRINT "TIME"
4710 MOVE 630,60:PRINT "50%"
4720 VDU4:GCOL3
4730 MOVE 10,760:FOR J=0 TO 499:DRAW (J*2.5)+10,(B(0,J)*20)+760:NEXT
4740 GCOL2:MOVE 10,(B(6,1)*1.6)+10
4750 FOR J=1 TO 499:DRAW (J*2.5)+10,(B(6,J)*1.6)+10:NEXT
4760 VDU5:MOVE 1000,700 :PRINT "F1-Ff":VDU4
4770 GCOL7:MOVE 10,(B(7,0)*1.6)+10
4780 FOR J=1 TO 499:DRAW (J*2.5)+10,(B(7,J)*1.6)+10:NEXT
4790 VDU5:MOVE 1000,660:PRINT "F1-Fb":VDU4
4800 GCOL5:MOVE 10,(B(9,0)*1.6)+10
4810 FOR J=1 TO 499:DRAW (J*2.5)+10,(B(9,J)*1.6)+10:NEXT
4820 VDU5:MOVE 1000,580:PRINT "F2-Ff":VDU4
4830 GCOL6:MOVE 10,(B(10,1)*1.6)+10
4840 FOR J=1 TO 499:DRAW (J*2.5)+10,(B(10,J)*1.6)+10:NEXT
4850 VDU5:MOVE 1000,540:PRINT "F2-Fb":VDU4
4860 Y$=GET$
4870 ENDPROC:REM**************************************************
4890 DEFPROCDRAWFORCESHOR:REM**********PLOTS HOR FORCES**************
4900 MODE12
4910 VDU 28,0,3,79,0:VDU 24,0;0;1279;955;:VDU29,100;100;:COLOUR 3
4920 GCOL7:MOVE 10,10:DRAW 10,825:MOVE 10,210:DRAW 1279,210
```

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4930 VDU5
4940 MOVE 20,210:DRAW 0,210:MOVE 20,410:DRAW 0,410:
4950 MOVE 20,610:DRAW 0,610:MOVE 20,810:DRAW 0,810
4960 MOVE 630,220:DRAW 630,200:MOVE 1260,220:DRAW 1260,210
4970 MOVE 30,830:PRINT "60N"
4980 MOVE 1120,180:PRINT "TIME"
4990 MOVE 630,180:PRINT "50%"
5000 VDU4:GCOL3
5010 MOVE 10,760:FOR J=0 TO 499:DRAW (J*2.5)+10,(B(0,J)*20)+760:NEXT
5020 GCOL1:MOVE 10,(B(5,0)*10)+210
5030 FOR J=1 TO 499:DRAW (J*2.5)+10,(B(5,J)*10)+210:NEXT
5040 VDU5:MOVE 1000,740:PRINT "F1-H":VDU4
5050 GCOL4:MOVE 10,(B(8,1)*10)+210
5060 FOR J=1 TO 499:DRAW (J*2.5)+10,(B(8,J)*10)+210:NEXT
5070 VDU5:MOVE 1000,680 :PRINT "F2-H":VDU4
5080 Y$=GET$
5090 ENDPROC:REM**************************************************
5110 DEFPROCPRINT1:REM******PRINTS DATA******************
5120 MODE0:CLS:@%=&20109:VDU14
5130 GCOL4:PRINTTAB(7 ,0) "H","Ff","Fb","H","Ff","Fb","X1","X2"
5140 FOR J=0 TO 499
5150 PRINT B(5,J),B(6,J),B(7,J),B(8,J),B(9,J),B(10,J),B(11,J),B(12,J)
5160 NEXT:VDU15
5170 PRINT:PRINT"PRESS SPACEBAR TO SEE RANGE OF MOTION":Y$=GET$:CLS
5180 VDU14
5190 GCOL4:PRINTTAB(7 ,0) "T","KNEE","HIP","SPINE"
5200 FOR J=0 TO 499
5210 PRINT B(0,J),B(1,J),B(2,J),B(3,J)
5220 NEXT:VDU15
5230 PRINT:PRINT"PRESS SPACEBAR TO CONTINUE":Y$=GET$
5240 ENDPROC:REM*******************************************
```

