Computerised Detection and Classification of Five Cardiac Conditions

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Abstract

An electrocardiogram (ECG) is a bioelectrical signal which records the heart's electrical activity versus time. It is an important diagnostic tool for assessing heart functions. The interpretation of ECG signal is an application of pattern recognition. The techniques used in this pattern recognition comprise: signal pre-processing, QRS detection, feature extraction and neural network for signal classification. In this project, signal processing and neural network toolbox will be used in Matlab environment. The processed signal source came from the Massachusetts Institute of Technology Beth Israel Hospital (MIT-BIH) arrhythmia database which was developed for research in cardiac electro-physiology.

Five conditions of ECG waveform were selected from MIT-BIH database in this research. The ECG samples were processed and normalised to produce a set of features that can be used in different structures of neural network and subsequent recognition rates were recorded. Backpropagation algorithm will be considered for different structures of neural network and the performance in each case will be measured. This research is focused on finding the best neural network structure for ECG signal classification and a number of signal pre-processing and QRS detection algorithms were also tested. The feature extraction is based on an existing algorithm.

The results of recognition rates are compared to find a better structure for ECG classification. Different ECG feature inputs were used in the experiments to compare and find a desirable features input for ECG classification. Among different structures, it was found that a three layer network structure with 25 inputs, 5 neurons in the output layer and 5 neurons in its hidden layers possessed the best performance with highest recognition rate of 91.8% for five cardiac conditions. The average accuracy rate for this kind of structure with different structures was 84.93%. It was also tested that 25 feature input is suitable for training and testing in ECG classification. Based on this result, the method of using important ECG features plus a suitable number of compressed ECG signals can dramatically decrease the complexity of the neural network structure, which can increase the testing speed and the accuracy rate of the network verification.

It also gives further suggestions to plan the experiments for the future work.

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NOTATIONS

A	Atrial premature beat
A/D	Analogy to digital
ANN	Artificial Neural network
AV	Atrio Ventricular
BP	Backpropagation
DBNN	Decision based neural network
DCT	Discrete Cosine Transform
DSP	Digital signal processing
ECG	Electrocardiogram
F	Fusion of paced and normal beats
FFT	Fast Fourier transform
FIR	Finite impulse response
GUI	Graphical user interface
HBR	Heart beat rate
I/O	Input/Output
IIR	Infinite impulse response
ISO	Isoelectric line
LMS	Least Mean Square
LVQ	Linear vector quantisation
MART	Multi-channel adaptive resonance theory
MIT-BIH	Massachusetts Institute of Technology Beth Israel Hospital database
MSE	Mean Squared Error
N	Normal
NLMS	Normalised LMS algorithms

P	Paced beats
PSD	Power spectral density
R	Right bundle branch block
RBBB	Right bundle branch block
SA	Sino Atrial
SNR	Signal to noise ratio
SOM	Self organization map
STD	Standard deviation

Chapter 1
Introduction

In the hospital and health community, there are considerable commercial interests in the classification of the Electrocardiogram signals (ECG). This research is aimed at developing a system that categorises the ECG signals. Signal processing techniques and artificial neural network (ANN) will be used in this project to implement a real time processing, intelligent, cost effective, and easy-to-use ECG diagnostic system. It also gives suggestion to improve the experiments and use of remote diagnostic medical systems for diagnosing at homes in the future. This research is currently at the experimental stage at the moment but will be realised in the future work.

The ECG is a bioelectric signal, which records the heart's electrical activity versus time; therefore it is an important diagnostic tool for assessing heart function. The electrical current due to the depolarisation of the Sinus Atria (SA) node stimulates the surrounding myocardium and spreads into the heart tissues. A small proportion of the electrical current flow to the body surface. By applying electrodes on the skin at the selected points, the electrical potential generated by this current can be recorded as an ECG signal.

The interpretation of the ECG signal is an application of pattern recognition. The purpose of pattern recognition is to automatically categorise a system into one of a number of different classes (Chazal D. P., 1998). An experienced cardiologist can easily diagnose various heart diseases just by looking at the ECG waveforms printout. In some specific cases, sophisticated ECG analysers achieve a higher degree of accuracy than that of cardiologist, but at present there remains a group of ECG waveforms that are too difficult to identify by computers. However, the use of computerised analysis of easily obtainable ECG waveforms can considerably reduce the doctor's workload. Some analysers assist the doctor by producing a diagnosis; others provide a limited number of parameters by which the doctor can make his diagnosis (Granit R., 2003).

As illustrated in Figure 1.1 there are four major steps to the ECG signal pattern recognition, namely, pre-processing of the signal, QRS detection, ECG feature extraction and ECG signal classification (Chazal D. P., 1998).

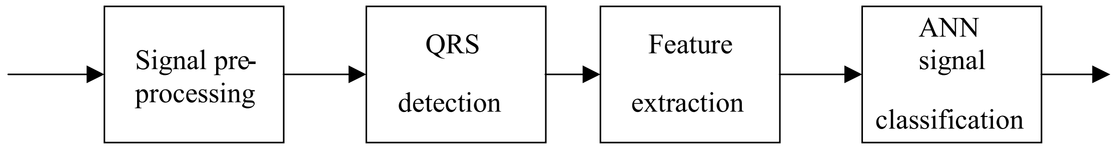

Figure 1.1 Pattern Recognition

The first step is the measurement of acquisition period, which requires a wide range of the ECG signal collection including different abnormalities. The data could be collected from real subjects in the future, but it is presently available from the database. The second step is QRS detection which to corresponds to the period of ventricular contraction or depolarisation. The third step is to find the smallest set of features that maximise the classification performance of the next step. ECG feature extraction is mainly used in this step.

The choice of features depends on the techniques used in the forth step. Consequently the set of features that are optimal for one technique are not necessarily optimal for another. Because of the unknown interactions of different sets of features, it is impossible to predict the optimum features for a chosen classification technique. Different techniques such as statistical classifiers, artificial neural network and artificial intelligence can be used for ECG classification. The artificial neural network will be used in this project to do the ECG classification. Neural networks are especially useful for classification function, which are tolerant of some imprecision if plenty of training data is available. If there are enough training data and sufficient computing resources for a neural network, it is possible to train a feed-forward neural network to perform almost any signal classification solution.

Generally, the ECG is one of the oldest and the most popular instrument-bound measurements in medical applications. It has followed the progress of instrumentation technology. Its most recent evolutionary step, to the computer-based system, has allowed patients to wear their computer monitor or has provided an enhanced, high resolution ECG that has opened new scene of ECG analysis and interpretations (Carr J. J. and John M.Brown J. M., 1998).

1.1 The Heart function and ECG

The heart contains four chambers and several one-way valves as shown in Figure 1.2. A wall or septum divides the heart into left and right sides, in a double pump configuration. Each side is then further divided into an upper chamber, the atrium, and a lower chamber, the ventricle. The right side of the heart receives de-oxygenated blood from the venous systems, which is then pumped to the lungs via the pulmonary loop, where the carbon dioxide in the blood is exchanged for oxygen. The left side of the heart receives the oxygenated blood from the lungs and pumps it into the systemic loop for distribution throughout the body.

The contraction of the various muscles of the heart enables the blood to be pumped. While the myocardial muscle cells can contract spontaneously, under normal conditions these contractions are triggered by action potentials originating from pacemaker cells situated in two areas of the heart – the Sino-Atrial (SA) and Atrio-Ventricular (AV) nodes. The SA pacemaker cells can spontaneously generate action potentials at 60-80 times per minute, but are themselves under the control of the sympathetic and parasympathetic nervous system. The SA node is generally the site to trigger the action potential for a heartbeat, but the AV node can take over this role if for some reason the SA node fails.

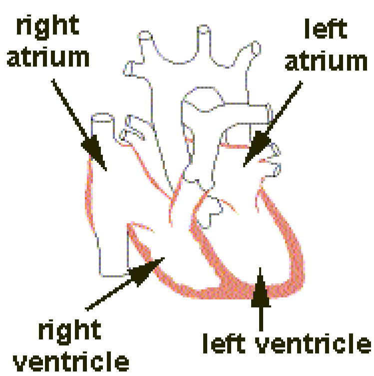

Figure1.2 The Structure of the heart

The normal cycle of a heartbeat has the following sequence of events:

a) The SA node generates an action potential, which spreads across both atria.

b) This spreading action potential results in the simultaneous contraction of the left and right atria.

c) This action potential is also passed to the AV node via the inter-nodal conducting fibres, taking about 40 msec.

d) During the contraction of the atria, blood from the atria is pushed to the respective ventricle.

e) The AV node's own action potential is triggered by the action potential arriving from the SA node. The AV action potential is spread to the ventricles via further conducting fibres, resulting in a delay of about 110 msec, which is sufficient time to ensure that the atrial contraction has finished.

f) The AV action potential triggers both ventricles to contract and push blood into the arterial system. The left ventricle supplies the systemic arterial system while the right ventricle supplies the pulmonary system where the blood is oxygenated by the lungs.

g) All muscles of the heart then relax and blood continues to flow due to the elastic recoil of the arterial walls. During this period both atria and ventricles fill with blood as it returns from the body via the venous system. A series of one-way valves at the input and outputs of the atria and ventricles determine the direction of blood flow.

1.2 Electrocardiography

The various propagating action potentials within the heart produce a current flow, which generates an electrical field that can be detected, in significantly attenuated form, at the body surface, via a differential voltage measurement system. The resulting measurement, when taken with electrodes in standardised locations, is known as the electrocardiogram (ECG). The ECG signal is typically in the range of $\pm 2mv$ and requires a recording bandwidth of 0.05 to 150Hz.

The ECG is a graphic representation of the electrical activity of the heart's conduction system recorded over a period of time. Under normal conditions, ECG tracings have a very predictable direction, duration, and amplitude. Because of this, the various components of the ECG tracing can be identified, assessed, and interpreted as to normal or abnormal function. The ECG is also used to monitor the heart's response to the therapeutic interventions. Because the ECG is such a useful tool in the clinical setting, the respiratory care practitioner must have a basic and appropriate understanding of ECG analysis. The essential knowledge components required for a systematic 12-ECG interpretation are discussed in the following chapter (Jardins T. D., 2002).

1.2.1 The standard 12 ECG system

The standard 12 ECG systems consist of four limb electrodes and six chest electrodes. Collectively, the electrodes (or leads) view the electrical activity of the heart from 12 different positions, 6 standard limb-leads and 6 pericardial chest-leads showed in Table1.1 (Jardins T. D., 2002). Each lead:

(1) Views the electrical activity of the heart from a different angle,

(2) has a positive and negative component, and

(3) monitors specific portions of the heart from the point of view of the positive electrode in that lead.

Table 1.1 ECG lead system. Source:(Jardins T. D., 2002)

Standard Leads	**Limb Leads**	**Chest Leads**
Biopolar Leads	Unipolar Leads	Unipolar Leads
Lead I Lead II Lead III	AVR AVL AVF	V1 V2 V3 V4 V5 V6

The explanation of this three lead system will be in the development history of the ECG diagnostic system.

The ECG, over a single cardiac cycle, has a characteristic morphology as shown in Figure 1.3 comprising a P wave, a QRS complex and a T wave. The normal ECG configurations are composed of waves, complexes, segments, and intervals recorded as voltage (on a vertical axis) against time (on a horizontal axis). A single waveform begins and ends at the baseline. When the waveform continues past the baseline, it changes into another waveform. Two or more waveforms together are called a complex. A flat, straight, or isoelectric line is called a segment. A waveform, or complex, connected to a segment is called an interval. All ECG tracings above the baseline are described as positive deflections. Waveforms below the baseline are negative deflections.

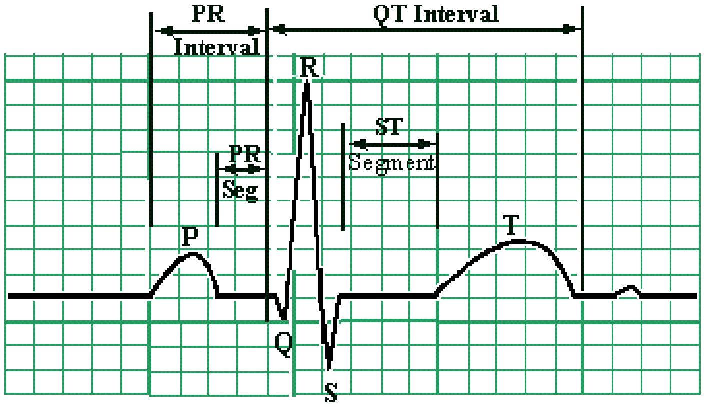

Figure 1.3 The Human ECG signal over one cardiac cycle

1.2.2 The P wave

The propagation of the SA action potential through the atria results in contraction of the atria (depolarisation), producing the P wave. The magnitude of the P wave is normally low (50-100uV) and 100 msec in duration.

1.2.3 The PR interval

The PR interval begins with the onset of the P wave (Pi) and ends at the onset of the Q wave (Qi). It represents the duration of the conduction through the atria to the ventricles. Normal measurement for PR interval is 120ms-200ms. It is shown in Figure 1.4.

Figure 1.4 **PR Interval**

The PR Segment begins with the endpoint of the P wave (Pt) and ends at the onset of the Q wave (Qi). It represents the duration of the conduction from the atrioventricular node, down the bundle of its end through the bundle branches to the muscle. It is shown in Figure 1.5.

Figure 1.5 **PR Segment**

1.2.4 The QRS complex

The *QRS complex* corresponds to the period of ventricular contraction or depolarisation. The atrial repolarisation signal is swamped by the much larger ventricular signal. It is the result of ventricular depolarisation through the Bundle Branches and Parkinje fibre.
The QRS complex is much larger signal than the P wave due to the volume of ventricular tissue involved, although some signal cancellation occurs as the waves of depolarisation in the left and right sides of the heart move in opposite directions. If either side of the heart is not functioning properly, the size of the QRS complex may increase. As shown in Figure 1.6.
QRS can be measured from the beginning of the first wave in the QRS to where the last wave in the QRS returns to the baseline. Normal measurement for QRS is 60ms-100ms.

Figure 1.6 **QRS Duration**

1.2.5 The ST segment

The ST segment represents the time between the ventricular depolarisation and the repolarisation. The ST segment begins at the end of the QRS complex (called J point) and ends at the beginning of the T wave. Normally, the ST segment measures 0.12 second or less.
The precise end of depolarisation (S) is difficult to determine as some of the ventricular cells are beginning to repolarise. It is shown in Figure 1.7.

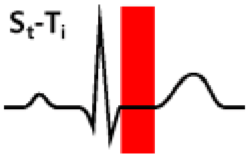

Figure1.7 **ST Segment**

1.2.6 The T wave

The T wave results from the repolarisation of the ventricles and is of a longer duration than the QRS complex because the ventricular repolarisation happens more slowly than depolarisation. Normally, the T wave has a positive deflection of about 0.5mv, although it may have a negative deflection. It may, however, be of such low amplitude that it is difficult to read. The duration of the T wave normally measures 0.20 second or less.

1.2.7 The QT interval

The QT interval begins at the onset of the Q wave (Qi) and ends at the endpoint of the T wave (Tt), representing the duration of the ventricular depolarisation/repolarisation cycle.

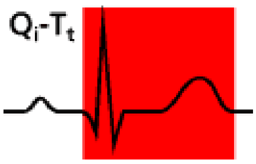

Figure 1.8 **QT Interval**

The normal QT interval measures about 0.38 second, and varies in males and females and with age. As a general rule, the QT interval should be about 40 percent of the measured R-R interval. The QT interval is shown in Figure 1.8.

1.2.8 Summary

Table 1.2 below provides approximate values for the duration of various waves and intervals in the normal adult ECG.

Table 1.2 Duration of waves and intervals in a normal adult human heart

Parameter	**Duration (Sec)**
Intervals	
P-R interval	0.12-0.20
Q-T interval	0.30-0.40
Waves	
P wave duration	0.08-0.10
QRS duration	0.06-0.10

In the normal rhythm, the PR interval should not exceed 0.20 second. The QRS duration should not exceed 0.10 second. The P wave duration should not exceed 0.10 second. The T wave should be at least 0.20 second wide. A heartbeat rate between 60 and 100 is considered "normal," so the R-R interval should be between 0.6 and 1 second (Dubowik K., 1999).

