MINIMIZATION OF NUMBER OF GAIT TRIALS FOR TRIPPING PROBABILITY TESTS USING ARTIFICIAL NEURAL NETWORKS

By

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STATEMENT OF RESPONSIBILITY

I hereby certify that I am responsible for the works submitted in this thesis, that the original work is my own expect as specified in acknowledgements and that neither the thesis nor the original work contained therein has been submitted to this or any other institution for higher degree.

[redacted]

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ABSTRACT

Minimum toe clearance (MTC) data has been used to quantify the probability of tripping (PT) during gait (Best, Begg and James, 1999). MTC data collection is very time consuming and there has been no research conducted to devise a methodology that has the potential to predict long-term histogram characteristics of MTC data (e.g. mean, standard deviation, skewness and kurtosis), based on the characteristics of MTC data collected from fewer gait trials. The aim of this study is to apply a novel technology, artificial neural network (ANN), to predict stabilized MTC characteristics (mean, M; standard deviation, SD; skewness, S; kurtosis, K) from relatively fewer gait trials. MTC data of 24 subjects (age range: 19-79 years) were collected during normal walking on a treadmill for 30 minutes.

Thirty-one back-propagation neural networks (BPNs) were developed using various combinations of input variables to predict 30-minute MTC characteristics. The network performance was evaluated using the percentage of error (POE) of the test results (i.e. difference between desired and predicted results divided by the desired result). BPN using 9 statistical inputs from 2-minute data showed better prediction accuracies (POE_M=22%, POE_{SD}=14.6%, POE_S=84% and POE_K=304.1%) than other BPNs (Fast Fourier Transform (FFT) coefficients, real data and also combinations of these). Furthermore, its predictions for three statistics (M, SD and S) (POE_M=14.2%, POE_{SD}=15.2% and POE_S=28.9%) were better than a multiple linear regression (MLR)

model (POE_M=19.0%, POE_{SD}=18.3% and POE_S=150.6%). Nine BPNs were subsequently developed using inputs obtained from 9 different data segment lengths (from 5 trials to 25-minute trials of MTC data). The results indicated that performance of the BPNs improved as the length of input data was increased. Specifically, predicted M and SD showed clear improvements (POE_M dropped from 20.4% to 14.6% and POE_{SD} decreased from 20.5% to 6.5%). Also, adding more input variables derived from input data further improved the performance of BPNs. BPN using 14 inputs (nine statistical data and five additional cumulative mean taken from 15-minutes data) performed better (overall POE_M=12.4%, POE_{SD}=10%, POE_S=66.6% and POE_K=136.7%) than a BPN using nine inputs taken from 15-minutes data (overall POE_M=16.3%, POE_{SD}=10.7%, POE_S=79.2% and POE_K=148.2%). These results indicate that BPN is very sensitive to the input variables. Proper selection of input variables appears to be vital in order to improve performance of BPNs. Finally, the performance of BPN in separately predicting four statistics was investigated. The results showed that using separate BPNs to predict four statistics generated better results than using a single BPN to predict all four statistics at the same time. BPN using fourteen inputs obtained from 15-minutes data to separately predict four statistics produced improved results (POE_M=10.6%, POE_{SD}=9.4%, POE_S=65.6% and POE_K=117.3%) compared to BPNs using nine inputs (POE_M=12.4%, POE_{SD}=10%, POE_S=66.6% and POE_K=136.7%). These results indicate that the predicting ability of BPNs is not only related to input variables, but also related to the complexity in mapping relationship between inputs and outputs.

In conclusion, pre-processing raw data, MTC data length, and the number of predicting outputs were found to be important in the performance of the BPNs. Although the predicting power of BPNs in gait data analysis has been highlighted by other researchers (Chau, 2001b), this research promotes further development of BPN technology in the area of tripping probability research.

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Σ	the sum of all terms
$\varphi(\cdot)$	non-linear transfer function
u	the linear combined input
δ	error value
w	connection weight

ABBREVIATIONS AND TERMINOLOGIES

ANN: Artificial Neural Network; computer algorithm, related to artificial intelligence, to simulate human brain's nervous systems (Dayhoff, 1990; Hubick, 1992).

MTC: minimum toe clearance; the lowest point the toe reaches during mid-swing phase.

M: Mean, refers to the average of a group of MTC values.

SD: standard deviation, used for describing the spread of a MTC distribution.

S: Skewness, refers to the degree to which the non-symmetric distribution differs from a normal curve.

K: Kurtosis, refers to the degree to which the shape of a distribution differs from a normal curve in terms of the 'peakedness' relative to the normal curve.

FFT: Fast Fourier Transformation, the frequency distribution of the MTC time series. In this study, it can be regarded as a feature extracting function, which reduces the number of coefficients to represent a curve. However, the features of the curves will be still preserved.

MLR: Multiple linear regression is a statistical model used for predicting dependent variables based on a (some) predictor(s).

AAE: Absolute actual error between desired MTC data and predicted /non-stabilized MTC data.

POE: Percentage of error between desired MTC data and predicted /non-stabilized MTC data

Trial: Refer to one gait cycle. There is one MTC value in each trial.

CHAPTER ONE

INTRODUCTION

Human gait is regarded as the most common of all human movements. It is also one of the most complex movements. Many factors (e.g. muscle contraction, motor coordination, energy flows, etc) are involved to complete a single gait cycle. Researchers have used gait measurements for various applications including management of patients with walking disorders and identification of individuals with altered lower limb motion (Winter, 1991; Oatis, 1995).

Since human gait is variable, it is quite common to use a mean value from multiple trials to represent an individual subject's gait characteristics instead of using a single trial (Winter, 1984; Hamill and McNiven, 1990), with the assumption that these trials form a normal distribution and represent typical gait characteristics. But Winter (1991) highlighted the complex nature of gait variability and that intra-subject variability is higher for trials collected days apart compared with trials collected minutes apart. Giakas and Baltzopoulos (1997) showed that the mean of ground reaction forces during gait parameters became stable (with variability limits <10%) after 10 trials. It is important to determine how many trials are required to obtain a stabilized gait parameter for an individual to ensure the reliability of the data used for analysis and drawing statistical conclusion.

The number of trials used to calculate mean values is seen to vary widely in the gait literature (commonly ranging from 4 to 25 trials), and there is usually no valid reason given why a certain number of trials are used in these studies. Recently, Best, Begg, Ball and James (2000) have shown that it takes far more trials (about 2000 trials) to stabilize minimum foot clearance statistics such as mean, standard deviation, skewness and kurtosis values. Increasing the number of gait trials would certainly help to find more stabilized descriptive statistics. But, there are many other constraints such as time, cost and disability that will affect the sample size. As a result, it is important to devise methodologies that would predict stabilized gait parameters from relatively fewer trials. Since human gait is a complex, chaotic activity with non-linear dynamic features (Winter, 1991), it is difficult to develop mathematical algorithms to model relationships between stabilized gait parameters and that derived from fewer gait trials.

Tripping over obstacles is regarded as one of the most commonly stated causes of falls in elderly people (Overstall, Exton-Smith, Imms, and Johson, 1997). During the swing phase of gait, minimum toe clearance (MTC) is used to quantify the probability of tripping (PT) during gait (Best, Begg and James, 1999). PT calculation requires a large amount of MFC data (up to 2000 gait trails). This requires lengthy time for MTC data collection and digitizing. Therefore, a methodology that has the potential to predict long-term histogram characteristics of MTC data, based on the characteristics of MTC data collected from fewer gait trials would reduce data collection and analysis time significantly.

Artificial Neural Network (ANN) technologies have been applied to solve numerous practical problems in many areas with extraordinary benefits (Dayhoff, 1990). In recent years, ANNs have been gradually used in predicting various parameters with high success rates (Chau, 2001b). ANN has been named as such because of similarities with the network of nerve cells in the brain and ANN architectures are motivated by models of our own brains and nerve cells (Dayhoff, 1990). ANNs 'learn' to associate inputs with known outputs and do not require an expert to provide it with a set of 'rules' or a knowledge base. An ANN is able to simulate the performance of the human expert to learn, recognize and forecast similarities and patterns (Vaughan, 1997).

One of the main characteristics of an ANN is that it can approximate any continuous function, regardless of its complexity. In the context of gait analysis, this property allows one to model relationships among gait variables, provided adequate data are available and requisite network complexity is computationally feasible. Sepulveda, Wells and Vaughan (1993) used this property of ANNs to study modeling of muscle activity and kinematic interactions, which with a traditional analytical approach would result in unmanageable relationships. Furthermore, ANNs can handle vast amounts of gait data at the same time, as demonstrated by the large study conducted by Holzreiter and KÖhle (1993). The other important characteristic of an ANN is its inherent non-linear mapping ability between inputs and outputs (Savelberg and Herzog, 1997).

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The main focus of this research is to apply the predictive power of ANN to predict stabilized gait characteristics from relatively fewer gait trials. There is no previous research reporting any such technique. It explores ANN technology for its suitability for predicting gait data. The results of this research would not only improve the efficiency of trip probability research by requiring fewer gait trials per subject, but also help to obtain reliable data for those subjects (elderly, pathological and children) who are not able to walk for a long time in order to provide stable gait parameters.

CHAPTER TWO

LITERATURE REVIEW

2.1 AN OVERVIEW OF GAIT ANALYSIS

2.1.1 What is Gait?

Walking is the most common form of locomotion and makes up a very large proportion of our normal activities of daily living. Gait describes the manner or style of walking rather than the walking process itself (Whittle, 1991). Although it looks like a simple motion, gait is regarded as one of the most complex and totally integrated movements, and has been described and analysed more than any other human movement (Winter, 1991).

A human gait cycle is defined as the time interval between two successive occurrences of one of the repetitive events of walking. Generally, a gait cycle is the time from one heel contact to the following heel contact of the same foot. Whittle (1991) has described the sequential components of a gait cycle as shown in Figure 2.1. It shows that the gait cycle begins at right heel contact and finishes at right heel contact. There are two periods of double support and two periods of single support in a gait cycle. The swing phase contributes approximately 40 per cent to the gait cycle, and is concurrent with the single support phase of the contra-lateral limb. The stance phase lasts for approximately 60 per cent of the gait cycle.

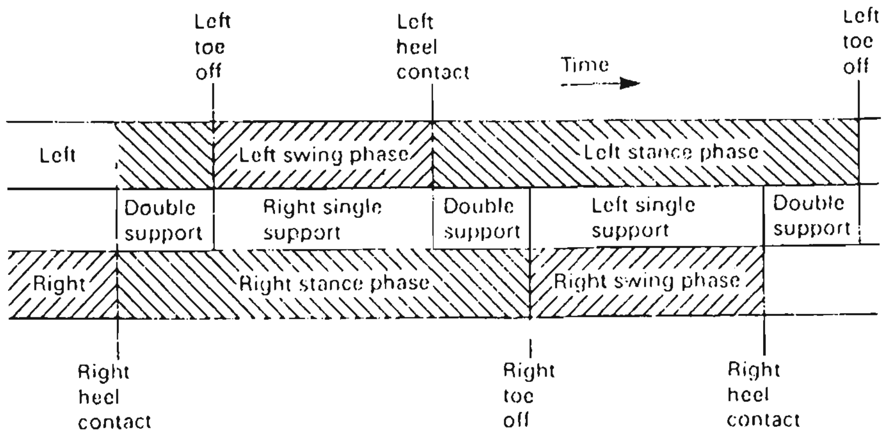


Figure 2.1 Timing of single and double support during a single gait cycle from right heel contact to next right heel contact (adapted from Whittle, 1991).

2.1.2 Goals and Techniques of Gait Analysis

Gait analysis has advanced considerably over the past century. It includes the systematic study of human walking. During the past decade, doctors, therapists, and many other researchers applied numerous approaches and methods to investigate the characteristics of gait. Accompanying an increase of research quality, gait analysis is being used to determine the outcome of various clinical procedures rather than simply monitoring the visible changes in gait. Oatis (1995) emphasized that the goals of gait analysis fall into five large categories to:

1. Describe the difference between a patient's performance and non-disabled subject's performance. Comparisons between the performance of disabled and normal performance are the most common use of gait analysis. The detailed description of normal locomotion is expected to provide an understanding of

the mechanisms of locomotion, so that deviations from normal characteristics can be quantified (e.g. White, Agouris, Selbie and Kirkpatrik, 1999; Steinwender, Saraph, Scheiber, Zwick, Uitz and Hackl, 2000).

2. Classify the severity of a disability (e.g. Selby-Silverstein, 1995; Dingwell, Ulbrecht, Boch, Becker, O'Gorman and Cavanagh, 1999; Lord and Hosein, 2000). Disability results in functional loss. Measures of disability have been used successfully in the evaluation of chronic disorders such as arthritis and low back pain.
3. Determine the efficacy of intervention. Treatment is often provided to improve functional performance, not to restore normal function. Clinicians and therapists often use pre-intervention status or functional abilities of comparable subjects to assess the effects of a treatment approach (Smidt and Mommens, 1980; Reisman, Burdett, Simon, and Norkin, 1985; Opara, Levangie, and Nelson, 1985).
4. Enhance performance. Gait analysis can provide important information to explain the mechanism of performance. Athletes have followed the advancement of motion analysis with anticipation and have utilized the technological advances in order to enhance their performance (Cavanagh and Lafortune, 1980).
5. Determine the mechanics of gait abnormality. Few studies have attempted to explain the abnormal phenomena in pathological gait pattern (Tardieu, Lespargot, Tabary and Bret, 1989). The comparison of the normal gait pattern with the abnormal gait pattern may yield sufficiently meaningful information to explain the abnormal performance.

Different investigators use different gait parameters for analysis. For example, clinical investigators tend to look at output measures such as stride length, cadence, and joint angles, so these researchers tend to focus on kinematics. Neurological researchers focus on EMG measures, whereas biomechanical investigators analyze all aspects of gait (Winter, 1991). Sagittal plane kinematics is probably the most commonly studied, best understood and most accurately reproduced in numerous studies of gait analysis (Sutherland, Kaufman, and Moitoza, 1994). Different techniques of gait analysis provide different outcome measures, such as kinematics analysis tells us the measurement of movement or geometric description of motion, but it does not provide any force related information. Thus, the various dependent measures are chosen depending on the research question that investigators are interested to look into. Whittle (1991) summarized the major techniques of gait analysis into the following:

1. Kinematics

Kinematics involves assessing the motion pattern of the human and often of each segment (foot, ankle, knee, hip, pelvis, and trunk). It is the measurement of movement, or geometric description of motion, in terms of displacements, velocity and accelerations (Gronley and Perry, 1984). Observation as a primary data-gathering method also is widely used in biomechanical functional study. Video-based data acquisition is used to determine the two- or three-dimensional trajectories, velocities and accelerations of the body segments (translational and angular) (Koff, 1995; Wu, 1995). Both reflective markers and light-emitting diodes are used in kinematic system to acquire body segment/joint positions (Whittle, 1991). It has been commonly used to obtain accurate kinematic gait parameters by biomechanical researchers. For example, Winter (1991) used reflective markers to acquire lower limb kinematic variables describing the trajectory of the foot during the swing phase, while Karst, Hageman, Jones and Bunner (1999) used light-emitting diodes to obtain both foot trajectory and temporal/distance measures.

2. Kinetics

Kinetics is a part of mechanics that deals with the study of forces, moments (internal and external) and the way they affect motion of objects and systems. It is often studied by solving the direct dynamic problem (e.g. measuring the forces and substituting them in the "equations of motion" to obtain the resulting motion). It is also studied by solving the inverse dynamic problem to obtain the forces responsible for the motion (Seliktar and Bo, 1995; Barnes and Berme, 1995). One of commonly used kinetic instrument in gait analysis is the force platform. It is frequently used to obtain a full three-dimensional description of the average ground reaction forces (Whittle, 1991). For example, Begg, Sparrow and Lythgo (1998) obtained vertical, medio-lateral and anterior-posterior forces during both unobstructed walking and walking over obstacles using force platform to investigate the process of gait control.

3. Muscle Activity or Electromyography (EMG)

EMG shows which muscles are active during different intervals of the gait cycle. EMG is the electrical record of the activation of muscle, and has been used in many applications (Soderberg and Knutson, 1995). It has been used to describe non-disabled adult gait, disabled and maturing childhood gait. Clinicians have often used dynamic EMG to guide decisions about type of orthopaedic surgery to be performed (Knutson and Soderberg, 1995).

4. *Mechanical Energy Analysis*

Human locomotion is the result of a complex energy interaction between the activation muscles of the different segments in motion. The energy consumption, and in particular energy transfers between the body segments in walking has been investigated by some investigators (Nielsen, Harris, Minton, Motley, Rowley and Wadsworth, 1990; Cobly, Kirkendall and Bruzga, 1999). Mechanical energy encompasses information relating mass, moment of inertia, linear velocity, angular velocity, and force. Many useful parameters have been obtained for the mechanical power, work and energy developed during able-bodied walking and running (Williams and Cavanagh, 1983). Such as Robertson and Winter (1980) discussed energy absorption and generation in gait, and found that the joint power was as important as the muscle power in causing energy changes in adjacent segments.

5. *Metabolic Cost*

Metabolic energy has been used during the past decades to estimate the mechanical efficiency of walking by looking at the difference in oxygen consumption between the basal states and walking at a given speed. The measurement of the metabolic energy expenditure provides global information on overall gait performance and a means of quantifying the overall physiologic penalty resulting from pathological gait (Blessey, 1976). The volume of oxygen consumed and the amount of oxygen consumed per minute during walking/running are often used to determine individual's gait efficiency (Winter, Quanbury, and Reimer, 1978).

2.1.3 Tripping and Falling in the Elderly

Falls are a leading cause of death and hospitalisation due to injuries in the elderly. The cost of falls to the health sector has been estimated to be larger than that of road trauma in Australia (NIPAC, 1999a). Falls among older individuals are the seventh leading cause of death and account for billions of dollars per year in hospitalisation costs (Ryan and Spellbring, 1996; Wolf and Gregor, 1999). Numerous researchers have reported that falls in the elderly is a serious health concern and the incidence of falls is expected to rise with the ageing of the population (NIPAC, 1999b). Oreskovich, Howard, Copass, and Carrico (1984) reported that almost 90% of older persons admitted to hospital due to a fall would not return to their previous level of independence. Prince, Corriveau, Hébert, and Winter (1997) also reported that 50% of those who sustain fractures to the hip are subsequently admitted to a long-term facility. Naturally, many researchers have focused on falls-related factors (Martin and Grabiner, 1999) such as age-related decline in gait performance (Whittle, 1991). Neurologic and cognitive impairment, and use of medications (e.g. sedatives and anti-depressants) are also important factors related to falls (Tinetti and Speechley, 1998).

2.1.3.1 Age-Related Changes in Walking Performance

Age-related changes in walking performance have been widely investigated by biomechanical investigators as possible factors leading to falls in the elderly (Winter, Palta, Frank and Walt, 1990). It becomes increasingly important to understand the effects of aging on movement and function because of longer average life and a growing elderly population. Many researchers have investigated gait patterns in healthy young and elderly individuals during normal unobstructed level walking with a view to documenting age-related declines in lower limb control that might be likely to lead to a fall (Hageman and Blanke, 1986; Blanke and Hageman, 1988).

Some studies have concentrated on straightforward outcome measures (temporal and spatial) of the gait cycle and consistently reported that elderly persons demonstrate shorter step and stride lengths, lower average velocities (Finley, Cody, and Finizie, 1969; Murray, Kory, and Sepic, 1970; Winter, 1991) and smaller stride width (Gabell and Nayak, 1984; Blanke and Hageman, 1989). Reduced walking speed and stride length have been proposed to reflect safer walking patterns adopted by the elderly.

The effect of age on joint angular range of motion (ROM) has been investigated by many researchers. Most investigators have found little difference in the joint ROM of the hip and knee between the young and elderly (Murray, Kory and Clarkson, 1969; Murray, Kory and Sepic, 1970). Blanke and Hageman (1989) also reported that there was little difference in ROM between young and elderly individuals at the ankle joint. Conversely, Ostrosky and VanSwearingen (1994) examined maximum flexion and extension angles during gait and reported significantly reduced maximum knee extension angle in the elderly group. Also, Begg and Sparrow (2000) found that the elderly participants had reduced knee and ankle angles at toe-off, reduced knee flexion during push-off and reduced ankle dorsiflexion during the swing phase. All of these findings suggest that these biomechanical characteristics of gait provide a useful indication of age-related degeneration in the control of gait.

2.1.3.2 Tripping Falls

Tripping is defined as an event whereby the lowest part of foot or shoe contacts the ground or a solid obstacle unintentionally, leading to a loss of balance and even a fall. People of all ages may trip at some stage while walking. It has been shown that older people who are more likely to fall due to a trip have a decline in reaction time, strength and balance (Prince, Corriveau, Hébert and Winter, 1997). Numerous researchers have reported that tripping over obstacles is one of the frequently stated causes of falls in elderly populations (Overstall, Exton-Smith, Imms, and Johson, 1997; Tinetti and Speechley, 1989; Cambell, Borrie and Spears, 1989; Pavol, Owings, Foley, and Grabiner, 1999). Blake, Morgan, Bendall, Dallosso, Ebrahim, Arie, Fentem, and Bassey (1988) have reported that tripping is responsible for up to 53% of falls in older adults. As a large proportion of falls occur due to trips, there is a need to identify factors that increase an individual's risk of a trip so that the occurrence of these trip-related falls may be reduced. For these reasons, a better understanding of the mechanisms for tripping is essential.

2.1.3.2.1 Swing Phase of Gait and Minimum Toe Clearance (MTC)

Since walking is one of the most common and necessary activities humans undertake, it is important that considerable effort has been dedicated to understanding the process further. To understand tripping and develop methods for avoiding tripping, it is important to identify those variables that are responsible for tripping. In order to have a better understanding of the timing of potential trip occurrence, a gait cycle is generally described as the time interval between two successive heel contact events of one foot

(See Figure 2.2). It consists of a stance phase (~60% of the total gait cycle) that starts from heel contact to toe off and a swing phase (~40% of the total gait cycle) that starts from toe off to next heel contact (Whittle, 1991). Figure 2.2 also shows six major events used to further divide the gait cycle. The stance phase consist of heel contact, foot flat, mid stance and heel off events, while the swing phase begins at toe off, and goes through mid swing, then finishes at next heel contact.

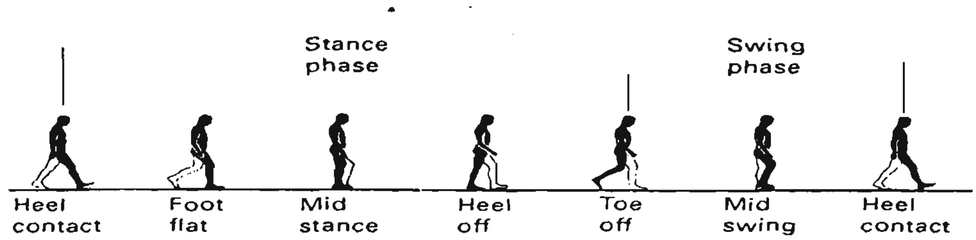


Figure 2.2 Six major events are used to divide the gait cycle into convenient periods (adapted from Whittle, 1991)

During the swing phase the following foot contact is prepared requiring a biomechanical balance. To complete a safe and normal movement of the body, the supporting limb should be stable showing appropriate muscle activity and allowing the advancement of the opposite limb in swing phase (Whittle 1991). Muscle activity and positioning of the swinging leg have to be appropriate in all the joints to allow a clear swing. Also the swing limb has to be pre-positioned before the initial contact. This requires a stable supporting limb and appropriate joint movement and muscle activity in the swing limb. Furthermore, the heel velocity has to be adjusted to gain a controlled heel contact (Winter, 1992).

Winter (1991) described swing phase characteristics of the gait cycle and the occurrence of minimum toe clearance (MTC) at mid swing phase (see second vertical line at about

80% of the gait cycle, Figure 2.3). At about 80% of the gait cycle toe reaches its minimum clearance (Line L2 in Figure 2.3), and then the toe rises to its maximum, up to 15 cm, prior to the next heel contact. In normal gait, the magnitude of MTC is quite low and is reported to be 1.29cm (Winter, 1992), the exact value that was also later reported by Karst Hageman, Jones and Bunner (1999). Dingwell, Ulbrecht, Boch, Becker, O'Gorman and Cavanagh (1999) reported that it was 0.9 cm. In these studies a reflective marker/light emitting-diode placed on the shoe has been used to estimate MTC, hence the values may not represent the real MTC. To estimate the real MTC, foot/shoe models need to be developed.

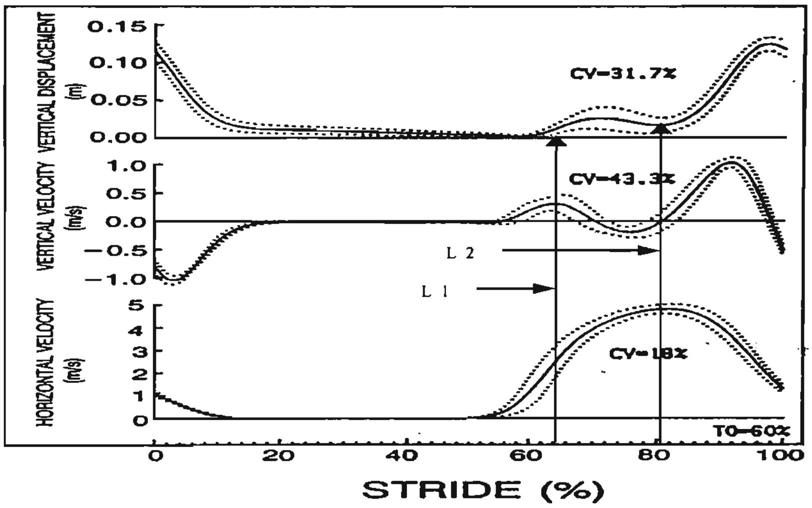


Figure 2.3 The displacement and velocity for the toe during normal walking. L1=toe off, and L2=MTC (adapted from Winter 1991, page 21)

Startzell and Cavanagh (1999) presented a model for three-dimensional measurements of foot motion using three virtual markers based in the middle of the foot. These authors described the outshoe shape of the shoe with respect to the ground and found accuracy to a conservative ±2mm. But their findings are limited to simulated trials and there was no data presented from subject's walking task. Best, Begg and James (1999) and Best, Begg, Ball and James (2000) presented a two-dimensional geometric model to predict

MTC, based on two markers placed on the forefoot. With these models, it is possible to accurately estimate the actual lowest point reached with the toe during the swing phase of the gait cycle. The predicted MTC was reported to be 1.035cm for a young subject walking on a treadmill for 1 hour (Best, Begg, Ball and James, 2000). Due to different subject groups and different laboratory procedures used to calculate MTC, there are some variations in reported MTC values across studies.

The variability in MTC data has the potential of causing irregular tripping (Best, Begg, Ball and James, 2000). Also, at MTC, the horizontal velocity of the toe has been estimated to be at its maximum. During this time the centre of gravity (COG) of the body is forward of the stance foot (see figure 2.4). The combination of COG and body's forward momentum means that the supporting limb cannot help in recovery from a possible trip at this instant. Hence, if a trip occurs at MTC, there is increased probability of falling.

Although some strategies have been identified to help people recover from a trip such as taking a forward step (Pavol, Owings, Foley and Grabiner, 1999). Tripping is more likely to lead to falling in elderly people because of their slower reaction time (Prince, Corriveau, Hébert and Winter, 1997).

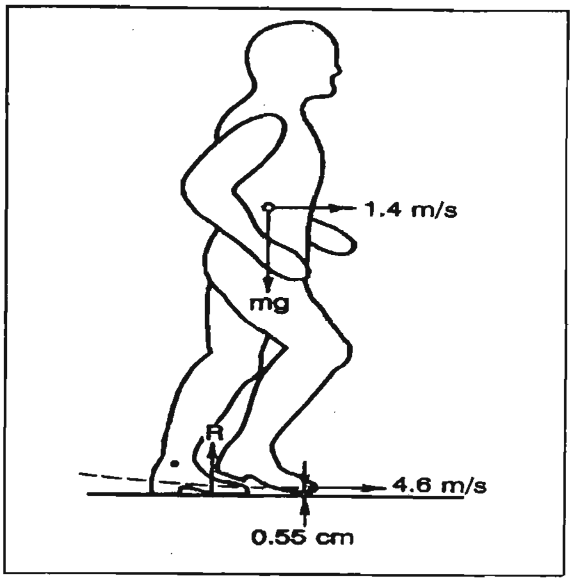


Figure 2.4 Position of body at MTC. (adapted from Winter, 1992)

Karst, Hageman, Jones, and Bunner (1999) highlighted that impaired control of MTC could cause tripping, and the conditions causing decreased MTC would increase the risk of tripping. MTC during walking has been recognised as a very important parameter of gait and this has given fresh impetus to researchers to study this parameter to investigate causes of falls due to tripping (Patla and Rietdyk, 1993; Best, Begg, Ball and James, 2000). The research conducted by Best, Begg and James (1999) models the variability in MTC data during 30-minute treadmill walking. They used Gaussian curve to model MTC data with skewness modelled by transforming MTC to $MTC^{0.21}$ (MTC data transformed by a power of 0.21). The probability of tripping was worked out via obtaining the relative area/integral of the Gaussian curve from a Z-score. This method to predict an individual's probability of tripping needs a large amount of MTC data. As MTC data collection is quite time consuming, some techniques are necessary to predict the characteristics (e.g. Mean, SD, skewness and kurtosis) of large MTC data sets from data collected from shorter time periods.

2.1.4 Variability of Gait Parameters and Accuracy of Mean Values

Without knowledge of variability of gait parameters, accurate assessment of human locomotion is difficult and may lead to incorrect conclusions. Hence, many investigators have studied variability of gait parameters (Wall and Crosbie, 1996; Mickelborough, Linden, Richards and Ennos, 2000). Winter (1984) investigated within-subject variability and found that the average cadence for 9 trials was 110 steps/min with a standard deviation of 2 steps/min. The variability in vertical and horizontal forces measured by coefficients of variation (CV, refers to root mean square of standard deviation of the moment over stride period /mean of absolute moment of force over stride period) were 7% and 20% respectively. Joint moment patterns at the hip and knee were highly variable (for hip, CV= 72%, knee CV= 67%). These results indicate that variability depends on the gait parameter and an adequate number of trials should be used to represent a subject's typical gait characteristics.

There are conflicting reports in the literature about the number of gait trials needed to appropriately describe reliable gait characteristics. Smith (1991) investigated within-subject variability in selected lower limb gait kinematics and kinetics and reported that only four trials would be enough for some gait variables (e.g. time-normalized joint angular displacements, moments of force powers and overall support moment force). Giakas and Baltzopoulos (1997) showed that the mean of ground reaction force parameters became stable during gait after 10 trials. Hamill and McNiven (1990) also investigated the number of trials required to establish a stable mean from 20 ground reaction force trials. The result showed that the cumulative mean of a subject's first maximum vertical force after 15 trials produced a stable mean value that fell within the bandwidth of the 20-trial mean ±0.25SD, and stayed in this range for the remaining trials. Vita and Bates (1988), on the other hand, reported that 25 trials were necessary to provide accurate ground reaction force data.

Karst, Hageman, Jones, and Bunner (1999) investigated within- and between-session reliability of foot trajectory measures and the traditional temporal-distance measures during gait in healthy elderly women using statistical techniques. Six sets of five trials each of natural and fast cadence gaits were collected and the MTC during swing phase, vertical and horizontal heel contact velocities and temporal-distance measures (step width, cadence, velocity, stride length, and time) were analysed. Pearson correlation coefficients were used to represent the reliability of variables within-session (test-retest) and between-session (test-retest). The results showed that intraclass correlation coefficients were greater than 0.87 for all, suggesting that the within-session test-retest reliability of all variables in natural and fast cadence was good.

The research on reliability and variability of gait parameters to date indicates that these are parameter-specific, and the investigators used varying number of gait trials (4 to 25) to calculate the mean value. Recently, Best, Begg, Ball and James (2000) investigated MTC variability while a subject walked on a treadmill for an hour. MTC values of every stride were collected and the stability of the Mean, SD, Skewness, and Kurtosis at different intervals were analysed (See Figure 2.5). The stabilized (1-hour, up to 2764 gait trials) mean value was seen to differ by 10% at ten-minute intervals down to 4% at 30-minute intervals. Also, all four statistics became relatively stable and repeatable at 30-minute interval. According to this study, longer gait trials (about 30 minutes of gait data, approximately 1382 gait trials), than have been traditionally used, are required to obtain stable descriptive statistics, especially for the purpose of tripping probability calculations which require extremely good accuracy of the four descriptive statistics (mean, standard deviation, skewness and kurtosis).

To obtain such stabilized descriptive statistics one would need to spend a lot of time digitising makers and calculating parameters. Furthermore, such a requirement (30 minutes) would create difficulties in certain populations eg., children, frail elderly, pathologic subjects. Consequently, it is important to devise a methodology that would predict stabilized gait parameters from relatively fewer gait trials.

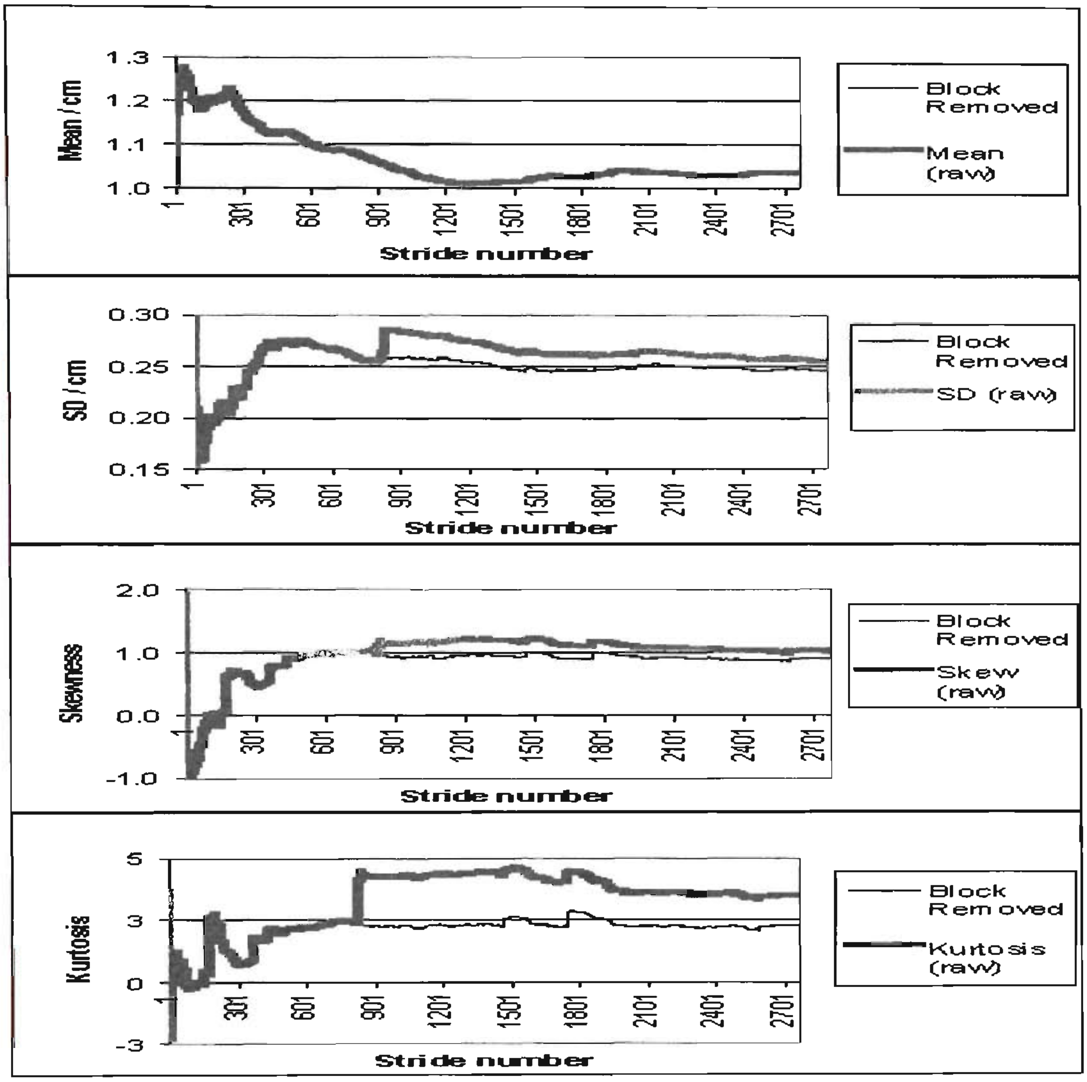


Figure 2.5 Stability of M, SD, S and K for 1-hour MTC data. These are derived by plotting the M of data (or SD, S, K) as it changes with the addition of each new data point. All graphs show one series (raw) containing all MTC data and a second series with an unusual block of 12 data points removed. These 12 extreme data points were generated when the subject might have been distracted in this brief period (adapted from Best, Begg, Ball and James, 2000).

2.2 AN OVERVIEW OF ARTIFICIAL NEURAL NETWORK

ANNs have been broadly used in industry with applications such as knowledge processing, robotic control, pattern recognition, speech recognition, speech understanding, speech synthesis and computer vision (Hubick, 1992). Applications of ANNs to study biological systems have appeared mostly within the past decade. In recent years, the non-linear modelling ability of ANN has facilitated the study of complicated relationships between gait variables, which have traditionally been difficult to model analytically, such as temporal dependence, curve correlations and high-directionality. ANN methods used to analyse gait data is unlike any previous technology. It has a highly flexible inductive, non-linear modelling ability.

2.2.1 What are Artificial Neural Networks (ANNs)?

An ANN is a computer algorithm designed to emulate the process of the brain. ANN took its name from the network of nerve cells in the brain (Dayhoff, 1990). Its architectures are motivated by models of our own brains and nerve cells. The field goes by many names, such as connectionism; parallel distributed processing, neuron-computing, natural intelligent systems, machine learning algorithms, and artificial neural networks (NeuralWare, 1991). ANNs learn by example. Figure 2.6 shows the ANN approach to a pattern classification problem.

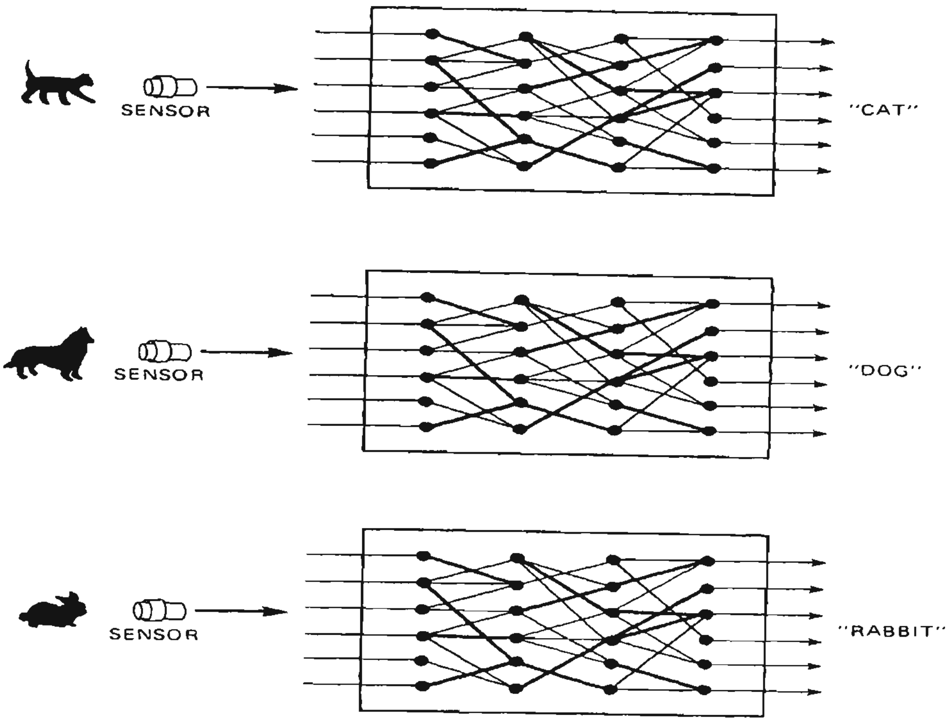


Figure 2.6 ANN approach to a pattern classification problem (adapted from Dayhoff, 1990)

During the learning phase, a set of input values (eg. animal shape parameters; see Figure 2.6) and known output values (eg. cat, dog and rabbit) are used for training an ANN. The connection strength that is associated with each interconnection is adjusted based on the prediction error of the network, and the expected output. During the testing phase, the ANN predicts an output, based on the inputs fed to it, using the knowledge it learnt during the training phase (Hubick, 1992; e.g. in Figure 2.6 it predicts shape input data whether it is a dog, cat or a rabbit). It 'learns' to associate inputs with known outputs during learning phase. Then, it is able to simulate the performance of a human expert to recognize similarities and patterns by the knowledge it learnt during testing phase (Vaughan, 1997). It does not require an expert to provide it with a set of 'rules' or a knowledge base. Well-developed ANNs can generalize on the tasks for which it is trained, enabling the network to provide the correct answer when presented with a new input pattern that has never been presented to the ANN during the training phase.

2.2.1.1 The Biological Neuron

Human brain consists of biological neural networks (NeuralWare, 1991). The most basic element of human brain is a specific type of cell, which provides us the abilities to think, remember and apply previous experiences. Human brain is a highly complex, non-linear, and parallel information-processing system (Vaughan, 1997). Human brain consists of tens of billions of neurons densely interconnected. Dendrites, soma (cell body), axon and synapses are the four basic components of all natural neurons. Figure 2.7 shows a simplified biological neuron and the relationship of its four components. Generally, a biological neuron receives inputs from other sources, combines them in some way, performs a nonlinear operation on the result, and then outputs the final result. Dayhoff (1990) described the axon as the output path of a neuron (see Figure 2.7). It connects to other neuron's dendrites, which are the input paths of a neuron, through a junction (synapses). The transmission of a pulse across this junction is chemical in nature and the amount of signal transferred depends on the amount of chemical released by the axon and received by the dendrites. When the brain learns, the synaptic efficiency is what is adjusted. The synapse combined with the processing of information in the neuron form the memory mechanism of the brain (NeuralWare, 1991).

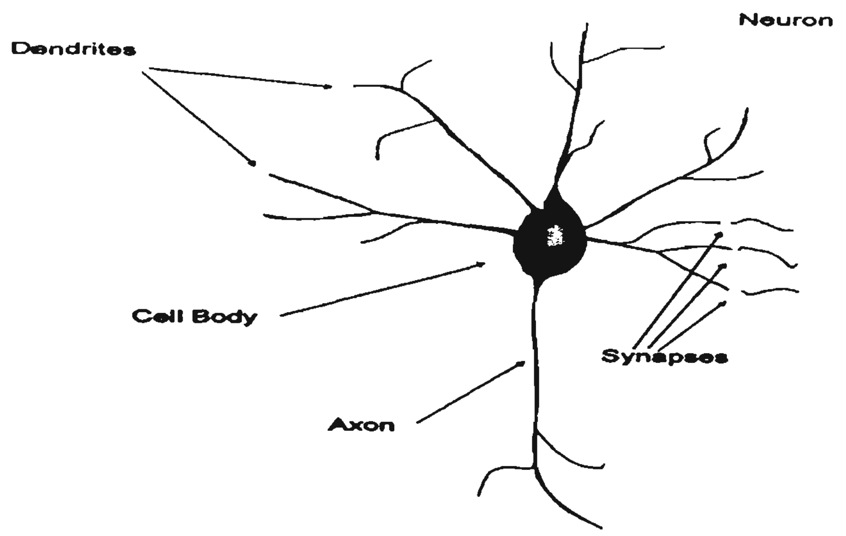


Figure 2.7 The basic structure of a biological neuron (adapted from NeuralWare, 1991)

2.2.1.2 The Artificial Neuron

The development of ANNs was inspired by the complexity of the brain, the way in which intelligence is coded by interconnections among the neurons or cells in the brain. It is an attempt to simulate, within specialized hardware or sophisticated software, the multiple layers of simple processing elements called neurons. The computer programs have similar structures to biological neural networks (see Figure 2.8).

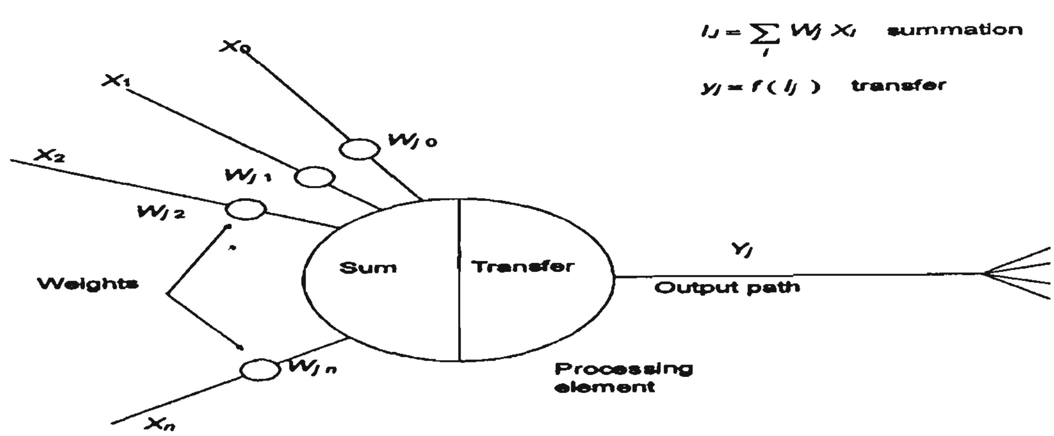


Figure 2.8 Schematic of processing unit (PE) from an artificial neural network (adapted from Sepulveda, Wells and Vaughan, 1993).

The artificial neuron, which is also called processing element (PE), is the basic unit of neural networks. It simulates the four basic functions of natural neurons. On the left are the multiple input paths (dendrites) to the PE, each arriving from another PE, which is connected to the PE shown at the centre. The different inputs to the network are represented by mathematical symbol (x_n). Each of the inputs is multiplied by a connection weight (w_n). The output from each neuron is determined by the nuclear processing, utilizing the transfer function, and the excitatory level of the connection of the incoming excitatory and inhibitory stimuli. The excitatory level of a connection site is also known as the connection weight and is thought to be the variable that determines the actual behaviour of a group of neurons.

Based on this simplified model of a PE, many PEs join together in above manner to make up an ANN. The interesting part of ANN is not the simplified model of a PE but the effects that result from the ways neurons are interconnected. PEs are often arranged into groups called layers. There are typically two layers with connections to the outside world: An input layer and an output layer.

2.2.2 Structure of an ANN

The basic structure of an ANN is shown in Figure 2.9. As mentioned before, neural networks are built of PEs that are usually arranged in layers, and the PEs in a layer are often connected to many PEs in other layers. The bottom layer is the input layer, which consists of PEs that receives input from the external environment. The top layer is the output layer, which consists of PEs that communicates the output of the system to the external environment. The layers between these two layers are called middle hidden layers. Figure 2.9 shows five elementary layers in a network; the input layer, output layer and the three hidden layers.

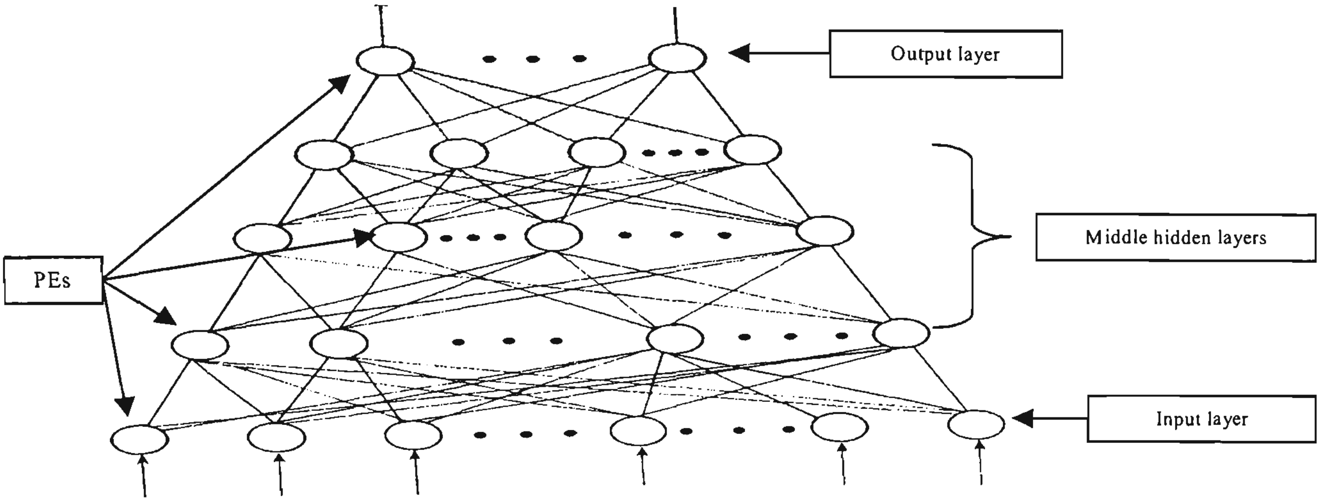


Figure 2.9 The basic architecture of ANNs

The ANN in Figure 2.9 is said to be fully connected in the sense that every PE in each layer of the network is connected to every other PE in the adjacent forward layer. Each hidden layer acts as a layer of "feature detectors" units that respond to specific features in the input pattern. Most ANNs have at least one hidden layer to extract higher-order statistics to create an internal representation from the input signals. Some ANNs use only two layers, directly mapping input patterns to a set of output patterns. This is sufficient when the input and output is similar and the encoding provided by the external environment alone can perform the mapping (Haykin, 1994).

The number of PEs required for the input and output layers depend on the number of input and output variables. Nevertheless, there appears to be no fixed rule to decide how many PEs should be in each hidden layer. Only a rule of thumb, for example, provided by NeuralWare (1991), can be used to set up the upper bound for the number of PEs in the hidden layer. Generally it should be no more than 50 PEs in the hidden layer. It is clear that larger numbers of PEs in the hidden layer has higher capability of capturing more features in the case of complex input pattern. If the number of the hidden PEs is greater than the essential minimum number, there is no enhancement in the performance of the ANN. On the contrary, there is increased tendency for the network to memorise the training patterns to give correct response instead of generalization. Hence, no fixed rules can be used to work out the correct number of PEs in the hidden layer. Instead, guidelines based on previous experiences in training the network in similar problems should be followed (Chau, 2000b).

2.2.3 Network Operation

The operation of an ANN can be divided into two phases (learning or training phase and testing phase). During the learning phase, the connection strength that is associated with each interconnection is adjusted based on the information offered to the ANN. Thus, the ANN becomes more knowledgeable about its inputs and outputs after the learning process. During the testing phase, the ANN predicts an output, based on what it has learnt previously during the learning phase (Hubick, 1992).

2.2.3.1 Learning

The definition of learning in the context of ANN is that a process by which the free parameters of an ANN are adapted through a continuing process of stimulation by the environment in which the ANN is embedded. The type of learning is determined by the manner in which the parameter changes take place (Haykin, 1994). Since all knowledge in ANNs are represented by weight, hence, learning is performed by change in connection weight. The change in connection weights mainly relates to the following two factors:

- Operation of PEs and
- Learning rules used for adjusting weight.

2.2.3.1.1 Operation of a Single PE

A PE is fundamental to the operation of an ANN. Figure 2.10 shows the basic structure of a PE in mathematical model. A PE in middle hidden layer generally has a number of input signals and a single output. In mathematical terms, a PE k in middle hidden layer can be described by following a pair of equations:

$$u_k = \sum_{i=1}^{p}(W_{ki}X_i) \qquad \text{Equation 2.1}$$

$$y_k = \varphi(u_k - \theta_k) \qquad \text{Equation 2.2}$$

Each input signal (X_i) is linked to a relative weight (W_{ki}), the effective input to the PE is the weighted total input (u_k) for all inputs signals. $\varphi(\cdot)$, the transfer function, defines the output of a PE in terms of the activity level at its input. y_k is the output signal of the PE. θ_k is the threshold, and has the effect of lowering the net input of the activation function. The linear combined input (u_k) is sent to the transfer function $\varphi(\cdot)$, which specifies the output (y_k) from the particular PE.