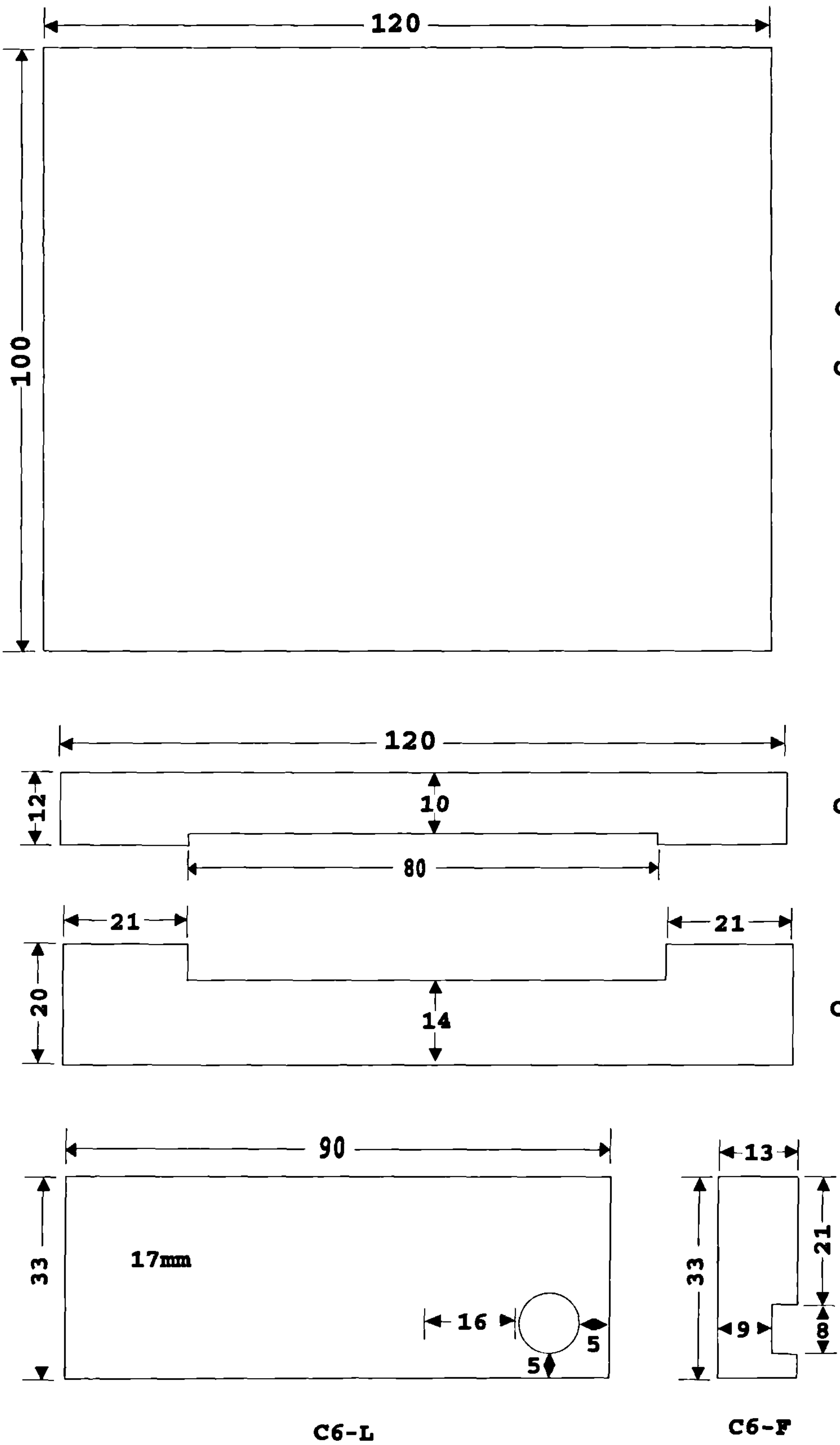

Figure E1: Components C1, C2 and C6.

