Non-invasive Blood Pressure Measurement Algorithm for all age groups

By

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dedicated to

My husband Yue Zhao and my son Brian Zhao

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ABSTRACT

Blood pressure is one of the most important fundamental signs of human cardiovascular health. Accurate measurement of blood pressure is essential in diagnosis and treatment of hypertension and ascertaining blood pressure related risk. Although the auscultatory method using the mercury sphygmomanometer is still considered as the most accurate non-invasive blood pressure measurement method, it is complicated and only suitable for clinical assessment. Currently, automatic self-monitoring blood pressure measurement devices are very popular in the market and widely used at home. Most of those devices are developed on the oscillometric method, as it requires less professional training and is less susceptible to external noise. However most of these devices work well on young healthy subjects, but show less accuracy in some subgroups such as older people.

A blood pressure measurement algorithm for an oscillometric method has been developed in this study. It can accurately determine blood pressure non-invasively for all age groups. A clinical data collection has been done on 86 subjects. Their blood pressure values determined through the auscultatory method were used as reference readings. The obtained cuff pressure oscillations were used for further analysis. The algorithm design process includes signal processing, heart beat detection, feature extraction and artificial neural network design. The algorithm with different features are compared and discussed. The results indicate successful development on measuring blood pressure values on all age groups. The algorithm using all of the selected features achieved A grade on British Hypertension Society protocol for both systolic and

diastolic pressure and also fulfilled the Association Advancement of Medical Instrumentation protocol. However, the developed algorithm takes a long calculation time. An alternative algorithm using 10 features was developed with lower hardware requirements and less calculation time at the cost of a bit less accuracy.

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STATEMENT OF ORIGINALITY

'I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the qualification of any other degree or diploma of a university or other institution of higher learning, except where due acknowledgment is made in the acknowledgments.'

…….. (signed)

…….. (date)

LIST OF UNIT, SYMBOLS AND ABBREVIATIONS

Symbols	Unit
Hz	Hertz
mmHg	Millimetre of mercury, unit for pressure, 133 Pascals

	Description
f	Frequency
ω	The angular frequency

Abbreviations

AAMI	Association for the Advancement of Medical Instrumentation
ABP	Arterial Blood Pressure
ANN	Artificial Neural Network
AUTEC	Auckland University of Technology Ethics Committee
BHS	British Hypertension Society
BP	Blood pressure
CP	Cuff pressure
DFT	Discrete Fourier Transform
DP	Diastolic pressure
FFT	Fast Fourier Transform
HB	Heart Beat
HR	Heart Rate
MAP	Mean Arterial Pressure
MHR	Mean Heart Rate
NIBP	Non-Invasive Blood Pressure
PCA	Principal Component Analysis
PEG	Performance Error Goal

PSD	Power Spectral Density
ROC	Rate of Change
SD	Standard Deviation
SP	Systolic pressure

Chapter 1 Introduction

1.1 Background

In the human body, blood is pumped into the arteries and then travels through the circulatory system. Blood pressure (BP) is the pressure exerted by the blood on the walls of the arteries. The term BP as generally used in the medical area refers to arterial blood pressure (ABP) [1, 2]. During each heartbeat, BP varies between systolic pressure (SP) and diastolic pressure (DP). SP is defined as the highest value of pressure that occurs when the heart contracts and ejects the blood in to the arteries. DP is determined as the lowest pressure value occurring between the each systole [3]. Mean arterial pressure (MAP) is defined as the average arterial pressure during a single cardiac cycle. The pulse pressure (PP) is defined as the difference between SP and DP. One ABP pulse is determined from the end of one heart contraction to the start of the next one as shown in Figure 1-1.

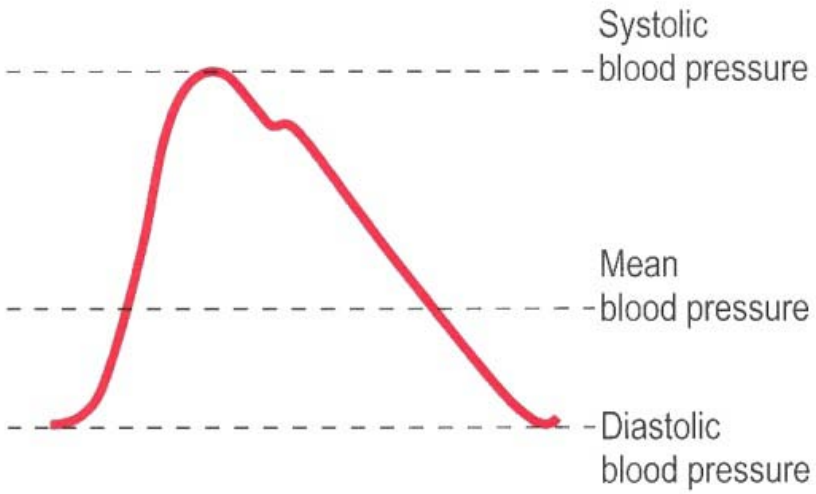


Figure 1-1: A typical ABP pulse

BP is not constant in the body, and it differs at various places. The pressure of the circulating blood decreases as blood passes through arteries, arterioles, capillaries, and veins. BP used in clinical practice without further specification normally refers to the arterial pressure measured at the patient's upper arm. The BP value is not always constant and can change during 24 hr according to an individual's activity such as stress, nutritional factors, drugs or diseases.

The typical BP values normally include two numbers SP and DP and the unit is millimetres of mercury (mmHg). The American Heart Association has published the recommendations of the joint national committee on the diagnosis, evaluation, and treatment of hypertension for classifying and defining blood pressure levels for adults (age 18 years and older) [4]. As shown in Table 1-1, the normal BP range is 100 mmHg ~ 139 mmHg for SP and 60 mmHg ~ 89 mmHg for DP. As BP is a powerful, consistent, and independent risk factor for cardiovascular and renal diseases. It is one of the principal vital parameters and the most commonly clinically measured. An accurate BP measurement is important not only for the general monitoring but also important for clinical applications.

Table 1-1: Changes in Blood Pressure Classification

JNC 6 Category	SBP/DBP	JNC 7 Category
Optimal	<120/80	→ Normal
Normal	120–129/80–84	→ Prehypertension
Borderline	130–139/85–89	
Hypertension	≥140/90	→ Hypertension
Stage 1	140–159/90–99	→ Stage 1
Stage 2	160–179/100–109	→ Stage 2
Stage 3	≥180/110	

The BP measurement had been studied for a long time. There are many techniques on BP measurement right now. Techniques are generally divided into two groups, direct and indirect [5]. The direct techniques of the BP measurement are also called invasive measurement which uses a catheter inserted into the blood vessel to measure the BP continuously for example to detect when the massive blood loss happens, powerful cardiovascular medications are applied to the patient and in general anaesthesia during operations. The direct method is very accurate and is accepted as the gold standard of arterial pressure recording. However the equipment and the procedure of invasive BP measurement require a professional setup, calibration and operation [5, 6]. Since the invasive measurement method has a high associated risk, non-invasive blood pressure (NIBP) measurement methods are most commonly used in present clinical practice [7].

1.2 Literature Review

As stated above, NIBP methods are more commonly used in our daily life. A number of NIBP methods are introduced. Furthermore, the analysis methods used in current automatic devices are introduced with more details in this section.

1.2.1 NIBP methods

Most of popular current NIBP methods are introduced. Their advantages and disadvantages are presented with details and their suitability in automatic devices are reviewed in this section.

1.2.1.1 Auscultatory Technique

The auscultatory method using a mercury column or other sphygmomanometer, occluding cuff and a stethoscope to listen to the sounds made by the blood flow in the

arteries, which are called Korotkoff sounds [7, 8]. This method is also called the Riva-Rocci/Korotkoff method [9]. The Korotkoff sounds are generated by the blood flow through the brachial artery. The observer determines the SP and DP values by identifying the five phases of the Korotkoff sound by using a stethoscope [10].

The auscultatory BP measurement consists of the following processes:

(a) selecting the proper cuff size for the patient, placing the cuff on the upper arm at roughly the same vertical height as the heart, and wrapping the cuff on the arm smoothly and snugly,

(b) inflating cuff to about 30 mmHg above SP rapidly,

(c) deflating at a rate of 2–3 mmHg per second and recording the auscultatory sounds,

(d) finishing the measurement when the sound finally disappears.

The observer then determines the patient's BP by the following five phases of auscultatory sounds in the measurement process [11].

Phase I: The first appearance of faint, repetitive, clear tapping sounds which gradually increase in intensity for at least two consecutive beats is the systolic BP

Phase II: A brief period may follow during which the sounds soften and acquire a swishing quality

Phase III: The return of sharper sounds, which become crisper to regain, or even exceed, the intensity of phase I sounds. The clinical significance, if any, to phases II and III has not been established

Phase IV: The distinct abrupt muffling of sounds, which become soft and blowing in quality

Phase V: The point at which all sounds finally disappear completely is the diastolic pressure

As described above, the auscultatory BP measurement technique is complicated and only suitable for clinic as assessment, which is normally conducted by professionally trained observers. Furthermore, it is also difficult to use this method in a noisy environment [12, 13].

1.2.1.2 Oscillometric Techniques

Currently most automatic devices are developed based on oscillometric techniques. The main difficultly of this method is to define SP, MAP and DP from the oscillation pulse. This method uses an occluding cuff placed on the brachial artery and inflated above SP. The sensor in the cuff will detect the pressure oscillations of the arterial wall during the cuff deflation [14]. The SP, MAP and DP would be defined from the oscillation amplitudes. Mostly the SP and DP values were estimated by using empirical algorithms however the manufactures of BP monitoring equipments always developed their own algorithms for SP and DP determination [15].

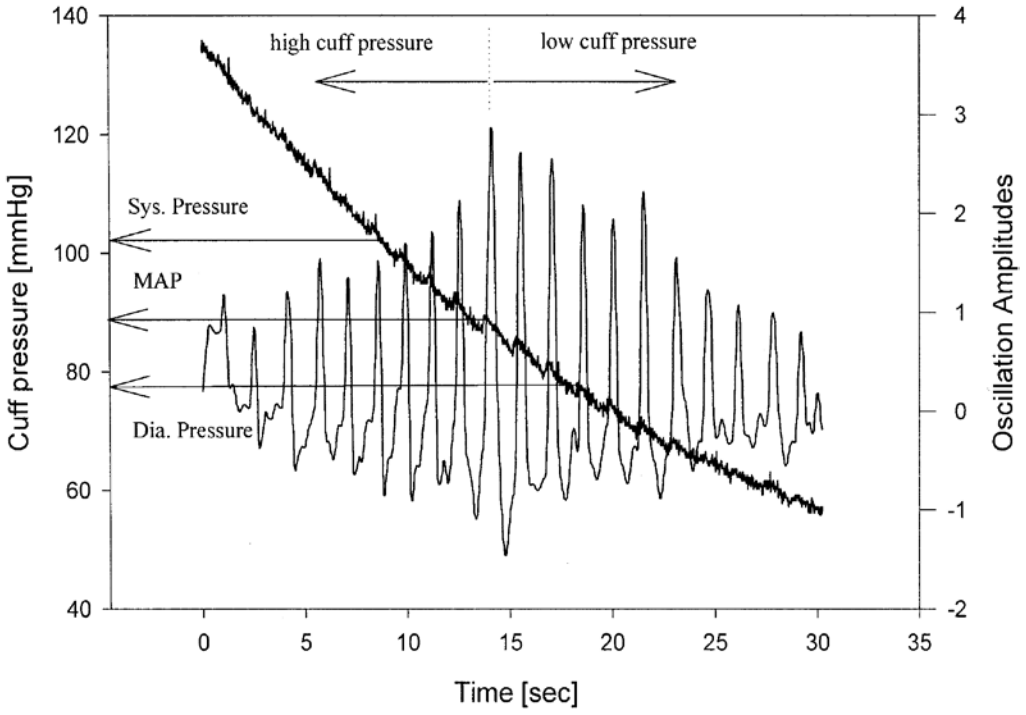


Figure 1-2: The oscillation signal presented with the thin line and the cuff signal presented with the dense decreasing line

Figure 1-2 indicates the relative position between SP, MAP, DP and cuff pressure (CP) obtained in normal blood pressure measurement process. In oscillometric method, it is anticipated that the CP value at maximum amplitude is equal to the subject's MAP [16, 17].

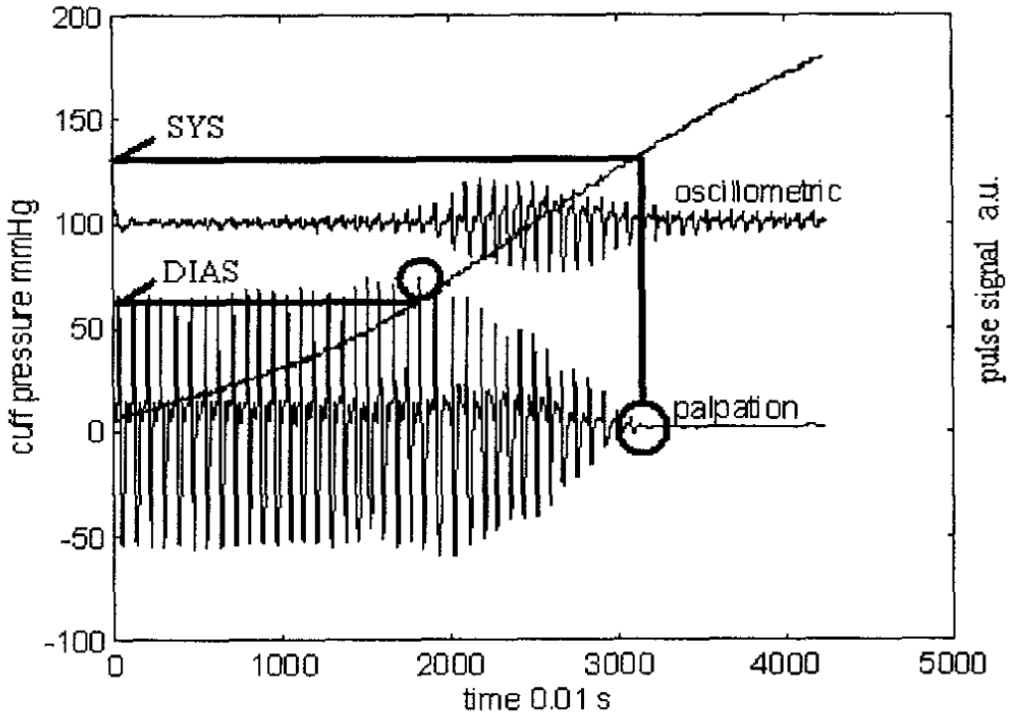
The SP and DP would be determined from the MAP using empirically fixed algorithms. The basis of estimating the MAP algorithm is the maximal-amplitude algorithm also called fixed ratio method. It calculates a ratio which is determined by dividing each HB amplitude over the maximum pulse amplitude. These ratios are used to compare with a fixed ratio to obtain the BP value. In the fixed ratio method, the pre-determined ratio is 0.69~0.86 for DP and 0.43~0.73 for SP respectively [18]. However different researches and manufacturers calculate their own ratios. Large numbers of measurements from a variety of people with a wide range of BP were required to minimize deviations between the estimated and the actual BP [5, 19].

The oscillometric method has two disadvantages: (1) artefact from the patient's motion, as these motions may appear very similar to a real arterial pulse which may lead to the changing of the oscillation pulse amplitudes; (2) irregular oscillation amplitudes which are caused by a large number of the cardiovascular diseases [16, 17, 20].

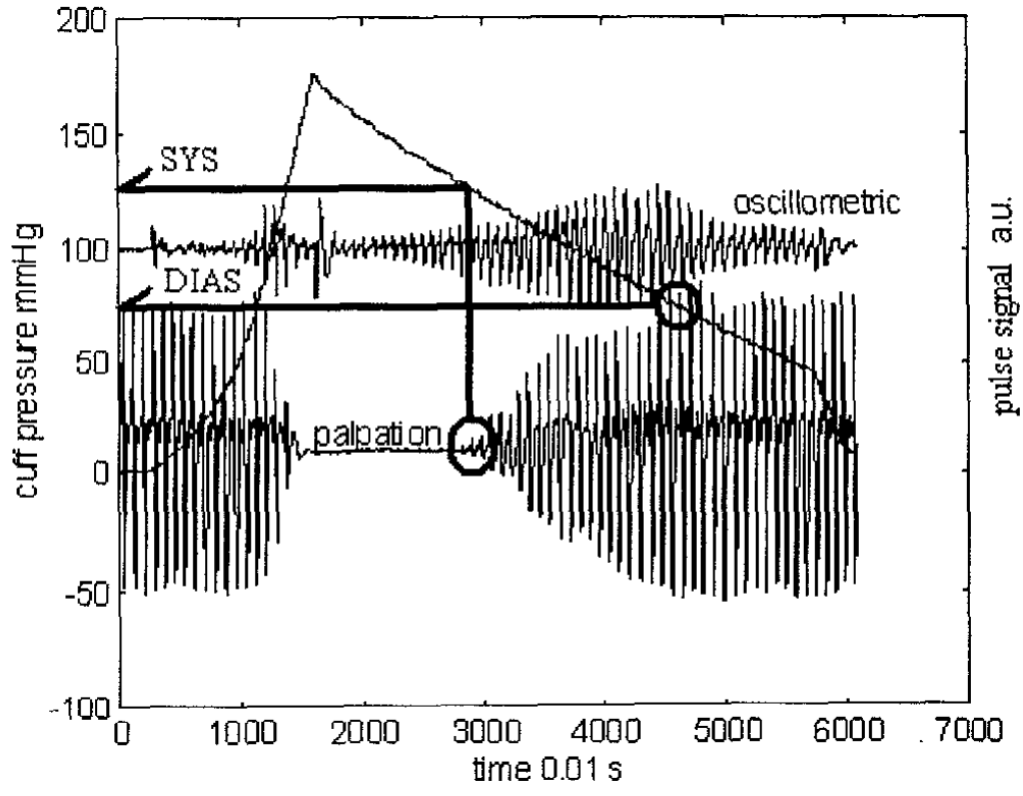
1.2.1.3 Electronic Palpation Method

The electronic palpation method for BP measuring based on an arm cuff and a wrist watch type sensor was first introduced in 1998 [21]. This method uses an arm cuff to occlude the brachial artery and then detect the pulsation of the radial artery on the wrist [22]. The measurement can be made either during the deflating or inflating process, but the inflation model was found to be more stable. Furthermore, it is more accurate than deflation model on both SP and DP determination.

Figure 1-3a shows the typical pressure oscillation signals and CP values in the inflation mode. The DP value is the point where pressure pulse amplitude starts decreasing while the SP value is point where the pulse amplitude drops to the nose level. Figure 1-3b shows the deflation mode which the SP value is determined at where the pressure pulse from the radial artery stars to present and the DP value appears at the point which the pressure pulse amplitude levels off and reach a plateau [22]. The results indicate the algorithm fulfils the AAMI standard when tested on healthy subjects however the accuracy for other groups is still questioned.



a



b

Figure 1-3: Typical pressure pulse signals and CP (a) the inflation mode; (b) the deflation mode [22]

1.2.1.4 Volume-Compensation and Volume-Oscillometric Method

Yamakoshi et al [23] developed two new types of NIBP measurement methods based on the characteristics of the pressure-volume relationship in the artery: volume-oscillometric method and volume-compensation method. Both of them are developed from the vascular unloading principle. These two methods use the photoelectric plethysmographic technique to determine the volume changes in the artery. The volume-oscillometric method can be used for long term ambulatory monitoring which can measure SP and MAP. In the volume-compensation method, BP can be measured beat-by -beat and the pressure waveform will be detected continuously and non-invasively [23].

A new method developed by Tanaka et al [24] based on the volume-compensation principles. In this method, the radial artery is completely compressed by employing a disk-type cuff for local pressurisation. And it also uses a nozzle-flapper type electro-pneumatic converter for the control of CP in order to give sufficiently great frequency response for the BP measurement. This method can be used in both rest and stressful conditions for SP and DP estimation. But the measurement accuracy is still below the AAMI standards.

1.2.1.5 Arterial Tonometry Method

This method is developed based on the principle of the tonometry devices which are used to measure the intra-ocular pressure. The arterial tonometry device consists of a pressure sensor and pneumatic actuator. It is placed on the wrist above the radial artery as shown in Figure 1-4. When the artery is applied with the hold-down pressure, the artery wall near the device is flattened. The configuration maximizes the energy that can

be transferred through the artery to the sensor, yielding pulses with the highest amplitude. The SP and DP value can be determined from the relative amplitude of the tonometry pulse. This method can be used for the continuous BP measurement application. However the difficulties of the placement sensitivity, calibration difficulties and motion sensitivity still need to be solved [5, 25].

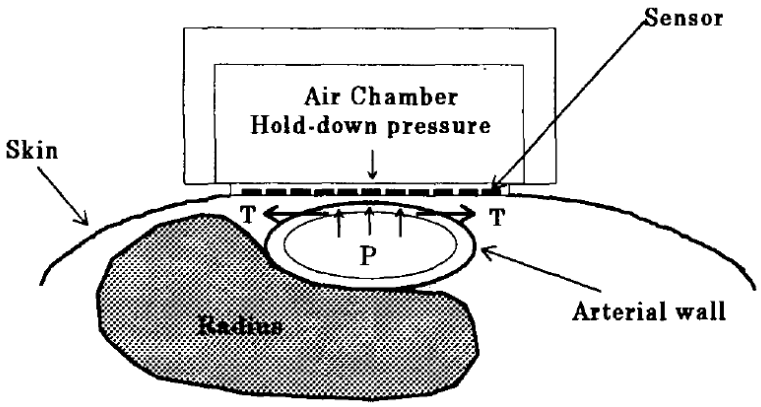


Figure 1-4: Illustrations of the principles of arterial tonometry

1.2.1.6 Pulse Wave Velocity Method

Pulse wave velocity method is based on the analyses of pulse wave which is produced when the heart pumping the blood. The changes of the BP are significantly related to the changes of the pulse wave which means the BP can be calculated from the pulse wave velocity. This method can be used for the continuous monitoring applications which can detect the sudden changes in BP to trigger an oscillometric cycle [5, 26].

1.2.1.7 Blood Pressure Measurement Using Dual - Cuffs

Kim et al [27] developed a new algorithm to determine BP by using two cuffs. This method determines SP and DP value by applying one cuff to detect the oscillometric waveform and another cuff placed on the forearm to detect the sound wave during systolic and diastolic region. The peak dots of the waveforms were measured from the

distal cuff. The SP point is determined when the positive and negative linear regression lines cross as shown in Figure 1-5. When the sharpness of the peak changes significantly DP point can be defined. In this research the DP determination is finished by manual procedure as the DP position is unclear. The results indicate this algorithm can be used for general application, however it is not suitable for all circumstance.

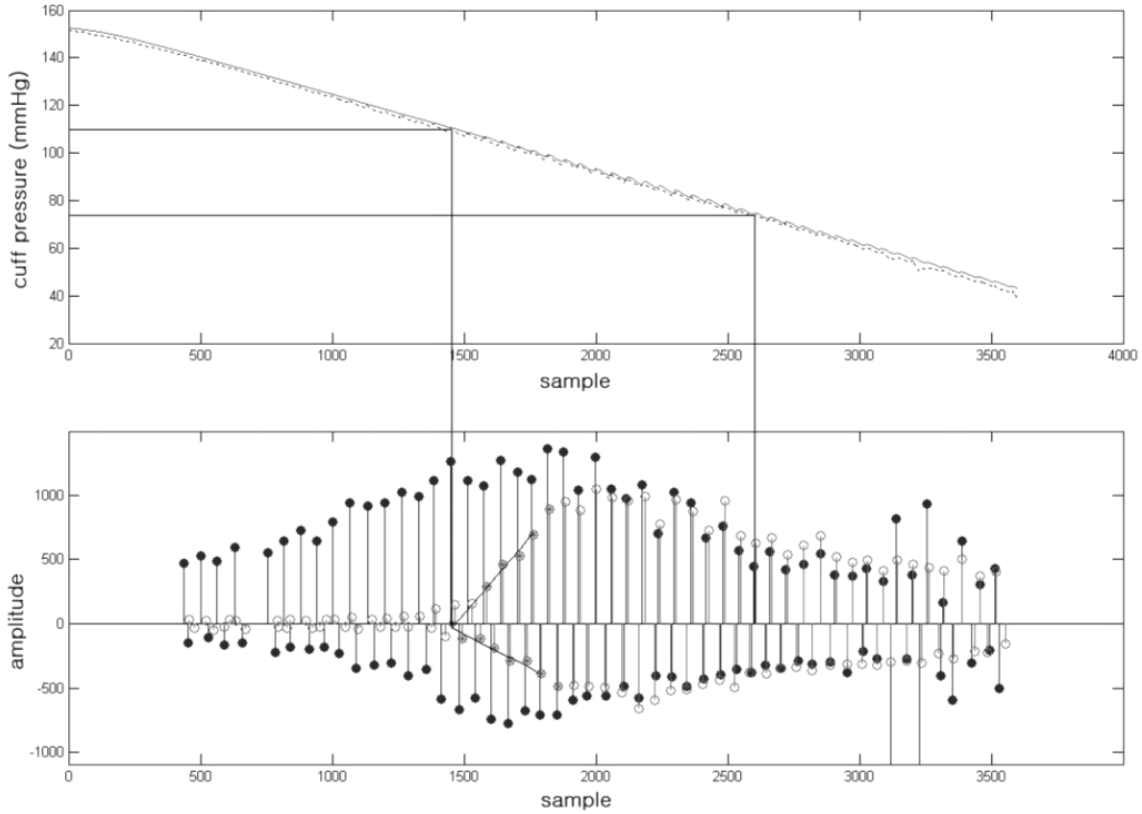


Figure 1-5: SP and DP determination on the cuff signals using SP point and DP point [27]

1.2.2 Analysis Method

Since the oscillometric method is the most suitable method for automatic devices, the analysis methods developed based on the oscillometric method are introduced with more details.