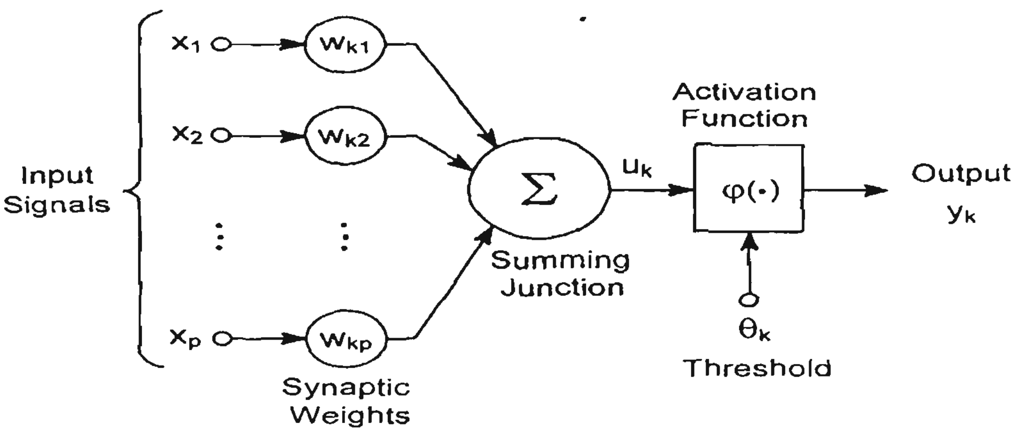


Figure 2.10 Operation of a PE (adapted from Haykin, 1994).

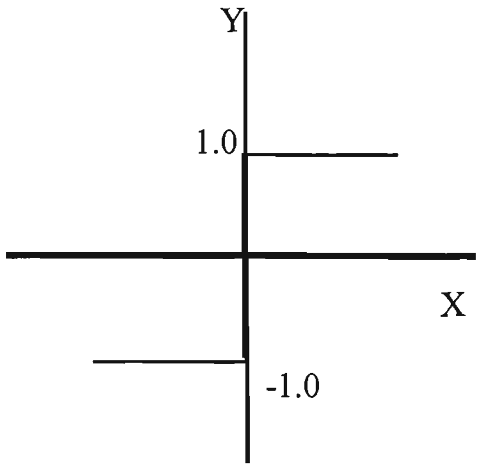
In summary, three basic elements of neuron model are described here:

- Each interconnection has an associated connection weight, given as w_{k1}, $w_{k2} \ldots w_{kp}$.
- The PE performs a weighted sum on the inputs

- Using a non-linear threshold function generates a result and which it passes directly to the output path of the PE.

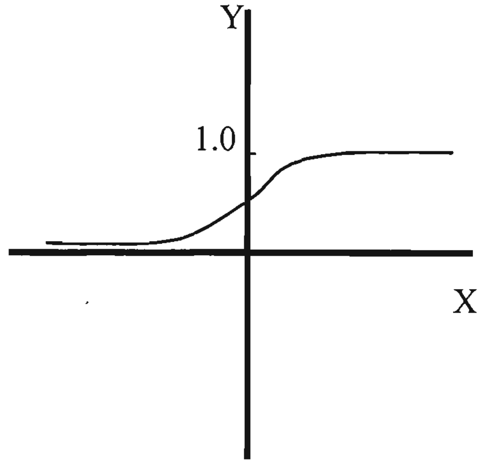
The transfer functions are used to limit the amplitude of the output of a PE. They are non-linear mathematical functions in the hidden layer(s). Normally, although not always, the transfer function for a given PE is fixed at the time a network is constructed. Figure 2.11 shows four commonly used transfer functions.

Hard Limiter



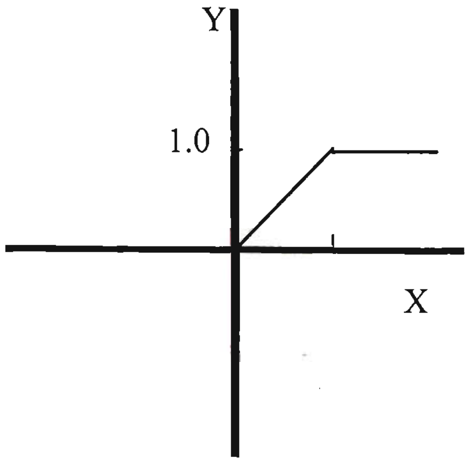
(1) X<0, Y = -1
X>0, Y= 1

Sigmoid Function



(2) $Y = 1/(1+e^{-X})$

Ramping Function

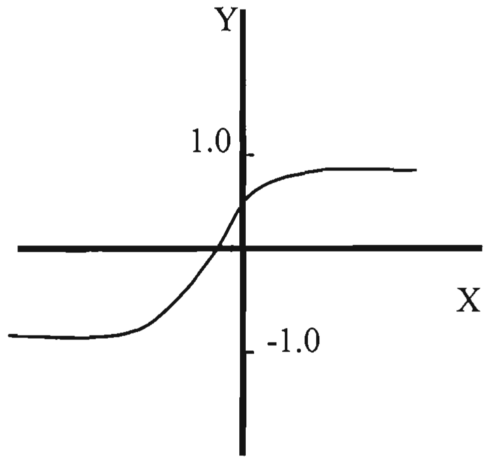


(2) X<0, Y=0

0<=X<=1, Y=X

X>1, Y=1

Hyperbolic Tangent



(4)

$$Y = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

Figure 2.11 Four commonly used transfer functions.

2.2.3.1.2 The Learning Rules

The processing of a single PE is very simple, despite the learning process of an entire ANN being quite complicated. Whatever kind of learning is used, an essential characteristic of any ANN is its learning rule. It implies the following three events (Hassoun, 1995):

1. The ANN is stimulated by an environment.
2. The ANN undergoes changes as a result of this stimulation.
3. The ANN responds in a new way to the environment, because of the changes that have occurred in its internal structure.

Unlike traditional expert systems where knowledge is made explicit in the form of rules, neural networks generate their own rules by learning from examples shown to them. When a pair of inputs and desired outputs are presented to an ANN, it tries to map the relationship between them. As the PE has no control over what input patterns are presented to it, the only way to correctly map the relationship is to modify the values of the connection weights on individual inputs. Hence, ANN learns by changing the weights on the inputs. The learning rule for a given network defines precisely how to change the weights in response to a given input and output pair. The following learning rules are commonly used.

2.2.3.1.2.1 Unsupervised Learning Rule

There is no external teacher or critic to oversee the learning process (see Figure 2.12). Generally, it does not give the ANN a desired output. In the other words, there are no specific examples of the function to be learned by the ANN (Hassoun, 1995).

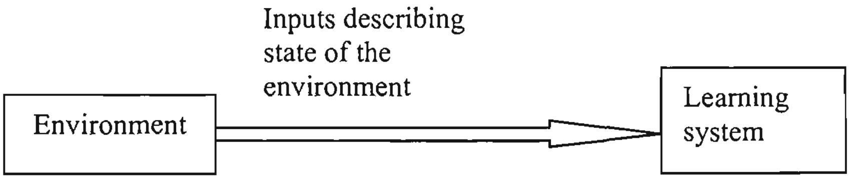


Figure 2.12 Diagram of unsupervised learning

1. Hebbian Learning Rule

It is the first and best known unsupervised learning rule named after in honour of the neuropsychologist Donald Hebb (1949). Hebb described it as, "When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic changes take place in one or both cells such that A's efficiency as one of the cell firing B, is increased". Haykin (1994) rephrased this learning rule into two parts:

- If two neurons on either side of a connection are activated simultaneously (e.g. synchronously), then the strength of that connection is selectively increased.
- If two PEs on either side of a connection are activated asynchronously, then that connection is selectively weakened or eliminated.

2. Competitive Learning Rule

It is used only in unsupervised learning network applications. There are three basic elements of a competitive learning rule (Hassoun, 1995):

- A set of PEs that are all the same except for some randomly distributed connection weights, and which respond differently to a given set of input patterns.
- A limit imposed in the "strength" of each PE.
- A mechanism that permits the PE to compete for the right to respond to a given subset of inputs, such that only one input PE, or only one PE per group is active at a time. The PE that wins the competitions is called a winner-takes-all PE.

3. Self-Organizing Feature Maps: Topology-Preserving Competitive Learning

It is a process of unsupervised learning whereby significant patterns or features in the input data are discovered. Kohonen feature map, which is commonly referred to as the self-organizing feature map, captures the topology and probability distribution of input data (Hassoun, 1995).

4. Reinforcement Learning Rule

It is the on-line learning of an input-output mapping through a process of trial and error designed to maximize a scalar performance index called a reinforcement signal. Haykin (1994) rephrases this rule as follow:

"If an action taken by learning system is followed by a satisfactory state of affairs then the tendency of the system to produce that particular action is strengthened or reinforced. Otherwise, the tendency of the system to produce that action is weakened".

2.2.3.1.2.2 Supervised Learning Rule

For each input stimulus, a desired output stimulus is presented to the system and the network gradually configures itself to achieve that desired input and output mapping.

1. ***Widrow-Hoff Learning Rule***

Widrow-Hoff learning rule is one of commonly used supervised learning rules (NeuralWare, 1991). It is based on reducing the error between the actual output of a PE and its desired output by continuously modifying incoming connection weights. This rule is originally used to train the linear unit, also known as the adaptive linear combiner element. It performs a gradient descent algorithm in weight space, and is guaranteed to converge to the unique set of weights that give the minimum mean square error between the desired and actual outputs for the example set.

2. ***Back Propagation Learning Rule***

It is the most popularly used generalization of the Widrow-Hoff rule and is applied to three layers of ANNs. Back-propagation is one of the easiest networks to understand. Its learning update procedure is intuitively appealing because it is based on a relatively simple concept: if an ANN gives the wrong answer, then connection weights are corrected so that the error is lessened and, as a result, future responses of the ANN are more likely to be correct (Dayhoff, 1990). The back-propagation learning algorithm involves a forward-propagating step followed by a back-propagating step. Both of these steps are done for each pattern presentation during training (NeualWare, 1991).

a) Forward-Propagating step

It begins when the input is presented and propagated forward through the ANN to compute an output value for each PE. In each successive layer, every PE sums its inputs and then applies to a transfer function (e.g. sigmoid function) to compute its output. All current outputs from each PE are compared with the desired output, and the difference between the actual output of the ANN and desired output, which is also called 'error', is computed.

b) The back-propagation step

It begins when an 'error' is generated. Then the ANN calculates error values for hidden PEs and changes for their incoming weights, starting with the output layer moving backward through the successive hidden layers. The ANN corrects its weights in such a way as to decrease the observed error in this step (Figure 2.13).

The process of adjusting incoming weights during back-propagation is shown in Figure 2.13. Back-propagation is widely used in ANN development and has been applied successfully in many applications such as character recognition, sonar target recognition, image classification, signal encoding, knowledge processing, and a variety of other pattern-analysis problems (Dayhoff, 1990).

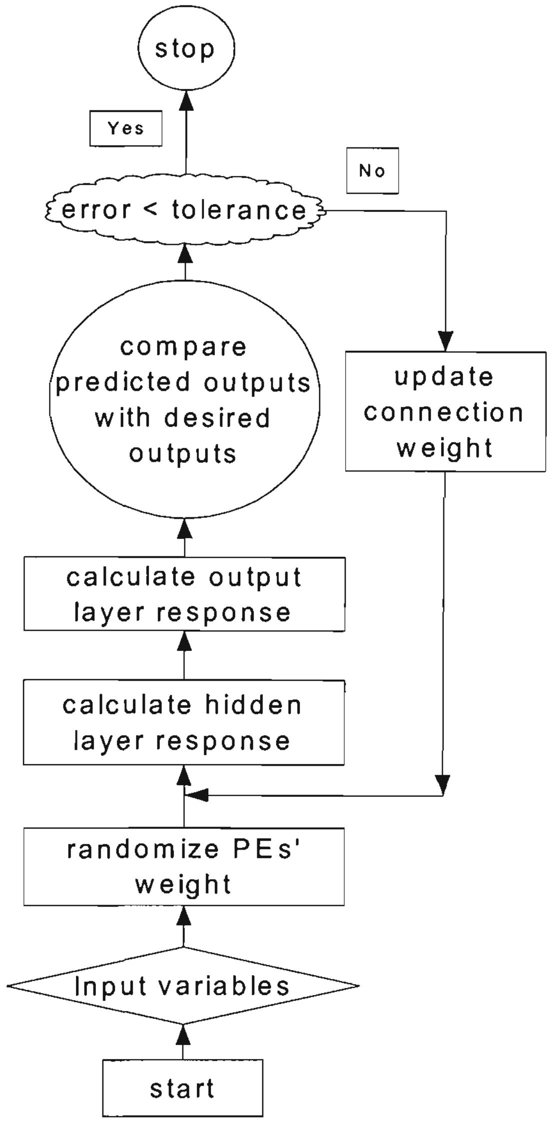


Figure 2.13 A flowchart showing the operation of Back-propagation algorithm

2.2.3.2 Testing

During the learning phase, an ANN stores knowledge (connection weights). During the testing phase, a set of testing data (data that has never been shown to the ANN during learning) is presented to the ANN to measure its performance. The inputs of the testing data are presented to the ANN. Then, they flow through all the fixed connection weights and generate a set of predicting outputs (see Figure 2.14).

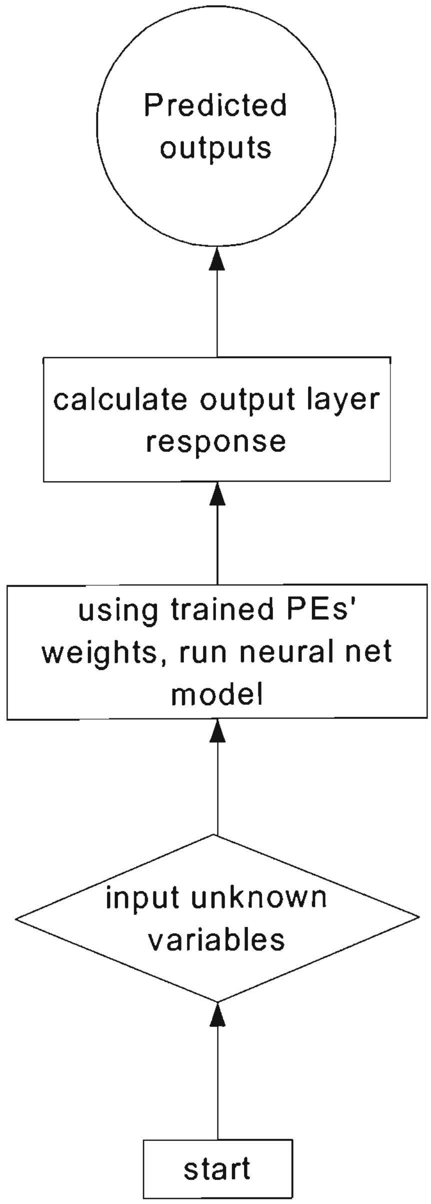


Figure 2.14 Flow diagram to represent the testing phase of an ANN

2.2.4 Characteristics of ANNs

A neural network is a massively parallel-distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It exhibits a surprising number of characteristics of the brain (Dayhoff, 1990). It simulates the processing of brain in two respects:

1. The network through a learning process acquires knowledge.
2. Interneuron connection strengths known as synaptic weights are used to store the knowledge.

Haykin (1994) summarized that the major features and benefits of a neural network which make it different from traditional computing and artificial intelligence. These are described as.

1. Non-linearity

A neuron is a non-linear device. Hence, an ANN made up of an interconnection of neurons is non-linear as well. It is a very important property of ANNs that is often used for mapping the non-linear relationship between inputs and outputs (Chau, 2001b).

2. Parallelism

ANNs utilize a parallel processing structure that has large number of processors and many interconnections between them. The massively parallel nature of

ANNs make them potentially fast for the computation of certain task. During both training and testing phase, the PEs in one layer all operate at the same time. Computation is distributed over more than one PE and is done simultaneously. Decisions are very quickly made. Furthermore, this feature of ANNs makes them suitable for implementation using very-large-scale-integrated technology. Thus, it is possible to use ANN as a tool for real-time applications involving pattern recognition, signal processing, and control (Barton and Lees, 1997).

3. *Input-Output Mapping*

The most common training scenarios utilize supervised learning, which involves the modification of the connection weights of ANNs by applying a set labelled training samples and task samples. Each example consists of a unique input signal and the corresponding desired response (outputs). During the training phase, the network is presented an example randomly selected from the training set, and then it produces an actual response that can be compared with the desired response. Initially, the network will probably produce the wrong answer. The connection weights of the network are modified so as to minimize the difference between desired response and the actual response. The training network is repeated for many examples in the training set until the network reaches a steady state, where there are no further significant changes in the connection weights (Savelberg and Lange, 1999).

ANNs learn the rules for processing the knowledge. Neither the knowledge nor the explicit rules for processing the knowledge are coded by the programmer. It does not require an expert in the relevant knowledge domain to develop an ANN. This reflects a radically different approach to computing compared to traditional methods (Lapham and Bartlett, 1995).

4. *Storage of Knowledge*

The connection weights are the memory units of an ANN. The values of the weights represent the current state of knowledge of the network. After training is completed, the connection weights are fixed. These final values of each connection weight are then used during testing phase. The knowledge within an ANN is not stored in particular memory locations but is distributed throughout the whole system (NeuralWare, 1991).

Knowledge an ANN learns is related to network structure (how the PEs in output layer connect to the PEs in the other layer(s)) and the relative weighting of each input to a PE (Dayhoff, 1990).

5. *Evidential Response*

An ANN can discover the distinguishing features needed to perform a classification task. In the context of pattern classification, an ANN can be designed to provide information not only about which particular pattern to select, but also about the confidence in the decision made. If the ambiguous patterns arise, this latter information may be used to reject it, and thereby improve the classification performance of the ANN (Barton and Lees, 1997).

6. *Mathematical Basis*

The programming of ANNs is based on mathematical methods. Although it broadly uses behavioural terms, such as learn, generalize and adapt etc., the ANN's behaviour is simple and quantifiable at each node. The computations performed in the neural network may be specified mathematically, and typically are similar to other mathematical methods already in use. Summing, weights, transfer function, learning rules all rely on mathematics (Hassoun, 1995; Haykin, 1994).

7. *Contextual information*

Every neuron in the network is potentially affected by the global activity of all others in the network. Knowledge is presented by the very structure and activation state of an ANN. Contextual information is dealt with naturally by the ANN (NeuralWare, 1991; Vaughan, 1997).

8. *Fault Tolerance*

ANN has the potential to be extremely fault tolerant in the sense that its performance is degraded slightly under adverse operating conditions (NeuralWare, 1991). When a neural or its connections are damaged, recall of a stored pattern impairs overall performance. However, owing to the distributed nature of information in the ANN, the damage has to be extensive before the overall response of the ANN is degraded seriously. Thus, performance is merely degraded rather than precipitating catastrophic failure (NeuralWare, 1991).

9. Adaptability

ANNs have built-in capability to adapt their connection weights to changes in the surrounding environment and thus can be easily retrained. Chau (2001b) has concluded that adaptability of ANNs mainly present in the aspects of learning, self-organizing and generalization. It often occurs when the connection weights are adjusted during learning. ANNs could develop their own algorithm by adjusting the weighted connections between the PEs. Generalization is the ability of ANN to respond to a new input pattern that is different from the inputs in the training set. It takes the ability to learn and self-adjust a step further (Dayhoff, 1990; Hassoun, 1995).

10. Neurobiological Analogy

ANNs can guide the research of biologists and engineers for new ideas to solve complex problems. For example, in functional electrical stimulation control systems, ANNs have been employed for feedback or adaptive control to assist paraplegic walking (Tong and Granat, 1998).

Since ANNs are driven by input and output data, this data-driven approach of ANN is also seen as its major limitations. ANN is based on an inductive modelling approach. It learns by examples presented to it. There is no causal knowledge presented to it. ANN is only capable of relating inputs to outputs. Learning rules used in ANN are implicit and not easily comprehensible. Specially, it is not based on biomechanical structures. Thus, it is unable to provide insight into the decisions that are made (Lapham and Bartlett, 1995).

2.2.5 Types of ANNs

Generally there are two characteristics that divide ANNs into different categories:

- Whether the network is given the correct answer during training, or whether the ANN is left to figure this out for itself.
- Whether the data flows through a ANN in the forward direction only, as opposed to both forward and backward (Neuralware, 1991).

The ANNs are subdivided into two types of ANN (supervised learning ANN and unsupervised learning ANN) according to the first characteristic. These two types of ANNs have been mentioned before (see section 2.2.3.1.2). The networks mainly fall into the following two categories according to the direction of data flow.

I. Feed-forward Neural Networks

It is a network where data flows only in the forward direction. It is faster than feedback ANNs and they are guaranteed to reach stability. Feed-forward networks are very popular due to their relative simplicity and stability. Back-propagation network (BPN) is an example of a feed-forward network and used for a variety of applications (NeuralWare, 1991). It is trained by supervised learning and has been broadly applied to character recognition, sonar target recognition, image classification, signal encoding, knowledge processing, and a variety of other pattern-analysis problems (Dayhoff, 1990). This learning rule has been widely used in gait analysis (Barton and Lee, 1997) The back-propagation learning algorithm involves a forward-propagating step followed by a backward-propagating step. Both steps are done for each pattern presentation during training.

II. Feedback Neural Network

Networks with connections that allow data flow both forward and backward are called Feedback networks (NeuralWare, 1991). Feedback loops permit trainability and adaptability. In some clinical studies, ANNs have been used for feedback or adaptive control to assist paraplegic walking (Tong and Granat, 1998). Recurrent Neural Networks is an example of feedback networks. It is a network with closed loops. It can perform functions like gait control or energy normalisation and choosing a maximum in complex system.

2.3 Applications of ANNs in Gait Analysis

Recent literature show that the applications of ANNs in gait analysis fall into two major categories: (1) Classification of gait patterns. (2) Prediction of gait parameters and variables.

2.3.1 Classification of Gait Patterns

The knowledge processing ability and pattern recognition ability of ANNs have been applied in gait research. Investigators have developed several ANNs to automatically classify a person's gait or diagnose a walking condition with neural networks. The most common application in gait analysis is to identify normal/abnormal gait patterns (Wu and Su, 2000). In a study undertaken by Hastings, Vannah, Gorton, and Masso (1995) the gait parameters of 52 spastic hemiplegia children were used to train an ANN for recognizing hemiplegia gait type. During testing, the network correctly recognised 33 out of 45 trials providing only moderate success (73%). The authors identified lack of data pre-processing as the main reason for limited success.

Lafuente, Belda, Sánchez-Lacuesta, Soler, and Prat (1997) developed a multilayer processing elements ANN to classify 97 subjects into four categories (control, ankle arthrosis, knee arthrosis and hip arthrosis). A feed forward network (one hidden layer) was trained using 77 subjects with ankle, knee or hip arthrosis and 62 control subjects without limb pathology. The inputs consisted of cadence, velocity and parameterisations of five kinetic magnitudes. Based on these inputs, a trained three-layered neural network distinguished the four gait categories with an accuracy of 80%, a statistically significant improvement over a traditional bayesian quadratic classifier. This study established the potential for multi-category classification of complicated pathological gait using ANNs.

Cai, Begg and Best (2000) successfully developed and trained a number of ANNs to differentiate between the gait characteristics of young and elderly people using walking velocity and four statistics of the MTC distribution (mean, standard deviation, skewness, kurtosis) as inputs. The output layer included two taps (young and elderly subject). An overall success rate of 83% in identifying the four subjects was found in this research. The influences of gait variable(s) in the identification process were also investigated by training and testing ANNs with different combinations of input variables. The results showed walking speed to be the significant parameter (recognition rate dropped to 58% without it), but kurtosis did not affect the results significantly. Skewness affected the results moderately (75% recognition rate without it). This study indicates that selection of input variables are important and can affect the performance of ANN in classification.

Barton and Lees (1997) applied ANNs to diagnose gait patterns under three conditions: normal gait, a simulation of leg length difference (20mm thick sole attached to the left shoe of subjects) and a simulation of leg mass difference (3.5 kg mass attached to left lower leg of subjects). The hip-knee joint angle diagrams were pre-processed using time normalization and also Fast Fourier Transformation (FFT) and acted as inputs. FFT is an approach to reflect the frequency distribution of temporal signal, which is used in pre-processing waveforms. ANNs were trained and tested four times with different data assigned as training and testing sets. The ANNs showed a success rate of 83% in identifying gait conditions.

Holzreiter and Köhle (1993) also successfully trained an ANN to distinguish 'healthy from pathological' gait using FFT coefficients computed from vertical components of two ground reaction forces as inputs. The data set comprised of 8173 pairs of footstrikes from 94 healthy and 131 pathological gait patterns. The data were randomly split into training and test sets. The results showed correct assignment (success) of about 95%.

A well-trained ANN appears to have good performance in knowledge processing. A large number of training data and also an appropriate data pre-processing technique are important to improve an ANN's performance.

2.3.2 Prediction of Gait Parameters

The highly non-linear modelling ability of ANN has encouraged researchers to use ANN techniques to map the elusive relationships, which have traditionally been difficult to model analytically, such as the relationship between EMG signal and muscle force. To date it is well accepted in the scientific community that the EMG signal is qualitatively related to the force produced by muscle. Past research has investigated the quantitative nature of the EMG-force relationship in skeletal muscles (Nussbaum, Martin, and Chaffin, 1997), but with limited success for dynamic contractions.

Savelberg and Herzog (1997) used a back-propagation neural network approach to predict cat gastrocnemius muscle force from EMG. Tendon forces and EMG signals were recorded from three cats when they walked at four different speeds. The ANN was trained with input consisting of averaged and rectified EMG values from current and previous 29 steps. The desired output consisted of the tendon force at current time. Intra-session, intra-subject and inter-subject generalization abilities were investigated. The neural network predicted the tendon force accurately from EMG in all three levels of generalization with cross-correlation coefficients ranging from 0.72 to 0.98. Based on the study of Savelberg and Herzog (1997), Liu, Herzog and Savelberg (1999) further investigated the ANN prediction of time–varying tendon force from EMG signals and 10 kinematic parameters with better prediction, in which the cross-correlation coefficients exceeded 0.91 in all cases. These results showed that the addition of kinematics improved the prediction of tendon force.

Sepulveda, Wells and Vaughan (1993) used an ANN to model the relationship between lower limb joint dynamics and muscle activity. They developed two sets of ANNs to map two different transformations: a) EMG data onto joint angles, and b) EMG data onto joint moments. Data for 16 lower limb muscles and three joint moments and angles (hip, knee and ankle) were obtained from the literature (Winter, 1987) to train and test the ANNs. Test results showed a difference of less than ±4.3° for the knee joint angle and ±7.7Nm for the ankle joint moment. These differences translated to less than 7%, highlighting the ANN's good predicting ability.

Savelberg and de Lange (1999) successfully trained an ANN to predict horizontal fore-aft component of the ground reaction force from insole foot pressure patterns. Five subjects participated in this study. The input variables were obtained from six gait trials from each subject. The pressure values for the eight selected regions of each trial were used to represent the characteristics of insole pressure. Hence, there were 48 input variables, and the output layer was the corresponding fore-aft component of the ground reaction force (F_y). The cross-correlation coefficients for intra-subjects showed that the amplitudes of both predicted deceleration and acceleration peaks of the F_y pattern differed by less than 10% from the desired ones. Also, the error in the timing of the signal (instant of reaching peak values and instant of zero crossing between deceleration and acceleration phases on the F_y time series) was estimated to be less than 25ms.

Prentice, Patla and Stacey (2001) developed an ANN to predict EMG activity of an individual walking to represent the general activation pattern of a particular gait condition. A three layer ANN was trained with 21 inputs (kinematic representation of the actual limb movement) and 8 outputs (the muscle activations of 8 muscles of the lower limb and trunk). The tested results showed that the predicted EMG patterns closely matched those recorded experimentally. Most muscle/gait conditions (94 out of 96) had root mean square error less than 0.10, exhibiting the appropriate magnitude and temporal phasing required for each modification. The highly non-linear mapping ability between inputs and outputs of ANN facilitates the prediction of gait parameters, which are difficult to be predicted using traditional methods.

2.4 Data Pre-processing

Generally, proper pre-processing of input variables and post-processing of output variables are necessary for good generalization performance of ANNs (Chau, 2001b). Sometimes, direct use of raw gait data causes saturation of PEs when the input values are too large (NeuralWare, 1991; Vaughan, 1997). ANN software usually uses a MinMax table, which is a pre-processing facility, to compute the 'lows' and 'highs' of each data field. Then, ANN computes proper scale and offset for each data field to avoid saturation of PEs (NeuralWare, 1991). Savelberg and Lange (1999) developed an ANN without pre-processing facility, and used a normalization technique to normalize the output signals (the fore-aft component of the ground reaction force) to values between –1 and 1. This range corresponded to the output range of the sigmoid transfer function used in the output layer of the ANN. Shi and Eberhart (1998) developed an ANN to differentiate sleep from wakefulness. Actigraph data were pre-processed by dividing by the maximum value.

In fact, pre-processing the raw data is a judicious way to select input variables (Chau, 2001b). Using all available variables would result in a very large ANN that would be difficult to train with the available computing resources. Proper pre-processing of raw data, therefore, is necessary to improve the efficiency and performance of ANNs (Dayhoff, 1990).

FFT is an approach to reflect the frequency distribution of temporal signal, which is used in pre-processing waveforms. It is usually regarded as a feature extracting function, which reduces the size of the pattern but still preserves the features of the curves. Barton and Lees (1997) used FFT to pre-process raw joint angle data during gait (hip and knee angles against time). 128 values in constant time intervals were obtained by normalization in time. FFT resulted 64 real coefficients and 64 imaginary coefficients. The coefficients of the lower frequencies were used, and resulted in 30 input variables. Holzreiter, and Köhle (1993) used similar techniques (FFT) to pre-process the raw data (the vertical force components of the measured gait patterns) as well. Previous research more or less used some form of data pre-processing techniques to pre-process raw data to generate effective inputs for ANNs such as FFT, scaling, normalization, rectification and averaging (Chau, 2001b).

2.5 Multiple Linear Regression Model vs ANN Model

Multiple linear regression (MLR) model, a powerful prediction tool, is commonly used in various research areas (Aron and Aron, 1999). The general purpose of MLR is to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable (Hair, Anderson, Tatham and Black, 1992). In general, MLR procedures estimate a linear equation of the form (Aron and Aron, 1999; Hair, Anderson, Tatham and Black, 1992).

$Y = a + b_1*X_1 + b_2*X_2 + ... + b_p*X_p$

Where,

Y: the dependent variable

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

$b_1, b_2 .. b_p$: raw score regression cofficients

a: the regression constant

MLR model has been widely used in biomechanical field (Chau, 2001a, Marras, Jorgensen, Granata and Wiand, 2001; Jorgensen, Marras, Granata and Wiand, 2001). Some researchers have compared the performances of MLR and ANN model. Herren, Sparti, Aminian and Schutz (1999) used both MLR and ANN methods to predict running speed and incline. Three parameters (e.g. parameters for speed were variance of frontal acceleration of the heel, variance of the frontal acceleration and median of the frontal acceleration of heel) that showed the best correlation with speed (or incline) by stepwise regression were used as independent variables for developing MLR. Ten similar parameters were used to develop ANN. The results showed that ANN allowed better prediction for speed and incline: the square root of mean square error (RMSE) of speed was $0.12ms^{-1}$, which was 0.5% lower than that obtained with MLR (RMSE=$0.14ms^{-1}$). For incline, the prediction error of MLR (RMSE=0.0263 rad, 2.63% slope) in incline was higher than that with the ANN (RMSE was 0.0142 rad, 1.42% slope).

During the last decade, the excellent relationship mapping ability of ANN has solved many complex problems in gait analysis. Furthermore, its flexible modelling ability facilitates the prediction of gait parameters, which are usually difficult to measure

(Chau, 2001b). Best, Begg and James (1999) reported that the long-term MTC data (about 1500-3000 gait trials) could be used to evaluate the probability of irregular tripping during locomotion. Nonetheless, it involves extremely time consuming MTC data collection and analysis procedures. Also, it is restricted by the walking ability of subjects eg. children and frail elderly are not able to walk on a treadmill for half an hour. For that reason, a methodology needs to be developed that is able to predict long-term histogram characteristics of MTC data based on the characteristics of MTC collected from fewer gait trials, so that probability of tripping can be estimated.

Based on the literature described in the literature review section, the non-linear modelling and knowledge processing abilities of ANN provide encouragement for the development of ANN system for predicting the characteristics of steady-state stabilized MTC data. Particularly, the ANN system is required to be developed to predict MTC characteristics relating to 30-minute gait recording from MTC data characteristics relating to fewer gait cycles e.g., 2-minute gait data. If this could be successfully done, then, it would enable tripping probability to be calculated from fewer gait trials, e.g., using 2-minutes gait data.

CHAPTER THREE

IMPORTANCE OF THIS RESEARCH

Gait analysis involves collection of a number of gait trials. Gait parameters, nevertheless, are variable. Traditionally, people use trials (5-25) to record gait parameters. Increasing the number of gait trials would help researchers to obtain stabilized gait parameters. There are many constraints including time, cost and disability of the subject that affect the sample size and research efficiency. There is a demonstrated need for research into modelling the relationship between gait characteristics derived from fewer gait trials and that derived from steady-state gait trials. The non-linear modelling ability of artificial neural network is demonstrated in this study.

The importance of this research is that this is the first study that investigates the possibility of using ANNs to predict stable characteristics of gait parameters, based on the characteristics of those parameters during the initial gait trials. The ANN technology has been widely used for classifying the characteristics of gait and modelling the relationship between the muscle forces and EMG signals during gait. There is no previous study to use the non-linear modelling ability of ANN to predict the stabilized gait parameters.

This research would improve the efficiency of research in collecting reliable gait data by requiring fewer gait trials per subject, specifically for trip probability testing (e.g.

Best, Begg and James, 1999). Furthermore, it would help researchers to obtain reliable data for those subjects who are not able to walk for a long time (e.g. frail elderly, pathological subjects and children).

During the last decade, ANNs have been used in various biomechanical applications with great success rates. Nonetheless, there has been limited application in gait analysis and biomechanics, and many of the studies look at classifying normal and pathological gaits. ANNs are particularly suitable for mapping the complex non-linear relationships between inputs and outputs. This research explores the exciting ANN technology for its suitability for predicting gait data and promotes further development of ANN technology in biomechanics.

CHAPTER FOUR

RESEARCH OBJECTIVES

4.1 General Aim

- To develop ANNs and investigate their ability to predict stabilized gait characteristics from gait characteristics of fewer trials.

4.2 Specific Aims

- To derive MTC data during gait and calculate Mean (M), Standard Deviation (SD), Skewness (S), Kurtosis (K).
- To develop ANNs and test performance of long term stabilized data prediction.
- To investigate the effect of data pre-processing on prediction accuracy.
- To examine the effect of data segment lengths on prediction accuracy.
- To compare statistical prediction and ANN prediction accuracies.

CHAPTER FIVE

METHODS

5.1 Subjects

Foot motion data and minimum toe clearance (MTC) data during 30 minutes of continuous gait trials on a treadmill were used to develop the ANNs. Twelve subjects' data for ANN training were obtained from the Biomechanics Unit's 'gait database'. Another twelve subjects' data were collected and analysed in the Biomechanical Lab of Victoria University. Currently, it takes about 18 hours of video digitisations time alone for each subject. Altogether 24 subjects' data were analysed during the time frame of this Masters project. The population studied comprised of twenty-four subjects with mixed gender (15 female and 9 male) and aged 19-79 years. Their health conditions were known by feedback via a questionnaire. Table 5.1 shows individual subject characteristics. The average age for all subjects was 37.1years.

Young subjects included Human Movement students at Victoria University, friends and work colleagues. All subjects had prior experience of treadmill walking and jogging. Elderly subjects were recruited from walking groups, local gymnasiums and the local neighbourhood. Each of the elderly subjects included in this study were regular walkers and were free of any injuries, musculoskeletal conditions or visual impairments that would affect normal locomotion.

Table 5.1 Individual subject characteristics. Y=Young, E=Elderly, M=Male, F=Female

SUBJECT	GENDER	AGE (YRS)	BODY MASS (KG)	STATURE (M)
Y1	F	28	55.8	1.65
Y2	F	27	62.6	1.75
Y3	F	24	53.6	1.60
Y4	F	30	77.2	1.66
Y5	F	28	84.2	1.66
Y6	F	29	58.2	1.67
Y7	F	28	65.2	1.65
Y8	F	34	64.3	1.67
Y9	F	31	62.1	1.65
Y10	F	28	70.1	1.76
Y11	M	29	77.5	1.85
Y12	M	23	66.3	1.76
Y13	M	22	80.1	1.74
Y14	M	29	82.1	1.82
Y15	M	34	87.2	1.78
Y16	M	30	84.1	1.82
Y17	M	33	64.3	1.66
Y18	M	19	62.3	1.71
Y19	M	27	74.9	1.84
E1	F	70	61.4	1.52
E2	F	65	63.2	1.63
E3	F	67	67.2	1.71
E4	F	77	75.2	1.60
E5	F	79	68.2	1.54
Average		37.1	69.5	1.70
SD		18.2	9.4	0.1

5.2 Apparatus

- Peak Motus system (Peak Performance Technologies Inc,. USA) was used for video digitisation, accessing and retrieving foot motion and MTC data from 30-minute gait trials under normal walking conditions on a treadmill.

- Neural Works Professional II/Plus 386 software (NeuralWare. Inc., USA) was used to develop and test 12 sets of ANNs.

- SPSS version 10.0 software (SPSS Inc., USA) was used to calculate statistical input and output variables for ANNs. Also during data analysis SPSS was used for comparing the desired output and predicted output by ANNs.

- Fast Fourier Transformation (FFT) software (Victoria University) was used for pre-processing of MTC data.

- IBM Pentium 133 MHz computer was used for building, training and testing ANNs.

5.3 Procedures for Collecting MTC Data

5.3.1 Data Collection

All of the foot motion data in this study were collected via a 50 Hz video on subjects during their normal treadmill walking using PEAK 2D motion analysis procedures.

5.3.1.1 Treadmill Set-up

Two, 2.5cm spherical, reflective reference markers were attached to each end of the treadmill for a 1.6m distance calibration required for the Peak motion analysis system. Another two, 2.5cm spherical, reflective markers were attached to each subject's left shoe at the great toe (TM) and 5th metatarsal head (MH) for analysing the motion of the foot during swing phase (see Figure 5.1).

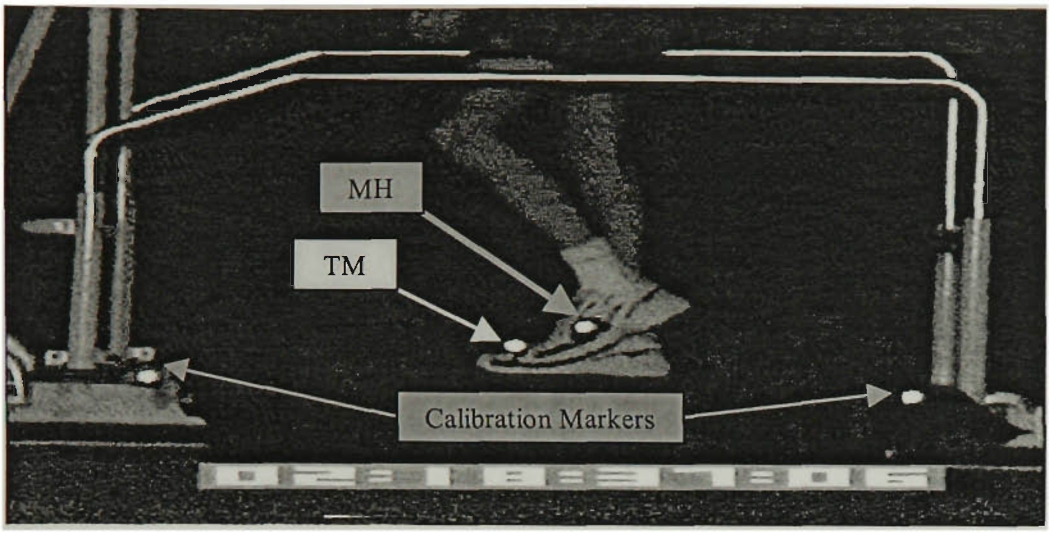


Figure 5.1 Placement of reflective markers on left foot and treadmill

5.3.1.2 Treadmill Walking Task

All subjects were asked to walk continuously on the treadmill for at least 30 minutes at a self-selected comfortable walking speed without holding safety rails. A self-selected walking speed is regarded as the best representation of overall walking performance (Kerrigan, Todd, Della Croce, Lipsitz and Collins, 1998). The longer period of walking was required to obtain MTC histogram for deriving stable MTC characteristics and probability of tripping calculation (see Best, Begg, Ball and James, 2000).

Subjects were requested to wear their own flat, comfortable shoes which would be suitable for walking (black shoes were preferred) and wear something cool due to the constant warm temperature regulated in the laboratory. All subjects were briefed on the use of the treadmill as a safety precaution. The protocol for data collection was approved by Human Research Ethic Committee at Victoria University.

5.3.1.3 Recording the Stationary Foot for Foot Modelling

In order to obtain the minimum toe clearance data for each stride during the walking task, a clear outline of the left shoe was required for the foot modelling procedure designed to calculate foot end-point (at the toe where it would contact the ground in the event of a trip). This technique is described in the Data Analysis section 5.3.2 (refer also to Figure 5.3). Hence, at the end of the walking task, experiment operator asked subjects to stand on the stationary treadmill with their left foot slightly elevated, and checked the video monitor to ensure the outline of the shoe. Specifically the bottom edge of the shoe was clearly visible. A light coloured sheet was place behind the shoe of subject who wore dark coloured shoes, which blended into the background of the darkened walls, to ensure a clear outline.

5.3.1.4 Experimental Set-up

Foot motion data were collected via a 50Hz video of subjects during their normal treadmill walking. A camera was positioned 9m from the treadmill, perpendicular to the plane of motion. Whittle (1991) indicated that perspective error during kinematic analysis in the sagittal plane is quite small compared to that in the frontal plane. The 9m-distance, in conjunction with the camera positioned at right angles to the participated foot clearance during swing phase, should eliminate perspective error (refer to Figure 5.2). The video camera with a shutter speed of 1/1000s, recorded a minimum of 30 minutes steady state, unobstructed treadmill walking.

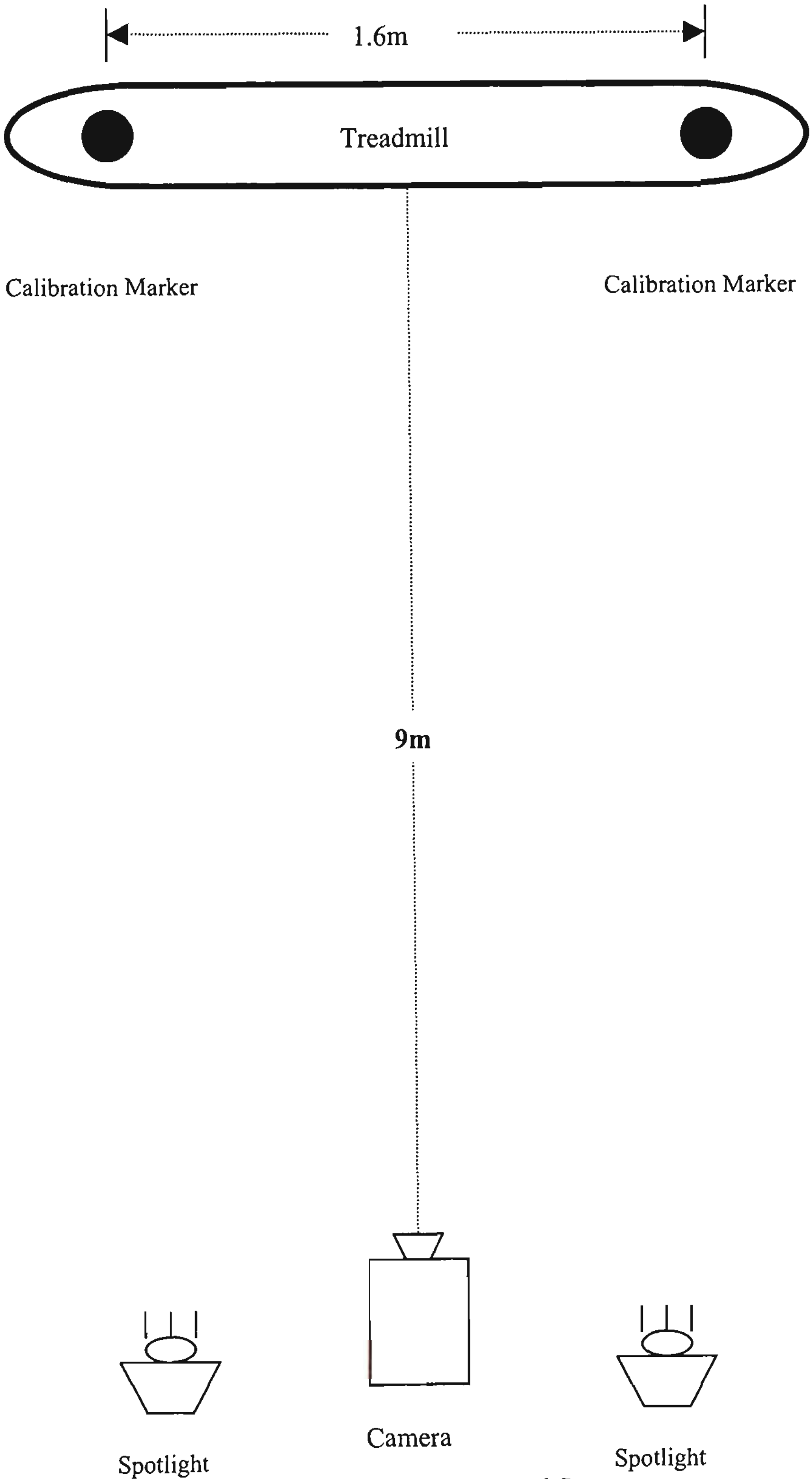


Figure 5.2 Experimental Set-up

5.3.2 Data Analysis

5.3.2.1 Digitising Using the Peak Motus System

Two-dimensional calibration procedures were performed using the two markers at each end of the treadmill (refer Figure 5.2). The distance between these two markers were preset to be a reference distance (e.g. 1.6m). These two markers were each manually digitised using the Peak Motus system. Then, Peak Motus calculated the average vertical, horizontal coordinates of the two reference markers on screen, and converted screen coordinates to real distance based on the information given by the operators. These coordinates were then used as the calibration for the entire trial.

Fifth metatarsal head (MH) and great toe (TM) markers were automatically digitised in the Peak Motus system for the entire walking task. Peak Motus system performed the location of the two markers and calculation of the 2D trajectories of the two markers as a function of time. Since the MTC value is directly related to the foot end-point, the foot end-point during entire waking task was predicted using a 2D geometric model (Figure 5.3). This process involved manual digitisation of foot end-point and automatic digitising of TM and MH for 0.5 second of video data (about 25 video field) and the Peak Motus system calculated the mean horizontal and vertical coordinates of each digitised point (TM, MH and foot end-point).

5.3.2.2 Geometric Model of the Foot

Peak Motus data were exported to a Microsoft Excel spreadsheet. A geometric model of the foot was used to predict foot end-point (PTP) at the toe where it clears the ground, which is used to calculate the MTC for each stride, as shown in Figure 5.3. The model calculates P_3 (PTP) from MH (P_2) and TM (P_1) coordinates.

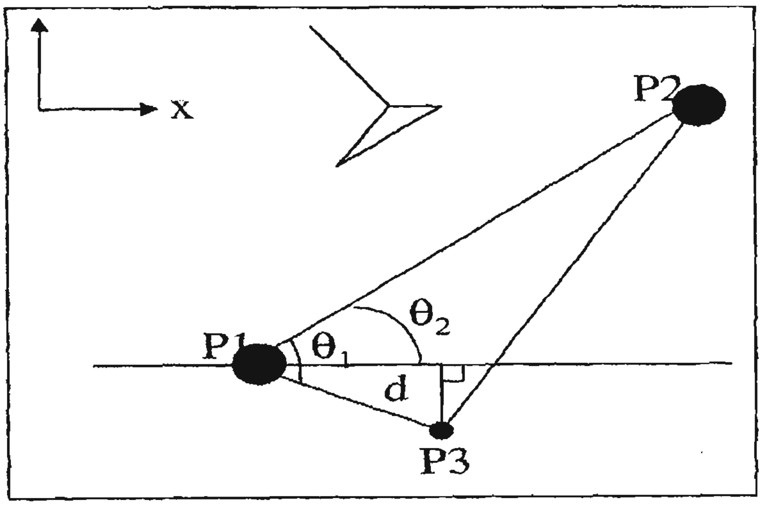


Figure 5.3 Geometric Model of the left foot (adapted from James, 1999)

P_1 = TM marker; P_2 = MH marker; P_3=PTP

The foot (and foot model) is shown here at mid-swing.

The vertical coordinate of the predicted toe position (PTP), y (P_3), was calculated using the following equation:

$$y(P_3) = y(P_1) - d \qquad \text{Equation 5.1}$$

The vertical position of PTP, $y(P_3)$, reaches a minimum value ($y(P_3)_{min}$; see Figure 5.4) during the left swing phase. Consequently, MTC data can be calculated for each gait cycle:

$$MFC = y(P_3)_{\min} - y_g \qquad \text{Equation 5.2}$$

where y_g is the ground reference, calculated as the minimum vertical coordinate of the manually digitised PTP. The vertical displacement of TM marker and PTP is shown in Figure 5.4. PTP vertical displacement is less than that of TM, and is likely to be an accurate representation of the foot end-point.

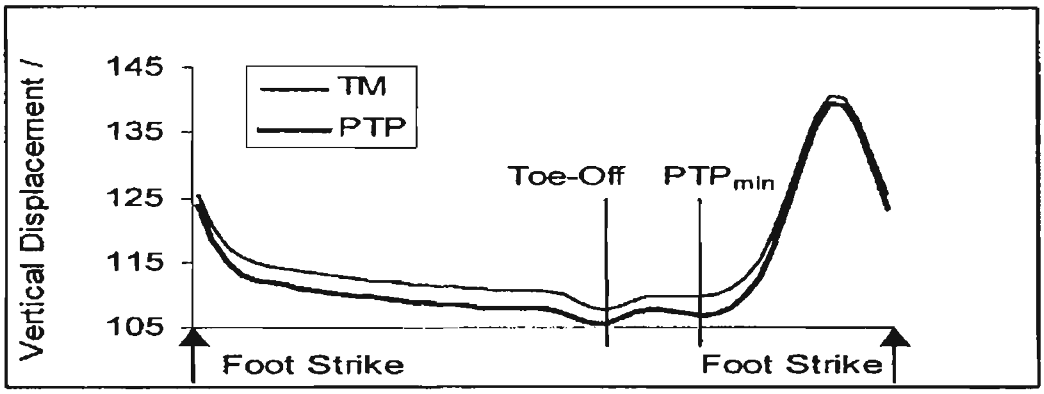


Figure 5.4 Vertical Displacement of TM and PTP Markers (adapted from James, 1999)

5.4 Development of ANN

5.4.1 Selecting Input Variables

In a recent review article, Chau (2001b) has emphasized the importance of proper pre-processing of input variables for good generalization performance of ANNs. In order to find out the effect of pre-processing of input variables to predict the stabilized MTC characteristics, seven ANNs were developed. 2-minute data were derived from 30-minute gait trial for each subject using the following equation:

2-minute data =2*(the number of gait trials during 30 minutes walking/30) Equation 5.3

As gait trials must be an integer number, the closest integer of the result was taken as the 2-minute's data.

The output of the ANNs had four statistics (mean, M; standard deviation, SD; skewness, S; kurtosis, K) derived from 30-minute gait trials, which were considered as stabilized MTC characteristics. The equations for calculating these four statistics are as follows:

$$M = \frac{\sum X}{N}$$ Equation 5.4

$$SD = \sqrt{\frac{\sum (X - M)^2}{N}}$$ Equation 5.5

$$S = \frac{\sum (X - M)^3}{(N-1)SD^3}$$ Equation 5.6

$$K = \frac{\sum (X - M)^4}{(N-1)SD^4} - 3 \qquad \text{Equation 5.7}$$

The skew for a normal distribution is zero, and symmetric data would also have skewness equal to zero. Negative values for the skewness indicate that data are skewed to the left and positive values for the skewness indicate that are skewed right.

The kurtosis for a standard normal distribution is three and the standard normal distribution is commonly considered that it has a kurtosis of zero from equation 5.7-3. Positive values calculated from Equation 5.7 indicate a "peaked" distribution and negative values indicate a "flat" distribution (Aron and Aron, 1999).

Seven different combinations of input variables were generated using the following data transformation techniques:

(a) Actual data normalized in time

Using actual data is a simple approach to represent the characteristics of MTC. The time intervals for 2-minute gait trials were normalized to 30 data points. Thirty actual MTC values were extracted for each subject by evenly dividing the number of gait trials into 30 intervals, and using the following formula:

$$V_i = [(V_{i2} - V_{i1}) * d] + V_{i1} \qquad \text{Equation 5.8}$$

where, V_i is the MTC value at interval i. V_{i2} is MTC value at the integer next to i (e.g. if i=3.6, then V_{i2} is the MTC value at interval 4), and V_{i1} is MTC value at the integer before i (e.g. if i=3.6, then V_{i1} is the MTC value at interval 3). d is the decimal part of i, i.e. 0.6.