1.3 Heart problems in this research

Changes from the normal morphology of the electrocardiogram can be used to diagnose many different types of arrhythmia or conduction problems. The electrocardiogram can be split into different segments and intervals, which relate directly to phases of cardiac conduction; limits can be set on these to diagnose abnormality. The physician normally uses the ECG and other factors to determine the gross condition of the heart.

There are a lot of heart problems, which can be diagnosed from different ECG waveforms. This project aims at classifying 5 different ECG waveforms from the database. They are: Normal (N), paced beats (P), right bundle branch block (R), atria premature beat (A) and fusion of paced and normal beats (F). They will be explained as follows (Wartak J., 1978).

1.3.1 Paced beats

This is the artificial beat from the device called pacemaker. A pacemaker is a treatment for dangerously slow heart beats. Without treatment, a slow heart beat can lead to weakness, confusion, dizziness, fainting, shortness of breath and death**.** Slow heart beats can be the result of metabolic abnormalities or occur as a result of blocked arteries to the heart's conduction system. These conditions can often be treated and a normal heart beat will resume. Slow heart beats can also be a side effect of certain medications in which case discontinuation of the medicine or a reduction in dose may correct the problem**.**

1.3.2 Right bundle branch block

Right bundle branch block (RBBB) can be suggested by the following ECG characters:

1) The QRS duration between 0.10 and 0.11sec (Incomplete RBBB) or 0.12sec. or more (complete RBBB);
2) Prolonged ventricular activation time or QR interval (0.03sec. or more in V1-V2);
3) Right axis deviation.

Incomplete RBBB often produce patterns similar to those of right ventricular hypertrophy. The ECG pattern of RBBB is frequently associated with ischemic, hypertensive, rheumatic and pulmonary heart disease, right ventricular hypertrophy and some drug intoxication; occasionally it may be found in healthy individuals.

1.3.3 Atrial premature beat (extrasystoles)

Occasionally, a rhythm may be interrupted by impulses originating outside of the SA node. These impulses occur before a normal SA discharge take place, spread throughout the heart and, if the myocardium is not refractory, they cause it to contract prematurely.
Extrasystoles originate either above (supraventricular) or below (ventricular) the atrioventricular node.
Extrasystoles may occur individually as rare of frequent events or in short or long runs. An extrasystole may be coupled with each normal beat (bigeminy) or each normal beat may be followed by two extrasysoles (trigeminy) or more extrasystoles.

1.3.4 Fusion of paced and normal beats

Ventricular fusion beats occur when impulses from an ectopic ventricular focus and supraventricular pacemaker simultaneously activate the ventricular pacemaker simultaneously activate the ventricules; the resulting QRS complex is of shorter duration as compared to those of ventricular origin.

Ventricular tachycardia is caused by rapid and regular discharge in an ectopic focus in any portion of the ventricular myocardium. Consequently, the ECG shows the following characteristic features:

1) A heart rate between 140 and 200 per minute; occasionally the rate may be slightly slower or faster;
2) Wide and bizarre QRS complexes;
3) Regular or slightly irregular RR intervals;
4) P waves of sinus or atrial origin occurring at a slower rate (60-14);
5) A P wave bears no fixed relationship to the QRS complex.

Ventricular tachycardia has a premature onset and its termination is followed by a pause. When the rate is below 150 per minute, the tracing may show ventricular capture beats or ventricular fusion beats characterised by a narrow QRS complex.

1.4 Development of the ECG diagnostic system

1.4.1 The development history

Kolliker and Mueller (Bronzino D. J. et al., 2000)using frogs discovered electric activity related to the heartbeat. Donder recorded the frog's heart muscle twitches, producing the first electrocardiographic signal. Waller originally observed the ECG in 1889 (Waller A. D., 1889) using his pet bulldog as the signal source and the capillary electrometer as the recording device. In 1903, Einthoven (D.Bronzino, 2000) enhanced the technology by employing the string galvanometer as the recording device and using a human subject with a variety of cardiac abnormalities.

Traditionally, the differential recording from a pair of electrodes in the body surface is referred to as a lead. Einthoven (D.Bronzino, 2000) defined three leads numbered with the Roman numerals II, III, and I. They are defined as:

$$\text{Lead}\, I = V_{LA} - V_{RA} \tag{1.1}$$

$$\text{Lead}\, II = V_{LL} - V_{RA} \tag{1.2}$$

$$\text{Lead}\, III = V_{LL} - V_{LA} \tag{1.3}$$

where the subscript RA=right arm, LA=left arm, and LL=left leg. Because the body is assumed purely resistive at ECG frequencies, the four limbs can be thought of as wires attached to the torso. Lead I could be recorded from the respective shoulders without a loss of cardiac information. The relationship of them is: I=I+III. The lead system presented in this research is largely focused on processing a modified limb II (MLII) obtained by placing the electrodes on the patient chest (Moody G. and Mark R., 1992).

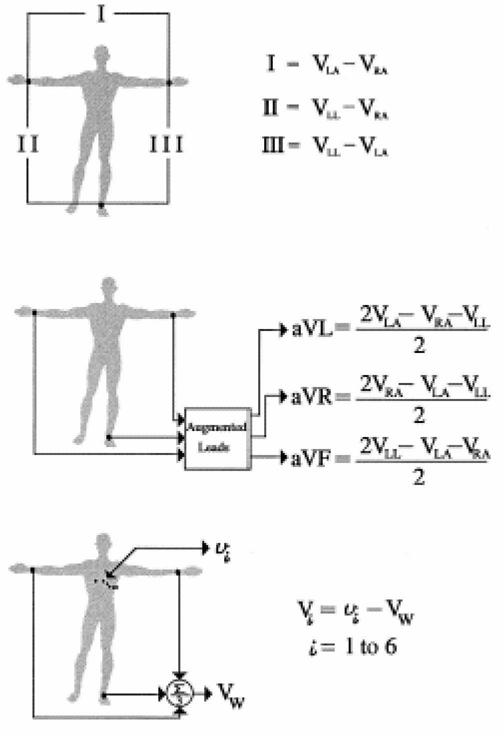

Figure 1.9 Development procedure of the 12-lead ECG

Not long after Einthoven described his string galvanometer, efforts were begun in the United Stated to create an electrocardiograph that used vacuum tubes. Between introduction of the string galvanometer and the hot stylus recorder for ECG, attempts were made to create direct inking ECG recorders. Despite the instant availability of inked recording of the ECG, those produced by the string galvanometer were superior, and it took some time for a competitor to appear. Such an instrument did appear in the form of the hot stylus recorder.

In 1933 Wilson added the concept of a “unipolar” recording, where tying the three limbs together creates a reference point and averaging their potentials so that individual recording sites on the limbs or chest surface would be differentially recorded with the same reference point.

However, from the mid-1930s until today, a standard 12-lead ECG system comprises 3 limb leads, 3 leads in which the limb potentials are referenced to a modified Wilson terminal, and 6 leads placed across the front of the chest and referenced to the Wilson terminal. Figure1.9 shows the development procedure of the 12-lead ECG and the 3-lead systems as were indicated in Table1.1.

The final step toward modern electrocardiography was the introduction of the hot stylus recorder by Haynes (Haynes J. R., 1936) of the Bell Telephone Laboratories in New York. Following the end of World War II, vacuum tube electrocardiographs with heated stylus recorders became very popular and are still in use today.The vectorcardiogram uses a weighted set of recording sites to form an orthogonal xyz lead set, providing as much information as the 12-lead system, but with fewer electrodes. Cardiac surface mapping uses many recording sites (>64 electrodes) arranged on the body so that the cardiac surface potential can be computed and analysed over time. Other subsets of the 12 lead ECG are used in limited mode recording situations such as the tape recorded ambulatory ECG (usually 2 leads) or intensive care monitoring at the bedside (usually 1 or 2 leads) or telemeter within regions of the hospital from patients who are not confined to bed (1 lead).

Automated ECG interpretation was one of the earliest uses of computers in medical applications. This was initially achieved by linking the ECG diagnostic machine to a centralised computer via phone lines or computer network. The modern ECG machine is completely integrated with an analogue front end, a high-resolution analogue to digital converter and a microcomputer (Bronzino D. J. et al., 2000).

1.4.2 Computerised ECG interpretation

Application of the computer to the ECG for machine interpretation was one of the earliest uses of computers in medicine (Jenkins J. M., 1981). Of primary interest in the computer-based systems was replacement of the human reader and elucidation of the standard waves and intervals. Originally this was performed by linking the ECG machine to a centralised computer via phone lines or computer network. The modern ECG diagnostic machine is completely integrated with an analogy front and end, a 12-to 16-bit analogy to digital (A/D) converter, a central computational microprocessor, and dedicated input and output (I/O) processor.

The above-mentioned systems can compute a measurement matrix derived from the 12 lead signals and analyse this matrix with a set of rules (such as neural network) to obtain the final set of interpretive statements (Pryor T. A. et al., 1980).

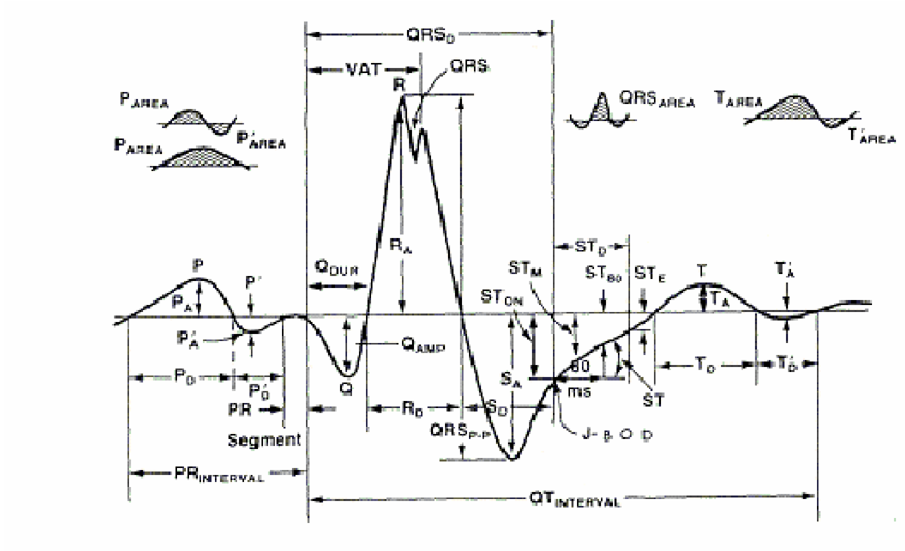

Figure 1.10.The ECG measurements that can be made with computer-based algorithm

Figure1.10 (Berbari J. E., 2000) shows the ECG of a heartbeat and the types of measurement that might be made on each of the component waves of the ECG and used for classifying each beat type and subsequent cardiac rhythm. The depiction of the 12 analogy signals and this set of interpretive statement form the final output, are shown in Figure 1.11 (D.Bronzino, 2000).

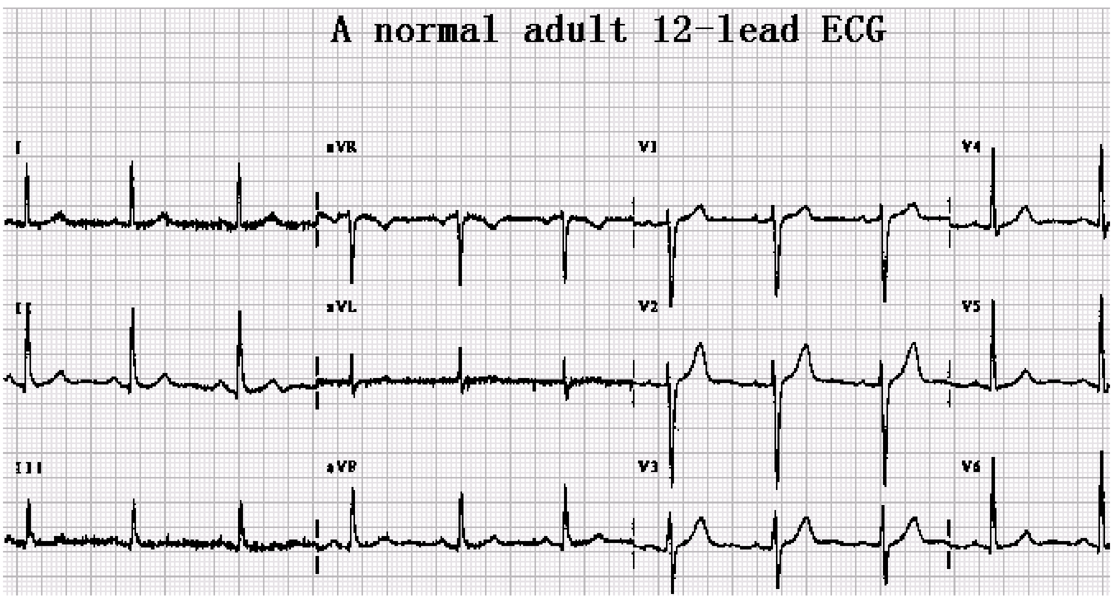

Figure 1.11 An example of an interpreted 12-lead ECG

The physician will over-read each ECG and modify or correct those statements, which are deemed inappropriate. The larger hospital based system will record this correction and maintain a large database of all ECGs accessible by any combination of parameters. There are hundreds of interpretive statements from which a specific diagnosis is made for each ECG, but there are only about five or six major classification groups for which the ECG is used. The first step is analysing an ECG requirement determination of the rate and rhythm for the atria and ventricles. Included here would be any conduction disturbances either in the relationship between the various chambers or within the chambers themselves. Then one can proceed to identify features that relate to the events that would occur with ischemia or an evolving myocardial infarction (Bronzino D. J. et al., 2000).

1.5 Aims and Objectives

The objectives of this research are:

- To carry out research into computerised ECG signal diagnostic systems.
- To design the desirable digital filter for the ECG noise removal using signal processing tools.
- To find the efficient features of the ECG signal.
- To use neural networks to do signal classification.
- To make suggestions on the future improvement of the experiment and development of the system into a remote control diagnostic system.

My contributions to this project can be listed as follows:

- To find a suitable method for the ECG diagnostic using Matlab environment.
- To find suitable features for improving the performance of diagnosis.
- To find the best neural network architecture for the ECG signal classification.

1.6 Thesis Organisation

The thesis is divided into 5 chapters. The rest of the thesis is organised as follows:

Chapter 1 is the introduction of the thesis. It describes the physiology of the normal heart condition and heart problems related with the ECG classification. It also gives the introduction of the ECG analysis history, development and computerised ECG interpretation.

Chapter 2 provides a brief overview of the background and theory of the research. The ECG signal analysis literature review and the main steps of the ECG classification are presented.

Chapter 3 is the method of this research project, which includes the ECG analysis procedures and tools are discussed. An introduction to Matlab experiment environment and signal processing and neural network toolboxes of Matlab, and MIT/BIH ECG database is presented. The experiments are based on the signal processing and artificial neural network techniques. The procedure, which includes signal pre-processing, QRS complex, efficient features extracted from the ECG waveform and the classification by the neural network are further discussed in relation to the employed experimental techniques.

Chapter 4 is the results and discussion of the experiments. The results and discussions based on the experiments from the Matlab toolbox, which include: the experiments of Signal pre-processing, QRS detection algorithm, ECG feature extraction and Neural Network classification results.

Chapter 5 is the conclusion of the project and also give the suggestion of the future works such as the improvement of the experiment and the on-line or tele-diagnostic of the ECG instrumentations.

Chapter 2
Background and Theory of Experiments

This chapter presents the theoretical background and theory of experiments in signal pre-processing, QRS detection, QT interval, ST segment analysis, ECG feature extraction and neural network classification.

2.1 Signal Pre-processing

It is to be expected that any ECG recognition system will have to operate in a noisy hospital environment. The ECG signal is normally corrupted with different types of noises. Often the information cannot be readily extracted from the raw signal, which must be processed first for a useful result.

2.1.1 Noise in the signal

There are many sources of noise in a clinical environment that can degrade the ECG signal. A noisy ECG signal extracted from the MIT/BIH database is shown in Figure 2.1.