1.2.2.1 Fuzzy Logic

Wang et al [28, 29] designed a model-based fuzzy logic control system for BP measurement by detecting the arterial volume pulse. This method based on the principles of the oscillometric method as the arterial vessel has the maximum compliance when the vessel volume pulses achieves to the maximum amplitude. A tonometer is used to detect the BP waveform and the vessel volume pulse continuously. Linear prediction is used to tracking the changing tendency of MAP beat-to-beat. The Kalman filter is used to reject the physiological and measurement disturbance of the vessel volume oscillation amplitude. The results show that for the MAP with changing rate of ±10, ±20 or ±30 mmHg, the synthetic fuzzy logic controller would adjust the chamber pressure with a mean square error of 1.9, 2.2 or 2.8 mmHg, respectively.

Lin et al [16] developed an algorithm to reduce the interference in the oscillation amplitudes in order to improve the accuracy of the arterial pressure determination. This algorithm is called recursive weighted regression algorithm. A fuzzy logic discriminator is used to reject the interference caused by the measurement motion disturbance or cardiovascular diseases and measure the oscillation pulses. The clinical results show this recursive weighted regression algorithm has the efficiency improvements on the accuracy of BP measurement compared to the traditional curve fitting algorithm. But the developed algorithm is only valid for young health people and does not meet the AAMI standards in all age groups.

1.2.2.2 Prediction and Smoothing Algorithm

Thomas J. Dorsett [30] developed an algorithm based on a Kalman filter to predict the next oscillometric pulse amplitude and CP. The Kalman equation has been used to

smooth the pulse amplitude data and predict the amplitude of the next pulse. Use of polynomial curve fitting generates the smooth curve for determining MAP, SP and DP. This algorithm is good at rejecting the patients' motion and has the capability to be used in ambulatory BP measurement.

1.2.2.3 Wave Character Method

Luo et al [31] developed a new algorithm based on the features point method and amplitude characteristic ratios method to determine BP values. In this method the difference of the adjoining pulse wave and the comparative ratios are detected by the difference comparative method. A different algorithm is developed to determine the turning points around the average pressure in order to improve the accuracy of the BP estimation. Its results indicate this method has improved the BP estimation accuracy. In clinical application, the new developed algorithm can identify the difference between cardiovascular patients and healthy subjects. However, the measurement results are still over-estimated in older people.

1.2.2.4 Neural Network

Artificial neural networks (ANN) were also used in previous studies to estimate BP. Before sending the data to the ANN, a low pass filter had been applied to reject the noise and smooth the waveform. Principle component analysis had been introduced as a processing step to decorrelate the oscillation amplitudes and extract the most effective components [32]. In this method, the feed-forward and cascade-forward neural network designs have been used for SP and DP determination. Gradient descent and an adaptive learning rate back propagation algorithm was used for the training. The result showed that the ANN was more accurate than the traditional fixed ratio method. However a

huge database is required for this method. Both under-training and over-training will affect the measurement accuracy.

1.2.2.5 Blood Pressure Classification

Colak et al [33, 34] developed a neuro-fuzzy approach to determine the BP value. The feature extraction section uses the Principal Component Analysis (PCA) and fuzzy sets to determine the pressure profiles from the oscillometric waveforms. The membership functions are estimated by employing neural networks. The appropriate features are selected based on the Gram-Schmidt orthogonal transform. The results indicate that the orthogonal features subset selection provided good classification on the data. The neural network gives more accurate determination on BP than traditional oscillometric method by using large dataset [35].

1.2.2.6 Other Algorithm

Moraes et al [19] developed a new pressure measurement algorithm based on the controlled linear deflation principle. The correlation of several quantities was studied which including the reference BP measurement, actual CP, pulse amplitude, characteristic ratios, age, weight, height, arm size. The SP and DP values are obtained based on the determined cross-relation between characteristic ratios and several parameters. Fixed percentile rule and characteristic rotation in relation to pressure is used to help the SP and DP estimation. The results show that the BP determination is more dependent on the actual CP, mean pressure, pulse amplitude and the arm size. The results show great improvement after the analysis and further study was suggested[14].

Zong et al [36] developed an algorithm to detect one set of ABP pulses. This algorithm uses a windowed and weighted slope sum function to determine the ABP waveform

features. The ABP pulses are detected by comparing with the reference ECG annotations selected from a plethysmographic database. The pulse onset is detected by transferring a low-pas filtered ABP signal into a slope sum function signal. The results show that the ABP pulse detection algorithm is more accurate than the oscillometric method based on measured CP oscillation amplitude.

Ball-llovera et al [18] developed an algorithm using mathematical methods applied to the pulse index waveform to determine the BP values. Height criteria are employed to determine the SP and DP values. This algorithm is used for the DOCTUS IV bed side monitoring and validated with at least 255 samples which measured by two observers using auscultatory method. The results indicate the algorithm fulfilled the AAMI standard which shows in Table 1-2.

Table 1-2: Results for the seat position

	Mean. (mmHg)	SD de. Dif (mmHg)	% Exceeding 5	10	15
Sis	0.09	5.35	22	5	0
Dias	-0.66	4.06	18	2	0

1.3 Thesis Overview

- Chapter 1 introduces the clinical factors of BP, the most popular BP measurement methods, and an analysis of the oscillometric method.
- Chapter 2 lists the theories used in the developed oscillometric BP measurement algorithm.
- Chapter 3 presents the experimental setup for clinical data collection.

- Chapter 4 describes the details of research methodology of this project.
- Chapter 5 documents the process of testing, improving and finalising the developed algorithm.
- Chapter 6 gives conclusions and future suggested work for this study.

Chapter 2 Theoretical Background

2.1 Introduction

This chapter describes the basic theoretical method used to develop the main algorithm in this thesis. The principles of digital signal processing and artificial neural network classification are described in detail. The two most commonly used international standard protocols for testing the accuracy and the validation of the developed algorithm are explained and listed with the requirements and procedures for testing the accuracy and the validation the developed algorithm.

2.2 Signal Processing

Signals are a set of variable data or information present in a system and may be classified as input, output, or internal. Since many signals are functions of time, mostly we use time as the independent variable in our analysis technique development [37, 38]. A signal can be categorized as either continuous-time or discrete-time. A continuous time signal has a value specified for all points in time and a discrete-time signal has a value specified at each discrete point in time and is unspecified between these points. Some continuous-time signals can be considered as discrete-time signals from inherently discrete processes. In this research, the signal measurements are recorded as discrete-time signals because the signals are recorded based on each heart beat (HB) which has finite bandwidth.

The main idea of signal processing is to extract useful information from the signal and extract the relationships between two or more signals, and produce a signal to be of a different, more useful, representation. There are three main steps for the signal processing as follows: (1) Discriminating desired and undesired signals to remove noise; (2) Extracting useful information, the signal maybe transferred to another useful form; (3) Obtain the feature values.

A signal can be presented and processed in the following domains: time domain, spatial domain, frequency domain and autocorrelation domain. The domain would be chosen as that which best represents the essential characteristics of the signal. This project will be focused on the time and frequency domain. The signal can be converted from time domain to frequency domain through the Fourier Transform.

2.2.1 Fourier Transform

The Fourier Transform is the generalisation of the Fourier series where function is represented by the sines and cosines. This method gives the description of a signal constructed from a wave which can be used to transfer a signal from the time domain to frequency domain. The original signal *x* dependent on time t is measured and represented as *x(t)*. The Fourier transform represents the signal in its frequency domain as shown in Equation 2.1. With the Fourier transform, the phase, frequencies and amplitudes of each sinusoid from the original signal can be calculated.

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} dt \tag{2.1}$$

where *x(t)* is multiplied by a succession of complex sinusoids of frequency *f* with cycles per second. The angular frequency ω in radian per second is another way to present the equation where $\omega = 2\pi f$ [39].

Equation 2.2 indicates the *X(f)* is a series of weighting factors of all the sinusoidal components that together add up to the original signal *x*(*t*). The original signal *x*(*t*) can also be reconstructed by weighting each of the sinusoidal components by *X(f)* and adding up the result using the Inverse Fourier transform (IFT) [40].

$$x(t) = \int_{-\infty}^{\infty} X(f) e^{j2\pi f t} df \tag{2.2}$$

2.2.2 Fast Fourier Transforms (FFT)

A Discrete Fourier series consists of combinations of sampled sine and cosine functions. Discrete Fourier transform (DFT) is used to transform a sampled time domain signal into a frequency domain signal. The DFT is important in signal processing for spectral analysis, convolution and correlation. The FFT was developed in 1965 by J.W. Cooley and J.W. Tukey [40]. It is an efficient algorithm for evaluating a DFT which gives the same output as the DFT but with faster calculation [41].

The DFT computes a finite number of samples. The definition for DFT (FFT) is shown in Equation (2.3).

$$X[k] = \sum_{n=0}^{N-1} x[n] \cdot e^{-j2\pi nk/N} \qquad \text{for } k = 0,\ 1,\ 2,\ \ldots N-1 \tag{2.3}$$

where *k* refers the frequency of each element, the number of time samples *x[n]* is the input to the DFT, *X [k]* is the DFT in N periods [41]. The FFT method relies on

breaking an *N*-point calculation into *N/2* point calculations, each of which is further broken down in to *N/4* point calculations.

The inverse DFT (IFFT) is shown in Equation 2.4.

$$x[n] = \frac{1}{N}\sum_{k=1}^{N} X[k]e^{j2\pi(n-1)(k-1)/N} \qquad \text{for } n = 1,\ 2,\ 3,\ \ldots N \tag{2.4}$$

The IFFT can be used to convert the signal from the frequency domain back to the time domain. The unwanted frequency components can be removed before applying the IFFT therefore the desired signal can be extracted by using FFT and IFFT.

2.2.3 Power Spectral Density (PSD)

The PSD is a method to indicate the power contribution of a signal in frequency spectra [41]. The PSD measures the average power of the signal during the specific frequency band. The unit of PSD is often expressed in watts per hertz (W/Hz). The power spectrum can be determined by applying a DFT to the signal and summing the squares of the real and imaginary and dividing by the number of points [40].

2.2.4 Filters

The reason for using filters is to remove unwanted noise from a raw signal. Many types of filters can be chosen based on the required bandwidth of the desired signals. Generally high pass, low pass, band-pass and band stop are the most used filters for noise removal [42]. The specification of key features of the filter such as the filter pass band determines the range of frequencies passed by the filter and is important during the filter design. It may affect the processed signal which will significantly relate to the accuracy of the result.

2.2.5 Normalisation

Before feature extraction, data pre-processing can be used to make signals having similar scales of useful information. The signals can be rescaled to a range which makes the extracted features easier to use in further analysis.

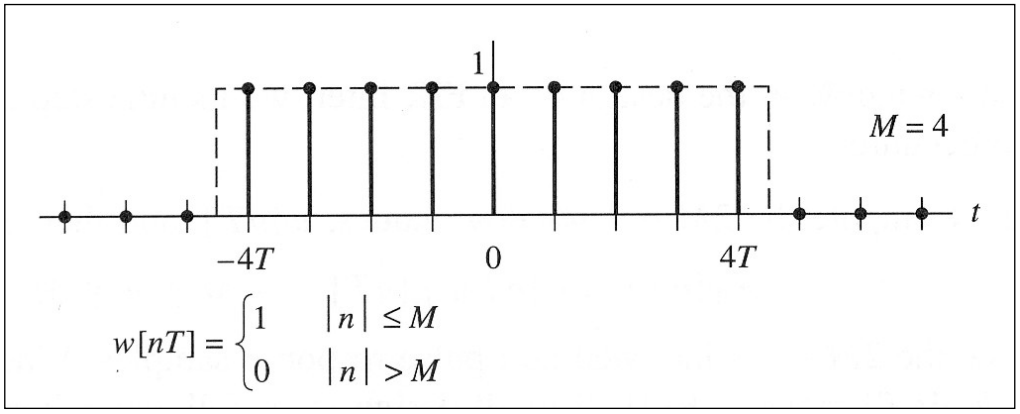
Normalisation is the technique which spreads a range of values uniformly over a specified range of the input. The most common method of normalisation is a simple linear mapping in which measured variable x can be mapped to a scaled variable y according to the Equation 2.5 [43].

$$y = \left(\frac{x - x_{\min}}{x_{\max} - x_{\min}} \right) \left(y_{\max} - y_{\min} \right) + y_{\min} \tag{2.5}$$

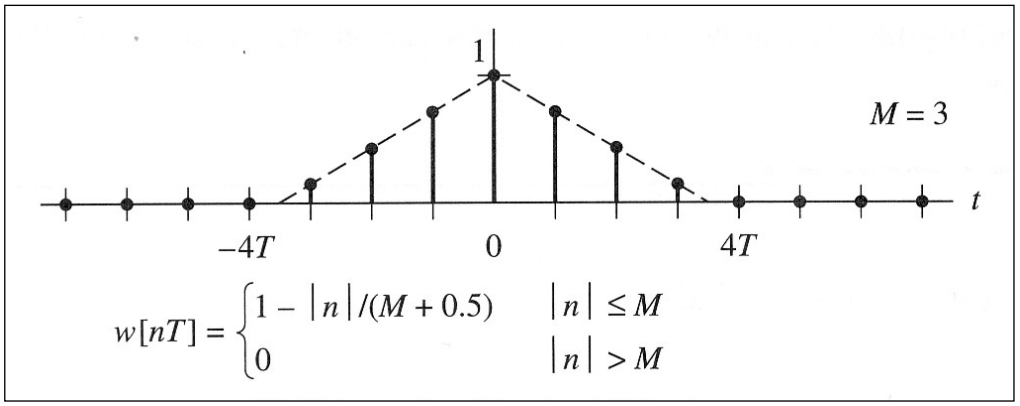
where x_{max} is the measured variable's maximum value, x_{max} is the measured variable's minimum value, y_{max} is the scaled variable's maximum value and y_{min} is the scaled variable's minimum value.

2.2.6 Windows

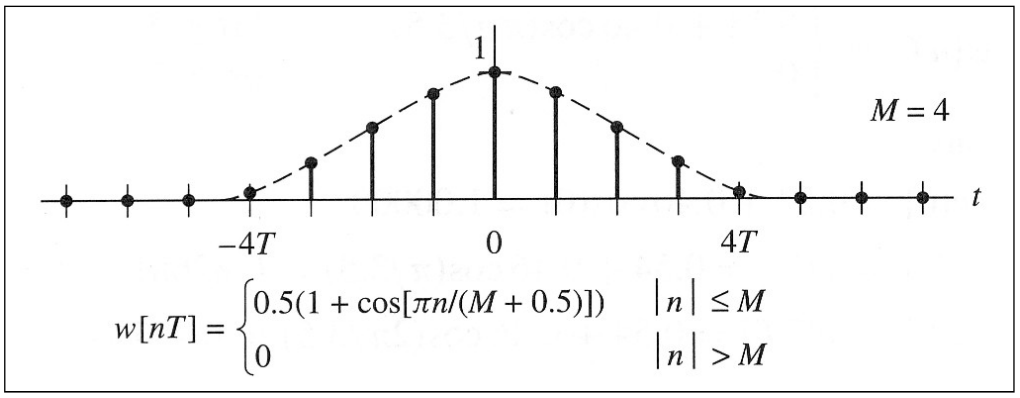
The purpose of using a window is to force the signal outside of a specific range to be zero [38]. Windowing creates a usable filter impulse response from an unusable one, but has attendant side effects in the frequency domain. The Rectangular window is the simplest window. However due to the sharp vertical edge of the rectangular window, it is not suitable for removing signals outside the pass band. This problem can be fixed by selecting a window with smoother edges such as Hann, Hamming, Blackman, and Kaiser Windows as shown in Figure 2-1 [44].


1
M = 4
t
−4T
0
4T
w[nT] = 1 |n| ≤ M
0 |n| > M

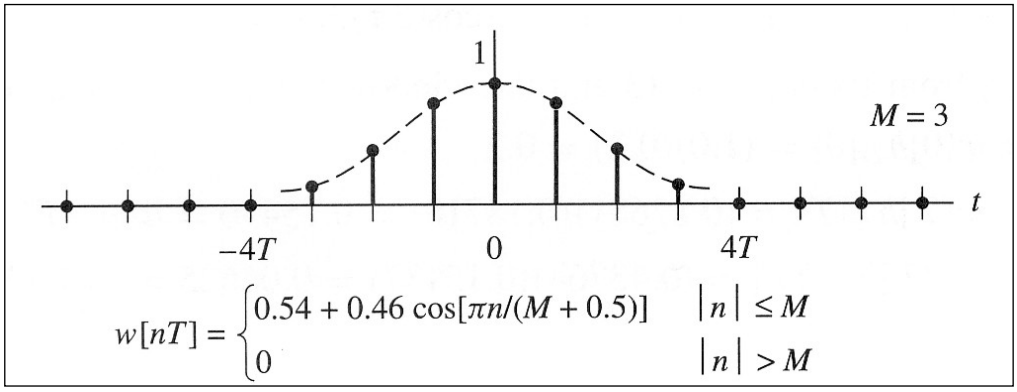
a


1
M = 3
t
−4T
0
4T
w[nT] = 1 − |n|/(M + 0.5) |n| ≤ M
0 |n| > M

b


1
M = 4
t
−4T
0
4T
w[nT] = 0.5(1 + cos[πn/(M + 0.5)]) |n| ≤ M
0 |n| > M

c



d

Figure 2-1: Window functions (a) Rectangular Window (b) Triangular (Bartlett) (c) Raised Cosine Window (d) Hamming Window

2.2.7 Feature Extraction

Feature extraction is most important for the pattern recognition process. It has great influence on the success of an application. The features can be extracted directly after the data pre-processing operations. Many types of feature variables can be selected depending on characteristic of the signal such as the perimeter feature, area feature, radii feature, corner feature and shape factor [43]. For this research, features from time and frequency domains were extracted for analysis in the next step.

2.3 Statistical Analysis and Classification

Artificial neural network classification is one of the artificial intelligence techniques used for the statistical analysis and classification. The following section gives a brief description of the theory of ANN on which this research is based.

2.3.1 Artificial Neural Network (ANN) Classification

An ANN is a mathematical computing paradigm that models the operations of biological neural systems. It is composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. In a trained artificial neural

network the intelligence of the network is stored in the values of the connections existing between the neurons. In artificial neural network terminology the values of the connections between the neurons are generally referred to as weights. During the training process, weights are adjusted until the network output matches the target. The ANN can be used for specific applications, such as pattern recognition, data classification and signal processing applications [45]. The advantage of using the ANN is listed as following

- Adaptive learning: The ANN can finish the task based on the provided information or initial experience.
- Self-Organisation: An ability to create a representation of the information received from the leaning process.
- Real Time Operation: For some special tasks, hardware devices can be developed and manufactured based on the capability of the designed ANN.

Various types of ANN can be use for different applications which are mainly classified into three types based on the learning approach: a) Supervised learning such as pattern recognition and regression analysis. b) Reinforcement learning such as control problems, games and sequential decision making. c) Unsupervised learning such as the general estimation problem. In this research, a supervised learning algorithm was selected for the designed ANN. In supervised learning algorithms, the ANN is adjusted and trained based on provided inputs and comparing the output and the target, until the output can match with the target.

A neuron is a nonlinear, parameterized bounded function which is the basic element of an ANN [43]. The neuron receives and weights the sum of the input data and calculates

the output by using various transfer functions [46]. A general model for a single neuron is shown in Figure 2-2.

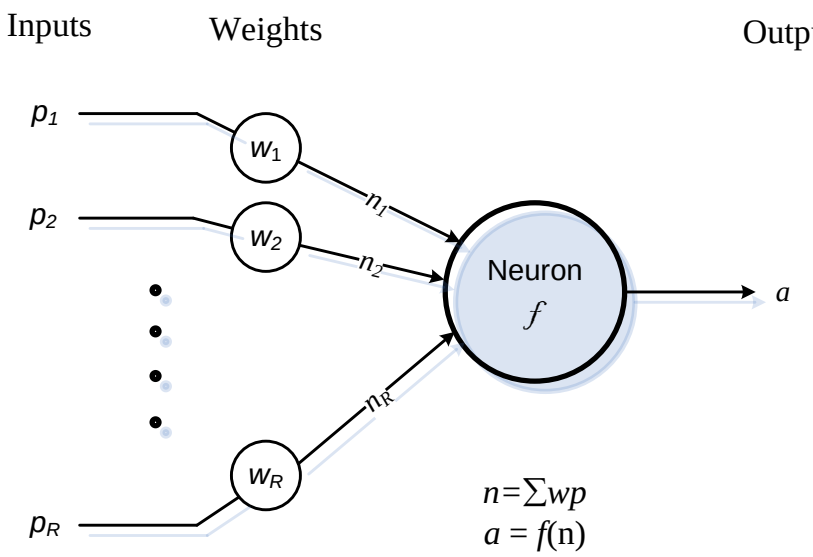


Figure 2-2: Diagram of a single layer neuron model and its transfer function.

Where variable P is the input of this model, R is the number of inputs, w is the weight of each input, n is the net weighted input to the neuron, and a is the output of the neuron. The inputs P_R are weighted by the respective weights W_R, summed and passed to the f produce the outputs. There are four types of transfer functions that can be selected for different as shown in Figure 2-3. These functions are:

- Hard-Limit Transfer function – Used to create the neurons to finish the decision-making classifications.
- Linear Transfer function – Used in linear approximation.
- Sigmoid Transfer function – Used to make the output value range from 0 to 1 which is normally selected for back-propagation networks.
- Tan-Sigmoid Transfer function – Similar to the Sigmoid Transfer function which produce the output in the range -1 to 1.

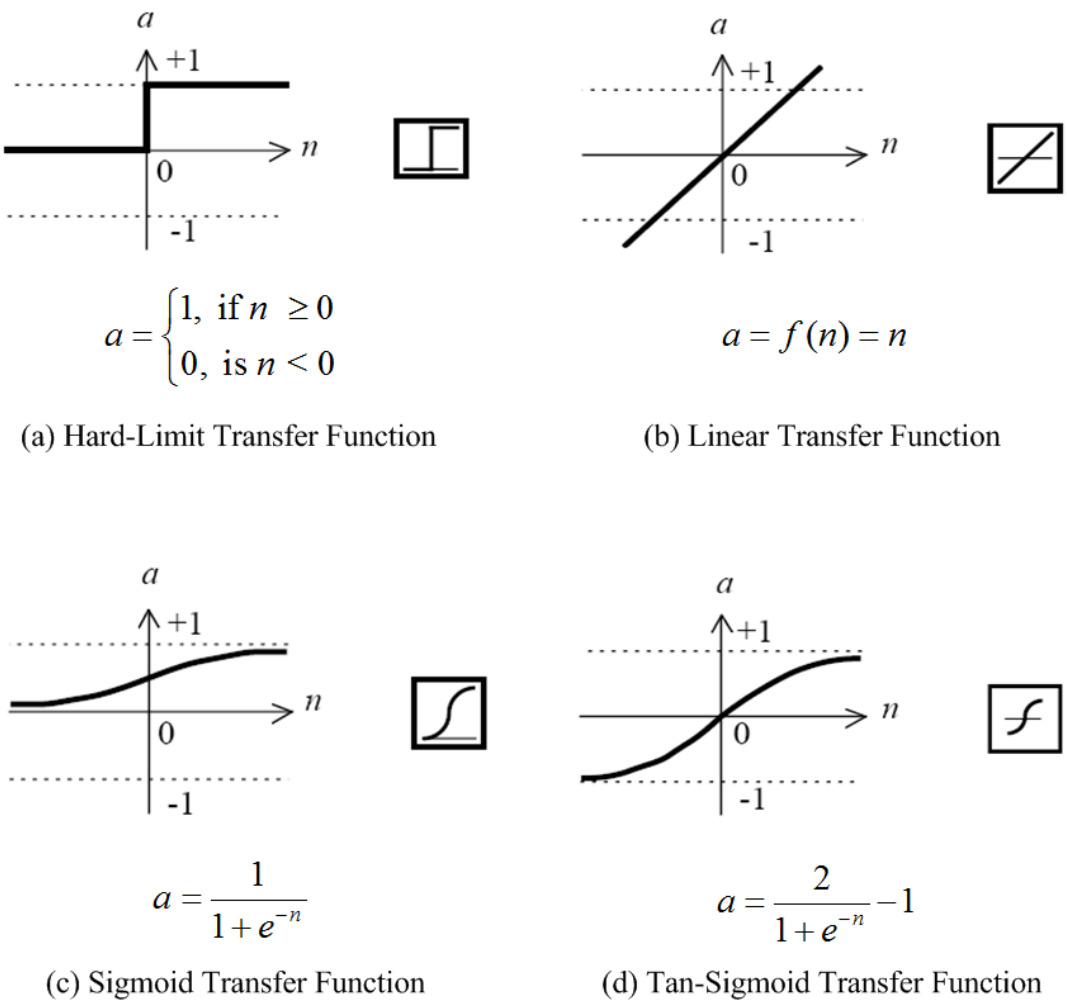


Figure 2-3: Transfer functions of a neuron.

ANNs can consist of many neurons connected in various possible topological ways. One ANN may have two or more neurons combined in one layer to construct a one-layer network. It also can have more neurons with several layers to construct a multi-layer network [43].

Figure 2-4 indicates an example two-layer network and the applied equations are shown under the ANN structure. Each layer has a weight matrix w, a bias vector b, and an output vector a. Two paradigms of ANNs can be used during the design process: they are feed-forward and feedback networks. Feed-forward networks allow the signal to

travel one direction from input to the output and are mostly used in pattern recognition [43, 47].