These 30 actual MTC values were used as input variables for both training and test sets.

(b) Fast Fourier Transform (FFT) Coefficients

The Fourier Transform is a mathematical technique for resolving a time-domain function into a frequency spectrum. It is an algorithm, which converts a sampled complex-valued function of time into a sampled complex-valued function of frequency (Chau, 2001b). In this study, FFT software transformed the MTC data to their equivalent frequency domain coefficients (see Figure 5.5) and has been used in many studies for pre-processing input signals (Barton and Lee, 1997). FFT results in a set of FFT coefficients (real and imaginary). This was done using custom made Fourier transform software developed at Victoria University. As most useful information of a curve is mainly present in the low frequency region (Barton and Lees, 1995), the coefficients relating to lower frequencies i.e., the first 30 coefficients (15 real and 15 imaginary) were selected for input to the network. This method of input data pre-processing has been used by other investigators (Sepulveda, Wells and Vaughan, 1993; Barton and Lees, 1997) and shown to be an effective method for feature extraction.

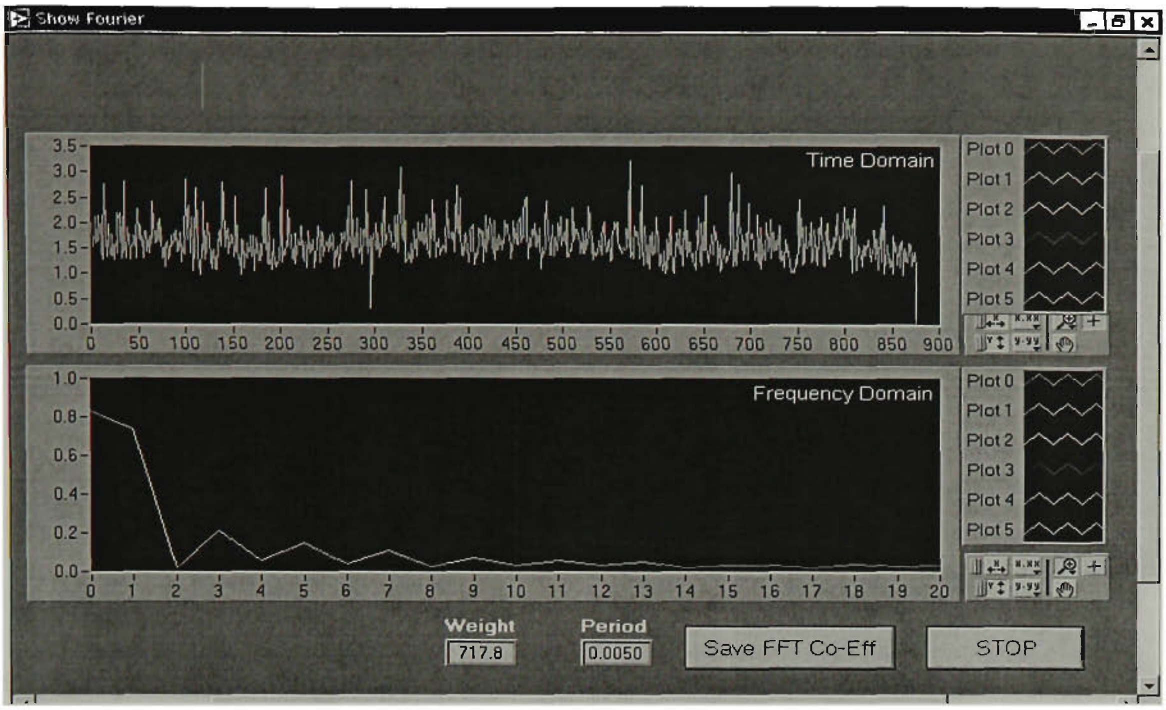


Figure 5.5 Output of FFT software showing time and frequency domain data. The graph on the top shows 15 minutes MTC data (time domain) for subject Y10. The graph on the bottom of the screen shows the equivalent MTC data (frequency domain) for subject Y10.

(c) Statistical parameters

Nine statistical parameters (Mean, Sum, SD, Minimum, Maximum, Variance, Range, Skewness and Kurtosis) were calculated from the MTC distribution for each of the input time intervals using the SPSS program (Aron and Aron, 1999). These parameters have been reported to represent main characteristics of a distribution function (Aron and Aron, 1999), and were used as inputs for both the training and test sets.

In addition to above three data types, combinations of these were used to test the effectiveness of data pre-processing on outcome results.

(d) Actual data + FFT coefficients (60 inputs)

(e) Actual data + Statistical data (39 inputs)

(f) FFT data + Statistical data (39 inputs)

(g) Actual + FFT + Statistical data (69 inputs)

Hence, combined with three pre-processed inputs, altogether seven different combinations of inputs were generated.

5.4.1.1 Development of Back Propagation Network (BPN)

5.4.1.1.1 Basic Structure of an ANN Developed for this Study

Back-propagation network (BPN) model has a number of advantages over other models (e.g. simplicity, easy to use and implement). In addition, it often acts as universal approximator for wide range of problems (Chau, 2001b; Dayhoff, 1990).

The typical structure of the developed BPN network is shown in Figure 5.6. The output layer had 4 processing elements (PEs). They were stabilized M, SD, S and K. The number of PEs making up the input layer depended on which combination of inputs was used to train and test the ANN (e.g. 30 PEs made up the input layer if only FFT coefficients were used as inputs). The number of PEs and layers making up the middle hidden layer changes from application to application and also depends on the complexity of the relationship between input and output data. As there is no precise rule to calculate the number of hidden layers, the number of PEs per layer required for convergence of training were determined experimentally. Chau (2001b) and NeuralWare (1991) have recommended that the BPN network developed with a single hidden layer, which includes sufficient PEs, can approximate any continuous function, regardless of its complexity. According to these studies, a three-layered BPN network is able to model any complex relationships. For that reason, in this study, all ANNs were developed with a single hidden layer.

The number of PEs in a hidden layer depends on inputs and outputs (NeuralWare, 1991):

Hidden layer PEs = (inputs +outputs) * (2/3) Equation 5.9

For example, a hidden layer between 20 inputs and 4 outputs would need 16 PEs.

The procedure underlying the development of the ANNs was followed (NeuralWare, 1991) and a number of tests by increasing and decreasing the number of PEs that resulted from above calculation (equation 5.9) were also conducted to find out the best structure of the BPN.

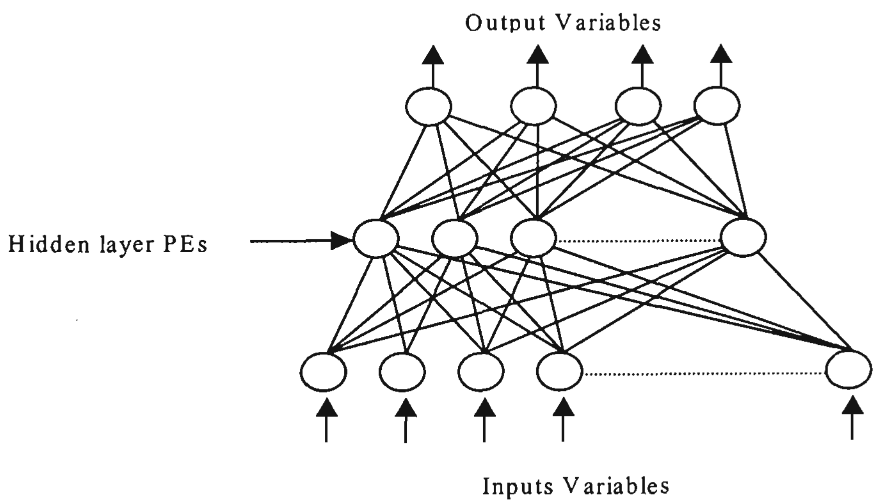


Figure 5.6 The basic structure of a BPN

Seven different BPN architectures, as shown in Table 5.2, were constructed to investigate the effect to BPNs' performance with different combinations of inputs. All the BPN configurations shown in Table 5.2 are the final ones, which had the best performance after numerous testing by adjusting the number of PEs in the hidden layer.

Table 5.2 Details of BPNs configurations. These configurations provided the best performance after hundreds of tests were conducted by adjusting the number of PEs in the hidden layer.

BPN	Input variables	Input PEs	PEs in the hidden layer	PEs in the output layer
Net 1	30 FFT coefficients	30	22	4
Net 2	30 Real MTC data	30	22	4
Net 3	9 statistics	9	8	4
Net 4	30 FT +30 Real data	60	32	4
Net 5	30 FT + 9 statistics	39	38	4
Net 6	30 Real data + 9 statistics	39	28	4
Net 7	30 Real data +30 FFT+9statistics	69	32	4

5.4.1.1.2 ANN learning and Transfer Function

ANN (NeuralWorks' professional II/plus software package) was used in designing, training and testing of the network. In this research, the "BackProp Builder" was employed to build different network configurations. It is a powerful tool that provides a fast and easy way to build networks by starting the standard network types and then adding necessary modifications. The standard network with particular learning rule and transfer function can be selected for training the desired network. Furthermore, the number of layers and the number of PEs in each layer can be specified by the user.

The "delta rule" learning combined with "Sigmoid Transfer Function", which generated the best results after various preliminary tests, was used to develop the BPNs. The actual weight update equations for the delta rule are as follows (NeuralWare, 1991):

$$w_{ij}' = w_{ij} + C_1 * e_i * x_{ij} + C_2 * m_{ij} \qquad \text{Equation 5.6}$$

$$m_{ij}' = w_{ij}' - w_{ij} \qquad \text{Equation 5.7}$$

C_1: learning coefficient 1 from the appropriate column of the learning and recall schedule.

C_2: learning coefficient 2.

x_i: input to the i^th PE.

w_i: initial weight vector for the i^th PE. w_{ij} is the connecting weight from the j^th input to the i^th PE.

w_i': the weight vector after it has been updated by the learning rule. $w_i' = (w_{i0}', w_{i1}', \ldots w_{in}')$

e: the error vector. If the current layer is the output layer, e is either the current error or the current error transformed by the derivative of the transfer function. Otherwise it may be the accumulated, transformed back-propagated error. The components of e are $e = (e_1 \ldots. e_n)$ where e_i is the error for the i_{th} PE in the current layer.

m_i: the memory of last change in weights for the i^th PE in the current layer.

The weights are changed in proportion to the error (e) and the input to that connection (x). The weight is updated when every pair of inputs and outputs are presented to the BPN.

5.4.1.2 Training and Testing Procedures

BPNs usually work well with large input data sets. Due to time constraints on data collection and analysis, MTC data of only 24 subjects were used for training and testing the BPNs. The training data set included 20 subjects' data and the test set had 4 subjects' gait data. Because of the limited number of subjects, the data were split into training and testing sets in six different ways, in order to cover the whole data range. In each group, there was an allocation of 16.7% of the total data to the test set, as shown in Table 5.3. The subjects' data in the shaded box were assigned to the testing set whereas data in the light boxes were assigned to the training set. Thus, each BPN was trained and tested six times. Similar method was also used by Barton and Lees (1997).

Table 5.3 Six ways the subject data were split into training and test sets. Subjects in shaded box were assigned to test set, and the remaining subjects in that column were assigned to the training set.

Subject 1-4	Subject 1-4	Subject 1-4	Subject 1-4	Subject 1-4	Subject 1-4
5-8	5-8	5-8	5-8	5-8	5-8
9-12	9-12	9-12	9-12	9-12	9-12
13-16	13-16	13-16	13-16	13-16	13-16
17-20	17-20	17-20	17-20	17-20	17-20
21-24	21-24	21-24	21-24	21-24	21-24
Group1	**Group 2**	**Group 3**	**Group 4**	**Group 5**	**Group 6**

The training strategy adopted and which led to repeatable results was as follows:

1) Delta learning style was used for adjusting the connection weights.
2) Sigmoid transfer function was used to transfer the internally generated sum for each PE to a potential output value.
3) 20 trials (epochs) with a decreasing learning rate ranging from 0.25 to 0.00001 was set.
4) 50000 iterations were used to train the BPN and the "Save best function" with test interval set to 3000 was selected to prevent over-training the BPN.

The details of training and testing data for Net 1, 2 and 3 are shown in Tables 5.4.1a to 5.4.1c in Appendix I.

5.4.2 Statistical Modelling to Predict MTC Statistics

Statistical techniques are often used for modelling the relationships between predictor variable(s) and dependent variable (Aron and Aron, 1999; Herrn, Sparti, Aminian and Schutz, 1999). In this study, stabilized four MTC statistics were also separately predicted using Multiple Linear Regression methods. Group 1 data (see Table 5.3) were used to model the relationship and evaluating its performance. The results were compared with BPNs' predictions.

Stepwise forward estimation method operated by SPSS software was used to calculate the regression coefficients for nine statistics calculated from 2-minute MTC data. This method is able to find the "best" regression model via examining the contribution of each predictor variable to the regression model (Hair, Anderson, Tatham and Black, 1992). A general MLR model developed for this research can be written as follows (Aron and Aron, 1999):

$$Y_i=a_i+(b_{1i})(X_M)+(b_{2i})(X_{SD})+(b_{3i})(X_{Variance})+(b_{4i})(X_S)+(b_{5i})(X_K)+(b_{6i})(X_{Range})+(b_{7i})(X_{Mimimum})+(b_{8i})(X_{Maximum})+(b_{9i})(X_{Sum})$$

where

Y_i:	the stabilized statistics (M, SD, S and K calculated from 30-minute data).
a_i:	the regression constant.
b_i:	the regression coefficient.
X:	the independent variables (nine statistics values, which were calculated from 2-minute MTC data).

5.4.3 Testing BPNs With Inputs Selected at Different Times

The purpose of this test was to investigate whether 2-minute input data taken from different locations within the 30 minutes data would affect the performance of the BPNs. Input data were selected from 5 different parts of 30 minutes data as illustrated in Figure 5.7.

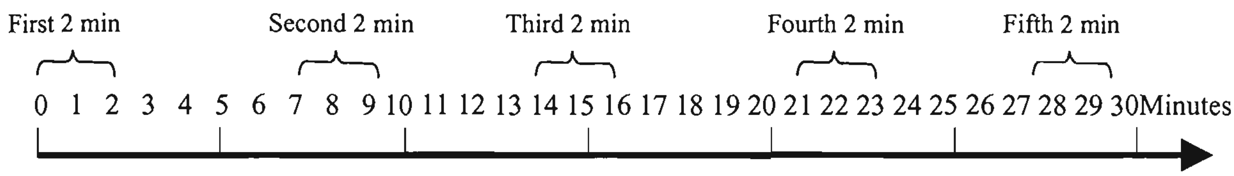


Figure 5.7 Figure illustrating sampling of input data at 5 different locations.

Four (Net 8-Net 11) additional BPNs were developed to predict the four stabilized MTC statistics from 9 statistical inputs relating to 2 minutes data. The architectures, learning style and transfer function of these BPNs were exactly the same as Net 3 shown in Table 5.2. These networks had 9 statistical inputs, 8 hidden layer PEs and 4 outputs (M, SD, S K).

The details of training and testing data for developing Net 8 to 11 are shown in Tables 5.4.3a to 5.4.3d in Appendix I.

5.4.4 Testing The Performance of BPNs with Different Input Data Segment Lengths

In this section, the performance of the developed BPN, in predicting steady-state stabilized MTC statistics from information relating to relatively fewer gait trials, was investigated. Data relating to relatively fewer gait trials were extracted from the 30-minute gait trial, and included 10 data segment lengths: the first 5, 10 and 20 gait trials, and the first 1, 2, 5, 10, 15, 20 and 25 minutes of MTC data. Nine statistical inputs were separately calculated for each of the above 10 data segment lengths. As the BPN for 2-minute data has already been developed (section 5.4.1.1), another nine BPNs were developed. The architectures and training strategies of these BPNs were same as Net 3 (see Table 5.2). The aim of this test is to find out the minimum number of gait trials required in predicting stabilized MTC statistics. All six groups of data (Table. 5.3) were used to train and test each of the BPNs.

Table 5.4 Characteristics of BPNs developed to test the effect of input data length on prediction performance.

BPNs	Input variables	Input PEs	PEs in the hidden layer	PEs in the output layer
Net 12	9 statistics (5 trials)	9	8	4
Net 13	9 statistics (10 trails)	9	8	4
Net 14	9 statistics (20 trials)	9	8	4
Net 15	9 statistics (1 minutes)	9	8	4
Net 16	9 statistics (5 minutes)	9	8	4
Net 17	9 statistics (10 minutes)	9	8	4
Net 18	9 statistics (15 minutes)	9	8	4
Net 19	9 statistics (20 minutes)	9	8	4
Net 20	9 statistics (25 minutes)	9	8	4

The details of training and testing data were shown in Tables 5.4.4a to 5.4.4i in Appendix I.

5.4.5 Selection of Input Variables

The performance of a developed ANN is highly sensitive to the choice of the appropriate selected input variables (Chau, 2001b). Discarding irrelevant variables and retaining only those that are potentially good predictors of the desired output variables would enhance network performance. In this section, the performances of BPNs were investigated by deleting and adding input variable(s) to the nine statistical inputs.

5.4.5.1 Increasing Characteristics of Input Data

In this section, the predicting accuracy of stabilized mean, M, was the focus. The nine statistics used in previous sections might well represent the characteristics of MTC data during different segment length. Although these inputs are able to reflect the general characteristics of MTC distribution, they do not provide information regarding the instantaneous change of MTC data. Best, Begg, Ball and James (2000) examined the 'stability' of MTC descriptive statistics (e.g. mean, SD, skew and kurtosis) as shown in Figure 5.8, which was derived by plotting each statistic e.g. mean, as they changed with the addition of new MTC data point. This type of graphical representation clearly indicates the trend of MTC. The nine statistics used in previous sections might represent the general characteristics of MTC data during different segment lengths, but they may not clearly indicate the trend of MTC over time. Hence, more information was added to the BPNs, to better represent the characteristics of MTC to investigate if this would improve the performance of BPN in predicting stabilized statistics, specially the stabilized M.

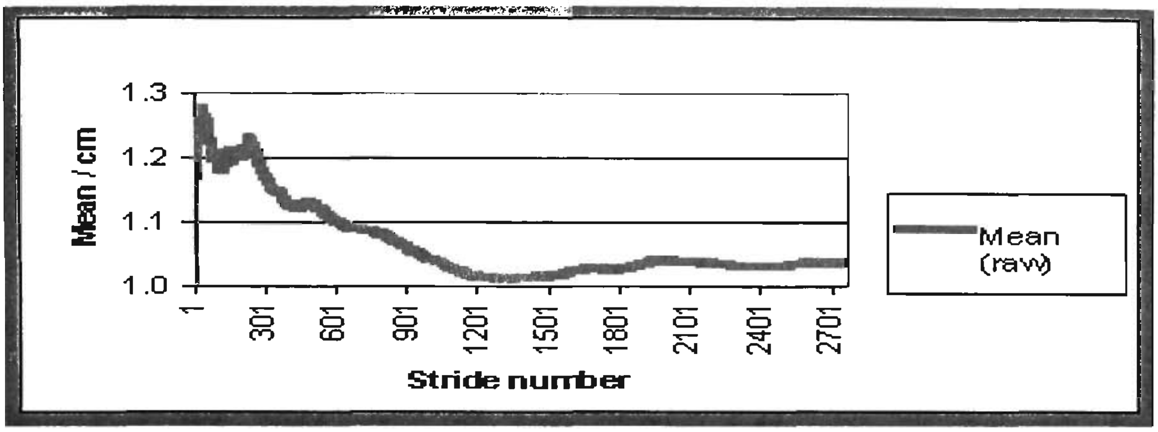


Figure 5.8 Stability of MTC mean for one subject for 1 hour (adapted from Best, Begg, Ball and James, 2000).

In order to provide more information to BPNs, 5 additional data were extracted and added to the input layer. For example, for 15-minute MTC data, 5 cumulative means at 14-, 13-, 12-, 11- and 10-minute time were calculated and added to BPN inputs. Three BPNs were developed for testing with 15-, 10- and 5 minutes MTC data. Five additional variables for 10-minute were the mean MTC values for the first 9-, 8-, 7-, 6- and 5-minute MTC data. Five additional variables for five minutes MTC data were slightly different. Four of them were calculated from the first 4-, 3-, 2- and 1-minute MTC data, and last one was the mean value of the first 5 trials' MTC data rather than the first single data.

Architectures of these BPNs are shown in Table 5.5. The training techniques of these BPNs were the same as Net 3 (see section 5.4.1.2). All six groups of data (Table. 5.3) were used to train and test these BPNs. Details of training and testing data sets are shown in Table 5.4.5a to 5.4.5c in Appendix 1.

Table 5.5 Characteristics of BPNs developed to test the effect of adding inputs on prediction performance.

BPN	Input variables	Input PEs	PEs in the hidden layer	PEs in the output layer
Net 21	14 statistics (5 minutes)	14	8	4
Net 22	14 statistics (10 minutes)	14	8	4
Net 23	14 statistics (15 minutes)	14	8	4

5.4.6 BPNs Developed for Separately Predicting Four Stabilized Statistics

In previous sections, all BPNs focused on predicting four statistics (M, SD, S and K) at the same time. BPNs modelled relationships between inputs and four outputs. The stored interconnection weights between input layer PEs and hidden layer PEs were related to all four output PEs during training. BPNs learnt the generalized relationships between input and all four outputs. They did not concentrate on learning the specific relationship between inputs and one output. The aim of this test was to examine whether BPNs predicting only one output statistic (e.g. M) would have better accuracy of prediction compared to the BPNs predicting all four statistics simultaneously.

Eight BPNs were developed to separately predict four stabilized statistics. The inputs variables used to develop Net 3 (nine inputs calculated from 2-minute data) and Net 23 (fourteen inputs calculated from 15-minute data) were used to develop these eight BPNs.

5.4.6.1 BPNs Developed with Nine Inputs

BPNs developed in this section were to investigate if separately predicting four statistics using nine statistical inputs would improve the performance of BPNs. The nine statistic variables (M, SD, variance, S, K, range, minimum, maximum and sum) derived from 2-minute MTC data were used as inputs to the BPNs (Net 24, 25, 26 and 27). The output variables of these four BPNs were respectively stabilized M (Net 24), SD (Net 25), S (Net 26) and K (Net 27). The architectures of these BPNs are shown in Table 5.6:

Table 5.6 Characteristics of BPNs developed to test the effect of individually predicting the stabilized statistics using nine statistical inputs.

BPN	Type of input variables	Input PEs	PEs in the hidden layer	PEs in the output layer
Net 24	9 statistics (2 minutes)	9	8	1 (M)
Net 25	9 statistics (2 minutes)	9	8	1 (SD)
Net 26	9 statistics (2 minutes)	9	8	1 (S)
Net 27	9 statistics (2 minutes)	9	8	1 (K)

Six groups of data were used to train and test each BPN (Table. 5.3). The training strategy adopted and which led to repeatable results, was the following:

1) Delta learning style was used for adjusting the connection weights.
2) Sigmoid transfer function was used to transfer the internally generated sum for each PE to a potential output value.
3) 20 trials (epochs) with a decreasing learning rate ranging from 0.25 to 0.00001 was set.
4) 50000 iterations were used to train the BPN and the "Save best function" with test interval set to 3000 was selected to prevent over-training the BPN.

5.4.6.2 BPNs Developed with Fourteen Inputs

The fourteen statistical variables (nine statistics calculated from the first 15-minute MTC data plus 5 mean MTC values calculated from the first 14-, 13-, 12-, 11- and 10-minute MTC data) were used as input variables to the BPNs (Net 28, 29, 30 and 31). The output variables of these four BPNs were respectively stabilized mean (Net 28), SD

(Net 29), skewness (Net 30) and kurtosis (Net 31). The architectures of BPNs are shown in Table 5.7:

Table 5.7 Characteristics of BPNs developed to test the effect of individually predicting the stabilized statistics using fourteen statistical inputs.

BPN	Input variables	Input PEs	PEs in the hidden layer	PEs in the output layer
Net 28	14 statistics (15 minutes)	14	8	1(M)
Net 29	14 statistics (15 minutes)	14	8	1(SD)
Net 30	14 statistics (15 minutes)	14	8	1(S)
Net 31	14 statistics (15 minutes)	14	8	1(K)

Six groups of data were used to train and test each BPN (Table. 5.3). The same training strategies as described in section 5.4.6.1 were used.

CHAPTER SIX

RESULTS AND DISCUSSION

In this chapter, the generalization ability of the neural networks was tested using predicted and desired results. Predicted results of the neural networks were compared with desired results to calculate BPN errors in their predictions and the implications of these results are discussed. Both absolute actual error (AAE) and the percentage of error (POE) of all predictions were determined using the following two formulae:

AAE = absolute (Desired Result – Predicted Result) Equation 6.1

POE = (AAE/ Desired Result)*100% Equation 6.2

The first section compares the performance of BPNs for different pre-processed inputs. The best prediction is then compared with predictions generated by statistical method (Multiple Linear Regression). Section 6.2 reports on results of the BPNs with input data selected from different parts within the total 30-minute duration. Nine statistical inputs calculated from 2-minute MTC data were used in this testing procedure. The results of BPNs developed with 10 different MTC data segment lengths are presented in section 6.3 to show how the prediction accuracy would be influenced by the length of input data. In section 6.4 results of BPNs with increased/reduced inputs are analysed. Finally, the results of BPNs developed to predict the four statistics individually are compared and discussed in section 6.5.

6.1 Optimising BPN Inputs

6.1.1 Effect of Input Variables and their Pre-processing on BPN Performance

In this section, input data are generated based on pre-processing the first 2-min raw MTC data using three different methods (actual data normalized in time, Fast Fourier Transforms and statistical technique). As each pre-processing method has its own way of describing the characteristics of 2-minute MTC data, their combinations might be able to more comprehensively represent characteristics than that provided by each individual method. Seven BPNs (Net1-Net7) were developed to predict the four stabilized statistics with Group1 data (see Table 5.3). The detailed individual results of the BPNs are shown in Table 6.1a to 6.1g (see testing results for Net1-7) in Appendix II.

Table 6.1 shows the overall results of four statistics predicted by the seven BPNs. These results show that overall all the BPNs had better performance in predicting M and SD, while had worse performance in S and K predictions. Furthermore, BPNs (Net 1, 4, 5, and 7), which used FFT coefficients, had largest error in predicting all four statistics. Net 2 developed with 30 real data performed well in predicting M and SD, nevertheless, it had poor performance in predicting S and K. The overall performance of Net 3 (nine statistical inputs) in predicting all four statistics was better than other BPNs. Especially the predictions for M, SD and S, which are regarded as the most important parameters for probability of tripping (PT) calculations (Best, Begg and James, 1999), had reasonable error.

Table 6.1 Prediction results of Net 1 to 7 developed with Group 1 data.

GROUP 1		M		SD		S		K	
Input variables		AAE (cm)	POE (%)	AAE (cm)	POE (%)	AAE	POE (%)	AAE	POE (%)
Net 1	30 FFT coefficients	0.305	28.9	0.084	24.7	0.722	104.7	4.660	508.2
Net 2	30 Real MTC data	0.155	12.9	0.050	13.9	0.735	144.4	4.778	468.2
Net 3	9 statistics	0.139	14.2	0.054	15.2	0.186	28.9	2.150	221.7
Net 4	30 FFT +30 Real	0.235	21.9	0.079	22.9	0.626	77.1	4.093	464.4
Net 5	30 FFT + 9 statistics	0.240	27.6	0.088	25.9	0.499	62.0	3.002	346.2
Net 6	30 Real + 9 statistics	0.145	12.6	0.054	15.3	0.292	58.9	2.210	236.7
Net 7	30 Real +30 FFT+9statistics	0.224	21.1	0.082	24.2	0.505	69.8	2.654	336.9

6.1.1.1 Good Performance of BPNs in Predicting Mean and SD

Net 2 (30 real data) performed the best predictions for both M and SD (POE_M=12.9% and POE_{SD}=13.9%). Net 6 using the combination of 30 real data and 9 statistics slightly improved the prediction accuracy for M (POE_M=12.6%), but slightly decreased the prediction accuracy for SD (POE_{SD}=15.3%) in comparison to Net 2. The BPN using the combination of 30 real data, 30 FFT coefficients and 9 statistics showed decreased prediction accuracy for M and SD further, with POE_M=21.1% and POE_{SD}=24.2%. These results indicated that increasing input variables sometimes improve the performance of the BPN, but also sometimes reduced the performance of the BPN. These also suggested that the input variables should be carefully selected. One of the characteristics of BPN is its ability to model relationships between inputs and outputs. This means inputs that provide better correlation with the outputs would result in better performance by the BPNs. Real data correlated to stabilized M/SD better than the FFT coefficients, because the FFT coefficients only represent frequency domain information of MTC data (see Figure 5.5 in Section 5.4.1) whereas real data provide the exact values. Then, the FFT coefficients would provide insufficient information to a BPN to predict a value. Input data including the FFT coefficients was seen to affect BPNs' performance, because the connection weights between PEs at the input layer and PEs at the hidden layer were influenced by the FFT coefficients (e.g. Net 1, 4, 5, 7). 9 statistics were found to describe the characteristics of 2-minute MTC data well. Their inclusion improved the prediction accuracy for M as shown in Table 6.1. Like real data, the statistical inputs also provided better prediction for M and SD.

6.1.1.2 Poor Performance of BPNs in Predicting Skewness and Kurtosis

Table 6.1 shows that the performance of the networks was, in general, poor in predicting S and K. To understand the reason for this, it is necessary to look at S and K calculations as shown below. S is a measure of symmetry, or more accurately, the lack of symmetry (Aron and Aron, 1999). It describes the distribution of MTC data deviated from a normal distribution curve. Mathematically, the value of S is:

$$S = \frac{\sum (X - M)^3}{(N-1)s^3}$$

The formula indicates that a data set exhibiting significant positive/negative skew depends on the result of

$$\sum (X - M)^3$$

The mathematical equation for calculating K also has been mentioned in section 5.4.1.

$$K = \frac{\sum (X - M)^4}{(N-1)SD^4} - 3$$

Any extreme data point in the distribution would affect K by a power of 4.

The above two formulas provide both polarity and value of S and K. A few extreme data in the distribution has the potential to affect both S & K significantly compared to

M & SD (see Figure 2.5 in section 2.1.4). For example, Figure 6.1 shows the first 2-minute MTC data for subject E5. An extreme MTC data point appeared at the 37th gait cycle. Four statistics of the first 36 MTC data are M=0.603cm, SD=0.193cm, S=-0.256 and K=-0.259, whereas, after adding this high value (MTC value at the 37th gait cycle) S and K changed significantly including their sign (S=0.444 and K=1.243), whereas M and SD had minimal change (M=0.622cm and SD=0.220cm). Even a single extreme data has the potential to cause a large change in both S and K. Such change in MTC data may be caused by subject's change in walking style due to some external distractions and might affect both the polarity and value of stabilized S and K. If this type of information were not presented in the input data, it would be unlikely for the networks to predict the stabilized S and K. Extreme data point(s) have the potential to affect stabilized S and K values more than M and SD values. If this type of extreme data are not presented to networks' training set, BPN would be unlikely to be able to model S and K accurately. This does not support the initial hypothesis that S and K derived from fewer gait trials might provide ANN significant information to predict stabilized S and K accurately.

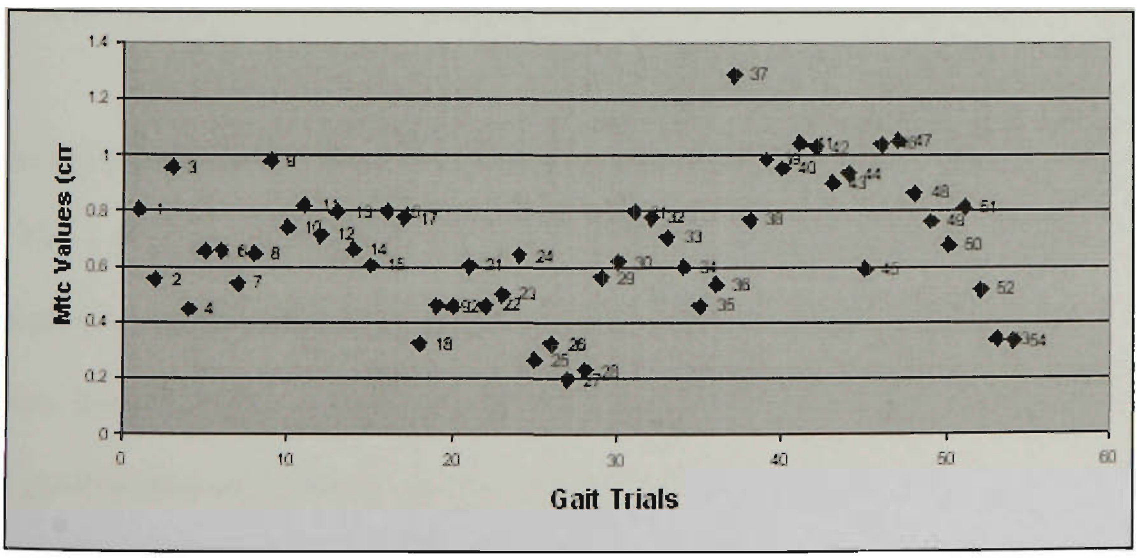


Figure 6.1 First 2-minute MTC data for subject E5 (E=Elderly). There were 54 gait cycles/trials in 2-minute treadmill walking test. A high MTC data point appeared at the 37th trial.

6.1.1.2.1 Polarity of S and K on Prediction Accuracy

In this research, both polarity and value of S and K were predicted by the BPNs. The above two formulas (see section 6.1.1.2) show that both S and K are related to every value in a set of MTC data by a power of 3 and 4 respectively. It is possible that one extreme data could affect either the value or the polarity of S and K (positive/negative). Calculations for AAE and POE have been described at the beginning of this chapter (see equations 6.1 and 6.2). It is worth noting that the wrong prediction in the polarity of S and K could amplify the value of AAE and POE. For example, the desired S for subject Y8 is -0.238 (negative skew), and the predicted S is 0.804 (positive skew). Calculated absolute error i.e., AAE_S is 1.042, and the corresponding percentage error (POE_S) is 437.4%. As shown in the previous section, this reversal of the sign of S is possible even by one extreme data point. Predicting both the polarity and value of S and K at the same time introduces more complexity in the development of a BPN. This may be one of the reasons why the S and K prediction errors are so large.

6.1.1.2.2 Effect of Variability of S and K on the Performance of BPN

The results in Table 6.1 show that the best results in predicting S and K were generated by Net 3 (POE_S= 28.9%, and the POE_K=221.7%). It seems to indicate that the nine statistics were able to better represent the characteristics of MTC data compared to other inputs. But the POEs were large, especially the POE_K, suggesting that these BPNs were not good predictors, especially for K. In the test, S and K for 30-minute MTC data were predicted from information related to 2-minute MTC data. Hence, the prediction accuracy would depend on how accurately the 2-minute MTC data were able to relate to S and K for 30-minute MTC data.

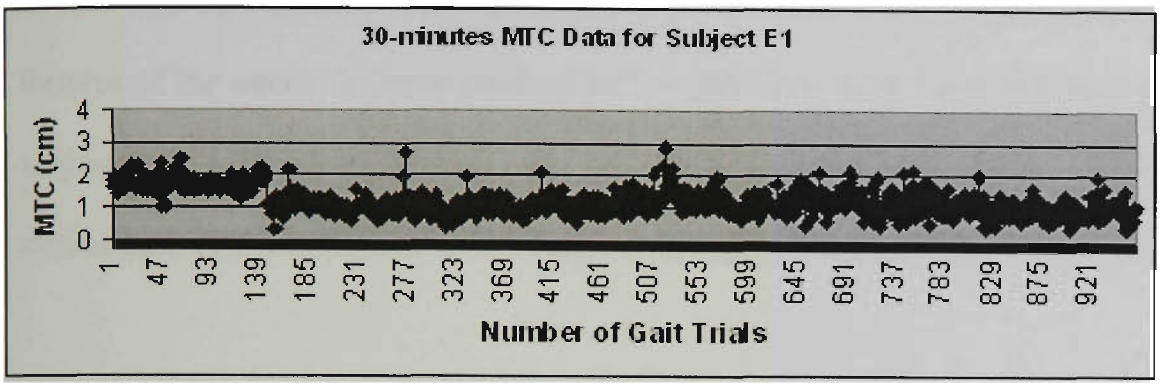
Table 6.2 shows a comparison of S and K between 2-minute MTC data and 30-minute MTC data for all subjects in Group 1. The averaged absolute difference for S is 0.433, and that for K is 1.195. These data suggest that both S and K of 2-minute data differ from their respective 30-minute data significantly (except S of subject Y7). Furthermore, the polarity of S for subjects E1 and Y8 are completely different when compared between their 2-minute and 30-minute data (for example, S for 2-minute MTC data for subject E1 is negative, whereas for 30-minute data it is positive). It was thought that some significantly high MTC value(s) after 2-minute walking could have changed the sign of S from a left-skewed distribution to a right-skewed distribution.

Table 6.2 Comparison of calculated S and K between 2-minute data and 30-minute data for individual subjects in Group 1.

SUBJECTS	2-MINUTE S	30-MINUTE S	ABSOLUTE DIFFERENCE	2-MINUTE K	30-MINUTE K	ABSOLUTE DIFFERENCE
Y1	0.144	0.511	0.368	0.381	0.716	0.335
E1	-0.200	0.685	0.884	1.408	0.453	0.956
Y7	2.449	2.456	0.006	6.678	7.145	0.467
Y8	0.238	-0.238	0.476	-0.430	2.593	3.023
Average			0.433			1.195

Figure 6.2 shows the MTC data for subjects E1 and Y8 during 30 minutes treadmill walking. Figure 6.2a shows the MTC data for subject E1 significantly changed after the 146th trail (approximately 4.5-minute treadmill walking). The average MTC for the first 146 MTC data is 1.73cm, and the average MTC for the rest of MTC data is 1.1cm. A number of high MTC data also appeared after the 146th trial. Those high MTC data might be responsible to change the distribution from negative skew to positive skew. In

subject Y8, there are also some extreme MTC data, which are sufficient to change the polarity of S between 2-minute and 30-minute data. More discussion about this has been presented in section 6.3.3.1. Hence, it is very unlikely that the BPNs would be able to find relationships for S and K between their 2-minute and 30-minute data.



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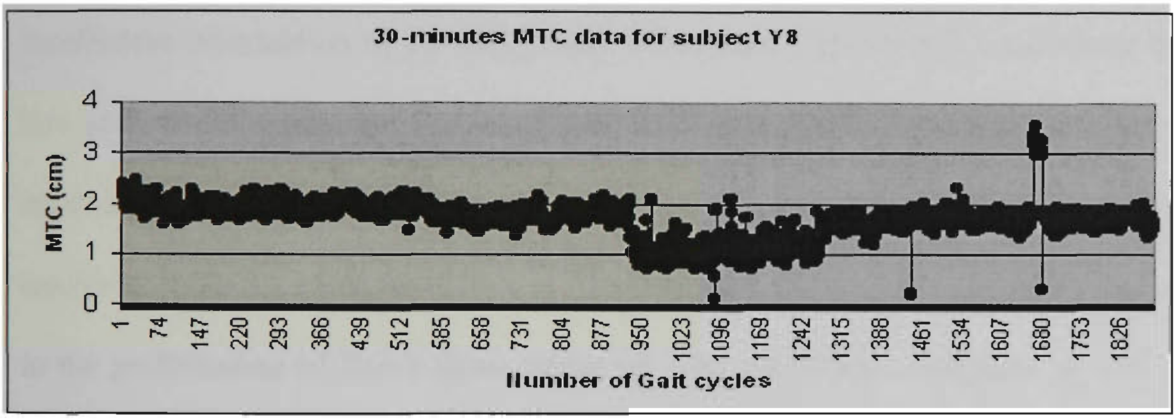


b

Figure 6.2 MTC data for subject E1 and Y8 during 30-minute gait trials

In summary, human gait is variable, and so is the MTC value from one gait cycle to the next one (Winter, 1991). Although, the nine statistical parameters have represented the characteristics of 2-minute MTC data well in predicting M and SD, these inputs provide insufficient information to the BPNs to correctly predict both the polarity and value of S and K for 30-minute data.

6.1.1.3 FFT Coefficients Provided Insufficient Information

FFT has been used in other research as one of the main data pre-processing techniques to train BPNs. It is often regarded as a feature extracting technique in frequency domain or curve fitting function, which reduces the size of the pattern but still preserves the features of the curve. In some studies, FFT coefficients have been shown to perform very well as ANN inputs (Barton and Lees, 1997; Holzreiter and Köhle, 1993). These studies used FFT coefficients in ANNs to classify gait characteristics.

The aim of this study was to predict exact values, and FFT coefficients provided insufficient information to the BPNs (see Table 6.1). The 30 FFT coefficients used in this study could extract the feature of the MTC curve, but it perhaps lacks in providing necessary information to accurately predict exact stabilized statistical values. The results in Table 6.1 show that Net 1 (FFT coefficients) performed poorly in comparison to the performance of Net 3 (nine statistics). The prediction accuracies of Net 1 were fairly low; POE_M=28.9%, POE_{SD}=24.7%, POE_S=104.7% and POE_K=508.2%. Furthermore, when FFT coefficients were added to the inputs, the performance of the BPNs deteriorated. For example, Net 3 with nine statistics performed considerably better (POE_M=14.2%, POE_{SD}=15.2%, POE_S=28.9% and POE_K=221.7%) than Net 5 with nine statistics and 30 FFT coefficients (POE_M=27.6%, POE_{SD}=25.9%, POE_S=62% and POE_K=346.2%). These results indicate that FFT coefficients did not map well the relationships between characteristics of MTC data derived from 2-minute data and that derived from 30-minute data, when applied to predict exact MTC data. The reason why FFT coefficients could not accurately predict stabilized statistics has been described in section 6.1.1.1.

6.1.1.4 Use of Raw Data to Represent MTC Characteristics

30 real data representing the features of MTC data were derived from 2-minute data and these are perhaps the most direct way to represent the MTC characteristics. The results in Table 6.1 show that Net 2 with 30 real data better predicted the stabilized M and SD (POE_M = 12.9% and POE_{SD} = 13.9%) than other BPNs. Nevertheless, it poorly predicted the stabilized S and K (POE_S =144.4% and POE_K=468.2%). These results demonstrate that the real values as inputs might efficiently improve the performance of BPN in predicting M and SD, but might provide insufficient information to BPNs in predicting S and K. Chau (2001b) concluded that the performance of the BPN is highly sensitive to the choice of input gait variables. Figure 6.3 shows the extraction of 30 real data for subject Y1. The diamonds in Figure 6.3 are the actual MTC data for 2-minute data, and the squares are the 30 real data extracted as inputs. As can be seen from Figure 6.3 although the 30 real data discribes well the trend of the curve well, many small and large values have been missed out. These missing values can be important to work out the skewness and kurtosis, as described earlier (see section 6.1.1.2).

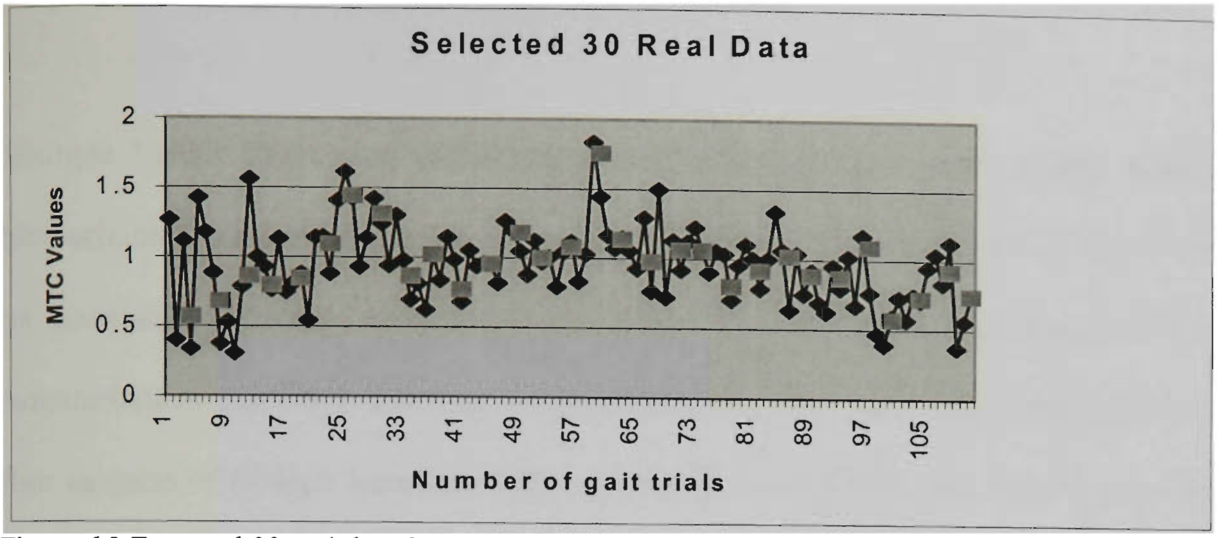


Figure 6.3 Extracted 30 real data for subject Y1. Dark diamonds are the actual MTC data for 2-minute (112 gait trials). Light squares are the extracted 30 real data.

Table 6.3 shows the four statistics (M, SD, S and K) calculated from 2-minute MTC data for subjects in the testing data set and also those four statistics calculated from 30 real data extracted from 2-minute data. Results show that both POE_M and POE_{SD} are relatively small (e.g. the maximum POE_M=9.4%, and the maximum POE_{SD}=16.9%).

Table 6.3 Comparison of four statistics (M, SD, S and K) calculated between 30 real data and 2-minute data for all subjects in the testing set (Group 1). Y=Young and E=Elderly. AAE is absolute actual error & POE is percentage of error.

	M (CM)				SD (CM)				S				K			
	2-min	30 Real	AAE	POE (%)	2-min	30 Real	AAE	POE (%)	2-min	30 Real	AAE	POE (%)	2-min	30 Real	AAE	POE (%)
Y1	0.950	0.967	0.017	1.8	0.285	0.247	0.038	13.3	0.144	1.148	1.005	700.0	0.381	2.629	2.249	590.4
E1	1.753	1.757	0.004	0.2	0.259	0.216	0.044	16.9	-0.200	-0.082	0.117	58.8	1.408	1.417	0.008	0.6
Y7	0.434	0.475	0.041	9.4	0.361	0.409	0.048	13.3	2.449	2.724	0.274	11.2	6.678	7.448	0.770	11.5
Y8	1.962	1.973	0.011	0.6	0.176	0.146	0.030	16.9	0.238	0.193	0.045	18.9	-0.430	-0.596	0.166	38.6
Average				3.0				15.1				197.2				160.2

Both POE_S and POE_K are very high (e.g. the maximum POE_S = 700%, and the maximum POE_K = 590.4). According to these results, the 30 real data even can not discribe the S and K of 2-minute data, it is very unlikely that they would be able to contain enough information for skewness and kurtosis of 30-minute data.

6.1.2 Prediction Outcomes of Statistical Modelling

Multiple Linear Regression (MLR) statistical techniques have been widely used in biomechanical analysis for many years (Chau, 2001b). MLR makes predictions based on associated variables (Aron and Aron, 1999). The results of MLR predictions are summarized in Table 6.4. The four stabilized statistics were separately predicted for the four subjects of Group1 based on different predictor variable(s). The results show that the average AAEs for M and SD were low (AAE_M=0.209cm, and AAE_{SD}=0.064cm). Also, their POE was less than 20% (POE_M=19%, and POE_{SD}=18.3%). But these prediction errors were more than the corresponding BPN predictions using similar data (see Net 3, Table 6.1, POE_M=14.2%, and POE_{SD}=15.2%).

POEs of predicted S and K by MLR method were too high (POE_S=150%, and POE_K=130%). These results indicate that the statistical modeling technique using MLR was able to predict M and SD with moderate accuracy, but the error was too high when applied to predict S and K. Also, MLR model performed poorly in predicting the polarity of S. For instance, S predicted for subject E1 was negative, but the desired skew was positive. Conversely, the neural network predicted polarity accurately for all subjects (see Table 6.5). Although the overall POE_K of MLR (130%) was less than that of BPN (221.7%), the prediction error for K was too high. These results indicate that multiple linear regression modelling perhaps lacks in its ability to describe the complex, non-linear relationships between 30-minute and 2-minute data.

Table 6.4 Tested results from MLR developed with Group 1 data.

Subjects	Desired M (cm)	Predicted M (cm)	Absolute Actual Error (cm)	Percentage of error (%)
Y1	0.860	1.024	0.164	19.1
E1	1.196	1.076	0.119	10.0
Y7	0.502	0.604	0.102	20.3
Y8	1.681	2.130	0.449	26.7
Average			0.209	19.0

Subjects	Desired SD (cm)	Predicted SD (cm)	Absolute. Actual Error (cm)	Percentage of error (%)
Y1	0.266	0.302	0.036	13.4
E1	0.378	0.290	0.088	23.3
Y7	0.359	0.339	0.020	5.6
Y8	0.361	0.249	0.112	31.0
Average			0.064	18.3

Subjects	Desired S	Predicted S	Absolute Actual Error	Percentage of error (%)
Y1	0.511	0.328	0.183	35.8
E1	0.685	0.243	0.441	64.5
Y7	2.456	1.311	1.144	46.6
Y8	-0.238	0.846	1.085	455.4
Average			0.713	150.6

Subjects	Desired K	Predicted K	Absolute Actual Error	Percentage of error (%)
Y1	0.716	0.573	0.143	20.0
E1	0.453	1.810	1.358	299.8
Y7	7.145	4.308	2.836	39.7
Y8	2.593	6.753	4.160	160.4
Average			2.124	130.0

Table 6.5 S and K predictions by Net 3 for all subjects in the testing data set in Group 1.

Subjects	Desired S	Predicted S	Absolute Actual Error	Percentage of error (%)
Y1	0.511	0.924	0.412	80.7
E1	0.685	0.489	0.196	28.6
Y7	2.456	2.321	0.135	5.5
Y8	-0.238	-0.236	0.002	0.7
Average			0.186	28.9
Subjects	**Desired K**	**Predicted K**	**Absolute Actual Error**	**Percentage of error (%)**
Y1	0.716	2.916	2.200	307.2
E1	0.453	2.589	2.136	471.7
Y7	7.145	9.451	2.306	32.3
Y8	2.593	0.637	1.957	75.5
Average			2.150	221.7

6.1.3 Overall Performance of BPNs Using Seven Combinations of Inputs

BPN learns relationships between its inputs and outputs by examples presented to it. Different training samples (examples) can provide BPNs with different relationships to model. In section 6.1.1, the performances of seven BPNs tested with Group 1 data were analysed. One group of training and testing data may not be able to correctly indicate performance of BPNs, because characteristics of the randomly selected 20 training samples may not fully cover characteristics of the testing data. Generally, the larger the sample size in training data set, the better the performance of BPN (NeuralWare, 1991; Holzreiter, and Köhle, 1993). A total of 24 subjects were used in this study because of time limitation in collecting and processing MTC data. It is therefore, necessary to train and test BPN with different combinations of training and testing samples (see section 5.4.1.2) to investigate the performance of BPN. This method of testing neural networks has been used in other studies, e.g. by Barton and Lees (1997). So overall performance of BPNs (Net1 to 7) was investigated using all six groups data (see Figure 5.3 for division of subjects into groups).

Table 6.6 is the summarized results of predictions by all groups. Detailed individual results of four statistics predicted by the BPNs are shown in Table 6.1a to 6.1g (testing results for Net1 to 7) in Appendix II. The average results for twenty-four subjects show that all BPNs performed reasonably well in predicting stabilized M and SD, but not well in predicting stabilized S and K. The best-predicted M was produced by Net 6 (30 real and 9 statistics inputs) with average POE_M=19.1%. 16 subjects' POE_M were less than 15%. 10 out of 16 subjects' POE_M were less than 10%. Six subjects' POE_M were greater than 30%. One of subject (E2) had extremely high error with POE_M=104.9%. These results indicate that 66.6% subjects' M could be accurately predicted by BPN with $POE_M<15\%$, whereas other 25% subjects had $POE_M>30\%$. The possible reason may be the limited training sample, which could not cover the characteristics of the testing set. This will also be discussed in later section (see section 6.4.2).

Net 2 (30 real inputs) generated the best-predicted SD (average $POE_{SD}=14.3\%$), but poor predictions in S ($POE_S = 104\%$) and K ($POE_K = 346.6\%$). Net 1 (with 30 FFT coefficients inputs) again had the poor predictions for all four statistics. BPNs using real data had better performance in predicting M than BPNs without them. For example, POE_M from Net 3 (9 statistics inputs) was 22%, while POE_M from Net 6 (9 statistics and 30 real data inputs) was 19.1%. Similarly, inclusion of nine statistics inputs also improved performance. For example, POE_M from Net 2 (30 real data inputs) was 21.5%, while POE_M from Net 6 (9 statistics and 30 real data inputs) was 19.1%. However, thirty real inputs did not improve the performance of BPNs in predicting other stabilized statistics.