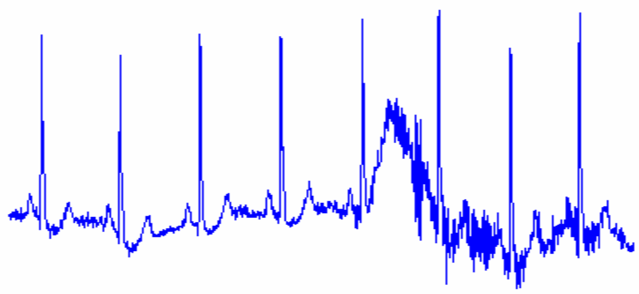

Figure 2.1: Typical ECG signal with noise

The common sources of ECG noise are:

- Power line interference,
- Muscle contraction noise,
- Electrode contact noise,
- Patient movement,

- Baseline wandering and ECG amplitude due to respiration,
- Instrumentation noise generated by electronic devices used in signal processing, and
- Electrosurgical noise, and other, less significant noise resource.

A brief description of these noise signals will be discussed as follows (Friesen G. M. and Jannett C. T. et al., 1990):

1) Power line interference

Power line interference consists of 50 Hz pickup and harmonics, which can be modelled as sinusoids and combination of sinusoids (Furno G. S. and Tompkins W. J., 1983). Typical parameters: Frequency content-50 Hz (fundamental) with harmonics; Amplitude-up to 50 percent of peak-to-peak ECG amplitude.

2) Muscle contraction noise,

Muscle contraction noise causes artificial milivolt-level potentials to be generated. The baseline electromygram is usually in the microvolt range and therefore is usually insignificant. Typical parameters: Standard deviation-10 percent of peak-to-peak ECG amplitude; Duration-50 ms; Frequency content-dc to 10000 Hz.

3) Electrode contact noise,

Electrode contact noise is transient interference caused by loss of contact between the electrode and skin, which effectively disconnects the measurement system from the subject. Typical parameters: Duration-1s; Amplitude-maximum recorder output; frequency-50 HZ time constant-about 1s.

4) Patient movement,

Patient movements are transient (but not step) baseline changes caused by variations in the electrode skin impedance with electrode motion. Typical parameters: Duration-100-500 ms; amplitude-500 percent of peak-to-peak ECG amplitude.

5) Baseline wandering and ECG amplitude due to respiration,

The drift of the baseline with respiration can be represented as a sinusoidal component at the frequency of respiration added to the ECG signal. Typical parameters: Amplitude variation-15 percent of peak-to-peak ECG amplitude; Baseline variation-15 percent of p-p ECG amplitude variation at 0.15 to 0.3 Hz

6) Instrumentation noise generated by electronic devices used in signal processing, and artifacts generated by electronic devices in the instrumentation system.

7) Electrosurgical noise,
Electrosurgical noise completely destroys the ECG and can be represented by a large amplitude sinusoid with frequencies approximately between 100 kHz and 1 MHz. Typical parameters: Amplitude-200 percent of peak-to-peak ECG amplitude; Frequency content-Aliased 100 kHz to 1 MHz; Duration-1-10s.

2.1.2 Signal processing and filters

Signal processing can be defined as the manipulation of a signal for the purpose of extracting information from the signal, extracting information about the relationship of two (or more) signals, or producing an alternative representation of the signal. Most commonly the manipulation process is specified by a set of mathematical equations, although qualitative or "fuzzy" rules are equally valid (Bruce N. E., 2001).

There are numerous specific motivations for signal processing, but many fall into the following categories:

(1) To remove unwanted signal components that are corrupting the signal of interest;
(2) To extract information by rendering it in a more obvious or more useful form;
(3) To predict future values of the signal in order to anticipate the behaviour of its source.

The first motivation clearly comprises the process of filtering to remove noise; most methods of signal processing implicitly provide some basis for discriminating desired from undesired signal component.

In some proposed signal processing methods (Hosseini H. G. et al., 1998b), digital filters can be designed and applied to ECG signals for noise cancellation. An adaptive filter is a digital filter with self-adjusting characteristics and in-built flexibility. In most cases where there is a spectral overlap between the signal and noise or if the band occupied by the noise is unknown or varies with time the fixed coefficient filter must vary and cannot be specified in advance.

Adaptive filtering techniques are an effective method in cancelling most interference polluting the ECG signal. An adaptive self-tuning filter structure was selected for minimising noise. This filter uses the least mean square (LMS) algorithm. The LMS algorithm was incorporated into Matlab software environment. The use of the graphical and interactive programming environment of Matlab enables viewing of the result of applying two stages of adaptive filter on noisy ECG signal. It is possible to decrease the computational load of LMS algorithm by using the FFT command and frequency domain implementation of a block of data instead of processing one sample at a time.

An alternative noise cancellation method is bandpass filtering. The bandpass filter proposed by Lo (Lo T. Y. and Tang P. C., 1982) was selected for noisy removal. This filter is the combination of a lowpass and highpass filter. A lowpass filter was implemented with the first side-lobe zero amplitude response placed at 50 Hz. This filter with a cutoff frequency at about 18 Hz can easily remove noise and other less important high-frequency components of the ECG signal. The cutoff frequency of the highpass filter is at about 1 Hz.

Besides the above-mentioned filters, there are still many other ways for signal pre-processing, such as filter bank or neural network. Moreover, diagnostic tools must be in variant to different noise sources and should be able to detect components of ECG signal even when the morphology of the ECG signal varies with respect to time.
In this project some available algorithm for noise reduction are outlined and a better algorithm was selected and tested.

2.2 QRS detection

The QRS complex is the most striking waveform within the electrocardiogram (ECG). Since it reflects the electrical activity within the heart during the ventricular contraction, the time of its occurrence as well as its shape provide much information about the current state of the heart. Due to its characteristic shape, it serves as the basis for the automated determination of the heart rate, as an entry point for classification scheme of the cardiac cycle, and it is often used in ECG data compression algorithms. In that

sense, QRS detection provides the fundamentals for almost all automated ECG analysis algorithms (Kohler B.U. et al., 2002).
The QT interval is one parameter that is needed to receive the maximum attention (Sahambi J. S. and Tandon S. N. et al., 2000). Normal QTc length is 420ms, but it maybe potential concern if QTc> 450 ms and it may increase the risk of tachyarrhythmia if QTc> 500 ms.

The shape of ST segment in the ECG is another important indication in the diagnosis of heart problem. So, the measurements taken on the ST segment forms another predominant factor in the interpretation phase of the ECG (Paul J. S. et al., 1998).

2.2.1 QRS detection algorithms

A large number of QRS detection scheme are described in the literature (Furno G. S. and Tompkins W. J., 1983). It is hard to compare all of them. Several considerations were used to limit the number of QRS detections schemes to a reasonable cross section of different basic techniques described in the literature. The two basic criteria used in selection were complexity and performance. Only relatively simple algorithms were used (Friesen G. M. and Jannett C. T. et al., 1990).

So, four basic types of algorithms were included in this research. The first three types are named by a two letters prefix “AF” for algorithms based on both amplitude and first derivative, “FD” for algorithms based on first derivate only, “FS” algorithm utilises both first and second derivate. The last one is “median” algorithm.

1) Algorithms based on both amplitude and first derivative (AF1, AF2, and AF3)
AF1 concept for this QRS detector was derived form the algorithm developed by Moriet-Mahoudeaux (Mahoudeaux P. M. et al., 1981). If X(n) represents a one-dimensional array of n sample points of the synthesised digitised ECG, an amplitude threshold is calculated as a fraction of the largest positive valued element of that array. A QRS candidate occurs when three consecutive points in the first derivative array exceed a positive slope threshold and followed within the next 100 ms by two consecutive points which exceed the negative threshold.

AF2 algorithm is an adaptation of the analog QRS detection scheme developed by Fraden and Neuman (Fraden J. and Neuman M. R., 1980).

AF3 concept was taken from Gustafson (Gustafson D. et al., 1977). The first derivative is calculated at each point of the ECG. The first derivative array is then searched for points which exceed a constant threshold, then the next three derivative values must also exceed the threshold. If these conditions are meet, point i can be classified as a QRS candidate if the next two sample points have positive slope amplitude products.

2) Algorithms based on first derivate only (FD1 and FD2)
FD1 algorithm was adapted from the one developed by Menard (Menrad A. et al., 1981).

FD2 algorithm is a modification of an early digital QRS detection scheme developed by Holsinger (Holsinger W. P. et al., 1971). The derivative is calculated for the ECG. This array is searched until a point is found that exceeds the slope threshold. A QRS candidate occurs if another point in the next three sample points exceeds the threshold.

3) Algorithm utilises both first and second derivate (FS1 and FS2)
FS1 algorithm is a simplification of the QRS detection scheme presented by Balda (Balda R.A. et al., 1977). The absolute values of the first and second derivate are calculated from the ECG. Two arrays are scaled and then summed. One of the array is scanned until a threshold is met or exceeded. Once this occurs, the next eight points are compared to the threshold. If six or more of these eight points meet or exceed the threshold, the criteria for identification of a QRS are met.

FS2 algorithm was adapted from the QRS detection scheme developed by Ahlstrom and Tompkins (Ahlstrom M. L. and Tompkins W. J., 1983). The rectified first derivative is calculated from the ECG. Then this first rectified derivative is smoothed. The rectified second derivative is calculated. The first smoothed derivative is added to the rectified second derivative. The maximum value of this array is determined and scaled to serve as the primary and secondary thresholds. The array of summed derivative is scanned until a point exceeds the primary threshold. In order to find a QRS candidate, the next six consecutive points must all meet or exceed the secondary threshold.

4) Algorithm based on median filter

A median filter is a non-linear filter for processing digital signal. It is also a good selection for QRS detection (Chazal D. P., 1998).

All of the above-mentioned algorithms have limitations. No algorithm expressed in this research is clearly superior for all sources of QRS complexes considered. The performance of these algorithms was in part attributable to QRS detection. This research will use all of them to find a better one for the detecting QRS complexes.

2.2.2 QT interval and ST segment analysis

a) QT interval analysis

QT interval reflects the electrical signal from ventricular depolarisation to depolarisation. QTc interval is the QT interval corrected for heart rate. In assessing QT interval variability, determination of absolute QT duration is relatively unimportant sometimes, but the method must be sensitive to subtle changes in QT interval from one beat to the next, as well as relatively insensitive to signal noise. The detection and localisation of the QT interval requires the detection of onsets and offsets of the QRS complex, the T-wave and J-point. This is done after reliable detection of the QRS complex.

b) ST segment detection:

The ST segment represents the part of the ECG signal between the QRS complex and T wave. Changes in the ST segment may indicate ischaemia caused by insufficient blood supply to the heart muscle. Evaluation and depression of the ST segment together with T-wave changes indicate that the zone of ischaemia is around the applied lead. Therefore, analysis of the ST segment is an important task in cardiac diagnosis (Hosseini H.G., 2001).

Some of the most recent literatures in the area of QT interval and ST segment analysis are summarised as follows:

Beat to beat QT interval variability was measured by automated analysis on the basis of 256 second records of the surface ECG. A QT variability index (QTVI) was calculated for each subject as the logarithm of the ratio of normalised QT variance to heart rate variance (Sahambi J. S. and Tandon S. N. et al., 2000).

Another new algorithm which is composed of several steps: pre-processing, QRS detection to position beats(Laguna P. et al., 1990), QRS onset and T-wave end definition, and selection of possible noisy beats in order to remove them. Algorithm for QT value selection is as follows:

$$QT = T_2 - QRS_1 \qquad QT_c = \frac{QT}{\sqrt{RR}} \tag{2.1}$$

$$QTP = T_1 - QRS_1 \qquad QTP_c = \frac{QTP}{\sqrt{RR}} \tag{2.2}$$

Where RR is the previous R-R interval. T1, T2 is defined as T wave peak, QRS_1 is defined as the first detected QRS waveform. QT, QTc, QTP, QTPc and RR measurement were obtained from 24-hour holter ECG signal processing.

In dynamic measurement of the QT interval, algorithms to automatically estimate the R, Q and T fiducial points have been developed and their sensitivity to baseline noise and wave morphology fluctuations have been tested on simulated ECGs (Nollo G. and Speranza G. et al., 1990). The variability of the QT and RR interval is analysed in the time and frequency domain.

An important limitation when using QT as an indirect marker of hypoglycaemia is the need to compensate for spontaneous variations in QTc. Calculation of the cumulative average and standard deviation is a simple statistical technique used for industrial process control. However, in this clinical situation the test cannot accurately discriminate between the two conditions. Hypoglycaemia also causes flattening of the T wave (Harris N. D. and Ireland R. H. et al., 2001).

In a real-time QT interval measurement method, the first step of data processing consisted of band pass filtering using a moving average filter proposed by Ligtenberg with a bandpass between 0.6 and 39 Hz in order to remove electromyographic artefact and to avoid baseline wander. After that a function of Spatial Velocity (FSV) was computed, point by point, to detect QRS complexes. This step includes two stages: the learning phase and the detection phase. QRS width and RR interval were measured; a mean value was computed for each one. The QT duration was the difference between the T wave offset and the QRS complex onset. The maximum and minimum QT intervals as well as its mean value were computed for each five-minute strip (Gonzalez R. and Fernadez R. et al., 2000).

Generally, the QT interval is an important indicator for the study of the ventricular repolarisation because it is a non-invasive measure of the process. This interval has been studied since the beginning of electrocardiology because of the evidence of a relationship between QT duration and different pathologies.

Many algorithms have been developed to study the QT interval, but these techniques are not considered as standard and research as are looking for better solution. The main problem is to define the T wave offset because it can be influenced by noise and baseline wonder.

Real time study of the QT interval is difficult for different reasons but is very useful while a cardiac patient is monitories in order to study the evolution of his cardiac activity after heart attack.

In one approach for ST segment analysis, a software was developed to detect the R wave. It can determine sustained capture, and calculate beat by beat and average ST level and slope on captured beats by five computer methods (single points, average, weighted average, linear least-squares, parabolic least-squares) (Jadvar H. et al., 1989). The single points method was given as an example:

$$ST\_level = (S_{R+60} - S_{R-60}) - rest\_ST \tag{2.3}$$

$$ST\_slope = f_s \times (S_{R+100} - S_{R+60}) / 10 \tag{2.4}$$

where f_s = sampling frequency (250Hz), ST point=R+80 ms, PR point=R-60 ms, rest_ST = average ST level in the rest ECG, S_i =ECG signal amplitude at the discrete time index i in mV, ST level is in mV, ST slope is in mV/s, S_{R+100} = R+100 ms.

In another approach (Paul J. S. et al., 1998), the ST segment waveform is extracted by identifying the J-point and the onset of the ensuing T wave. The fiducial points are obtained by separating out the QRS complex and T wave using eigen filters in the DCT (Discrete Cosine Transform) domain. The method extracted the ST segment features from ECG cycles successfully. Generally, in this research two features from ST segment will be analysed and extracted by the exiting algorithm (Hosseini H.G., 2001).

2.3 ECG feature extraction

After pre-processing, the second stage towards classification is to extract features from the signals. The features, which represent the classification information contained in the signals, are used as inputs to the classifier used in the classification stage.

The goal of the feature extraction stage is to find the smallest set of features that enables acceptable classification rates to be achieved. In general, the developer cannot estimate the performance of a set of features without training and testing the classification system. Therefore, a feature selection is an iterative process that involves trailing different feature sets until acceptable classification performance is achieved.

Feature extraction is a key step in most pattern analysis tasks; the procedure is often carried out intuitively and heuristically. The general guidelines are:

- Discrimination: features of pattern in different classes should have significantly different values.
- Reliability: features should have similar values for pattern of the same class.
- Independence: features should not be strongly corrected to each other.
- Optimality: some redundant features should be deleted. A small number of features are preferred for reducing the complexity of the classifier. Among a number of approaches for the task, the principal component analysis has, by far, been the most widely used approach.

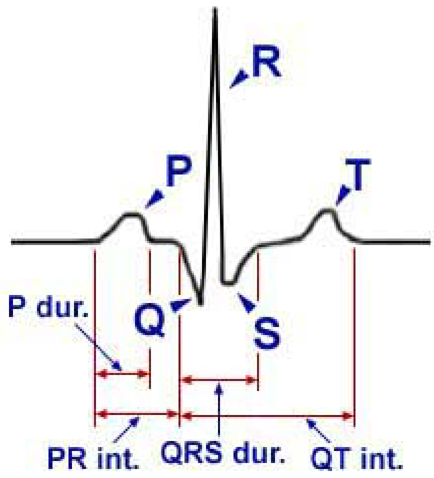

Figure 2.2 ECG feature extraction

In one work by Chazal, 178 features were abstracted from a QRS complex for a representative ECG beat. After applying the transforms to the features there were a total of 229 transformed features. Methods for calculating these features were determined from many existing ECG literatures (Chazal D. P., 1998).