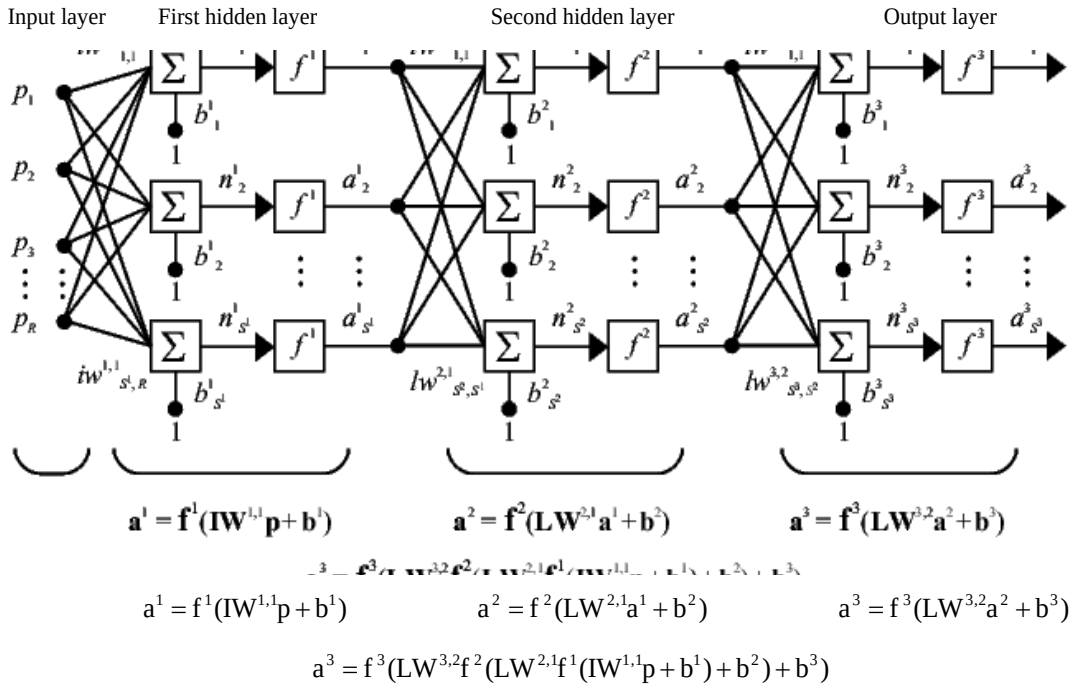


Figure 2-4: Multilayer neuron model with two hidden layers

After an ANN has been designed, it needs to be trained to computes result. A highly popular algorithm is the back-propagation algorithm. It consists of two phases through the network which are forward pass and backward pass. In forward pass, the input vector is inserted into the network and its effect propagates from the input layer to the hidden layer and calculates the output from the output layer with fixed weights. The output data is checked against the target data. Then the error-correction rule is used which helps to modify the weights in the backward process. The error signal is produced and propagated back to the network. The new output data can be calculated with the adjusted weight which should be closer to the desired target data [48].

2.3.2 Principal Component Analysis (PCA)

PCA is a standard technique used for data reduction which generally reduces the factors to a minimal but sufficient representation of underlying information [43]. It is also called the Karhunen-Loeve transformation which reduces the feature vector dimension while retaining most useful information by constructing a linear transformation matrix. This technique can be used to reduce the unnecessary input features in designed ANNs.

2.3.3 Bland and Altman Plot

Bland and Altman Plot is a graphic method used to assess the agreement between two results of approaches results based on the same subjects [49]. Figure 2-5 indicates an example of the Bland and Altman plot. It shows the difference between two measurement methods based on testing with the same sample. This graphic method can be used to compare the newly developed algorithm with a gold standard (reference value). The reference value was taken by two observers by using the Auscultatory method. The mean difference of two methods is indicated on the diagram as a horizontal solid line. The information within two Mean ±1.96 SD (standard deviation) solid lines shows the 95% distribution of the difference values.

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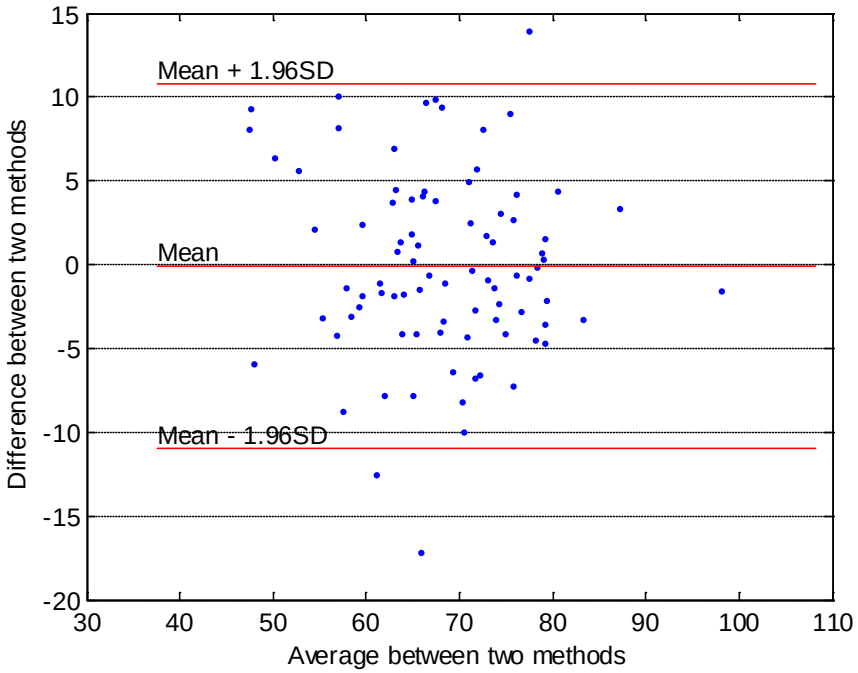


Figure 2-5: An example of a Bland and Altman Plot

2.4 Standard Protocols

An accurate measurement result is not only important for casual users but also has great influence for clinical applications. Any developed NIBP measurement device needs to show its accuracy with respect to specified criteria. AAMI and BHS international standard protocols are commonly used for validation of the device's accuracy [7].

AAMI published and revised a standard for electronic or automated sphygmomanometers which includes the protocol for testing the accuracy of NIBP measurement devices [7, 50]. It recommended at least 85 subjects should be studied for the device's validation. At least 80% of the tested subjects should have an SP (DP) value within the range 100 mmHg to 160 mmHg (60 mmHg to 100 mmHg). At least10% of the subjects should be above and below that range. The AAMI standard requires the test of SP and DP separately. The mean difference between the testing results and the

reference values should be no more than ±5 mmHg with a standard deviation of 8 mmHg or less.

The BHS also published and revised a protocol for testing the accuracy of BP measurement for automatic and semiautomatic devices [51]. This standard can be used for both direct and indirect device validation. Its accuracy criteria uses a grading system based on the percentages of testing results differing from the reference readings by ≤ 5 mmHg, ≤ 10 mmHg and ≤ 15 mmHg for both SP and DP [52]. The Grades are identified from the percentage of readings within different levels as shown in Table 2-1. To achieve a grade all three percentages must be equal to or greater than the tabulated values.

Table 2-1 Grading criteria used by the British Society of Hypertension

Grade	Absolute difference between reference and test device (%)		
	≤ 5 mmHg	≤ 10 mmHg	≤ 15 mmHg
A	60	85	95
B	50	75	90
C	40	65	85
D	Worse than C		

Both standards are used for the validating the accuracy of the designed algorithm. The experimental procedures were followed by the AAMI standard which described in detail in next chapter.

2.5 Objective

Many algorithms have been developed for automotive BP measurement based on the oscillometric method. However, most algorithms had been developed based on general applications. For older people and other special applications, the measurement accuracy may not be satisfactory. This project is going to develop a NIBP measurement algorithm which can work accurately for adult subjects including the elderly. It is based on a beat-by-beat pattern recognition approach using the oscillometric method. The designed algorithm will be validated on a wider range of people in line with international standards.

The procedure of this research included

- To create a new database for collected data from all age groups.
- To develop a NIBP algorithm based on a beat-by-beat pattern recognition approach.
- Validate the designed algorithm on all age groups, in line with the accepted standards (AAMI and BHS).

Chapter 3 Experiment and Research Methodology

3.1 Introduction

This chapter describes the experimental setup for the clinical trials and the development of the ANN BP measurement algorithm. This algorithm was developed based on the features of changing signal patterns during the blood pressure measurement. The research methodology used in this project included data collection, signal processing and feature extractions and the development of an ANN BP estimation algorithm. MATLAB® R2008a (The MathWorks, U.S.) software was used for the algorithm development. In signal processing, noise and unused signals were eliminated from initial signal. HB and heart rate (HR) of the measured results were identified by the designed program. Waveform features of each HB were extracted and used as the input data for the ANN classifier to analyse the relationship between CP and SP or DP at each HB. A BP value was then calculated based on the output of the ANN classifier.

3.2 Clinical trial

The data used for this research were collected from AUT Wellesley campus for healthy people and North Bridge Retirement Village in Northcote, Auckland for people aged above 59 years old. The ethics approval was approved by the Auckland University of Technology Ethics Committee (AUTEC) and attached in Appendix II. The data collection process met the structure and the requirements of the AAMI standard protocol. Two observers were well trained before the data collection. The device used during the data collection was provided by Pulsecor Ltd.

3.2.1 Apparatus

The data collection was conducted using an inflatable cuff, a device provided by Pulsecor, one laptop and one teaching stethoscope as shown in Figure 3-1. The cuff was a Trimline blood pressure cuff (Trimline Medical Products Corp, NJ, and USA) and used to collect data from the brachial artery. The device was provided by Pulsecor Ltd which used with Vasomon R software for the data recording. The bell mode side of a 3M™ Littmann® dual-head teaching stethoscope was used to measure blood pressure by the two observers using the auscultatory method at the same time.

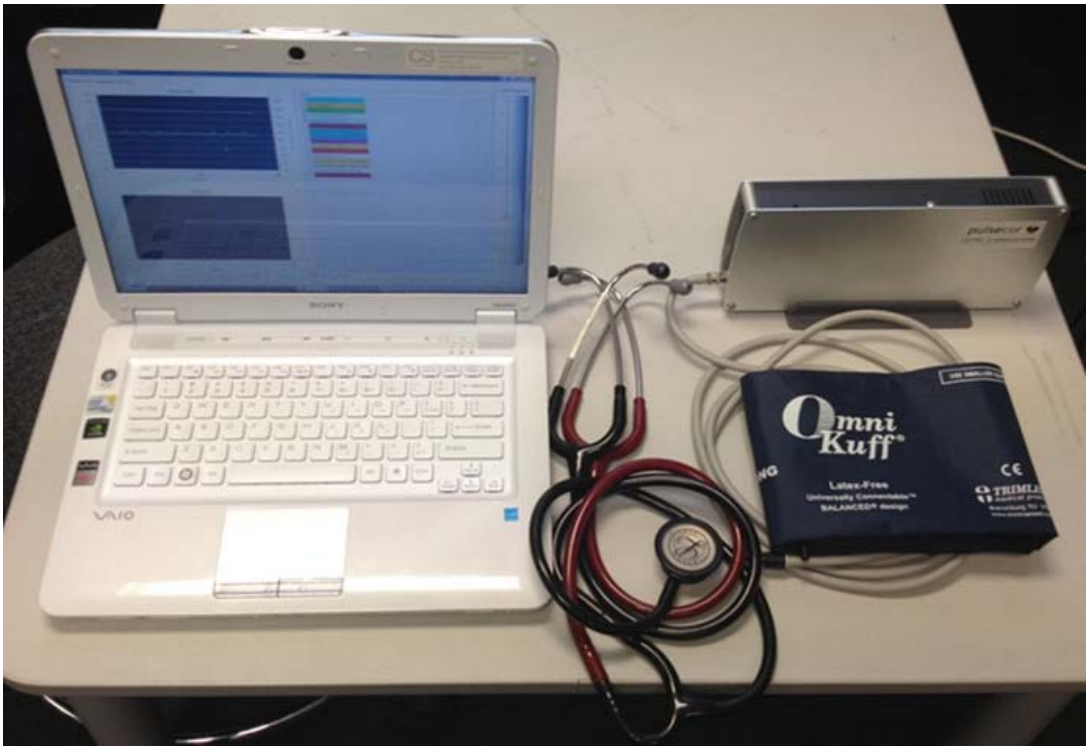


Figure 3-1: Actual apparatus used in the data collection

3.2.2 Data Collection Procedures

CP oscillations during the BP measurement process were collected in this research. Before the data collection, the subjects were required to take a rest for 5 minutes. During the data collection, CP signals were measured by the pressure sensor in

Pulsecor's device and saved in the database in the computer for further analysis. The obtained data were transferred to the computer through Vasomon R software as shown in Figure 3-2.

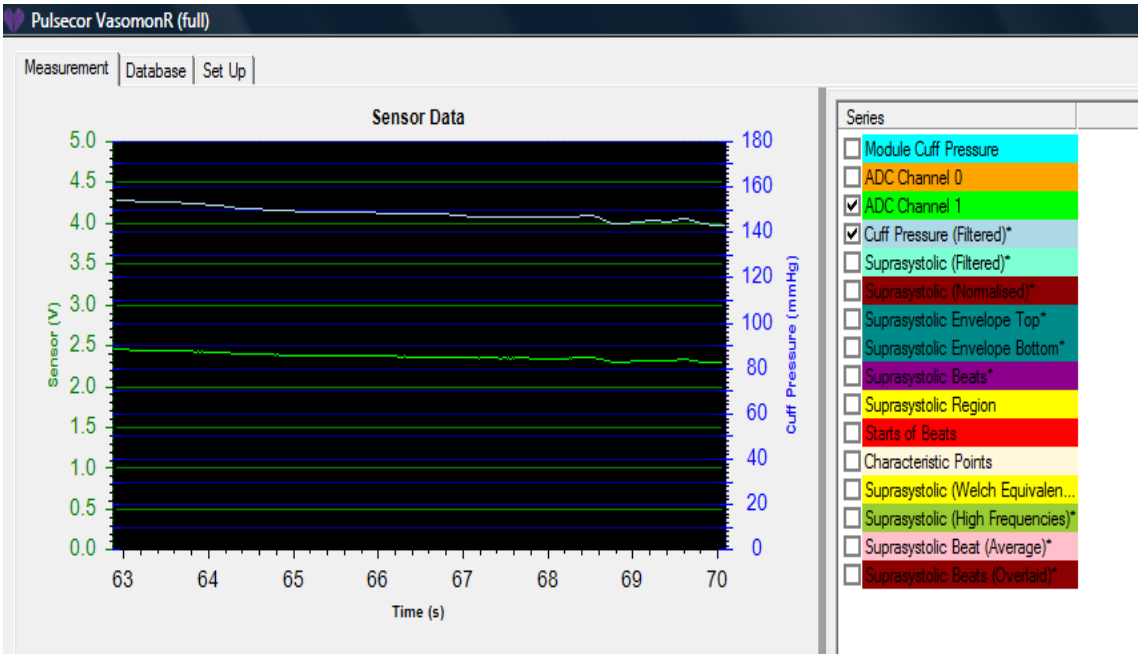


Figure 3-2: Vasomon R program data collection, the gray curve: cuff pressure, green curve: raw signal from the connected pressure sensor

As required in the AAMI standard [52], the reference BP readings were recorded by two well-trained observers using the Auscultatory method. The readings were accepted when the difference of the two observers' reading was within ±5 mmHg. The SP and DP values were chosen as the average reading of the two observers. 40 readings were used as reference readings for ANN training and 258 for testing of the designed algorithm.

The data used in this research was collected from AUT Wellesley campus and Northbridge Retirement Village, Auckland. Ethics approval was submitted and approved by the AUTEC with the reference number 08/232.

3.3 BP Detecting Process

In this project, a unique signal processing method and brand new ANN classification algorithm were developed to improve the NIBP measurement accuracy. Similar to existing oscillometric BP measurement methods, the proposed BP measurement method used the recorded CP oscillations during the measurement to determine the subject's BP. In a similar way, the oscillation waveform changes from beat to beat [53]. Features from each HB were used to analyse the waveform changes from a supra-systolic pressure region to the sub-diastolic pressure region (that is, the waveforms changed in shape as the cuff was deflated from supra-systolic to sub-diastolic pressure). The ANN classifier was designed to classify the relationship between CP and SP or DP at each HB from the supra-systolic region to the sub-diastolic region. The flowchart in Figure 3-3 shows the four steps included in the designed algorithm:

1. Collect the data from the subjects.
2. Process the original signal in order to obtained the desired features
3. ANN classification to analyse the extracted features.
4. Calculate the BP value based on the ANN output.

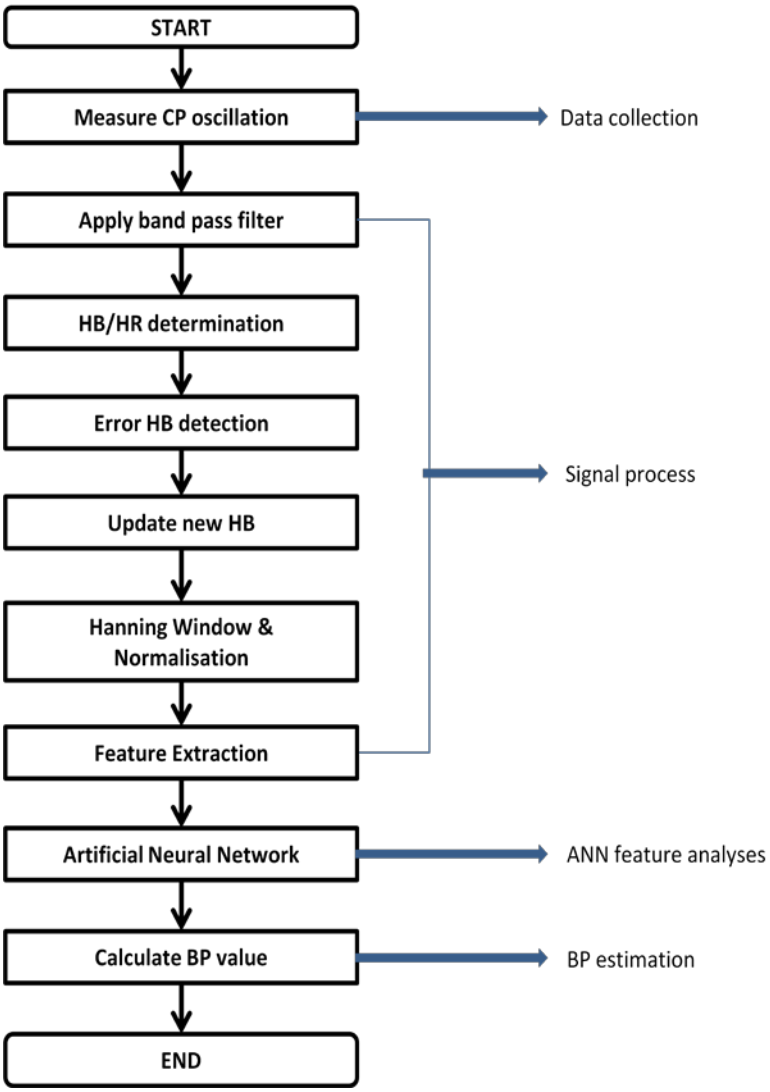


Figure 3-3: The procedures of BP determination in this study.

3.4 Signal Processing

After signal was collected, the oscillating signal was then exported to the MATLAB program for signal processing to eliminate noise from the original signals. As shown in Figure 3-4, the raw signal contained the measured CP for the whole BP measurement process. The signal during the CP decreasing was extracted as the desired signal for this algorithm. It showed that lots of high frequency noise was contained in the desired signal. Since most of the BP pulse signals are contained between 0.5 and 25Hz [54], a band-pass filter (0.5 ~ 25Hz) was selected to filter out noise.

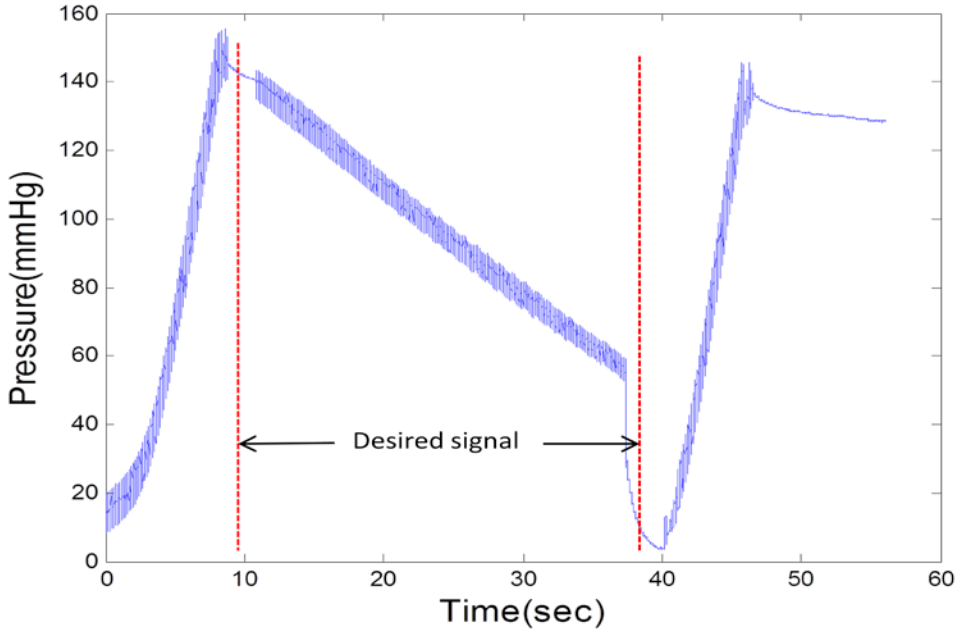


Figure 3-4: Saved pressure signal during BP measurement in the database: the data between the red dashed lines are used for analysis in the next step.

The oscillation waveforms obtained after the band pass filter are shown in Figure 3-5. By visualizing the oscillation waveform, it changes from beat to beat from supra-systolic region to the sub-diastolic region.

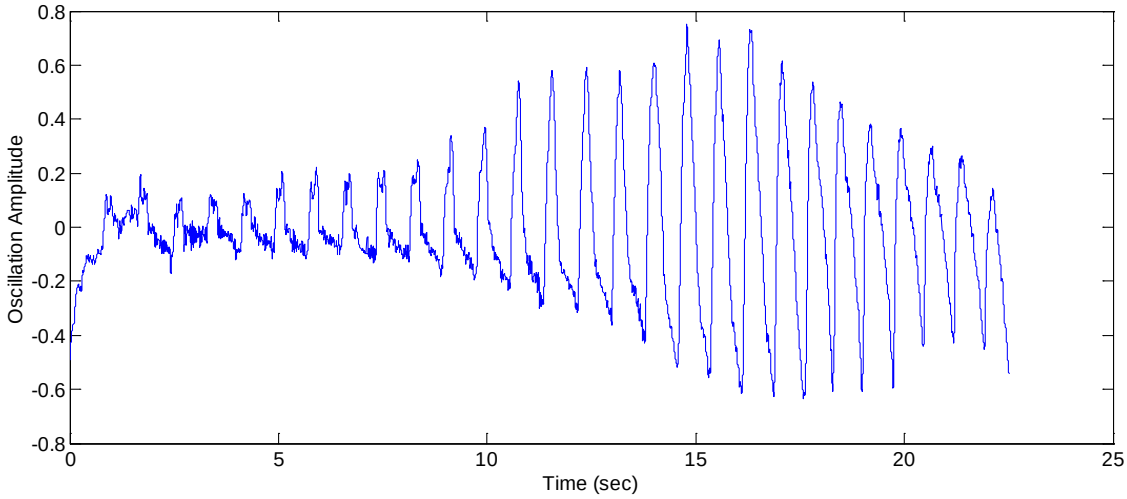


Figure 3-5: Desired signal after band-pass filtering

3.4.1 Heart Beat Identification

The designed BP identification method was developed based on a beat by beat pattern recognition approach. Therefore, the subjects' HB needs to be determined for further analysis.

In this study, the starting point of each HB was defined from foot to foot. Because human beings' HR is normally less than 180 beat per minute [55], a second order Butterworth Low-Pass Filter at 3 Hz was applied to the original signals to remove the unwanted signal before HB extraction. As shown in Figure 3-6, all of the peaks (green dot in lower chart) in the wave were detected and identified. The starting points (blue circle in upper chart) were then defined as the minimum points between two maximum points (between the red dash lines).