Table 6.6 Accuracy of four stabilized statistics predicted by the BPNs (Net 1 to Net 7) developed using all six groups' data. Net 1: 30 FFT coefficients, Net2: 30 Real data, Net 3: nine statistical inputs, Net 4: 30 FFT coefficients+30 real data, Net5: 30 FFT coefficients+9 statistics, Net 6: 30 real data+9 statistics, Net 7: 30 FFT coefficients+30 real data+9 statistics.

BPN	M		SD		S		K	
	Average AAE (cm)	Average POE (%)	Average AAE (cm)	Average POE (%)	Average AAE	Average POE (%)	Average AAE	Average POE (%)
Net 1	0.395	34.9	0.068	23.0	0.903	149.8	4.869	449.6
Net 2	0.214	21.5	0.054	14.3	0.709	104.0	4.562	346.6
Net 3	0.240	22.0	0.042	14.6	0.550	84.0	4.062	304.1
Net 4	0.246	23.0	0.066	22.6	0.836	124.1	5.044	539.1
Net 5	0.279	26.6	0.053	18.6	0.789	119.6	4.130	230.7
Net 6	0.218	19.1	0.061	21.1	0.581	119.1	4.267	304.2
Net 7	0.230	21.5	0.054	19.1	0.727	112.4	4.061	273.1

Although, real data and nine statistics could potentially improve the performance of BPNs in predicting M, but their combination did not improve the performance in predicting other statistics. POE_{SD} increased from14.6% to 21.1% when real data were added to statistical inputs.

Pre-processing of input data appeared to affect the performance of BPNs significantly. As mentioned before, FFT coefficients were used quite often and exhibited the excellent feature extraction ability in previous research (Chau, 2001b). In this study, they performed poorly in predicting exact statistical values. Consequently, FFT coefficients were excluded from further study. The real data only provided better performance for M and SD prediction, but showed decreased performance in predicting others. Thirty real data points were not able to describe well the feature of long-term data and were excluded from further testing. The performance of Net 3 (nine statistics) in predicting all four statistics showed relatively better predicting ability. Any other inputs combined with nine statistics did not improve the predicting performance of the BPNs significantly. Among all the input combinations, statistical inputs seemed to be the best choice, and therefore were used in subsequent BPN training and testing.

6.1.4 Summary of Performance of BPNs Using Different Combinations of Inputs and MLR Model

Both neural networks and multiple linear regression models showed good accuracy to predict stabilized M and SD, but performed poorly for S and K. Results show that prediction results using multiple regression method were not as good as the BPNs. Multiple regression model incorrectly differentiated the polarity of S, but the BPN (Net 3) correctly differentiated them. Although, overall prediction accuracy was not good for

BPNs for S and K (POE_S=28.9%, POE_K=221.7%), in comparison to multiple regression method (POE_S=166.2%, POE_K=410%) the predicting ability of BPN was better.

In addition, the results of BPNs developed with different combination of input data showed that Net 3 (with nine statistics inputs) seemed to perform the best. Nine statistics seemed to better represent the feature of MTC data derived from different data segments compared to other pre-processing techniques. There might be three other possibilities that might affect the accuracy of predictions as discussed below:

1. The MTC data derived from the first 2-minute gait trials may not provide enough information to the BPNs (Net 3) to predict stabilized statistics. However, the 2-minute data derived from other parts within the 30-minute data might provide more useful information to BPN.
2. The MTC data derived from the 2-minute gait trials might not provide enough information to the BPN (Net 3). Thus, the effects of increasing more data (data length) to the inputs need to be tested.
3. Nine statistics might not be the best inputs. So effects of additional information to the BPN inputs need to be investigated.

In the next sections, results from further tests explore the issues raised above.

6.2 Effect of Different Blocks of MTC Data on Performance of BPN

The aim of this section was to investigate whether nine statistical inputs calculated from 2-minute data segment derived from five different parts of 30-minute data would affect the performance of the BPNs. BPNs developed in this section were trained and tested with Group 1 data. The testing results in Table 6.7 and Figure 6.4 show that 2-minute data taken from different locations generated different results. For example, the best result for subject Y1 was from Net 8 (7-9min) with POE_M of 6.6%, while POE_M for the same subject was 34.8% predicted by Net 9 (14-16min). Corresponding AAE_M increased from 0.057cm to 0.299cm.

K for all the subjects was poorly predicted by all the BPNs. S for most subjects (except S for Y8 predicted by Net 3 with POE_S=0.7%) was also poorly predicted by all the BPNs. Some BPNs (Net 3 and 8) moderately predicted M (average POE_M=20.7%) for all subjects. SD was relatively predicted well by all BPNs. Average POEs of four statistics were quite different. None of the four statistical predictions (M, SD, S and K) show any clear trend (Figure 6.4), meaning the predicting ability of 2-minute data does not depend on where that 2-minute data is taken. Although SD appears to decrease up to 21-23 min (averaged POE_{SD}=10.5%) and then rise for 28-30 min data (averaged POE_{SD}=18.2%), it is unlikely that Net 11 (28-30min) was overtrained. This is because of the set up of overtraining prevention in the network (see section 5.4.1.2). One reason for the poor SD prediction might be a substantial difference in training or testing data set (as highlighted in Figures 6.5a and 6.5b).

Table 6.7 Testing results of BPNs developed with 2-minute MTC data selected from 5 different parts of 30 minutes (Group 1 data and nine statistics only).

NET 3	M				SD				S				K			
0-2min	Desired	Predicted	AAE (cm)	POE (%)	Desired	Predicted	AAE (cm)	POE (%)	Desired	Predicted	AAE	POE (%)	Desired	Predicted	AAE	POE (%)
Y1	0.860	0.945	0.086	9.9	0.266	0.287	0.021	7.7	0.511	0.924	0.412	80.7	0.716	2.916	2.200	307.2
E1	1.196	1.371	0.176	14.7	0.378	0.294	0.084	22.2	0.685	0.489	0.196	28.6	0.453	2.589	2.136	471.7
Y7	0.502	0.606	0.104	20.7	0.359	0.330	0.029	8.2	2.456	2.321	0.135	5.5	7.145	9.451	2.306	32.3
Y8	1.681	1.871	0.190	11.3	0.361	0.279	0.082	22.6	-0.238	-0.236	0.002	0.7	2.593	0.637	1.957	75.5
Average			0.139	14.2			0.054	15.2			0.186	28.9			2.150	221.7

Net 8	M				SD				S				K			
7-9min	Desired	Predicted	AAE (cm)	POE (%)	Desired	Predicted	AAE (cm)	POE (%)	Desired	Predicted	AAE	POE (%)	Desired	Predicted	AAE	POE (%)
Y1	0.860	0.803	0.057	6.6	0.266	0.268	0.002	0.6	0.511	0.735	0.224	43.9	0.716	1.168	0.452	63.2
E1	1.196	0.876	0.320	26.7	0.378	0.321	0.057	15.2	0.685	1.550	0.865	126.4	0.453	6.686	6.233	1376.5
Y7	0.502	0.620	0.118	23.6	0.359	0.311	0.048	13.3	2.456	1.461	0.995	40.5	7.145	4.130	3.015	42.2
Y8	1.681	2.029	0.348	20.7	0.361	0.245	0.116	32.1	-0.238	0.293	0.531	223.0	2.593	5.975	3.382	130.4
Average			0.211	19.4			0.056	15.3			0.654	108.4			3.271	403.1

Net 9	M				SD				S				K			
14-16min	Desired	Predicted	AAE (cm)	POE (%)	Desired	Predicted	AAE (cm)	POE (%)	Desired	Predicted	AAE	POE (%)	Desired	Predicted	AAE	POE (%)
Y1	0.860	1.159	0.299	34.8	0.266	0.335	0.069	25.9	0.511	1.255	0.744	145.4	0.716	6.051	5.335	745.0
E1	1.196	1.280	0.084	7.0	0.378	0.309	0.069	18.2	0.685	0.601	0.084	12.3	0.453	2.451	1.998	441.3
Y7	0.502	0.972	0.470	93.8	0.359	0.332	0.027	7.5	2.456	1.375	1.081	44.0	7.145	5.413	1.732	24.2
Y8	1.681	1.944	0.264	15.7	0.361	0.380	0.019	5.3	-0.238	0.369	0.607	255.0	2.593	4.058	1.465	56.5
Average			0.279	37.8			0.046	14.2			0.629	114.2			2.633	316.8

Net 10	M				SD				S				K			
21-23min	Desired	Predicted	AAE (cm)	POE (%)	Desired	Predicted	AAE (cm)	POE (%)	Desired	Predicted	AAE	POE (%)	Desired	Predicted	AAE	POE (%)
Y1	0.860	0.931	0.071	8.3	0.266	0.303	0.037	13.9	0.511	1.366	0.854	167.2	0.716	5.790	5.074	708.6
E1	1.196	1.372	0.176	14.7	0.378	0.346	0.032	8.5	0.685	1.531	0.847	123.7	0.453	9.821	9.368	2068.8
Y7	0.502	0.677	0.175	34.9	0.359	0.348	0.011	3.0	2.456	2.748	0.292	11.9	7.145	13.993	6.848	95.8
Y8	1.681	2.384	0.703	41.9	0.361	0.301	0.060	16.7	-0.238	-0.736	0.498	209.0	2.593	0.748	1.845	71.1
Average			0.281	24.9			0.035	10.5			0.623	127.9			5.784	736.1

Net 11	M				SD				S				K			
28-30min	Desired	Predicted	AAE (cm)	POE (%)	Desired	Predicted	AAE (cm)	POE (%)	Desired	Predicted	AAE	POE (%)	Desired	Predicted	AAE	POE (%)
Y1	0.860	0.965	0.105	12.3	0.266	0.303	0.037	13.8	0.511	0.484	0.028	5.4	0.716	-0.064	0.780	108.9
E1	1.196	0.961	0.235	19.7	0.378	0.318	0.060	15.9	0.685	0.403	0.281	41.1	0.453	-0.536	0.989	218.3
Y7	0.502	0.962	0.460	91.8	0.359	0.333	0.026	7.3	2.456	0.702	1.754	71.4	7.145	1.609	5.536	77.5
Y8	1.681	2.084	0.404	24.0	0.361	0.232	0.129	35.7	-0.238	-0.587	0.349	146.6	2.593	0.505	2.088	80.5
Average			0.301	36.9			0.063	18.2			0.603	66.1			2.348	121.3

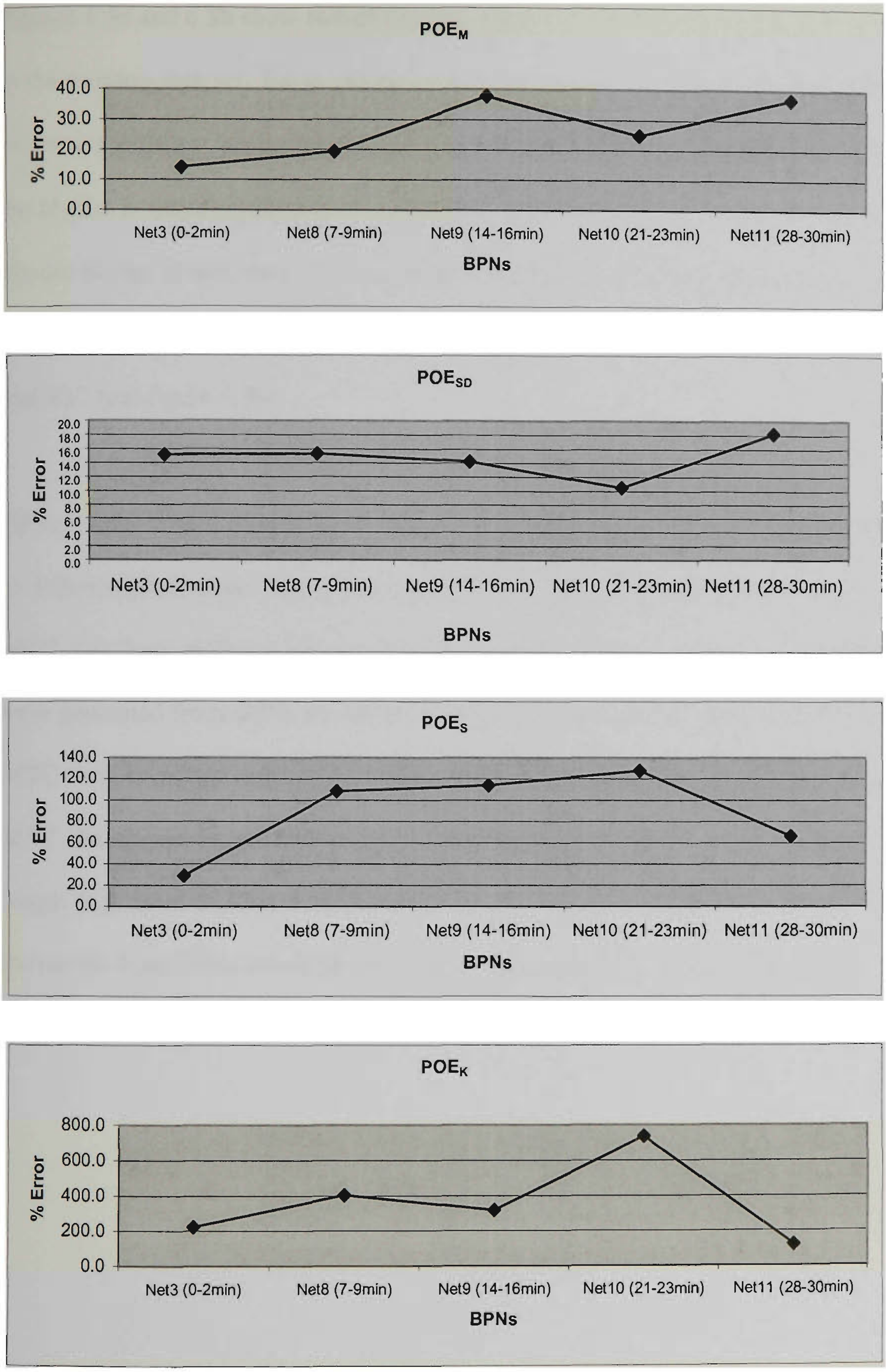


Figure 6.4 Average POE of all statistics (M, SD, S and K) generated by Net 8-11 and Net 3.

POE=Percentage of error.

Figures 6.5a and 6.5b show two of the nine statistical inputs (M and SD) for all subjects in the training data set. These graphs (Figure 6.5a and 6.5b) reveal that both M and SD values are different across the five 2-minute blocks. Sometimes the variability between the blocks is quite significant. For example, M for subject Y5 during the first four 2-minute blocks is less than 0.67cm, whereas for the 28-30 minutes block it is 1.089cm. Significant variations across blocks can also be seen for SD for subjects E2, E4, Y11 and Y17 (see figure 6.5b).

BPNs trained with different inputs whereas expecting same outputs would certainly lead to different predictions during testing. This might be one of the reasons why 2-minute MTC data from different blocks generated varying results. The results obtained so far were generated from BPNs developed with 2-minutes data and indicated that 2-minutes MTC data could not provide sufficient information to BPNs for predicting stabilized MTC characteristics. It is necessary to obtain nine statistics from increased MTC data length (e.g. from 5-, 10-, 15-minute MTC data) to develop BPNs. In the next section, the results from BPNs developed with increased data length will be discussed.

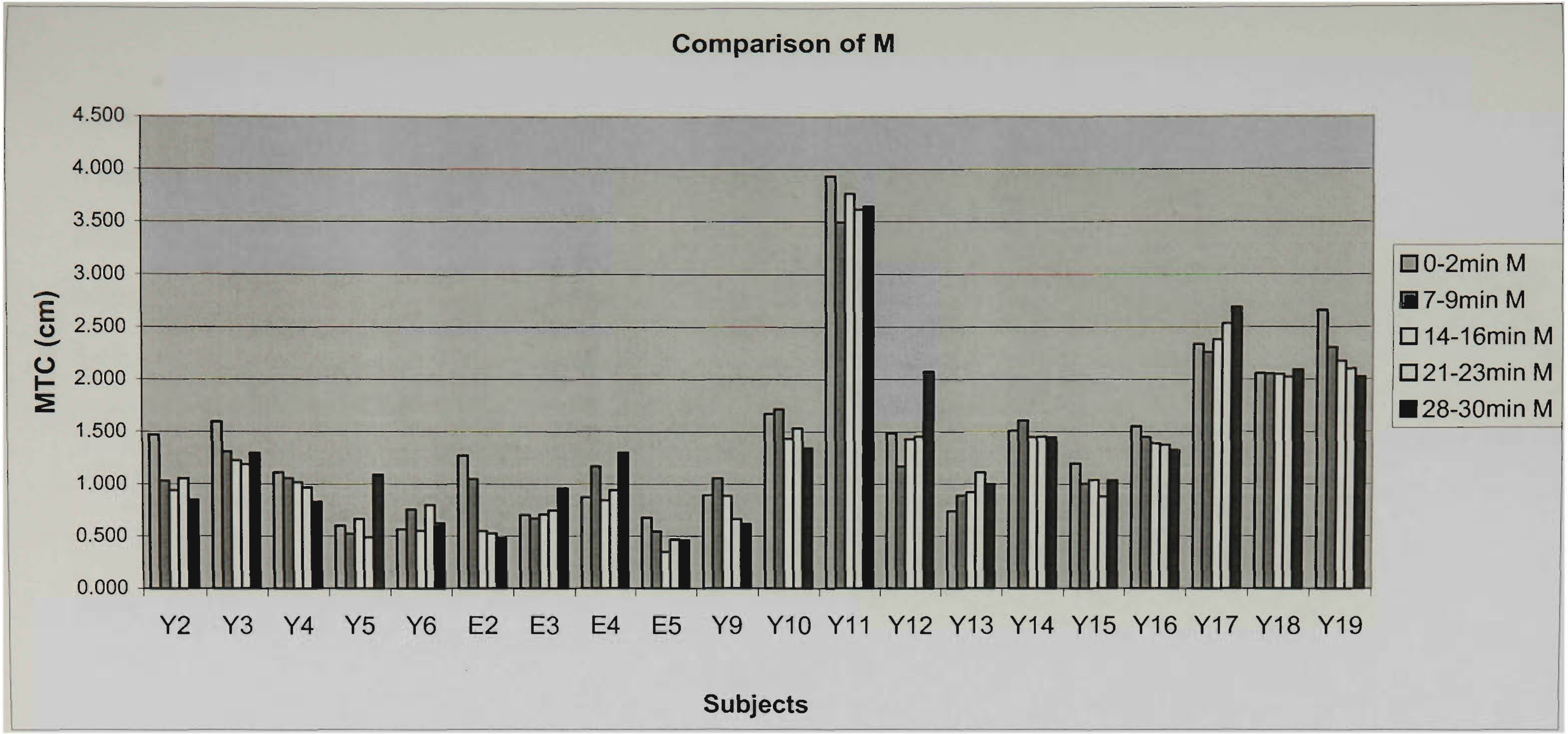


Figure 6.5a M calculated from 5 different 2-minute MTC data segments for each subject in the training data set.

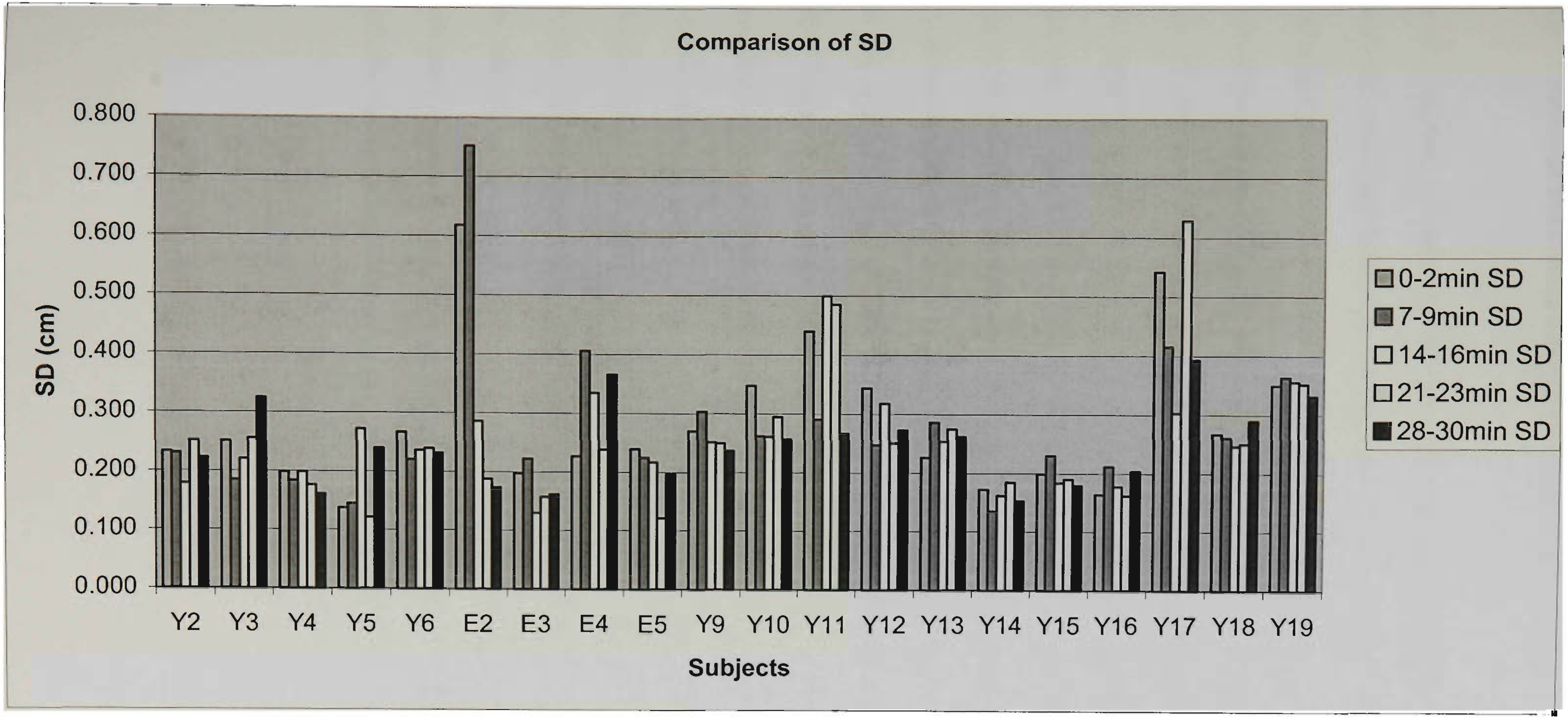


Figure 6.5b SD calculated from 5 different 2-minute MTC data segments for each subject in the training data set.

6.3 Effect of MTC Data Length on Prediction Accuracy

In this section, another nine BPNs were separately developed and tested with nine statistics calculated from nine varying data segment lengths as inputs to predict the stabilized statistics. Nine different data segment lengths were extracted from the 30-minute gait trial, and they included the first 5, 10 and 20 gait trials, and the first 1-, 5-, 10-, 15-, 20- and 25- minute equivalent gait trials. These nine BPNs together with Net 3 are designed to give an indication if whether information collected from increased MTC data segment lengths would improve the performance of the BPN. The average POE and AAE results for 24 subjects are shown in Table 6.8. The details of prediction results by BPNs developed with six groups of data are shown in Appendix II (see Tables 6.8a to 6.8i and 6.5c). The results show that both M and SD were better predicted by each BPN (maximum average POE_M=22.6% generated by Net 15 using 5-minute data, maximum average POE_{SD}=20.5% generated by Net 12 using 5 trials MTC data,), whereas both S and K were poorly predicted by each BPN (minimum average POE_S=55.6% generated by Net 20 using 25-minute data, minimum average POE_K=148.2% generated by Net 18 using 15-minute data). These results indicate that the nine statistical inputs calculated even from 25–minute data provided insufficient information in predicting S and K. Nevertheless, trends of POE change for all statistics indicate that increasing MTC data length certainly improves the performance of BPN.

Table 6.8 Testing results of 10 BPNs developed with the nine statistical inputs calculated from ten different MTC data segment lengths. Average AAE and POE for 24 subjects are shown in this table.

	M		SD		S		K	
	Average AAE (cm)	Average POE (%)	Average AAE (cm)	Average POE (%)	Average AAE	Average POE (%)	Average AAE	Average POE (%)
Net 12 (5trials)	0.239	20.4	0.061	20.5	0.715	105.3	4.912	330.7
Net 13 (10trials)	0.247	21.3	0.060	20.2	0.813	126.3	5.205	408.3
Net 14 (20trials)	0.256	21.3	0.058	19.9	0.828	106.4	5.600	352.6
Net 15 (1min)	0.263	22.6	0.263	18.2	0.263	116.8	0.263	330.4
Net 3 (2min)	0.240	22.0	0.042	14.6	0.550	84.0	4.062	304.1
Net 16 (5min)	0.222	19.7	0.039	13.7	0.549	89.1	4.062	274.5
Net 17 (10min)	0.194	15.2	0.033	13.4	0.491	77.1	3.197	158.6
Net 18(15min)	0.203	16.3	0.030	10.7	0.486	79.2	3.077	148.2
Net 19 (20min)	0.192	15.3	0.018	6.5	0.416	62.3	2.776	154.5
Net 20 (25min)	0.180	14.6	0.018	6.5	0.329	55.6	2.789	172.7

6.3.1 Effect of MTC Data Length on M Prediction

POE_M predicted by Net 3 and 12-16 are approximately 21% (Figure 6.6). There is a clear trend showing that the prediction accuracy increased when the MTC data segment length increased. The biggest improvement appeared with Net 17 developed with 10-minute MTC data. After that there was little improvement in mean MTC prediction accuracy between 10-minute data and 25-minute data. A notable point is that the different BPNs generated the best average POE_M for different groups of data. For example, Net 17 (10-minute data) generated the best average POE_M for Group 1 data, which was 3.0%. Net 19 (20-minute data) generated the best average POE_M for Group 2 data, which was 6.8%. Figure 6.6 also shows that nine statistical inputs from at least 10-minute MTC data improve the ability of the BPN to predict M.

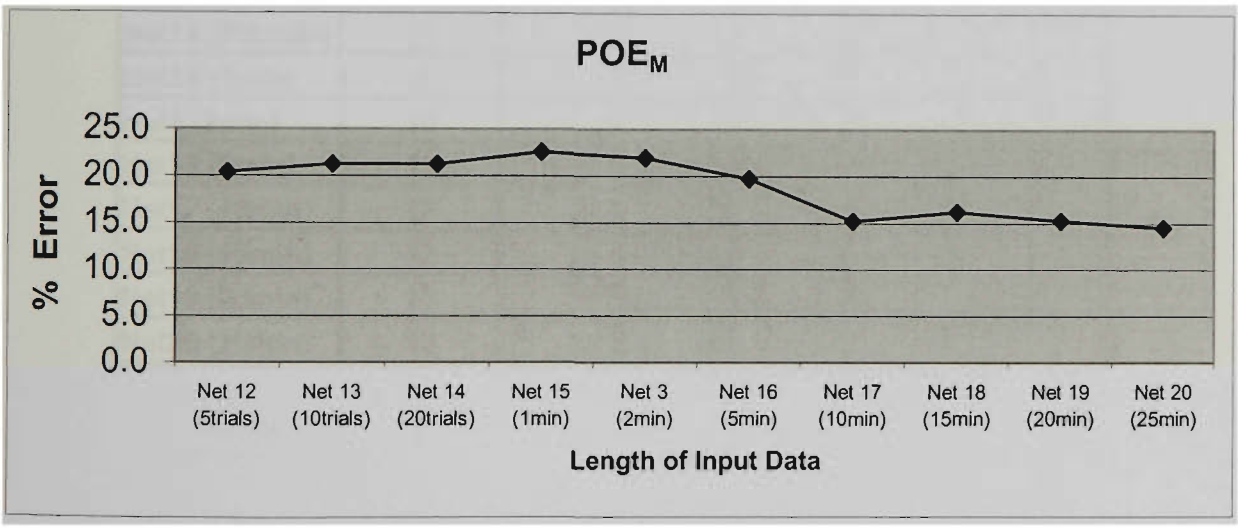


Figure 6.6 Average POE_M for 24 subjects generated by 10 BPNs based on data length varying from 5 trials to 25-minute

The best POE_M for all of the twenty-four subjects was generated by Net 20 (25-minute data) with an average POE_M of 14.6% (see Table 6.8). In fact, the overall POE_M was affected by some subjects' high POE_M values. Table 6.9 shows the number of subjects under four POE scales. Net 20 using 25-minute data had 7 subjects' POE_M>20%, especially subject E2 with POE_M=56.6%. 17 subjects' POE_M were less than 15%, and 13 out of these 17 subjects' POE_M were less than 10%. In fact these 13 subjects' POE_M were less than 6% (details in Table 6.8i in Appendix II). Although Net 17 using 10-minute data had the same number of subjects in each POE scale, the prediction accuracies were slightly lower i.e. POE_M for the 13 subjects were just below 9%.

Table 6.9 Classification of subjects into four POE_M scales

BPNs	POE_M			
	POE<=10%	10%<POE<=15%	15%<POE<=20%	POE>20%
Net12 (5trials)	7	6	4	7
Net13 (10 trials)	11	1	2	10
Net14 (20trails)	11	3	3	7
Net15 (1min)	8	4	1	11
Net3 (2min)	10	5	2	7
Net16 (5min)	11	2	3	8
Net17 (10min)	13	4	0	7
Net18 (15min)	12	4	1	7
Net19 (20min)	13	3	0	8
Net20 (25min)	13	4	0	7

6.3.2 Effect of MTC Data Length on SD Prediction

Like M, there was a clear trend showing that the prediction accuracy of SD increased as the MTC data increased (Figure 6.7). POE_{SD} predicted by Net 12 (5trials), 13 (10 trials), 14 (20 trials) and 15 (1 min) slightly improved, nonetheless, the first significant improvement was found for Net 3 (2-minute MTC data) where POE_{SD} dropped down to 15.2%. A second significant improvement occurred with BPN developed between 10- and 20-minute data. 20-minute data generated the best prediction for SD with an average error of 6.5%.

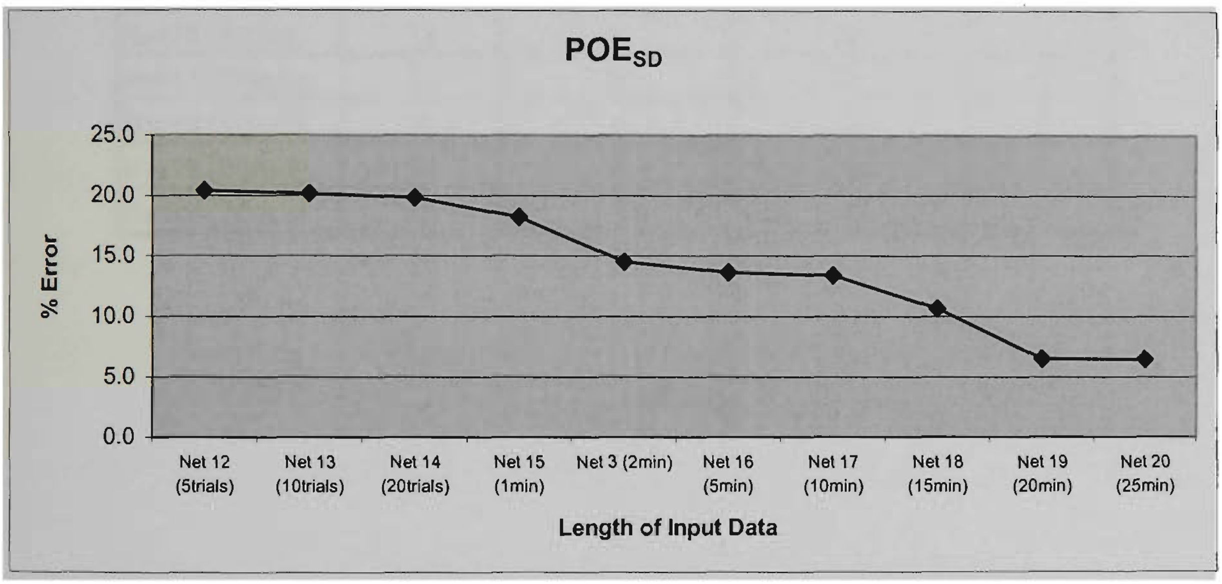


Figure 6.7 Average POE_{SD} for 24 subjects generated by 10 BPNs based on data length varying from 5 trials to 25-minute.

Although Figure 6.7 displayed no significant change between average POE_{SD} of 20-minute data and 25-minute data (Net 20), actually, there were significant improvement in prediction accuracy of individual subjects for 25-minute data. Table 6.10 shows the number of subjects in 4 POE scales. Both 20– and 25-minute data had 22 subjects with

POE_{SD}<15%. But 20-minute data only had 18 subjects' POE_{SD}<10%, while 25-minute data had 21 subjects' POE_{SD} less than 10%. This result confirms that increasing data length improves the performance of BPN in predicting stabilized SD.

Table 6.10 Classification of subjects into four POE_{SD} scales

BPNs	POE_{SD}			
	POE<=10%	10%<POE<=15%	15%<POE<=20%	POE>20%
Net12 (5trials)	6	2	3	13
Net13 (10 trials)	8	3	1	12
Net14 (20trails)	4	8	5	7
Net15 (1min)	6	6	3	9
Net3 (2min)	13	2	3	6
Net16 (5min)	13	4	2	5
Net17 (10min)	14	5	2	3
Net18 (15min)	15	3	3	3
Net19 (20min)	18	4	1	1
Net20 (25min)	21	1	0	2

6.3.3 Effect of MTC Data Length on Predicting S and K

Neither skewness nor kurtosis was accurately predicted. However, there was a clear trend to show that the prediction accuracy for S and K increased when the MTC data segment length increased (see Figure 6.8 and 6.9). Figure 6.8 shows the average POE_S of 24 subjects generated by 10 BPNs. Although the reducing trend of POE_S was not as clear as that of POE_{SD}, it did still indicate that the prediction accuracy of S improved with increased input data. The best prediction for S was found with BPN developed with 25-minute data (Net 20), which generated the POE_S=55.6%. Results in Figure 6.8 also show that there were two major improvements in predictions. The first improvement occurred at Net 3 when POE_S dropped to 84%. There were no change between Net 3 (2-minute data) and Net 18 (15-minute data). The second significant improvement was found by Net 19 (20-minute data), which generated 62.3% error. Although POE_S reduced with data, the prediction accuracy was still poor.

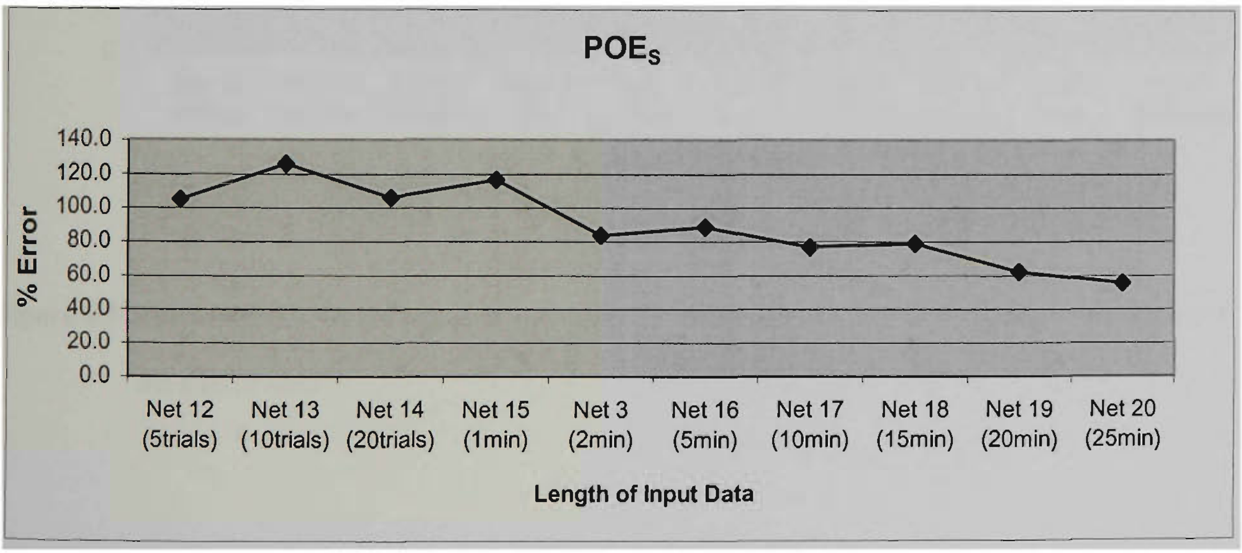


Figure 6.8 Average POE_S for 24 subjects generated by 10 BPNs based on data length varying from 5 trials to 25-minute

Figure 6.9 shows the average POE_K of 24 subjects generated by 10 BPNs. The POE_K results seemed to be the worst of the four statistics. The best prediction was generated by Net 18 (15-minute data) with POE_K = 148.2%. The prediction accuracy slightly improved between Net 13 (10 trials) and Net 16 (5-minute data); POE_K dropped from 408% to 274.5%. Significant improvement occurred by Net 17 (10-minute data) with a POE_K of 158.6%. Afterwards the prediction accuracy stayed fairly constant (~155%). While the best prediction for K was found with Net 18 (POE_k=148.2%), but these errors are unacceptably high. The reason why POE_S and POE_K were poorly predicted even by 25-minute data will be discussed in the next section (section 6.3.3.1).

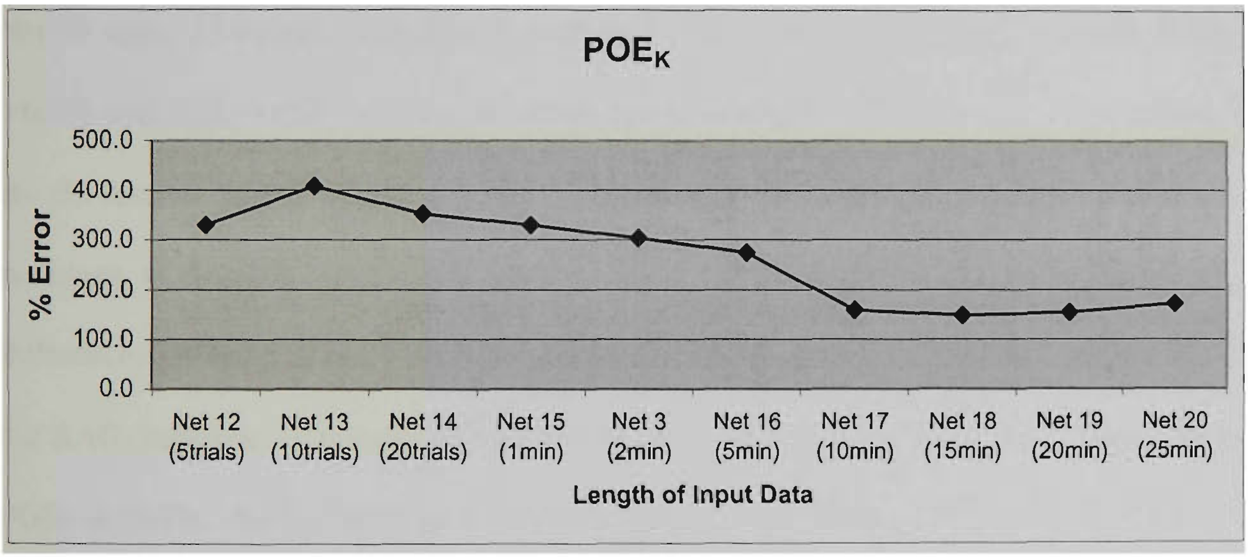


Figure 6.9 Average POE_K for 24 subjects generated by 10 BPNs based on data length varying from 5 trials to 25-minute

6.3.3.1 Possible Reasons for Poor Prediction of S and K

The results in the previous sections show that the performance of BPNs can be improved by increasing input MTC data. M and SD could be predicted with reasonable accuracy but skewness and kurtosis could not be predicted accurately. Even BPN using 25-minute data poorly predicted S and K. As BPN learns by examples via mapping the relationship between its inputs and outputs, whether the inputs could correctly represent the characteristics or not is very important. In order to explain this, the variability of S and K at different MTC data lengths for one subject (Y8) are presented in Table 6.9.

Net 20 using 25-minute data poorly predicted both S and K of subject Y8 with POE_S =103% and POE_K=154.1% (see also Table 6.8 g in Appendix II). S and K at 30-minute are the desired outputs whereas S and K calculated from other data segment were used as inputs to develop BPNs. The data in Table 6.11 show that there are significant differences between S and K as inputs and the desired S and K outputs. For example, the AAE_S between 25-minute data and 30-minute data is 0.707, and the corresponding POE_S is 300%. AAE_K between 25-minute data and 30-minute is 2.254, and POE_K is 90%.

Table 6.11 S and K for subject Y8 calculated at different data point.

	5TRIALS	10TRIALS	20TRIALS	1 MIN	2MIN	5MIN	10MIN	15MIN	20MIN	25MIN	30MIN
S	0.923	-0.104	-0.168	0.101	0.238	0.385	0.203	-0.815	-0.914	-0.945	-0.238
K	0.471	0.030	-0.548	-0.379	-0.430	-0.131	0.063	3.766	-0.113	0.339	2.593

Figure 6.10 shows MTC for the subject Y8 during 30-minute gait trials. MTC data were steady up to the first 913 gait trials (about 14-minute data). MTC then dropped by 0.6cm and did not recover to the first 14-minute's data. Some extreme values appeared after about 1673 gait trials (26^{th}-minute data). These high values were responsible to cause abrupt change in stabilized S and K, such as S=–0.945 at 25-minute, but S=–0.238 at 30-minute. Also during this time K increased from 0.339 to 2.593 (see table 6.9).

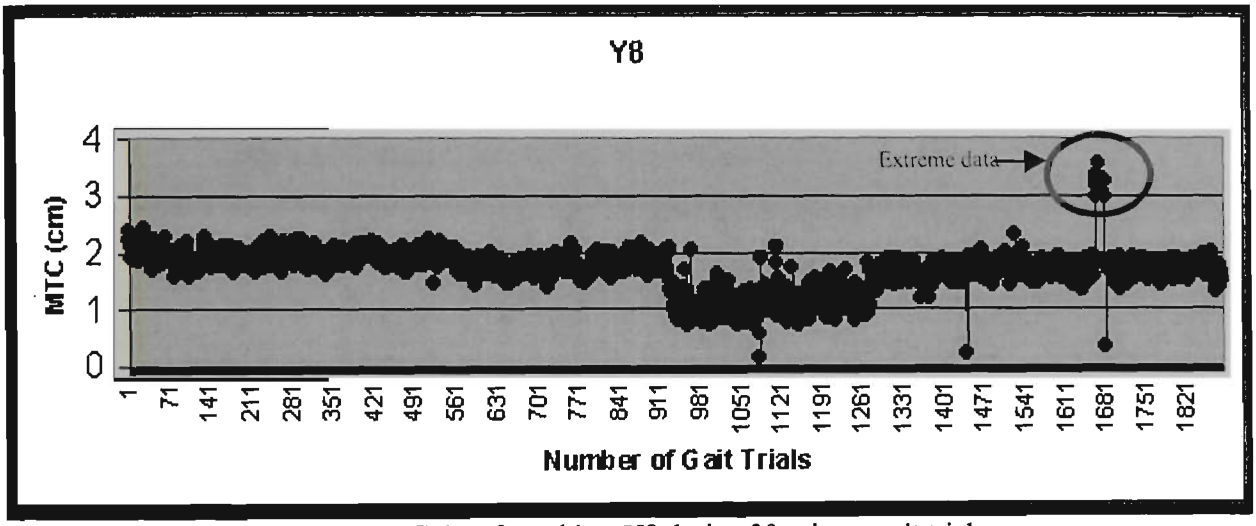


Figure 6.10 MTC data for subject Y8 during 30-minute gait trials

As stated earlier (see section 6.1.1.2), both S and K are very sensitive to extreme data. These outliers not only change the magnitude of S and K, but also have the potential to cause a change in the sign of S and K. The seemingly random variations in S and K shown in table 6.11 highlight the difficulty in predicting long term S and K.

The other possible reason for the poor performance by BPN in predicting S and K might be the limited sample size. BPN learns by examples. In this study, randomly selected 20 subjects' data were used for training BPN and 4 subjects' data were used for testing. It might be that BPN did not learn sufficiently with those training samples. In other words, the characteristics of training data set might not be enough to cover the characteristics of testing data set.

Net 20, developed with Group 5 data, performed better than other group's data in predicting the statistics (see also Table 6.8i in Appendix II). Table 6.12 shows testing results of Net 20 developed with Group 5 data. POE_S for each subject is quite accurate with an average POE_S=4.2%. Although K was poorly predicted, the average POE_K=82% was still better than other groups' data (see Table 6.8i in Appendix II).

Table 6.12 Testing results of Net 20 developed with Group 5 data.

Group5	M				SD				S				K			
	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.348	0.057	4.0	0.368	0.334	0.033	9.1	0.928	0.912	0.016	1.7	1.701	5.725	4.024	236.6
Y13	0.989	0.955	0.033	3.4	0.277	0.279	0.002	0.6	0.438	0.422	0.015	3.5	0.899	0.264	0.635	70.6
Y14	1.495	1.434	0.061	4.1	0.197	0.253	0.057	28.8	1.120	1.067	0.053	4.7	11.946	10.161	1.786	14.9
Y15	1.011	0.892	0.119	11.8	0.265	0.287	0.021	8.0	1.200	1.116	0.084	7.0	4.420	4.162	0.258	5.8
Average			0.068	5.8			0.028	11.6			0.042	4.2			1.676	82.0

Table 6.12 also shows that both average POE_M and POE_{SD} are very low (5.8% and 11.6%). It appears that the training set data in Group 5 provided sufficient information to cover the characteristics of testing data, as reflected by the good accuracy of predictions.

6.4 Effect of Additional Inputs on The Performance of BPN

In section 6.1.4, three possibilities that might affect the accuracy of predictions have been discussed. The results from the first two issues have been discussed in section 6.2 and 6.3. In this section, the effects of additional information to BPN inputs will be discussed.

6.4.1 Testing Results Using Fourteen Inputs (Nine Statistics + Five Cumulative Means)

M and SD are the commonly used statistics in gait analysis, and in last section (section 6.3 Table 6.8), the BPNs with nine statistical inputs moderately predicted M (POE_M>14.6%). In this section, five cumulative M values were added to the inputs. The aim was to investigate whether increased inputs would improve the performance of BPN in predicting stabilized statistics. Net 21, 22 and 23 (Table 6.13), using fourteen inputs (nine statistical inputs and five cumulative mean values), calculated from 5-, 10- and 15-minute MTC data were developed to predict the stabilized four statistics.

Table 6.13 shows average results for four statistics for six groups. The details of the testing results are shown in Appendix II (Tables 6.13a to 6.13c, Net 21 to 23). The results show that the prediction accuracy of all statistics improved via increasing the MTC data. But this was not the case with BPNs developed with nine statistical inputs (see results from Net 16 to 18, Table 6.8). For example, POE_M of Net 21, 22 and 23 (see Table 6.13) using fourteen inputs calculated from 5-, 10- and 15-minute data were 19.4%, 14.2% and 12.4%, whereas POE_M of Net 16, 17 and 18 (see Table 6.8 in section

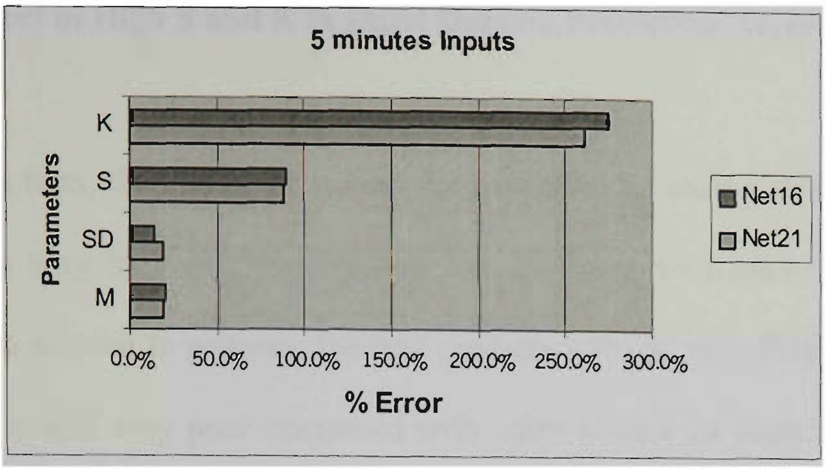
6.3) using nine inputs were respectively 19.7%, 15.2% and 16.3%. Fourteen inputs calculated from 15-minute data seemed to provide better BPN in predicting M and SD.

Table 6.13 Testing results of 3 BPNs developed with the fourteen statistical inputs calculated from 3 different MTC data segment lengths.

	MEAN		SD		SKEWNESS		KURTOSIS	
Net 21 (5min)	AAE (cm)	POE (%)	AAE (cm)	POE (%)	AAE	POE (%)	AAE	POE (%)
Group 1	0.180	16.0	0.056	16.0	0.294	62.4	3.655	325.6
Group 2	0.146	15.0	0.023	15.0	0.347	52.2	1.297	135.6
Group 3	0.315	44.5	0.048	44.5	0.567	127.2	1.468	791.6
Group 4	0.341	17.2	0.032	17.2	0.382	43.3	1.806	67.1
Group 5	0.146	12.0	0.032	12.0	0.638	64.8	5.328	109.1
Group 6	0.270	11.7	0.044	11.7	0.915	177.9	9.792	133.4
Average	0.233	19.4	0.039	19.4	0.524	88.0	3.891	260.4
Net 22 (10min)	AAE (cm)	POE (%)	AAE (cm)	POE (%)	AAE	POE (%)	AAE	POE (%)
Group 1	0.044	4.4	0.059	16.7	0.216	53.5	1.948	178.0
Group 2	0.112	12.0	0.020	7.6	0.374	61.0	0.572	67.7
Group 3	0.202	28.7	0.026	8.3	0.735	151.0	2.234	531.7
Group 4	0.324	13.1	0.027	8.8	0.301	34.2	2.635	98.6
Group 5	0.187	14.3	0.053	23.8	0.353	36.4	2.459	84.0
Group 6	0.276	12.7	0.045	16.6	0.868	86.5	9.590	122.9
Average	0.191	14.2	0.038	13.6	0.475	70.4	3.240	180.5
Net 23 (15min)	AAE (cm)	POE (%)	AAE (cm)	POE (%)	AAE	POE (%)	AAE	POE (%)
Group 1	0.105	10.3	0.039	10.9	0.240	38.1	1.435	122.8
Group 2	0.039	5.4	0.015	6.1	0.284	42.9	0.843	81.8
Group 3	0.155	21.7	0.015	4.7	0.588	118.0	1.876	346.8
Group 4	0.332	16.9	0.028	9.8	0.411	47.8	2.973	95.2
Group 5	0.112	9.1	0.032	14.2	0.255	27.9	1.483	45.2
Group 6	0.248	11.1	0.040	14.4	0.974	125.1	10.051	128.4
Average	0.165	12.4	0.028	10.0	0.459	66.6	3.110	136.7

Figure 6.11 shows a comparison of POE between nine inputs and fourteen inputs. It shows that all BPNs using fourteen inputs had improved prediction accuracy for M and S. But POE_{SD} (19.4%) for Net 21 (fourteen inputs) was worse than that of Net 16 (13.7%) using nine inputs. Figure 6.10b shows that SD and K predicted by Net 22 (POE_{SD}=13.6% and POE_K=180.5%) using fourteen inputs were not as good as Net 17

(POE_{SD}=13.4% and POE_K=158.6%) using nine inputs. In spite of this, the prediction accuracy of four statistics generated by Net 23 (14 inputs from 15-minute data) was better than those generated by Net 18 (9 inputs from 15-minute data). Each POE of Net 23 (14 inputs) was lower than that of Net 18 (9 inputs). These results indicate that five added inputs improved predicting M and S, but did not improve the performances of all the BPNs in predicting the SD and K. Performance of BPN using fourteen inputs was also improved by increasing input data lengths. Both adding more input characteristics and increasing input data length were found to improve the performance of BPN.