In another work 30 features were extracted for a neural network using a backpropagation training algorithm (Pretorius L.C. et al., 1992). These features will be the input of the next stage.

With the above-mentioned features, the more the input the more complex will be the network structure of the classification. The classification speed will become so slow in the normal personal computer that it cannot be accepted in research. To solve this problem, important and basic features from ECG waveform will be introduced from the introduced literature. Moreover, the compressed form of the signal is added to the extracted features to check the improvement of the classification performance in classification stage.

The selected features in this research are based on the existing feature extraction algorithm (Hosseini H. G. et al., 1999). The ECG features can be divided into two main categories: morphological and statistical features.

Figure2.2 illustrates a general indication of the P wave, QRS complex, T wave, and U wave as well as the ST segment, P-R and Q-T intervals in a normal ECG cycle. A group of important morphological parameters such as: the QRS complex duration, R-R interval, P-R interval, Q-T interval, ST segment, and R wave amplitude can be detected by applying different signal processing techniques such as QRS detection, QT interval and ST segment analysis.

The ECG features can be extracted from the QRS complex, the ST segment, the statistical, and power spectral density (PSD) of the signal. The selected features are explained below(Hosseini H. G. et al., 1999):

2.3.1 Morphological feature

2.3.1.1 The QRS complex features

The **QRS duration** is one of the main characteristics of this complex and can be used in analysing and classifying of the ECG signal.

The **QRS area** is defined as the area located above the isoelectric line (ISO) and between the Q and S points

The **R-R interval** is the distance between two subsequent QRS complex and represent the heart beat rate (HBR).

The **PR interval** represents the time lag from the start of atrial depolarisation to the start of ventricular depolarisation and allows atrial systole to occur.

The **R wave amplitude** is the amplitude of the R wave. That is the highest distance of the height of R wave.

The **R-T interval** is the intervals between the peaks of QRS complex and the consecutive peaks of T waves. It is the time interval from the peak of a ventricular depolarisation to the consecutive peak of the ventricular polarisation.

2.3.1.2 The QT interval and ST segment feature

The **Q-T interval** is the longest distance between the Q wave and the T wave.

The **ST segment** represents the part of the ECG signal between the QRS complex and T wave changes. The analysis of the ST segment is another important task in heart conditions diagnosis.

The S point is identified as the first inflection after the R-wave. In normal ECG, the S point can be recognised as a relative minimum after the R-wave. Generally, it can be recognised by a change in the slope of the ECG signal. The T-wave is the inflection after the S point and within 0.75 of the RR interval (Hosseini H. G. et al., 1998a).

Three important features from ST segment are introduced which are ST slope, ST segment area and ST level.
The **ST slope** is the most important feature of the ECG for investigating myocardial ischaemia (Hosseini H.G., 2001).

Other important features of the ST-segment are ST segment area and ST level.
The **ST-segment area** is the area between the ST-segment and the isoelectric-level from J to T points.

The **ST level** is the maximum deviation from the isoelectric level. The isoelectric level is determined between the offset of the P-wave and the onset of the Q-wave.

2.3.2 Statistical features

The most basic step to extract statistical of the ECG signal is to take the n pre-aligned time sampled values $A(t_1),...,A(t_n)$ and form a vector A.

$$A = [a_1, a_2 ..., a_n] = [A(t_1), A(t_2),..., A(t_n)] \qquad (2.5)$$

$A(t_i)$ is a random vector variable due to ECG signal characteristic. This random vector A can define a large number of statistical features. Some of these statistical features which will be used in this research are discussed:

The expectation or mean of a random vector is one important feature. It is defined by:

$$E[x(n)] = N^{-1}\sum_{n=0}^{N-1} x_n \tag{2.6}$$

where E denotes expectation of a time series with data values x(n), n=0,1,…,N-1, and N is the number of data points. This parameter can be employed as one of the statistical ECG features for classification of cardiac arrhythmia.

Covariance matrix is another important statistical feature which indicates the dispersion of the distribution. The variance of the time series x(n) is defined by:

$$\mathrm{var}[x(n)] = a = E\{[x(n) - M]^2\} \tag{2.7}$$

The autocovariance of x(n) is given by:

$$C(m) = a_a = E\{[x(n) - M][x(n+m) - M]\} \tag{2.8}$$

Or

$$C(m) = a_a = E\{[x(n) - M][x(n) - M]^T\} \tag{2.9}$$

Where m denotes the lag in the data points and $[x(n) - M]^T$ is the transpose of the matrix $[x(n) - M]$.

Autocorrelation matrix of x(n) is related to the covariance matrix and contains the same amount of information, the autocorrelation matrix of the n-dimensional vector x(n) is defined by:

$$S = E\{x(n)x(n)^T\} \tag{2.10}$$

The correlation coefficient can be used in place of the autocorrelation to classify the selected ECG beats. If C is the covariance matrix, then correlation coefficient form a matrix whose (i,j) element is as follows:

$$CC(i, j) = C(i, j) / \sqrt{C(i,i)C(j, j)} \tag{2.11}$$

Identifying the highest cross correlation between a set of stored templates and an unknown ECG signal can perform the classification of the ECG signal. The template, which has given the maximum cross correlation, would be the match candidate with the unknown ECG signal.

The PSD features: The PSD of a signal is a measurement of its energy at various frequencies. The PSD can be calculated by multiplying the FFT of the signal and its conjugate.

The standard deviation (STD) of the QRS complex can be computed from the FFT of the QRS complex and its complex conjugate(Hosseini H. G. et al., 1999).

2.3.3 Compressed ECG samples

As introduced in the previous, ECG compression methods have attempted to reduce the dimensionality of the ECG data while retaining all clinically significant features including the P-wave, QRS complex, and the T-wave. The compressed signal enables designers to improve performance of arrhythmia classifier networks for real-time processing. A large number of ECG data compression techniques have been proposed in the literature (Hamilton P. et al., 1991; Hutchens G. et al., 1990; Nashash H. A., 1995). These techniques have been divided into direct, transformation, and parameter extraction methods(Nave G. and Cohen A., 1993).

To conclude this paragraph, morphological and statistical features derived from normal and abnormal ECG signals are introduced which will be used in this research by the existing feature extracting algorithm. The compressed form of the signal is added to the extracted features enable us to check the improvement of the classification performance in a classification stage.

2.4 Neural network classification

Artificial neural networks (ANN) have been trained to perform complex function in various fields of application including pattern recognition, identification, classification, speech, vision and control system.

A neural network is a massively parallel-distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects (Chazal D. P., 1998):

1) Knowledge is acquired by the network through a learning process,
2) Inter-neuron connection strengths known as synaptic weights are used to store the knowledge.

In theory, neural networks can do anything a normal digital computer can do. We can train a neural network to perform a particular input leads to a specific target output. Such a situation is shown in Figure 2.3 (Demuth H. and Beale M., 2001). There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network.

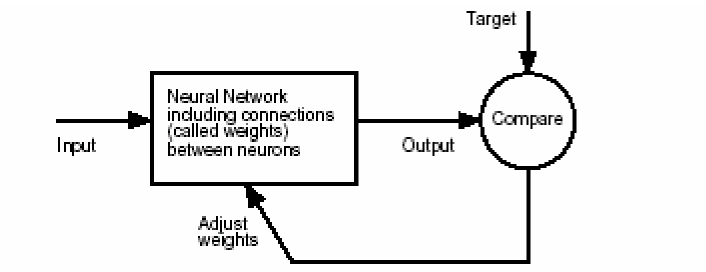

Figure 2.3: Neural Network adjust system

In practice, neural network have been trained to perform complex function in various fields of application. They are especially useful for signal classification. If there are enough training examples and enough computing resources it is possible to train a feed-forward neural network to perform almost any mapping to an arbitrary level of precision.

2.4.1 The Neuron Model and Architectures

2.4.1.1 The neuron

The simplest NN is the single layer perceptron. It is a simple net that can decide whether an input belongs to one of two possible classes. Figure2.4 displays a schematic diagram of a perceptron the output of which is passed through a nonlinearity called a transfer function. This transfer function is of different types; the most popular is a sigmoidal logistic function.

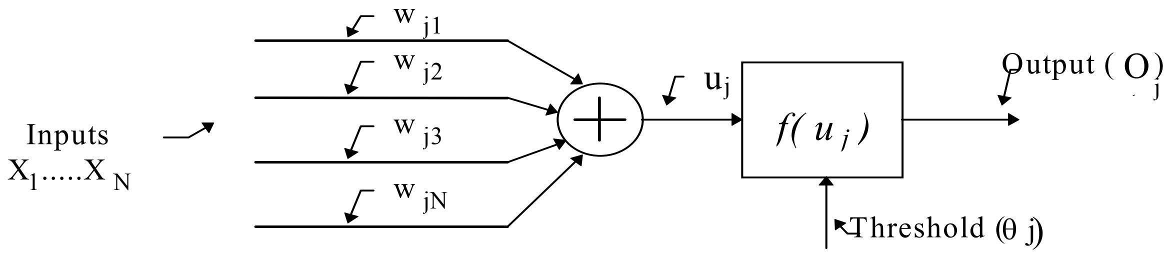

Figure 2.4 Neural Model

A simple description of the operation of a neuron is that it processes the electric currents, which arrive on its dendrites, and transmits the resulting electric currents to other connected neurons using its axon. The classical biological explanation of this processing is that the cell carries out a summation of the incoming signals on its dendrites. If this summation exceeds a certain threshold, the neuron responds by issuing a new pulse, which is propagated along its axon. If the summation is less than the threshold the neuron remains inactive.

$$u_j = \sum_{i=1}^{N} w_{ji} x_i \tag{2.12}$$

$$O_j = f(u_j - \theta_j) \tag{2.13}$$

In these two equations, each set of synapses is characterised by a weight or strength of its own. A signal X, at the input of synapse i connected to neuron j is multiplied by the synaptic weight W_{ji}. It is important to make a note of the manner in which the subscripts of the synaptic weight W_{ji} are written. The first subscript refers to the neuron in question and the second subscript refers to the input end of the synapse to which the weight refers. The weight W_{ji} is positive if the associated synapse is excitatory, it is negative if the synapse is inhibitory.

An adder sums the input signals, weighted by the respective synapses of the neuron.

The amplitude of the output of a neuron limits an activation function. The activation function is also referred to as a squashing function in that it squashes the permissible amplitude range of the output signal to some finite value.

2.4.1.2 Transfer function

Many transfer functions have been included in Matlab neural network toolbox. The most commonly used functions are log-sigmoid, tan-sigmoid and linear transfer functions.

Multi-layer networks often use the log-sigmoid transfer function as shown in Figure 2.5.

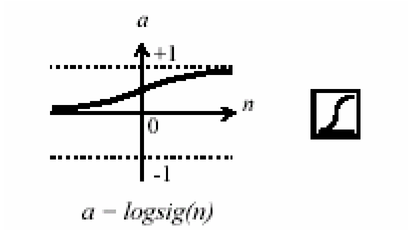

Figure 2.5 Log-Sigmoid Transfer function

Math expression: $y = \dfrac{1}{1+e^{-s}}$ (2.14)

Alternatively, multiplayer network may use the tan-sigmoid transfer function as shown in Figure 2.6.

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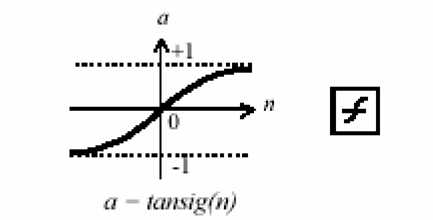

Figure 2.6 Tan-Sigmoid Transfer Function

Math expression: $y = \dfrac{1-e^{-s}}{1+e^{-s}}$ (2.15)

Occasionally, the linear transfer function purelin is used as shown in Figure 2.7.

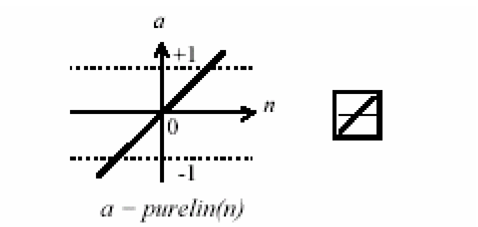

Figure 2.7:Linear Transfer Function

Math expression: $y = f(s) = s$ (2.16)

The sigmoid transfer function squashes the input, which may have any value between plus and minus infinity into the range of 0 to 1. This transfer function is commonly used in back-propagation networks, in part because it is differentiable.

2.4.1.3 Single-layer feed-forward network

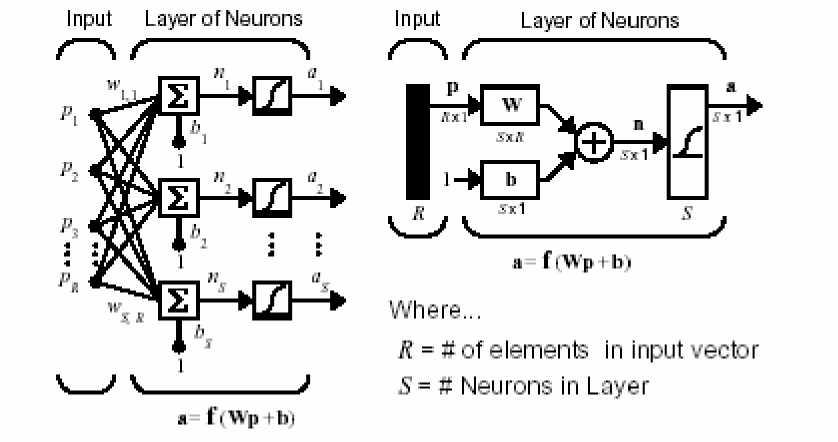

Figure 2.8 Single-layer feed-forward network(Demuth H. and Beale M., 2001)

A layered neural network is a network of neurons organised in the form of layers. Figure 2.8 shows the simplest form of a layered network, which has an input layer of source nodes that projects onto an output layer of neurons but not vice versa. In other words, this network is strictly of a feed forward type. The designation 'single-layer' refers to the output layer of computation nodes. The input layer of source nodes does not count, because no computation is performed there.

A one-layer network with *R* input elements and *S* neurons are shown in Figure 2.8. In this network each element of the input vector ***p*** is connected to each neuron input through the weight matrix ***Wp***. The *ith* neuron has a summer that gathers its weighted inputs and bias to form its own scalar output *n(i)*. The various *n(i)* taken together form an *S*-element net input vector ***n***. Finally, the neuron layer outputs form a column vector ***a***. It is shown the expression for ***a*** at the bottom of the Figure.

It is common for the number of inputs to a layer to be different from the number of neurons. A layer is not constrained to have the number of its inputs equal to the number of its neurons.

2.4.1.4 Matrix-vector input

A neuron with a single R-element input vector, $p_1, p_2, ...p_R$, is shown in Figure 2.9. The individual element inputs are multiplied by weights, $w_{1,1}, w_{1,2}, ...w_{1,R}$.

The weighted values are fed to the summing junction. Their sum is simply ***Wp***, the dot product of the (single row) matrix ***W*** and the vector ***p***.

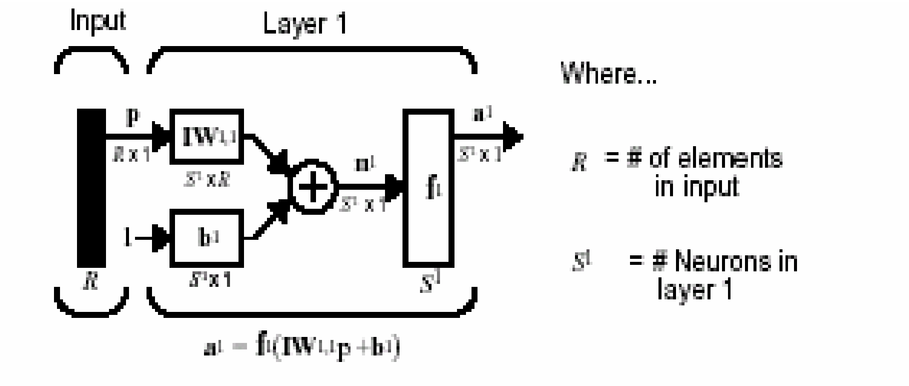

Figure 2.9: A neuron with a single R-element input vector (Howard Demuth, 2001)

The neuron has a bias *b*, which is summed with the weighted inputs to form the net input *n*. This sum, *n*, is the argument of the transfer function *f*.

$$n = w_{1,1}p_1 + w_{1,2}p_2 + ... + w_{1,R}p_R + b \tag{2.17}$$

A *layer* of a network is defined in Figure 2.9 shown above. A layer includes the combination of the weights, the multiplication and summing operation (here realised as a vector product ***Wp***), the bias *b*, and the transfer function *f*. The array of inputs, vector **p**, will not be included in or called a layer.