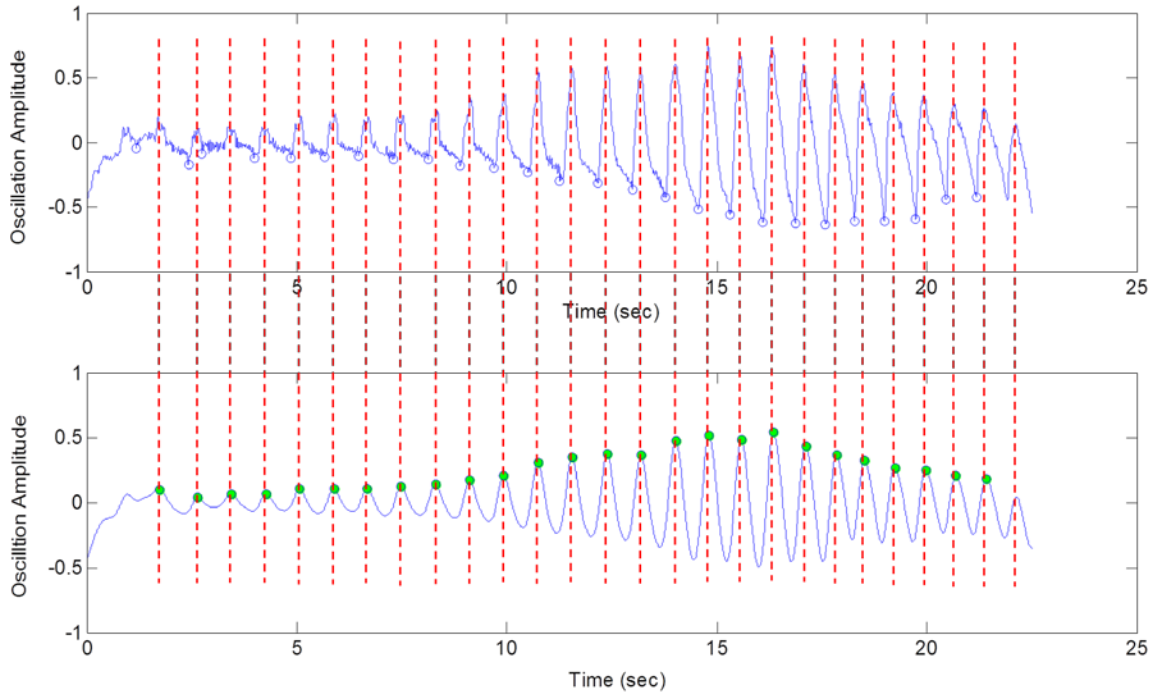


Figure 3-6: Desired signal after band-pass filtering: Blue line is the oscillating signal. Green circles indicate the minimum points of all HB. Blue circles defined as the starting point of each HB.

CP values were recorded at the same time during the HB detection. CP value at each starting point was used as the corresponding CP at each HB.

During the measurement some external noises such as those caused by arm movements may also be present as a pulse in the waveform. If the program incorrectly identifies erroneous pulses as real HBs then the accuracy of the result may be affected.

Error checking process was designed to detect the error pulses and delete them to reduce the unwanted signals. HR and mean HR (MHR) were calculated to help estimate the error pulses. The calculation of HR was one divided by the time difference between two minimum points, as shown in Equation 3.1. The MHR is the average value of all of the obtained HR, as shown in Equation 3.2.

$$HR = \frac{1}{TIME(2) - TIME(1)} \tag{3.1}$$

$$MHR = \frac{\sum HR}{No.of\ HB} \tag{3.2}$$

After calculating the HR of each HB and the MHR, the error checking algorithm proceeded to detect the error pulses. The error pulse was removed if a pulse did not pass the error checking program. In the processed signals, any obtained individual HR over 130% or less than 70% of the MHR was considered as erroneous as shown in Figure 3-7. The detected error pulse was eliminated and the new MHR was calculated again based on the remaining pulses. The algorithm was repeated to check the new MHR with the remaining pulses again and again until all the individual HR were within the desired range of ±30% of the MHR. If there were more than five error pulses detected in this process, the system would display an error message. After the error checking process, each HB was segmented and saved as an individual HB for further analysis.

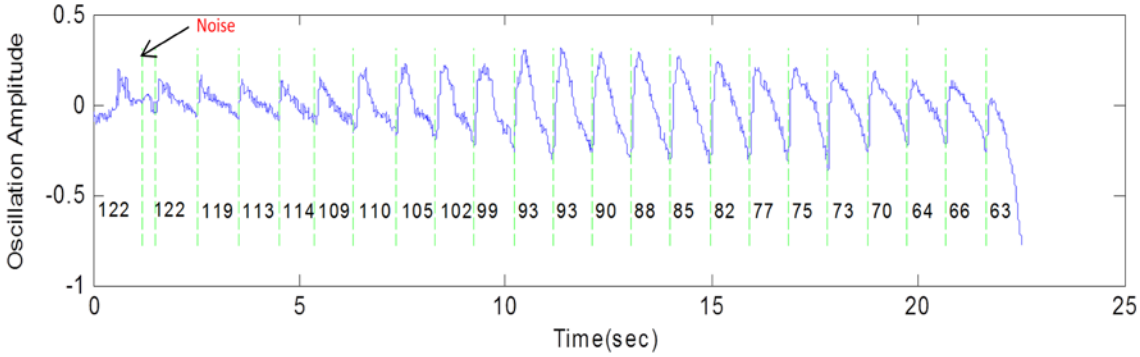


Figure 3-7: Blue line is the oscillating signal. Green dashed lines indicate the start of each HB.

3.4.2 Signal Normalisations

Since this research was proposed to identify the subjects' BP through the features of the waveforms, a signal normalization process was carried out after HR identification. The normalization processes are:

(1) The value of the starting point of each HB was shifted to zero.

(2) The ending point was shifted to zero. Hann window was used to smooth both edges of each individual HB, which was designed based on the length of each HB.

(3) The amplitude, which was the value between the starting point and the peak, was scaled to 1.

Figure 3-8 is an example of how one HB had been shifted, normalised and windowed before feature extraction.

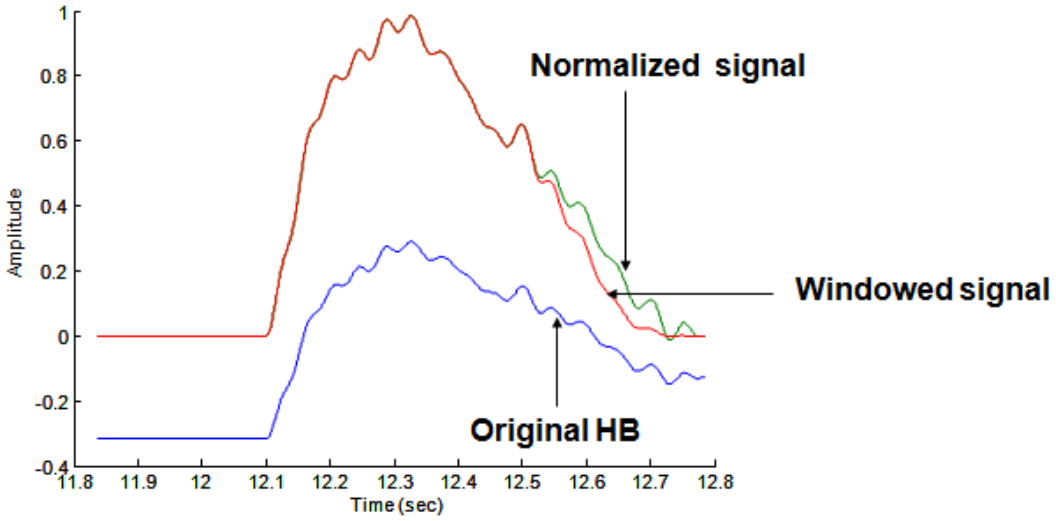


Figure 3-8: Blue line is one original HB from subject 5. Red line is the normalized signal. Green line is the windowed signal.

3.4.3 Features Extraction

As described in Chapter 2, features from each individual HB would be selected as the input data for the ANN in the next step. MATLAB was used to extract features and all extracted features were saved in an Excel spreadsheet for ANN training and testing purposes. Both time domain and frequency domain features were included.

Based on previous research [56], 6 features extracted from the time domain were:

- Total amplitude of all the turning points.
- Area under the curve.
- Positive and negative Rate of Change (*ROC*).
- Positive and negative slope of each HB (*Pdt*).

FFT was used to calculate the features relating to different frequency bands. Features from the frequency domain were extracted after FFT was applied to all HBs. As described before, most wanted signals were contained within 0.5~25Hz. Features from frequency domain were: Magnitudes and PSD values at frequency ranges between

0.5~5 Hz, 5~10Hz, 10~15Hz, 15~25Hz. All the features are detailed in the following section. The value of Magnitudes and PSD in different frequency ranges were calculated by ***funMag*** and ***funPSD,*** the flowcharts are shown in Figure 3-10.

- **Total turning points amplitude (*funAmp*)** was developed to calculate the total amplitude of each HB. The turning points of each HB were defined and then all the amplitudes of those points were determined from point to point. The total turning point amplitude was calculated as the sum of all amplitudes. The result was returned to the main program and saved in the Excel datasheet. Flowchart of ***funAmp*** displayed in Figure 3-9a.
- **Area under the curve (*funArea*):** The area under the curve was calculated using integration under a signal function. The trapezoidal numerical integration (***trapz)*** function was applied to define the area under the curve. The result was returned to the main program and saved in the Excel datasheet. The flowchart of ***funArea*** is displayed in Figure 3-9b.
- ***funROC*** was developed to calculate the maximum and minimum rate of change at each turning point of each HB. Firstly each turning point was detected and then the amplitudes of the change between all the points were defined. The function of Rate of change was calculated as the amplitude over the change of time, the equation is shown in Equation 3.3.

$$\text{Rate of Change} = \frac{\text{Change in amplitude}}{\text{Change in time}} \tag{3.3}$$

- ***fundPdt*** was developed to find the maximum positive and minimum negative slope of each HB. It used the same equation as ***funROC,*** but this function was used based on each data point instead of each turning point. The flowchart of ***fundPdt*** is shown in Figure 3-9d.

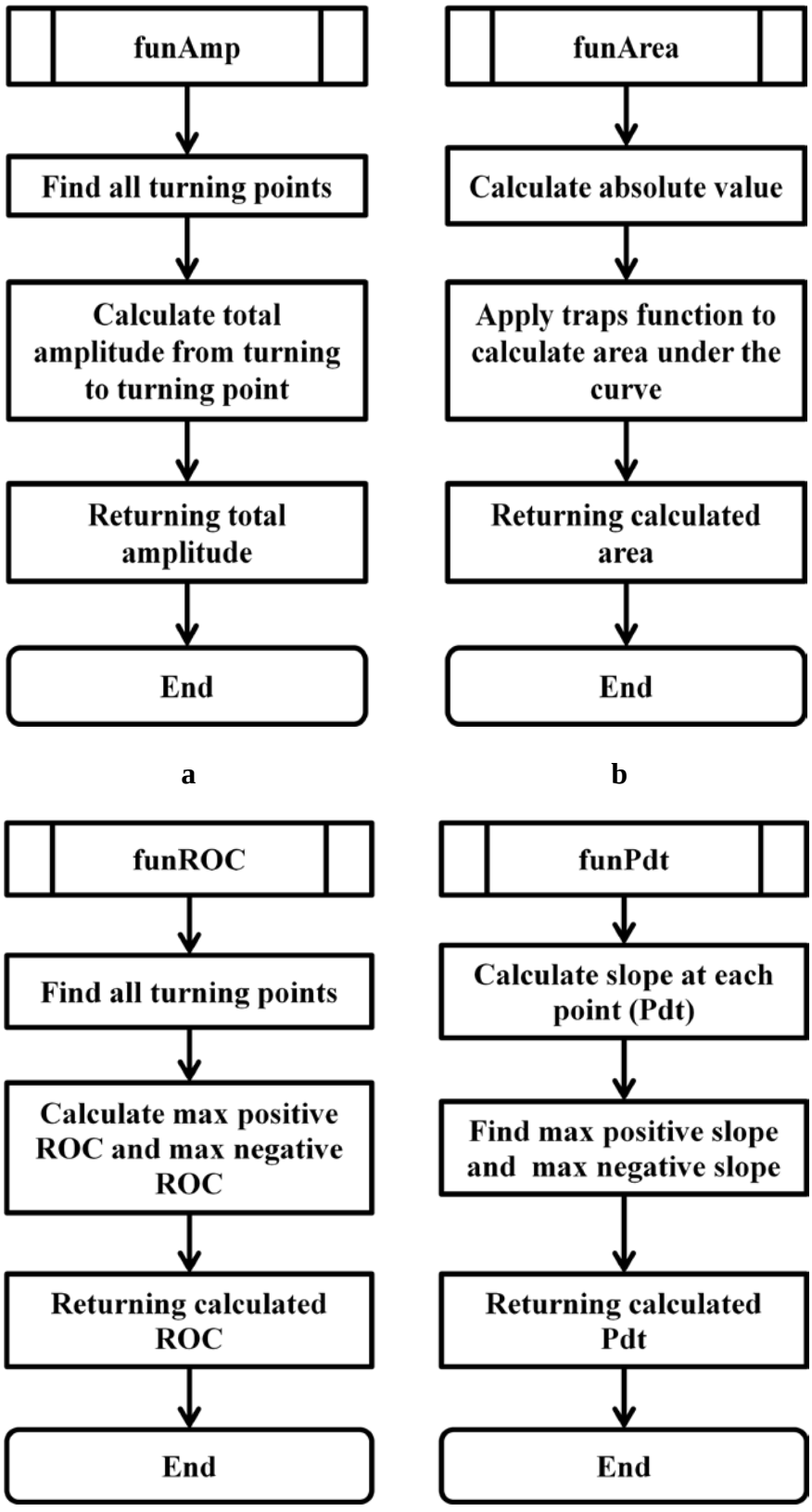


Figure 3-9: Feature extraction from time domain. (a) Flowchart of *funAmp*. (b) Flowchart of *funArea*. (c) Flowchart of *funROC*. (d) Flowchart of *fundPdt*.

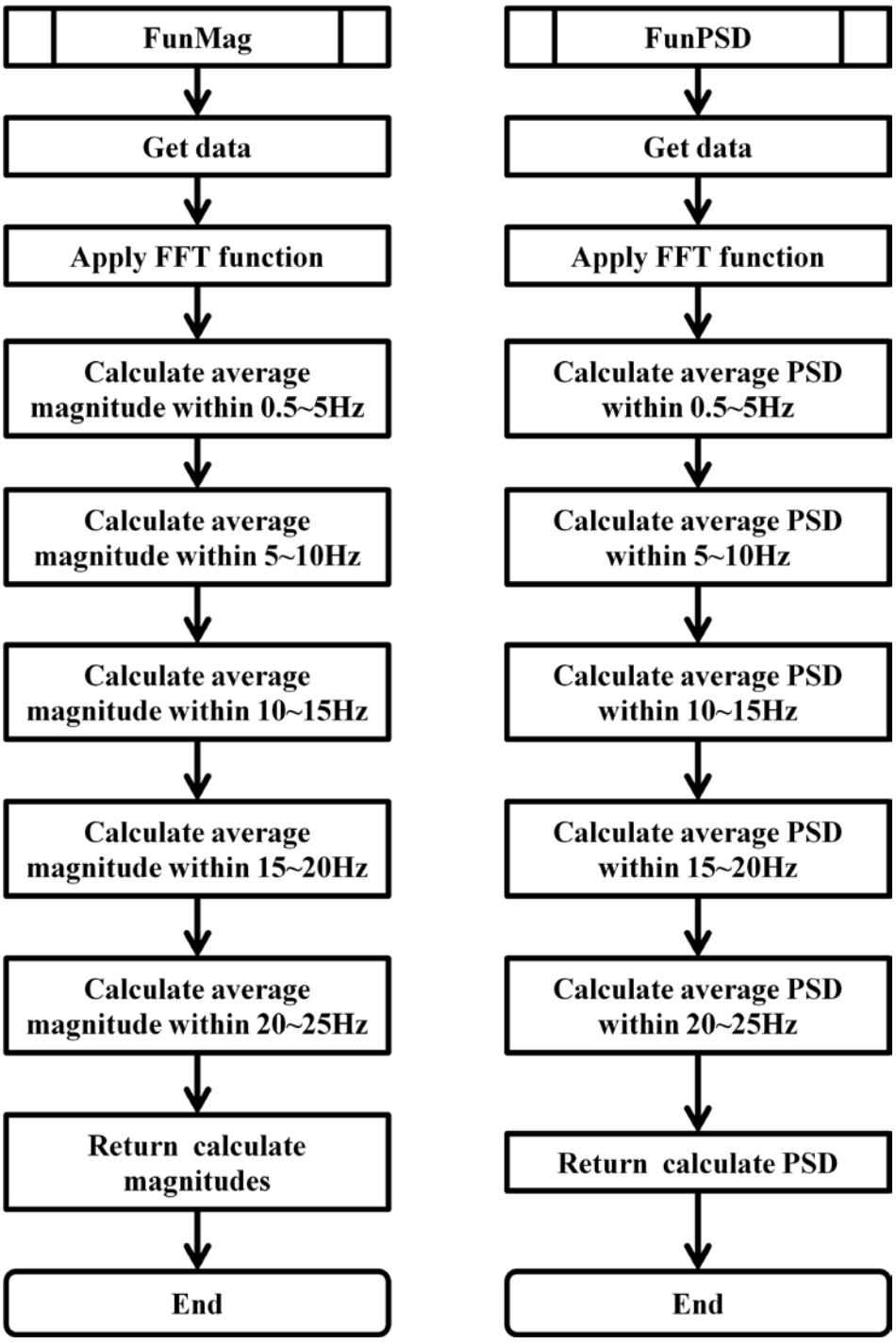


Figure 3-10: Feature extraction from frequency domain. (a) Flowchart of *funMag.* (b) Flowchart of *funPSD.*

3.5 Artificial Neural network

As the measured signal waveform changed from the supra-systolic pressure region to the sub-diastolic region, the SP and DP values were to be identified based on analysing the extracted features from each HB. An ANN classifier was developed to determine the relationship between CP, SP and DP. The structure of the ANN classifier had been designed initially and the ANN training parameters were also selected at this stage. 20 training subjects were selected randomly from the database. After the ANN was trained based on these 20 subjects, new data would be inserted to test the algorithm.

3.5.1 Design of the ANN

An ANN was designed to analyse the features of each HB in order to get a more accurate BP reading. The main idea of designing an ANN was to use the simplest structures to give the best results without overfitting the data. The designed ANN included: one input layer, one hidden layer and one output layer structure as shown in Figure 3-13. The steps for designing the ANN are shown below:

1. Collect the data – Extract enough useful features as the input of ANN.
2. Create a network – design and initialise the ANN.
3. Initialize the network – Initialize weights and biases.
4. Train the network – adjust the weights and biases.
5. Simulate the network – validate the network and apply new input data.

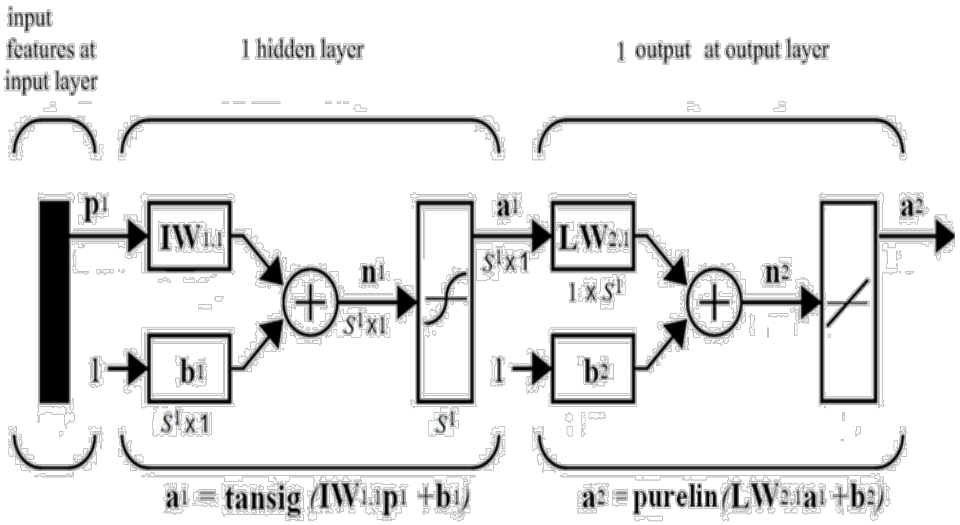


Figure 3-11: Neural network developed for ANN classification algorithms.

As described in Chapter 2, each ANN inputs contained the input training matrix and the target matrix. Features extracted from 20 subjects based on each HB were selected as the input training matrix. In this research, SP and DP values were calculated separately. The same ANN structure was developed for determining SP and DP, the only difference between these two ANNs was the input target matrix. The input target was the ideal outputs of the ANN for SP (DP). One hidden layer was designed with 3 neurons and tan-sigmoid transfer function. For the training process, the ANN would train and adjust weights until the output matched the targets. The output layer was designed to calculate the difference between the CP and SP or DP value. The linear transfer function was used to calculate the output.

Once both networks had been created weights and biases were initialized by selecting a constant initial random seed (0), the network was ready to be trained. Both ANNs were trained in the same way to make for easier comparison in the next step. Levenberg-Marquardt backpropagation training function was selected for faster training [57]. PAC was applied to reduce the dimension of the input data set. The mapstd function was used to calculate the zero mean data set for each data dimension. processpca function

was applied to process input data sets using PCA so that each row was uncorrelated. Training parameters were selected as shown:

No. of epochs or iterations: 500

Performance error goal (PEG): 0.01 (0.1% error)

Maximum performance gradient: 1×10^{-10}

3.5.2 ANN Outputs

In the ANN training process, the same 20 input training features with different output targets (SP and DP) were inserted. As mentioned before the ANN classifier was designed to analyse the relationship between CP, SP and DP. The SP and DP values were determined from the outputs of the ANN.

In the oscillometric method, the oscillation waveform is analysed to get the occurrence of the SP and DP during the decreasing CP. The BP value can be estimated by the corresponding pressure in the CP curve. This means at systolic pressure, CP value equals the SP value. Similarly, CP equals DP at the diastolic pressure. The equations shown in Equation 3.4 and Equation 3.5 indicate the relationship between CP and SP (DP). SA (DA) was the difference between CP and SP (DP). The ANN classifier was designed to calculate the value of SA and DA. From the equation, when SA (DA) equals zero the corresponding CP was identified as the SP (DP) value.

$$SP = CP - SA \tag{3.4}$$

$$DP = CP - DA \tag{3.5}$$

The input features used for the ANN training process were selected after the signal processing. All the input training features and targets were assembled as the input matrix: each HB with 16 features was gathered in a column vector. The target of each output from the ANN was obtained by CP minus the SP or DP reference reading value as shown in Figure 3-12. An example of ANN targets and results is shown in Figure 3-13. The red dots and blue dots indicate the ANN outputs for SP and DP and two black lines are the trendline of ANN outputs. Two arrowheads indicate the occurrence point of SP (DP) which can identify the SP and DP value based on the correlated CP value. The ***ployfit*** function in Matlab® software was used to calculate the polynomial coefficient of the trendline based on the ANN outputs and CP value. ***ployval*** function in Matlab® software was used to calculate the CP value at which the ANN output (SP) was zero which defined as the SP value. DP was calculated in a similar way based on the DP ANN outputs.

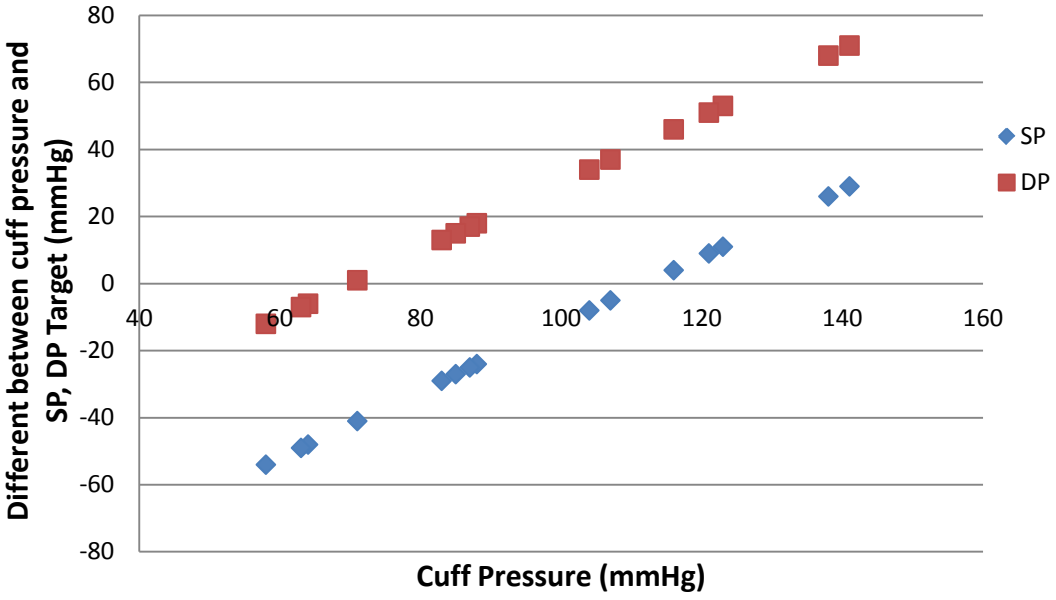


Figure 3-12: ANN output target chart.