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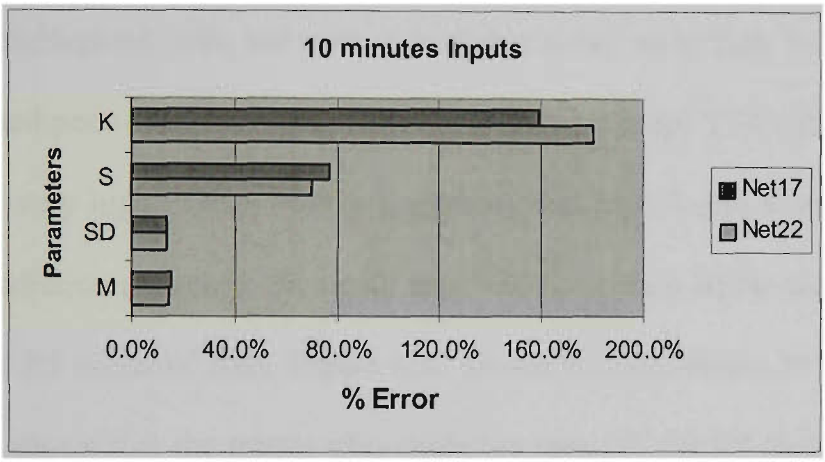

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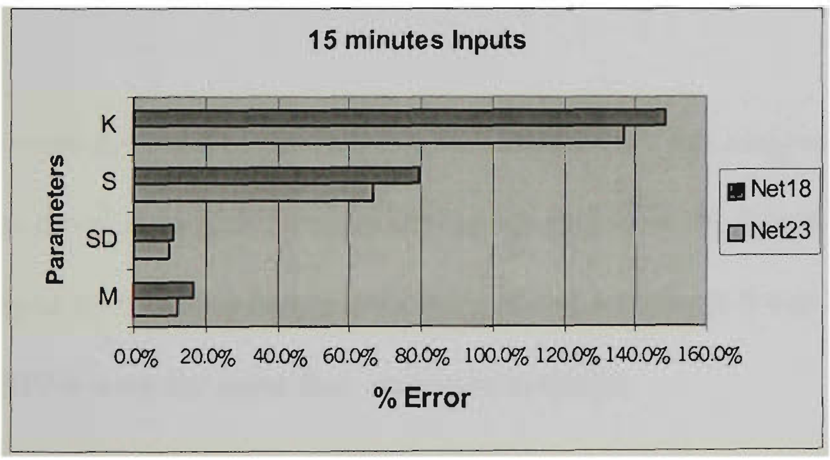

c

Figure 6.11 POE comparison between BPNs using nine inputs and BPNs using fourteen inputs. Nets 16-18 used nine inputs. Nets 21-23 used fourteen inputs. a)=5-minute data, b)=10-minute data and c)=15-minute data.

6.4.2 Effect of High S and K in Input Data on Prediction Accuracy: A Case Study

In pervious tests, the POE_M for subject E2 generated by most BPNs (Net 3 and Net 13 to 23) was very high (47.7%-180.3%). Net 23 using 14 inputs calculated from 15-minute data seemed to generate the best prediction for M with POE_M =47.7%. But this prediction is still very poor compared with other results. In order to explore this, the inputs and desired outputs for Net 23 are shown in Table 6.14. It was found that the all subjects (highlighted with red colour in Table 6.14) with high S and K in the input variables had poor predictions for M (POE_M>19%), except Y14 with POE_M=6.7%. But Y14 had a very high POE_{SD} (44%). It appears that high S and K might be responsible for bad prediction accuracy. To verify this, additional two BPNs were developed using E1, E2 and E5 subjects' data. Figure 6.12 shows the cumulative M for subjects E1, E2 and E5. It shows that the trends of cumulative mean (CM) for these three subjects are very similar. E1 and E5 had low S and K, but E2 had high S and K.

E1 and E5 were assigned to the training set, whereas E3 was assigned to the testing set. Net A1 was developed with fourteen inputs adapted from the inputs of Net 23. Net A2 was developed with twelve inputs (all inputs of Net A1 except S and K). The outputs for these two BPNs were the same four stabilized statistics.

Table 6.14 Inputs and desired outputs of 24 subjects for Net 23. Subjects highlighted with red colour had high S and K inputs and poor POE_M. Subject Y14 highlighted with blue colour had high S and K inputs, and poor POE_{SD}.

		INPUT VARIABLES														DESIRED OUTPUT VARIABLES			
	Subjects	10min mean	11min mean	12min mean	13min mean	14min mean	15min mean	15min SD	15min variance	15min skewness	15min kurtosis	15min range	15min minimum	15min maximum	15min sum	30min mean	30min SD	30min skewness	30min kurtosis
Group 1	Y1	0.865	0.871	0.862	0.861	0.872	0.880	0.280	0.078	0.373	0.198	1.729	0.160	1.889	731.609	0.860	0.266	0.511	0.716
	E1	1.340	1.316	1.293	1.280	1.265	1.250	0.405	0.164	0.563	-0.251	2.370	0.341	2.711	602.276	1.196	0.378	0.685	0.453
	Y7	0.483	0.491	0.499	0.530	0.566	0.579	0.413	0.171	1.867	4.035	2.820	0.001	2.821	516.565	0.502	0.359	2.456	7.145
	Y8	1.917	1.898	1.885	1.875	1.873	1.858	0.183	0.034	-0.815	3.766	1.648	0.780	2.428	1752.013	1.681	0.361	-0.238	2.593
Group 2	Y2	1.172	1.143	1.114	1.096	1.087	1.073	0.304	0.093	0.899	1.122	2.132	0.357	2.490	830.156	0.995	0.283	1.080	1.878
	Y3	1.418	1.399	1.393	1.380	1.366	1.361	0.283	0.080	0.522	1.712	2.241	0.517	2.758	1039.759	1.318	0.285	0.457	1.028
	Y4	1.151	1.140	1.131	1.135	1.126	1.118	0.207	0.043	0.237	0.738	1.608	0.539	2.147	773.345	1.005	0.236	0.298	0.425
	Y5	0.619	0.616	0.616	0.608	0.609	0.601	0.182	0.033	0.817	2.464	1.407	0.168	1.575	277.783	0.636	0.254	1.132	1.827
Group 3	Y6	0.653	0.669	0.681	0.688	0.695	0.688	0.269	0.072	0.231	0.083	1.655	0.022	1.677	439.729	0.672	0.263	0.367	0.049
	E2	0.862	0.832	0.812	0.792	0.767	0.760	0.502	0.252	2.193	7.008	3.817	0.118	3.936	404.569	0.657	0.397	2.807	12.599
	E3	0.621	0.622	0.615	0.616	0.625	0.629	0.184	0.034	0.744	2.534	1.569	0.109	1.678	383.826	0.734	0.213	0.315	0.242
	E4	0.942	0.981	0.991	1.000	0.980	0.961	0.455	0.207	1.111	1.191	2.863	0.025	2.889	607.079	1.000	0.415	0.813	0.781
Group 4	E5	0.518	0.513	0.504	0.497	0.488	0.480	0.226	0.051	0.802	0.709	1.262	0.025	1.287	197.914	0.443	0.206	0.852	1.559
	Y9	0.854	0.861	0.853	0.854	0.856	0.860	0.298	0.089	0.963	4.802	3.228	0.000	3.228	699.714	0.793	0.292	0.838	3.180
	Y10	1.655	1.640	1.638	1.627	1.628	1.614	0.337	0.114	1.039	2.437	2.913	0.325	3.237	1413.873	1.522	0.328	0.863	3.466
	Y11	3.613	3.628	3.679	3.705	3.726	3.752	0.427	0.183	-0.623	4.717	4.500	0.880	5.379	3147.879	3.649	0.423	-0.892	8.891
Group 5	Y12	1.232	1.218	1.233	1.256	1.284	1.312	0.333	0.111	0.721	0.757	2.552	0.131	2.683	1065.297	1.405	0.368	0.928	1.701
	Y13	0.933	0.951	0.959	0.964	0.978	0.979	0.280	0.078	0.314	0.808	1.999	0.133	2.132	781.496	0.989	0.277	0.438	0.899
	Y14	1.619	1.600	1.583	1.568	1.558	1.548	0.211	0.045	1.493	15.607	2.999	0.788	3.787	1196.441	1.495	0.197	1.120	11.946
	Y15	1.125	1.126	1.114	1.100	1.092	1.088	0.260	0.067	0.989	2.336	1.888	0.527	2.415	751.650	1.011	0.265	1.200	4.420
Group 6	Y16	1.517	1.504	1.487	1.476	1.468	1.463	0.199	0.040	0.310	2.782	1.930	0.837	2.766	1148.627	1.413	0.202	0.226	1.474
	Y17	2.297	2.296	2.295	2.305	2.304	2.319	0.381	0.145	4.460	51.284	7.154	0.086	7.241	1904.252	2.383	0.418	4.266	40.436
	Y18	2.066	2.083	2.097	2.112	2.113	2.110	0.289	0.084	0.228	1.050	2.365	1.011	3.376	1629.046	2.073	0.285	-0.206	3.054
	Y19	2.479	2.443	2.420	2.379	2.355	2.345	0.432	0.187	-0.132	1.193	3.553	0.200	3.753	1599.036	2.216	0.432	-0.111	1.606

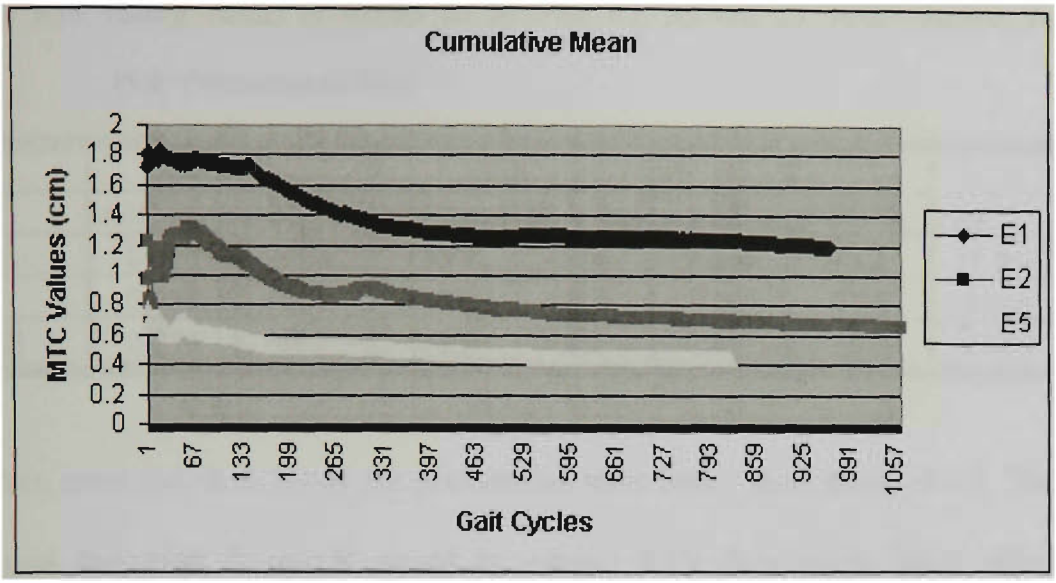

Figure 6.12 The cumulative mean (CM) of subjects E1, E2 and E5 showing similar trends

The training strategy adopted and which led to repeatable results was mainly the same as described before (see section 5.4.5.1). But learning iterations were set to 1000, and test interval was set to 4 to prevent over training A1 and A2.

Table 6.15 shows the AAE and POE of all four statistics for the three BPNs (A1, A2 and Net 23). The results in Table 6.15 show that POE_M of net A2 (6.1%) was significantly lower that that of net A1 (63.1%). More details of these testing results for A1 and A2 are shown in Table 6.15a in Appendix II.

Table 6.15 Testing results of subject E2 by Nets A1, A2 and 23. AAE=Absolute Actual Error; POE=Percentage of Error.

	M		SD		S		K	
	AAE (cm)	POE (%)	AAE (cm)	POE (%)	AAE	POE (%)	AAE	POE (%)
A1	0.415	63.1	0.054	13.6	2.057	73.3	11.862	94.2
A2	0.040	6.1	0.081	20.5	1.448	51.6	8.346	66.2
Net 23	0.314	47.7	0.009	2.3	0.547	19.5	2.870	22.8

In fact, most (M, S & K) of A2 predictions were better than those of A1. These results suggest that high S and K found in subject E2's data might have affected its M prediction accuracy. Table 6.15 also shows that SD, S and K predictions for subject E2 via Net 23 were better than those generated by A1 and A2. These results also highlight the importance of the training sample size. Net 23 was trained with 20 subjects' data, whereas nets A1 & A2 were trained using only 2 subjects. Therefore, Nets A1 and A2 might have limited generalization ability.

In this section, five new BPNs were developed to investigate the effect of additional input variables on the performance of BPNs. The results demonstrate that selecting input variables are very important in the performance of BPN. Some inputs (e.g. five added inputs) were able to improve the performance of BPN (Net 23) in predicting stabilized variables (specially M). On the contrary, some inputs misled the BPN in predicting some stabilized variables (e.g. high skewness and kurtosis reduced the predicting ability of A1 in predicting M). The most important observation is that the different stabilized variables were sensitive to different input variables. Discretely selecting input variables is very important for the performance of BPN. The current results suggest that 15-minute MTC data provide reasonable accuracy in predicting the stabilized M and SD.

The BPNs developed in previous sections predicted four statistics at the same time. As the different stabilized variables were sensitive to different input variables, thus the following section focused on investigating the performance of BPN in separately predicting stabilized statistics.

6.5 Separately Predicting the Four Stabilized Statistics

Prediction results of separately predicting stabilized statistics using 2-minute input data are shown in Table 6.16. Details of testing results of Nets 24, 25, 26 and 27 are shown in Table 6.16a in Appendix II. Table 6.16 shows average AAE and POE results of all groups. Average POE_M generated by Net 24 was 17.6%, which is considerably better than that generated by Net 3 (22.0%), which predicted four stabilized statistics at the same time. POE_{SD} (14.3%) generated by Net 25 did not change much compared to Net 3 (14.6%). Kurtosis seemed to have the biggest improvement with POE_K of 304.1% generated by Net 3 dropped down to 265.4% generated by Net 27 whereas prediction accuracy of skewness slightly decreased (84% compared to 86.9%).

Table 6.16 Testing results of Nets 24, 25, 26 and 27 (2-minute inputs) predicting outputs separately

NET 24	M		NET 25	SD		NET 26	S		NET 27	K	
	Average AAE (cm)	Average POE (%)		Average AAE (cm)	Average POE (%)		Average AAE	Average POE (%)		Average AAE	Average POE (%)
Group 1	0.137	10.1	Group 1	0.059	16.9	Group 1	0.256	40.7	Group 1	1.461	215.4
Group 2	0.143	13.4	Group 2	0.028	10.5	Group 2	0.327	46.1	Group 2	1.720	180.9
Group 3	0.293	40.9	Group 3	0.054	15.1	Group 3	0.586	126.2	Group 3	1.003	908.0
Group 4	0.431	25.0	Group 4	0.025	10.5	Group 4	0.639	71.9	Group 4	3.546	80.8
Group 5	0.156	13.4	Group 5	0.034	14.9	Group 5	0.581	62.0	Group 5	5.055	111.5
Group 6	0.066	3.1	Group 6	0.049	17.9	Group 6	1.064	174.8	Group 6	9.584	95.8
Average	0.204	17.6	Average	0.042	14.3	Average	0.575	86.9	Average	3.728	265.4

Table 6.17 shows average results of all the groups for 15-minute input data. The details of testing results of Nets 28-31 are shown in Table 6.17a in Appendix II. Average POE_M generated by Net 28 was 10.6%, which is 20% better than that generated by Net 23 (12.4%), which predicted four stabilized statistics at the same time. POE_{SD} (9.4%) generated by Net 29 did not change much compared to Net 23 (10%). POE_S stayed around 66% generated by both BPNs (Net 30 and 23). Kurtosis seemed to have

significant improvement with POE_K of 136.7% generated by Net 23 dropped down to 117.3% generated by Net 31.

Table 6.17 Testing results by Nets 28, 29, 30 and 31 (15-minute input).

NET 28	M		NET 29	SD		NET 30	S		NET 31	K	
	Average AAE (cm)	Average POE (%)		Average AAE (cm)	Average POE (%)		Average AAE	Average POE (%)		Average AAE	Average POE (%)
Group 1	0.104	7.6	Group 1	0.039	11.1	Group 1	0.220	38.8	Group 1	1.379	79.7
Group 2	0.050	6.5	Group 2	0.017	6.6	Group 2	0.254	34.9	Group 2	0.616	57.4
Group 3	0.142	20.6	Group 3	0.014	4.3	Group 3	0.573	118.3	Group 3	1.963	309.1
Group 4	0.296	14.0	Group 4	0.026	8.9	Group 4	0.348	40.5	Group 4	2.378	84.2
Group 5	0.111	8.6	Group 5	0.029	12.3	Group 5	0.241	27.3	Group 5	1.212	44.7
Group 6	0.126	6.3	Group 6	0.036	13.3	Group 6	0.842	132.9	Group 6	9.608	128.5
Average	0.138	10.6	Average	0.027	9.4	Average	0.413	65.5	Average	2.859	117.3

Using separate BPNs to predict four statistics generated improved results compared to using one BPN to predict them at the same time. Architecture of a typical BPN is shown in Figure 6.13 to explain this. The back-propagation learning algorithm involves a forward-propagating step followed by a back-propagating step. Figure 6.13 illustrates the back propagating step. δ values are calculated for all processing units and weight changes are calculated for all interconnections. The calculations begin at the output layer and progress backward through the network to the input layer. Each PE in the output layer produces a single real number for its output, which is compared to the target output specified in the training set (see Figure 6.13a), based on this difference, an error value is calculated for each PE in the output layer as shown in Figure 6.13b. Then connection weights are adjusted for all the interconnections that go into the output layer. Next an error value is calculated for each of the PEs in the hidden layer that is just below the output layer (Figure 6.13c). Then the weights are adjusted for all interconnections that go into the hidden layer.

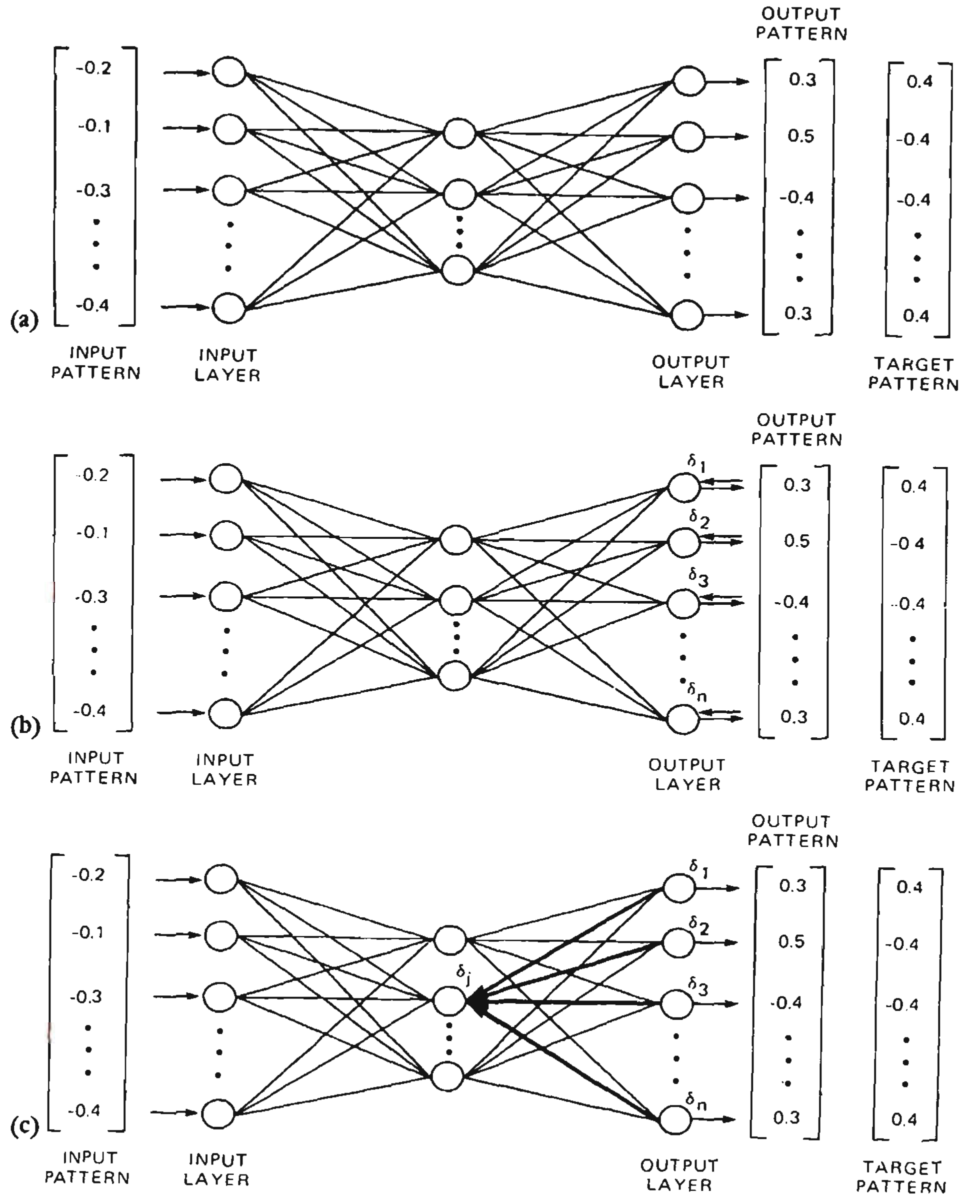

Figure 6.13 Basic back-propagation dynamics. (a) After forward propagation, the target pattern is compared to the output pattern. (b) δ values are calculated for the output layer. Arrows represent flow of information. After δ values are calculated for the output layer, its incoming weights are adjusted. (c) δ values are calculated for the hidden layer. Heavy lines indicate that δ values are communicated from the output layer to the hidden layer. After δ values are calculated for the hidden layer, its incoming weights are adjusted (adapted from Dayhoff, 1991).

The process is continued until the last layer of weights has been adjusted. The connection weight adjustment between a PE (i) at input layer and a PE (j) at the middle hidden layer is carried out as follow:

$w_{ji}=C_1*\delta_j*a_i$

where,

w_{ji} is the adjusted weight. δ_j is error value of PE (j) at hidden layer. C_1 is learning rate. a_i is activation level of PE (i) at input layer. This equation indicates that the amount of adjustment depends on three factors: C_1, δ_j *and* a_i. This weight adjustment equation indicates that the adjustment of weight between PEs at input layer and PEs at the middle hidden layer is related to δ_j. δ_j is calculated based on all PEs at output layer. Hence, the adjustment of connection weight between PEs is related to all PEs at the output layer.

For that reason, adjusted incoming weights of PEs in the middle hidden layer would be different between a BPN developed with four PE in the output layer and a BPN developed with one PE in the output layer. BPN with single output would have dedicated connection weights relating to the inputs and the output and are expected to provide better results. This has been reflected in better prediction results by Nets 28, 29, 30 and 31 compared to Net 23. Although Nets 24-27 (2-minute inputs, single output) were developed to separately predict the stabilized statistics, the results were not as good as the results generated by Net 23 (15-minute data & four outputs). It indicates that 2-minute data were not the best inputs. Nets 28-31 using 15-minute MTC data generated much improved predictions. S and K errors were still not satisfactory which indicates that further study needs to be carried out to find the best inputs for predicting stabilized S and K.

CHAPTER SEVEN

CONCLUSION AND FURTHER STUDY

Tripping is a commonly reported cause of falls. Minimum toe clearance plays a major role in quantifying the probability of tripping. Best, Begg and James (1999) used a Gaussian curve to model a histogram of a group of MTC data from a subject with skewness modelled by transforming MTC to a power of 0.21 ($MTC^{0.21}$), Z-score was calculated. Then the probability of tripping is obtained by calculating the relative of Gaussian curve from the Z-score. Such as for MTC=1, PT=47% means that the subject hitting a 1.0cm unseen obstacle is a chance of 47%. It needs a large amount of minimum toe clearance data to work out the probability of tripping via obtaining the relative area of the Gaussian curve from a z-score. To obtain such amount of MTC data one would need to spend a lot of time digitising markers and calculating parameters. Furthermore, subjects, in certain population (e.g. children and frail elderly), are not able to walk on a treadmill for 30 minutes to generate such amount of MTC data. It is important to devise the innovative ANN model for predicting stabilized gait parameters from relatively fewer gait trials.

The results of this research highlight that both neural networks and multiple linear regression models showed good accuracy to predict stabilized M and SD, but performed poorly for S and K. A BPN developed with nine statistical inputs derived from 2-minute data generated better prediction for M (POE_M=14.2%), SD (POE_{SD}=15.2%) and S

(POE_S=150%) than the multiple linear regression models (POE_M=19%, POE_{SD}=18.3% and POE_S=28.9%).

ANN is very sensitive to its inputs. Proper pre-processed inputs would significantly improve the performance of BPNs. By comparing the performances of seven BPNs developed with seven different combinations of inputs (e.g. FFT coefficients, real data and statistical inputs), it was found that FFT coefficients provided insufficient information to BPNs in predicting the specific MTC values (e.g. M). Any BPN that included FFT coefficients performed relatively poorly. Nine statistics were found to better represent the feature of input MTC data compared to other pre-processing techniques (e.g. FFT coefficients and real data).

Furthermore, nine statistical inputs calculated from 2-minute data, which was derived from five different parts of 30-minute data segment, provided different predictions for the BPNs. It indicated that information obtained from 2-minute data length might not be enough to successfully develop BPN for predicting the stabilized statistics.
By comparing the performances of 10 BPNs developed with inputs derived from 10 different MTC data segment lengths, it was concluded that the performance of BPN could be improved via increasing the MTC data segment lengths. M and SD were accurately predicted with , but skewness and kurtosis predictions were not.

Following on from above results, additional input variables were tested. Three BPNs developed with 14 inputs derived from 3 different MTC data segment lengths (5-, 10-, 15-minute) showed that they had better predictions than BPNs developed with 9 inputs. 15-minute MTC data seemed to be the minimum number of gait trials that should be used to develop BPN for better predictions. Furthermore, extreme S and K values in inputs were found to affect the performance of BPN in accurately predicting some variables (e.g. M). Sample size is also very important for the performance of BPNs. The larger the sample size, the better the performance of BPNs.

The results of this research also confirmed that BPNs are able to predict stabilized statistics better if developed to predict them separately compared to predicting four statistics at the same time.

One limitation of this study was the limited sample size (24 subjects), because of the nature of the project and time intensive data collection and digitisation procedures. Currently, 30-minute data are required to estimate tripping risks in individuals. This research has demonstrated that even with 24 subjects' data the length of data collection and digitisation can be reduced significantly with the help of neural networks. Future studies may focus on increased sample size to investigate the performance of neural networks. Furthermore, the subjects involved in this study were all healthy adults. Different population groups (e.g. elderly fallers, children and amputee etc.) may also be included in the further studies to examine data prediction accuracy of the networks in these important population groups.

The other limitation of this research was that the sensitivity of the gait measures to large unpredictable disturbances to lower limb trajectory due to distraction, which directly change the magnitude of minimum toe clearance, was hardly to be modelled based on information provided to BPN. This is because the individual sensitivity of the gait measures due to distraction is unpredictable and not logical. Further studies are needed to train/test ANNs with information related to the sensitivity of gait measure due to distraction.

This research focused on using single hidden layer networks for predicting stabilized statistics. Further studies may concentrate on developing multiple hidden layers and investigate their performance. Different pre-processing of input data was found to affect the performance of BPNs significantly. Further pre-processing of input data to improve S and K predictions will be important and useful, e.g., including more input characteristics.

The potential of BPNs to be applied for predicting some stabilized gait parameters has been highlighted in this research. Future study may be useful to use neural networks to predict complex gait parameters from simpler gait parameters. For instance, using force platform outputs to predict body centre of mass excursions and velocities.

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APPENDIX I

Training and Testing Data

Table 5.4.1a FFT input coefficients and desired outputs for twenty-four subjects used for developing Net 1

30 FFT Coefficients		Input Variables																	
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
	Y1	0.942	-0.10918	-0.02875	-0.03081	0.041067	0.015524	-0.02903	-0.02819	0.008957	-0.007	-0.02185	-0.00467	-0.0029	-0.0359	-0.01683	0	-0.03919	-0.0583
Group 1	E1	1.726	0.002439	-0.05394	-0.04084	-0.01502	-0.0808	-0.06201	-0.01041	0.026474	-0.06564	-0.05816	0.03725	-0.03067	-0.03351	-0.02688	0	-0.03391	0.015067
	Y7	0.431	0.017034	-0.04722	-0.02931	0.001152	0.020689	0.089618	-0.00929	-0.08759	0.00529	-0.01267	0.047041	-0.00134	0.016915	-0.02252	0	0.086336	-0.0301
	Y8	1.946	-0.01104	-0.03095	-0.0295	0.013997	-0.00281	-0.00255	-0.04157	-0.00401	-0.00692	0.011824	-0.00845	-0.0187	-0.02044	0.011804	0	-0.0863	-0.05023
	Y2	1.455	0.067407	-0.01565	-0.0397	-0.01691	0.049462	0.02205	0.012011	-0.00252	0.007526	-0.01898	0.010303	0.005338	0.005363	-0.01763	0	-0.04843	0.015466
Group 2	Y3	1.581	-0.011	-0.04202	-0.08499	-0.08718	-0.03504	-0.01097	-0.00528	-0.00312	-0.03318	-0.04575	0.008919	-0.00603	0.019324	-0.00883	0	-0.02133	-0.06453
	Y4	1.1	-0.03083	-0.02635	-0.00142	-0.00634	0.003178	0.005278	-0.00372	-0.03287	-0.04698	0.023646	-0.01287	0.035	-0.0559	0.00496	0	0.018589	-0.04598
	Y5	0.593	0.015034	-0.02297	-0.00529	0.011247	-0.00082	-0.00725	-0.02387	0.006415	-0.02825	-0.02582	-0.00383	-0.00473	-0.0086	0.004977	0	-0.05394	-0.00114
	Y6	0.561	0.007225	-0.03048	-0.08793	0.029988	-0.01523	-0.00282	0.005761	-0.00792	-0.03847	0.032494	0.014387	0.002639	-0.03787	-0.01898	0	0.097733	0.012656
Group 3	E2	1.254	-0.18348	-0.01811	-0.16551	-0.09149	0.077332	0.007853	0.024049	0.026608	0.122283	-0.00149	-0.0333	-0.038	-0.04247	-0.02034	0	0.077053	0.07175
	E3	0.697	-0.0115	0.034011	0.060018	0.00046	-0.01336	-0.04049	-0.00889	0.022608	0.007027	-0.019	0.005997	0.003452	-0.00882	-0.00244	0	-0.00964	-0.02464
	E4	0.865	0.054343	0.018914	0.049233	-0.01146	-0.02184	0.013202	-0.03756	0.022607	0.006741	-0.01809	0.019991	0.037353	-0.0026	-0.00216	0	-0.05595	-0.04083
	E5	0.666	0.035501	-0.13135	-0.02921	-0.01501	-0.00148	0.001233	0.038737	-0.0069	-0.0014	-0.0224	0.023337	0.030881	-0.00858	0.02728	0	0.089195	-0.06142
Group 4	Y9	0.887	-0.13848	-0.0822	0.033754	0.004416	-0.04193	-0.03925	-0.01041	-0.02288	-0.004	0.005123	0.012001	-0.03385	0.003499	-0.02069	0	0.084066	0.011466
	Y10	1.659	-0.00943	0.004891	-0.05062	-0.03281	-0.04409	-0.0977	0.032791	-0.00798	-0.03805	-0.07182	-0.06182	-0.01822	0.016746	0.006998	0	-0.02742	0.010958
	Y11	3.899	-0.00861	-0.03478	-0.05381	-0.0347	0.035517	-0.02981	-0.07595	0.007278	-0.04275	-0.06786	-0.01627	-0.0969	-0.04145	0.072572	0	-0.16177	-0.0039
	Y12	1.474	-0.00332	0.011739	0.06195	-0.05334	0.025727	-0.0349	-0.01761	0.035468	-0.03763	-0.02421	0.044115	-0.01303	0.000272	5.49E-05	0	-0.00943	0.009338
Group 5	Y13	0.734	0.071546	0.049976	0.00657	-0.00705	0.020291	-0.03088	0.019902	-0.03705	-0.05622	0.008904	-0.01604	-0.01514	0.001548	0.014818	0	-0.05294	0.00155
	Y14	1.496	0.066468	0.001453	-0.01543	-0.00173	-0.06191	-0.00838	-0.02248	-0.01955	-0.01223	-0.03986	-0.01698	-0.02396	0.00629	-0.01193	0	0.042697	0.042975
	Y15	1.184	-0.07113	-0.02443	0.003864	-0.05399	0.015503	-0.06585	-0.0265	-0.02162	-0.03437	0.028871	-0.01926	0.028981	-0.07083	0.01885	0	-0.07993	-0.02779
	Y16	1.537	-0.0273	-0.00881	0.020917	-0.038	-0.01771	-0.00574	0.015208	-7.9E-05	-0.01483	-0.00039	-0.01995	-0.02396	-0.00411	-0.01495	0	-0.07838	-0.02016
Group 6	Y17	2.317	-0.10272	-0.03435	0.071395	-0.12252	-0.01739	0.033186	-0.07331	-0.00868	-0.00554	-0.07159	0.013386	0.046078	-0.05185	-0.05003	0	0.130402	-0.11289
	Y18	2.038	-0.02601	-0.01621	-0.00158	-0.04776	0.013529	0.0293	0.010378	-0.08215	-0.03222	-0.09219	-0.024	-0.02593	-0.01231	-0.01401	0	0.070344	0.026425
	Y19	2.629	-0.01196	-0.04586	-0.14256	-0.01466	-0.02836	-0.1206	-0.0045	-0.02543	-0.01487	-0.01969	0.064747	-0.06341	-0.02747	-0.07403	0	-0.001	-0.10546

Continued on next page

30 FFT Coefficients

		Input Variable												Output Variables			
		19	20	21	22	23	24	25	26	27	28	29	30	Mean	SD	Skewness	Kurtosis
	Y1	0.028549	0.015796	-0.00693	-0.02752	0.036352	-0.00088	1.43E-05	-0.08318	-0.04275	-0.05492	0.002699	0.002407	0.860	0.266	0.511	0.716
Group 1	E1	0.018898	0.013209	-0.02638	-0.03249	-0.03237	-0.04359	-0.08577	-0.05046	-0.04704	-0.04075	-0.01568	-0.04451	1.196	0.378	0.685	0.453
	Y7	-0.03414	-0.01997	-0.04552	-0.00828	0.111614	-0.04169	-0.02851	-0.03476	0.019702	0.04498	0.028335	0.028087	0.502	0.359	2.456	7.145
	Y8	-0.04282	-0.00028	-0.01474	-0.05394	-0.01441	-0.00574	-0.01443	-0.0075	-0.02459	-0.02084	-0.0144	-0.03082	1.681	0.361	-0.238	2.593
	Y2	0.004852	-0.04599	-0.01243	-0.05795	-0.05162	0.003105	-0.0352	-0.00082	-0.07227	-0.04368	-0.01401	-0.05944	0.995	0.283	1.080	1.878
Group 2	Y3	-0.00141	0.035164	-0.04108	-0.00074	0.009651	-0.04088	-0.0289	0.044755	0.027594	0.020115	-0.01423	-0.02657	1.318	0.285	0.457	1.028
	Y4	0.060984	-0.0283	-0.02278	-0.01721	-0.00334	-0.02099	-0.00124	-0.015	-0.01259	9.85E-05	-0.00338	-0.01938	1.005	0.236	0.298	0.425
	Y5	0.012963	0.022327	-0.01998	-0.02288	-0.01817	0.019996	-0.03374	-0.0189	-0.02166	0.005157	0.0051	-0.0075	0.636	0.254	1.132	1.827
	Y6	-0.07718	-0.00085	-0.00755	-0.04591	-0.0416	0.001137	-0.00638	-0.02661	-0.02746	-0.01375	-0.02037	0.029406	0.672	0.263	0.367	0.049
Group 3	E2	-0.22212	-0.01669	0.099477	0.160808	0.046105	-0.01153	-0.07413	0.037971	-0.01079	-0.00028	-0.14803	-0.07426	0.657	0.397	2.807	12.599
	E3	-0.04824	0.006985	-0.0042	-0.031	-0.00142	0.016519	-0.0817	-0.00894	0.00018	-0.03483	0.021243	-0.00317	0.734	0.213	0.315	0.242
	E4	0.030661	0.003564	-0.0072	-0.0176	-0.06836	-0.03775	-0.00596	-0.02004	0.000616	-0.04305	0.001492	0.01787	1.000	0.415	0.813	0.781
	E5	-0.01306	-0.02244	-0.00786	-0.07899	0.013434	-0.06061	-0.0099	-0.0168	-0.0408	-0.00839	0.019166	-0.00984	0.443	0.206	0.852	1.559
Group 4	Y9	0.015155	0.006671	0.009535	0.042706	0.010798	0.017817	-0.00013	-0.01726	-0.02419	-0.00317	-0.01766	-0.00362	0.793	0.292	0.838	3.180
	Y10	0.0262	-0.06296	-0.02942	-0.01601	-0.01224	-0.0115	-0.01233	-0.0473	-0.03285	-0.04441	-0.06487	-0.02711	1.522	0.328	0.863	3.466
	Y11	-0.0242	-0.02183	0.0184	0.003371	-0.0309	-0.00332	-0.0346	-0.1482	-0.07731	-0.00431	-0.07763	-0.07168	3.649	0.423	-0.892	8.891
	Y12	0.002479	0.055536	0.003757	-0.03295	0.003707	0.038026	0.018661	0.019357	0.039177	0.007432	-0.00699	-0.069	1.405	0.368	0.928	1.701
Group 5	Y13	-0.00754	0.010922	-0.0221	0.002768	0.019696	0.008456	-0.01427	0.001309	-0.00818	-0.03702	-0.02094	-0.05297	0.989	0.277	0.438	0.899
	Y14	0.025728	0.017917	0.011687	0.015931	-0.00487	-0.02533	-0.01829	-0.01613	-0.00598	-0.02949	-0.03545	-0.03184	1.495	0.197	1.120	11.946
	Y15	0.013456	-0.001	-0.03579	0.00438	-0.00904	0.004056	-0.00663	0.008152	0.020326	-0.00104	0.017665	-0.01933	1.011	0.265	1.200	4.420
	Y16	0.001867	0.000289	-0.02665	-0.00174	-0.02586	-0.018	-0.02256	0.002974	-0.01668	-0.00131	-0.01127	-0.03494	1.413	0.202	0.226	1.474
Group 6	Y17	0.056425	0.037065	-0.08218	0.024076	0.02356	-0.05127	-0.02335	-0.01874	-0.06769	0.009266	0.030184	-0.06748	2.383	0.418	4.266	40.436
	Y18	0.070982	0.014804	-0.0036	-0.02092	-0.00602	-0.05157	-0.01084	0.012278	-0.02265	-0.00186	-0.03701	-0.01949	2.073	0.285	-0.206	3.054
	Y19	0.020295	-0.02957	0.026766	-0.00986	0.058828	-0.01394	0.013373	-0.05562	-0.0596	-0.00865	-0.09199	-0.04176	2.216	0.432	-0.111	1.606

Table 5.4.1b 30 real data inputs and desired outputs for twenty-four subjects used for developing Net 2.

30 Real Inputs

		Input Variables																	
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
	Y1	0.571682	0.679012	0.863172	0.794835	0.843863	1.092005	1.442393	1.313381	0.863851	1.017666	0.770272	0.953481	1.18034	0.997643	1.080084	1.756988	1.1379	0.976071
Group 1	E1	1.676981	1.84845	1.53216	1.814467	2.009681	1.696631	1.702031	2.028523	2.07636	1.650805	1.581092	1.870501	1.586717	1.919845	1.765312	1.53541	1.753701	1.558872
	Y7	0.418917	0.829222	0.354047	0.309804	0.450279	0.395856	0.379841	0.398824	0.315849	0.173088	0.261831	0.31233	0.368504	0.33593	0.231676	0.21987	0.528706	0.206253
	Y8	2.226588	2.174714	1.983979	1.948563	2.148094	2.268857	2.205206	1.952851	2.052888	1.899567	2.019209	2.07851	1.96452	1.997364	2.044662	2.045694	1.90045	1.881949
	Y2	2.148796	1.372798	1.417224	1.252514	1.737598	1.817887	1.560978	1.476148	1.166151	1.496338	1.473672	1.510693	1.11188	1.516224	1.150978	1.339253	1.42829	1.503246
Group 2	Y3	1.218388	1.659104	1.609215	1.739649	2.512655	1.860558	1.493068	1.747324	1.374985	1.223438	1.190693	1.786363	1.497615	1.770051	1.585301	1.307996	1.615302	1.659289
	Y4	0.883304	1.040767	0.993189	0.875267	1.110942	1.153353	0.99494	1.206046	1.226827	1.007869	0.81583	0.989835	1.12966	0.81369	1.335705	1.121822	1.154204	1.325143
	Y5	0.655642	0.6325	0.425741	0.577524	0.611971	0.813324	1.112432	0.670467	0.551926	0.616499	0.592836	0.572529	0.425844	0.698002	0.621872	0.654764	0.652329	0.675631
	Y6	0.464493	0.592365	0.443493	0.677982	0.463844	0.924633	0.34067	0.469798	0.363699	0.458575	0.518094	0.298319	0.631995	0.43647	0.765913	0.869587	0.370057	0.340664
Group 3	E2	1.124234	0.426427	1.518705	2.359805	1.2696	0.825367	0.636848	0.992478	0.661688	1.269045	1.888744	1.438829	1.617622	1.836476	2.008257	1.326385	1.227073	2.319134
	E3	1.024945	0.830135	0.842283	0.848676	0.593356	0.536762	0.481956	0.822187	0.577133	0.468299	1.034477	0.749989	0.590684	0.849965	0.618488	0.677827	0.70997	0.661066
	E4	1.265093	1.045501	0.889178	0.919899	1.187181	0.983622	0.830787	0.946289	1.094181	0.770628	1.060216	0.652462	0.720632	0.56436	0.864555	0.814535	0.802356	0.727697
	E5	0.605357	0.651199	0.657938	0.56143	0.98373	0.808032	0.765532	0.640604	0.795761	0.323179	0.458636	0.517577	0.557845	0.278448	0.196417	0.495532	0.727219	0.750175
Group 4	Y9	0.479844	0.578564	0.631974	0.817139	0.847559	0.937269	0.719956	0.984462	1.017474	0.857375	1.027804	0.746082	0.883988	0.896502	0.900051	1.043041	1.157175	1.230909
	Y10	1.71414	1.645533	1.582259	2.154423	1.799034	1.630896	1.564701	2.087474	1.585811	1.907227	1.450744	1.718931	1.865813	1.690275	1.814349	1.596865	2.277595	1.715306
	Y11	4.551198	3.926896	4.339367	4.403191	4.191679	3.796785	4.923521	4.125196	3.997508	4.244925	4.345118	4.188115	3.984304	4.05285	4.207748	3.848978	3.793078	3.730809
	Y12	1.663033	1.360171	2.046603	1.203175	1.308547	1.302475	1.608043	1.387154	1.663952	1.38488	1.367149	1.728636	1.475647	1.513704	1.035709	1.345863	1.21022	1.619017
Group 5	Y13	1.164978	0.74735	0.859375	0.894396	0.746609	0.978084	0.843144	0.760002	0.85692	0.50452	0.432237	1.049244	0.951686	0.73146	0.504929	0.520537	0.554891	0.846078
	Y14	1.680141	1.292304	1.430843	1.463049	1.594151	1.434886	1.568855	1.477257	1.610942	1.556715	1.319702	1.309552	1.263014	1.587362	1.413842	1.564452	1.410747	1.347769
	Y15	0.863547	1.271588	1.3325	1.148454	1.23947	1.245926	1.352483	1.340586	1.372888	1.22181	1.349931	1.209444	1.430122	1.086416	1.11758	1.169554	1.050097	1.477724
	Y16	1.749546	1.602879	1.552248	1.523708	1.717863	1.589825	1.735909	1.726883	1.754505	1.692936	1.592555	1.603584	1.463904	1.638714	1.647259	1.312061	1.510884	1.756809
Group 6	Y17	2.204877	2.249982	2.09388	2.344866	2.211852	2.326942	1.963469	2.273313	2.087814	2.148613	2.37699	2.47916	2.182957	2.247868	2.235363	2.238388	2.285716	2.268913
	Y18	2.096852	1.707784	1.460804	1.179655	2.282257	1.998823	1.615017	1.940843	2.078054	1.948566	2.183951	2.014375	2.20863	1.972946	1.904093	1.925378	2.302564	2.269737
	Y19	2.939344	2.398822	2.949648	3.402879	2.640704	2.983837	2.868671	2.714412	2.609069	2.20563	2.063509	2.410006	2.522172	2.551416	2.533797	2.471125	3.085228	2.862342

Continued on next page

Table 5.4.1c Statistical inputs and desired outputs for twenty-four subjects used for developing Net 3.

9 Statistical Inputs		Input Variables									Output Variables			
2 minutes		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
	Y1	0.950285	0.284892	0.081163	0.143527	0.380858	1.528641	0.306728	1.835369	105.4817	0.860	0.266	0.511	0.716
Group 1	E1	1.753157	0.259405	0.067291	-0.19951	1.408457	1.408535	0.969578	2.378113	112.2021	1.196	0.378	0.685	0.453
	Y7	0.434445	0.361208	0.130471	2.449254	6.678282	2.017986	0.066208	2.084194	51.69892	0.502	0.359	2.456	7.145
	Y8	1.961909	0.175759	0.030891	0.237556	-0.42996	0.862457	1.565392	2.427849	247.2006	1.681	0.361	-0.238	2.593
	Y2	1.469094	0.232387	0.054004	0.669586	0.775362	1.220634	1.052231	2.272865	149.8476	0.995	0.283	1.080	1.878
Group 2	Y3	1.596651	0.250652	0.062826	0.668006	2.119628	1.607273	1.045189	2.652462	161.2617	1.318	0.285	0.457	1.028
	Y4	1.112273	0.197798	0.039124	0.242299	0.603573	1.105022	0.618046	1.723068	102.3291	1.005	0.236	0.298	0.425
	Y5	0.602448	0.13773	0.018969	0.224521	3.000456	0.894348	0.218084	1.112432	36.74934	0.636	0.254	1.132	1.827
	Y6	0.567987	0.266293	0.070912	0.361401	-0.68866	1.191534	0.021992	1.213526	48.27891	0.672	0.263	0.367	0.049
Group 3	E2	1.271775	0.617523	0.381335	0.932044	1.078433	3.152653	0.313582	3.466234	89.02422	0.657	0.397	2.807	12.599
	E3	0.705645	0.197121	0.038857	0.324885	1.056548	1.140524	0.271061	1.411585	56.45157	0.734	0.213	0.315	0.242
	E4	0.874885	0.227157	0.0516	0.365614	0.306617	1.15419	0.401197	1.555387	73.49032	1.000	0.415	0.813	0.781
	E5	0.678189	0.239162	0.057198	0.080526	-0.29636	1.090959	0.196417	1.287376	36.6222	0.443	0.206	0.852	1.559
Group 4	Y9	0.894683	0.270406	0.07312	-0.09988	-0.59671	1.145169	0.330421	1.47559	97.52042	0.793	0.292	0.838	3.180
	Y10	1.672838	0.347712	0.120904	1.15005	2.078217	1.879181	0.988689	2.86787	195.7221	1.522	0.328	0.863	3.466
	Y11	3.933929	0.439883	0.193497	-2.54782	20.43606	4.18589	0.879555	5.065445	440.6	3.649	0.423	-0.892	8.891
	Y12	1.487907	0.343707	0.118135	0.964831	1.473358	2.092694	0.590038	2.682732	162.1819	1.405	0.368	0.928	1.701
Group 5	Y13	0.740544	0.226514	0.051309	0.422026	-0.01993	1.091549	0.259594	1.351143	79.23816	0.989	0.277	0.438	0.899
	Y14	1.510385	0.172617	0.029797	0.287	0.628224	0.902305	1.120827	2.023132	155.5696	1.495	0.197	1.120	11.946
	Y15	1.196403	0.198592	0.039439	-0.13086	-0.28466	0.99206	0.67958	1.67164	111.2655	1.011	0.265	1.200	4.420
	Y16	1.552009	0.164021	0.026903	-0.01999	-0.44206	0.803658	1.185947	1.989605	162.961	1.413	0.202	0.226	1.474
Group 6	Y17	2.337921	0.542161	0.293938	7.245583	63.01975	5.375527	1.865089	7.240616	257.1713	2.383	0.418	4.266	40.436
	Y18	2.058045	0.266983	0.07128	-0.86933	1.819021	1.603958	1.011204	2.615162	211.9787	2.073	0.285	-0.206	3.054
	Y19	2.657557	0.350142	0.122599	0.439942	0.547654	1.883487	1.855717	3.739204	241.8377	2.216	0.432	-0.111	1.606

Table 5.4.3a Training data and testing data used for developing Net 8

Training set					Input Variables								Output Variables		
		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum		Mean	SD	Skewness	Kurtosis
7-9minutes	Y2	1.028	0.230	0.053	0.796	1.021	1.319	0.491	1.810	106.929		0.995	0.283	1.080	1.878
	Y3	1.308	0.185	0.034	0.074	-0.115	0.884	0.832	1.715	133.435		1.318	0.285	0.457	1.028
	Y4	1.056	0.183	0.034	0.024	-0.163	0.888	0.624	1.512	98.227		1.005	0.236	0.298	0.425
	Y5	0.522	0.145	0.021	0.426	0.087	0.668	0.254	0.922	32.360		0.636	0.254	1.132	1.827
	Y6	0.755	0.220	0.048	-0.064	0.127	1.137	0.106	1.242	64.919		0.672	0.263	0.367	0.049
	E2	1.047	0.752	0.566	1.686	3.203	3.766	0.170	3.936	74.372		0.657	0.397	2.807	12.599
	E3	0.671	0.223	0.050	1.688	5.645	1.343	0.334	1.678	54.338		0.734	0.213	0.315	0.242
	E4	1.165	0.406	0.165	0.304	-0.726	1.592	0.428	2.021	99.027		1.000	0.415	0.813	0.781
	E5	0.543	0.225	0.050	0.712	0.414	1.000	0.153	1.153	29.866		0.443	0.206	0.852	1.559
	Y9	1.055	0.303	0.092	-0.182	1.135	1.940	0.000	1.940	114.991		0.793	0.292	0.838	3.180
	Y10	1.714	0.262	0.069	0.535	0.502	1.408	1.102	2.510	200.543		1.522	0.328	0.863	3.466
	Y11	3.491	0.291	0.084	0.166	-0.052	1.390	2.847	4.237	391.034		3.649	0.423	-0.892	8.891
	Y12	1.168	0.247	0.061	1.461	4.202	1.558	0.770	2.328	127.271		1.405	0.368	0.928	1.701
	Y13	0.891	0.286	0.082	0.668	1.764	1.905	0.133	2.039	95.365		0.989	0.277	0.438	0.899
	Y14	1.606	0.135	0.018	0.076	-0.409	0.631	1.288	1.919	165.435		1.495	0.197	1.120	11.946
	Y15	1.001	0.230	0.053	2.797	15.496	1.836	0.579	2.415	93.132		1.011	0.265	1.200	4.420
	Y16	1.446	0.212	0.045	-0.297	-0.179	1.049	0.904	1.952	151.844		1.413	0.202	0.226	1.474
	Y17	2.260	0.416	0.173	6.872	61.430	4.224	1.794	6.018	248.616		2.383	0.418	4.266	40.436
	Y18	2.054	0.261	0.068	-0.173	0.188	1.494	1.336	2.830	211.514		2.073	0.285	-0.206	3.054
	Y19	2.305	0.364	0.132	-1.778	9.256	2.681	0.295	2.975	209.749		2.216	0.432	-0.111	1.606
Tesing Set		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum		Mean	SD	Skewness	Kurtosis
	Y1	0.791	0.246	0.061	0.897	1.156	1.313	0.300	1.613	87.747		0.860	0.266	0.511	0.716
	E1	1.026	0.307	0.095	3.078	14.345	2.150	0.561	2.711	66.681		1.196	0.378	0.685	0.453
	Y7	0.538	0.317	0.100	2.946	10.039	1.960	0.202	2.162	64.058		0.502	0.359	2.456	7.145
	Y8	1.919	0.134	0.018	-0.219	0.269	0.759	1.463	2.223	241.735		1.681	0.361	-0.238	2.593

Table 5.4.3b Training and testing data used for developing Net 9.