The input vector elements enter the network through the weight matrix ***W***.

$$W = \begin{pmatrix} w_{1,1} w_{1,2} ......w_{1,R} \\ w_{2,1} w_{2,2} ......w_{2,R} \\ \vdots \\ w_{S,1} w_{S,2} ......w_{S,R} \end{pmatrix} \tag{2.18}$$

The row indices on the elements of matrix **W** indicate the destination neuron of the weight and the column indices indicate which source is the input for that weight. Thus, the indices in W_{12} say that the strength of the signal from the second source *to* the first (and only) neuron is W_{12}.

2.4.1.5 Multi-layer feed-forward network

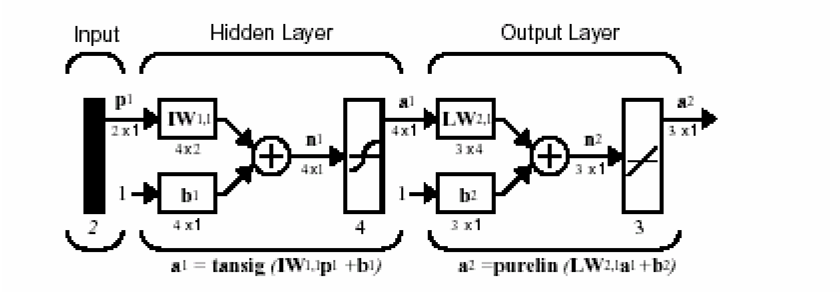

Figure 2.10 Multi-layer feed-forward network(Demuth H. and Beale M., 2001)

The second class of feed forward neural networks is multi-layer, shown in Figure 2.10. It may distinguish itself by the presence of one or more hidden layers, whose computation nodes are correspondingly called hidden neurons or hidden units. The function of the hidden neurons is to intervene between the external input and the network output. By adding one or more hidden layers, the network is enabled to extract higher-order statistics and is particularly valuable when the size of the input layer is large.

Each neuron in the hidden layer is connected to a local set of source nodes that lie in its immediate neighbourhood. Likewise, each neuron in the output layer is connected to a local set of hidden neurons. Thus, each hidden neurons responds essentially to local variations of the source signal.

A network can have several layers. Each layer has a weight matrix W, a bias vector b, and an output vector a. To distinguish between the weight matrices, output vectors and so on, for each of these layers, we will append the number of the layer to the names for each of these variables. For instance, the weight matrix and output vector for the first layer are denoted as *W1* and *A1,* for the second layer these variables are designated as *W2, A2* and so on.

The network shown above has R1 inputs, S1 neurons in the first layer, S2 neurons in the second layer, etc. It is common for different layers to have different numbers of neurons. A constant input 1 is fed to the biases for each neuron.

The outputs of each intermediate layer are the inputs to the following layer. Thus layer 2 can be analysed as a one-layer network with *S1* inputs, *S2* neurons, and an *S1xS2* weight matrix *W2*. The input to layer 2 is *a1*, the output is *a2*. Now that we have identified all the vectors and matrices of layer 2 we can treat it as a single layer network on its own. This approach can be taken with any layer of the network. The layers of a multi-layer network play different roles. A layer that produces the network output is called an *output layer*. All other layers are called *hidden layers*. (Demuth H. and Beale M., 2001)

Multiple layer networks are quite powerful. For instance, a network of two layers, where the first layer is sigmoid and the second layer is linear, can be trained to approximate any function (with a finite number of discontinuities) arbitrarily well. This kind of two-layer network is used extensively in backpropagation neural network.

2.4.1.6 Nodes, inputs and layers required

The number of nodes must be large enough to form a decision region, which is as complex as required by the given problem. However, it cannot be so large that the many weights required cannot be reliably estimated from the available training data. No more than three layers are required in perceptron like feed-forward networks, because a three-layer network can generate complex decision regions.

The number of nodes in the second layer must be greater than one when decision regions are disconnected or meshed and cannot be formed from one convex area. The number of second layer nodes required in the worst case is equal to the number of disconnected regions in input distributions. The number of nodes in the first layer must typically be sufficient to provide three or more edges for each convex area generated by every second-layer node. Typically there should be more than three times as many nodes in the second as in the first layer.

2.4.2 Training Algorithm

2.4.2.1 Backpropagation

Generalising the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer function created backpropagationn. Input vectors and the corresponding output vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined.

Standard backpropagation is a gradient decent algorithm, as is the Widrow-Hoff learning rule. The term backpropagation refers to the manner in which the gradient is computed for nonlinear multiplayer networks. There are numbers of variations on the basic algorithm which are based on other standard optimisation techniques, such as conjugate gradient and Newton methods

The backpropagation neural network is a feed-forward network that usually has hidden layers, as shown in Figure2.10. The activation function for this type of network is generally the sigmoid function. Since the activation function for these nodes is the sigmoid function above, the output from each node is given by (Hasnain S. K. U. and Asim S. M., 1999)

$$\sigma_i^k = F(a_i^k) \qquad (2.19)$$

where a_i is the total input to node *i*, which is given by:

$$\sigma_i^k = \sum_{j=1}^{n} w_{ij} a_j^K + \theta_i \qquad (2.20)$$

Note how the weights are indexed. Weight w_{ij} is the weight of the connection from node *j* to node *i*. Now, as for the perceptron, we will minimise the error in the network by using the gradient descent algorithm to adjust the weights. So the change in the weight from node *j* to node *i* is given by

$$\Delta_K W_{ij} = -\alpha \frac{\partial E^K}{\partial W_{ij}} \qquad (2.21)$$

where E^k is the mean square error for the K_{th} pattern. The error for a hidden node i is calculated from the errors of the nodes in the next layer to which node i is connected. This is how the error of the network is backpropagated.

So, putting it all together, the change for weight W_{ij}, where node *i* is in a hidden layer, is given by:

$$\begin{aligned}\Delta_k w_{ij} &= \alpha\delta_i^k\sigma_j^k \\ &= \alpha\left(F'\left(a_k^k\right)\sum_{n=1}^{Np+1}\delta_n^k w_{ni}\right)\sigma_j^k \\ &= \alpha\left(\sigma_i^k\left(1-\sigma_i^k\right)\sum_{n=1}^{N_{p+1}}\delta_n^k w_{ni}\right)\sigma_j^k \qquad (2.22)\end{aligned}$$

The changes in the weights of the network, which allow the network to learn, are now totally defined. This generalised delta rule for backpropagation neural networks defines how the weights between the outputs layer and the hidden layer change, and how the weights between other layers change also. This network is called backpropagation because the errors in the network are fed backward, or backpropagated, through the network.

Generalisation is perhaps the most useful feature of a backpropagation network. Since the network uses supervised training, a set of input patterns can be organised into groups and fed to the network. The network will "observe" the patterns in each group, and will learn to identify the characteristics that separate the groups. Often, these characteristics are such that a trained network will be able the correct groups, even if the patterns are noisy. The network learns to ignore the irrelevant data in the input patterns.

2.4.2.2 Conjugate Gradient Algorithm

The basic backpropagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient). This is the direction in which the performance function is decreasing most rapidly. Although the function decreases most rapidly along the negative of the gradient, this does not necessarily produce the fastest convergence. In the conjugate gradient algorithms a search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions.

In most of the conjugate gradient algorithms the step size is adjusted at each iteration. A search is made along the conjugate gradient direction to determine the step size which will minimise the performance function along that line(Demuth H. and Beale M., 2001). There are different search functions that are included in the toolbox and we will discuss one of them.

Fletcher-Reeves Update:
All of the conjugate gradient algorithms start out by searching in the steepest descent direction (negative of the gradient) on the first iteration.

$$P_0 = -g_0 \tag{2.23}$$

A line search is then performed to determine the optimal distance to move along the current search direction:

$$X_{k+1} = X_k + \alpha_k P_k \tag{2.24}$$

Then the next search direction is determined so that it is conjugate to previous search direction. The general procedure for determining the new search direction is to combine the new steepest descent direction with the previous search direction:

$$P_k = -g_k + \beta_k P_{k-1} \tag{2.25}$$

The various version of conjugate gradient are distinguished by the manner in which the constant βk is computed. For the Fletcher-Reeves update the procedure is

$$\beta_k = \frac{g_k^T g_k}{g_{k-1}^T g_{k-1}} \tag{2.26}$$

This is the ratio of the norm squared of the current gradient to the norm squared of the previous gradient.

The conjugate gradient algorithm is usually much faster than variable learning rate backpropagation. Although the result will vary from one problem to another, the conjugate gradient algorithms require only a little more storage than the simpler algorithms, so they are often a good choice for networks with a large number of weights.

2.4.2.3 Levenberg-Marquardt (TrainLM)

The Levenberg-Marquardt algorithm appears to be the fastest method for training moderate-sized feedforward neural network. The Levenberg-Marquardt algorithm was designed to approach second order training speed without having to compute the Hassian matrix. When the performance function has the form of a sum of squares (as is typical in training feedforward networks), then the Hessian matrix can be approximated Newton's method. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible.

2.4.3 Neural network application in ECG classification

Pattern classification is perhaps the most important application of artificial neural network. In fact a large number of different approaches to computerised ECG signal classification have been proposed in the literature.

A new neural network called MART (multi-channel adaptive resonance theory) was developed by Carpenter and Grossberg. It has been considerably modified with the objective of carrying out an adaptive and self-organising classification of multi-channel pattern. MART carries out a process that is characterised by on-line and unsupervised learning, updating its weights with each QRS that is presented as input data. MART uses a non-supervised learning process with regard to the morphologies that are presented in the input data, storing a representation of each of them. Another important characteristic of MART is the selective evaluation of the beat class differences in each channel, as a function of the signal quality (Barro S. M. and Delgado F., 1998).

An artificial neural network (ANN) structured as an auto-associator is implemented to perform arrhythmia detection because of its capability to reject unknown or ambiguous pattern. Both a static and a recurrent ANN approach are implemented in several architecture to detect ischemic episodes. While the first approach features an easier learning process, the second one is able to learn the input signal evolution even on a reduced training set. Several ANN's structure combined with different pre-processing and post-processing techniques are designed and evaluated for arrhythmia classification, ischemia detection, and recognition of chronic myocardial diseases (Silipo R. and Marchesi C., 1998). Every ANN has been tested and compared with the most common traditional ECG analysers on appropriate database. Thus, based on the results, the ANN's approach is shown to be capable of dealing with ambiguous nature of the ECG signal.

In another research project, a novel approach to demonstrate the feasibility of having a patient-adaptable ECG beat classification algorithm was developed. A self organisation map/linear vector quantisation (SOM/LVQ) based approach was presented to illustrate that these requirements can be met. (Yu H. H. and Tompkins W. J., 1997).

Another method uses the principle of a Kohonen self-organising feature map and a one layer perceptron (Conde T., 1994).

Supervised learning networks based on a decision-based formulation are explored. More specifically, a decision based neural network (DBNN) is proposed, which combines the perceptron-like learning rule and hierarchical nonlinear network structure (Kung S. Y. and Taur J. S., 1995).

Recent results from another application to both simulated and real registers are shown and benchmarked with the classical LMS (Least Mean-Square) and normalised LMS (NLMS) algorithms. Outcomes indicate that the Finite Impulse Response (FIR) network is a reliable method for the fatal ECG recovery (Camps G., 2001).

There are shortcomings associated with all of the above-mentioned techniques. For example, some techniques suffer from long processing times, other classifiers may depend on the patient ECG waveform characteristics, and a few of the classifiers require noise and artifact removal. Moreover, many of the proposed algorithms analyse only one part of the signal and hence detect only one or two abnormalities(Miller A. S. Blott B. H. and Hames T. K., 1992). It is observed that there exist more than 40 symbols in the MIT/BIH ECG database (Moody G. and Mark R., 1992) to describe the number of different waveforms. Current analysers have failed to cluster all abnormalities.

The other common problem of intelligent ECG signal classification is that structural complexity grows as the size of the training parameters increases. Moreover, performance of the analysers is poor in recognising a specific type of ECG when it occurs only rarely in a patient's ECG record. In this research, several neural network architectures were designed for comparing their performance to detect and classify up to 5 different ECG waveforms.

Chapter 3

Research Methodology

The methods of ECG signal diagnostic involve signal acquisition, noise removal, QRS detection, features extraction and artificial neural network (ANN) techniques for signal classification. The output can be used for ECG signal classification or making a report of the patient's heart condition.

The experimental procedure is as follows:

1) ECG signal acquisition
2) ECG signal pre-processing for noise removal
3) QRS complex and QT interval detection
4) Efficient feature extraction for applying to the input of ANN
5) Neural Network for the classification

In this project the development of an ECG signal analyser using extracted data obtained from the MIT/BIH database will be investigated. In the experimental phase with real subjects, Labview will be employed for data acquisition. Labview has a number of features such as using noise reduction filter and multi-channel data acquisition channel. A multi-channel data logger system, which has more channels, can be considered instead of Labview. But at this stage the above-mentioned tools will not be used.

3.1 Experimental Tools

3.1.1 The Matlab Environment

Matlab is a powerful, comprehensive, and easy to use environment for technical computations. It provides engineers, scientist, and other technical professionals with a single interactive system that integrates numeric computation, visualisation, and programming. Matlab includes a family of application specific solutions called toolboxes.

One of its greatest strengths is that Matlab allows building its own reusable tools. Customised special functions and programs can be easily created in Matlab code.

Biomedical engineers use Matlab in research, design, and manufacturing of medical devices and to develop embedded algorithms and systems for medical instrumentation.

Matlab has several advantages over other traditional means of numerical computing.

- It allows quick and easy coding in a very high level language.
- Data structures require minimal attention, in particular, arrays need not be declared before first use.
- An interactive interface allows rapid experimentation and easy debugging.
- High-quality graphic and visualisation facilities are available.
- Matlab M-files are completely portable across a wide range of platforms.
- Toolboxes can be added to extend the system, giving, for example, specialised signal processing facilities.

Furthermore, Matlab is a modern programming language and problem-solving environment: it has sophisticated data structures, contains built in debugging and profiling tools, and supports object oriented programming. These factors make Matlab to be an excellent language for teaching and a powerful tool for research and practical problem solving.

3.1.1.1 Signal processing toolbox

The Signal Processing Toolbox is a collection of Matlab functions that provides a rich, customisable framework for analogy and digital signal processing (DSP). Graphical user interfaces (GUIs) support interactive designs and analyses, while command-line functions support advanced algorithm development. The Signal Processing Toolbox is the ideal environment for signal analysis and DSP algorithm development. It uses industry-tested signal processing algorithms that have been carefully chosen and implemented for maximum efficiency and numeric reliability. Functions are mostly implemented as M-file routines written in the Matlab language, giving access to the source code and algorithms. The open-system philosophy of Matlab and the toolboxes enables making changes to existing functions or adding own experiments.

The main features of the signal processing toolbox are as follows(Little J. N. and Shure L., 2001):

- A comprehensive set of signal and linear system models
- Tools for analogy filter design
- Tools for finite impulse response (FIR) and infinite impulse response (IIR) digital filter design, analysis, and implementation
- The most widely used transforms, such as fast Fourier transform (FFT) and discrete cosine transform (DCT)
- Methods for spectrum estimation and statistical signal processing

3.1.1.2 Neural Network Toolbox

The Neural Network Toolbox extends the Matlab computing environment to provide tools for the design, implementation, visualisation, and simulation of neural networks. Neural networks are very powerful tools that are used in applications where formal analysis would be difficult or impossible, such as pattern recognition and non-linear system identification and control. The Neural Network Toolbox provides a comprehensive support for many proven network paradigms, as well as a graphical user interface that enables the experiment to design and manage the networks. The toolbox's modular, open, and extensible design simplifies the creation of customised functions and networks.