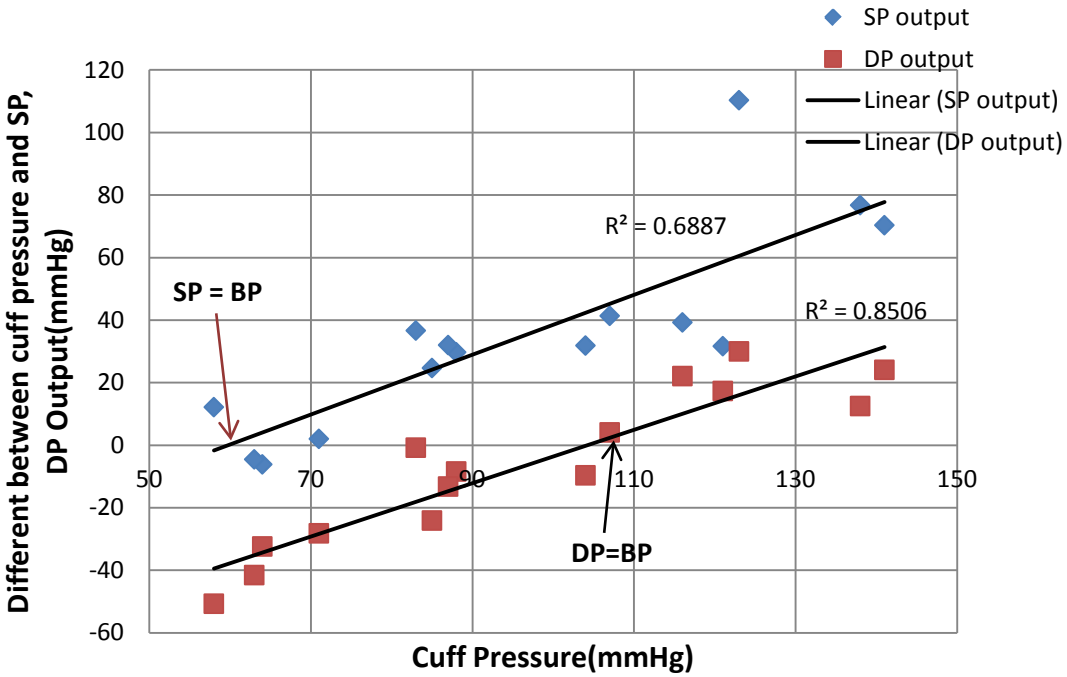


Figure 3-13: ANN Classification outputs and the targets. The blue dots are the SP output of ANN classification. The red dots are the DP output of ANN classification.

3.6 Summary

Signal processing procedures were developed which included filtering the noise, identifying each HB, error detection, normalisation and windowing identified HBs. Feature extraction was developed to extract useful input features for BP classification. The initial ANN classifier has been designed and trained with selected structure, input features and parameters to determine BP. After training the network, a new data set can be presented to the network for BP determination and validation of the network with R-squared value of 0.6887 for SP determination and 0.8506 for DP determination. The ***polyval*** function was used to calculate SP and DP values from the SA, DA and CP.

Chapter 4 Algorithm Testing, Improvement and Finalisation

4.1 Introduction

After the ANN was developed, new data was presented to test the algorithm. The testing results indicated some measurement errors especially in older people. Improvements were done to finalise the ANN with the best results on all age groups. New features were introduced to the ANN to give more useful information in order to improve the accuracy of BP estimation. Different numbers of training inputs were tested to find out the best setting of input training data. The most important features were selected for an efficient ANN which would recognise the limitations of time efficiency and hardware requirements. The ANN was also tested with different numbers of neurons, different parameters values and different training function in order to find the best ANN structure for the final algorithm. The accuracy of the final algorithm was compared with previous ANN and fixed ratio method as described in Chapter 1 [23]. A total of 92 subjects were measured in data collection and stored in the database and used for improving the ANN. For the final validation, 258 measurements collected from 86 subjects were used for the design and testing process.

4.2 Initial ANN

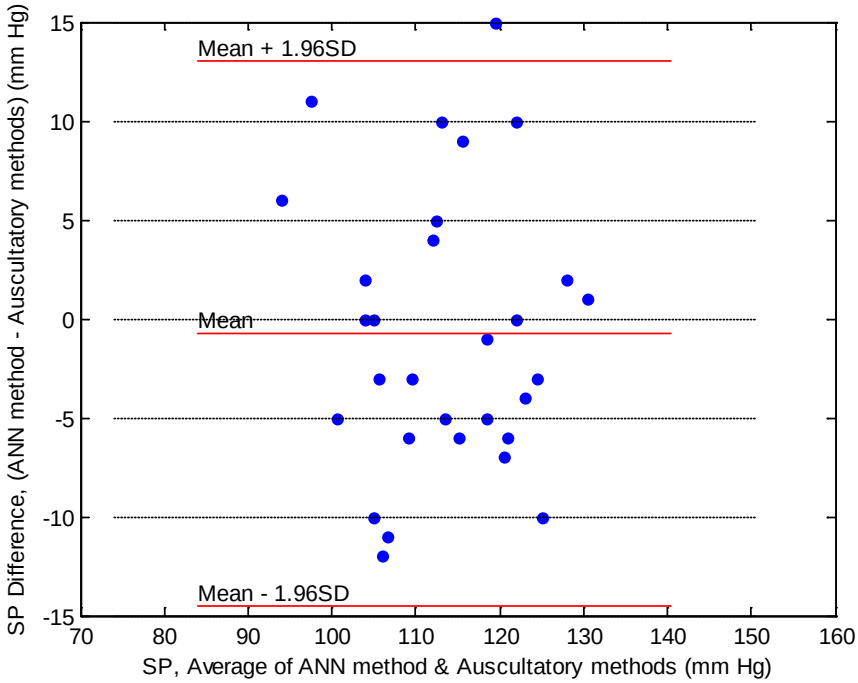
After the initial ANN was developed, new testing data could be used to test the accuracy of the algorithm. This project was aimed at developing an accurate BP measurement algorithm for all age groups. Two groups of measured data were selected to test the algorithm. In Group 1, 30 measurements were selected from young healthy subjects and Group 2 included 30 measurements randomly selected from all age groups (above 16

years old). The testing results of two groups were compared to the Auscultatory method as shown in Figure 4-1 and compared to AAMI and BHS standards as shown in Table 4-1.

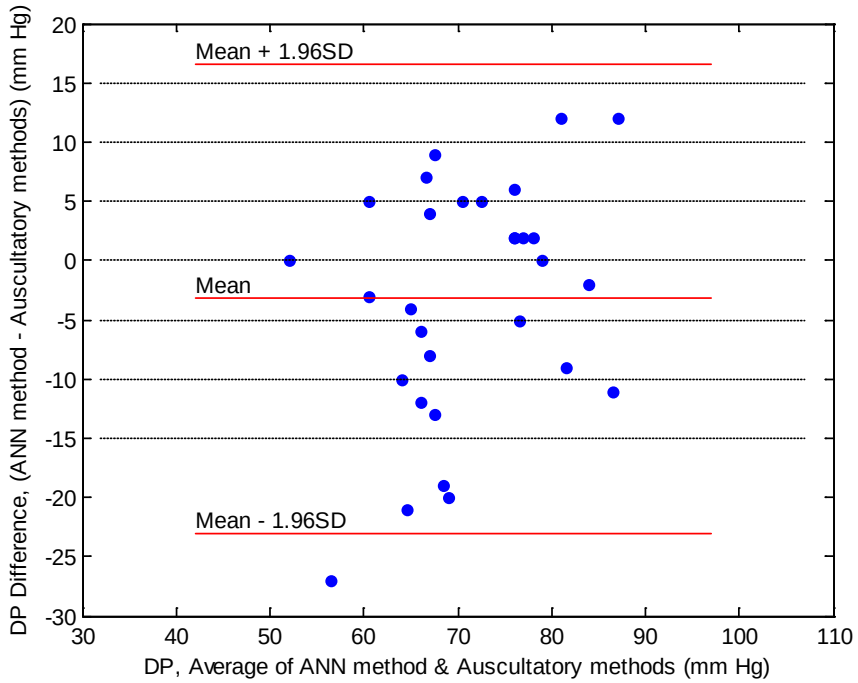
As shown in Table 4-1, the algorithm tested in healthy subjects had better estimation results in SP calculation than DP. It passed the AAMI standard in SP but failed DP estimation. The ANN with young healthy data achieved a B Grade according to the BHS standard for SP estimation. It was also less accurate in DP estimation: it only achieved C grade according to the BHS standard. Figure 4-1 indicated that all the results were within ±15 mmHg difference to SP. Half of the results were within ±5 mmHg different range. DP estimation had less accurate results compared to SP estimation. It had 4 testing data with an absolute difference of more than 15 mmHg compared to the reference reading. Only 46.1% of results had less than 5 mmHg absolute difference compared with the targets.

Table 4-1: Results from on 35 healthy and 35 randomly selected subjects compared with standard protocols by using developed algorithm.

Method	**Systolic Pressure**					**Diastolic Pressure**					**Standard (SP/DP)**	
	Measurement Error		Absolute difference (%)			Measurement Error		Absolute difference (%)			AAMI	BHS
	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Pass/ Fail	Grades
Healthy	-0.73	7.4	53.3	86.6	100	-3.2	10	46.1	70	86.7	P/F	B/C
Random	-0.8	9.9	36.7	76.7	86.7	-0.2	13.8	46.7	60	76.7	F/F	D/D



a

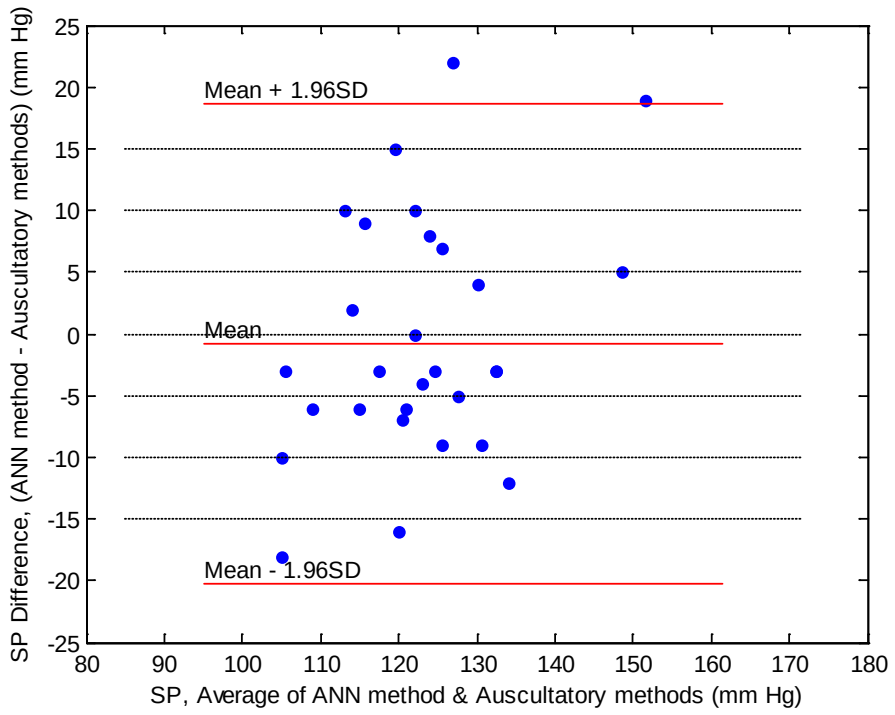


b

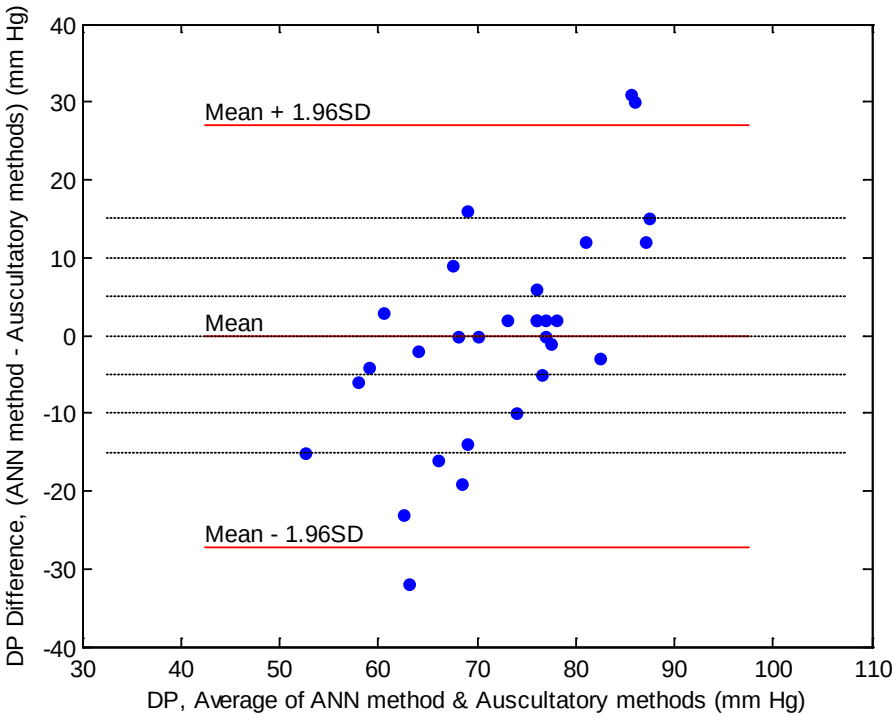
Figure 4-1: Bland and Altman plot of initial ANN and Auscultatory result compared from 35 healthy measurements. (a) Systolic Pressure. (b) Diastolic Pressure.

30 measurements randomly selected from the data base were tested. The developed algorithm failed both standards as shown in Table 4-1. The results with randomly selected data had worse accuracy compared to the healthy data. The results within ±5 mmHg difference had a huge drop from 53.3% to 36.6% in SP estimation when presented with randomly selected data instead of healthy data. Figure 4-2 showed there were 4 results out of ±15 mmHg difference range in SP estimation. For DP estimation, the results of the difference within ±5 mmHg were the same when using the randomly selected testing data. However, the accuracy of the absolute difference within 10 mmHg and 15 mmHg were also decreased when presented with randomly selected data. Some results had more than 30 mmHg absolute differences compared with the target in DP estimation.

The results of the initial designed algorithm were not accurate enough for subjects with a wider age range. Although the ANN tested with healthy data achieved a B grade in SP estimation, it failed DP measurement against the AAMI standard and only had a C grade for DP. The algorithm gave worse results when presented with testing data randomly selected from the database. Therefore more improvements were needed to improve the accuracy of the ANN.



a



b

Figure 4-2: Bland and Altman plot of initial ANN and Auscultatory result compared from 35 randomly selected measurements. (a) Systolic Pressure. (b) Diastolic Pressure.

4.3 ANN Improvements

The results of the initial designed algorithm showed that more improvements were required to improve the accuracy of the algorithm. The improvement process only focused on development of the ANN classifier, and there was no change to the signal processing. Three improvement processes are discussed in this chapter. The first step was to introduce new features to the algorithm. The second step was to test different numbers of training data. The third step was to test different numbers of ANN parameters and different training functions to give the most suitable ANN structure for this project. The final ANN structure was decided based on the testing results.

4.3.1 Feature Selection

With 16 features selected, the algorithm still indicated low accuracy on BP estimation. This means the 16 features may not provide enough information to the ANN for BP calculation. Therefore, two new input features were introduced to the ANN to try to improve the measurement accuracy.

HBcp was defined as the CP at each HB. As described before the outputs of the ANN were the differences between CP and SP (DP). This feature was selected to help the ANN to analyse the relationship between CP, SP and DP.

Rmax was defined by determining the maximum and minimum points of each HB. Then the amplitude of each HB was calculated as the difference between maximum and minimum points. The ratio ***(Rmax)*** of the HB amplitude over the maximum amplitude was calculated.

16 features with two newly added features (totalling 18 features) were trained and tested with 35 randomly selected measurements. The ANN with 16 input features was trained

and tested by adding one new feature at a time. The testing results are shown in Table 4-2.

Table 4-2: Result of 35 randomly selected data compared to the standard protocols by using 16, 17 and 18 input training features.

Methods	**Systolic Pressure**					**Diastolic Pressure**					**Standard (SP/DP)**	
	Measurement Error		Absolute difference (%)			Measurement Error		Absolute difference (%)			AAMI	BHS
	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Pass/ Fail	Grade
Random	-6.3	9.9	36.7	76.7	86.7	-5.9	13.8	46.7	60	76.7	F/F	D/D
Add HBcp	-1.9	7.6	53.3	86.7	94.2	-2.5	8.1	48.6	74.2	87.1	P/F	C/C
Add Rmax	4.6	11.1	48.6	78.7	82.9	-4.1	9.8	46.7	62.9	86.7	F/F	C/D
Add HBcp &Rmax	0.86	6.8	60	86.7	100	-1	7.9	53.3	86.7	93.3	P/P	A/B

The ANN with 17 input features (***HBcp*** added) passed the AAMI standard on SP estimation but failed on DP calculation. Results of BP estimation achieved a C grade according to the BHS standard for SP and DP. The proportion of absolute differences within 5 mmHg compared to the target output had significantly increased from 36.7% to 53.3% when ***HBcp*** was included in the ANN for SP estimation. The proportion of absolute differences within 5 mmHg for DP result also showed a 2% improvement when using ***HBcp***. The added feature ***HBcp*** improved the accuracy for the algorithm and was selected for the further development.

The ANN with 17 input features (***Rmax*** added) failed the AAMI standard and only achieved C grade in SP estimation and D in DP estimation. In both SP and DP estimations, the accuracy of the results was still improved compared to the ANN results with 16 input features.

The ANN with 18 inputs (ratio and CP added) was tested. The testing result on 35 randomly selected subjects passed the AAMI standard for both SP and DP estimations. The algorithm achieved an A grade in SP estimation and B grade in DP estimation. The results of the proportion of differences within ±5 mmHg were the highest results over all which improved up to 60% in SP estimation. All the SP results had less than ±15 mmHg difference compared to the target. For DP estimation, the accuracy of the results was lower than SP. Only half of the output had less ±5 mmHg difference compared with the target. However the accuracy of the ANN with 18 input features was improved compared to 16 input features. 18 input features were selected for further ANN developments.

4.3.1.1 Training Data

This project would test the proposed BP measurement method not only on healthy people but also on wider range of people. The developed ANN algorithm showed less accuracy when the presented data had higher SP. In the initial design of ANN, the input training data were selected randomly from the database. These testing data selected were studied, and it was evident that inaccurate results occurred more frequently with high SP values. The Training data were re-selected based on the SP value of the subjects. The purpose of re-selecting the training dataset was to make sure the training data covered all the range of SP. Since age may affect the accuracy of the BP estimation, training data from different age groups was reselected to give more representative BP readings.

The SP range of collected data was from 90 mmHg to 159 mmHg. As shown in Table 4-3 the collected data could be divided into three categories: desirable, pre-hypertension and Stage 1 hypertension. The training data used for ANN was selected from these three

ranges. The data used for the training data contained at least 30% of the training data selected from each SP range.

Table 4-3: BP range categories.

Category	systolic, mmHg	diastolic, mmHg
Hypotension	< 90	< 60
Desirable	90–119	60–79
Pre-hypertension	120–139	or 80–89
Stage 1 Hypertension	140–159	or 90–99
Stage 2 Hypertension	160–179	or 100–119
Hypertensive Crisis	≥ 180	or ≥ 120

20, 30, 40 and 50 input training data set were selected based on the selection requirement to test the algorithm. The result was shown in Table 4-4. All ANNs with different numbers of input training data passed AAMI and BHS standards. The ANN accuracy was improved when using more training data. In SP estimation, all ANN SP results achieved an A grade. The accuracy of DP estimation improved to A grade when increased the training data. SP and DP results both had A grades with 30, 40 and 50 training data. The accuracy of the ANN decreased when using 50 training data which suggests the ANN was over trained. Both ANNs with 30 and 40 training data had quite similar results. In SP estimation, only the accuracy of the ±10 mmHg difference category increased nearly 3% when using 40 training data. However, the DP results of 40 training data also increased nearly 3% in both 5 mmHg and 10 mmHg absolute difference categories. Therefore the ANN with 40 training data had been selected for the next step of testing.

Table 4-4: Results with 50 measurements compared with standard protocols with different numbers of inputs.

Methods	Systolic Pressure					Diastolic Pressure					Standard (SP/DP)	
	Measurement Error		Absolute difference (%)			Measurement Error		Absolute difference (%)			AAMI	BHS
	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Pass/ Fail	Grade
20 Data	-0.86	6.4	60	86.6	100	-2.7	7.5	53.3	86.7	93.3	P/P	A/B
30 Data	-1.4	5.7	63.5	91.4	100	-0.22	6.2	60	88.5	100	P/P	A/A
40 Data	0.8	5.5	63.5	94.3	100	-1.8	5.6	62.8	91.4	100	P/P	A/A
50 Data	-2.6	5.8	60	91.4	98.7	-1.8	6.2	60	88.5	100	P/P	A/A

Features

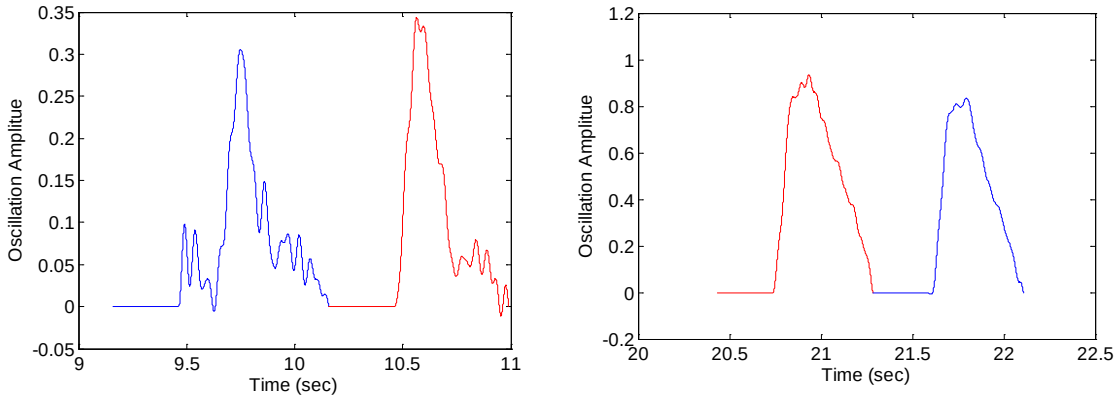
After introducing two new features to ANN, the accuracy of the BP measurement algorithm had been improved. The algorithm had already passed both standards and had A grade according to the BHS standard protocol. However it used more than 2 minutes for the training time with 18 features (Intel E8400 Dual Core 3.0GHz, 4GB ram). In practice, limitations should be considered during the device design for example time efficiency and hardware cost. Higher hardware requirements are an important influence in device design. This section describes an efficient method for feature selection. The numbers of features was reduced to increase the calculation efficiency and also reduce the hardware requirements.

As described before, each HB waveform contained useful information as the measured signal changed from supra-systolic to systolic region and diastolic to sub-diastolic region. Features containing the most useful information were kept and others discarded to improve efficiency. Firstly, two new added features were kept for the efficient method because they had great contribution to improving the accuracy of the ANN when using 18 features. The initial selected 16 features was compared and analysed

from one HB to another. The 8 more important input features were selected from the initial 16 features. 4 features were selected from time domain: **Area under the curve, Total Amplitude of each turning point, Positive Pdt and Positive Roc.** 4 features from the frequency domain were **Magnitudes** and **PSD** from both **0.5 ~5Hz, 5~10Hz**. PCA was also applied to reduce the dimension of the input data set in order to give better results during the analysis process.

4.3.1.2 Time Domain

In the normalisation process, HBs were selected and compared to find out the most important features. Before each HB waveform was rescaled, the HB amplitude increased from the supra-systolic region, the maximum amplitude occurred between systolic pressure and diastolic pressure and then the amplitude decreased after the maximum amplitude. The total absolute difference between turning points was selected as the amplitude of each HB and changed in different pressure region shown Figure 4-3.



a **b**

Figure 4-3: Consecutive HBs. The blue pulse is the HB from a supra-systolic (sub-diastolic) region. The red pulse is the HB at systolic (diastolic) region. (a) HB pulse from supra-systolic to SP. b) HBs from DP to sub-diastolic

After the normalisation and windowing, Figure 4-4 indicated the selected HB waveforms from different pressure regions. The shape of each HB pulse changed significantly from supra-systolic to sub diastolic region. **Area under the curve** was selected for the efficiency algorithm. After comparing 26 subjects' **PosPdt** ,**PosRoc**, **NegPdt** and **NegRoc** feature value. Both **PosPdt** and **PosRoc** value indicate big increases after diastolic pressure region. These two features were kept as the input features for the further analysis.