Training set					Input Variables								Output Variables		
		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum		Mean	SD	Skewness	Kurtosis
	Y2	0.936	0.178	0.032	0.390	-0.551	0.781	0.572	1.352	97.379		0.995	0.283	1.080	1.878
	Y3	1.222	0.220	0.049	0.076	0.938	1.264	0.581	1.845	124.599		1.318	0.285	0.457	1.028
	Y4	1.018	0.198	0.039	0.113	-0.101	0.911	0.586	1.496	94.628		1.005	0.236	0.298	0.425
	Y5	0.665	0.272	0.074	0.902	1.980	1.487	0.185	1.672	41.252		0.636	0.254	1.132	1.827
	Y6	0.555	0.236	0.056	0.554	-0.104	1.137	0.116	1.253	47.707		0.672	0.263	0.367	0.049
	E2	0.548	0.286	0.082	2.115	7.436	1.814	0.134	1.947	38.877		0.657	0.397	2.807	12.599
	E3	0.710	0.130	0.017	0.891	2.302	0.769	0.469	1.238	57.493		0.734	0.213	0.315	0.242
	E4	0.842	0.334	0.112	0.459	-0.189	1.516	0.255	1.771	71.547		1.000	0.415	0.813	0.781
	E5	0.350	0.217	0.047	1.933	6.822	1.187	0.020	1.206	19.241		0.443	0.206	0.852	1.559
14-16	Y9	0.885	0.252	0.063	-0.110	-0.167	1.199	0.287	1.486	96.445		0.793	0.292	0.838	3.180
minutes	Y10	1.433	0.261	0.068	0.645	1.195	1.530	0.819	2.348	167.696		1.522	0.328	0.863	3.466
	Y11	3.766	0.500	0.250	0.071	-0.628	2.455	2.773	5.228	421.750		3.649	0.423	-0.892	8.891
	Y12	1.428	0.318	0.101	0.146	-0.776	1.559	0.797	2.356	155.611		1.405	0.368	0.928	1.701
	Y13	0.922	0.253	0.064	0.496	0.238	1.296	0.462	1.758	98.616		0.989	0.277	0.438	0.899
	Y14	1.450	0.161	0.026	0.222	1.115	0.965	1.057	2.022	149.309		1.495	0.197	1.120	11.946
	Y15	1.036	0.184	0.034	0.366	1.947	1.146	0.527	1.674	96.309		1.011	0.265	1.200	4.420
	Y16	1.388	0.177	0.031	-0.004	0.337	0.937	0.898	1.835	145.724		1.413	0.202	0.226	1.474
	Y17	2.382	0.303	0.092	-3.000	20.529	2.743	0.274	3.017	262.048		2.383	0.418	4.266	40.436
	Y18	2.048	0.247	0.061	-0.396	1.315	1.444	1.166	2.610	210.988		2.073	0.285	-0.206	3.054
	Y19	2.174	0.356	0.127	0.115	-0.523	1.570	1.413	2.983	197.852		2.216	0.432	-0.111	1.606
Tesing Set		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum		Mean	SD	Skewness	Kurtosis
	Y1	0.869	0.292	0.085	0.603	0.923	1.630	0.259	1.889	96.441		0.860	0.266	0.511	0.716
	E1	1.174	0.280	0.078	0.464	0.084	1.338	0.717	2.055	76.280		1.196	0.378	0.685	0.453
	Y7	0.595	0.306	0.094	1.131	1.403	1.618	0.151	1.769	70.781		0.502	0.359	2.456	7.145
	Y8	1.336	0.407	0.165	0.267	-1.369	1.381	0.702	2.083	168.335		1.681	0.361	-0.238	2.593

Table 5.4.3.c Training data and testing data used for developing Net 10.

Training set					Input Variables								Output Variables		
		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum		Mean	SD	Skewness	Kurtosis
	Y2	1.056	0.251	0.063	0.527	0.858	1.400	0.460	1.860	109.840		0.995	0.283	1.080	1.878
	Y3	1.188	0.255	0.065	0.488	0.423	1.278	0.663	1.941	121.163		1.318	0.285	0.457	1.028
	Y4	0.967	0.176	0.031	0.177	-0.047	0.866	0.630	1.495	89.941		1.005	0.236	0.298	0.425
	Y5	0.487	0.121	0.015	0.492	0.362	0.537	0.250	0.787	30.201		0.636	0.254	1.132	1.827
	Y6	0.799	0.239	0.057	0.052	-0.572	1.069	0.300	1.369	68.707		0.672	0.263	0.367	0.049
	E2	0.529	0.187	0.035	0.998	2.230	1.089	0.151	1.240	37.581		0.657	0.397	2.807	12.599
	E3	0.750	0.157	0.025	0.540	0.255	0.772	0.370	1.142	60.745		0.734	0.213	0.315	0.242
	E4	0.944	0.239	0.057	0.592	0.164	1.090	0.534	1.625	80.260		1.000	0.415	0.813	0.781
	E5	0.467	0.122	0.015	1.205	2.998	0.676	0.251	0.927	25.674		0.443	0.206	0.852	1.559
21-23 minutes	Y9	0.667	0.250	0.062	0.473	0.113	1.267	0.173	1.440	72.746		0.793	0.292	0.838	3.180
	Y10	1.536	0.295	0.087	-0.279	2.275	2.027	0.273	2.301	179.663		1.522	0.328	0.863	3.466
	Y11	3.614	0.485	0.236	-2.047	14.511	4.249	0.498	4.747	404.759		3.649	0.423	-0.892	8.891
	Y12	1.450	0.251	0.063	0.546	0.355	1.307	0.911	2.218	158.091		1.405	0.368	0.928	1.701
	Y13	1.112	0.275	0.076	-0.254	1.296	1.719	0.066	1.785	119.034		0.989	0.277	0.438	0.899
	Y14	1.453	0.185	0.034	0.470	1.963	1.192	1.025	2.217	149.653		1.495	0.197	1.120	11.946
	Y15	0.879	0.190	0.036	0.196	-0.504	0.865	0.461	1.326	81.722		1.011	0.265	1.200	4.420
	Y16	1.373	0.161	0.026	0.378	0.095	0.840	0.996	1.837	144.149		1.413	0.202	0.226	1.474
	Y17	2.532	0.629	0.395	2.771	11.015	4.090	1.766	5.856	278.477		2.383	0.418	4.266	40.436
	Y18	2.021	0.250	0.063	0.116	-0.258	1.166	1.409	2.575	208.185		2.073	0.285	-0.206	3.054
	Y19	2.100	0.352	0.124	0.069	-0.151	1.697	1.298	2.996	191.122		2.216	0.432	-0.111	1.606
Tesing Set		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum		Mean	SD	Skewness	Kurtosis
	Y1	0.790	0.228	0.052	0.927	2.645	1.465	0.289	1.753	87.661		0.860	0.266	0.511	0.716
	E1	1.223	0.337	0.113	0.359	0.287	1.646	0.460	2.106	79.496		1.196	0.378	0.685	0.453
	Y7	0.379	0.278	0.077	3.220	10.993	1.552	0.089	1.641	45.137		0.502	0.359	2.456	7.145
	Y8	1.622	0.186	0.035	-3.624	25.606	1.731	0.212	1.943	204.343		1.681	0.361	-0.238	2.593

Table 5.4.3 d Training data and testing data used for developing Net 11.

Training set					Input Variables								Output Variables		
		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum		Mean	SD	Skewness	Kurtosis
	Y2	0.849	0.222	0.049	3.576	21.386	1.898	0.463	2.361	88.313		0.995	0.283	1.080	1.878
	Y3	1.295	0.324	0.105	0.155	-0.350	1.573	0.469	2.043	132.088		1.318	0.285	0.457	1.028
	Y4	0.831	0.161	0.026	0.078	-0.117	0.857	0.421	1.278	77.303		1.005	0.236	0.298	0.425
	Y5	1.089	0.239	0.057	0.369	-0.067	1.148	0.580	1.728	67.536		0.636	0.254	1.132	1.827
	Y6	0.629	0.232	0.054	0.822	0.927	1.338	0.096	1.434	54.083		0.672	0.263	0.367	0.049
	E2	0.482	0.173	0.030	0.780	1.622	0.946	0.192	1.138	34.192		0.657	0.397	2.807	12.599
	E3	0.959	0.162	0.026	-0.044	0.046	0.837	0.550	1.386	77.678		0.734	0.213	0.315	0.242
	E4	1.301	0.366	0.134	0.077	-0.399	1.737	0.465	2.201	110.609		1.000	0.415	0.813	0.781
	E5	0.464	0.196	0.039	1.897	6.830	1.248	0.080	1.328	25.519		0.443	0.206	0.852	1.559
28-30 minutes	Y9	0.618	0.237	0.056	0.829	0.510	1.208	0.187	1.395	67.394		0.793	0.292	0.838	3.180
	Y10	1.343	0.256	0.066	-0.755	4.844	1.949	0.053	2.002	157.159		1.522	0.328	0.863	3.466
	Y11	3.644	0.267	0.071	0.168	-0.086	1.299	3.028	4.326	408.096		3.649	0.423	-0.892	8.891
	Y12	2.074	0.272	0.074	1.296	2.978	1.519	1.561	3.080	226.111		1.405	0.368	0.928	1.701
	Y13	1.000	0.262	0.069	1.172	3.107	1.641	0.515	2.156	106.975		0.989	0.277	0.438	0.899
	Y14	1.450	0.153	0.023	0.832	1.798	0.896	1.140	2.037	150.813		1.495	0.197	1.120	11.946
	Y15	1.033	0.179	0.032	0.568	0.747	1.011	0.660	1.671	96.079		1.011	0.265	1.200	4.420
	Y16	1.323	0.203	0.041	0.368	0.644	1.197	0.828	2.026	138.922		1.413	0.202	0.226	1.474
	Y17	2.689	0.393	0.155	0.989	1.457	2.080	1.925	4.006	295.810		2.383	0.418	4.266	40.436
	Y18	2.094	0.290	0.084	-0.496	2.342	1.951	0.881	2.831	215.700		2.073	0.285	-0.206	3.054
	Y19	2.024	0.332	0.110	0.311	-0.367	1.587	1.356	2.943	184.202		2.216	0.432	-0.111	1.606
Tesing Set		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum		Mean	SD	Skewness	Kurtosis
	Y1	0.839	0.285	0.081	0.971	2.184	1.727	0.342	2.070	93.129		0.860	0.266	0.511	0.716
	E1	0.960	0.306	0.094	0.568	0.603	1.527	0.404	1.932	62.384		1.196	0.378	0.685	0.453
	Y7	0.489	0.324	0.105	3.345	13.630	2.111	0.133	2.244	58.238		0.502	0.359	2.456	7.145
	Y8	1.692	0.131	0.017	-0.328	-0.034	0.700	1.305	2.005	213.250		1.681	0.361	-0.238	2.593

Table 5.4..4 a Nine statistical inputs and desired outputs used for developing Net 12.

9 Statistical Inputs		Input Variables									Output Variables			
5 trials		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
	Y1	0.91013	0.505175	0.255201	-0.4053	-2.97084	1.086704	0.339062	1.425766	4.550648	0.860	0.266	0.511	0.716
Group 1	E1	1.809694	0.131614	0.017322	-0.19099	-0.47607	0.343268	1.631212	1.97448	9.048472	1.196	0.378	0.685	0.453
	Y7	0.449766	0.143082	0.020472	2.010254	4.22282	0.352509	0.347961	0.70047	2.248829	0.502	0.359	2.456	7.145
	Y8	2.222913	0.102432	0.010492	0.923419	0.470895	0.249363	2.130577	2.37994	11.11457	1.681	0.361	-0.238	2.593
	Y2	1.960433	0.262291	0.068796	-0.4806	0.153746	0.691456	1.581409	2.272865	9.802165	0.995	0.283	1.080	1.878
Group 2	Y3	1.33649	0.178133	0.031731	-0.53768	-0.38598	0.456764	1.081383	1.538147	6.682449	1.318	0.285	0.457	1.028
	Y4	1.193758	0.29761	0.088571	-0.18083	-2.4672	0.663067	0.882225	1.545292	5.968792	1.005	0.236	0.298	0.425
	Y5	0.683472	0.099056	0.009812	0.077357	-1.90214	0.238779	0.560635	0.799414	3.417359	0.636	0.254	1.132	1.827
	Y6	0.637043	0.214086	0.045833	0.131399	-0.76147	0.549311	0.376291	0.925602	3.185215	0.672	0.263	0.367	0.049
Group 3	E2	0.75216	0.459587	0.21122	1.16038	-0.1899	1.037525	0.419401	1.456926	3.760799	0.657	0.397	2.807	12.599
	E3	0.945267	0.087584	0.007671	-0.98548	0.902353	0.221664	0.809061	1.030725	4.726337	0.734	0.213	0.315	0.242
	E4	1.211228	0.263943	0.069666	-0.36628	1.264848	0.728799	0.826588	1.555387	6.056141	1.000	0.415	0.813	0.781
	E5	0.684661	0.201659	0.040666	0.325356	-1.11497	0.508551	0.447779	0.956329	3.423306	0.443	0.206	0.852	1.559
Group 4	Y9	0.516204	0.064228	0.004125	0.331962	-0.89596	0.160133	0.44511	0.605244	2.58102	0.793	0.292	0.838	3.180
	Y10	1.722555	0.176116	0.031017	1.083476	1.511194	0.462528	1.538822	2.00135	8.612777	1.522	0.328	0.863	3.466
	Y11	4.348082	0.375649	0.141112	-0.41434	-1.98989	0.868114	3.85302	4.721134	21.74041	3.649	0.423	-0.892	8.891
	Y12	1.487223	0.211635	0.044789	-0.46817	-2.80375	0.466061	1.230354	1.696415	7.436114	1.405	0.368	0.928	1.701
Group 5	Y13	0.990971	0.306221	0.093772	-1.65447	2.489015	0.735557	0.47757	1.213127	4.954857	0.989	0.277	0.438	0.899
	Y14	1.620821	0.100251	0.01005	-0.47632	-2.6822	0.223177	1.496626	1.719803	8.104107	1.495	0.197	1.120	11.946
	Y15	1.024872	0.222445	0.049482	0.89088	-1.34642	0.50402	0.84111	1.34513	5.12436	1.011	0.265	1.200	4.420
	Y16	1.733583	0.108845	0.011847	-0.22425	-2.28423	0.248459	1.59692	1.845379	8.667915	1.413	0.202	0.226	1.474
Group 6	Y17	2.288274	0.121524	0.014768	0.235803	-2.81469	0.257942	2.172394	2.430336	11.44137	2.383	0.418	4.266	40.436
	Y18	2.09647	0.2857	0.081625	-0.92593	-1.26391	0.654335	1.682404	2.336739	10.48235	2.073	0.285	-0.206	3.054
	Y19	2.484672	0.343328	0.117874	0.259301	-1.31379	0.820774	2.129852	2.950626	12.42336	2.216	0.432	-0.111	1.606

Table 5.4.4 b Nine statistical inputs and desired outputs for every subject used for developing Net 13

9 Statistical Inputs		Input Variables									Output Variables			
10 trials		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
	Y1	0.781986	0.437598	0.191492	0.245521	-1.9197	1.119038	0.306728	1.425766	7.819863	0.860	0.266	0.511	0.716
Group 1	E1	1.767922	0.161444	0.026064	-1.3466	2.484738	0.576321	1.398159	1.97448	17.67922	1.196	0.378	0.685	0.453
	Y7	0.468868	0.169843	0.028847	1.86462	2.541416	0.509522	0.347961	0.857483	4.688682	0.502	0.359	2.456	7.145
	Y8	2.145373	0.135306	0.018308	-0.10431	0.029725	0.456799	1.923141	2.37994	21.45373	1.681	0.361	-0.238	2.593
	Y2	1.70274	0.332264	0.110399	0.591035	-1.11543	0.919639	1.353226	2.272865	17.0274	0.995	0.283	1.080	1.878
Group 2	Y3	1.538027	0.264461	0.069939	-0.1583	-0.35218	0.860012	1.081383	1.941395	15.38027	1.318	0.285	0.457	1.028
	Y4	1.112417	0.217174	0.047165	1.003657	0.142016	0.663067	0.882225	1.545292	11.12417	1.005	0.236	0.298	0.425
	Y5	0.636323	0.110094	0.012121	-0.29385	0.263936	0.373673	0.425741	0.799414	6.363234	0.636	0.254	1.132	1.827
	Y6	0.568345	0.204355	0.041761	0.040824	-0.37759	0.685665	0.239937	0.925602	5.683453	0.672	0.263	0.367	0.049
Group 3	E2	1.095112	0.76438	0.584277	0.775865	-0.60707	2.190697	0.313582	2.504278	10.95112	0.657	0.397	2.807	12.599
	E3	0.869626	0.104052	0.010827	0.382058	-1.15189	0.305097	0.725628	1.030725	8.696264	0.734	0.213	0.315	0.242
	E4	1.107482	0.22945	0.052647	0.557208	-0.09402	0.728799	0.826588	1.555387	11.07482	1.000	0.415	0.813	0.781
	E5	0.699606	0.175222	0.030703	0.461127	-0.60763	0.535952	0.447779	0.98373	6.996058	0.443	0.206	0.852	1.559
Group 4	Y9	0.536798	0.121879	0.014854	1.466889	2.217792	0.393417	0.422966	0.816383	5.367981	0.793	0.292	0.838	3.180
	Y10	1.794941	0.216091	0.046695	0.692577	-1.06035	0.596665	1.538822	2.135487	17.94941	1.522	0.328	0.863	3.466
	Y11	4.131531	0.349216	0.121952	0.889085	-0.67389	0.949203	3.771931	4.721134	41.31531	3.649	0.423	-0.892	8.891
	Y12	1.464282	0.18595	0.034577	0.14487	-1.89658	0.481053	1.230354	1.711407	14.64282	1.405	0.368	0.928	1.701
Group 5	Y13	1.015618	0.259641	0.067413	-1.01556	0.803686	0.873573	0.47757	1.351143	10.15618	0.989	0.277	0.438	0.899
	Y14	1.53673	0.145418	0.021146	-0.68997	0.12407	0.46283	1.256973	1.719803	15.3673	1.495	0.197	1.120	11.946
	Y15	1.179116	0.224893	0.050577	-0.72407	-1.33242	0.58519	0.84111	1.4263	11.79116	1.011	0.265	1.200	4.420
	Y16	1.639814	0.150049	0.022515	-0.19576	-0.80534	0.44508	1.400299	1.845379	16.39814	1.413	0.202	0.226	1.474
Group 6	Y17	2.245168	0.149931	0.022479	0.052365	-0.89686	0.462799	1.998169	2.460968	22.45168	2.383	0.418	4.266	40.436
	Y18	1.95972	0.282886	0.080025	-0.12062	-1.13475	0.826222	1.510517	2.336739	19.5972	2.073	0.285	-0.206	3.054
	Y19	2.633229	0.423237	0.17913	0.432212	-0.65265	1.278103	2.129852	3.407955	26.33229	2.216	0.432	-0.111	1.606

Table 5.4.4 c Nine statistical inputs and desired outputs for every subject used for developing Net 14.

9 Statistical Inputs		Input Variables									Output Variables			
20 trials		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
	Y1	0.84812	0.362949	0.131732	0.199134	-0.67407	1.255288	0.306728	1.562016	16.96241	0.860	0.266	0.511	0.716
Group 1	E1	1.820629	0.216007	0.046659	0.465557	0.609902	0.916969	1.398159	2.315128	36.41258	1.196	0.378	0.685	0.453
	Y7	0.447136	0.177983	0.031678	2.231155	4.074055	0.661411	0.304226	0.965637	8.94273	0.502	0.359	2.456	7.145
	Y8	2.104258	0.14499	0.021022	-0.1676	-0.54787	0.52079	1.85915	2.37994	42.08517	1.681	0.361	-0.238	2.593
	Y2	1.630104	0.278804	0.077732	0.738083	0.08645	1.030868	1.241997	2.272865	32.60207	0.995	0.283	1.080	1.878
Group 2	Y3	1.705463	0.331819	0.110104	0.809416	2.632785	1.571079	1.081383	2.652462	34.10927	1.318	0.285	0.457	1.028
	Y4	1.111193	0.207313	0.042979	0.958105	0.681679	0.780864	0.805508	1.586372	22.22385	1.005	0.236	0.298	0.425
	Y5	0.671146	0.148062	0.021922	1.239313	3.18526	0.686691	0.425741	1.112432	13.42293	0.636	0.254	1.132	1.827
	Y6	0.562049	0.203744	0.041512	0.153991	-0.73841	0.685665	0.239937	0.925602	11.24098	0.672	0.263	0.367	0.049
Group 3	E2	1.024463	0.6052	0.366267	1.039903	0.449368	2.190697	0.313582	2.504278	20.48926	0.657	0.397	2.807	12.599
	E3	0.745153	0.196481	0.038605	-0.39097	-0.87209	0.671424	0.359301	1.030725	14.90306	0.734	0.213	0.315	0.242
	E4	1.029987	0.199756	0.039902	0.91193	0.868287	0.796325	0.759062	1.555387	20.59974	1.000	0.415	0.813	0.781
	E5	0.671171	0.173113	0.029968	-0.12067	-0.36693	0.660551	0.323179	0.98373	13.42343	0.443	0.206	0.852	1.559
Group 4	Y9	0.593527	0.188428	0.035505	0.849957	-0.40896	0.59911	0.354187	0.953297	11.87055	0.793	0.292	0.838	3.180
	Y10	1.763894	0.334604	0.11196	1.36941	3.136469	1.477474	1.289597	2.767071	35.27787	1.522	0.328	0.863	3.466
	Y11	4.146485	0.348294	0.121309	0.724854	-0.42877	1.155793	3.740833	4.896626	82.9297	3.649	0.423	-0.892	8.891
	Y12	1.468263	0.273447	0.074773	0.826782	0.165781	0.973579	1.110268	2.083847	29.36527	1.405	0.368	0.928	1.701
Group 5	Y13	0.900317	0.233693	0.054612	0.132778	-0.70503	0.873573	0.47757	1.351143	18.00634	0.989	0.277	0.438	0.899
	Y14	1.518398	0.134269	0.018028	-0.23016	-0.87573	0.46283	1.256973	1.719803	30.36795	1.495	0.197	1.120	11.946
	Y15	1.200126	0.176563	0.031175	-0.70122	0.053389	0.63611	0.84111	1.47722	24.00251	1.011	0.265	1.200	4.420
	Y16	1.640492	0.15801	0.024967	0.19587	0.017489	0.635952	1.353653	1.989605	32.80983	1.413	0.202	0.226	1.474
Group 6	Y17	2.235103	0.158669	0.025176	0.866277	0.669202	0.637886	1.998169	2.636055	44.70207	2.383	0.418	4.266	40.436
	Y18	1.946221	0.365761	0.133781	-1.07202	0.697925	1.325535	1.011204	2.336739	38.92442	2.073	0.285	-0.206	3.054
	Y19	2.738366	0.393647	0.154958	0.321353	-0.51684	1.392624	2.129852	3.522476	54.76732	2.216	0.432	-0.111	1.606

Table 5.4.4 d Nine statistical inputs and desired outputs for every subject used for developing Net 15.

9 Statistical Inputs		Input Variables									Output Variables			
1 minute		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
	Y1	0.97217	0.293171	0.085949	-0.19858	0.107082	1.308236	0.306728	1.614964	54.44152	0.860	0.266	0.511	0.716
Group 1	E1	1.782342	0.217303	0.04722	0.798868	0.320164	0.916969	1.398159	2.315128	58.81727	1.196	0.378	0.685	0.453
	Y7	0.363733	0.132082	0.017446	2.555384	9.841458	0.811321	0.154316	0.965637	21.82399	0.502	0.359	2.456	7.145
	Y8	2.054657	0.15434	0.023821	0.101498	-0.37874	0.725575	1.702274	2.427849	129.4434	1.681	0.361	-0.238	2.593
	Y2	1.527451	0.260219	0.067714	0.516621	0.36492	1.198085	1.07478	2.272865	79.42744	0.995	0.283	1.080	1.878
Group 2	Y3	1.612382	0.287055	0.082401	0.832905	2.108008	1.571079	1.081383	2.652462	82.23149	1.318	0.285	0.457	1.028
	Y4	1.07894	0.191934	0.036839	0.245774	0.797473	0.968326	0.618046	1.586372	50.71018	1.005	0.236	0.298	0.425
	Y5	0.651203	0.132702	0.01761	1.222545	3.829931	0.686691	0.425741	1.112432	20.18731	0.636	0.254	1.132	1.827
	Y6	0.507618	0.226687	0.051387	0.366868	-0.7818	0.845505	0.092297	0.937801	21.82759	0.672	0.263	0.367	0.049
Group 3	E2	1.239659	0.638608	0.40782	0.459672	-0.86087	2.206719	0.313582	2.5203	44.62771	0.657	0.397	2.807	12.599
	E3	0.734739	0.203042	0.041226	0.703326	1.705603	1.052284	0.359301	1.411585	30.12428	0.734	0.213	0.315	0.242
	E4	0.934465	0.218728	0.047842	0.321348	0.435338	1.071767	0.48362	1.555387	40.18198	1.000	0.415	0.813	0.781
	E5	0.594524	0.209811	0.044021	-0.17692	-0.56424	0.787313	0.196417	0.98373	16.64666	0.443	0.206	0.852	1.559
Group 4	Y9	0.805589	0.282055	0.079555	0.266904	-0.49855	1.145169	0.330421	1.47559	44.30738	0.793	0.292	0.838	3.180
	Y10	1.703662	0.326859	0.106837	1.292078	2.435599	1.531578	1.26973	2.801308	100.5161	1.522	0.328	0.863	3.466
	Y11	4.095839	0.345681	0.119495	0.733691	0.223134	1.529312	3.536133	5.065445	229.367	3.649	0.423	-0.892	8.891
	Y12	1.475719	0.323442	0.104614	0.909492	0.672413	1.50592	0.959633	2.465553	81.16454	1.405	0.368	0.928	1.701
Group 5	Y13	0.794966	0.221362	0.049001	0.256366	-0.32508	0.999439	0.351704	1.351143	42.92819	0.989	0.277	0.438	0.899
	Y14	1.461432	0.147318	0.021703	-0.42376	-0.41546	0.589464	1.130339	1.719803	75.99447	1.495	0.197	1.120	11.946
	Y15	1.258027	0.176298	0.031081	-0.65312	0.527094	0.74359	0.82814	1.57173	59.12728	1.011	0.265	1.200	4.420
	Y16	1.631493	0.137935	0.019026	0.020268	0.342998	0.679829	1.309776	1.989605	86.46912	1.413	0.202	0.226	1.474
Group 6	Y17	2.212526	0.156572	0.024515	0.625449	0.644943	0.744076	1.891979	2.636055	121.6889	2.383	0.418	4.266	40.436
	Y18	1.970349	0.262176	0.068736	-1.21422	2.475344	1.325535	1.011204	2.336739	102.4582	2.073	0.285	-0.206	3.054
	Y19	2.631087	0.350624	0.122937	0.364377	0.348354	1.666759	1.855717	3.522476	121.03	2.216	0.432	-0.111	1.606

Table 5.4.4 e Nine statistical inputs and desired outputs for every subject used for developing Net 16.

9 Statistical Inputs		Input Variables									Output Variables			
5 minute		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
	Y1	0.955976	0.281818	0.079421	0.2355	-0.04915	1.528641	0.306728	1.835369	263.8493	0.860	0.266	0.511	0.716
Group 1	E1	1.66414	0.315795	0.099726	-0.93644	2.519263	2.132578	0.341456	2.474033	266.2624	1.196	0.378	0.685	0.453
	Y7	0.387592	0.344393	0.118607	3.160712	11.36029	2.276577	0.012424	2.289001	115.5025	0.502	0.359	2.456	7.145
	Y8	1.941934	0.152403	0.023227	0.384666	-0.13073	0.862457	1.565392	2.427849	611.7091	1.681	0.361	-0.238	2.593
	Y2	1.31292	0.300198	0.090119	0.681442	0.548165	1.777253	0.71238	2.489632	337.4204	0.995	0.283	1.080	1.878
Group 2	Y3	1.563403	0.225477	0.05084	0.514426	1.393501	1.611069	1.041393	2.652462	397.1045	1.318	0.285	0.457	1.028
	Y4	1.174352	0.212994	0.045366	0.456613	1.730628	1.578987	0.568348	2.147335	270.101	1.005	0.236	0.298	0.425
	Y5	0.637879	0.173541	0.030116	0.706793	1.429209	1.018525	0.218084	1.236609	97.59546	0.636	0.254	1.132	1.827
	Y6	0.535696	0.237458	0.056386	0.417407	-0.24259	1.191534	0.021992	1.213526	113.5675	0.672	0.263	0.367	0.049
Group 3	E2	0.969913	0.542301	0.29409	1.248427	2.270618	3.347881	0.118353	3.466234	171.6746	0.657	0.397	2.807	12.599
	E3	0.647765	0.198975	0.039591	0.520081	0.991051	1.27478	0.136805	1.411585	130.2007	0.734	0.213	0.315	0.242
	E4	0.756515	0.262343	0.068824	0.199608	0.097497	1.530046	0.025341	1.555387	158.8682	1.000	0.415	0.813	0.781
	E5	0.566868	0.223074	0.049762	0.619377	0.048996	1.100744	0.186632	1.287376	77.66092	0.443	0.206	0.852	1.559
Group 4	Y9	0.809781	0.240011	0.057605	0.31411	-0.26291	1.148411	0.327179	1.47559	220.2605	0.793	0.292	0.838	3.180
	Y10	1.615272	0.348386	0.121373	1.315182	2.533054	1.934468	0.988689	2.923157	471.6594	1.522	0.328	0.863	3.466
	Y11	3.744167	0.423741	0.179556	-1.30438	12.66273	4.499672	0.879555	5.379227	1048.367	3.649	0.423	-0.892	8.891
	Y12	1.313717	0.321548	0.103393	1.20613	2.244064	2.092694	0.590038	2.682732	356.0173	1.405	0.368	0.928	1.701
Group 5	Y13	0.888162	0.257986	0.066557	0.190806	-0.14353	1.321598	0.259594	1.581192	236.2511	0.989	0.277	0.438	0.899
	Y14	1.641657	0.191478	0.036664	-0.13415	-0.18751	1.022884	1.120827	2.143711	423.5476	1.495	0.197	1.120	11.946
	Y15	1.210902	0.232126	0.053883	0.689969	1.880403	1.58562	0.67958	2.2652	279.7183	1.011	0.265	1.200	4.420
	Y16	1.560414	0.183555	0.033693	1.44622	8.271211	1.680599	1.085617	2.766216	408.8285	1.413	0.202	0.226	1.474
Group 6	Y17	2.303011	0.470579	0.221445	4.203676	48.04568	7.154308	0.086308	7.240616	631.025	2.383	0.418	4.266	40.436
	Y18	2.036991	0.260194	0.067701	-0.10052	1.117076	2.022156	1.011204	3.03336	525.5437	2.073	0.285	-0.206	3.054
	Y19	2.627224	0.38992	0.152038	-0.77348	5.993416	3.553139	0.199524	3.752663	599.007	2.216	0.432	-0.111	1.606

Table 5.4.4 f Nine statistical inputs and desired outputs for every subject used for developing Net 17

9 Statistical Inputs		Input Variables									Output Variables			
10 minute		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
	Y1	0.865076	0.287617	0.082724	0.394703	0.125182	1.675449	0.15992	1.835369	478.3871	0.860	0.266	0.511	0.716
Group 1	E1	1.340073	0.440042	0.193637	0.202637	-0.75517	2.370009	0.341456	2.711464	430.1635	1.196	0.378	0.685	0.453
	Y7	0.483192	0.367306	0.134913	2.42627	6.496509	2.287601	0.0014	2.289001	287.4995	0.502	0.359	2.456	7.145
	Y8	1.91707	0.149172	0.022252	0.202973	0.063098	1.015873	1.411976	2.427849	1205.837	1.681	0.361	-0.238	2.593
	Y2	1.172497	0.30226	0.091361	0.772946	0.945738	2.132183	0.357449	2.489632	605.0083	0.995	0.283	1.080	1.878
Group 2	Y3	1.418233	0.272745	0.07439	0.276616	0.875071	2.022533	0.629929	2.652462	723.2987	1.318	0.285	0.457	1.028
	Y4	1.150633	0.203351	0.041351	0.324818	1.06454	1.578987	0.568348	2.147335	530.442	1.005	0.236	0.298	0.425
	Y5	0.618838	0.178242	0.03177	1.089543	3.571263	1.357363	0.218084	1.575447	190.6021	0.636	0.254	1.132	1.827
	Y6	0.653396	0.275665	0.075991	0.341125	-0.00405	1.654672	0.021992	1.676664	278.3466	0.672	0.263	0.367	0.049
Group 3	E2	0.861931	0.568503	0.323196	1.792121	4.612269	3.817293	0.118353	3.935646	305.1235	0.657	0.397	2.807	12.599
	E3	0.621344	0.198094	0.039241	0.925078	2.858819	1.568891	0.109089	1.67798	250.4017	0.734	0.213	0.315	0.242
	E4	0.941885	0.446638	0.199485	1.261907	1.866476	2.863297	0.025341	2.888638	396.5337	1.000	0.415	0.813	0.781
	E5	0.518443	0.216912	0.047051	0.780309	0.413108	1.215013	0.072363	1.287376	141.5349	0.443	0.206	0.852	1.559
Group 4	Y9	0.854169	0.302568	0.091547	0.332909	0.14364	1.940296	0	1.940296	463.8135	0.793	0.292	0.838	3.180
	Y10	1.65487	0.333456	0.111193	1.109525	2.94758	2.912712	0.324745	3.237457	966.4439	1.522	0.328	0.863	3.466
	Y11	3.613134	0.395025	0.156045	-0.46511	7.616087	4.499672	0.879555	5.379227	2023.355	3.649	0.423	-0.892	8.891
	Y12	1.231805	0.299207	0.089525	1.146994	2.911285	2.552208	0.130524	2.682732	666.4067	1.405	0.368	0.928	1.701
Group 5	Y13	0.933222	0.278519	0.077573	0.309939	0.529919	1.92469	0.133377	2.058067	496.4743	0.989	0.277	0.438	0.899
	Y14	1.61944	0.199888	0.039955	2.367989	25.95925	2.665798	1.120827	3.786625	834.0117	1.495	0.197	1.120	11.946
	Y15	1.124528	0.273702	0.074913	0.888351	1.997462	1.86877	0.54629	2.41506	518.4074	1.011	0.265	1.200	4.420
	Y16	1.517192	0.188018	0.035351	0.51251	4.539437	1.862697	0.903519	2.766216	793.4912	1.413	0.202	0.226	1.474
Group 6	Y17	2.29668	0.427725	0.182948	4.736626	48.96947	7.154308	0.086308	7.240616	1258.581	2.383	0.418	4.266	40.436
	Y18	2.065941	0.275588	0.075949	0.15668	0.866981	2.182159	1.011204	3.193363	1061.894	2.073	0.285	-0.206	3.054
	Y19	2.478952	0.40454	0.163653	-0.46914	3.50079	3.553139	0.199524	3.752663	1127.923	2.216	0.432	-0.111	1.606

Table 5.4.4 g Nine statistical inputs and desired outputs for every subject used for developing Net 18.

9 Statistical Inputs		Input Variables									Output Variables			
15 minute		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
	Y1	0.880396	0.279829	0.078305	0.373188	0.197895	1.728954	0.15992	1.888874	731.6089	0.860	0.266	0.511	0.716
Group 1	E1	1.249535	0.405372	0.164326	0.563386	-0.25089	2.370009	0.341456	2.711464	602.2757	1.196	0.378	0.685	0.453
	Y7	0.579109	0.413016	0.170582	1.866508	4.035466	2.819569	0.0014	2.820969	516.5655	0.502	0.359	2.456	7.145
	Y8	1.857914	0.183381	0.033629	-0.81516	3.765698	1.647938	0.779911	2.427849	1752.013	1.681	0.361	-0.238	2.593
	Y2	1.072553	0.30423	0.092556	0.898529	1.122114	2.132183	0.357449	2.489632	830.156	0.995	0.283	1.080	1.878
Group 2	Y3	1.360941	0.282779	0.079964	0.522424	1.712399	2.241268	0.51675	2.758018	1039.759	1.318	0.285	0.457	1.028
	Y4	1.11755	0.207128	0.042902	0.237364	0.738172	1.608032	0.539303	2.147335	773.3445	1.005	0.236	0.298	0.425
	Y5	0.601262	0.181916	0.033094	0.816686	2.463905	1.407412	0.168036	1.575447	277.7831	0.636	0.254	1.132	1.827
	Y6	0.688151	0.2688	0.072253	0.23146	0.082718	1.654672	0.021992	1.676664	439.7287	0.672	0.263	0.367	0.049
Group 3	E2	0.760468	0.502463	0.252469	2.192961	7.00806	3.817293	0.118353	3.935646	404.569	0.657	0.397	2.807	12.599
	E3	0.629223	0.184296	0.033965	0.744354	2.534155	1.568891	0.109089	1.67798	383.8258	0.734	0.213	0.315	0.242
	E4	0.960568	0.454557	0.206622	1.111213	1.190939	2.863297	0.025341	2.888638	607.0789	1.000	0.415	0.813	0.781
	E5	0.480373	0.226187	0.05116	0.801519	0.708737	1.262008	0.025368	1.287376	197.9138	0.443	0.206	0.852	1.559
Group 4	Y9	0.859599	0.298126	0.088879	0.963382	4.802099	3.228222	0	3.228222	699.7135	0.793	0.292	0.838	3.180
	Y10	1.614011	0.33707	0.113616	1.038575	2.43681	2.912712	0.324745	3.237457	1413.873	1.522	0.328	0.863	3.466
	Y11	3.751942	0.427273	0.182562	-0.62329	4.717199	4.499672	0.879555	5.379227	3147.879	3.649	0.423	-0.892	8.891
	Y12	1.311942	0.332749	0.110722	0.721013	0.757201	2.552208	0.130524	2.682732	1065.297	1.405	0.368	0.928	1.701
Group 5	Y13	0.979318	0.279702	0.078233	0.313682	0.808284	1.998806	0.133377	2.132183	781.4958	0.989	0.277	0.438	0.899
	Y14	1.54779	0.211187	0.0446	1.492621	15.60659	2.998999	0.787626	3.786625	1196.441	1.495	0.197	1.120	11.946
	Y15	1.087772	0.259535	0.067358	0.988985	2.335845	1.88787	0.52719	2.41506	751.6504	1.011	0.265	1.200	4.420
	Y16	1.463219	0.199108	0.039644	0.309648	2.782209	1.929703	0.836514	2.766216	1148.627	1.413	0.202	0.226	1.474
Group 6	Y17	2.31943	0.381004	0.145164	4.459691	51.28442	7.154308	0.086308	7.240616	1904.252	2.383	0.418	4.266	40.436
	Y18	2.110164	0.289291	0.083689	0.227751	1.049862	2.364559	1.011204	3.375763	1629.046	2.073	0.285	-0.206	3.054
	Y19	2.344628	0.432466	0.187026	-0.13158	1.192832	3.553139	0.199524	3.752663	1599.036	2.216	0.432	-0.111	1.606

Table 5.4.4 h Nine statistical inputs and desired outputs for every subject used for developing Net 19.

9 Statistical Inputs		Input Variables									Output Variables			
20 trials		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
	Y1	0.84812	0.362949	0.131732	0.199134	-0.67407	1.255288	0.306728	1.562016	16.96241	0.860	0.266	0.511	0.716
Group 1	E1	1.820629	0.216007	0.046659	0.465557	0.609902	0.916969	1.398159	2.315128	36.41258	1.196	0.378	0.685	0.453
	Y7	0.447136	0.177983	0.031678	2.231155	4.074055	0.661411	0.304226	0.965637	8.94273	0.502	0.359	2.456	7.145
	Y8	2.104258	0.14499	0.021022	-0.1676	-0.54787	0.52079	1.85915	2.37994	42.08517	1.681	0.361	-0.238	2.593
	Y2	1.630104	0.278804	0.077732	0.738083	0.08645	1.030868	1.241997	2.272865	32.60207	0.995	0.283	1.080	1.878
Group 2	Y3	1.705463	0.331819	0.110104	0.809416	2.632785	1.571079	1.081383	2.652462	34.10927	1.318	0.285	0.457	1.028
	Y4	1.111193	0.207313	0.042979	0.958105	0.681679	0.780864	0.805508	1.586372	22.22385	1.005	0.236	0.298	0.425
	Y5	0.671146	0.148062	0.021922	1.239313	3.18526	0.686691	0.425741	1.112432	13.42293	0.636	0.254	1.132	1.827
	Y6	0.562049	0.203744	0.041512	0.153991	-0.73841	0.685665	0.239937	0.925602	11.24098	0.672	0.263	0.367	0.049
Group 3	E2	1.024463	0.6052	0.366267	1.039903	0.449368	2.190697	0.313582	2.504278	20.48926	0.657	0.397	2.807	12.599
	E3	0.745153	0.196481	0.038605	-0.39097	-0.87209	0.671424	0.359301	1.030725	14.90306	0.734	0.213	0.315	0.242
	E4	1.029987	0.199756	0.039902	0.91193	0.868287	0.796325	0.759062	1.555387	20.59974	1.000	0.415	0.813	0.781
	E5	0.671171	0.173113	0.029968	-0.12067	-0.36693	0.660551	0.323179	0.98373	13.42343	0.443	0.206	0.852	1.559
Group 4	Y9	0.593527	0.188428	0.035505	0.849957	-0.40896	0.59911	0.354187	0.953297	11.87055	0.793	0.292	0.838	3.180
	Y10	1.763894	0.334604	0.11196	1.36941	3.136469	1.477474	1.289597	2.767071	35.27787	1.522	0.328	0.863	3.466
	Y11	4.146485	0.348294	0.121309	0.724854	-0.42877	1.155793	3.740833	4.896626	82.9297	3.649	0.423	-0.892	8.891
	Y12	1.468263	0.273447	0.074773	0.826782	0.165781	0.973579	1.110268	2.083847	29.36527	1.405	0.368	0.928	1.701
Group 5	Y13	0.900317	0.233693	0.054612	0.132778	-0.70503	0.873573	0.47757	1.351143	18.00634	0.989	0.277	0.438	0.899
	Y14	1.518398	0.134269	0.018028	-0.23016	-0.87573	0.46283	1.256973	1.719803	30.36795	1.495	0.197	1.120	11.946
	Y15	1.200126	0.176563	0.031175	-0.70122	0.053389	0.63611	0.84111	1.47722	24.00251	1.011	0.265	1.200	4.420
	Y16	1.640492	0.15801	0.024967	0.19587	0.017489	0.635952	1.353653	1.989605	32.80983	1.413	0.202	0.226	1.474
Group 6	Y17	2.235103	0.158669	0.025176	0.866277	0.669202	0.637886	1.998169	2.636055	44.70207	2.383	0.418	4.266	40.436
	Y18	1.946221	0.365761	0.133781	-1.07202	0.697925	1.325535	1.011204	2.336739	38.92442	2.073	0.285	-0.206	3.054
	Y19	2.738366	0.393647	0.154958	0.321353	-0.51684	1.392624	2.129852	3.522476	54.76732	2.216	0.432	-0.111	1.606

Table 5.4.4i Nine statistical inputs and desired outputs for every subject used for developing Net 20

9 Statistical Inputs		Input Variables									Output Variables			
25 minute		Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
	Y1	0.848994	0.265258	0.070362	0.482208	0.556287	1.745907	0.15992	1.905827	1175.857	0.860	0.266	0.511	0.716
Group 1	E1	1.240101	0.379364	0.143917	0.642019	0.328802	2.517195	0.341456	2.85865	997.0412	1.196	0.378	0.685	0.453
	Y7	0.51699	0.373746	0.139686	2.322306	6.20109	2.819569	0.0014	2.820969	768.7644	0.502	0.359	2.456	7.145
	Y8	1.66554	0.349412	0.122089	-0.94501	0.339467	2.298889	0.12896	2.427849	2618.229	1.681	0.361	-0.238	2.593
	Y2	1.030824	0.281605	0.079301	1.00334	1.575896	2.132183	0.357449	2.489632	1328.732	0.995	0.283	1.080	1.878
Group 2	Y3	1.329743	0.282277	0.07968	0.424401	1.110788	2.241268	0.51675	2.758018	1691.433	1.318	0.285	0.457	1.028
	Y4	1.038919	0.226298	0.051211	0.195325	0.257408	1.712841	0.434494	2.147335	1198.913	1.005	0.236	0.298	0.425
	Y5	0.582304	0.200446	0.040179	1.119917	3.297389	1.515915	0.155876	1.671791	448.3743	0.636	0.254	1.132	1.827
	Y6	0.676686	0.270941	0.073409	0.314039	-0.05363	1.674265	0.002399	1.676664	720.6706	0.672	0.263	0.367	0.049
Group 3	E2	0.682704	0.42294	0.178878	2.629698	10.83396	3.817293	0.118353	3.935646	604.8759	0.657	0.397	2.807	12.599
	E3	0.691761	0.196803	0.038731	0.467846	0.946609	1.568891	0.109089	1.67798	697.9865	0.734	0.213	0.315	0.242
	E4	0.975271	0.416247	0.173262	0.937362	1.129515	2.863297	0.025341	2.888638	1027.936	1.000	0.415	0.813	0.781
	E5	0.445788	0.207339	0.042989	0.832284	1.33978	1.286665	0.000711	1.287376	305.8106	0.443	0.206	0.852	1.559
Group 4	Y9	0.824694	0.287342	0.082565	0.913837	3.869602	3.228222	0	3.228222	1119.109	0.793	0.292	0.838	3.180
	Y10	1.554876	0.330747	0.109394	0.906007	3.513248	3.353092	0.161732	3.514824	2270.119	1.522	0.328	0.863	3.466
	Y11	3.663188	0.430294	0.185153	-0.69865	6.81984	5.073464	0.305763	5.379227	5124.8	3.649	0.423	-0.892	8.891
	Y12	1.333189	0.316087	0.099911	1.001956	3.10153	3.318454	0.130524	3.448978	1803.804	1.405	0.368	0.928	1.701
Group 5	Y13	0.984226	0.27699	0.076723	0.34119	0.672003	2.066067	0.066116	2.132183	1308.036	0.989	0.277	0.438	0.899
	Y14	1.505614	0.201813	0.040729	1.136216	12.64715	3.324232	0.462393	3.786625	1939.231	1.495	0.197	1.120	11.946
	Y15	1.018386	0.275798	0.076065	1.183613	4.291151	2.47983	0.18003	2.65986	1173.181	1.011	0.265	1.200	4.420
	Y16	1.431958	0.197511	0.039011	0.273192	1.882651	1.955082	0.811134	2.766216	1871.57	1.413	0.202	0.226	1.474
Group 6	Y17	2.34616	0.413965	0.171367	4.907783	49.72911	7.154308	0.086308	7.240616	3211.893	2.383	0.418	4.266	40.436
	Y18	2.07328	0.284033	0.080675	0.036096	2.361588	3.22052	0.155243	3.375763	2666.238	2.073	0.285	-0.206	3.054
	Y19	2.26173	0.426027	0.181499	-0.09611	1.600638	3.784801	0.103783	3.888584	2567.064	2.216	0.432	-0.111	1.606

Table 5.4.5 a Fourteen statistical inputs and desired outputs for subject used for developing Net 21

14 Statistical Inputs		Input Variables														Output Variables			
5 minute		5trials mean	1min mean	2min mean	3min mean	4min mean	5min Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
	Y1	0.91012958	0.97217003	0.95028547	0.90668659	0.93531815	0.9559759	0.281818	0.079421	0.2355	-0.04915	1.528641	0.306728	1.835369	263.8493	0.860	0.266	0.511	0.716
Group 1	E1	1.8096944	1.78234152	1.7531572	1.74175052	1.71457885	1.66414	0.315795	0.099726	-0.93644	2.519263	2.132578	0.341456	2.474033	266.2624	1.196	0.378	0.685	0.453
	Y7	0.44976576	0.36373309	0.43444467	0.38259205	0.37612327	0.3875923	0.344393	0.118607	3.160712	11.36029	2.276577	0.012424	2.289001	115.5025	0.502	0.359	2.456	7.145
	Y8	2.2229134	2.054657	1.96190937	1.94825025	1.937827	1.9419335	0.152403	0.023227	0.384666	-0.13073	0.862457	1.565392	2.427849	611.7091	1.681	0.361	-0.238	2.593
	Y2	1.960433	1.52745077	1.46909425	1.46288213	1.36280894	1.3129197	0.300198	0.090119	0.681442	0.548165	1.777253	0.71238	2.489632	337.4204	0.995	0.283	1.080	1.878
Group 2	Y3	1.3364898	1.6123822	1.5966507	1.5944349	1.57881712	1.5634034	0.225477	0.05084	0.514426	1.393501	1.611069	1.041393	2.652462	397.1045	1.318	0.285	0.457	1.028
	Y4	1.19375838	1.07894004	1.11227251	1.14008599	1.16392688	1.1743524	0.212994	0.045366	0.456613	1.730628	1.578987	0.568348	2.147335	270.101	1.005	0.236	0.298	0.425
	Y5	0.6834717	0.65120344	0.60244816	0.60086446	0.62863465	0.6378788	0.173541	0.030116	0.706793	1.429209	1.018525	0.218084	1.236609	97.59546	0.636	0.254	1.132	1.827
	Y6	0.63704302	0.50761849	0.56798713	0.56155592	0.54335072	0.5356958	0.237458	0.056386	0.417407	-0.24259	1.191534	0.021992	1.213526	113.5675	0.672	0.263	0.367	0.049
Group 3	E2	0.75215984	1.23965854	1.27177459	1.13976395	1.07875476	0.9699131	0.542301	0.29409	1.248427	2.270618	3.347881	0.118353	3.466234	171.6746	0.657	0.397	2.807	12.599
	E3	0.94526744	0.73473865	0.7056446	0.68290792	0.65203129	0.6477646	0.198975	0.039591	0.520081	0.991051	1.27478	0.136805	1.411585	130.2007	0.734	0.213	0.315	0.242
	E4	1.21122814	0.93446466	0.87488479	0.78429737	0.76487674	0.7565152	0.262343	0.068824	0.199608	0.097497	1.530046	0.025341	1.555387	158.8682	1.000	0.415	0.813	0.781
	E5	0.6846611	0.59452364	0.67818893	0.60719729	0.59243811	0.5668681	0.223074	0.049762	0.619377	0.048996	1.100744	0.186632	1.287376	77.66092	0.443	0.206	0.852	1.559
Group 4	Y9	0.51620408	0.80558882	0.89468271	0.85364995	0.85418164	0.8097811	0.240011	0.057605	0.31411	-0.26291	1.148411	0.327179	1.47559	220.2605	0.793	0.292	0.838	3.180
	Y10	1.7225554	1.70366215	1.67283834	1.63559139	1.6123935	1.615272	0.348386	0.121373	1.315182	2.533054	1.934468	0.988689	2.923157	471.6594	1.522	0.328	0.863	3.466
	Y11	4.348082	4.09583875	3.93392862	3.87611418	3.81275851	3.7441672	0.423741	0.179556	-1.30438	12.66273	4.499672	0.879555	5.379227	1048.367	3.649	0.423	-0.892	8.891
	Y12	1.4872228	1.47571893	1.48790743	1.40480054	1.34038319	1.313717	0.321548	0.103393	1.20613	2.244064	2.092694	0.590038	2.682732	356.0173	1.405	0.368	0.928	1.701
Group 5	Y13	0.99097134	0.79496644	0.74054357	0.82725077	0.84706036	0.8881621	0.257986	0.066557	0.190806	-0.14353	1.321598	0.259594	1.581192	236.2511	0.989	0.277	0.438	0.899
	Y14	1.6208214	1.4614321	1.51038456	1.57044071	1.61337521	1.6416572	0.191478	0.036664	-0.13415	-0.18751	1.022884	1.120827	2.143711	423.5476	1.495	0.197	1.120	11.946
	Y15	1.024872	1.25802723	1.19640344	1.18805899	1.2010606	1.2109016	0.232126	0.053883	0.689969	1.880403	1.58562	0.67958	2.2652	279.7183	1.011	0.265	1.200	4.420
	Y16	1.733583	1.63149275	1.55200922	1.54102939	1.54713852	1.5604143	0.183555	0.033693	1.44622	8.271211	1.680599	1.085617	2.766216	408.8285	1.413	0.202	0.226	1.474
Group 6	Y17	2.2882744	2.21252622	2.33792058	2.35004753	2.32519095	2.303011	0.470579	0.221445	4.203676	48.04568	7.154308	0.086308	7.240616	631.025	2.383	0.418	4.266	40.436
	Y18	2.09647	1.97034913	2.05804515	2.05156207	2.04861493	2.0369911	0.260194	0.067701	-0.10052	1.117076	2.022156	1.011204	3.03336	525.5437	2.073	0.285	-0.206	3.054
	Y19	2.4846718	2.63108696	2.65755676	2.65228584	2.60520383	2.6272238	0.38992	0.152038	-0.77348	5.993416	3.553139	0.199524	3.752663	599.007	2.216	0.432	-0.111	1.606

Table 5.4.5 b Fourteen statistical inputs and desired outputs for every subject used for developing Net 22

14 Statistical Inputs		Input Variables														Output Variables			
10 minute		5min mean	6min mean	7min mean	8min mean	9min mean	10min Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
	Y1	0.95597589	0.91122425	0.87506958	0.8712459	0.85626009	0.865076126	0.287617	0.082724	0.394703	0.125182	1.675449	0.15992	1.835369	478.3871	0.860	0.266	0.511	0.716
Group 1	E1	1.66413999	1.57813907	1.49621811	1.43142797	1.39079489	1.34007335	0.440042	0.193637	0.202637	-0.75517	2.370009	0.341456	2.711464	430.1635	1.196	0.378	0.685	0.453
	Y7	0.38759226	0.41781382	0.44804856	0.46081982	0.4680872	0.483192438	0.367306	0.134913	2.42627	6.496509	2.287601	0.0014	2.289001	287.4995	0.502	0.359	2.456	7.145
	Y8	1.94193354	1.93255101	1.93768512	1.93311615	1.93399083	1.917069908	0.149172	0.022252	0.202973	0.063098	1.015873	1.411976	2.427849	1205.837	1.681	0.361	-0.238	2.593
	Y2	1.31291968	1.27783778	1.2509945	1.23105864	1.20115804	1.172496618	0.30226	0.091361	0.772946	0.945738	2.132183	0.357449	2.489632	605.0083	0.995	0.283	1.080	1.878
Group 2	Y3	1.56340337	1.49154616	1.45456617	1.43776577	1.42203683	1.418232704	0.272745	0.07439	0.276616	0.875071	2.022533	0.629929	2.652462	723.2987	1.318	0.285	0.457	1.028
	Y4	1.17435239	1.17696388	1.17496752	1.15991053	1.14865142	1.150633425	0.203351	0.041351	0.324818	1.06454	1.578987	0.568348	2.147335	530.442	1.005	0.236	0.298	0.425
	Y5	0.63787882	0.6358318	0.63723846	0.62394931	0.61152362	0.618838074	0.178242	0.03177	1.089543	3.571263	1.357363	0.218084	1.575447	190.6021	0.636	0.254	1.132	1.827
	Y6	0.53569583	0.54550292	0.57117123	0.60497554	0.61211584	0.653395769	0.275665	0.075991	0.341125	-0.00405	1.654672	0.021992	1.676664	278.3466	0.672	0.263	0.367	0.049
Group 3	E2	0.96991313	0.90294064	0.86180475	0.87062694	0.90459932	0.861930651	0.568503	0.323196	1.792121	4.612269	3.817293	0.118353	3.935646	305.1235	0.657	0.397	2.807	12.599
	E3	0.64776462	0.64132971	0.6258965	0.61873417	0.63589809	0.62134413	0.198094	0.039241	0.925078	2.858819	1.568891	0.109089	1.67798	250.4017	0.734	0.213	0.315	0.242
	E4	0.7565152	0.76444086	0.76220885	0.7829542	0.85231193	0.941885259	0.446638	0.199485	1.261907	1.866476	2.863297	0.025341	2.888638	396.5337	1.000	0.415	0.813	0.781
	E5	0.56686805	0.53951941	0.51750959	0.51593202	0.52318377	0.518442725	0.216912	0.047051	0.780309	0.413108	1.215013	0.072363	1.287376	141.5349	0.443	0.206	0.852	1.559
Group 4	Y9	0.80978111	0.77726597	0.75524166	0.77762952	0.82205016	0.854168574	0.302568	0.091547	0.332909	0.14364	1.940296	0	1.940296	463.8135	0.793	0.292	0.838	3.180
	Y10	1.61527199	1.62918018	1.63839574	1.65263607	1.65522199	1.654869668	0.333456	0.111193	1.109525	2.94758	2.912712	0.324745	3.237457	966.4439	1.522	0.328	0.863	3.466
	Y11	3.74416719	3.72486911	3.6816558	3.6722226	3.6393712	3.613133583	0.395025	0.156045	-0.46511	7.616087	4.499672	0.879555	5.379227	2023.355	3.649	0.423	-0.892	8.891
	Y12	1.31371699	1.28824371	1.26389751	1.25339107	1.24291317	1.231805401	0.299207	0.089525	1.146994	2.911285	2.552208	0.130524	2.682732	666.4067	1.405	0.368	0.928	1.701
Group 5	Y13	0.88816207	0.91155099	0.92316443	0.90977105	0.91768581	0.933222417	0.278519	0.077573	0.309939	0.529919	1.92469	0.133377	2.058067	496.4743	0.989	0.277	0.438	0.899
	Y14	1.64165721	1.64868347	1.63394956	1.63503291	1.62778114	1.619440258	0.199888	0.039955	2.367989	25.95925	2.665798	1.120827	3.786625	834.0117	1.495	0.197	1.120	11.946
	Y15	1.21090156	1.20242744	1.15992365	1.14547005	1.12319692	1.124527961	0.273702	0.074913	0.888351	1.997462	1.86877	0.54629	2.41506	518.4074	1.011	0.265	1.200	4.420
	Y16	1.56041431	1.56393963	1.55500386	1.55583272	1.53130671	1.517191637	0.188018	0.035351	0.51251	4.539437	1.862697	0.903519	2.766216	793.4912	1.413	0.202	0.226	1.474
Group 6	Y17	2.30301099	2.31924618	2.32156401	2.30394273	2.30863776	2.296679871	0.427725	0.182948	4.736626	48.96947	7.154308	0.086308	7.240616	1258.581	2.383	0.418	4.266	40.436
	Y18	2.03699114	2.05771069	2.04964324	2.05217948	2.05028287	2.065941115	0.275588	0.075949	0.15668	0.866981	2.182159	1.011204	3.193363	1061.894	2.073	0.285	-0.206	3.054
	Y19	2.62722385	2.61787333	2.58200556	2.54652527	2.52191106	2.478952346	0.40454	0.163653	-0.46914	3.50079	3.553139	0.199524	3.752663	1127.923	2.216	0.432	-0.111	1.606

Table 5.4.5c Fourteen statistical inputs and desired outputs for every subject used for developing Net 23.