The main features of Neural Network toolbox are as follows (Demuth H. and Beale M., 2001):

- Support for the most commonly used supervised and unsupervised network architectures
- A comprehensive set of training and learning functions
- Modular network representation, allowing an unlimited number of input setting layers, and network interconnections
- Pre- and post-processing functions for improving network training and assessing network performance

3.1.2 Signal acquisition and MIT/BIH ECG database

The source of ECGs included in the MIT-BIH Arrhythmia database is a set of over 4000 long-term Holter recordings. Approximately 60% of these recordings were obtained from in-patients. The database contains 23 records (numbered from 100 to 124 inclusive with some numbers missing) chosen at random from this set, and 25 records (numbered from 200 to 234 inclusive, again with some numbers missing) selected from the same set to include a variety of rare but clinically important phenomena that would not be well-represented by a small sample of Holter recordings. Each of the 48 records is slightly over 30 minutes long.

The first group of patients is intended to serve as a representative sample of the variety of waveforms and artifacts that an arrhythmia detector might encounter in routine clinical use. A table of random numbers was used to select tapes, and then to select half-hour segments of them. Human experts excluded segments selected in this way only if neither of the two ECG signals was of adequate quality for analysis.

Records in the second group were chosen to include complex ventricular, junctional, and supraventricular arrhythmia and conduction abnormalities. Several of these records were selected because the rhythm, QRS morphology variation, or signal quality might be expected to present significant difficulty to arrhythmia detector; these records have gained considerable notoriety among database users. The subject was 25 men aged 32 to 89 years, and 22 women aged 23 to 89 years (Mark, 1992). ECG records of 100, 118, 232, 104, 114, 217, 106 and 233 from the database will be used in this research.

In conclusion introduction of the method, in the pre-processing stage of ECG signals, Matlab was used for removal of noise components. Different Matlab filter functions from signal processing toolbox were employed for this purpose. The Matlab filter and other functions will also be used for software implementation of feature extraction, morphology classification. The neural network toolboxes will conclude the end of this period of research.

3.2 Experiment1: Signal Pre-processing

The first experimental method in this research is to extract non-noise signal from ECG data coming from a variety of sources. Digital signal processing techniques provide a flexible and effective solution. These techniques can be applied to source such as ECG data to enhance the quality of bio-signals and help us to detect significant signal events.

3.2.1 Filter design and filtering

A filter alters or removes unwanted components from signals. Depending on the frequency range that the filters either pass or attenuate, filters can be classified into:

- Low-pass filter which passes low frequencies but attenuates high frequencies,
- High-pass filter which passes high frequencies but attenuates low frequencies,
- Bandpass filter which passes a certain band of frequencies,
- Band-stop filter, which attenuates a certain band of frequencies.

3.2.1.1 Filter implementation and analysis

A digital filter's output *y(n)* is related to its input *x(n)* by convolution with its impulse response *h(n)*

$$y(n) = h(n) * x(n) = \sum_{m=-\infty}^{\infty} h(n-m)x(m) \tag{3.1}$$

Matlab toolbox provides a rich and customisable support for the key areas of filter design and spectral analysis. It is easy to implement a design technique that suits the application, design digital filters directly, or create analogy prototypes and discrete them.

3.2.1.2.Filters and transfer functions

The Z-transform of a digital filter's output *Y(z)* related to the z-transform of the input *X(z)* by:

$$Y(z) = H(z)X(z) = \frac{b(1) + b(2)z^{-1} + ... + b(nb+1)z^{-nb}}{a(1) + a(2)z^{-1} + ...a(na+1)z^{-na}} X(z) \tag{3.2}$$

Where *H(z)* is the filter's transfer function. Here, the constants *b(i)* and *a(i)* are the filter coefficients and the order of the filter is the maximum of *na* and *nb*.

Many standard names for filters reflect the number of a and b coefficients present:

- When *nb*=0(that is, b is a scalar), the filter is an Infinite Impulse Response (IIR).
- When *na*=0(that is, a is a scalar), the filter is a Finite Impulse Response (FIR).

Filter is implemented as a transposed direct from II structure (Little J. N. and Shure L., 2001):

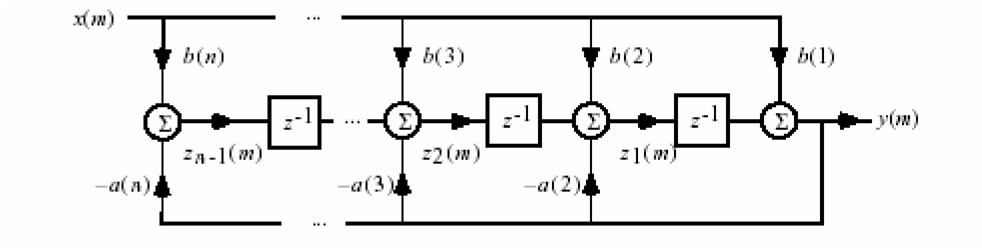

Figure 3.1 Filter structure

Where n-1 is the filter order. This is a canonical form that has the minimum number of the delay elements.

At sample m, filter computes the difference equations:

$$
\begin{aligned}
&y(m) = b(1)x(m) + z_1(m-1) \\
&z_1 = b(2)x(m) + z_2(m-1) - a(2)y(m) \\
&\ldots\ldots = \ldots\ldots \\
&z_{n-2}(m) = b(n-1)x(m) + z_{n-1}(m-1) - a(n-1)y(m) \\
&z_{n-1}(m) = b(n)x(m) - a(n)y(m)
\end{aligned}
\qquad (3.3)
$$

3.2.1.3 Different types of filters (IIR and FIR)

If the classification method is based on their impulse response, digital filter are divided into two classes, infinite impulse response (IIR) and finite impulse (FIR) filters. The input and output signals to the filter are related by the convolution sum, which is given in equation3.4 for the IIR and in equation3.5 for FIR.

$$y(n) = \sum_{k=0}^{\infty} h(k)x(n-1) \qquad (3.4)$$

$$y(n) = \sum_{k=0}^{N-1} h(k)x(n-k) \qquad (3.5)$$

The choice between FIR and IIR filters depends largely on the relative advantage of the two filter types. Generally:

Use IIR when the only important requirement is sharp cut-off filters and high throughput, as IIR filters, especially those using elliptic characters, will give fewer coefficients than FIR.

Use FIR if the number of filter coefficients is not too large and, in particular, if little or no phase distortion is desired (Ifeachor E. C. and Jervis B. W., 1993).

3.2.1.4 Median filter

If your data contains outliers, spikes or filers, you can consider a median filter. The median filter is based on a statistical, or non-linear algorithm. The advantage of the median filter is that it neatly removes outliers while adding no phase distortion. In contrast, regular IIR and FIR filters are nowhere near as effective at removing outliers, even with high orders. The price paid is speed (Jamal R. and Pichlik H., 1998).

The function *medfilt1* in signal processing toolbox implements one-dimensional median filtering, a non-linear technique that applies a sliding window to a sequence. The median filter replaces the centre value in the window with the median value of all the points within the window.

The design of digital filters is an extensive topic whose practical implementation is eased considerably by the availability of modern computer software. Often we will refer to commands in the Matlab Signal Processing Toolbox that may be utilised for designing different type of digital filters.

The principles and algorithm for designing digital filters and the advantages and limitations of various methods in biomedical applications will be discussed in the next section.

3.2.2 Different type of filters for use with Matlab

The signal processing toolbox provides functions that support a range of filter design methodologies. They will be introduced as follows.

3.2.2.1 Filter design steps

In the experiment, we use remez, Fir1, Fir2, Yuelwalk, Butterworth, ellip, Chebyshev I and II and median filter to do the signal processing and get the result. The design of a digital filter involves five steps (Ifeachor E. C. and Jervis B. W., 1993):

- Specification of the filter requirements;
- Calculation of suitable filter coefficients;
- Representation of the filter by a suitable structure;

- Analysis of the effects of finite word length on filter performance;
- Implementation of filter in software and/or hardware.

The principles and algorithm for these IIR, FIR and median will be introduced as follows:

3.2.2.2 IIR filters

IIR filter is mainly consisting of Butterworth, Chebyshev I and II, elliptic (Little J. N. and Shure L., 2001);

Table 3.1 Matlab functions for IIR filters

Filter Type	Design Function
Butterworth	[b, a]=butter (n, Wn, options)
Chebyshev type I	[b, a]=cheby1 (n, Rp, Wn, options)
Chebyshev type II	[b, a]=cheby2 (n, rs, Wn, options)
Elliptic	[b, a]= ellip (n, Rp, Rs, Wn, options)

The above-mentioned IIR filters design lowpass, bandpass, highpass, and bandstop digital and analog filters. Different Matlab IIR functions are explained as follows:

>>[b,a] = butter(n,Wn)

Designs an order n lowpass digital Butterworth filter with cutoff frequency Wn. It returns the filter coefficients in length n + 1 row vectors b and a.

>>[b,a] = cheby1(n,Rp,Wn)

Designs an order n lowpass digital Chebyshev filter with cutoff frequency Wn and Rp decibels of ripple in the passband.

>>[b,a] = cheby2(n,Rs,Wn)

Designs an order n lowpass digital Chebyshev type II filter with cutoff frequency Wn and stopband ripple R decibels down from the peak passband value.

>>[b,a] = ellip(n,Rp,Rs,Wn)

Designs an order n lowpass digital elliptic filter with cutoff frequency Wn, Rp decibels of ripple in the passband, and a stopband Rs decibles down from the peak value in the passband.

3.2.2.3 FIR filters

FIR filter is mainly consist of Parks-McClellan (remez), fir1, fir2 and Yulewalk.

Table 3.2 Matlab functions for FIR filters

Filter Type	Design Function
Parks-McClellan (remez)	b=remez (n, f, m)
Fir1	b=fir1 (n, Wn)
Fir2	b=fir2 (n, f, m)
Yulewalk	b=yulewalk (n, f, m)

The above-mentioned IIR filters design lowpass, bandpass, highpass, and bandstop digital and analog filters. Different FIR Matlab functions are explained as follows:

>> b = remez(n,f,m)

It returns row vector b containing the n+1 coefficients of the order n FIR filter whose frequency-amplitude characteristics match those given by vectors f and m.

>> b = fir1(n,Wn)

It returns row vector b containing the n+1 coefficients of an order n lowpass FIR filter. This is a Hamming-windowed, linear-phase filter with cutoff frequency Wn.

>> b = fir2(n,f,m)

It returns row vector b containing the n+1 coefficients of an order n FIR filter. The frequency-magnitude characteristics of this filter match those given by vectors f and m:

>> [b,a] = yulewalk(n,f,m)

It returns row vectors b and a containing the n+1 coefficients of the order n IIR filter whose frequency-magnitude characteristics approximately match those given in vectors f and m.

3.2.2.4 Median filter

y=medfilt1 (x, n) applies an order n, one-dimensional median filter to vector x, y is the same length as x; the function treats the signal as if it is 0 beyond the end points.

3.2.2.5 Filter implementation

The above-mentioned techniques were implemented using Matlab. The main steps in this process comprised of:

- Loading data from an ASCII file or MAT-file with Matlab's load command,
- Applying different filter functions to the loaded signals,
- Using plot command to draw different results of the filter functions,
- Choosing the best filters based on their performance.
- Signal to noise ratio (SNR) calculation for quantitative measurement

3.2.3 SNR calculation for quantitative measurement

The performance of the selected filters will be compared by visual evaluation but also need to be evaluated by the quantitative measurements. I calculated signal to noise ration (SNR) for the quantitative measurement purposes. The SNR is defined as

$$SNR = 10\log_{10}\left(\frac{sumsqr\_of\_signal}{sumsqr\_of\_noise}\right) \tag{3.6}$$

The ECG signal without noise can be obtained from MIT/BIH database and various percentage of noise will be added. A random function is used to produce the noise signal. The selected filter is coming from the better visual result in the experiment. The SNR will be calculated by adding the appropriate percentage noise to these filters. This is the verification of the visual performance judgement.

3.3 Experiment2: QRS complex detection

The second experiment is preparing QRS complex detection, Q-T interval and ST segment analysis on the signals.

3.3.1 The algorithms for QRS complex detection

The QRS complex is a graphical representation of the electrical activity caused by the depolarisation of the ventricle mass of the heart. Conventional QRS vector cardiographic features were chosen to represent the diagnostic information of the ECG. Before extracting the features, it is necessary to isolate the QRS complexes from the rest of the ECG recording.

The first step towards this process is to identify the regions in the ECG recording where QRS complexes are believed to exist. From a signal-processing perspective, the QRS complexes usually contain higher frequencies and larger amplitudes than the rest of the signal. Once these complexes are located the next step is to determine the onset and offset points for each QRS complex and to identify the component waves of the QRS complex.

Algorithm based on first derivate, first and second derivative, amplitude and first derivate and median filter were used in the experiments (Friesen G. M. and Jannett C. T. et al., 1990):

1) Algorithms based both amplitude and first derivative (AF)

a) Algorithm AF1

Let X(n)=X(0), X(1),…X(8191) represent a one-dimensional array of sample points of the synthesised digitised ECG. An amplitude threshold is calculated as a fraction of the largest positive valued element of that array.

$$\begin{aligned} &Amplitude\_threshold = 0.3 * \max(X(n))........0 < n < 8191 \\ &QRS = (y > threshold) \end{aligned} \tag{3.7}$$

The first derivative is calculated at each point of X(n)

$$Y(n) = X(n+1) - X(n-1) ....1 < n < 8190 \qquad (3.8)$$

A QRS candidate occurs when three consecutive points in the first derivative array exceed a positive slope threshold.

b) Algorithm AF2

A threshold is calculated as a fraction of the peak value of the ECG.

$$\text{Amplitude threshold}=0.4\max[(X(n))] \quad 0<n<8191 \qquad (3.9)$$

The first derivative is calculated at each point of the clipped, rectified array:

$$Y(2)=Y1(n+1)-Y1(n-1) \quad 1<n<8190 \qquad (3.10)$$

A QRS candidate occurs when a point in Y2(n) exceeds the fixed constant threshold.

c) Algorithm AF3

The first derivative is calculated at each point of the ECG.

$$\begin{aligned} &Y(n) = x(n+1) - x(n-1) >= 0.15 \\ &Threshold = 0.15\max(data) \\ &QRS = (y(i) > threshold) \end{aligned} \qquad (3.11)$$

If these conditions are met, point i can be classified as a QRS candidate.

2) algorithms based on first derivate only (FD)

a) Algorithm FD1

$$\begin{aligned} &Y(n) = -2x(n-2) - x(n-1) + x(n+1) + 2x(n+2) \\ &Slope\_threshold = 0.7\max(data) \end{aligned} \quad 2<n<8189 \qquad (3.12)$$

The first derivative array was searched until a point is found that exceeds the slope threshold. The first point that exceeds the slope threshold is taken as the onset of a QRS candidate.

b) Algorithm FD2

The first derivative is calculated for the ECG

$$Y(n)=X(n+1)-X(n-1) \quad 1<n<8190 \tag{3.13}$$

This array is searched until a point is found that exceeds the slope threshold Y(i)>0.45.

A QRS candidate occurs if another point in the next three sample points exceeds the threshold

3) Algorithm utilises both first and second derivate

a) Algorithm FS1

The absolute values of the first and second derivate are calculated from the ECG.

$$\begin{aligned} &Y0(n) = ABS[X(n+1) - X(n-1)] \\ &Y1(n) = ABS[X(n+2) - 2X(n) + X(n-2)] \quad 2<n<8189 \\ &Y(2) = 1.3Y(0) + 1.1Y(1) \end{aligned} \tag{3.14}$$

If six or more of these eight points meet or exceed the threshold, the criteria for identification of a QRS are met.

b) Algorithm FS2

The rectified first derivative is calculated from the ECG.

$$\left.\begin{aligned} &Y0(n) = ABS[X(n+1) - X(n-1)] \\ &Y1(n) = [Y0(n-1) + 2Y0(n) + Y0(n+1)/4] \\ &Y2(n) = ABS[X(n+2) - 2X(n) + X(n-2)] \\ &Y3(n) = Y1(n) + Y2(N) \\ &\Pr imary\_threshold = 0.8\max[Y3(n)] \\ &Second\_threshold = 0.1\max[Y3(n)] \end{aligned}\right. \quad 3<n<8188 \tag{3.15}$$

In order to find a QRS candidate, the next six consecutive points must all meet or exceed the secondary threshold.

4) Algorithm based on median filter

A non-recursive median filter with window size 2n+1 is defined as(Chazal D. P., 1998):

$$Y(n)=median[y(n-m),\ldots y(n-1), x(n),x(n+1),\ldots x(n+m)] \tag{3.16}$$

Median filters with a window width of 2n+1 have some properties, making them well suited to QRS detection

- They provide non-liner high pass filtering. The amount of smoothing increases with the width of the filter window.
- They do not smear out sharp discontinuities in the input signal, providing the duration of the discontinuity is greater than n+1 points long.
- A signal spike of width n or less will be eliminated.