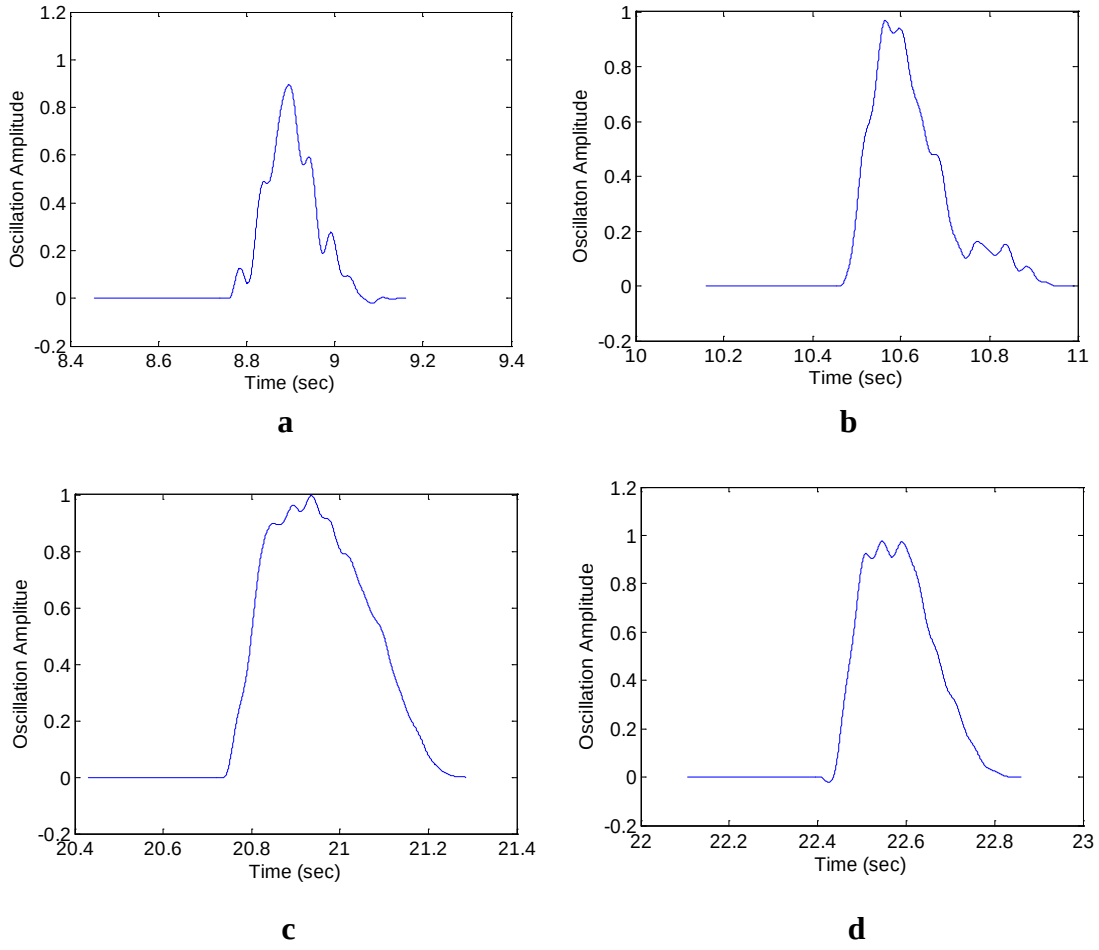


Figure 4-4: These four diagrams indicate the shape of HB pulse changed from supra-systolic region to sub-diastolic region. (a) One HB from Supra-systolic region. (b) HB at systolic region. (c) HB at diastolic region. (d) One HB from Sub-diastolic region

4.3.1.3 Frequency Domain

Before normalization, the FFT was applied to the band - pass filtered signal. It indicated that most useful information was contained between 0.5Hz to 10Hz. The features within in 0.5~10Hz were selected: Mag 0.5~5Hz, Mag 5~10 Hz, PSD 0.5~5Hz and PSD 0.5~5Hz were kept for as the input features.

Feature testing

After the number of features were reduced, the ANN with 8 input features was tested and compared with the initial ANN (16 input features). These 8 input features included the **Area under the curve, Total Amplitude of each turning point, Positive Pdt, Positive Roc** and **the magnitudes and PSD from both 0.5 ~5Hz, 5~10Hz**. Both ANN were trained with 20, 30 and 40 randomly selected training data and compared to the standards. 35 measurements from different BP range bands were selected and tested for each training set. This step was performed to make sure the selected 8 features contained a similar amount of information compared to the 16 input features. The results shown in Figure 4-5 and Table 4-6 indicate that both ANNs did not pass the AAMI and BHS standards in SP and DP estimation. However results showed very similar percentage values for the differences within ±5 mmHg, ±10 mmHg and ±15 mmHg between 16 and 8 input features. With different numbers of training data the results were not very different between these two ANNs which means most important features were contained within the selected 8 features.

Table 4-5: SP results on 35 measurements compared with standard protocols by using different numbers of training inputs.

16 Training Inputs						8 Training Inputs						
Methods	Systolic Pressure					Systolic Pressure					Standard (SP/DP)	
	Measurement Error		Absolute difference (%)			Measurement Error		Absolute difference (%)			AAMI	BHS
	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Pass/ Fail	Grades
20 Subjects	-0.7	9.3	36.7	76.7	86.7	-1.1	12.3	44.3	62.9	77.1	F/F	D/D
30 Subjects	-0.67	9.4	38.5	75.7	87.9	-1.7	13.2	42.9	67.1	77.1	F/F	D/D
40 Subjects	0.5	8.4	54.3	68.6	82.9	-1.1	13	42.9	62.9	71.4	F/F	D/D

Table 4-6: DP results on 35 measurements compared with standard protocols by using different numbers of training inputs.

16 Training Inputs						8 Training Inputs						
Methods	Diastolic Pressure					Diastolic Pressure					Standard (SP/DP)	
	Measurement Error		Absolute difference(%)			Measurement Error		Absolute difference(%)			AAMI	BHS
	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Pass/ Fail	Grades
20 Subjects	1.1	13.3	34.2	60	71.4	-5	10.5	42.8	57	85	F/F	D/D
30 Subjects	2.2	13.2	35.7	57	69	-5	9.2	34.5	66.7	77.1	F/F	D/D
40 Subjects	-5.2	14.1	37.4	51.9	77.6	-5.7	9.6	38.5	68.6	80.1	F/F	D/D

Two new introduced features were then added to the existing 8 features. 35 measurements were used for testing the ANN with 10 input features and the results were compared to the ANN with 18 features. 30 and 40 training data were used to check the accuracy of this 10 inputs ANN. The results in Table 4-7 show the ANN with 10 input features passed the AAMI standard in both SP and DP estimation. The results also confirmed 40 training data had higher accuracy results than 30 training data. The accuracy of the results improved from B grade to A grade when the ANN was presented with 40 training data.

Table 4-7: Results of 35 measurements compared with standard by using 10 and 18 features with different numbers of training data.

Method	Systolic Pressure					Diastolic Pressure					Standard (SP/DP)	
	Measurement Error		Absolute difference (%)			Measurement Error		Absolute difference (%)			AAMI	BHS
	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Pass/ Fail	Grades
10Inputs with 30D	-0.86	7.0	57.8	88.6	98.7	-1.7	7.5	51.4	82.9	91.2	P/P	B/B
10Inputs with 40D	-1.4	6.3	60	91.2	100	-0.22	6.7	60	88.5	98.7	P/P	A/A
18Inputs with 30D	-1.4	5.7	63.5	91.4	100	-0.22	6.2	60	88.5	100	P/P	A/A
18Inputs with 40D	0.1	5.5	63.5	94.3	100	-1.8	5.6	62.8	91.4	100	P/P	A/A

Overall the ANN with 10 input features passed both AAMI and BHS standards. The calculation time was reduced to around 1 minute from 2 minutes as mentioned in Section 5.3.1.1. However the accuracy of this ANN was lower than the ANN with 18 input features. With the limitations on time efficiency and hardware requirements an ANN with 10 features still could be used to give accurate BP measurement. The aim of this project was to design an accurate BP measurement algorithm. ANN with 18 input features was selected for the final algorithm as it gave more accurate results compared to 10 input features.

ANN structure

After the input features and number of training inputs were selected, different numbers of neurons and parameter settings used for the ANN were tested and compared, as described in this section. A network with the simplest efficiency structure was selected to complete the task without over fitting the data and to calculate the output with less error. Different training functions were tested and the final algorithm was selected from the best testing results. Another 31 measurements were selected for the testing process.

1, 3, 5, 10 and 15 different numbers of hidden layer neurons were tested as 5 different structures of ANN. The number of hidden layer neurons chosen affects the training time of the network. The aim of this process was to find out the smallest number of neurons with the best results for this algorithm. The ANN was tested on 30 measurements. 5 different ANNs were tested and compared to the reference Auscultatory readings; the results are shown in Table 4-8.

Table 4-8: Result of 31 measurements compared with standard with ANN using different numbers of neurons

Methods	**Systolic Pressure**			**Diastolic Pressure**			**Standard (SP/DP)**
	Absolute difference (%)			Absolute difference (%)			BHS
Neuron number	≤ ±5	≤ ±10	≤ ±15	≤ ±5	≤ ±10	≤ ±15	Grades
1	67.7	90.3	100	61.3	87.1	96.1	A/A
3	61.3	87.1	96.7	61.3	87.1	90.3	A/B
5	48.5	80.7	90.3	45.1	77.4	87.1	C/C
10	45.1	77.4	83.8	38.7	72.7	80.7	D/D
15	38.7	71	83.8	38.7	67.7	71	D/D

The BP calculation results with different numbers of neurons indicated the ANN with 1 neuron had the best result in both SP and DP estimation. For 3 neurons the SP result achieved an A grade but was less accurate than 1 neuron. In the DP calculation with 3 neurons, both absolute differences within 5 mmHg and 10 mmHg were the same as for 1 neuron. The accuracy of the absolute differences less than 15 mmHg dropped to 90.3%. The accuracy of ANNs with 5, 10 and 15 neurons decreased when the neuron number increased.

As shown above, the ANNs with 1 and 3 neurons had more accurate results. ANNs with 1, 2 and 3 neurons were tested again with the same data. Two different methods were

used to test the accuracy of these three ANNs. The first method was comparing the SP and DP results with the standard as used before. The second method was to check the ANN output of each HB thoroughly as described below. A total of 1092 HBs from 30 subjects were used for testing purposes. For BP measurement, the differences within ±5 mmHg and ±10 mmHg indicate the most important accuracy information in a BP measurement algorithm. The second method was to check the testing error of each ANN output without these two ranges. When the output from one HB was more than ±5 mmHg (±10 mmHg) compared to the target output one error was counted. Both results of the two testing methods are shown in Table 4-9.

Table 4-9: Results of 30 measurements by using different numbers of neuron for ANN training

Methods	**Systolic Pressure**			**Diastolic Pressure**			**Standard (SP/DP)**
	Absolute difference (%)			Absolute difference (%)			BHS
Neuron number	≤ ±5	≤ ±10	≤ ±15	≤ ±5	≤ ±10	≤ ±15	Grades
1	67.7	90.3	100	61.3	87.1	96.7	A/A
2	71	90.3	100	61.3	90.3	96.7	A/A
3	61.3	87.1	96.7	61.3	87.1	90.3	A/B

a) Results of 31 measurements compared with the standard by using 1, 2 and 3 neurons for ANN.

No. of Neurons	**Total No. of Outputs**	**Systolic pressure**		**Diastolic pressure**	
		No. of output with Error >5 mmHg	No. of output with Error >10 mmHg	No. of output with Error >5 mmHg	No. of output with Error >10 mmHg
1	1092	387	118	453	142
2	1092	345	110	442	128
3	1092	449	138	461	138

b) Testing error counted for differences of more than ±5 mmHg and 10mmHg.

The results indicated that both methods showed more accurate results with 2 hidden layer neurons in the ANN. The ANN with 2 neurons had the highest accuracy within the three ANNs. The absolute difference within 5 mmHg increased up to 71% in SP estimation. For DP calculation, the difference within ±5 mmHg was the same for 1, 3 and 5 neurons. As shown in Table 4-9 (a), results of the ANNs with 1 and 2 neurons were little different. Testing errors were checked through each HB to find out the most suitable neuron number for the final ANN. The ANN with 2 neurons had the smallest testing error compared with 1 and 3 neurons in both SP and DP estimation. Table 4-9 (b) shows that the ANN with 2 neurons had 345 HBs with an output error more than 5 mmHg compared to the target in SP calculation. In DP estimation, the ANN with 2 neurons had 442 HB outputs with more than ±5 mmHg testing error compared with the target and 128 outputs were more than ±10 mmHg different compared to the target output.

The Levenberg-Marquardt back-propagation ***(Trainlm)*** training function was used in the initial design of training the network for reasons of speed. More training functions were tried to train the network. BFGS Quasi-Newton backpapagation ***(Trainbfg)*** and the Variable Learning Rate ***(Trainbr)*** were selected and tested. ***Trainbfg*** function is an efficient training function; it requires more storage and more computation but less iteration during the training and it is suitable for small networks. ***Trainbr*** training function automatically determines the optimal regularization parameters during the training. Different training functions were used to test the algorithm with 1 and 2 neurons, the results of different training functions as shown in Table 4-10.

Table 4-10: Results of 30 measurements compared with standard by using different training functions and different numbers of neurons ANN.

Methods	Systolic Pressure			Diastolic Pressure			Standard (SP/DP)
	Absolute difference (%)			Absolute difference (%)			BHS
Tranfer functions	≤ ±5	≤ ±10	≤ ±15	≤ ±5	≤ ±10	≤ ±15	Grades
Trainlm- 1 neuron	67.7	90.3	100	64.5	87.1	100	A/A
Trainbfg- 1 neuron	67.7	90.3	100	61.3	87.1	96.7	A/A
Trainbr- 1 neuron	61.3	87.1	96.7	61.3	87.1	96.7	A/A
Trainlm- 2 neuron	71	90.3	100	67.7	90.3	100	A/A
Trainbfg- 2 neuron	71	90.3	100	61.3	90.3	96.7	A/A
Trainbr- 2neuron	64.5	87.1	100	61.3	87.1	96.7	A/B

The results of ***Trainlm*** and ***Trainbfg*** training functions were quite similar. For both ANNs trained with 1 and 2 neurons, the algorithm with ***Trainbr*** had less accurate results compared to others. Testing errors were counted to check the accuracy of the ANN with ***Trainlm*** and ***Trainbfg*** training functions to find the best training function for the final algorithm.

A total of 1092 HBs from 30 subjects were used for testing the ANNs. 30 measurements containing a total of 857 HBs were selected to train the ANN. The weights and biases were initialised by using 0~100 random seeds. The ANN with 1 and 2 neurons were selected for the further comparisons. Different numbers of training epochs and PEGs were chosen to test the network based on 1 and 2 neurons with the results as shown in Table 4-11: Testing error counted chart by using ANNs with different ANN parameters, different training functions and different numbers neurons. 300 and 500 training epochs were selected and the PEGs were set as 0.1 and 0.01. All new input data were tested with one neuron and two neurons separately. ***Trainlm*** and ***Trainbfg*** training function were used to train the network using different algorithms. The ANN outputs were

checked and compared with the target based on different ANN structures. All the results from each HB were compared to the targets and results summarised in Table 4-11.

Table 4-11: Testing error counted chart by using ANNs with different ANN parameters, different training functions and different numbers neurons

Trainlm		**Total No. of Outputs**	**1Neuron**		**1 Neuron**	
			Systolic Pressure		**Diastolic Pressure**	
PEG	Epoch		Error ≤ 5 mmHg	Error ≤ 10 mmHg	Error ≤ 5 mmHg	Error ≤ 10 mmHg
0.1	300	1092	421	142	454	169
0.01	300	1092	497	238	517	270
0.1	500	1092	372	107	406	149
0.01	500	1092	385	119	445	177

a) Testing errors of ANN when used ***Trainlm*** training function, 1 neuron, with different ANN parameters: 0.1(0.01) PEG and 300(500) Epoch.

Trainlm		**Total No. of Outputs**	**2 Neurons**		**2 Neurons**	
			Systolic Pressure		**Diastolic Pressure**	
PEG	Epoch		Error ≤ 5 mmHg	Error ≤10 mmHg	Error ≤5 mmHg	Error ≤ 10 mmHg
0.1	300	1092	313	173	436	151
0.01	300	1092	325	182	517	170
0.1	500	1092	309	108	358	102
0.01	500	1092	345	126	383	133

b) Testing error of ANN when used ***Trainlm*** training function, 2 neurons, with different parameters: 0.1(0.01) PEG and 300(500) Epoch.

Trainbfg		**Total No. of Outputs**	**1 Neuron**		**1 Neuron**	
			Systolic Pressure		**Diastolic Pressure**	
PEG	Epoch		Error ≤5 mmHg	Error ≤10 mmHg	Error ≤5 mmHg	Error ≤10 mmHg
0.1	300	1092	503	293	483	290
0.01	300	1092	573	245	520	284
0.1	500	1092	384	112	432	148
0.01	500	1092	398	127	457	227

c) Testing errors of ANN when used ***Trainbfg*** training function, 1 neuron, with different parameters: 0.1(0.01) PEG and 300(500) Epoch.

Trainbfg		**Total No. of Outputs**	**2 Neurons**		**2 Neurons**	
			Systolic Pressure		Diastolic Pressure	
PEG	Epoch		Error ≤ 5 mmHg	Error ≤ 10 mmHg	Error ≤ 5 mmHg	Error ≤ 10 mmHg
0.1	300	1092	398	193	528	274
0.01	300	1092	401	245	547	303
0.1	500	1092	326	126	422	148
0.01	500	1092	378	129	435	156

d) Testing errors of ANN when used ***Trainbfg*** training function, 2 neurons, with different parameters: 0.1(0.01) PEG and 300(500) Epoch.

The results showed in Table 4-11 (a) and (b) indicate the ANNs with 500 epochs and 0.1 PEG with the ***Trainlm*** training function had the best results compared to others. The count of errors in these ANNs was the smallest compared to other structures. The results in Table 4-11 (a) and (b) also indicate the ANN with 2 neurons had better results which had 63(48) less output errors on ≥ 5 mmHg for SP(DP) compared to the ANN with 1 neuron. A total of 309 outputs had a difference of more than 5 mmHg absolute difference compared to the target and 108 outputs had an absolute difference of more than 10 mmHg in SP estimation. For DP, 358 outputs had testing errors more than 5 mmHg and 149 outputs had more than a 10 mmHg absolute difference compared with the target outputs.

The results in Table 4-11 (b) and (c) indicate that the result of ***Trainbfg*** training function had less accuracy compared to the ANN trained with ***Trainlm***. It also showed that the ANN with 2 neurons, 500 epochs and 0.1 PEG had better results compared other settings. In SP calculation, 326 ANN outputs had a testing error of more than ±5 mmHg compared to the output target. 129 outputs had an absolute difference of more than 10 mmHg. For DP estimation, 435 ANN outputs had more than a 5 mmHg

absolute testing error. 156 outputs were more than 10 mmHg in absolute difference compared with the target output.

Overall the ANN with 18 input features, 40 training data, 2 neurons, 500 epoch and 0.1 PEG trained with ***Trainlm*** training function had best results compared to other ANNs. This ANN was selected for the final BP measurement algorithm and more data would be selected for validating this algorithm.

4.4 Algorithm results

After the BP measurement algorithm was finalised, the algorithm was compared with other NIBP measurement methods to show the advantages of this algorithm. Two methods were selected to compare with the developed algorithm: a previous ANN and the traditional fixed ratio method. After the comparison, the developed algorithm was tested with 258 measurements as a final validation. The results were compared with the Auscultatory Method and shown in Bland and Altman plots. The mean, SD and the measurements errors are describe in the tables.

4.4.1 Different method results comparison

30 measurements randomly selected from the database were tested with the traditional fixed ratio method [18], previous ANN method and the final algorithm [56]. In the fixed ratio method, the ratios used for determining BP were 53% and 73% for SP and DP and were calculated based on 40 measured readings of the Auscultatory method. The results of three algorithms were compared with the Auscultatory Method. AAMI and BHS standard protocols were used to compare the three methods, as shown in Table 4-12.

Table 4-12: Results of three methods comparing with standard protocols

Method	Systolic Pressure					Diastolic Pressure					Standard (SP/DP)	
	Measurement Error		Absolute difference (%)			Measurement Error		Absolute difference (%)			AAMI	BHS
	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Pass/ Fail	Grade
Final ANN	0.53	5.2	69.8	97.5	100	-0.56	6.2	63.5	94.3	97.5	P/P	A/A
Previous ANN	-1.4	7.8	60	83.3	90	-1.5	8.7	60	76.7	90	P/F	B/B
Fixed Ratio	3.4	7.9	56.7	83.3	90	-2.9	10	50	73.3	86.7	P/F	B/C

The results showed in Table 4-12 indicate that the developed ANN had the best BHS grade of the three methods. It was the only method fulfilling both AAMI and BHS standard protocols and both SP and DP estimation had A Grade according to the BHS standard.

In SP calculation, all three methods passed the AAMI standard. The previous ANN and fixed ratio method had less accurate results than the developed method, having, respectively, 60% and 56.7% of absolute differences within 5 mmHg compared to the reference readings. The developed ANN had more accurate results compared to the other two methods. When using the developed method, the SP calculation results of less than 5 mmHg increased to 69.8% with the same testing data. The absolute difference within 10 mmHg was 97.5% for the developed ANN, but less accurate with other two methods at 88.3%.

In DP calculation, only the developed method passed both standards. The previous ANN method and fixed ratio method had B and C in BHS grades. The developed ANN had the best results with 63.5% of the results having less than 5 mmHg absolute difference from the target. The accuracy of the fixed ratio method had less than 13.5% with the same testing data. For the absolute difference within 10 mmHg, the developed

ANN still had the highest accuracy results at 88.9%. The previous ANN had higher results compared to the fixed ratio method.

The developed ANN had the best results of the three methods based on the same testing data. The previous ANN was less accurate when used for a wider range of people. It failed the AAMI standard in DP estimation and had a B grade in both SP and DP estimation. The results of the fixed ratio method indicated the lowest accuracy of the three methods. Overall the developed ANN was the most suitable NIBP measurement algorithm for estimating accurate BP values for all age groups.

4.4.2 Final Algorithm Validation

The final algorithm was validated on 258 measurements collected from 86 subjects. 40 random selected subjects in all age groups involving 1157 HBs total were used for ANN training. 10 and 18 input features were tested separately. 79 measurements were used for testing the algorithm with 10 input features. A total of 258 measurements were used to test the final ANN which contained all 18 input features.

Both ANNs classification were trained with 2 neurons and the ***Trainlm*** training function. The algorithms were set to have the PEG and epoch values as 0.1, and 500. The random seeds was selected from 0~100 for the final algorithm. Results of the final algorithm were compared with Auscultatory Method and shown in a Bland Altman plot. AAMI and BHS standard protocols were used to evaluate the results.

Table 4-13 shows that the results of the efficient algorithm (use 10 input features) met both AAMI and BHS standard protocol requirements. Both SP and DP results tested on 79 measurements pass the AAMI standard. The BP estimation result satisfied the BHS standards in Grade A in both SP and DP estimation. The SP and DP results of 10 input

features had quite similar results. The proportion of absolute differences within 5 mmHg is 66.5% on SP estimation which was only 1.4% more than DP results. There was no SP or DP result with more than 15 mmHg absolute difference compared with the target. For SP calculation results 6 outputs had more than a 10 mmHg absolute difference compared to the target. In DP results only 5 of 79 results were more than the 10 mmHg absolute difference. It also indicated the accuracy of the ANN was improved with the changed parameters and training functions. The efficient ANN could be used if there were limitations on the device capabilities.

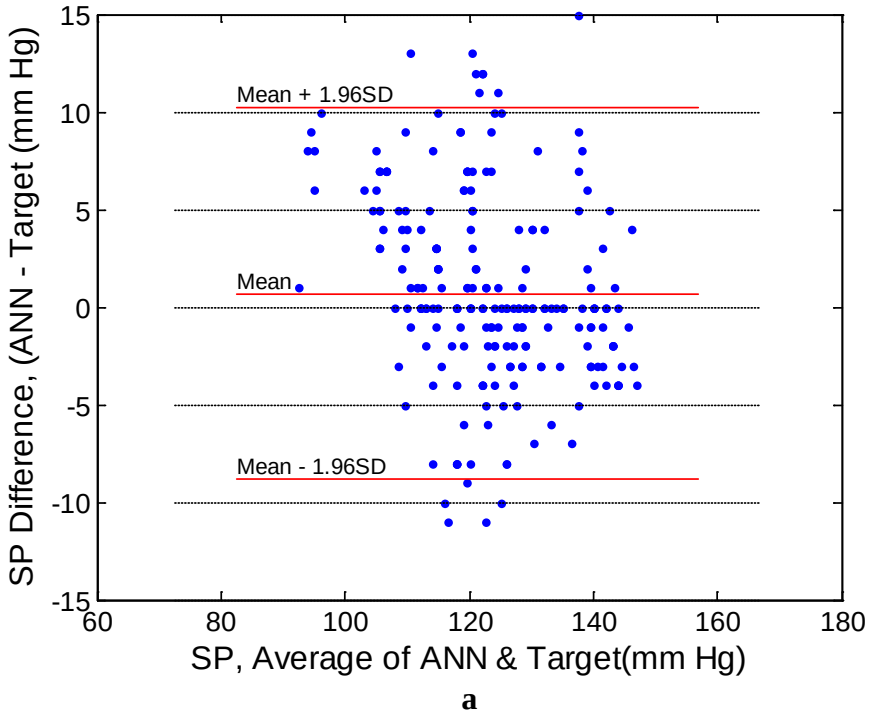
Table 4-13: Results of efficient algorithm compared with standard protocols

Method	**Systolic Pressure**					**Diastolic Pressure**					**Standard (SP/DP)**	
	Measurement Error		Absolute difference (%)			Measurement Error		Absolute difference (%)			AAMI	BHS
	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Pass/ Fail	Grade
Final ANN	0.9	5.6	66.7	92.3	100	-0.53	5.5	65.8	93.6	100	P/P	A/A
Efficient ANN	-1.4	6.3	60	91.2	100	-1.22	6.7	60	88.5	98.7	P/P	A/A

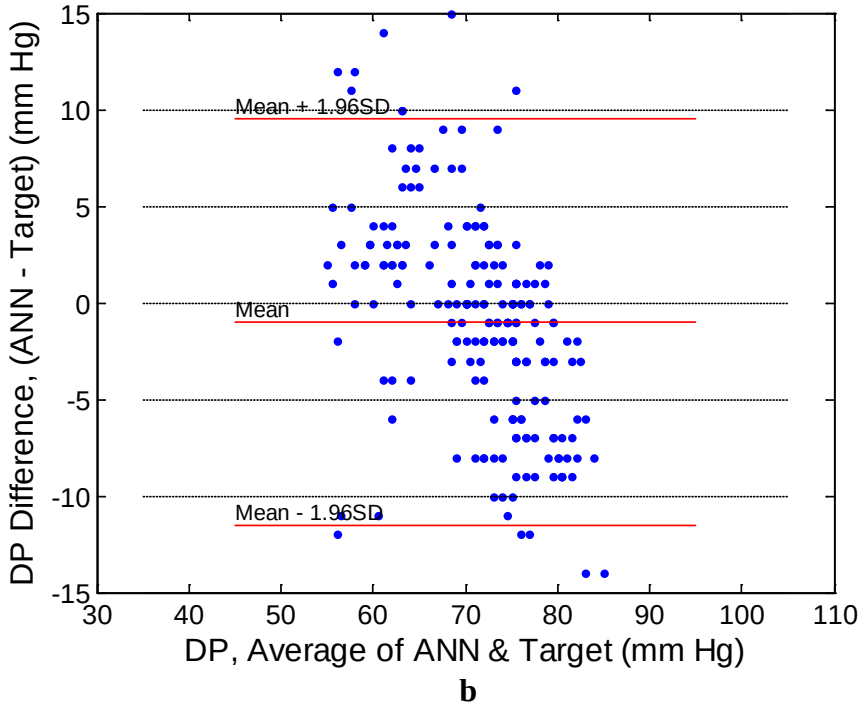
The final ANN was tested with a total of 258 measurements from the 86 subjects. 18 input features, 40 training data were selected for the final ANN. The testing results of the final algorithm are shown in Figure 4-5 and

Table 4-14. The final algorithm passed both AAMI and BHS standards and achieved an A grade in both SP and DP estimation. 75% of the results had less than a ±5 mmHg difference compared with the targets in SP calculation. For SP results, there was no SP value wotj more than a 15 mmHg absolute difference compared with the target results. Only 7 SP results out of 258 results had more than a 10 mmHg absolute differences compared with the target. The accuracy of DP estimation on less than a 5 mmHg difference was 7.4% lower than SP. 15 DP results had more than 10 mmHg absolute difference with the target which was similar to the SP estimation.