14 Statistical Inputs		Input Variables														Output Variables			
15 minute		10min mean	11min mean	12min mean	13min mean	14min mean	15min Mean	SD	Variance	Skewness	Kurtosis	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
	Y1	0.86507613	0.87050936	0.86197457	0.86146154	0.87198419	0.880395781	0.279829	0.078305	0.373188	0.197895	1.728954	0.15992	1.888874	731.6089	0.860	0.266	0.511	0.716
Group 1	E1	1.34007335	1.31638924	1.29257042	1.27972961	1.2646913	1.249534649	0.405372	0.164326	0.563386	-0.25089	2.370009	0.341456	2.711464	602.2757	1.196	0.378	0.685	0.453
	Y7	0.48319244	0.49119003	0.49887102	0.52959763	0.56626187	0.579109258	0.413016	0.170582	1.866508	4.035466	2.819569	0.0014	2.820969	516.5655	0.502	0.359	2.456	7.145
	Y8	1.91706991	1.89761704	1.88457849	1.87523211	1.87284191	1.857913715	0.183381	0.033629	-0.81516	3.765698	1.647938	0.779911	2.427849	1752.013	1.681	0.361	-0.238	2.593
	Y2	1.17249662	1.14306801	1.11381987	1.09644257	1.08673528	1.072553002	0.30423	0.092556	0.898529	1.122114	2.132183	0.357449	2.489632	830.156	0.995	0.283	1.080	1.878
Group 2	Y3	1.4182327	1.39946332	1.39308711	1.38000382	1.36642182	1.360940732	0.282779	0.079964	0.522424	1.712399	2.241268	0.51675	2.758018	1039.759	1.318	0.285	0.457	1.028
	Y4	1.15063342	1.14044663	1.13067083	1.13497503	1.12561421	1.117549919	0.207128	0.042902	0.237364	0.738172	1.608032	0.539303	2.147335	773.3445	1.005	0.236	0.298	0.425
	Y5	0.61883807	0.61552331	0.61590053	0.60783464	0.60900371	0.60126211	0.181916	0.033094	0.816686	2.463905	1.407412	0.168036	1.575447	277.7831	0.636	0.254	1.132	1.827
	Y6	0.65339577	0.66928095	0.68065162	0.68801562	0.69477053	0.688151358	0.2688	0.072253	0.23146	0.082718	1.654672	0.021992	1.676664	439.7287	0.672	0.263	0.367	0.049
Group 3	E2	0.86193065	0.83220912	0.81178051	0.79230047	0.76723546	0.760468	0.502463	0.252469	2.192961	7.00806	3.817293	0.118353	3.935646	404.569	0.657	0.397	2.807	12.599
	E3	0.62134413	0.62172101	0.61533061	0.61616228	0.62523552	0.62922256	0.184296	0.033965	0.744354	2.534155	1.568891	0.109089	1.67798	383.8258	0.734	0.213	0.315	0.242
	E4	0.94188526	0.98139299	0.99050781	0.99997706	0.98019394	0.960567947	0.454557	0.206622	1.111213	1.190939	2.863297	0.025341	2.888638	607.0789	1.000	0.415	0.813	0.781
	E5	0.51844273	0.51269443	0.50360183	0.49703176	0.48816666	0.480373262	0.226187	0.05116	0.801519	0.708737	1.262008	0.025368	1.287376	197.9138	0.443	0.206	0.852	1.559
Group 4	Y9	0.85416857	0.86134851	0.85297215	0.85380078	0.85641311	0.85959892	0.298126	0.088879	0.963382	4.802099	3.228222	0	3.228222	699.7135	0.793	0.292	0.838	3.180
	Y10	1.65486967	1.6399343	1.63793943	1.62716325	1.62754148	1.614010552	0.33707	0.113616	1.038575	2.43681	2.912712	0.324745	3.237457	1413.873	1.522	0.328	0.863	3.466
	Y11	3.61313358	3.62821026	3.67867104	3.70547219	3.72612476	3.75194173	0.427273	0.182562	-0.62329	4.717199	4.499672	0.879555	5.379227	3147.879	3.649	0.423	-0.892	8.891
	Y12	1.2318054	1.21837646	1.23258955	1.25570601	1.28391778	1.311941647	0.332749	0.110722	0.721013	0.757201	2.552208	0.130524	2.682732	1065.297	1.405	0.368	0.928	1.701
Group 5	Y13	0.93322242	0.9507996	0.95937426	0.96420263	0.97817375	0.979318039	0.279702	0.078233	0.313682	0.808284	1.998806	0.133377	2.132183	781.4958	0.989	0.277	0.438	0.899
	Y14	1.61944026	1.59986192	1.58333422	1.56831531	1.55755669	1.547789764	0.211187	0.0446	1.492621	15.60659	2.998999	0.787626	3.786625	1196.441	1.495	0.197	1.120	11.946
	Y15	1.12452796	1.12550191	1.11426861	1.10002334	1.09204206	1.087771881	0.259535	0.067358	0.988985	2.335845	1.88787	0.52719	2.41506	751.6504	1.011	0.265	1.200	4.420
	Y16	1.51719164	1.50449586	1.48703314	1.47553731	1.46827341	1.463218742	0.199108	0.039644	0.309648	2.782209	1.929703	0.836514	2.766216	1148.627	1.413	0.202	0.226	1.474
Group 6	Y17	2.29667987	2.29630439	2.29494295	2.30514146	2.30387736	2.319430089	0.381004	0.145164	4.459691	51.28442	7.154308	0.086308	7.240616	1904.252	2.383	0.418	4.266	40.436
	Y18	2.06594111	2.08305728	2.0971804	2.11167138	2.11296236	2.110163516	0.289291	0.083689	0.227751	1.049862	2.364559	1.011204	3.375763	1629.046	2.073	0.285	-0.206	3.054
	Y19	2.47895235	2.44322304	2.42034485	2.37911266	2.35529786	2.34462793	0.432466	0.187026	-0.13158	1.192832	3.553139	0.199524	3.752663	1599.036	2.216	0.432	-0.111	1.606

APPENDIX II

Testing Results of Various Network Models

Table 6.1a Testing results by Net 1 for 24 subjects

NET 1	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	1.390	0.530	61.6	0.266	0.329	0.063	23.6	0.511	0.845	0.334	65.4	0.716	5.371	4.655	650.1
E1	1.196	1.528	0.333	27.8	0.378	0.310	0.068	18.1	0.685	0.775	0.090	13.2	0.453	6.160	5.707	1260.3
Y7	0.502	0.537	0.035	7.0	0.359	0.213	0.146	40.6	2.456	0.625	1.830	74.5	7.145	-0.874	8.019	112.2
Y8	1.681	1.358	0.323	19.2	0.361	0.302	0.059	16.4	-0.238	0.395	0.633	265.8	2.593	2.335	0.259	10.0
Average			0.305	28.9			0.084	24.7			0.722	104.7			4.660	508.2
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.416	0.421	42.4	0.283	0.306	0.023	8.2	1.080	0.203	0.876	81.2	1.878	1.644	0.234	12.4
Y3	1.318	1.270	0.048	3.6	0.285	0.342	0.056	19.8	0.457	1.767	1.310	286.8	1.028	9.840	8.811	857.0
Y4	1.005	0.981	0.024	2.4	0.236	0.284	0.048	20.4	0.298	0.879	0.582	195.5	0.425	3.586	3.161	744.6
Y5	0.636	1.039	0.402	63.2	0.254	0.282	0.028	11.1	1.132	0.440	0.692	61.1	1.827	0.891	0.936	51.2
Average			0.224	27.9			0.039	14.9			0.865	156.1			3.286	416.3
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.524	0.147	21.9	0.263	0.233	0.030	11.4	0.367	0.495	0.128	34.9	0.049	-2.393	2.443	4942.7
E2	0.657	1.564	0.906	137.9	0.397	0.314	0.083	21.0	2.807	0.459	2.349	83.7	12.599	3.562	9.037	71.7
E3	0.734	0.686	0.048	6.6	0.213	0.262	0.049	23.3	0.315	1.078	0.763	242.0	0.242	1.373	1.131	467.6
E4	1.000	0.698	0.303	30.2	0.415	0.245	0.170	41.0	0.813	1.052	0.239	29.4	0.781	1.849	1.068	136.7
Average			0.351	49.2			0.083	24.2			0.870	97.5			3.420	1404.7
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	1.195	0.752	169.6	0.206	0.310	0.105	50.9	0.852	0.901	0.049	5.7	1.559	4.403	2.844	182.4
Y9	0.793	1.018	0.225	28.4	0.292	0.280	0.012	4.3	0.838	0.645	0.193	23.0	3.180	1.610	1.570	49.4
Y10	1.522	1.055	0.466	30.6	0.328	0.232	0.096	29.2	0.863	-0.568	1.431	165.8	3.466	-4.155	7.621	219.9
Y11	3.649	1.931	1.718	47.1	0.423	0.374	0.049	11.5	-0.892	0.784	1.677	187.9	8.891	8.173	0.719	8.1
Average			0.790	68.9			0.065	24.0			0.837	95.6			3.188	114.9
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.359	0.046	3.3	0.368	0.295	0.073	19.8	0.928	0.312	0.616	66.4	1.701	2.413	0.712	41.9
Y13	0.989	0.940	0.049	4.9	0.277	0.250	0.027	9.7	0.438	-0.118	0.555	126.9	0.899	-2.651	3.550	394.9
Y14	1.495	1.531	0.036	2.4	0.197	0.341	0.144	73.2	1.120	0.444	0.675	60.3	11.946	2.963	8.984	75.2
Y15	1.011	1.023	0.012	1.2	0.265	0.262	0.003	1.2	1.200	0.432	0.768	64.0	4.420	1.442	2.978	67.4
Average			0.035	2.9			0.062	26.0			0.653	79.4			4.056	144.8
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.158	0.255	18.1	0.202	0.306	0.104	51.8	0.226	0.723	0.497	219.3	1.474	3.209	1.736	117.8
Y17	2.383	1.398	0.985	41.3	0.418	0.335	0.082	19.7	4.266	0.761	3.504	82.2	40.436	4.062	36.374	90.0
Y18	2.073	1.124	0.949	45.8	0.285	0.310	0.025	8.7	-0.206	1.097	1.303	633.2	3.054	4.482	1.428	46.7
Y19	2.216	1.749	0.468	21.1	0.432	0.354	0.077	17.9	-0.111	0.472	0.583	526.2	1.606	4.491	2.885	179.6
Average			0.664	31.6			0.072	24.5			1.472	365.2			10.605	108.5

Table 6.1b Testing results by Net 2 for 24 subjects

NET 2	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.851	0.008	1.0	0.266	0.270	0.003	1.3	0.511	0.880	0.369	72.2	0.716	2.602	1.886	263.4
E1	1.196	1.607	0.412	34.4	0.378	0.320	0.058	15.3	0.685	0.740	0.056	8.1	0.453	6.426	5.974	1319.2
Y7	0.502	0.471	0.031	6.1	0.359	0.241	0.118	32.8	2.456	0.981	1.475	60.1	7.145	1.284	5.861	82.0
Y8	1.681	1.850	0.169	10.1	0.361	0.339	0.022	6.1	-0.238	0.804	1.042	437.4	2.593	7.987	5.393	207.9
Average			0.155	12.9			0.050	13.9			0.735	144.4			4.778	468.2
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.250	0.255	25.7	0.283	0.312	0.029	10.2	1.080	0.789	0.291	26.9	1.878	4.536	2.659	141.6
Y3	1.318	1.508	0.191	14.5	0.285	0.333	0.047	16.6	0.457	0.850	0.393	86.0	1.028	6.512	5.484	533.4
Y4	1.005	0.983	0.022	2.2	0.236	0.298	0.062	26.3	0.298	0.962	0.664	223.1	0.425	3.941	3.516	828.1
Y5	0.636	0.529	0.107	16.8	0.254	0.262	0.008	3.0	1.132	0.993	0.139	12.3	1.827	1.136	0.691	37.8
Average			0.144	14.8			0.036	14.0			0.372	87.1			3.087	385.2
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.502	0.169	25.2	0.263	0.242	0.021	8.1	0.367	1.073	0.706	192.4	0.049	0.699	0.650	1314.3
E2	0.657	1.237	0.579	88.2	0.397	0.296	0.101	25.5	2.807	0.713	2.095	74.6	12.599	4.020	8.578	68.1
E3	0.734	0.620	0.114	15.6	0.213	0.253	0.041	19.1	0.315	1.078	0.763	242.0	0.242	1.511	1.269	524.8
E4	1.000	0.771	0.229	22.9	0.415	0.265	0.150	36.1	0.813	1.031	0.218	26.9	0.781	2.580	1.799	230.3
Average			0.273	38.0			0.078	22.2			0.946	134.0			3.074	534.4
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.669	0.225	50.8	0.206	0.266	0.061	29.5	0.852	0.768	0.085	9.9	1.559	0.329	1.230	78.9
Y9	0.793	0.916	0.123	15.5	0.292	0.287	0.005	1.8	0.838	0.902	0.064	7.7	3.180	2.679	0.501	15.7
Y10	1.522	1.395	0.127	8.3	0.328	0.318	0.010	3.0	0.863	0.886	0.023	2.7	3.466	5.983	2.517	72.6
Y11	3.649	2.697	0.952	26.1	0.423	0.396	0.027	6.3	-0.892	1.137	2.030	227.5	8.891	16.592	7.701	86.6
Average			0.357	25.2			0.026	10.1			0.550	61.9			2.987	63.5
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.207	0.198	14.1	0.368	0.308	0.059	16.1	0.928	0.740	0.188	20.3	1.701	3.628	1.927	113.3
Y13	0.989	0.586	0.403	40.8	0.277	0.266	0.011	3.8	0.438	0.914	0.476	108.8	0.899	0.908	0.009	1.0
Y14	1.495	1.343	0.152	10.2	0.197	0.321	0.125	63.3	1.120	0.751	0.369	32.9	11.946	4.807	7.139	59.8
Y15	1.011	0.991	0.020	2.0	0.265	0.298	0.033	12.4	1.200	0.886	0.314	26.2	4.420	3.480	0.940	21.3
Average			0.193	16.7			0.057	23.9			0.337	47.1			2.504	48.8
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.394	0.019	1.3	0.202	0.323	0.121	60.0	0.226	0.649	0.423	186.9	1.474	4.078	2.604	176.7
Y17	2.383	2.147	0.235	9.9	0.418	0.363	0.055	13.2	4.266	0.276	3.990	93.5	40.436	5.612	34.824	86.1
Y18	2.073	1.856	0.217	10.5	0.285	0.346	0.060	21.2	-0.206	0.401	0.607	295.1	3.054	4.966	1.912	62.6
Y19	2.216	2.383	0.167	7.5	0.432	0.373	0.059	13.6	-0.111	0.135	0.246	221.7	1.606	6.040	4.434	276.1
Average			0.160	7.3			0.074	27.0			1.316	199.3			10.944	150.4

Table 6.1c Testing results by Net 3 for 24 subjects

NET 3	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.945	0.086	9.9	0.266	0.287	0.021	7.7	0.511	0.924	0.412	80.7	0.716	2.916	2.200	307.2
E1	1.196	1.371	0.176	14.7	0.378	0.294	0.084	22.2	0.685	0.489	0.196	28.6	0.453	2.589	2.136	471.7
Y7	0.502	0.606	0.104	20.7	0.359	0.330	0.029	8.2	2.456	2.321	0.135	5.5	7.145	9.451	2.306	32.3
Y8	1.681	1.871	0.190	11.3	0.361	0.279	0.082	22.6	-0.238	-0.236	0.002	0.7	2.593	0.637	1.957	75.5
Average			0.139	14.2			0.054	15.2			0.186	28.9			2.150	221.7
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.322	0.327	32.9	0.283	0.308	0.025	8.8	1.080	0.548	0.531	49.2	1.878	3.013	1.136	60.5
Y3	1.318	1.498	0.180	13.7	0.285	0.326	0.041	14.4	0.457	0.630	0.173	37.9	1.028	4.478	3.450	335.5
Y4	1.005	0.966	0.039	3.9	0.236	0.275	0.039	16.4	0.298	0.481	0.183	61.5	0.425	0.965	0.540	127.2
Y5	0.636	0.591	0.046	7.2	0.254	0.243	0.011	4.3	1.132	0.595	0.538	47.5	1.827	-0.094	1.921	105.1
Average			0.148	14.4			0.029	11.0			0.356	49.0			1.762	157.1
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.598	0.074	11.0	0.263	0.251	0.012	4.5	0.367	1.196	0.829	225.9	0.049	1.947	1.897	3839.0
E2	0.657	1.842	1.185	180.3	0.397	0.410	0.013	3.3	2.807	2.315	0.493	17.6	12.599	18.199	5.601	44.5
E3	0.734	0.622	0.113	15.3	0.213	0.246	0.034	15.8	0.315	1.028	0.713	226.1	0.242	1.342	1.100	454.9
E4	1.000	0.742	0.258	25.8	0.415	0.258	0.157	37.9	0.813	0.970	0.157	19.4	0.781	1.685	0.904	115.8
Average			0.408	58.1			0.054	15.4			0.548	122.2			2.376	1113.5
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.669	0.225	50.8	0.206	0.268	0.062	30.1	0.852	0.798	0.054	6.4	1.559	-0.234	1.793	115.0
Y9	0.793	0.814	0.022	2.7	0.292	0.278	0.014	4.9	0.838	0.753	0.085	10.1	3.180	0.486	2.694	84.7
Y10	1.522	1.504	0.017	1.1	0.328	0.348	0.020	6.2	0.863	1.178	0.315	36.5	3.466	7.921	4.455	128.5
Y11	3.649	2.221	1.428	39.1	0.423	0.401	0.022	5.2	-0.892	1.396	2.288	256.5	8.891	16.022	7.131	80.2
Average			0.423	23.5			0.030	11.6			0.686	77.4			4.018	102.1
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.286	0.119	8.5	0.368	0.336	0.032	8.7	0.928	1.059	0.131	14.1	1.701	5.569	3.868	227.5
Y13	0.989	0.663	0.325	32.9	0.277	0.265	0.012	4.3	0.438	0.725	0.287	65.6	0.899	0.167	0.732	81.4
Y14	1.495	1.273	0.222	14.8	0.197	0.289	0.092	46.8	1.120	0.077	1.043	93.1	11.946	-0.247	12.193	102.1
Y15	1.011	0.970	0.041	4.1	0.265	0.273	0.007	2.8	1.200	0.248	0.952	79.3	4.420	-0.727	5.147	116.4
Average			0.177	15.1			0.036	15.7			0.603	63.0			5.485	131.9
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.385	0.028	2.0	0.202	0.282	0.080	39.6	0.226	0.184	0.042	18.7	1.474	1.745	0.271	18.4
Y17	2.383	1.989	0.394	16.5	0.418	0.431	0.013	3.2	4.266	1.427	2.839	66.6	40.436	11.758	28.678	70.9
Y18	2.073	1.929	0.144	6.9	0.285	0.338	0.053	18.4	-0.206	0.176	0.381	185.4	3.054	4.094	1.040	34.0
Y19	2.216	2.227	0.011	0.5	0.432	0.376	0.056	13.0	-0.111	0.313	0.424	382.6	1.606	5.942	4.336	270.0
Average			0.144	6.5			0.050	18.5			0.922	163.3			8.581	98.3

Table 6.1d Testing results by Net 4 for 24 subjects

NET 4	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	1.092	0.232	27.0	0.266	0.317	0.051	19.2	0.511	0.998	0.487	95.3	0.716	4.092	3.376	471.5
E1	1.196	1.733	0.537	45.0	0.378	0.298	0.080	21.2	0.685	0.577	0.108	15.8	0.453	6.267	5.815	1284.1
Y7	0.502	0.463	0.038	7.6	0.359	0.215	0.144	40.1	2.456	0.862	1.594	64.9	7.145	0.027	7.118	99.6
Y8	1.681	1.813	0.132	7.9	0.361	0.322	0.039	10.9	-0.238	0.078	0.316	132.7	2.593	2.532	0.062	2.4
Average			0.235	21.9			0.079	22.9			0.626	77.1			4.093	464.4
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.310	0.316	31.8	0.283	0.301	0.018	6.3	1.080	0.132	0.948	87.8	1.878	0.759	1.119	59.6
Y3	1.318	1.359	0.042	3.2	0.285	0.348	0.062	21.8	0.457	1.480	1.023	223.8	1.028	9.145	8.117	789.4
Y4	1.005	1.001	0.004	0.4	0.236	0.278	0.042	17.9	0.298	1.007	0.709	238.3	0.425	4.178	3.754	884.2
Y5	0.636	0.742	0.106	16.6	0.254	0.262	0.008	3.1	1.132	0.582	0.551	48.6	1.827	0.005	1.822	99.7
Average			0.117	13.0			0.033	12.3			0.808	149.6			3.703	458.2
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.469	0.203	30.2	0.263	0.231	0.032	12.3	0.367	0.437	0.070	19.1	0.049	-3.086	3.136	6344.8
E2	0.657	1.330	0.673	102.4	0.397	0.301	0.096	24.3	2.807	0.246	2.562	91.2	12.599	1.107	11.491	91.2
E3	0.734	0.702	0.032	4.4	0.213	0.271	0.059	27.7	0.315	1.223	0.908	288.1	0.242	2.822	2.580	1066.6
E4	1.000	0.654	0.346	34.6	0.415	0.241	0.174	42.0	0.813	1.174	0.361	44.4	0.781	2.518	1.737	222.4
Average			0.313	42.9			0.090	26.6			0.975	110.7			4.736	1931.2
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.764	0.321	72.4	0.206	0.299	0.094	45.7	0.852	1.184	0.332	38.9	1.559	2.613	1.054	67.6
Y9	0.793	0.901	0.108	13.6	0.292	0.275	0.017	5.9	0.838	0.940	0.103	12.2	3.180	2.660	0.520	16.3
Y10	1.522	1.392	0.130	8.5	0.328	0.236	0.092	28.1	0.863	-0.603	1.466	169.9	3.466	-3.205	6.671	192.5
Y11	3.649	2.819	0.830	22.7	0.423	0.389	0.034	8.0	-0.892	-0.099	0.793	88.9	8.891	7.746	1.145	12.9
Average			0.347	29.3			0.059	21.9			0.673	77.5			2.347	72.3
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.082	0.323	23.0	0.368	0.274	0.094	25.6	0.928	0.507	0.421	45.4	1.701	2.154	0.454	26.7
Y13	0.989	0.585	0.404	40.8	0.277	0.227	0.050	18.0	0.438	0.206	0.232	53.0	0.899	-3.144	4.043	449.6
Y14	1.495	1.353	0.143	9.5	0.197	0.324	0.127	64.7	1.120	0.380	0.740	66.1	11.946	1.692	10.255	85.8
Y15	1.011	1.070	0.059	5.8	0.265	0.265	0.000	0.1	1.200	0.604	0.596	49.7	4.420	2.614	1.806	40.9
Average			0.232	19.8			0.068	27.1			0.497	53.5			4.139	150.8
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.318	0.095	6.7	0.202	0.317	0.116	57.2	0.226	0.647	0.421	186.0	1.474	3.644	2.170	147.3
Y17	2.383	2.028	0.354	14.9	0.418	0.366	0.052	12.5	4.266	0.284	3.981	93.3	40.436	5.369	35.067	86.7
Y18	2.073	1.650	0.423	20.4	0.285	0.338	0.053	18.6	-0.206	0.743	0.949	461.2	3.054	5.941	2.887	94.5
Y19	2.216	2.269	0.053	2.4	0.432	0.382	0.049	11.5	-0.111	0.293	0.404	364.4	1.606	6.453	4.847	301.8
Average			0.231	11.1			0.068	25.0			1.439	276.2			11.243	157.6

Table 6.1e Testing results by Net 5 for 24 subjects

NET 5	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	1.382	0.522	60.7	0.266	0.344	0.077	29.1	0.511	0.821	0.310	60.6	0.716	4.468	3.752	524.1
E1	1.196	1.494	0.299	25.0	0.378	0.288	0.090	23.7	0.685	0.409	0.276	40.3	0.453	3.927	3.474	767.2
Y7	0.502	0.619	0.117	23.4	0.359	0.252	0.107	29.7	2.456	1.281	1.175	47.8	7.145	3.442	3.702	51.8
Y8	1.681	1.659	0.021	1.3	0.361	0.284	0.077	21.3	-0.238	-0.002	0.236	99.3	2.593	1.512	1.081	41.7
Average			0.240	27.6			0.088	25.9			0.499	62.0			3.002	346.2
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.422	0.428	43.0	0.283	0.293	0.010	3.5	1.080	0.110	0.970	89.8	1.878	1.423	0.455	24.2
Y3	1.318	1.288	0.030	2.3	0.285	0.334	0.049	17.1	0.457	1.360	0.903	197.5	1.028	7.921	6.893	670.4
Y4	1.005	0.916	0.089	8.9	0.236	0.269	0.033	14.1	0.298	0.753	0.455	153.0	0.425	2.372	1.947	458.6
Y5	0.636	0.846	0.210	32.9	0.254	0.251	0.002	1.0	1.132	0.328	0.805	71.1	1.827	-0.230	2.057	112.6
Average			0.189	21.8			0.024	8.9			0.783	127.8			2.838	316.5
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.549	0.123	18.3	0.263	0.252	0.012	4.4	0.367	0.974	0.607	165.4	0.049	0.112	0.063	126.8
E2	0.657	1.528	0.871	132.5	0.397	0.378	0.019	4.8	2.807	1.540	1.267	45.1	12.599	10.540	2.059	16.3
E3	0.734	0.689	0.045	6.1	0.213	0.266	0.053	25.1	0.315	1.338	1.023	324.5	0.242	3.113	2.871	1187.0
E4	1.000	0.725	0.276	27.5	0.415	0.242	0.173	41.7	0.813	1.166	0.353	43.5	0.781	2.741	1.960	250.9
Average			0.329	46.1			0.064	19.0			0.813	144.6			1.738	395.3
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.881	0.438	98.7	0.206	0.294	0.089	43.1	0.852	0.713	0.140	16.4	1.559	0.812	0.747	47.9
Y9	0.793	0.908	0.115	14.5	0.292	0.271	0.022	7.4	0.838	0.611	0.227	27.1	3.180	0.457	2.722	85.6
Y10	1.522	1.377	0.144	9.5	0.328	0.285	0.043	13.0	0.863	0.169	0.694	80.5	3.466	0.604	2.863	82.6
Y11	3.649	2.230	1.419	38.9	0.423	0.423	0.001	0.2	-0.892	1.457	2.349	263.2	8.891	14.262	5.371	60.4
Average			0.529	40.4			0.038	15.9			0.852	96.8			2.926	69.1
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.247	0.158	11.3	0.368	0.309	0.058	15.9	0.928	0.931	0.003	0.3	1.701	4.979	3.278	192.8
Y13	0.989	0.824	0.165	16.7	0.277	0.243	0.033	12.1	0.438	0.259	0.178	40.8	0.899	-1.580	2.479	275.7
Y14	1.495	1.460	0.035	2.4	0.197	0.316	0.120	60.9	1.120	0.216	0.903	80.7	11.946	1.461	10.485	87.8
Y15	1.011	0.927	0.084	8.3	0.265	0.250	0.016	5.9	1.200	0.304	0.896	74.7	4.420	0.180	4.240	95.9
Average			0.111	9.7			0.057	23.7			0.495	49.1			5.121	163.0
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.193	0.220	15.6	0.202	0.288	0.087	42.9	0.226	0.487	0.260	115.0	1.474	2.252	0.778	52.8
Y17	2.383	2.518	0.135	5.7	0.418	0.439	0.021	5.1	4.266	0.629	3.636	85.3	40.436	9.157	31.279	77.4
Y18	2.073	1.376	0.697	33.6	0.285	0.319	0.034	12.0	-0.206	0.752	0.958	465.7	3.054	4.323	1.269	41.5
Y19	2.216	2.169	0.047	2.1	0.432	0.378	0.054	12.4	-0.111	0.202	0.313	282.3	1.606	4.904	3.298	205.4
Average			0.275	14.2			0.049	18.1			1.292	237.0			9.156	94.3

Table 6.1f Testing results by Net 6 for 24 subjects

NET 6	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.908	0.048	5.6	0.266	0.282	0.016	6.0	0.511	0.980	0.468	91.6	0.716	3.141	2.425	338.7
E1	1.196	1.637	0.442	36.9	0.378	0.301	0.077	20.3	0.685	0.244	0.441	64.4	0.453	2.778	2.325	513.4
Y7	0.502	0.521	0.019	3.8	0.359	0.307	0.052	14.5	2.456	2.378	0.078	3.2	7.145	9.712	2.567	35.9
Y8	1.681	1.752	0.071	4.2	0.361	0.288	0.073	20.3	-0.238	-0.056	0.182	76.4	2.593	1.072	1.522	58.7
Average			0.145	12.6			0.054	15.3			0.292	58.9			2.210	236.7
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.450	0.456	45.8	0.283	0.219	0.064	22.8	1.080	0.334	0.745	69.0	1.878	4.465	2.587	137.8
Y3	1.318	1.337	0.019	1.4	0.285	0.364	0.078	27.5	0.457	1.161	0.704	154.1	1.028	5.612	4.584	445.8
Y4	1.005	0.968	0.037	3.7	0.236	0.247	0.012	4.9	0.298	0.776	0.478	160.8	0.425	2.886	2.461	579.8
Y5	0.636	0.725	0.089	13.9	0.254	0.156	0.098	38.5	1.132	0.597	0.536	47.3	1.827	4.225	2.397	131.2
Average			0.150	16.2			0.063	23.4			0.616	107.8			3.007	323.6
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.584	0.087	13.0	0.263	0.305	0.041	15.7	0.367	1.115	0.748	203.9	0.049	1.145	1.095	2216.1
E2	0.657	1.347	0.690	104.9	0.397	0.401	0.004	1.0	2.807	1.752	1.055	37.6	12.599	8.279	4.320	34.3
E3	0.734	0.668	0.067	9.1	0.213	0.281	0.068	32.2	0.315	1.227	0.911	289.1	0.242	2.556	2.314	956.9
E4	1.000	0.828	0.173	17.2	0.415	0.239	0.176	42.4	0.813	1.254	0.441	54.3	0.781	4.979	4.198	537.5
Average			0.254	36.1			0.072	22.8			0.789	146.2			2.982	936.2
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.630	0.187	42.2	0.206	0.271	0.065	31.8	0.852	0.686	0.167	19.5	1.559	-0.412	1.971	126.4
Y9	0.793	0.887	0.095	11.9	0.292	0.220	0.072	24.7	0.838	0.447	0.391	46.6	3.180	1.112	2.068	65.0
Y10	1.522	1.352	0.170	11.2	0.328	0.292	0.035	10.8	0.863	0.648	0.215	24.9	3.466	3.767	0.301	8.7
Y11	3.649	3.034	0.615	16.9	0.423	0.505	0.082	19.5	-0.892	-0.438	0.454	50.9	8.891	1.496	7.395	83.2
Average			0.267	20.5			0.064	21.7			0.307	35.5			2.934	70.8
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.375	0.030	2.1	0.368	0.236	0.131	35.7	0.928	0.690	0.238	25.7	1.701	5.702	4.002	235.3
Y13	0.989	0.675	0.314	31.8	0.277	0.257	0.020	7.0	0.438	0.669	0.232	52.9	0.899	0.335	0.564	62.7
Y14	1.495	1.368	0.127	8.5	0.197	0.315	0.119	60.4	1.120	0.311	0.808	72.2	11.946	1.436	10.510	88.0
Y15	1.011	1.066	0.055	5.4	0.265	0.249	0.016	6.1	1.200	0.329	0.871	72.6	4.420	0.732	3.688	83.4
Average			0.132	12.0			0.071	27.3			0.537	55.8			4.691	117.4
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.248	0.165	11.7	0.202	0.300	0.098	48.8	0.226	0.716	0.490	216.3	1.474	2.982	1.508	102.4
Y17	2.383	1.554	0.828	34.8	0.418	0.452	0.034	8.1	4.266	2.420	1.846	43.3	40.436	11.031	29.405	72.7
Y18	2.073	1.783	0.290	14.0	0.285	0.289	0.004	1.3	-0.206	0.592	0.798	387.9	3.054	7.202	4.148	135.8
Y19	2.216	2.052	0.165	7.4	0.432	0.400	0.032	7.4	-0.111	0.547	0.658	593.6	1.606	5.647	4.041	251.6
Average			0.362	17.0			0.042	16.4			0.948	310.3			9.775	140.6

Table 6.1g Testing results by Net 7 for 24 subjects

NET 7	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	1.086	0.227	26.4	0.266	0.336	0.069	26.1	0.511	1.024	0.513	100.3	0.716	4.992	4.276	597.2
E1	1.196	1.689	0.494	41.3	0.378	0.294	0.083	22.1	0.685	0.205	0.479	70.0	0.453	3.537	3.084	681.0
Y7	0.502	0.457	0.045	8.9	0.359	0.250	0.109	30.3	2.456	1.603	0.853	34.7	7.145	4.860	2.285	32.0
Y8	1.681	1.812	0.132	7.8	0.361	0.295	0.067	18.4	-0.238	-0.061	0.177	74.3	2.593	1.622	0.972	37.5
Average			0.224	21.1			0.082	24.2			0.505	69.8			2.654	336.9
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.299	0.304	30.6	0.283	0.293	0.010	3.6	1.080	0.266	0.814	75.4	1.878	1.421	0.456	24.3
Y3	1.318	1.412	0.094	7.1	0.285	0.330	0.044	15.5	0.457	1.142	0.685	149.9	1.028	7.112	6.084	591.7
Y4	1.005	0.982	0.023	2.3	0.236	0.274	0.038	16.0	0.298	0.773	0.475	159.7	0.425	2.878	2.454	577.9
Y5	0.636	0.663	0.027	4.2	0.254	0.241	0.013	5.0	1.132	0.501	0.631	55.7	1.827	-0.779	2.606	142.6
Average			0.112	11.1			0.026	10.0			0.651	110.2			2.900	334.1
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.492	0.179	26.7	0.263	0.246	0.017	6.5	0.367	0.860	0.493	134.4	0.049	-0.528	0.577	1168.4
E2	0.657	1.493	0.836	127.2	0.397	0.378	0.019	4.8	2.807	1.714	1.094	39.0	12.599	10.871	1.727	13.7
E3	0.734	0.661	0.073	10.0	0.213	0.273	0.060	28.4	0.315	1.448	1.133	359.3	0.242	2.866	2.625	1085.1
E4	1.000	0.672	0.329	32.8	0.415	0.239	0.176	42.4	0.813	1.274	0.461	56.8	0.781	3.165	2.384	305.2
Average			0.354	49.2			0.068	20.5			0.795	147.3			1.828	643.1
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.693	0.250	56.4	0.206	0.285	0.079	38.4	0.852	0.709	0.143	16.8	1.559	0.906	0.653	41.9
Y9	0.793	0.877	0.085	10.7	0.292	0.269	0.024	8.1	0.838	0.607	0.231	27.5	3.180	0.829	2.351	73.9
Y10	1.522	1.428	0.093	6.1	0.328	0.274	0.053	16.3	0.863	0.066	0.797	92.4	3.466	0.749	2.717	78.4
Y11	3.649	2.713	0.935	25.6	0.423	0.424	0.001	0.2	-0.892	0.564	1.456	163.2	8.891	10.785	1.894	21.3
Average			0.341	24.7			0.039	15.7			0.657	75.0			1.904	53.9
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.286	0.119	8.5	0.368	0.300	0.068	18.4	0.928	0.716	0.212	22.8	1.701	4.016	2.316	136.2
Y13	0.989	0.656	0.332	33.6	0.277	0.237	0.040	14.4	0.438	0.472	0.035	8.0	0.899	-1.480	2.380	264.7
Y14	1.495	1.430	0.065	4.3	0.197	0.315	0.118	60.2	1.120	0.235	0.885	79.0	11.946	0.998	10.948	91.6
Y15	1.011	1.062	0.051	5.1	0.265	0.250	0.016	6.0	1.200	0.173	1.027	85.6	4.420	0.048	4.372	98.9
Average			0.142	12.9			0.060	24.7			0.539	48.8			5.004	147.8
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.301	0.112	7.9	0.202	0.301	0.099	49.3	0.226	0.502	0.275	121.7	1.474	2.917	1.443	97.9
Y17	2.383	2.125	0.258	10.8	0.418	0.424	0.006	1.4	4.266	0.812	3.454	81.0	40.436	7.528	32.908	81.4
Y18	2.073	1.652	0.420	20.3	0.285	0.323	0.038	13.3	-0.206	0.593	0.799	388.3	3.054	5.078	2.024	66.3
Y19	2.216	2.242	0.026	1.2	0.432	0.375	0.056	13.0	-0.111	0.224	0.335	302.2	1.606	5.539	3.933	244.9
Average			0.204	10.1			0.050	19.2			1.216	223.3			10.077	122.6

Table 6.8a Testing results by Net 12 for 24 subjects

NET 12	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.985	0.125	14.6	0.266	0.358	0.091	34.3	0.511	0.899	0.387	75.8	0.716	1.035	0.319	44.6
E1	1.196	1.619	0.424	35.4	0.378	0.295	0.083	22.0	0.685	0.746	0.062	9.0	0.453	7.272	6.819	1505.9
Y7	0.502	0.294	0.208	41.4	0.359	0.275	0.084	23.4	2.456	1.391	1.065	43.4	7.145	1.353	5.791	81.1
Y8	1.681	1.955	0.275	16.3	0.361	0.329	0.032	8.9	-0.238	0.957	1.195	501.6	2.593	11.006	8.412	324.4
Average			0.258	26.9			0.073	22.2			0.677	157.5			5.335	489.0
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.860	0.866	87.1	0.283	0.355	0.072	25.6	1.080	0.451	0.628	58.2	1.878	5.342	3.464	184.5
Y3	1.318	1.181	0.137	10.4	0.285	0.289	0.004	1.4	0.457	0.700	0.243	53.2	1.028	3.978	2.950	286.9
Y4	1.005	1.098	0.093	9.3	0.236	0.297	0.061	25.9	0.298	0.860	0.562	188.9	0.425	4.104	3.679	866.5
Y5	0.636	0.560	0.076	12.0	0.254	0.233	0.021	8.4	1.132	1.217	0.085	7.5	1.827	4.067	2.240	122.6
Average			0.293	29.7			0.040	15.3			0.380	77.0			3.083	365.1
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.631	0.041	6.1	0.263	0.257	0.006	2.3	0.367	1.020	0.653	177.9	0.049	1.030	0.981	1984.8
E2	0.657	0.800	0.143	21.8	0.397	0.284	0.113	28.4	2.807	0.457	2.351	83.7	12.599	-2.082	14.681	116.5
E3	0.734	0.809	0.075	10.2	0.213	0.265	0.052	24.5	0.315	1.085	0.769	244.0	0.242	3.189	2.947	1218.6
E4	1.000	0.989	0.011	1.1	0.415	0.289	0.126	30.4	0.813	0.587	0.226	27.8	0.781	0.251	0.530	67.8
Average			0.068	9.8			0.074	21.4			1.000	133.4			4.785	847.0
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.757	0.314	70.9	0.206	0.281	0.075	36.6	0.852	1.102	0.250	29.3	1.559	2.219	0.660	42.3
Y9	0.793	0.668	0.125	15.7	0.292	0.247	0.045	15.5	0.838	1.135	0.297	35.5	3.180	2.369	0.811	25.5
Y10	1.522	1.277	0.244	16.1	0.328	0.378	0.050	15.2	0.863	1.450	0.587	68.0	3.466	7.999	4.533	130.8
Y11	3.649	2.424	1.225	33.6	0.423	0.389	0.034	8.0	-0.892	0.816	1.709	191.5	8.891	13.988	5.097	57.3
Average			0.477	34.1			0.051	18.9			0.711	81.1			2.775	64.0
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.308	0.097	6.9	0.368	0.276	0.091	24.8	0.928	0.502	0.426	45.9	1.701	3.990	2.290	134.6
Y13	0.989	0.749	0.239	24.2	0.277	0.260	0.017	6.2	0.438	0.442	0.004	1.0	0.899	-1.198	2.097	233.2
Y14	1.495	1.432	0.064	4.3	0.197	0.272	0.075	38.4	1.120	0.474	0.646	57.7	11.946	5.131	6.815	57.0
Y15	1.011	0.878	0.133	13.2	0.265	0.314	0.049	18.5	1.200	1.241	0.041	3.4	4.420	4.818	0.398	9.0
Average			0.133	12.1			0.058	21.9			0.279	27.0			2.900	108.5
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.522	0.109	7.7	0.202	0.286	0.084	41.8	0.226	0.216	0.010	4.5	1.474	2.608	1.134	77.0
Y17	2.383	2.008	0.374	15.7	0.418	0.322	0.096	22.9	4.266	0.026	4.240	99.4	40.436	3.852	36.584	90.5
Y18	2.073	1.863	0.210	10.1	0.285	0.326	0.040	14.2	-0.206	0.124	0.329	160.1	3.054	3.527	0.473	15.5
Y19	2.216	2.097	0.119	5.4	0.432	0.372	0.059	13.7	-0.111	0.287	0.397	358.8	1.606	5.782	4.176	260.0
Average			0.203	9.7			0.070	23.2			1.244	155.7			10.592	110.7

Table 6.8b Testing results by Net 13 for 24 subjects

NET 13	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.578	0.281	32.7	0.266	0.305	0.038	14.4	0.511	1.344	0.833	163.0	0.716	1.879	1.163	162.4
E1	1.196	1.736	0.541	45.2	0.378	0.280	0.098	25.8	0.685	0.438	0.247	36.0	0.453	7.116	6.663	1471.4
Y7	0.502	0.467	0.034	6.8	0.359	0.265	0.094	26.2	2.456	0.976	1.479	60.2	7.145	0.989	6.155	86.2
Y8	1.681	2.164	0.484	28.8	0.361	0.320	0.041	11.4	-0.238	0.481	0.719	301.8	2.593	8.579	5.985	230.8
Average			0.335	28.4			0.068	19.5			0.819	140.3			4.991	487.7
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.675	0.680	68.4	0.283	0.359	0.076	26.7	1.080	0.879	0.200	18.5	1.878	7.158	5.280	281.2
Y3	1.318	1.377	0.059	4.5	0.285	0.324	0.039	13.6	0.457	0.836	0.379	83.0	1.028	5.488	4.460	433.8
Y4	1.005	1.050	0.045	4.5	0.236	0.329	0.093	39.5	0.298	1.109	0.812	272.7	0.425	5.022	4.598	1082.9
Y5	0.636	0.509	0.128	20.1	0.254	0.232	0.022	8.8	1.132	0.883	0.249	22.0	1.827	1.442	0.386	21.1
Average			0.228	24.4			0.058	22.2			0.410	99.0			3.681	454.7
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.569	0.102	15.2	0.263	0.243	0.021	7.9	0.367	1.090	0.723	197.0	0.049	1.566	1.517	3068.8
E2	0.657	1.052	0.394	60.0	0.397	0.271	0.126	31.8	2.807	0.210	2.598	92.5	12.599	-1.493	14.092	111.9
E3	0.734	0.763	0.029	4.0	0.213	0.257	0.045	21.0	0.315	1.151	0.836	265.1	0.242	3.474	3.232	1336.1
E4	1.000	0.969	0.031	3.1	0.415	0.283	0.132	31.8	0.813	0.944	0.131	16.2	0.781	3.297	2.516	322.1
Average			0.139	20.6			0.081	23.1			1.072	142.7			5.339	1209.7
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.720	0.277	62.4	0.206	0.260	0.054	26.3	0.852	0.882	0.030	3.5	1.559	1.250	0.309	19.8
Y9	0.793	0.462	0.331	41.7	0.292	0.308	0.016	5.4	0.838	1.432	0.594	70.9	3.180	1.335	1.845	58.0
Y10	1.522	1.575	0.054	3.5	0.328	0.330	0.002	0.6	0.863	0.877	0.014	1.6	3.466	7.169	3.703	106.8
Y11	3.649	2.410	1.239	34.0	0.423	0.407	0.015	3.6	-0.892	0.982	1.874	210.1	8.891	14.408	5.517	62.0
Average			0.475	35.4			0.022	9.0			0.628	71.5			2.843	61.7
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.315	0.090	6.4	0.368	0.256	0.111	30.3	0.928	0.377	0.551	59.3	1.701	3.619	1.918	112.8
Y13	0.989	0.768	0.220	22.3	0.277	0.297	0.020	7.2	0.438	1.065	0.628	143.4	0.899	2.675	1.776	197.6
Y14	1.495	1.355	0.140	9.4	0.197	0.301	0.104	52.8	1.120	0.615	0.504	45.0	11.946	4.319	7.627	63.8
Y15	1.011	1.001	0.010	1.0	0.265	0.247	0.018	6.8	1.200	0.545	0.655	54.6	4.420	2.528	1.891	42.8
Average			0.115	9.8			0.063	24.3			0.584	75.6			3.303	104.2
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.490	0.077	5.4	0.202	0.296	0.094	46.7	0.226	0.268	0.042	18.5	1.474	2.255	0.781	53.0
Y17	2.383	2.093	0.290	12.2	0.418	0.333	0.085	20.2	4.266	-0.002	4.267	100.0	40.436	3.478	36.958	91.4
Y18	2.073	1.713	0.360	17.4	0.285	0.330	0.045	15.7	-0.206	0.366	0.572	278.0	3.054	3.878	0.824	27.0
Y19	2.216	2.192	0.024	1.1	0.432	0.389	0.042	9.8	-0.111	0.463	0.573	517.7	1.606	7.332	5.726	356.6
Average			0.188	9.0			0.066	23.1			1.364	228.6			11.072	132.0