3.3.2 QT interval and ST segment analysis

a) QT interval analysis:

Once the QRS onset ($\tau_{QRSoneset}$) and T wave offset ($\tau_{Toffset}$) have been detected, the QT interval is defined as the time interval between two points:

This is the longest distance between Q wave and T wave which will be calculated by Matlab.

b) ST segment analysis

The relevant points of the ST segment are indicated in Figure 3.2. The S point is identified as the first inflection after the R-wave. In normal ECG, the S point can be recognised as the first inflection after the R-wave. In normal ECG, the S point can be recognised as a relative minimum after the R wave. The T wave is the inflection after the S point and within 0.75 of the RR interval. The T wave peak, which is the maximum absolute value, relative to the isoeletric line, can be found between J+80ms (J80) and R+400ms. The T point is among the most difficult features to identify. If this point is not detected, the J+120ms can be assumed as the position of the T point(Hosseini H.G., 2001).

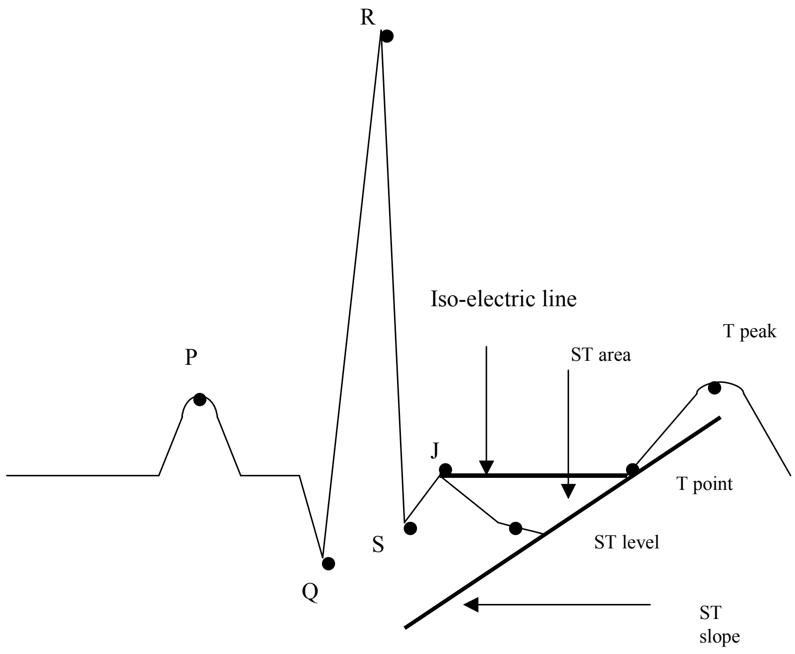

Figure 3.2. The relevant ST segment points in ECG signal

In order to extract accurate features from the ST segment, precise detection of the T wave is required. This technique is used on the exiting algorithms (Hosseini H.G., 2001), and will be illustrated in the next experimental method in this research.

3.4 Experiment3: ECG feature extraction

The third stage for ECG signal analysis is to extract efficient features from the signals. The features, which represent the classification information contained in the signals, are used as inputs to the classifier.

The problem faced in feature extraction is to determine what features are to be used. If there are too many features are extracted and used, the training process of the neural network will be more complex. On the other hand, if too few features are selected the classification information may be insufficient for achieving the acceptable Moreover, training of the network will be also difficult and testing results will be poor. In this research, a total of 8 features from QRS complex, QT interval and ST segment plus 4 ECG statistical features and 13 compressed samples will be used.

3.4.1 QRS complex features

Matlab was used to calculate QRS duration, R-R, P-R, Q-T intervals and R amplitude from ECG waveforms. The FD1 algorithm proposed for QRS complex detection was applied to the ECG signal to detect the R-wave. The Q-wave and S-wave were also determined by finding a change in the slope of the ECG signal before and after the R-wave.

The area under the QRS complex was obtained by assuming a triangular shape for this area and the QRS duration was calculated using the following equation.

QRS duration = 2x(Area under the QRS complex) / (R-wave amplitude) (3.17)

The **QRS duration** is one of the main characteristics of this complex and can be used in analysis and classification of the ECG signal.

The QRS area is defined as the area located above the isoelectric line (ISO) and between the Q and S points, this area is calculated approximately as shown in the following equation:

$$QRS\_Area = \frac{QRS\_duration}{sample\_rate} \sum_{n=Q}^{S} (data_n - ISO) \quad (3.18)$$

The **PR interval** represents the time lag from the start of atrial depolarisation to the start of ventricular depolarisation and allows atrial systole to occur.

The **R-R interval (RR_int)** is the distance between two subsequent QRS complexes and represents the heart beat rate (HBR).

$$HBR = Round(60 * samp - rate / RR\_\mathrm{int}(i)) \quad (3.19)$$

The **R wave amplitude** is the amplitude of R wave, which is the highest distance of the height of R wave.

The **R-T interval** is the intervals between the peaks of QRS complex and the consecutive peaks of T waves.

3.4.2 QT interval feature

The **Q-T interval** is the longest distance between Q wave and T wave.

Once the QRS onset ($\tau_{QRSonset}$) and T wave offset ($\tau_{Toffset}$) have been detected, the QT interval is defined as the time interval between two points:

$$QT = \tau_{Toffset} - \tau_{QRSonset} \tag{3.20}$$

3.4.3 ST segment features

After detecting the QRS complex and the position of the R-wave, the level and slope of the ST segment were calculated. To extract accurate features from the ST segment, precise detection of the T wave is required. QRS detection techniques have been applied to the detection of the T wave with acceptable performance. The signal interval after the QRS complex is tested for a maximum slope. During this process if the maximal slope is less than half of that measured for the QR segment of the QRS waveform, it can be considered as a T wave; otherwise, it is the next QRS complex.

Accurate detection of the T wave improves the accuracy of the ST segment features. A method was developed to detect the location of T waves in the interval between J80 and a point located at a 400 ms interval after the R-peak (Hosseini, 1999). The method of detecting T waves uses a similar principle to that used for P wave detection and finds the first maximum value of the signal in the selected interval. If the R-R interval were less than 1.1s, the search for the T wave would be performed in an interval between J80 and half of the RR interval. This is an extra condition to the algorithm for high heartbeat rate signals in order to prevent any error due to the misdetection of the second R wave as the T wave.

Two important features namely ST slope and ST area were used in this research. The method of extracting these features from the ST segment is explained as follows (Hosseini H.G., 2001):

The ST slope of the segment parameter can be determined by calculating the difference between the amplitude of the staring point of the ST segment (J-point) and its ending point (J80). The J-point is defined as the first inflection point after the S point, or may be the S point itself in certain ECG waveforms. The ST area can be calculated by summing all sample values between the J and T points after subtracting the isoelectric-line value from each point.

3.4.4 The Statistical features

A total of four statistical features will be used in this research. They are:

- Mean or expectation vector,
- QRS energy,
- Autocorrelation coefficient,
- Maximum amplitude of signal histogram.

The expectation vector feature was employed to distinguish between three different classes of the ECG signals using two pre-selected thresholds
as follows:

$$THR1 = 0.2MAX(M). \tag{3.21}$$

$$THR2 = 0.7MAX(M). \tag{3.22}$$

where M is the expectation vector of the input data.

Other statistical features such as correlation coefficient, autocorrelation were employed as a mechanism for computerised cardiac arrhythmia classification.

The PSD features: Two features were extracted based on the PSD calculation. These features are:

- The frequency of maximum energy component in the signal
- The total energy of each pre-aligned ECG beat.

3.4.5 Compression of the ECG samples

In this research, not only the above-mentioned features were used but compressed ECG waveforms were also used to increase the accuracy of the classification. A fixed 52 sample interval centred at the QRS complex was selected with compression ratio CR = 4 to form second part of input vectors of the network. This vector contains 13 compressed ECG samples.

The set of 12 extracted features plus 13 compressed samples formed the input vector ith N = 25 elements for each heartbeat. Arranging the input vector using this small number of features for each heartbeat. Instead of using the whole raw ECG samples (about 360 sample per heartbeat) decreased the complexity of the classifiers. A list of 25 extracted features character and source is shown in Table 3.3:

Table 3.3 25 extracted features used in the research

Feature	Type	Source	Description
1	M	R, S waves	R-S interval
2	M	P, R waves	P-R interval
3	M	QRS complex	QRS area
4	M	Q, T waves	Q-T interval
5	M	R waves	R amplitude
6	M	R waves	HBR
7	M	ST segment	ST-area
8	M	ST segment	ST-slope
9	S	QRS complex	QRS energy
10	S	ECG waves	Auto correlation coefficient
11	S	ECG waves	Mean or expectation vector
12	S	Histogram	Maximum amplitude of signal histogram
13-25	C	ECG waveform	13 compressed ECG sample

M: Morphological features
S: Statistical features
C: Compressed signals

The size of the input layer of a multi-layer ANN-based network could be determined according to the size of input vector, which in this case was equal to 25 neuron nodes. The number of the hidden layer neuron nodes consequently could be chosen as small enough for fast training and yet sufficiently large to give adequate network accuracy.

Construction of the input vector based on the extracted features and compressed information of the signal improved the performance of the ANN-based classifiers.

3.5 Experiment4: Neural network for ECG classification

Developing a classifier involves choosing an appropriate classifier model and then using the training algorithm to train and then test the input signal to classify them into different categories.

Backpropagation algorithm will be used in this experiment as a training function to train feedforward neural networks to solve ECG signal classification problems.

There are generally four steps in the training process:

1. Assemble the training data
2. Create the network object
3. Train the network
4. Simulate the network response to new inputs

The backpropagation training algorithm is an iterative gradient algorithm designed to minimise the mean square error between the actual output to a multi-layer feed-forward perceptron and the desired output. It requires continuous differentiable non-linearity.

3.5.1 Design a Neural Network

In order to diagnose heart conditions using neural network technique, the most common ECG waveforms were selected from the MIT/BIH database. The selected ECG waveform which will be used in this project are divided into five categories, namely normal (N), paced beats (P), right bundle branch block (R), atrial premature beat (A), and fusion of paced and normal beats (F).

Different neural network architectures were designed for detecting and classifying these five different ECG waveforms. The performances of different neural network architectures were compared for choosing the best architecture.

A set of 25 object-sensitive ECG features was selected to form the input vector of the network. They are shown in Table 3.3.

Either 12 extracted features or 25 input features (features plus 13 compressed signal) were used for minimising the structural complexity of the network. They will also be used to compare the performance of the training and testing results of the ANN implementation.

3.5.1.1.Problem definition

To achieve clustering of the ECG waveforms into five different classes, the number of neurons in output layer should be either 3 or 5. Both were used to decide upon analysing the experimental results. A target vector was arranged as the desired output for each class. It is a set of Boolean value vectors. Accompanying each record in the MIT/BIH database there is an annotation file in which each heartbeat has been identified by expert cardiologist annotators. This annotated information can be employed for designing the target vector and evaluating the classifier performance.

Based on the size of output vector, the heart conditions were defined as follows Table 3.4, Table 3.5:

Table 3.4 The 3 output target vector

Signal	Vector	Heat condition
N	[1 0 0]	Normal
A	[0 1 0]	Atrial premature beat
P	[0 0 1]	Pace beat
R	[1 1 0]	Right bundle branch block
F	[1 0 1]	Fusion of paced and normal beats

Table3.5 The 5 output target vector

Signal	Vector	Heat condition
N	[1 0 0 0 0]	Normal
A	[0 1 0 0 0]	Atrial premature beat
P	[0 0 1 0 0]	Pace beat
R	[0 0 0 1 0]	Right bundle branch block
F	[0 0 0 0 1]	Fusion of paced and normal beats

The training and testing data used in this research comes form the MIT/BIH database and was extracted by the existing feature extraction algorithm.

The training data sets contain five classes of ECG waveforms (N, P, R, A, F). ECG signal from the MIT/BIH database is pre-processed to form input vectors of neural network. Each network structure will use 100 samples to train the network for each class. These training data sets contained a total of 641 N, 248 P, 270 R, 158 A, and 120 F.

The testing data was randomly selected to evaluate the performance of the algorithms after all details of the algorithms and parameters had been finalised.

The test data sets contain a wide range of ECG waveforms for testing the signal classifier network. These test data sets contained a total of 104 N, 236 P, and 115 R, 104 A, and 101 F beats.

The multi-layer feed-forward backpropagation networks are designed for diagnosing the heart conditions by ECG signals. The multi-layer feed-forward networks consist of N layers and the transfer function of neurons can be any differentiable transfer function such as ‘Log sigmoid’, ‘Hyperbolic sigmoid’ or ‘Linear’ transfer functions. Weighted input signals apply to the first layer named input layer. Each subsequent layer has weighted inputs coming from the previous layer. All layers have biases. The last layer is the network output. Each layer’s weights and biases are initialised with the specific initialisation algorithm. The network training is done with the specific initialisation. The network training is done with training function of Gradient Descent with momentum and adaptive learning rate Back-propagation. The network performance is measured according to the Mean squared Error (MSE) performance function.

A 25- or 12-element input vector is defined as a matrix of input vectors for one sample to compare the neural network performance. The input vector is defined for each heartbeat and the corresponding element in the target vector is also defined with a combination of 1s or 0s to represent each of the class. Each input vector will use 100 samples. Output vectors include 3- or 5- vectors. The network is required to classify 5 heart conditions by responding with this output vector. Each output vector represents one of 5 classes.

To compare the performances of different networks, the same conditions were kept in initialising the networks. The same training parameters and learning function were also adopted during the training process.

Log sigmoid transfer function was used as the neurons transfer function in different layers. It calculates a layer’s output from its net input.

Learning function of Gradient Descent with momentum and bias adjustment was used for network learning. Learning occurs according to the defined gradient, learning rate, and momentum constant. The weight change matrix dW, for the given neurons was calculated from the neurons' input P, error E, the weight (or bias) W, learning rate Lr, and momentum constant MC according to the learning function:

$$dW = MC * d\,W_p + (1 - MC) * Lr*gW \qquad (3.23)$$

where, dW_p is the previous weight change matrix. It is stored and read from the learning state matrix Lr. gW is the gradient matrix with respect to performance.

3.5.1.2 Training algorithm

The Levenberg-Marquardt backpropagation was used to train the multi-layer feed-forward backpropagation networks. It is very fast but requires a lot of memory to run. For each epoch, if the network performance decreases toward the goal, the learning rate is increased. If the performance increases, the learning rate is then adjusted and the change, which increased the performance, is not made. Different network architectures have been evaluated to find an optimum solution to the problem of intelligent ECG signal diagnosis. Among the vast number of network architectures, 4 networks were selected to compare and choose a better ECG signal classifier.

3.5.2 Architecture

Different network architectures were used in this research. Table 3.6 shows different definitions of the network structures. The main network architectures were NET1, NE2, NET3 and NET4. NET1 which consists of three network architectures with 12 inputs, 3 outputs and hidden layer of 5, 8 and 12 defined as NET1_5, NET1_8 and NET1_12. Other networks NET2, NET3 and NET4 have also the same definition method as NET1, shown in Table 3.6.

Table 3.6 The Definition of Neural Network Architecture in this research

Network	Input layer	Output layer	Hidden layer	Network Definition
NET1	12	3	5	NET1_5
			8	NET1_8
			12	NET1_12
NET2	12	5	5	NET2_5
			8	NET2_8
			12	NET2_12
NET3	25	3	5	NET3_5
			8	NET3_8
			12	NET3_12
NET4	25	5	5	NET4_5
			8	NET4_8
			12	NET4_12

3.5.2.1 Neural Network Architecture 1 (NET1)

Figure 3.3 depicts a two-layer log-sigmoid/log-sigmoid neural network. It has 12 inputs to receive 12 extracted ECG features and 3 neurons in its output layer to identify 5 classes of heart conditions. Log-sigmoid/log-sigmoid transfer function was selected because its output range (0 to 1) is perfect for learning to output Boolean values.