In the developed algorithm, SP estimation was more accurate than DP. As indicated in Figure 4-5 although most DP results were within the range of ≤5 mmHg difference, only 13 DP results had no difference with the target DP value. More SP results had the same value as the target outputs. It also indicated that the ANN classifier gave most SP value greater than the target output. DP values estimated by the ANN were mostly less than the target. Overall the final algorithm had been successfully designed to fulfil both AAMI and BHS standards with testing on data collected from all age groups.



a



b

Figure 4-5: The Bland and Altman plot comparing ANN with 18 inputs, 40 training data, and 258 testing data. (a) Systolic Pressure. (b) Diastolic Pressure.

Table 4-14: Results of final algorithm compared with standard protocols.

Method	**Systolic Pressure**					**Diastolic Pressure**					**Standard (SP/DP)**	
	Measurement Error		Absolute difference (%)			Measurement Error		Absolute difference (%)			AAMI	BHS
	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Mean	SD	≤ ±5	≤ ±10	≤ ±15	Pass/ Fail	Grade
Final ANN	0.698	4.87	75	95.96	100	-1.01	5.37	67.6	93.6	100	P/P	A/A

4.5 Summary

The initial ANN classifier was improved and finalised, tested and results compared. New training input features were selected to improve the accuracy for all age band subjects. Different numbers of input training data were tested with the same testing data. The input training data were reselected based on different BP ranges. ***Trainlm,*** ***Trainbfg*** and ***Trainbr*** training functions were tested with different neurons, numbers of

training epochs and PEG values. Another two different NIBP measurement methods were compared with the final ANN. 86 subjects with 258 measurements were used to validate the final algorithm.

Chapter 5 Conclusion and Future work

5.1 Introduction

This chapter describes the conclusions of this research and describes future work. A summary of the work including the signal processing process and the ANN classification is given. The testing results of this research are described. Some possible further developments based on this algorithm are listed in the future work section.

5.2 Conclusion

Whereas traditionally, the method had been used to calculate the BP value by using fixed ratio. In this research a different approach was used to determine the SP and DP values. This research involved removing noise from a raw signal, tracking each individual HB, extracting useful features and designing the initial ANN classifier to analysis the features and calculate the SP and DP values. Improvements and modifications were developed to increase the accuracy of the algorithm. An efficient feature selection algorithm was developed to cater to more limited hardware.

5.2.1 Signal processing and Feature extraction

A band-pass filter (0.5 ~25 Hz) was designed to filter out most unwanted noise to get the oscillometric waveform. A method was developed to determine and segment each individual HB. An error rejection algorithm was designed for removing external tremors. Each individual HB was normalised and a Hann window applied before the

feature extraction. A feature extraction algorithm was developed based on both time and frequency domain features, which were:

- 6 features selected from time domain: **Area under the curve, Total Amplitude from all turning points, positive and negative ROC, maximum positive and minimum negative slope of each HB**.
- 10 features selected from the frequency domain: **Magnitudes** and **PSD** values at frequency range between **0.5~5 Hz, 5~10Hz, 10~15Hz, 15~25Hz**.
- 2 new features selected to improve the accuracy of the designed algorithm: Cuff pressure at each HB (**HBcp**) and the ratio (**Rmax**) of the HB amplitude over the maximum amplitude.

5.2.2 ANN Classification

The ANN classifier was initially developed which consisted of 3 neurons, single–hidden layer, 16 inputs and 1 output were designed for SP (DP). Training was performed with the ***Trainbfg*** training function. After testing the initial algorithm with people having a full range of BPs, improvements were developed for increasing the accuracy of the designed algorithm. Two new features were added and the trained ANN exhibited great improvement in the accuracy of the developed algorithm. A method was developed to compare the accuracy of ANN with different ANN structures and parameters. The ANN constructed by 2 neurons and 18 inputs trained with the ***Trainlm*** training function was chosen for the final algorithm. The final algorithm was tested with the data collected from all age groups which fulfilled both AAMI and BHS standard protocols. The mean difference (SD) between the observers and the developed algorithm were 0.698(4.87) mmHg for SP and -1.01(5.37) mmHg for DP.

An efficient method had been developed for the limitation of the hardware requirement which can reduce the calculation time by 50% including:

- Reduced the input training features from 18 to 10.
- Less accuracy than the final algorithm; a mean difference (SD) between the observers and efficient algorithm were -1.4(6.3) mmHg for SP and -1.22(6.7) mmHg for DP.
- Fulfilled both AAMI and BHS standards.

5.3 Future work

This research successfully developed an NIBP measurement algorithm with good results. However the work needs to be done on the developed algorithm for implementation on a device.

The reference values are very important in this algorithm. During the algorithm development, the reference values were used as a gold standard for comparison with the algorithm. For further development of this algorithm the data collection process should use observers with professional training to minimize the reading error for the reference values.

This algorithm used the ANN classifier to analyse the features from each HB and determine a BP value. Feature selection was one of the factors directly affecting the accuracy of results. Different features could be selected with different methods to improve the accuracy of BP estimation. For developing new algorithms for some subgroups such as pregnant women, new features also need to be selected.

Although the efficient method was less accurate compared to the final algorithm a new algorithm may be designed based on the efficient method to produce an accurate, low

cost device. This algorithm was successfully tested on young healthy and older people. But the accuracy of other subgroups such as pregnant women, arrhythmia, diabetics and other patients with diseases is still untested. New algorithms for these subjects can be developed.

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APPENDIX

APPENDIX I	Matlab codes
APPENDIX II	Ethical approval
APPENDIX III	Participant Information Sheet
APPENDIX IV	Consent Form

APPENDIX I Matlab code

Signal Processing and Feature Extraction

```
% plot waveform
%remove noise
%get max&min point
%detect HB
%HB checking

clear all, clc;
load('G:\thesis\data\exp24.mat')

B=ADCC1;
A = (B * 5/ 4096 - 0.2) * 68.4;
fs=2000;
MinInd1=find(A(:,1))+15000; %shift
A=A(MinInd1:end,:);
MaxInd=find(A(:,1)==max(A(:,1))); %find the max cuff pressure
A=A(MaxInd:end,:); %ignore  signals before max cuff presure
x=A(:,1);
MinInd3=find(x(:,1))+5; %shift
x=x(MinInd3:end-2000,:);
 [b,a]=butter(1,0.5/1000,'high'); %filter
xfilt=filtfilt(b,a,x);
 [b1,a1]=butter(2,25/1000); %filter
xfilt2=filtfilt(b1,a1,xfilt);
MaxInd2=find(xfilt2(:,1))+1000; %shift
xfilt2=xfilt2(MaxInd2:end,:);
t=(0:length(xfilt2)-1)/fs;        % times of sampling instants
 [b2,a2]=butter(2,2/1000); %filter
xfilt1=filtfilt(b2,a2,xfilt2);
% get Max & Min points
MinPeakInd=funFindMin(xfilt1)+1;
MaxPeakInd=funFindMax(xfilt1)+1;

ind1=[];
ind2=[];
Beat=[];
for i=1:length(MinPeakInd)-2
       [Max
indices]=max(xfilt2(MinPeakInd(i):MinPeakInd(i+1),1));  %find max
point
 [Min MinInd]=min(xfilt2(MaxPeakInd(i):MaxPeakInd(i+1),1)); %find min
point
 indices=indices+MinPeakInd(i)-1;
 MinInd=MinInd+MaxPeakInd(i)-1;
   ind1(i)=indices;
   ind2(i)=MinInd;

    if i>1
       Beat(i-1)=fs/(ind2(i)-ind2(i-1));   %beat rate in beats per
second
      disp(['Heart Rate: ' num2str(round(Beat*60))]);
    end
end
%check HB meanBeat=mean(Beat(1:end));
disp(['Mean Beat: ' num2str((meanBeat*60))]);
ind1=ind1(1:end-1);
```

```
ind3=ind2(2:end);
ind2=ind2(1:end-1);
  i=1;
   while i<length(Beat)
       if (Beat(i)< (meanBeat/1.42))
           if i==1
               if Beat(1)> Beat(2)
                   Beat=Beat(3:end);
                   ind1=ind1(3:end);
                   ind2=ind2(3:end);
                   ind3=ind3(3:end);
               else
                   Beat=Beat(2:end);
                   ind1=ind1(2:end);
                   ind2=ind2(2:end);
                   ind3=ind3(2:end);
               end
           else
               if Beat(i) > Beat(i+1)
                   Beat=[Beat(1:i-1) Beat(i+2:end)];
                   ind1=[ind1(1:i-1) ind1(i+2:end)];
                   ind2=[ind2(1:i-1) ind2(i+2:end)];
                   ind3=[ind3(1:i-1) ind3(i+2:end)];
               else
                  Beat=[Beat(1:i-1) Beat(i+1:end)];
                  ind1=[ind1(1:i-1) ind1(i+1:end)];
                  ind2=[ind2(1:i-1) ind2(i+1:end)];
                  ind3=[ind3(1:i-1) ind3(i+1:end)];
               end
           end
       else
           if Beat(i)>(meanBeat*1.3)
               if i==1
                   if Beat(1)< Beat(2)
                        Beat=Beat(3:end);
                        ind1=ind1(3:end);
                        ind2=ind2(3:end);
                        ind3=ind3(3:end);
                   else
                        Beat=Beat(2:end);
                        ind1=ind1(2:end);
                        ind2=ind2(2:end);
                        ind3=ind3(2:end);
                   end
               else
                   if  Beat(i)< Beat(i+1)
                       Beat=[Beat(1:i-1) Beat(i+2:end)];
                       ind1=[ind1(1:i-1) ind1(i+2:end)];
                                ind2=[ind2(1:i-1) ind2(i+2:end)];
                                ind3=[ind3(1:i-1) ind3(i+2:end)];
                            else
                                Beat=[Beat(1:i-1) Beat(i+1:end)];
                                ind1=[ind1(1:i-1) ind1(i+1:end)];
                                ind2=[ind2(1:i-1) ind2(i+1:end)];
                                ind3=[ind3(1:i-1) ind3(i+1:end)];
                            end
                         end
                        end
                    end
                    i=i+1;
                end
```

```
  for i=1:length(Beat)-1
BP(i)=round(x(ind3(i)));
 SP=110;
 SPdif(i)=BP(i)-SP;
 DP=78;
 DPdif(i)=BP(i)-DP;
end
       newmeanBeat=mean(Beat(1:end));
%Normalise
 i=1;
 while i<(length(ind3))
 ind2(i)=ind2(i)-round(0.25*newmeanBeat*fs);
 ind3(i)=ind3(i)-round(0.25*newmeanBeat*fs);
 temp1=ind2(i); temp2=ind3(i);
 xx=xfilt2(temp1:temp2);
 tt=t(temp1:temp2);
 xx(1:round(0.25*newmeanBeat*fs))=xx(round(0.25*newmeanBeat*fs));
 shifttt=t(ind2(i));
 ttshift=tt-shifttt;
 Norx=ttshift'*(xx(end)-xx(round(0.25*newmeanBeat*fs)))/(tt(end)-
        tt(round(0.25*newmeanBeat*fs)));
 xxshift=xx-Norx;
 xxshift=xxshift-xxshift(end);
 xxshift(1:round(0.25*newmeanBeat*fs))=0;

 xxshiftMin=min(xxshift);
 xxshiftMax=max(xxshift);
 xxNor=xxshift/(xxshiftMax-xxshiftMin);

 % Aplly Hann window
 N=round((fs/newmeanBeat)*0.6);  %calculate number of Hann
 Window = hann(N);
 Window1=Window(1:N/2);
 Window2=Window(N/2:end);
 %Window=tukeywin(N,0.5);
 xxWin1=xxNor(1:N/2).*Window1;
 xxWin2=xxNor((end-N/2):end).*Window2;
 xxWin=[xxWin1 ; xxNor((N/2):(end-N/2-2)) ; xxWin2];
 subplot(6,6,i)
 plot(tt,xxshift)

 TotAmp(i)=funAmp(xxWin);
 Area(i)=funArea(xxWin);
 dpdt(i,:)=fundPdt(xxWin,tt);
 roc(i,:)=funROC(xxWin,tt);
 Mag(i,:)=funMag(xxWin,tt,N,fs);
 PSD(i,:)=funPSD(xxWin,tt,N,fs);

 Feature=[[TotAmp]' [Area]' abs(dpdt)  abs(roc) abs(Mag) PSD ];
 Feature=[Feature]';


  cd('H:\thesis\ANN1')

  Text = {'Amplitude';'Area';'Pos dPdt';'Neg dPdt';'Pos ROC';'Neg ROC';
       'Mag 5';'Mag 10';'Mag 15';'Mag 20';'Mag 25';'PSD 5';'PSD
       10';'PSD 15';'PSD 20';'PSD 25';'BP';'SP';'DP'};
      xlswrite('features2',Text,'exp24');
      xlswrite('features2',Feature,'exp24','B1');
```

```
      xlswrite('features2',BP,'exp24','B20');
      xlswrite('features2',SPdif,'exp24','B21');
      xlswrite('features2',DPdif,'exp24','B22');
  i=i+1
  end
```

ANN classification SP and DP

```
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

%% SP Determination
clear all
cd('G:\thesis\ANN modification')

pTrain1 = xlsread('features18IR', 'exp1', 'B1:Q18');
tTrain1 = xlsread('features18IR', 'exp1', 'B19:Q19');
bp1 = xlsread('features18IR', 'exp1', 'B18:Q18');

pTrain2 = xlsread('features18IR', 'exp2', 'B1:V18');
tTrain2 = xlsread('features18IR', 'exp2', 'B19:V19');
bp2 = xlsread('features18IR', 'exp2', 'B18:V18');

pTrain3 = xlsread('features18IR', 'exp3', 'B1:U18');
tTrain3 = xlsread('features18IR', 'exp3', 'B19:U19');
bp3 = xlsread('features18IR', 'exp3', 'B18:U18');

pTrain4 = xlsread('features18IR', 'exp4', 'B1:X18');
tTrain4 = xlsread('features18IR', 'exp4', 'B19:X19');
bp4 = xlsread('features18IR', 'exp4', 'B18:X18');

pTrain5 = xlsread('features18IR', 'exp5', 'B1:U18');
tTrain5 = xlsread('features18IR', 'exp5', 'B19:U19');
bp5 = xlsread('features18IR', 'exp5', 'B18:U18');



pTrain7 = xlsread('features18IR', 'exp7', 'B1:U18');
tTrain7 = xlsread('features18IR', 'exp7', 'B19:U19');
bp7 = xlsread('features18IR', 'exp7', 'B18:U18');

pTrain8 = xlsread('features18IR', 'exp8', 'B1:S18');
tTrain8 = xlsread('features18IR', 'exp8', 'B19:S19');
bp8 = xlsread('features18IR', 'exp8', 'B18:S18');

pTrain9 = xlsread('features18IR', 'exp9', 'B1:U18');
tTrain9 = xlsread('features18IR', 'exp9', 'B19:U19');
bp9 = xlsread('features18IR', 'exp9', 'B18:U18');



pTrain11 = xlsread('features18IR', 'exp11', 'B1:X18');
tTrain11 = xlsread('features18IR', 'exp11', 'B19:X19');
bp11 = xlsread('features18IR', 'exp11', 'B18:X18');

pTrain12 = xlsread('features18IR', 'exp12', 'B1:AB18');
tTrain12 = xlsread('features18IR', 'exp12', 'B19:AB19');
bp12 = xlsread('features18IR', 'exp12', 'B18:AB18');
```

```
pTrain13 = xlsread('features18IR', 'exp13', 'B1:AA18');
tTrain13 = xlsread('features18IR', 'exp13', 'B19:AA19');
bp13 = xlsread('features18IR', 'exp13', 'B18:AA18');

pTrain14 = xlsread('features18IR', 'exp14', 'B1:V18');
tTrain14 = xlsread('features18IR', 'exp14', 'B19:V19');
bp14 = xlsread('features18IR', 'exp14', 'B18:V18');

pTrain15 = xlsread('features18IR', 'exp15', 'B1:W18');
tTrain15 = xlsread('features18IR', 'exp15', 'B19:W19');
bp15 = xlsread('features18IR', 'exp15', 'B18:W18');

pTrain16 = xlsread('features18IR', 'exp16', 'B1:R18');
tTrain16 = xlsread('features18IR', 'exp16', 'B19:R19');
bp16 = xlsread('features18IR', 'exp16', 'B18:R18');

pTrain17 = xlsread('features18IR', 'exp17', 'B1:X18');
tTrain17 = xlsread('features18IR', 'exp17', 'B19:X19');
bp17 = xlsread('features18IR', 'exp17', 'B18:X18');

pTrain18 = xlsread('features18IR', 'exp18', 'B1:U18');
tTrain18 = xlsread('features18IR', 'exp18', 'B19:U19');
bp18 = xlsread('features18IR', 'exp18', 'B18:U18');


pTrain19 = xlsread('features18IR', 'exp19', 'B1:K18');
tTrain19 = xlsread('features18IR', 'exp19', 'B19:K19');
bp19 = xlsread('features18IR', 'exp19', 'B18:K18');

pTrain20 = xlsread('features18IR', 'exp20', 'B1:AA18');
tTrain20 = xlsread('features18IR', 'exp20', 'B19:AA19');
bp20 = xlsread('features18IR', 'exp20', 'B18:AA18');

pTrain22 = xlsread('features18IR', 'exp22', 'B1:V18');
tTrain22 = xlsread('features18IR', 'exp22', 'B19:V19');
bp22 = xlsread('features18IR', 'exp22', 'B18:V18');

pTrain23 = xlsread('features18IR', 'exp23', 'B1:V18');
tTrain23 = xlsread('features18IR', 'exp23', 'B19:V19');
bp23 = xlsread('features18IR', 'exp23', 'B18:V18');

pTrain24 = xlsread('features18IR', 'exp24', 'B1:Y18');
tTrain24 = xlsread('features18IR', 'exp24', 'B19:Y19');
bp24 = xlsread('features18IR', 'exp24', 'B18:Y18');

pTrain25 = xlsread('features18IR', 'exp25', 'B1:T18');
tTrain25 = xlsread('features18IR', 'exp25', 'B19:T19');
bp25 = xlsread('features18IR', 'exp25', 'B18:T18');

pTrain26 = xlsread('features18IR', 'exp26', 'B1:P18');
tTrain26 = xlsread('features18IR', 'exp26', 'B19:P19');
bp26 = xlsread('features18IR', 'exp26', 'B18:P18');

pTrain33 = xlsread('features18IR', 'exp33', 'B1:U18');
tTrain33 = xlsread('features18IR', 'exp33', 'B19:U19');
bp33 = xlsread('features18IR', 'exp33', 'B18:U18');
```

```
pTrain41 = xlsread('features18IR', 'exp41', 'B1:AB18');
tTrain41 = xlsread('features18IR', 'exp41', 'B19:AB19');
bp41 = xlsread('features18IR', 'exp41', 'B18:AB18');

pTrain43 = xlsread('features18IR', 'exp43', 'B1:AB18');
tTrain43 = xlsread('features18IR', 'exp43', 'B19:AB19');
bp43 = xlsread('features18IR', 'exp43', 'B18:AB18');

pTrain44 = xlsread('features18IR', 'exp44', 'B1:AA18');
tTrain44 = xlsread('features18IR', 'exp44', 'B19:AA19');
bp44 = xlsread('features18IR', 'exp44', 'B18:AA18');

pTrain45 = xlsread('features18IR', 'exp45', 'B1:T18');
tTrain45 = xlsread('features18IR', 'exp45', 'B19:T19');
bp45 = xlsread('features18IR', 'exp45', 'B18:T18');


pTrain71a = xlsread('features18IR', 'exp71', 'B1:AI18');
tTrain71a = xlsread('features18IR', 'exp71', 'B19:AI19');
bp71a = xlsread('features18IR', 'exp71', 'B18:AI18');



pTrain73a = xlsread('features18IR', 'exp73a', 'B1:AB18');
tTrain73a = xlsread('features18IR', 'exp73a', 'B19:AB19');
bp73a = xlsread('features18IR', 'exp73a', 'B18:AB18');

pTrain73b = xlsread('features18IR', 'exp73b', 'B1:Y18');
tTrain73b = xlsread('features18IR', 'exp73b', 'B19:Y19');
bp73b = xlsread('features18IR', 'exp73b', 'B18:Y18');


pTrain72 = xlsread('features18IR', 'exp72', 'B1:AH18');
tTrain72 = xlsread('features18IR', 'exp72', 'B19:AH19');
bp72 = xlsread('features18IR', 'exp72', 'B18:AH18');

pTrain88 = xlsread('features18IR', 'exp88', 'B1:Y18');
tTrain88 = xlsread('features18IR', 'exp88', 'B19:Y19');
bp88 = xlsread('features18IR', 'exp88', 'B18:Y18');


pTrain = [pTrain1 pTrain2 pTrain3 pTrain4 pTrain5 pTrain7 pTrain8
pTrain9 pTrain11 pTrain12 pTrain13 pTrain14 pTrain15 pTrain18 pTrain19
pTrain20 pTrain22 pTrain23 pTrain26 pTrain88 pTrain73a pTrain73b
pTrain72 pTrain45 pTrain24 pTrain33 pTrain71a pTrain41 pTrain43
pTrain44];
tTrain = [tTrain1 tTrain2 tTrain3 tTrain4 tTrain5 tTrain7 tTrain8
tTrain9 tTrain11 tTrain12 tTrain13 tTrain14 tTrain15 tTrain18 tTrain19
tTrain20 tTrain22 tTrain23 tTrain26 tTrain88 tTrain73a tTrain73b
tTrain72 tTrain45 tTrain24 tTrain33 tTrain71a tTrain41 tTrain43
tTrain44];

state=0;
[pn,ps1] = mapstd(pTrain);
```

```
[ptrans,ps2] = processpca(pn, 0.02);
net=newff(ptrans,tTrain,2,{'tansig' 'purelin'},'Trainlm');
 rands(0,100);
 net.initFcn = 'initlay';
 net.layers{1}.initFcn = 'initwb';
 net.inputweights{1,1}.initFcn='rands';
 net.layerWeights{1,1}.initFcn = 'rands';
 net.biases{1}.initFcn='rands';
  net.performFcn = 'msereg';
  net.performParam.ratio = 0.5;
  net.trainParam.show=50;
  net.trainParam.epochs=500;
  net.trainParam.goal=0.01;
  net1=train(net,ptrans,tTrain);
  pnewn78b = mapstd('apply',pTrain1,ps1);
  pnewtrans78b = processpca('apply',pnewn1,ps2);
  a78b = sim(net78b,pnewtrans78b);
  linearcofe1=polyfit(a78b,bp78b,1);
  sysp1=polyval(linearcofe1,0);
  disp(['sp78b:' num2str(sysp1)]);
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

%% DP Determination
clear all
cd('G:\thesis\ANN modification\New Folder')
pTrain1 = xlsread('features1', 'exp1', 'B1:Q10');
tTrain1 = xlsread('features1', 'exp1', 'B12:Q12');
bp1 = xlsread('features1', 'exp1', 'B10:Q10');
pTrain2 = xlsread('features1', 'exp2', 'B1:V10');
tTrain2 = xlsread('features1', 'exp2', 'B12:V12');
bp2 = xlsread('features1', 'exp2', 'B10:V10');
pTrain3 = xlsread('features1', 'exp3', 'B1:U10');
tTrain3 = xlsread('features1', 'exp3', 'B12:U12');
bp3 = xlsread('features1', 'exp3', 'B10:U10');
pTrain4 = xlsread('features1', 'exp4', 'B1:X10');
tTrain4 = xlsread('features1', 'exp4', 'B12:X12');
bp4 = xlsread('features1', 'exp4', 'B10:X10');
pTrain5 = xlsread('features1', 'exp5', 'B1:U10');
tTrain5 = xlsread('features1', 'exp5', 'B12:U12');
bp5 = xlsread('features1', 'exp5', 'B10:U10');
pTrain6 = xlsread('features1', 'exp6', 'B1:S10');
tTrain6 = xlsread('features1', 'exp6', 'B12:S12');
bp6 = xlsread('features1', 'exp6', 'B10:S10');
pTrain7 = xlsread('features1', 'exp7', 'B1:X10');
tTrain7 = xlsread('features1', 'exp7', 'B12:X12');
bp7 = xlsread('features1', 'exp7', 'B10:X10');
pTrain8 = xlsread('features1', 'exp8', 'B1:S10');
tTrain8 = xlsread('features1', 'exp8', 'B12:S12');
bp8 = xlsread('features1', 'exp8', 'B10:S10');
pTrain9 = xlsread('features1', 'exp9', 'B1:U10');
tTrain9 = xlsread('features1', 'exp9', 'B12:U12');
bp9 = xlsread('features1', 'exp9', 'B10:U10');
pTrain10 = xlsread('features1', 'exp10', 'B1:AC10');
tTrain10 = xlsread('features1', 'exp10', 'B12:AC12');
bp10 = xlsread('features1', 'exp10', 'B10:AC10');
pTrain11 = xlsread('features1', 'exp11', 'B1:X10');
tTrain11 = xlsread('features1', 'exp11', 'B12:X12');
bp11 = xlsread('features1', 'exp11', 'B10:X10');
pTrain12 = xlsread('features1', 'exp12', 'B1:AB10');
tTrain12 = xlsread('features1', 'exp12', 'B12:AB12');
bp12 = xlsread('features1', 'exp12', 'B10:AB10');
```

```
pTrain13 = xlsread('features1', 'exp13', 'B1:AA10');
tTrain13 = xlsread('features1', 'exp13', 'B12:AA12');
bp13 = xlsread('features1', 'exp13', 'B10:AA10');

pTrain14 = xlsread('features1', 'exp14', 'B1:V10');
tTrain14 = xlsread('features1', 'exp14', 'B12:V12');
bp14 = xlsread('features1', 'exp14', 'B10:V10');

pTrain15 = xlsread('features1', 'exp15', 'B1:W10');
tTrain15 = xlsread('features1', 'exp15', 'B12:W12');
bp15 = xlsread('features1', 'exp15', 'B10:W10');

pTrain16 = xlsread('features1', 'exp16', 'B1:S10');
tTrain16 = xlsread('features1', 'exp16', 'B12:S12');
bp16 = xlsread('features1', 'exp16', 'B10:S10');

pTrain17 = xlsread('features1', 'exp17', 'B1:X10');
tTrain17 = xlsread('features1', 'exp17', 'B12:X12');
bp17 = xlsread('features1', 'exp17', 'B10:X10');

pTrain18 = xlsread('features1', 'exp18', 'B1:U10');
tTrain18 = xlsread('features1', 'exp18', 'B12:U12');
bp18 = xlsread('features1', 'exp18', 'B10:U10');


pTrain19 = xlsread('features1', 'exp19', 'B1:L10');
tTrain19 = xlsread('features1', 'exp19', 'B12:L12');
bp19 = xlsread('features1', 'exp19', 'B10:L10');

pTrain20 = xlsread('features1', 'exp20', 'B1:AC10');
tTrain20 = xlsread('features1', 'exp20', 'B12:AC12');
bp20 = xlsread('features1', 'exp20', 'B10:AC10');

pTrain22 = xlsread('features1', 'exp22', 'B1:V10');
tTrain22 = xlsread('features1', 'exp22', 'B12:V12');
bp22 = xlsread('features1', 'exp22', 'B10:V10');

pTrain23 = xlsread('features1', 'exp23', 'B1:X10');
tTrain23 = xlsread('features1', 'exp23', 'B12:X12');
bp23 = xlsread('features1', 'exp23', 'B10:X10');

pTrain24 = xlsread('features1', 'exp24', 'B1:Z10');
tTrain24 = xlsread('features1', 'exp24', 'B12:Z12');
bp24 = xlsread('features1', 'exp24', 'B10:Z10');

pTrain25 = xlsread('features1', 'exp25', 'B1:T10');
tTrain25 = xlsread('features1', 'exp25', 'B12:T12');
bp25 = xlsread('features1', 'exp25', 'B10:T10');

pTrain26 = xlsread('features1', 'exp26', 'B1:Q10');
tTrain26 = xlsread('features1', 'exp26', 'B12:Q12');
bp26 = xlsread('features1', 'exp26', 'B10:Q10');

pTrain33 = xlsread('features1', 'exp33', 'B1:R10');
tTrain33 = xlsread('features1', 'exp33', 'B12:R12');
bp33 = xlsread('features1', 'exp33', 'B10:R10');
```

```
pTrain41 = xlsread('features1', 'exp41', 'B1:AB10');
tTrain41 = xlsread('features1', 'exp41', 'B12:AB12');
bp41 = xlsread('features1', 'exp41', 'B10:AB10');

pTrain42 = xlsread('features1', 'exp42', 'B1:AB10');
tTrain42 = xlsread('features1', 'exp42', 'B12:AB12');
bp42 = xlsread('features1', 'exp42', 'B10:AB10');

pTrain43 = xlsread('features1', 'exp43', 'B1:AB10');
tTrain43 = xlsread('features1', 'exp43', 'B12:AB12');
bp43 = xlsread('features1', 'exp43', 'B10:AB10');

pTrain44 = xlsread('features1', 'exp44', 'B1:Y10');
tTrain44 = xlsread('features1', 'exp44', 'B12:Y12');
bp44 = xlsread('features1', 'exp44', 'B10:Y10');

pTrain45 = xlsread('features1', 'exp45', 'B1:R10');
tTrain45 = xlsread('features1', 'exp45', 'B12:R12');
bp45 = xlsread('features1', 'exp45', 'B10:R10');

pTrain71a = xlsread('features1', 'exp71', 'B1:AI10');
tTrain71a = xlsread('features1', 'exp71', 'B12:AI12');
bp71a = xlsread('features1', 'exp71', 'B10:AI10');

pTrain73a = xlsread('features1', 'exp73a', 'B1:AA10');
tTrain73a = xlsread('features1', 'exp73a', 'B12:AA12');
bp73a = xlsread('features1', 'exp73a', 'B10:AA10');

pTrain73b = xlsread('features1', 'exp73b', 'B1:Y10');
tTrain73b = xlsread('features1', 'exp73b', 'B12:Y12');
bp73b = xlsread('features1', 'exp73b', 'B10:Y10');

pTrain72 = xlsread('features1', 'exp72', 'B1:AG10');
tTrain72 = xlsread('features1', 'exp72', 'B12:AG12');
bp72 = xlsread('features1', 'exp72', 'B10:AG10');

pTrain88 = xlsread('features1', 'exp88', 'B1:Y10');
tTrain88 = xlsread('features1', 'exp88', 'B12:Y12');
bp88 = xlsread('features1', 'exp88', 'B10:Y10');

pTrain78b = xlsread('features1', 'exp78b', 'B1:AI10');
tTrain78b = xlsread('features1', 'exp78b', 'B12:AI12');
bp78b = xlsread('features1', 'exp78b', 'B10:AI10');

pTrain = [pTrain1 pTrain2 pTrain3 pTrain4 pTrain5 pTrain7 pTrain8
pTrain9 pTrain11 pTrain12 pTrain13 pTrain14 pTrain15 pTrain18 pTrain19
pTrain20 pTrain22 pTrain23 pTrain26 pTrain60 pTrain73a pTrain73b
pTrain72 pTrain45 pTrain24 pTrain33 pTrain71a pTrain41 pTrain43
pTrain44];
tTrain = [tTrain1 tTrain2 tTrain3 tTrain4 tTrain5 tTrain7 tTrain8
tTrain9 tTrain11 tTrain12 tTrain13 tTrain14 tTrain15 tTrain18 tTrain19
tTrain20 tTrain22 tTrain23 tTrain26 tTrain60 tTrain73a tTrain73b
tTrain72 tTrain45 tTrain24 tTrain33 tTrain71a tTrain41 tTrain43
tTrain44];

state=0;
[pn,ps1] = mapstd(pTrain);
```

```
[ptrans,ps2] = processpca(pn, 0.02);
net=newff(ptrans,tTrain,2,{'tansig' 'purelin'},'Trainlm');
 rands(0,100);
 net.initFcn = 'initlay';
 net.layers{1}.initFcn = 'initwb';
 net.inputweights{1,1}.initFcn='rands';
 net.layerWeights{1,1}.initFcn = 'rands';
 net.biases{1}.initFcn='rands';
 net.performFcn = 'msereg';
 net.performParam.ratio = 0.5;
 net.trainParam.show=50;
 net.trainParam.epochs=500;
 net.trainParam.goal=0.01;
 net1=train(net,ptrans,tTrain);
 pnewn78b = mapstd('apply',pTrain78b,ps1);
 pnewtrans78b = processpca('apply',pnewn78b,ps2);
 a78b = sim(net1,pnewtrans78b);
 linearcofe78b=polyfit(a78b,bp78b,1);
 sysp78b=polyval(linearcofe78b,0);
 disp(['sp78b:' num2str(sysp78b)]);
```