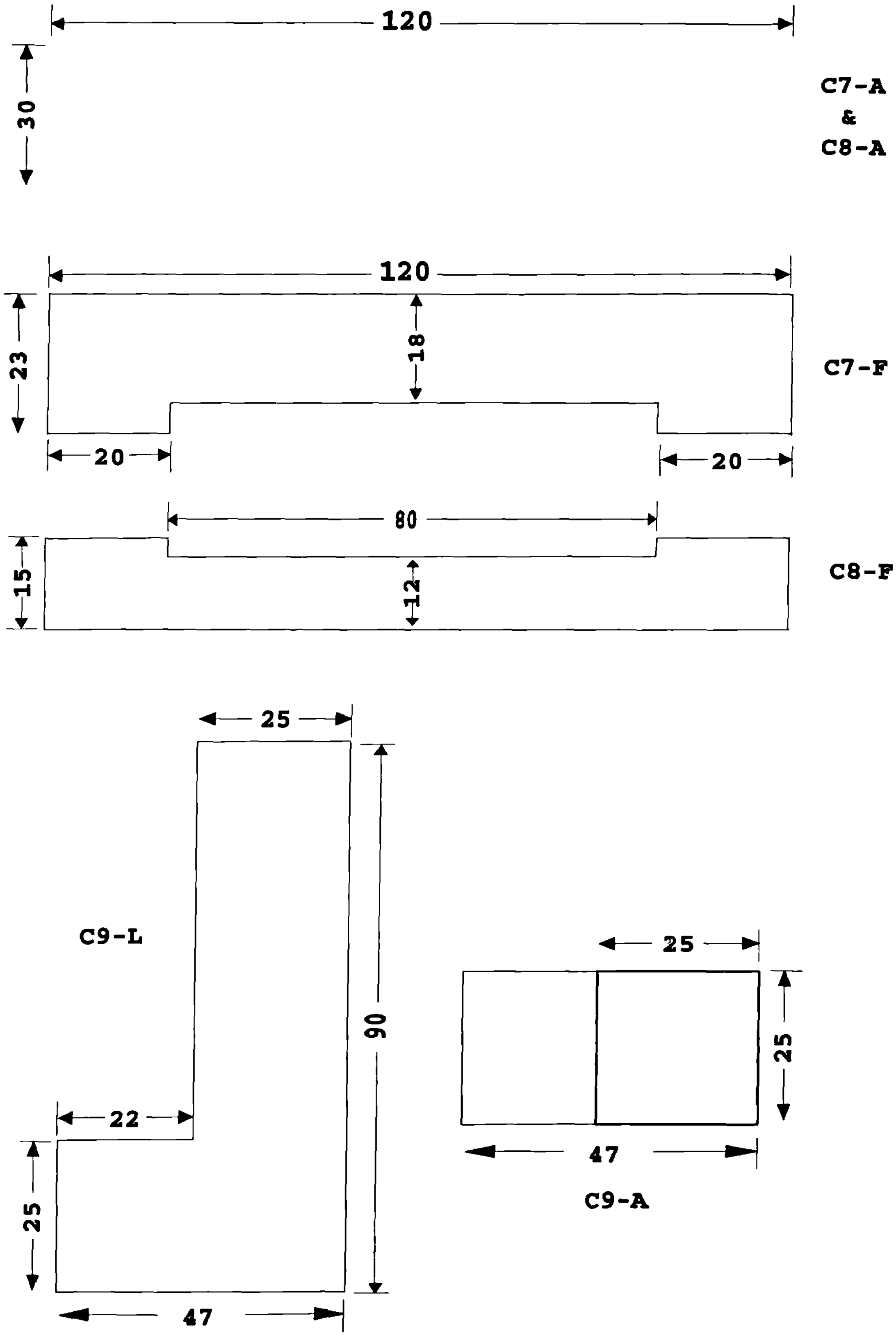

Figure E2: Components C7, C8 and C9.