Table 6.8c Testing results by Net 14 for 24 subjects

NET 14	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.783	0.076	8.9	0.266	0.293	0.027	10.2	0.511	1.061	0.549	107.5	0.716	1.951	1.235	172.5
E1	1.196	1.700	0.504	42.2	0.378	0.318	0.059	15.7	0.685	0.714	0.030	4.3	0.453	6.773	6.320	1395.6
Y7	0.502	0.344	0.158	31.4	0.359	0.287	0.072	20.0	2.456	1.425	1.030	42.0	7.145	1.367	5.778	80.9
Y8	1.681	2.184	0.503	29.9	0.361	0.300	0.062	17.1	-0.238	0.377	0.615	258.2	2.593	9.029	6.436	248.2
Average			0.310	28.1			0.055	15.7			0.556	103.0			4.942	474.3
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.519	0.525	52.8	0.283	0.353	0.070	24.8	1.080	0.988	0.092	8.5	1.878	6.950	5.073	270.2
Y3	1.318	1.386	0.068	5.2	0.285	0.387	0.102	35.7	0.457	1.508	1.051	230.0	1.028	7.808	6.780	659.4
Y4	1.005	1.031	0.026	2.6	0.236	0.330	0.094	39.7	0.298	1.294	0.996	334.7	0.425	5.678	5.253	1237.3
Y5	0.636	0.663	0.027	4.2	0.254	0.340	0.086	34.0	1.132	1.917	0.785	69.3	1.827	5.657	3.829	209.5
Average			0.161	16.2			0.088	33.6			0.731	160.6			5.234	594.1
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.621	0.050	7.5	0.263	0.229	0.034	12.9	0.367	0.817	0.450	122.6	0.049	1.121	1.072	2168.8
E2	0.657	1.224	0.567	86.3	0.397	0.277	0.120	30.2	2.807	-0.217	3.024	107.7	12.599	-3.875	16.473	130.8
E3	0.734	0.720	0.014	1.9	0.213	0.225	0.013	5.9	0.315	0.593	0.277	88.0	0.242	0.831	0.589	243.7
E4	1.000	0.882	0.118	11.8	0.415	0.285	0.130	31.3	0.813	1.220	0.407	50.1	0.781	4.394	3.613	462.5
Average			0.187	26.9			0.074	20.1			1.040	92.1			5.437	751.4
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.765	0.322	72.6	0.206	0.228	0.022	10.8	0.852	0.416	0.436	51.2	1.559	0.093	1.467	94.1
Y9	0.793	0.675	0.117	14.8	0.292	0.262	0.031	10.5	0.838	0.943	0.105	12.6	3.180	1.414	1.765	55.5
Y10	1.522	1.344	0.178	11.7	0.328	0.388	0.060	18.2	0.863	1.704	0.841	97.5	3.466	9.021	5.555	160.3
Y11	3.649	2.370	1.279	35.0	0.423	0.412	0.011	2.6	-0.892	1.136	2.029	227.4	8.891	14.527	5.635	63.4
Average			0.474	33.5			0.031	10.5			0.853	97.2			3.606	93.3
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.284	0.121	8.6	0.368	0.328	0.039	10.7	0.928	0.963	0.035	3.8	1.701	5.217	3.517	206.8
Y13	0.989	0.804	0.185	18.7	0.277	0.260	0.017	6.1	0.438	0.592	0.154	35.3	0.899	1.407	0.508	56.5
Y14	1.495	1.408	0.088	5.9	0.197	0.279	0.083	42.0	1.120	0.134	0.985	88.0	11.946	2.900	9.046	75.7
Y15	1.011	1.061	0.050	4.9	0.265	0.248	0.017	6.4	1.200	0.088	1.112	92.7	4.420	0.923	3.496	79.1
Average			0.111	9.5			0.039	16.3			0.572	54.9			4.142	104.5
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.448	0.035	2.5	0.202	0.312	0.111	54.8	0.226	0.284	0.058	25.5	1.474	2.756	1.282	87.0
Y17	2.383	1.973	0.409	17.2	0.418	0.362	0.056	13.4	4.266	0.168	4.098	96.1	40.436	4.245	36.191	89.5
Y18	2.073	1.428	0.645	31.1	0.285	0.319	0.034	11.8	-0.206	0.390	0.596	289.6	3.054	3.113	0.059	1.9
Y19	2.216	2.284	0.067	3.0	0.432	0.381	0.051	11.8	-0.111	0.012	0.123	111.2	1.606	5.028	3.422	213.1
Average			0.289	13.5			0.063	23.0			1.219	130.6			10.239	97.9

Table 6.8d Testing results by Net 15 for 24 subjects

NET 15	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.849	0.011	1.3	0.266	0.288	0.021	8.0	0.511	0.930	0.419	81.9	0.716	2.170	1.454	203.1
E1	1.196	1.547	0.351	29.4	0.378	0.312	0.066	17.4	0.685	0.797	0.113	16.5	0.453	6.389	5.936	1311.0
Y7	0.502	0.294	0.208	41.5	0.359	0.231	0.128	35.6	2.456	0.940	1.515	61.7	7.145	0.147	6.998	97.9
Y8	1.681	2.246	0.565	33.6	0.361	0.313	0.049	13.5	-0.238	0.568	0.806	338.5	2.593	10.557	7.963	307.1
Average			0.284	26.4			0.066	18.6			0.713	124.6			5.588	479.8
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.461	0.466	46.9	0.283	0.342	0.059	20.8	1.080	0.885	0.195	18.1	1.878	5.837	3.959	210.9
Y3	1.318	1.557	0.239	18.1	0.285	0.376	0.090	31.6	0.457	1.056	0.599	131.0	1.028	6.565	5.537	538.5
Y4	1.005	0.945	0.060	6.0	0.236	0.282	0.046	19.6	0.298	0.866	0.568	190.9	0.425	3.689	3.264	768.8
Y5	0.636	0.553	0.083	13.0	0.254	0.289	0.035	13.8	1.132	1.351	0.219	19.3	1.827	3.446	1.619	88.6
Average			0.212	21.0			0.058	21.4			0.395	89.8			3.595	401.7
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.505	0.167	24.9	0.263	0.227	0.037	14.0	0.367	1.011	0.644	175.6	0.049	1.089	1.039	2103.0
E2	0.657	1.147	0.489	74.5	0.397	0.287	0.110	27.7	2.807	-0.078	2.886	102.8	12.599	-3.522	16.120	128.0
E3	0.734	0.649	0.085	11.6	0.213	0.264	0.051	24.1	0.315	1.161	0.846	268.4	0.242	2.193	1.951	806.6
E4	1.000	0.794	0.206	20.6	0.415	0.259	0.156	37.7	0.813	0.892	0.079	9.8	0.781	1.913	1.132	144.9
Average			0.237	32.9			0.089	25.9			1.114	139.1			5.061	795.6
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.741	0.298	67.2	0.206	0.228	0.022	10.9	0.852	0.505	0.348	40.8	1.559	0.184	1.375	88.2
Y9	0.793	0.868	0.075	9.4	0.292	0.279	0.014	4.7	0.838	0.860	0.022	2.7	3.180	1.827	1.353	42.6
Y10	1.522	1.424	0.097	6.4	0.328	0.386	0.058	17.6	0.863	1.461	0.598	69.2	3.466	8.181	4.714	136.0
Y11	3.649	2.306	1.342	36.8	0.423	0.418	0.005	1.1	-0.892	1.277	2.170	243.2	8.891	15.024	6.133	69.0
Average			0.453	30.0			0.025	8.6			0.784	89.0			3.394	83.9
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.291	0.114	8.1	0.368	0.343	0.025	6.8	0.928	1.077	0.149	16.1	1.701	5.464	3.763	221.3
Y13	0.989	0.715	0.273	27.7	0.277	0.264	0.013	4.6	0.438	0.796	0.359	81.9	0.899	1.794	0.895	99.5
Y14	1.495	1.370	0.125	8.4	0.197	0.275	0.078	39.7	1.120	0.250	0.870	77.7	11.946	3.481	8.465	70.9
Y15	1.011	1.134	0.123	12.2	0.265	0.261	0.004	1.5	1.200	0.305	0.895	74.6	4.420	2.401	2.019	45.7
Average			0.159	14.1			0.030	13.2			0.568	62.6			3.786	109.3
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.528	0.115	8.2	0.202	0.288	0.086	42.6	0.226	0.112	0.115	50.6	1.474	2.560	1.086	73.7
Y17	2.383	2.106	0.277	11.6	0.418	0.332	0.086	20.6	4.266	-0.063	4.328	101.5	40.436	3.838	36.598	90.5
Y18	2.073	1.575	0.497	24.0	0.285	0.316	0.031	10.7	-0.206	0.334	0.540	262.3	3.054	3.690	0.635	20.8
Y19	2.216	2.185	0.031	1.4	0.432	0.376	0.056	12.9	-0.111	0.297	0.407	367.8	1.606	5.842	4.236	263.8
Average			0.230	11.3			0.065	21.7			1.348	195.5			10.639	112.2

Table 6.8e Testing results by Net 16 for 24 subjects

NET 16	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	1.010	0.151	17.5	0.266	0.294	0.028	10.5	0.511	0.836	0.325	63.5	0.716	2.661	1.945	271.6
E1	1.196	1.626	0.430	36.0	0.378	0.329	0.048	12.8	0.685	0.472	0.212	31.0	0.453	3.669	3.217	710.3
Y7	0.502	0.501	0.001	0.1	0.359	0.355	0.004	1.1	2.456	2.762	0.307	12.5	7.145	12.368	5.224	73.1
Y8	1.681	1.623	0.058	3.4	0.361	0.214	0.147	40.8	-0.238	-0.569	0.331	138.9	2.593	-2.082	4.676	180.3
Average			0.160	14.3			0.057	16.3			0.294	61.5			3.765	308.8
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.231	0.236	23.8	0.283	0.311	0.027	9.7	1.080	0.698	0.382	35.4	1.878	3.091	1.213	64.6
Y3	1.318	1.439	0.121	9.2	0.285	0.288	0.002	0.8	0.457	0.171	0.286	62.5	1.028	1.779	0.750	73.0
Y4	1.005	1.058	0.053	5.3	0.236	0.277	0.041	17.5	0.298	0.454	0.156	52.6	0.425	1.543	1.119	263.4
Y5	0.636	0.560	0.076	12.0	0.254	0.245	0.009	3.4	1.132	0.708	0.424	37.5	1.827	0.399	1.429	78.2
Average			0.122	12.6			0.020	7.8			0.312	47.0			1.128	119.8
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.535	0.137	20.4	0.263	0.249	0.014	5.4	0.367	1.164	0.797	217.2	0.049	1.455	1.406	2844.6
E2	0.657	1.577	0.919	139.9	0.397	0.393	0.004	0.9	2.807	2.178	0.630	22.4	12.599	14.556	1.957	15.5
E3	0.734	0.549	0.185	25.2	0.213	0.245	0.032	15.1	0.315	1.084	0.769	243.8	0.242	1.366	1.124	464.7
E4	1.000	0.724	0.276	27.6	0.415	0.268	0.147	35.4	0.813	1.086	0.273	33.6	0.781	2.199	1.417	181.5
Average			0.379	53.3			0.049	14.2			0.617	129.3			1.476	876.6
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.623	0.180	40.6	0.206	0.267	0.061	29.7	0.852	0.747	0.105	12.3	1.559	-0.819	2.379	152.6
Y9	0.793	0.813	0.020	2.5	0.292	0.274	0.019	6.4	0.838	0.609	0.229	27.3	3.180	-0.239	3.419	107.5
Y10	1.522	1.504	0.018	1.2	0.328	0.332	0.005	1.4	0.863	0.969	0.106	12.3	3.466	6.438	2.972	85.7
Y11	3.649	2.543	1.106	30.3	0.423	0.393	0.030	7.0	-0.892	0.876	1.768	198.1	8.891	14.792	5.901	66.4
Average			0.331	18.7			0.029	11.1			0.552	62.5			3.668	103.0
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.155	0.250	17.8	0.368	0.322	0.045	12.3	0.928	1.052	0.124	13.4	1.701	4.440	2.740	161.1
Y13	0.989	0.851	0.138	14.0	0.277	0.283	0.006	2.1	0.438	0.627	0.190	43.3	0.899	0.541	0.358	39.8
Y14	1.495	1.412	0.083	5.6	0.197	0.276	0.079	40.3	1.120	-0.387	1.506	134.5	11.946	-2.098	14.045	117.6
Y15	1.011	1.027	0.016	1.6	0.265	0.284	0.018	6.9	1.200	0.472	0.728	60.6	4.420	0.814	3.606	81.6
Average			0.122	9.7			0.037	15.4			0.637	63.0			5.187	100.0
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.333	0.080	5.6	0.202	0.285	0.084	41.4	0.226	0.304	0.077	34.1	1.474	2.296	0.823	55.8
Y17	2.383	1.911	0.472	19.8	0.418	0.437	0.019	4.6	4.266	1.612	2.654	62.2	40.436	12.021	28.415	70.3
Y18	2.073	1.982	0.090	4.4	0.285	0.328	0.043	15.0	-0.206	0.089	0.295	143.3	3.054	4.023	0.969	31.7
Y19	2.216	2.439	0.222	10.0	0.432	0.398	0.033	7.7	-0.111	0.383	0.493	445.3	1.606	7.983	6.377	397.1
Average			0.216	10.0			0.045	17.2			0.880	171.2			9.146	138.7

Table 6.8f Testing results by Net 17 for 24 subjects

NET 17	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.856	0.004	0.5	0.266	0.279	0.013	4.9	0.511	0.603	0.092	18.0	0.716	0.080	0.636	88.9
E1	1.196	1.109	0.087	7.3	0.378	0.361	0.017	4.6	0.685	0.803	0.119	17.3	0.453	1.910	1.457	321.8
Y7	0.502	0.509	0.007	1.5	0.359	0.321	0.038	10.6	2.456	2.221	0.234	9.5	7.145	7.980	0.835	11.7
Y8	1.681	1.728	0.048	2.8	0.361	0.196	0.166	45.9	-0.238	-0.702	0.464	194.8	2.593	-2.182	4.776	184.1
Average			0.036	3.0			0.059	16.5			0.227	59.9			1.926	151.6
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.121	0.127	12.7	0.283	0.304	0.021	7.4	1.080	0.600	0.480	44.4	1.878	2.010	0.132	7.0
Y3	1.318	1.408	0.090	6.8	0.285	0.294	0.009	3.1	0.457	0.100	0.357	78.1	1.028	0.941	0.087	8.5
Y4	1.005	1.024	0.019	1.9	0.236	0.245	0.009	3.7	0.298	0.098	0.200	67.0	0.425	-0.367	0.792	186.5
Y5	0.636	0.504	0.132	20.8	0.254	0.216	0.038	14.8	1.132	0.816	0.316	27.9	1.827	0.756	1.072	58.6
Average			0.092	10.6			0.019	7.3			0.338	54.4			0.521	65.2
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.646	0.026	3.8	0.263	0.271	0.008	2.9	0.367	0.950	0.583	158.9	0.049	0.204	0.155	313.5
E2	0.657	1.377	0.720	109.5	0.397	0.399	0.002	0.5	2.807	2.351	0.456	16.3	12.599	13.229	0.631	5.0
E3	0.734	0.521	0.213	29.0	0.213	0.240	0.028	13.0	0.315	1.165	0.850	269.6	0.242	1.426	1.184	489.4
E4	1.000	1.115	0.115	11.5	0.415	0.358	0.057	13.7	0.813	1.750	0.937	115.3	0.781	7.306	6.525	835.4
Average			0.268	38.4			0.023	7.5			0.707	140.0			2.124	410.8
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.540	0.096	21.8	0.206	0.242	0.037	17.9	0.852	0.588	0.264	31.0	1.559	-2.230	3.789	243.0
Y9	0.793	0.822	0.029	3.6	0.292	0.302	0.010	3.4	0.838	0.724	0.114	13.6	3.180	-0.218	3.398	106.8
Y10	1.522	1.576	0.055	3.6	0.328	0.350	0.023	6.9	0.863	1.022	0.159	18.5	3.466	7.390	3.924	113.2
Y11	3.649	2.467	1.182	32.4	0.423	0.392	0.030	7.2	-0.892	0.386	1.278	143.2	8.891	9.936	1.045	11.7
Average			0.340	15.3			0.025	8.8			0.454	51.6			3.039	118.7
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.102	0.303	21.6	0.368	0.319	0.048	13.2	0.928	1.021	0.093	10.0	1.701	4.677	2.976	175.0
Y13	0.989	0.865	0.124	12.5	0.277	0.276	0.000	0.1	0.438	0.561	0.123	28.1	0.899	0.482	0.417	46.3
Y14	1.495	1.664	0.169	11.3	0.197	0.351	0.154	78.3	1.120	1.594	0.475	42.4	11.946	14.220	2.273	19.0
Y15	1.011	1.005	0.005	0.5	0.265	0.288	0.023	8.5	1.200	0.631	0.569	47.4	4.420	1.664	2.755	62.3
Average			0.150	11.5			0.056	25.0			0.315	32.0			2.105	75.7
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.506	0.093	6.6	0.202	0.269	0.067	33.1	0.226	0.077	0.150	66.2	1.474	2.787	1.313	89.1
Y17	2.383	1.621	0.762	32.0	0.418	0.407	0.011	2.7	4.266	1.262	3.003	70.4	40.436	10.229	30.208	74.7
Y18	2.073	2.146	0.073	3.5	0.285	0.336	0.051	17.9	-0.206	-0.042	0.164	79.7	3.054	4.418	1.364	44.7
Y19	2.216	2.398	0.181	8.2	0.432	0.399	0.032	7.4	-0.111	0.202	0.313	282.4	1.606	6.590	4.984	310.3
Average			0.277	12.6			0.040	15.3			0.907	124.7			9.467	129.7

Table 6.8g Testing results by Net 18 for 24 subjects

NET 18	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.871	0.012	1.4	0.266	0.275	0.009	3.4	0.511	0.487	0.025	4.8	0.716	-0.409	1.125	157.1
E1	1.196	1.152	0.044	3.7	0.378	0.358	0.020	5.3	0.685	0.633	0.051	7.5	0.453	0.900	0.447	98.7
Y7	0.502	0.718	0.217	43.2	0.359	0.370	0.011	3.1	2.456	1.876	0.580	23.6	7.145	5.833	1.312	18.4
Y8	1.681	1.906	0.226	13.4	0.361	0.227	0.134	37.2	-0.238	-0.548	0.310	130.1	2.593	-0.186	2.779	107.2
Average			0.124	15.4			0.044	12.3			0.241	41.5			1.416	95.3
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	0.999	0.005	0.5	0.283	0.289	0.006	2.2	1.080	0.678	0.402	37.2	1.878	1.987	0.109	5.8
Y3	1.318	1.317	0.001	0.1	0.285	0.287	0.002	0.6	0.457	0.337	0.120	26.2	1.028	2.227	1.198	116.6
Y4	1.005	0.971	0.034	3.3	0.236	0.228	0.008	3.2	0.298	0.126	0.171	57.6	0.425	-0.045	0.470	110.7
Y5	0.636	0.470	0.166	26.1	0.254	0.207	0.047	18.6	1.132	0.804	0.329	29.0	1.827	0.730	1.098	60.1
Average			0.051	7.5			0.016	6.1			0.255	37.5			0.719	73.3
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.664	0.008	1.2	0.263	0.271	0.008	2.9	0.367	0.846	0.479	130.5	0.049	-0.329	0.379	766.2
E2	0.657	1.110	0.452	68.8	0.397	0.388	0.008	2.1	2.807	2.167	0.640	22.8	12.599	9.221	3.378	26.8
E3	0.734	0.506	0.228	31.0	0.213	0.225	0.013	6.0	0.315	1.144	0.829	263.0	0.242	1.622	1.380	570.5
E4	1.000	1.102	0.102	10.2	0.415	0.377	0.038	9.1	0.813	1.326	0.513	63.1	0.781	3.488	2.707	346.5
Average			0.198	27.8			0.017	5.1			0.615	119.9			1.961	427.5
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.530	0.087	19.5	0.206	0.243	0.038	18.3	0.852	0.770	0.082	9.6	1.559	-1.231	2.790	178.9
Y9	0.793	1.097	0.304	38.4	0.292	0.323	0.031	10.7	0.838	1.627	0.789	94.2	3.180	8.216	5.036	158.4
Y10	1.522	1.534	0.013	0.8	0.328	0.348	0.021	6.3	0.863	0.999	0.136	15.8	3.466	6.949	3.482	100.5
Y11	3.649	2.494	1.155	31.6	0.423	0.408	0.015	3.6	-0.892	0.287	1.179	132.2	8.891	8.908	0.017	0.2
Average			0.390	22.6			0.026	9.7			0.547	63.0			2.831	109.5
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.200	0.205	14.6	0.368	0.329	0.039	10.6	0.928	0.756	0.172	18.6	1.701	3.211	1.511	88.8
Y13	0.989	0.904	0.085	8.6	0.277	0.282	0.005	1.9	0.438	0.580	0.142	32.5	0.899	0.857	0.042	4.7
Y14	1.495	1.525	0.030	2.0	0.197	0.291	0.094	47.9	1.120	1.055	0.064	5.7	11.946	10.555	1.391	11.6
Y15	1.011	0.944	0.067	6.6	0.265	0.265	0.000	0.2	1.200	0.567	0.633	52.7	4.420	1.425	2.994	67.8
Average			0.097	7.9			0.035	15.1			0.253	27.4			1.485	43.2
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.527	0.114	8.0	0.202	0.259	0.057	28.4	0.226	0.031	0.195	86.2	1.474	2.788	1.314	89.2
Y17	2.383	1.319	1.064	44.7	0.418	0.367	0.051	12.2	4.266	1.130	3.136	73.5	40.436	8.628	31.808	78.7
Y18	2.073	2.296	0.223	10.8	0.285	0.340	0.054	19.1	-0.206	-0.129	0.077	37.5	3.054	4.678	1.623	53.2
Y19	2.216	2.256	0.039	1.8	0.432	0.417	0.014	3.3	-0.111	0.496	0.606	547.4	1.606	7.061	5.455	339.7
Average			0.360	16.3			0.044	15.7			1.004	186.2			10.050	140.2

Table 6.8h Testing results by Net 19 for subjects

NET 19	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.872	0.012	1.4	0.266	0.270	0.004	1.4	0.511	0.425	0.086	16.9	0.716	-0.679	1.395	194.9
E1	1.196	1.167	0.028	2.4	0.378	0.358	0.020	5.3	0.685	0.701	0.016	2.4	0.453	1.408	0.955	210.9
Y7	0.502	0.695	0.193	38.5	0.359	0.368	0.009	2.4	2.456	2.040	0.415	16.9	7.145	6.628	0.517	7.2
Y8	1.681	1.907	0.226	13.5	0.361	0.369	0.007	2.0	-0.238	-0.391	0.152	64.0	2.593	-1.218	3.812	147.0
Average			0.115	13.9			0.010	2.8			0.168	25.0			1.670	140.0
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	0.978	0.017	1.7	0.283	0.277	0.006	2.1	1.080	0.748	0.332	30.7	1.878	2.387	0.510	27.2
Y3	1.318	1.340	0.022	1.7	0.285	0.272	0.013	4.7	0.457	0.245	0.212	46.4	1.028	1.792	0.763	74.3
Y4	1.005	0.997	0.008	0.8	0.236	0.222	0.014	6.0	0.298	0.068	0.229	77.0	0.425	-0.609	1.034	243.4
Y5	0.636	0.490	0.147	23.0	0.254	0.207	0.047	18.5	1.132	1.041	0.091	8.1	1.827	1.780	0.048	2.6
Average			0.048	6.8			0.020	7.8			0.216	40.6			0.589	86.9
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.638	0.033	5.0	0.263	0.269	0.005	2.0	0.367	0.815	0.448	122.0	0.049	-0.574	0.623	1261.4
E2	0.657	1.062	0.405	61.6	0.397	0.397	0.001	0.1	2.807	2.356	0.452	16.1	12.599	11.017	1.582	12.6
E3	0.734	0.553	0.182	24.7	0.213	0.213	0.000	0.2	0.315	0.935	0.619	196.5	0.242	0.853	0.611	252.5
E4	1.000	1.132	0.131	13.1	0.415	0.389	0.026	6.2	0.813	1.026	0.213	26.2	0.781	2.552	1.771	226.8
Average			0.188	26.1			0.008	2.1			0.433	90.2			1.147	438.3
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.550	0.107	24.1	0.206	0.233	0.027	13.1	0.852	0.760	0.092	10.8	1.559	-1.200	2.759	176.9
Y9	0.793	1.086	0.293	37.0	0.292	0.323	0.031	10.6	0.838	1.627	0.790	94.2	3.180	7.911	4.732	148.8
Y10	1.522	1.503	0.019	1.3	0.328	0.358	0.031	9.3	0.863	1.029	0.166	19.3	3.466	6.841	3.375	97.4
Y11	3.649	2.403	1.246	34.1	0.423	0.423	0.000	0.1	-0.892	0.546	1.439	161.2	8.891	9.963	1.072	12.1
Average			0.416	24.1			0.022	8.3			0.622	71.4			2.984	108.8
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.210	0.195	13.9	0.368	0.317	0.050	13.7	0.928	0.640	0.288	31.0	1.701	2.977	1.276	75.0
Y13	0.989	0.924	0.065	6.6	0.277	0.271	0.006	2.1	0.438	0.464	0.026	5.9	0.899	0.450	0.449	50.0
Y14	1.495	1.544	0.049	3.3	0.197	0.254	0.057	29.1	1.120	1.086	0.033	3.0	11.946	10.990	0.956	8.0
Y15	1.011	0.932	0.079	7.9	0.265	0.293	0.028	10.4	1.200	1.100	0.100	8.3	4.420	4.385	0.035	0.8
Average			0.097	7.9			0.035	13.8			0.112	12.1			0.679	33.4
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.483	0.070	5.0	0.202	0.211	0.009	4.5	0.226	-0.071	0.298	131.4	1.474	2.743	1.270	86.2
Y17	2.383	1.451	0.931	39.1	0.418	0.399	0.019	4.6	4.266	1.190	3.076	72.1	40.436	8.905	31.531	78.0
Y18	2.073	2.171	0.098	4.7	0.285	0.281	0.004	1.5	-0.206	-0.267	0.062	29.9	3.054	4.083	1.029	33.7
Y19	2.216	2.270	0.053	2.4	0.432	0.407	0.024	5.6	-0.111	0.227	0.338	305.2	1.606	6.123	4.517	281.3
Average			0.288	12.8			0.014	4.0			0.943	134.7			9.587	119.8

Table 6.8i Testing results by Net 20 for 24 subjects

NET 20	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.871	0.012	1.4	0.266	0.262	0.004	1.6	0.511	0.455	0.056	11.0	0.716	-0.456	1.172	163.7
E1	1.196	1.216	0.020	1.7	0.378	0.364	0.014	3.7	0.685	0.703	0.018	2.7	0.453	1.517	1.064	235.0
Y7	0.502	0.680	0.178	35.5	0.359	0.372	0.013	3.5	2.456	2.160	0.295	12.0	7.145	7.297	0.153	2.1
Y8	1.681	1.930	0.249	14.8	0.361	0.345	0.016	4.4	-0.238	-0.483	0.245	103.0	2.593	-1.404	3.997	154.1
Average			0.115	13.3			0.012	3.3			0.154	32.2			1.596	138.7
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	0.976	0.018	1.9	0.283	0.269	0.014	5.1	1.080	0.697	0.383	35.5	1.878	2.087	0.209	11.2
Y3	1.318	1.354	0.037	2.8	0.285	0.268	0.017	6.1	0.457	0.179	0.278	60.9	1.028	1.333	0.304	29.6
Y4	1.005	0.983	0.022	2.2	0.236	0.215	0.021	8.9	0.298	0.117	0.180	60.6	0.425	-0.479	0.903	212.8
Y5	0.636	0.483	0.153	24.1	0.254	0.203	0.051	20.1	1.132	1.068	0.065	5.7	1.827	1.733	0.094	5.1
Average			0.058	7.7			0.026	10.0			0.227	40.7			0.378	64.7
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.712	0.040	5.9	0.263	0.270	0.007	2.5	0.367	0.689	0.322	87.6	0.049	-0.804	0.854	1727.2
E2	0.657	1.030	0.373	56.8	0.397	0.397	0.000	0.0	2.807	2.658	0.150	5.3	12.599	13.034	0.436	3.5
E3	0.734	0.628	0.106	14.5	0.213	0.214	0.002	0.7	0.315	0.678	0.363	115.1	0.242	-0.078	0.320	132.3
E4	1.000	1.145	0.144	14.4	0.415	0.391	0.024	5.7	0.813	1.185	0.372	45.8	0.781	3.380	2.598	332.7
Average			0.166	22.9			0.008	2.3			0.302	63.5			1.052	548.9
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.579	0.135	30.5	0.206	0.228	0.023	11.0	0.852	0.809	0.043	5.0	1.559	-0.811	2.370	152.0
Y9	0.793	1.098	0.306	38.5	0.292	0.312	0.020	6.8	0.838	1.344	0.507	60.5	3.180	6.293	3.113	97.9
Y10	1.522	1.570	0.048	3.2	0.328	0.347	0.019	5.9	0.863	0.861	0.002	0.2	3.466	6.644	3.178	91.7
Y11	3.649	2.511	1.138	31.2	0.423	0.404	0.019	4.5	-0.892	-0.067	0.825	92.5	8.891	6.982	1.909	21.5
Average			0.407	25.8			0.020	7.1			0.344	39.6			2.643	90.8
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.348	0.057	4.0	0.368	0.334	0.033	9.1	0.928	0.912	0.016	1.7	1.701	5.725	4.024	236.6
Y13	0.989	0.955	0.033	3.4	0.277	0.279	0.002	0.6	0.438	0.422	0.015	3.5	0.899	0.264	0.635	70.6
Y14	1.495	1.434	0.061	4.1	0.197	0.253	0.057	28.8	1.120	1.067	0.053	4.7	11.946	10.161	1.786	14.9
Y15	1.011	0.892	0.119	11.8	0.265	0.287	0.021	8.0	1.200	1.116	0.084	7.0	4.420	4.162	0.258	5.8
Average			0.068	5.8			0.028	11.6			0.042	4.2			1.676	82.0
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.486	0.073	5.2	0.202	0.209	0.008	3.7	0.226	-0.121	0.348	153.5	1.474	2.212	0.738	50.1
Y17	2.383	1.418	0.965	40.5	0.418	0.422	0.004	1.1	4.266	1.446	2.820	66.1	40.436	9.173	31.264	77.3
Y18	2.073	2.093	0.020	1.0	0.285	0.310	0.025	8.8	-0.206	-0.183	0.022	10.9	3.054	4.029	0.975	31.9
Y19	2.216	2.219	0.003	0.1	0.432	0.413	0.018	4.2	-0.111	0.315	0.426	384.7	1.606	6.190	4.584	285.4
Average			0.265	11.7			0.014	4.5			0.904	153.8			9.390	111.2

Table 6.13a Testing results by Net 21 for 24 subjects

NET 21	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.912	0.052	6.1	0.266	0.294	0.028	10.3	0.511	0.888	0.376	73.6	0.716	2.663	1.947	271.9
E1	1.196	1.836	0.641	53.6	0.378	0.356	0.022	5.9	0.685	0.394	0.290	42.4	0.453	4.061	3.608	796.8
Y7	0.502	0.481	0.021	4.1	0.359	0.338	0.021	5.8	2.456	2.668	0.213	8.7	7.145	11.860	4.715	66.0
Y8	1.681	1.685	0.004	0.2	0.361	0.208	0.153	42.5	-0.238	-0.536	0.297	124.9	2.593	-1.757	4.351	167.8
Average			0.180	16.0			0.056	16.1			0.294	62.4			3.655	325.6
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.363	0.368	37.0	0.283	0.321	0.038	13.5	1.080	0.543	0.537	49.7	1.878	3.379	1.502	80.0
Y3	1.318	1.426	0.108	8.2	0.285	0.282	0.003	1.2	0.457	0.172	0.285	62.3	1.028	1.966	0.938	91.2
Y4	1.005	1.046	0.041	4.0	0.236	0.274	0.038	16.2	0.298	0.486	0.188	63.2	0.425	1.645	1.221	287.5
Y5	0.636	0.568	0.069	10.8	0.254	0.242	0.012	4.7	1.132	0.753	0.379	33.5	1.827	0.300	1.528	83.6
Average			0.146	15.0			0.023	8.9			0.347	52.2			1.297	135.6
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.531	0.140	20.9	0.263	0.250	0.014	5.2	0.367	1.206	0.839	228.5	0.049	1.326	1.277	2584.0
E2	0.657	1.425	0.768	116.8	0.397	0.399	0.002	0.5	2.807	2.351	0.457	16.3	12.599	14.874	2.275	18.1
E3	0.734	0.601	0.133	18.1	0.213	0.248	0.036	16.7	0.315	1.061	0.746	236.6	0.242	1.179	0.937	387.3
E4	1.000	0.780	0.220	22.0	0.415	0.274	0.141	33.9	0.813	1.038	0.225	27.7	0.781	2.164	1.383	177.1
Average			0.315	44.5			0.048	14.1			0.567	127.2			1.468	791.6
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.572	0.128	29.0	0.206	0.257	0.052	25.1	0.852	0.807	0.046	5.3	1.559	-0.096	1.655	106.2
Y9	0.793	0.742	0.051	6.4	0.292	0.265	0.028	9.5	0.838	0.635	0.202	24.2	3.180	-0.008	3.188	100.3
Y10	1.522	1.544	0.023	1.5	0.328	0.336	0.008	2.5	0.863	0.784	0.079	9.2	3.466	5.466	2.000	57.7
Y11	3.649	2.489	1.160	31.8	0.423	0.381	0.042	9.8	-0.892	0.307	1.199	134.4	8.891	9.273	0.382	4.3
Average			0.341	17.2			0.032	11.7			0.382	43.3			1.806	67.1
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.189	0.217	15.4	0.368	0.329	0.039	10.6	0.928	0.994	0.066	7.1	1.701	4.946	3.245	190.8
Y13	0.989	0.769	0.220	22.2	0.277	0.279	0.002	0.7	0.438	0.684	0.246	56.3	0.899	0.460	0.439	48.9
Y14	1.495	1.357	0.139	9.3	0.197	0.267	0.070	35.8	1.120	-0.406	1.525	136.2	11.946	-2.243	14.189	118.8
Y15	1.011	1.001	0.010	1.0	0.265	0.281	0.015	5.8	1.200	0.487	0.713	59.5	4.420	0.980	3.440	77.8
Average			0.146	12.0			0.032	13.2			0.638	64.8			5.328	109.1
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.404	0.009	0.6	0.202	0.292	0.090	44.4	0.226	0.310	0.084	36.9	1.474	2.628	1.154	78.3
Y17	2.383	1.623	0.760	31.9	0.418	0.419	0.002	0.4	4.266	1.543	2.723	63.8	40.436	9.036	31.400	77.7
Y18	2.073	2.003	0.070	3.4	0.285	0.341	0.055	19.4	-0.206	0.178	0.384	186.7	3.054	4.211	1.156	37.9
Y19	2.216	2.458	0.242	10.9	0.432	0.404	0.027	6.3	-0.111	0.359	0.470	424.4	1.606	7.065	5.459	339.9
Average			0.270	11.7			0.044	17.6			0.915	177.9			9.792	133.4

Table 6.13b Testing results by Net 22 for 24 subjects

NET 22	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.829	0.031	3.6	0.266	0.277	0.011	4.1	0.511	0.569	0.058	11.4	0.716	0.176	0.540	75.4
E1	1.196	1.316	0.120	10.1	0.378	0.380	0.002	0.6	0.685	0.616	0.068	10.0	0.453	2.489	2.037	449.8
Y7	0.502	0.484	0.018	3.5	0.359	0.304	0.055	15.2	2.456	2.146	0.309	12.6	7.145	7.732	0.588	8.2
Y8	1.681	1.688	0.007	0.4	0.361	0.193	0.169	46.7	-0.238	-0.667	0.429	179.9	2.593	-2.036	4.629	178.5
Average			0.044	4.4			0.059	16.7			0.216	53.5			1.948	178.0
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.180	0.185	18.6	0.283	0.309	0.026	9.1	1.080	0.537	0.543	50.3	1.878	2.258	0.380	20.2
Y3	1.318	1.431	0.113	8.6	0.285	0.296	0.011	3.7	0.457	0.067	0.390	85.4	1.028	1.058	0.030	2.9
Y4	1.005	1.053	0.048	4.8	0.236	0.244	0.008	3.3	0.298	0.061	0.236	79.3	0.425	-0.377	0.802	188.9
Y5	0.636	0.534	0.102	16.1	0.254	0.217	0.036	14.3	1.132	0.805	0.327	28.9	1.827	0.752	1.075	58.8
Average			0.112	12.0			0.020	7.6			0.374	61.0			0.572	67.7
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.586	0.086	12.8	0.263	0.268	0.005	1.8	0.367	1.035	0.668	181.9	0.049	0.410	0.361	730.6
E2	0.657	1.109	0.452	68.7	0.397	0.393	0.003	0.8	2.807	2.480	0.328	11.7	12.599	13.152	0.553	4.4
E3	0.734	0.560	0.175	23.8	0.213	0.245	0.032	15.1	0.315	1.197	0.881	279.6	0.242	1.520	1.278	528.4
E4	1.000	0.906	0.094	9.4	0.415	0.351	0.064	15.4	0.813	1.875	1.063	130.7	0.781	7.524	6.743	863.3
Average			0.202	28.7			0.026	8.3			0.735	151.0			2.234	531.7
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.493	0.049	11.1	0.206	0.236	0.030	14.6	0.852	0.663	0.189	22.2	1.559	-1.426	2.985	191.5
Y9	0.793	0.761	0.032	4.1	0.292	0.300	0.007	2.5	0.838	0.768	0.070	8.4	3.180	0.229	2.951	92.8
Y10	1.522	1.624	0.102	6.7	0.328	0.354	0.026	8.0	0.863	0.917	0.054	6.3	3.466	6.770	3.304	95.3
Y11	3.649	2.537	1.112	30.5	0.423	0.380	0.043	10.1	-0.892	-0.001	0.891	99.9	8.891	7.593	1.298	14.6
Average			0.324	13.1			0.027	8.8			0.301	34.2			2.635	98.6
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.211	0.194	13.8	0.368	0.326	0.041	11.3	0.928	1.011	0.082	8.9	1.701	5.268	3.567	209.8
Y13	0.989	0.824	0.164	16.6	0.277	0.275	0.002	0.7	0.438	0.593	0.155	35.5	0.899	0.537	0.362	40.3
Y14	1.495	1.864	0.369	24.7	0.197	0.345	0.148	75.3	1.120	1.661	0.542	48.4	11.946	15.299	3.352	28.1
Y15	1.011	1.033	0.022	2.2	0.265	0.287	0.021	8.1	1.200	0.568	0.632	52.7	4.420	1.865	2.555	57.8
Average			0.187	14.3			0.053	23.8			0.353	36.4			2.459	84.0
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.504	0.091	6.4	0.202	0.268	0.066	32.6	0.226	0.124	0.103	45.3	1.474	2.747	1.273	86.4
Y17	2.383	1.822	0.561	23.5	0.418	0.390	0.028	6.7	4.266	1.256	3.010	70.6	40.436	9.312	31.124	77.0
Y18	2.073	2.162	0.089	4.3	0.285	0.342	0.056	19.7	-0.206	0.022	0.228	110.6	3.054	4.511	1.457	47.7
Y19	2.216	2.581	0.364	16.4	0.432	0.400	0.031	7.2	-0.111	0.022	0.133	119.6	1.606	6.112	4.506	280.5
Average			0.276	12.7			0.045	16.6			0.868	86.5			9.590	122.9

Table 6.13c Testing results by Net 23 for 24 subjects

NET 23	Mean				S.D				Skew				Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.816	0.044	5.1	0.266	0.271	0.005	1.7	0.511	0.494	0.017	3.3	0.716	-0.326	1.042	145.5
E1	1.196	1.182	0.014	1.1	0.378	0.362	0.016	4.1	0.685	0.564	0.121	17.7	0.453	1.500	1.047	231.3
Y7	0.502	0.598	0.097	19.3	0.359	0.350	0.009	2.6	2.456	1.890	0.565	23.0	7.145	6.074	1.071	15.0
Y8	1.681	1.946	0.265	15.8	0.361	0.234	0.128	35.3	-0.238	-0.496	0.258	108.2	2.593	0.016	2.578	99.4
Average			0.105	10.3			0.039	10.9			0.240	38.1			1.435	122.8
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	0.997	0.003	0.3	0.283	0.287	0.004	1.4	1.080	0.641	0.439	40.7	1.878	2.154	0.276	14.7
Y3	1.318	1.344	0.026	2.0	0.285	0.287	0.002	0.7	0.457	0.321	0.136	29.8	1.028	2.484	1.456	141.6
Y4	1.005	1.010	0.005	0.5	0.236	0.226	0.010	4.3	0.298	0.089	0.208	70.0	0.425	-0.025	0.449	105.8
Y5	0.636	0.516	0.120	18.9	0.254	0.208	0.046	18.0	1.132	0.778	0.354	31.3	1.827	0.635	1.193	65.3
Average			0.039	5.4			0.015	6.1			0.284	42.9			0.843	81.8
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.647	0.025	3.7	0.263	0.270	0.007	2.6	0.367	0.837	0.469	127.9	0.049	-0.182	0.232	468.7
E2	0.657	0.971	0.314	47.7	0.397	0.388	0.009	2.3	2.807	2.260	0.547	19.5	12.599	9.728	2.870	22.8
E3	0.734	0.535	0.199	27.2	0.213	0.228	0.015	7.0	0.315	1.142	0.826	262.2	0.242	1.405	1.164	481.0
E4	1.000	1.083	0.083	8.3	0.415	0.387	0.028	6.8	0.813	1.321	0.508	62.6	0.781	4.020	3.239	414.6
Average			0.155	21.7			0.015	4.7			0.588	118.0			1.876	346.8
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.483	0.039	8.9	0.206	0.237	0.031	15.3	0.852	0.906	0.054	6.3	1.559	-0.237	1.796	115.2
Y9	0.793	0.976	0.183	23.1	0.292	0.319	0.027	9.2	0.838	1.751	0.913	109.0	3.180	8.059	4.879	153.4
Y10	1.522	1.663	0.141	9.3	0.328	0.358	0.030	9.3	0.863	0.834	0.029	3.3	3.466	6.496	3.030	87.4
Y11	3.649	2.684	0.965	26.4	0.423	0.400	0.023	5.4	-0.892	-0.243	0.649	72.7	8.891	6.705	2.186	24.6
Average			0.332	16.9			0.028	9.8			0.411	47.8			2.973	95.2
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.225	0.180	12.8	0.368	0.336	0.031	8.5	0.928	0.753	0.175	18.9	1.701	3.404	1.704	100.2
Y13	0.989	0.887	0.101	10.3	0.277	0.282	0.005	1.8	0.438	0.590	0.153	34.9	0.899	0.863	0.036	4.0
Y14	1.495	1.595	0.100	6.7	0.197	0.283	0.086	44.0	1.120	1.142	0.022	2.0	11.946	10.673	1.274	10.7
Y15	1.011	0.944	0.067	6.6	0.265	0.258	0.007	2.7	1.200	0.531	0.668	55.7	4.420	1.500	2.920	66.1
Average			0.112	9.1			0.032	14.2			0.255	27.9			1.483	45.2
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.444	0.031	2.2	0.202	0.252	0.050	24.9	0.226	0.089	0.138	60.9	1.474	2.604	1.130	76.7
Y17	2.383	1.884	0.499	20.9	0.418	0.380	0.038	9.1	4.266	0.989	3.277	76.8	40.436	7.918	32.518	80.4
Y18	2.073	2.259	0.186	9.0	0.285	0.345	0.060	20.9	-0.206	-0.034	0.172	83.5	3.054	4.798	1.743	57.1
Y19	2.216	2.493	0.276	12.5	0.432	0.420	0.011	2.6	-0.111	0.198	0.309	279.2	1.606	6.418	4.812	299.6
Average			0.248	11.1			0.040	14.4			0.974	125.1			10.051	128.4

Table 6.15a The testing result by Net A1 and Net A2

	MEAN				SD				SKENWESS				KURTOSIS			
	Desired	Predicted	AAE (cm)	POE (%)	Desired	Predicted	AAE (cm)	POE (%)	Desired	Predicted	AAE	POE (%)	Desired	Predicted	AAE	POE (%)
Net A1	0.657	0.697	0.040	6.1	0.397	0.315	0.081	20.5	2.807	1.359	1.448	51.6	12.599	4.253	8.346	66.2
Net A2	0.657	1.072	0.415	63.1	0.397	0.343	0.054	13.6	2.807	0.750	2.057	73.3	12.599	0.737	11.862	94.2

Table 6.16a Testing results by Net 24, 25, 26 and 27 for 24 subjects

	Net 24 Mean				Net 25 S.D				Net 26 Skewness				Net 27 Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.903	0.043	5.1	0.266	0.295	0.028	10.7	0.511	0.840	0.329	64.4	0.716	2.519	1.803	251.9
E1	1.196	1.395	0.200	16.7	0.378	0.296	0.082	21.6	0.685	0.539	0.146	21.3	0.453	3.014	2.561	565.5
Y7	0.502	0.504	0.002	0.4	0.359	0.326	0.033	9.2	2.456	2.051	0.405	16.5	7.145	7.672	0.528	7.4
Y8	1.681	1.985	0.304	18.1	0.361	0.267	0.094	26.0	-0.238	-0.094	0.145	60.7	2.593	1.641	0.952	36.7
Average			0.137	10.1			0.059	16.9			0.256	40.7			1.461	215.4
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.360	0.366	36.8	0.283	0.302	0.019	6.6	1.080	0.482	0.598	55.4	1.878	3.145	1.267	67.5
Y3	1.318	1.500	0.183	13.9	0.285	0.320	0.035	12.2	0.457	0.553	0.096	21.0	1.028	4.380	3.352	326.0
Y4	1.005	1.015	0.010	1.0	0.236	0.270	0.034	14.3	0.298	0.515	0.217	73.1	0.425	1.565	1.141	268.6
Y5	0.636	0.624	0.013	2.0	0.254	0.231	0.023	9.1	1.132	0.737	0.395	34.9	1.827	0.708	1.120	61.3
Average			0.143	13.4			0.028	10.5			0.327	46.1			1.720	180.9
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.559	0.113	16.8	0.263	0.256	0.008	2.9	0.367	1.205	0.838	228.3	0.049	1.506	1.457	2947.4
E2	0.657	1.374	0.717	109.1	0.397	0.420	0.023	5.8	2.807	2.202	0.605	21.6	12.599	12.391	0.208	1.6
E3	0.734	0.639	0.095	12.9	0.213	0.242	0.030	13.9	0.315	1.058	0.742	235.5	0.242	1.583	1.341	554.5
E4	1.000	0.754	0.246	24.6	0.415	0.258	0.157	37.9	0.813	0.970	0.157	19.3	0.781	1.786	1.005	128.7
Average			0.293	40.9			0.054	15.1			0.586	126.2			1.003	908.0
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.676	0.233	52.6	0.206	0.268	0.062	30.4	0.852	0.839	0.013	1.5	1.559	0.354	1.205	77.3
Y9	0.793	0.836	0.044	5.5	0.292	0.286	0.007	2.2	0.838	0.760	0.078	9.3	3.180	0.879	2.301	72.3
Y10	1.522	1.460	0.062	4.1	0.328	0.355	0.027	8.4	0.863	1.034	0.171	19.8	3.466	6.507	3.041	87.7
Y11	3.649	2.265	1.384	37.9	0.423	0.419	0.004	1.0	-0.892	1.402	2.294	257.2	8.891	16.528	7.637	85.9
Average			0.431	25.0			0.025	10.5			0.639	71.9			3.546	80.8
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.257	0.148	10.5	0.368	0.341	0.027	7.3	0.928	0.955	0.027	2.9	1.701	5.106	3.406	200.3
Y13	0.989	0.672	0.317	32.1	0.277	0.263	0.014	4.9	0.438	0.763	0.326	74.5	0.899	0.512	0.387	43.0
Y14	1.495	1.346	0.150	10.0	0.197	0.284	0.087	44.4	1.120	0.060	1.059	94.6	11.946	0.102	11.845	99.1
Y15	1.011	1.020	0.009	0.9	0.265	0.273	0.007	2.8	1.200	0.288	0.912	76.0	4.420	-0.164	4.583	103.7
Average			0.156	13.4			0.034	14.9			0.581	62.0			5.055	111.5
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.412	0.001	0.1	0.202	0.280	0.078	38.6	0.226	0.289	0.063	27.7	1.474	2.586	1.112	75.5
Y17	2.383	2.410	0.028	1.2	0.418	0.431	0.013	3.2	4.266	0.963	3.303	77.4	40.436	7.201	33.235	82.2
Y18	2.073	1.858	0.214	10.3	0.285	0.334	0.049	17.1	-0.206	0.301	0.506	246.1	3.054	3.829	0.775	25.4
Y19	2.216	2.237	0.021	0.9	0.432	0.376	0.056	12.9	-0.111	0.274	0.385	347.8	1.606	4.819	3.213	200.0
Average			0.066	3.1			0.049	17.9			1.064	174.8			9.584	95.8

Table 6.17a Testing results by Net 28, 29, 30 and 31 for 24 subjects

	Net 28 Mean				Net 29 S.D				Net 30 Skewness				Net 31 Kurtosis			
Group1	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y1	0.860	0.819	0.040	4.7	0.266	0.275	0.009	3.4	0.511	0.538	0.026	5.2	0.716	-0.232	0.948	132.4
E1	1.196	1.194	0.001	0.1	0.378	0.365	0.013	3.4	0.685	0.593	0.091	13.3	0.453	0.704	0.251	55.4
Y7	0.502	0.526	0.025	4.9	0.359	0.363	0.004	1.2	2.456	1.973	0.482	19.6	7.145	5.706	1.438	20.1
Y8	1.681	2.030	0.349	20.8	0.361	0.230	0.131	36.3	-0.238	-0.517	0.279	117.3	2.593	-0.286	2.879	111.0
Average			0.104	7.6			0.039	11.1			0.220	38.8			1.379	79.7
Group2	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y2	0.995	1.024	0.030	3.0	0.283	0.289	0.006	2.3	1.080	0.683	0.397	36.8	1.878	2.113	0.236	12.6
Y3	1.318	1.337	0.019	1.5	0.285	0.289	0.004	1.3	0.457	0.368	0.089	19.5	1.028	2.282	1.253	121.9
Y4	1.005	1.039	0.034	3.4	0.236	0.228	0.008	3.4	0.298	0.150	0.148	49.7	0.425	0.194	0.231	54.4
Y5	0.636	0.521	0.116	18.2	0.254	0.204	0.050	19.5	1.132	0.749	0.383	33.8	1.827	1.085	0.743	40.6
Average			0.050	6.5			0.017	6.6			0.254	34.9			0.616	57.4
Group3	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y6	0.672	0.595	0.077	11.4	0.263	0.273	0.010	3.7	0.367	0.873	0.506	137.8	0.049	-0.066	0.116	234.2
E2	0.657	0.913	0.256	38.9	0.397	0.390	0.007	1.6	2.807	2.436	0.372	13.2	12.599	8.555	4.043	32.1
E3	0.734	0.501	0.233	31.8	0.213	0.224	0.011	5.2	0.315	1.077	0.762	241.8	0.242	1.985	1.743	720.5
E4	1.000	1.002	0.002	0.2	0.415	0.388	0.027	6.6	0.813	1.465	0.652	80.2	0.781	2.730	1.949	249.5
Average			0.142	20.6			0.014	4.3			0.573	118.3			1.963	309.1
Group4	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
E5	0.443	0.490	0.046	10.4	0.206	0.234	0.029	14.0	0.852	0.847	0.005	0.6	1.559	-0.109	1.668	107.0
Y9	0.793	0.922	0.129	16.3	0.292	0.311	0.019	6.4	0.838	1.643	0.805	96.1	3.180	8.008	4.828	151.8
Y10	1.522	1.568	0.047	3.1	0.328	0.360	0.032	9.8	0.863	0.812	0.051	5.9	3.466	5.973	2.506	72.3
Y11	3.649	2.689	0.960	26.3	0.423	0.446	0.023	5.5	-0.892	-0.363	0.529	59.3	8.891	9.402	0.511	5.7
Average			0.296	14.0			0.026	8.9			0.348	40.5			2.378	84.2
Group5	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y12	1.405	1.187	0.219	15.6	0.368	0.336	0.032	8.7	0.928	0.748	0.180	19.4	1.701	3.239	1.538	90.5
Y13	0.989	0.886	0.102	10.3	0.277	0.286	0.009	3.4	0.438	0.607	0.169	38.7	0.899	1.126	0.226	25.2
Y14	1.495	1.605	0.109	7.3	0.197	0.264	0.068	34.4	1.120	1.135	0.015	1.4	11.946	11.474	0.473	4.0
Y15	1.011	0.997	0.014	1.3	0.265	0.258	0.008	2.9	1.200	0.600	0.600	50.0	4.420	1.809	2.610	59.1
Average			0.111	8.6			0.029	12.3			0.241	27.3			1.212	44.7
Group6	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE(cm)	POE(%)	Desired	Predicted	AAE	POE(%)	Desired	Predicted	AAE	POE(%)
Y16	1.413	1.502	0.089	6.3	0.202	0.251	0.050	24.6	0.226	0.117	0.110	48.5	1.474	3.043	1.569	106.5
Y17	2.383	2.328	0.054	2.3	0.418	0.380	0.038	9.2	4.266	1.535	2.730	64.0	40.436	9.649	30.788	76.1
Y18	2.073	2.190	0.117	5.7	0.285	0.337	0.052	18.1	-0.206	-0.069	0.137	66.4	3.054	4.647	1.593	52.1
Y19	2.216	2.460	0.243	11.0	0.432	0.426	0.006	1.3	-0.111	0.280	0.391	352.7	1.606	6.091	4.485	279.2
Average			0.126	6.3			0.036	13.3			0.842	132.9			9.608	128.5

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