Functions code

```
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

%function to find area under the curve
%return a value
function Area=funArea(xxWin)

xx=abs(xxWin);
%Calculate area under the curve
Area=trapz(xx);

++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

%function to find total amplitude of each peak
%return a value
function Amp=funAmp(x)

%find turning pt
TPInd=funTurnPt(x)+1;

FirstInd=max(find(x(1:TPInd(1))==0));
LastInd=min(find(x(TPInd(end):end)==0))+TPInd(end)-1;
TPInd=[FirstInd TPInd LastInd];

Amp=0;
for j=1:length(TPInd)-1
    Amp=Amp+abs(x(TPInd(j+1))-x(TPInd(j)));
end

++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

%function to find dPdt for each point
%return two values; max/min dPdt
function dPdt=fundPdt(x,t)

dpdt=[];
dpdt(1:length(x))=0;
```

```
for j=2:length(x)-1
    %calculate dP/dt at each point
    dpdt(j)=(x(j+1)-x(j-1))/(t(j+1)-t(j-1));
end

dPdt(1)=max(dpdt);  %max dPdt
dPdt(2)=min(dpdt);  %min dPdt

++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

%function to find minimum turning point
%return indices
function ind=funFindMin(x)

xDiff=diff(x);
j=1;
ind=[];
for i=1:length(xDiff)-1
    if xDiff(i)<0 && xDiff(i+1)>0
        ind(j)=i;
        j=j+1;
    end
end
if isempty(ind)
    ind=1;
end

++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

%function to find maximum turning point
%return indices
function ind=funFindMax(x)

xDiff=diff(x);
j=1;
ind=[];
for i=1:length(xDiff)-1
    if xDiff(i)>0 && xDiff(i+1)<0
        ind(j)=i;
        j=j+1;
    end
end
if isempty(ind)
    ind=1;
end

++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

% Beat Detection

function
[Beat,IndMax,IndMin1,IndMin2)]=funHB(meanBeat,Beat,IndMax,IndMin1,IndM
in2)
  i=1;

 while i<=length(Beat)

         if (Beat(i)< (meanBeat/1.42))
             if i==1
```

```
            if Beat(1)> Beat(2)

               Beat=Beat(3:end);
               IndMax=IndMax(3:end);
               IndMin1=IndMin1(3:end);
               IndMin2=IndMin2(3:end);
             else
                Beat=Beat(2:end);
                IndMax=IndMax(2:end);
                IndMin1=IndMin1(2:end);
                IndMin2=IndMin2(2:end);
             end
            else
              if Beat(i) > Beat(i+1)

                 Beat=[Beat(1:i-1) Beat(i+2:end)];
                 IndMax=[IndMax(1:i-1) IndMax(i+2:end)];
                 IndMin1=[IndMin1(1:i-1) IndMin1(i+2:end)];
                 IndMin2=[IndMin2(1:i-1) IndMin2(i+2:end)];

               else
                 Beat=[Beat(1:i-1) Beat(i+1:end)];
                 IndMax=[IndMax(1:i-1) IndMax(i+1:end)];
                 IndMin1=[IndMin1(1:i-1) IndMin1(i+1:end)];
                 IndMin2=[IndMin2(1:i-1) IndMin2(i+1:end)];

                end
               end
          else
              if Beat(i)>(meanBeat*1.3)
                  if i==1
                      if Beat(1)< Beat(2)

                           Beat=Beat(3:end);
                           IndMax=IndMax(3:end);
                           IndMin1=IndMin1(3:end);
                           IndMin2=IndMin2(3:end);

                      else
                           Beat=Beat(2:end);
        IndMax=IndMax(2:end);
        IndMin1=IndMin1(2:end);
        IndMin2=IndMin2(2:end);

    end
else
    if  Beat(i)< Beat(i+1)

        Beat=[Beat(1:i-1) Beat(i+2:end)];
        IndMax=[IndMax(1:i-1) IndMax(i+2:end)];
        IndMin1=[IndMin1(1:i-1) IndMin1(i+2:end)];
        IndMin2=[IndMin2(1:i-1) IndMin2(i+2:end)];

    else

  Beat=[Beat(1:i-1) Beat(i+1:end)];
  IndMax=[IndMax(1:i-1) IndMax(i+1:end)];
  IndMin1=[IndMin1(1:i-1) IndMin1(i+1:end)];
  IndMin2=[IndMin2(1:i-1) IndMin2(i+1:end)];
```

```
        end

 end


                    end
                end
                i=i+1;
            en
```

```
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
```

```
%function to find mean magnitude for different frequency range


function Mag=funMag(xxWin,tt,N,fs)

   xxWinfft=fft(xxWin);
   NoX=ceil(length(xxWinfft)/2);
   HalfX=xxWinfft(1:NoX);
   F=fs*(0:NoX-1)/length(xxWinfft);

   Y=HalfX;


        ind5=min(find(F>0.5));
        ind10=min(find(F>5));
        ind15=min(find(F>10));
        ind20=min(find(F>15));
        ind25=min(find(F>20));
        ind35=max(find(F<25));

        %calculate mean magnitude
        Mag(1)=mean(Y(ind(0.5):ind5));   %freq between 5~35Hz
        Mag(2)=mean(Y(ind5:ind10));
        Mag(3)=mean(Y(ind10:ind15));
        Mag(4)=mean(Y(ind15:ind20));
        Mag(5)=mean(Y(ind20:ind25));


++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

%function to find mean PSD for different frequency range
%return a vector
function PSD=funPSD(xxWin,tt,N,fs)


%fft calculation
xxfft=fft(xxWin);
NoX=ceil(length(xxfft)/2);
F=fs*(0:NoX-1)/length(xxfft);

%PSD
Pxx=xxfft.*conj(xxfft)/length(xxfft);
HalfPxx=Pxx(1:NoX);
```

```
P=HalfPxx;

ind5=min(find(F>0.5));
ind10=min(find(F>5));
ind15=min(find(F>10));
ind20=min(find(F>15));
ind25=min(find(F>20));
ind35=max(find(F<25));

%calculate mean PSD
PSD(1)=mean(P(ind(0.5):ind5,:));
PSD(2)=mean(P(ind5:ind10,:));
PSD(3)=mean(P(ind10:ind15,:));
PSD(4)=mean(P(ind15:ind20,:));
PSD(5)=mean(P(ind20:ind25,:));


++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

%function to find the max. positive/negative rate of change
%return two values
function ROC=funROC(xx,tt)

TPInd=funTurnPt(xx)+1;
FirstInd=max(find(xx(1:TPInd(1))==0));
LastInd=min(find(xx(TPInd(end):end)==0))+TPInd(end)-1;
TPInd=[FirstInd TPInd LastInd];

roc=[];
for j=1:length(TPInd)-1
    %calculate rate of change
    roc(j)=(xx(TPInd(j+1))-xx(TPInd(j)))/(tt(TPInd(j+1))-tt(TPInd(j)));
end

ROC(1)=max(roc);
ROC(2)=min(roc);


++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

%funtion to find the rise time
%return a value

function RT= funRT(t,ind2,ind1)

RT=[];
for i=1:length(ind1)-1
    RT=t(ind1(i))-t(ind2(i));
end


++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

%function to find each turning point
%return indices
function ind=funTurnPt(x)

xDiff=diff(x);
j=1;
```

```
ind=[];
for i=1:length(xDiff)-1
    if (xDiff(i)>0 && xDiff(i+1)<0) || (xDiff(i)<0 && xDiff(i+1)>0)
        ind(j)=i;
        j=j+1;
    end
end
if isempty(ind)
    ind=1;
end

++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
```

APPENDIX II Ethic approval

M E M O R A N D U M

Auckland University of Technology Ethics Committee (AUTEC)

To:	Ahmed Al-Jumaily
From:	**Madeline Banda** Executive Secretary, AUTEC
Date:	18 November 2008
Subject:	Ethics Application Number 08/232 **Creation of a database of blood pressure signals collected using Pulsecor's wideband external pulse (WEP) monitor.**

Dear Ahmed

Thank you for providing written evidence as requested. I am pleased to advise that it satisfies the points raised by the Auckland University of Technology Ethics Committee (AUTEC) at their meeting on 13 October 2008 and that I have approved your ethics application, including the requested amendments allowing an additional researcher and an extension to the storage time of data and consent forms. This delegated approval is made in accordance with section 5.3.2 of AUTEC's *Applying for Ethics Approval: Guidelines and Procedures* and is subject to endorsement at AUTEC's meeting on 8 December 2008.

Your ethics application is approved for a period of three years until 18 November 2011.

I advise that as part of the ethics approval process, you are required to submit the following to AUTEC:

- A brief annual progress report using form EA2, which is available online through *http://www.aut.ac.nz/about/ethics*. When necessary this form may also be used to request an extension of the approval at least one month prior to its expiry on 18 November 2011;
- A brief report on the status of the project using form EA3, which is available online through *http://www.aut.ac.nz/about/ethics*. This report is to be submitted either when the approval expires on 18 November 2011 or on completion of the project, whichever comes sooner;

It is a condition of approval that AUTEC is notified of any adverse events or if the research does not commence. AUTEC approval needs to be sought for any alteration to the research, including any alteration of or addition to any documents that are provided to participants. You are reminded that, as applicant, you are responsible for ensuring that research undertaken under this approval occurs within the parameters outlined in the approved application.

Please note that AUTEC grants ethical approval only. If you require management approval from an institution or organisation for your research, then you will need to make the arrangements necessary to obtain this.

When communicating with us about this application, we ask that you use the application number and study title to enable us to provide you with prompt service. Should you have any further enquiries regarding this matter, you are welcome to contact Charles Grinter, Ethics Coordinator, by email at charles.grinter@aut.ac.nz or by telephone on 921 9999 at extension 8860.

On behalf of the AUTEC and myself, I wish you success with your research and look forward to reading about it in your reports.

Yours sincerely

Madeline Banda
Executive Secretary
Auckland University of Technology Ethics Committee
Cc: Ashis Mookerjee Ashis.mookerjee@aut.ac.nz, Hai Lan, Wayne Hing

APPENDIX III Participant Information Sheet

Participant Information Sheet

AUT UNIVERSITY
TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Date Information Sheet Produced:

23 March 2012

Project Title

Creation of a database of brachial artery deformation during blood pressure measurement using MRI device

An Invitation

The Cardiovascular System Dynamics Group of the Institute of Biomedical Technologies is working with Pulsecor Limited to develop non-invasive techniques for the accurate estimation of blood pressure both in clinical environment and in ambulatory environment. For the development of these techniques, we need to establish the numerical model for further research first. To investigate the effects of tissue properties in blood pressure measurement, we want to measure blood pressure signals, occlusive cuff pressure and arm deformation simultaneously. We invite you to participate in this research by allowing us to measure your blood pressure signals and arm deformation image using a safe, commercially available blood pressure monitor and MRI device.

The data collected through this research will be used validate the current numerical model, to develop and test methods of accurately estimating blood pressure and ambulatory blood pressure measurement.

Your participation is entirely voluntary and you may withdraw at any time prior to the completion of data collection.

What is the purpose of this research?

The aim of this project is to create a database of arm deformation under the occlusive cuff during blood pressure measurement using MRI device. Blood pressure waveforms will be recorded using Pulsecor's wideband external pulse (WEP) monitor simultaneously. The recordings will be used to establish the database for validate the current numerical model of the blood pressure measurement which is used to investigate oscillometric method and ambulatory blood pressure method.

Data collected in this research project will be used by a number of researchers from within the university to develop and test blood pressure measurement algorithms.

Aggregated data from this research will be included in publications and presentations of the researchers.

How was I chosen for this invitation?

We are interested in establishing the range of blood pressure signals and arm deformation during blood pressure measurement. We are inviting people to participate according to their age, gender and arm size criteria in this research.

What will happen in this research?

The entire blood pressure measuring process will be carried out by using a commercially-available blood pressure monitor (Pulsecor's WEP monitor). The upper arm deformation will be recorded by MRI device simultaneously. These MRI data will be used to establish the 3D model of the upper arm. Combining with blood pressure signals, the results can be used to comparing current numerical model.

Please note that the recorded data will be archived and securely stored till 1 January 2025.

What are the discomforts and risks?

The cuff based technique for the measurement of blood pressure and MRI technique have been used in the clinical environment for a large part of the past 20 years. No physical discomforts or incapacity have been noted in people who used these techniques (we do not anticipate any ACC claims due to our measurement).

Participants may feel embarrassed if their blood pressure is outside the normal range (they might prefer to be told in private). MRI is a non contact measuring technique. Common MRI side effects are headaches, dizziness, sweating, nausea, fatigue. These symptoms of MRI side effect are temporary, mostly caused by the noise during scan. No further action required.

How will my privacy be protected?

You will be given a random number which will be recorded in our database to ensure the confidentiality of the collected data; the database will not contain your name. Your name will be recorded on the Consent Form which will only be accessed by the Project Manager for administrative purposes. Only anonymised data will be available to the individual researchers.

The database will be securely stored within the AUT Institute of Biomedical Technologies, where access to it will be controlled.

What are the costs of participating in this research?

Your participation will require approximately 50 minutes of your time and not more that 70 minutes.

How is this research being funded?

Pulsecor Limited (a NZ-based manufacturer of cardiovascular monitors) will be providing their WEP monitors for data collection. They will also provide training to the people collecting the data on how to use their monitors. The Managing Director of the company (Dr. Andrew Lowe) is also a member of the research team.

What opportunity do I have to consider this invitation?

You are welcome to consider this invitation for as long as it takes you to make up your mind whether you would like to participate or not. We are happy to answer any questions that you may have.

Furthermore, since your participation is entirely voluntary, you may choose to withdraw at any time and for any reason prior to the completion of data collection.

How do I agree to participate in this research?

If you wish to participate, please sign and return the consent form attached with this information sheet.

You may also keep this participation information sheet and a copy of the consent form if you wish to.

Will I receive feedback on the results of this research?

Yes. Unless you have indicated otherwise in your consent form, the results of your measurement will be verbally conveyed to you immediately after measurement. All participants will be mailed a letter from the Project Manager confirming your blood pressure reading.

Findings of this research will be listed on the Institute of Biomedical Technologies website, www.ibtec.org.nz. You are welcome to check the website at a later date to view the feedback on this research.

Whom do I contact for further information about this research?

Researcher Contact Details:

Name: Andrew Lowe email: andrew.lowe@pulsecor.com Phone: 280-3504

This document contains a total of 3 pages. Please ensure that you read all the pages before signing the Consent Form.

Name: Ashis Mookerjee email: ashis.mookerjee@aut.ac.nz Phone: 921-9999 extn. 8617

Name: Mohammad Al-Rawi email: malrawi@aut.ac.nz Phone: 921-9999 extn. 8617

Project Manager Contact Details:

Name: Hai Lan email: hlan@aut.ac.nz Phone: 921-9999 extn. 8617

Project Supervisor Contact Details:

Name: Ahmed Al-Jumaily email: ahmed.al-jumaily@ aut.ac.nz Phone: 921-9777

What do I do if I have concerns about this research?

Any concerns regarding the nature of this project should be notified in the first instance to the Project Supervisor or the Project Manager. Their contact details are listed above.

Concerns regarding the conduct of the research should be notified to the Executive Secretary, AUTEC, Madeline Banda, *madeline.banda@aut.ac.nz* , 921 9999 extn. 8044.

Approved by the Auckland University of Technology Ethics Committee on 18th Nov 2008, AUTEC Reference number 08/232.

This document contains a total of 3 pages. Please ensure that you read all the pages before signing the Consent Form.

APPENDIX IV Consent Form

Consent Form

Project title:	Creation of a database of blood pressure signals collected using Pulsecor's wideband external pulse monitor		
Project Manager:	Ashis Mookerjee	**Project Supervisor:**	Ahmed Al-Jumaily
Researchers:	Andrew Lowe, Hai Lan, Wayne Hing and Xiaoqi Ma		

- I have read and understood the information provided about this research project in the Information Sheet dated 23 March 2012.
- I have had the opportunity to ask questions and have them answered.
- I understand that I may withdraw any information that I have provided for this project at any time prior to data collection without being disadvantaged in any way.
- I agree to discuss my health condition and answer all questions asked correctly to the best of my knowledge.
- I agree to have my blood pressure readings recorded and archived as part of an anonymous database. I am aware that this information will be maintained for a period of 15 years (i.e. up to 1 December 2023).
- I am aware that the data collected from this project may be provided on the Institute of Biomedical Technologies website, www.ibtec.org.nz, in an anonymous form.
- My blood pressure readings should be communicated to me in a private confidential manner (please tick one): Yes o No o

Participant's signature: ..... Date: .....

Participant's name: .....

Participant's Contact Details:

.....

.....

.....

Approved by the Auckland University of Technology Ethics Committee on 18th Nov 2008 AUTEC Reference number 08/232

Note: A copy of the completed consent form will be mailed to the address provided.

FOR OFFICIAL USE ONLY

Participant's age band (please circle one): 20-29 30-39 40-49 50-59 60-69 70-79

Participant's gender (please circle one): male female

Other relevant details (please tick all relevant items): pregnant o smoker o

on cardiovascular medication o if yes, which: .....

Database reference number: ..... Data recorded by: .....