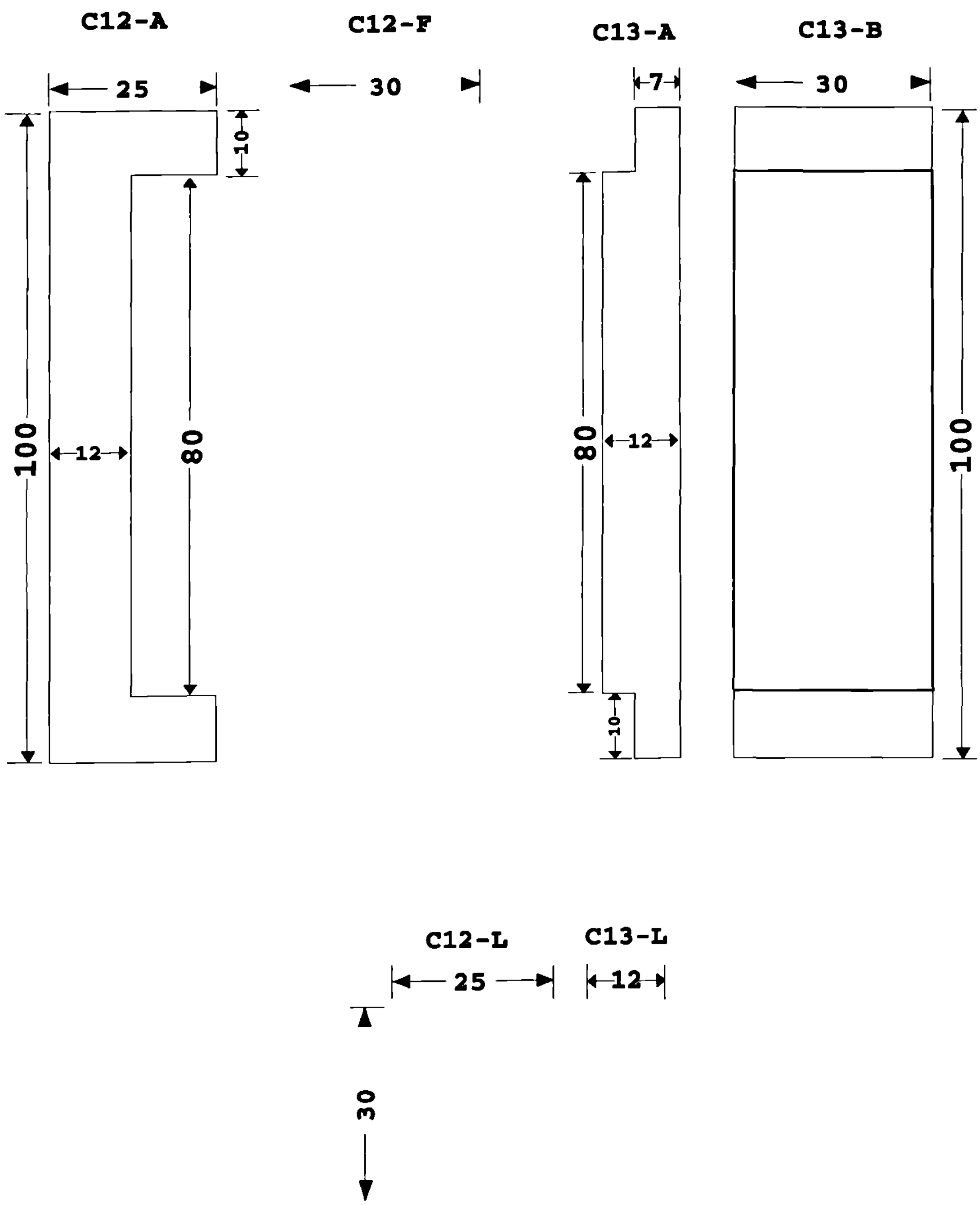

Figure E3: Components C12 and C13.

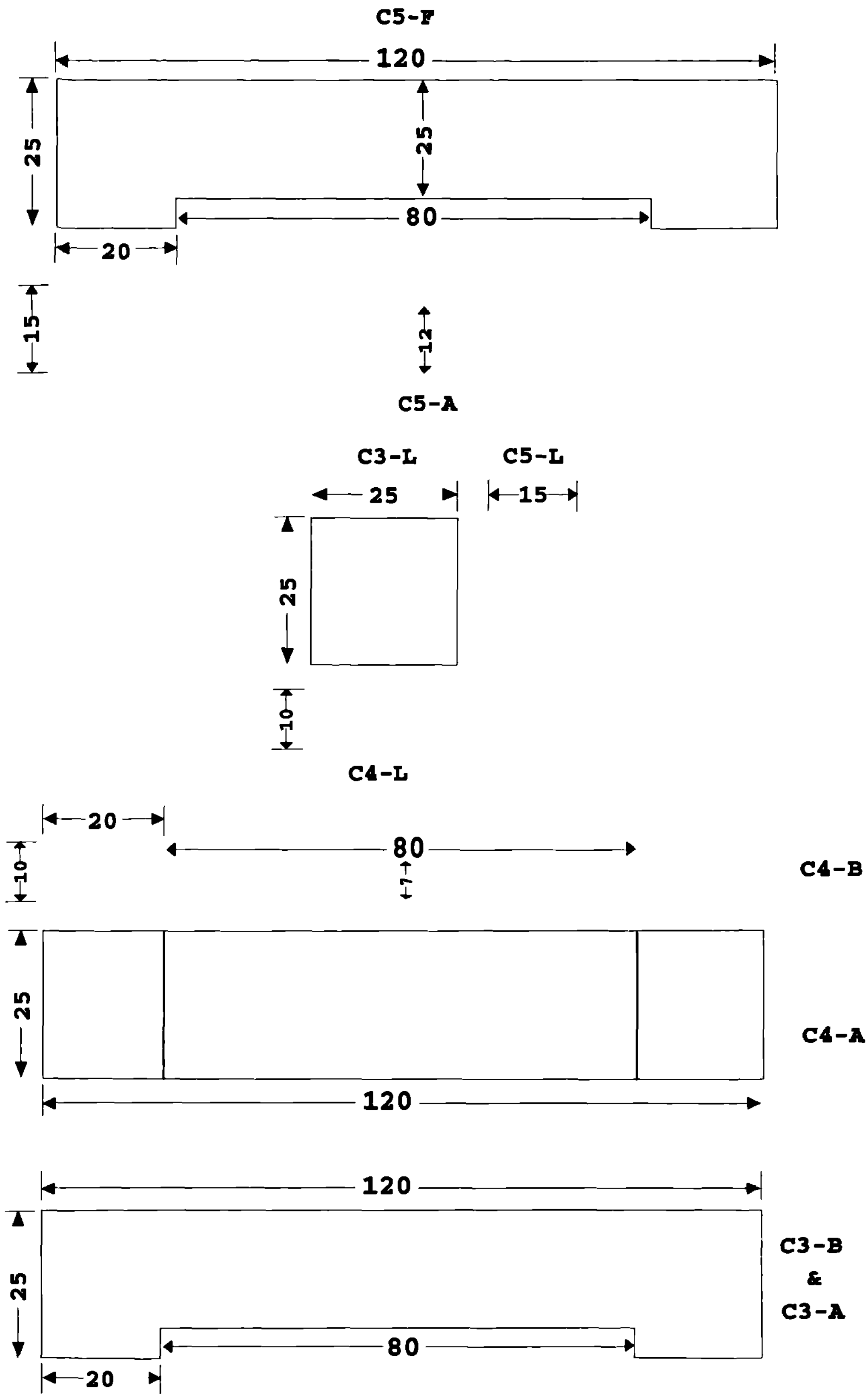

Figure E4: Components C3, C4 and C5.

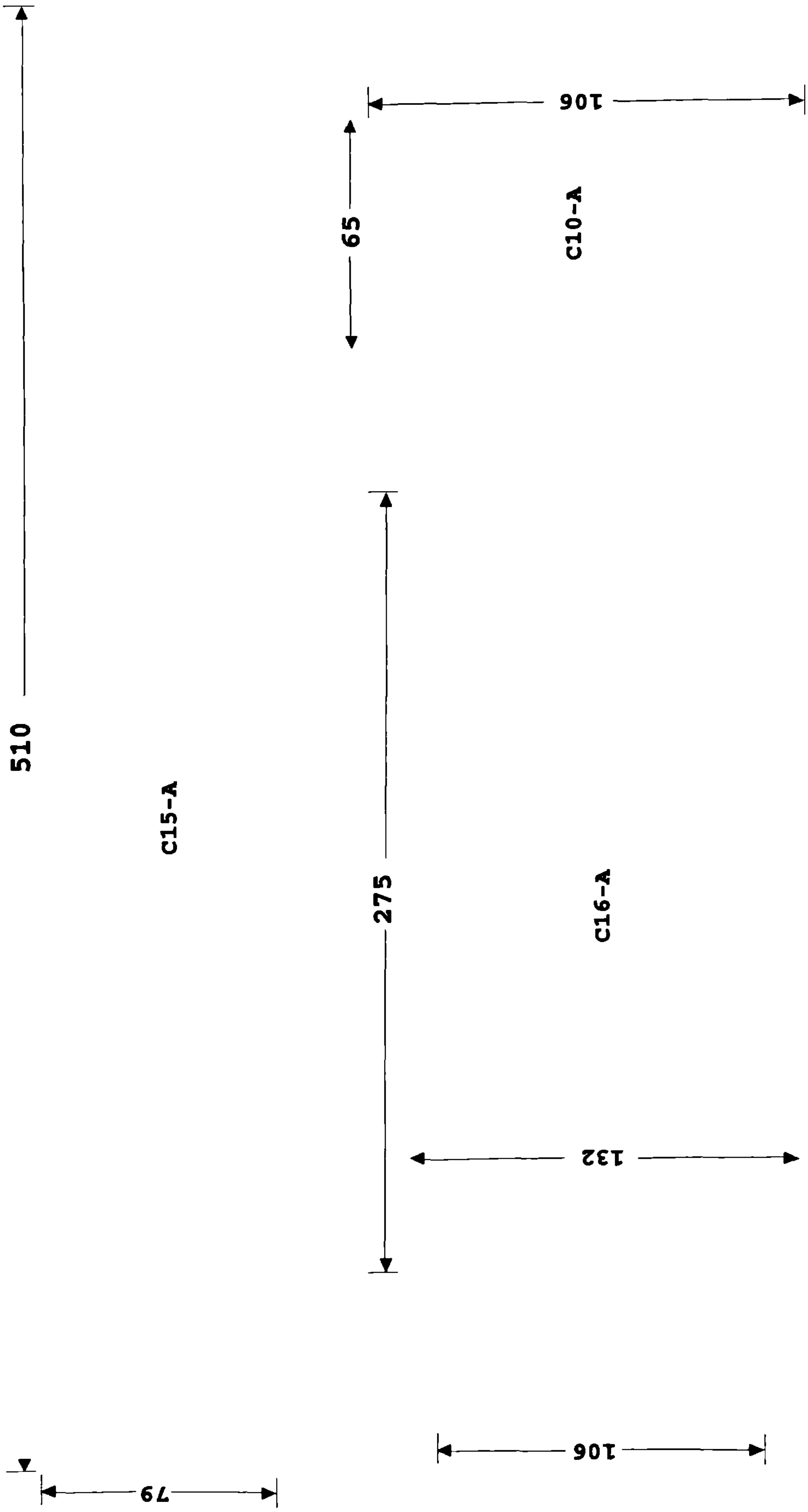

Figure E5: Components C10, C15 and C16.

APPENDIX F

Related publications

Gioftsos G and Grieve DW, 1994.

The use of neural networks to recognise patterns of human gait under normal and abnormal conditions: a preliminary study. (Abstract)
J. of Biomechanics 1994;27(6):777.

Gioftsos G and Grieve DW, 1993.

Αξιολόγηση της βάδισης με την χρήση της τεχνητής νοημοσύνης. (Abstract)
VIIth congress of the Hellenic Scientific Society of Physiotherapy, Athens - December 1993.

Gioftsos G and Grieve DW, 1994.

The use of neural networks to recognise patterns of human movement. Gait patterns.
Submitted to Clinical Biomechanics.

Gioftsos G and Grieve DW, 1994.

The use of neural networks to distinguish patterns of human movement. Stepping patterns.
Submitted to J of Electromyography & Kinesiology.

Gioftsos G, Grieve DW and Sarsilmaz, 1994.

The use of neural networks to recognise standing postures associated with imagined moods of human subjects.
Submitted to Gait & Posture.

THE USE OF NEURAL NETWORKS TO RECOGNISE PATTERNS OF HUMAN GAIT UNDER NORMAL AND ABNORMAL CONDITIONS: A PRELIMINARY STUDY

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INTRODUCTION

Gait analysis is used for diagnostic or clinical assessment purposes. It is of interest to know whether purely objective analysis of gait data can be sensitive to alteration of pattern without resort to subjective impressions (5).

Neural Networks (NN) are a relatively new method of multivariate analysis. They can be taught to recognise different patterns by repeated presentation of examples (training). They have been used in many areas (1,2,3,6,8) and "they are a potential useful tool for recognizing subtle diagnostic patterns in multivariate data" (4).

This study aims to apply Neural Networks to human gait analysis in order to examine the capacity of this technique in recognising artificially altered patterns of movement.

METHODS

Temporal parameters of gait (double support phase, left and right single support phases) were measured in msec during walking with seven different speeds (0.30, 0.45, 0.60, 0.75, 0.90, 1.05 and 1.20 statures/sec within an acceptable range of $\pm$ 0.05), under normal walking conditions (CD1) and under two abnormal conditions, either with a 3.5Kg mass strapped to the right ankle (CD2) or with the right knee splinted in extension (CD3).

Ten male and ten female volunteers (Ht=1.72 ± 0.07m, Wt=70 ± 10.6Kg, Age=26 ± 5yrs) participated. None had a history of locomotor disturbance.

Data of 5 men and 5 women (DG1:Data Group 1) were used for classification (training) and the rest (DG2:Data Group 2) for recognition (recall). Successful pattern recognition correctly identified the speed in a particular walking condition using the temporal parameters of gait as an input. The classification techniques used were the NN and the Linear discriminant analysis (LDA). The chosen NN was the back-propagation recurrent paradigm (7). A three layered feed-forward network was constructed with three input, nine hidden and seven output units. Its learning rate was 0.02 and its momentum factor was 0.9.

The DG1 from CD1 was used for the training of the NN and the DG2 from CD1 was used to test the NN and vice versa. The process was also repeated for CD2 and CD3. As a result, six NN were trained and their characteristics are summarised in Table 1. The same procedure was carried out using LDA.

RESULTS

Table 1 includes the results obtained from the use of the two different techniques (LDA and NN) in the analysis of the studied models. The Chi-square test shows statistically significant difference between NN and LDA for the overall results during classification using the training file ($P<0.001$) and no statistically significant difference from the recognition of the recall file.

Table 1: The results of the models studied with the characteristics of the trained networks.

Models studied	TrF‡	ClF‡	Training cycles	Total RMSE†	Max RMSE†	No of Successful recognised patterns out of 70 LDA tr*	rc*	NN tr	rc
1: CD1	DG1	DG2	2228	0.099	0.743	51	52	68	61
2: CD1	DG2	DG1	3006	0.096	0.992	61	50	69	50
3: CD2	DG1	DG2	1430	0.078	0.516	54	47	69	50
4: CD2	DG2	DG1	1864	0.090	0.635	54	49	68	52
5: CD3	DG1	DG2	3071	0 091	0.971	49	47	68	47
6: CD3	DG2	DG1	2420	0.080	0.537	54	39	69	45
					Overall	323	284	411	305

* tr: classification results using the training file, rc: results from the recognition using the recall file.

† RMSE: root mean square of error.

‡ TrF: training file, ClF: recall file.

DISCUSSION

The better overall performance of the NN (LDA:75% and NN:98%) with a training file can be explained by its ability to learn a particular set of data.

The present preliminary study shows that the accuracy of the NN to recognise unknown patterns of human movement correctly is at least as high as that of other methods (LDA:70% and NN:73%). As a result NN is a useful classification tool particularly in the analysis of complicated problems where statistics cannot be applied because of its ability to extract features from the input data. The observed results are similar to the results obtained from the application of the NN to other research areas such as cardiology, cancer diagnosis and liver diseases (2,3,6).

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ΑΞΙΟΛΟΓΗΣΗ ΤΗΣ ΒΑΔΙΣΗΣ ΜΕ ΤΗ ΧΡΗΣΗ ΤΗΣ ΤΕΧΝΗΤΗΣ ΝΟΗΜΟΣΥΝΗΣ

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ΑΝΑΚΟΙΝΩΣΗ

Η ανάλυση της βάδισης χρησιμοποιειται για σκοπούς επιστημονικού - ερευνητικού ενδιαφέροντος όπως επίσης και για να διαγνώσει παθολογικά προβληματα ή να αξιολογήσει παθολογικά μοντέλα κίνησης. Κύριος σκοπός της είναι η περιγραφη και ο διαχωρισμός διαφορετικών κινήσεων, ο οποίος επιτυγχάνεται με τη χρήση στατιστικής ή expert systems. Παραμένει όμως πάντα υπαρκτή η ανάγκη ανεύρεσης νέων τεχνικών με καλύτερη απόδοση στην αξιολόγηση μοντέλων κίνησης όπως η βάδιση.

Η τεχνητή νοημοσύνη (νευρωνικά δίκτυα) είναι μια νέα σχετικά τεχνική για την αναγνώρηση μοντέλων η οποία έχει χρησιμοποιηθεί επιτυχώς σε πολλά προβλήματα που αποσχολούν την επιστήμη. Τα νευρωνικά δίκτυα είναι ένα σύνολο μαθηματικών εξισώσεων και μπορούν να "διδαχθούν" με την επανάληψη σωστών παραδειγμάτων, ωστε να αναγνωρίζουν οποιοδήποτε άγνωστο μοντέλο.

Σκοπός μας είναι να εφαρμοσουμε την τεχνική αυτη σε προβλήματα αναγνώρισης (αξιολόγησης) της ανθρώπινης κίνησης ελπίζοντας να διευρύνουμε τις ικανότητές μας για πιο ακριβή αξιολόγηση.

Οι χρονικές παράμετροι της βάδισης (χρόνος διπλής στήριξης, χρόνος δεξιάς και αριστερης μονής στήριξης) 20 υγιών εθελοντών, καταγράφηκε κατά τη διάρκεια βάδισης υπό 7 διαφορετικές ταχύτητες (0.30,0.45,0.60,0.75,0.90,1.05 και 1.20 ύψος/sec) και υπό 3 διαφορετικές συνθήκες (φυσιολογική βάδιση, βάδιση με το δεξιό γόνατο σε έκταση και βάδιση με προσθήκη 3.5 Kg στο επιπεδο του κατω τριτημόριου της κνήμης).

Τα δεδομένα που συγκεντρωθηκαν, χωρίστηκαν σε δυο ισάριθμα τμήματα. Σκοπός μας ήταν να χρησιμοποιήσουμε το ένα τμήμα για να μελετήσουμε τα μοντέλα κίνησης και να παράγουμε τα κριτήρια βάση των οποίων θα μπορούμε να αναγνωρίζουμε παρόμοιες κινήσεις. Ελέγξαμε την ακρίβεια αυτων των κριτηρίων με το να αξιολογήσουμε τα μοντέλα κίνησης του δεύτερου τμηματος των δεδομένων. Η μελέτη των δεδομένων έγινε συγχρόνως με τη χρήση τεχνητής νοημοσύνης και στατιστικής (**Linear Discriminant analysis**).

Οι 20 περιπτωσεις που αναλυθηκαν, ομαδοποιηθηκαν σε 2 βασικές κατηγορίες. Το McNemar's τεστ εδειξε οτι στην πρωτη κατηγορια δεν υπαρχει στατιστικη σημαντικη διαφορα μεταξυ νευρωνικων δικτυων και στατιστικης, η οποία ομως παρατηρείται στην δευτερη κατηγορία. Σε γενικες γραμμές ομως η τεχνητή νοημοσυνη ειχε παντοτε το μεγαλυτερο ποσοστό επιτυχίας και ανεμένεται να αποδειχθεί ενα χρησιμο "εργαλειο" σε κλινικά προβλήματα.

Ευχαριστουμε θερμα το 'Ιδρυμα Κρατικων Υποτροφιων Ελλαδος (ΙΚΥ) για την οικονομικη ενισχυση.