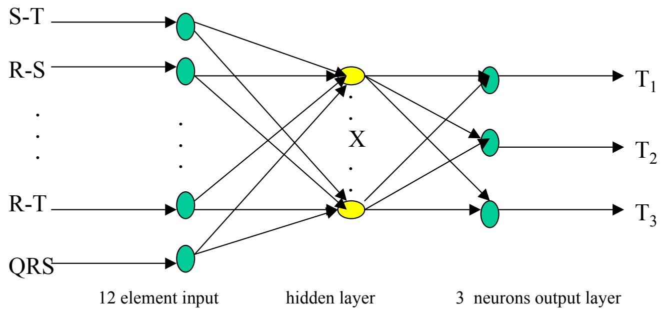

Figure 3.3 NET1 architecture with 12 inputs and 3 neurons in its output layer

The hidden layer of NET1 was first selected with 5 neurons. This number was picked by experience, then changed into 8 and 12 for comparing system performance during experiments. In the experiment, these three network structures were defined as network NET1_5, NET1_8 and NET1_12.

The target vector is a 3-element vector in this case. The network should respond with 1s or 0s in the different position of the class presented to the network. Each output vector corresponds to one class. A log-sigmoid transfer function was also used for hidden layer and output layer. For example, class N (normal) is to be represented by a 1 in the first element and 0's in the other elements. If the heart condition is N, the output vector should be [1 0 0].

3.5.2.2 Neural Network Architecture 2 (NET2)

Figure 3.4 depicts the flow diagram of the multi-layer back propagation network with 12 inputs and 5 neurons in its output layer. A log-sigmoid/log-sigmoid transfer function was used for hidden and output layers. The hidden layer first used 5 neurons, then changed into 8 and 12 for comparing system performance. In the experiment, these three network structures were defined as network NET2_5, NET2_8 and NET2_12.

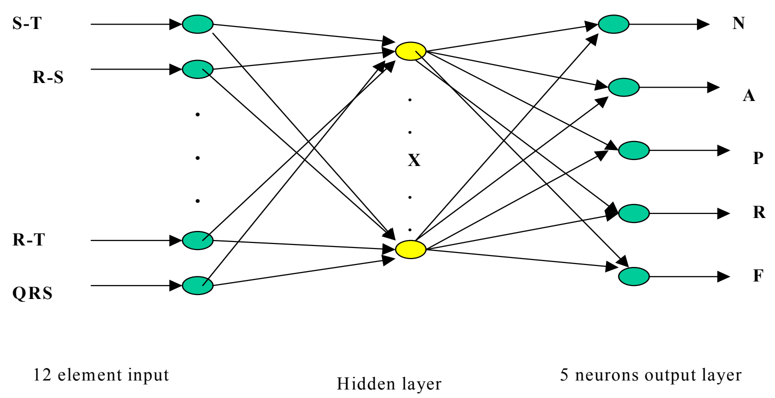

Figure 3.4 NET2 architecture with 12 inputs and 5 neurons in its output layer

The target vector is a 5-element vector in this case. Each output vector is corresponding to one class. The network should respond with a 1 in the position of the class presented to the network. All other values in the output vector should be 0. For example, class N (normal) is to be represented by a 1 in the first element and 0's in other elements. If the heart condition is N, the output vector should be [1 0 0 0 0 0].

3.5.2.3 Neural Network Architecture 3 (NET3)

The NET3 showed in Figure 3.5 is similar to that in Figure3.3, but 25 features were used for inputs including 12 compress signals from ECG database. Therefore the input vector of neural network is a 25-element vector. The purpose of them is to investigate what change the neural network performance will be when input elements are increased, and how about diagnosis precision will be changed with the compressed signals. In the experiment, these three networks structure were defined as network NET3_5, NET3_8 and NET3_12.

The target vector is also 3-element vector in NET3, which is similar to the target vector of NET1.

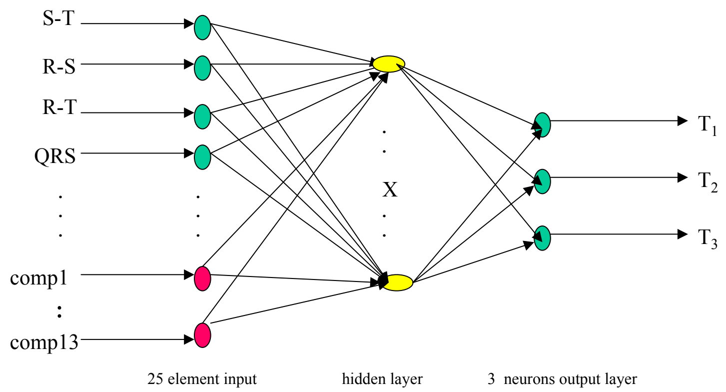

Figure 3.5 NET3 architecture with 25 inputs and 3 neurons in its output layer

3.5.2.4 Neural Network Architecture 4 (NET4)

Figure 3.6 shows NET4 which is similar to that of Figure 3.4. Firstly, its hidden layer has 5 neurons and then is changed to 8 and 12 for comparing system performance. The target vector is a 5-element vector in this case. The input is a 25-element vector with 12 features and 13 compressed signals from ECG database. In the experiment, this three network structures were defined as network NET4_5, NET4_8 and NET_12.

The target vector is an 5-element vector in NET4, which is similar to the target vector of NET2.

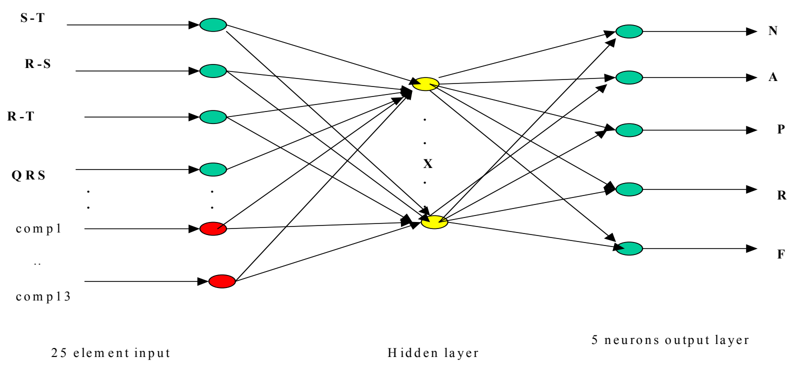

Figure3.6 NET4 architecture with 25 inputs and 5 neurons in its output layer

3.5.3 Initialisation

To compare the performances of different networks, the same condition was kept in initialising the networks. The same training parameters and learning function during were adopted in training process.

Nguyen-Widrow initialisation algorithm was used in this research. This algorithm chooses values in order to distribute the active region of each neuron in the layer evenly across the layer's input space. It generates initial weight and bias values for a layer, so that the actived regions of the layer's neurons will be distributed roughly evenly over the input space. The Nguyen-Widrow initialisation algorithm has advantages over purely random weights and biases with few neurons wasted (all the neurons are in the input space) and the training works faster (each area of the input space has neurons).

3.5.4 Training

The example of the data for training is shown in Figure 3.7 (R.Mark, 1992).

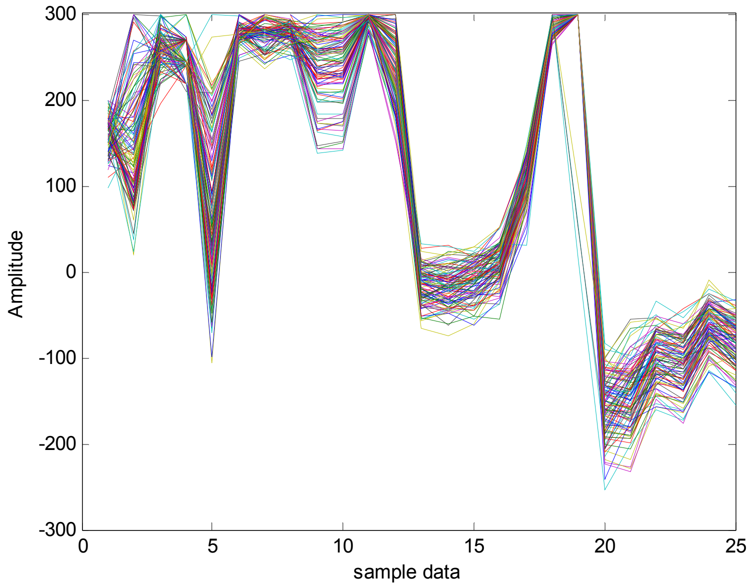

Figure 3.7 The training data sample

The Levenberg-Marquardt backpropagation was used to train the multi-layer feed-forward backpropagation networks. The training data sets were selected from the most common ECG waveforms in the MIT/BIH database. 5 classes with 100 samples in each were selected to train the networks

Training parameters are chosen delicately. Maximum Epoch was 20000. Minimum Gradient limited 0.00001, Goal 0.005. The training networks were done to evaluate the performance of the algorithms after all details of the algorithms and parameters had been finalised. The training result details are shown in Chapter 4.

3.5.5 Testing:

A testing data example is shown in Figure 3.8 (R.Mark, 1992):

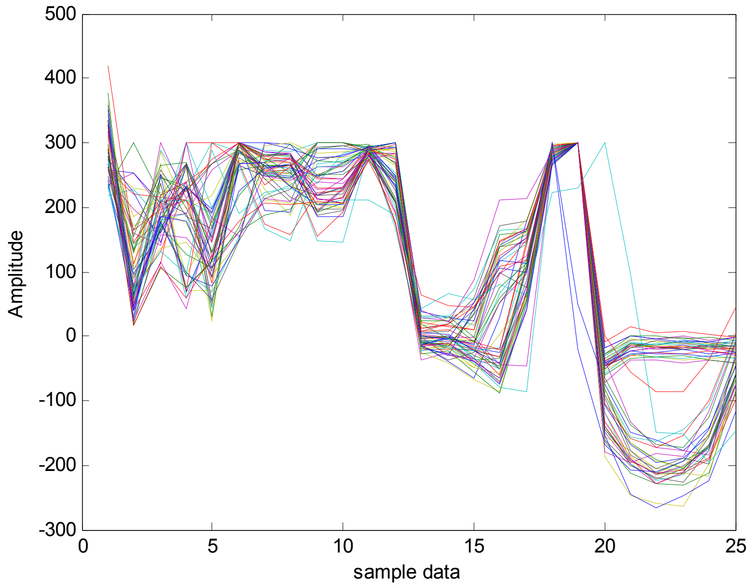

Figure3.8: A testing data sample

In order to compare the recognition behaviour of the networks for five ECG classes, recognition rate can be defined and used in evaluating the performance of the classifiers. The corresponding recognition rates for the selected ECG waveforms were assigned as in Table 3.7:

Table 3.7 Recognition rate assigned to relevant ECG waveforms

Average recognition rate	ECG
Nr	Normal (N)
Pr	Paced beats (P)
Rr	Right bundle branch block (R)
Ar	Atrial premature beat (A)
Fr	Fusion f paced and normal beats(F)

The first and second test was performed using NET1 and NET2 with 12 basic features from 5 ECG classes. The third and fourth test was performed by NET3 and NET4 using test signals consist of 12 basic features plus 13 compressed samples. All of the results are shown in Chapter 4.

Chapter 4

Results and Discussions

4.1 Results and Discussions of experiment1 (pre-processing)

The graphical and signal generation commands in Matlab enable us viewing the results of noise cancellation methods applied to ECG signals. An ECG record from MIT/BIH database was imported in ASCII format to Matlab environment for the experiments.

The result of signal processing is based on applying digital filters on the selected ECG signal from MIT/BIH database. Based on the experimental results of different filter structures, it was found that Remez, Filr1, Fir2, Yulewalk and median filters have a better performance in removing noises from the ECG signals. Figures 4.2, 4.3, 4.4, 4.9, and 4.10 illustrate the results of the above-mentioned filters to the ECG signals. It was found that Butterworth, elliptic, Chebyshev1 and Chebyshev2 filters have poor performance in removing noise from the selected ECG signal as shown in Figures 4.5, 4.6, 4.7, and 4.8.

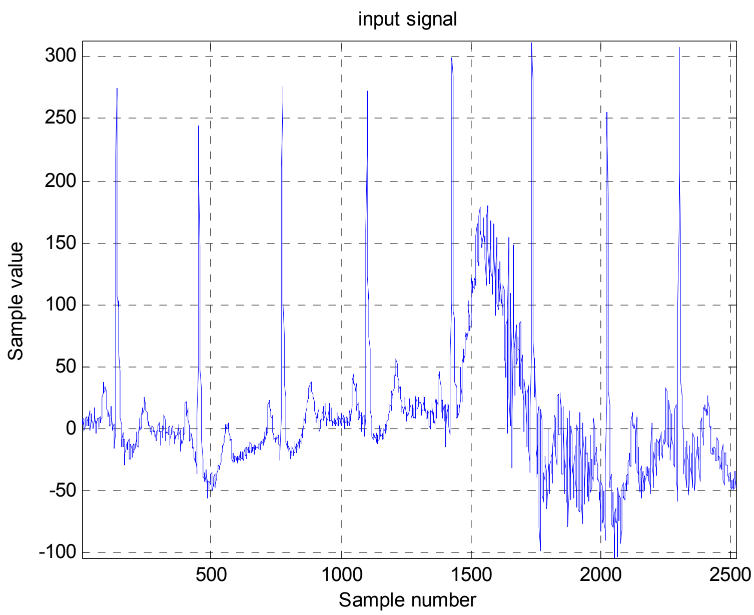

Figure 4.1 The noisy signal selected from MIT/BIH database for the pre-processing experiments.

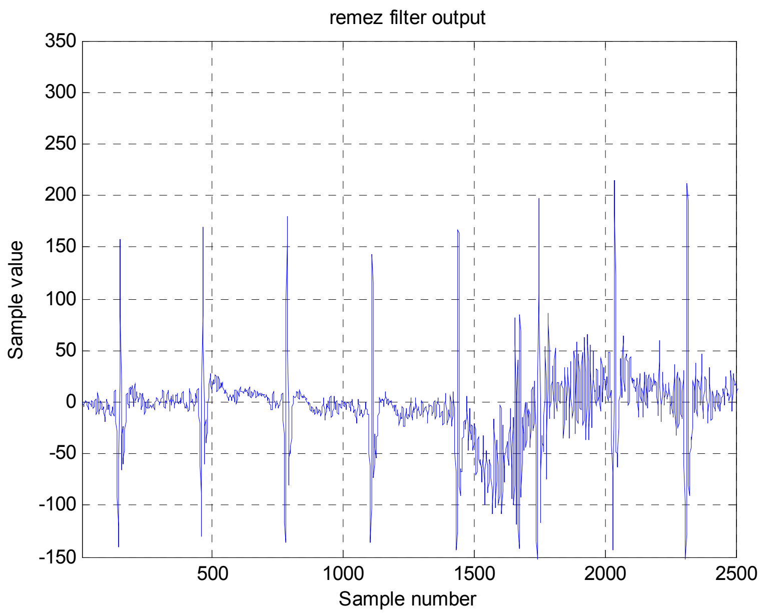

Figure 4.2 The result of signal de-noising by remez filter.

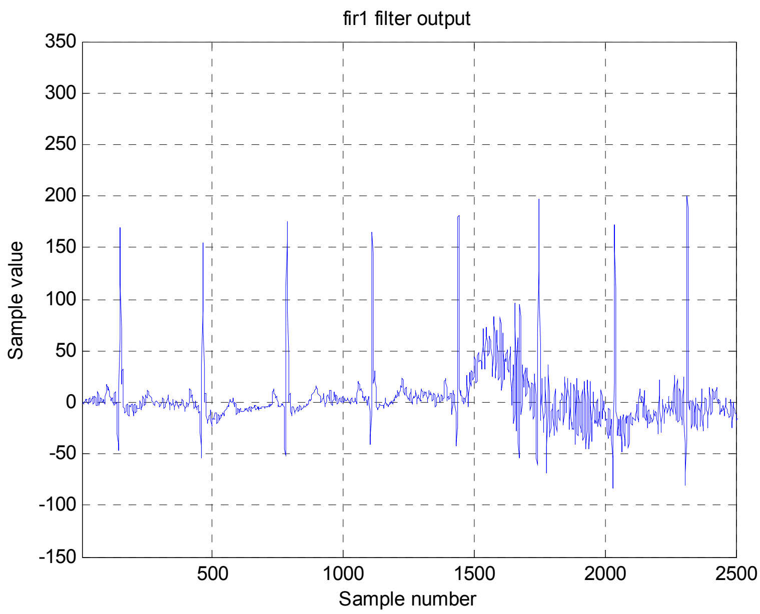

Figure 4.3 The result of signal de-noising by Fir1 filter.

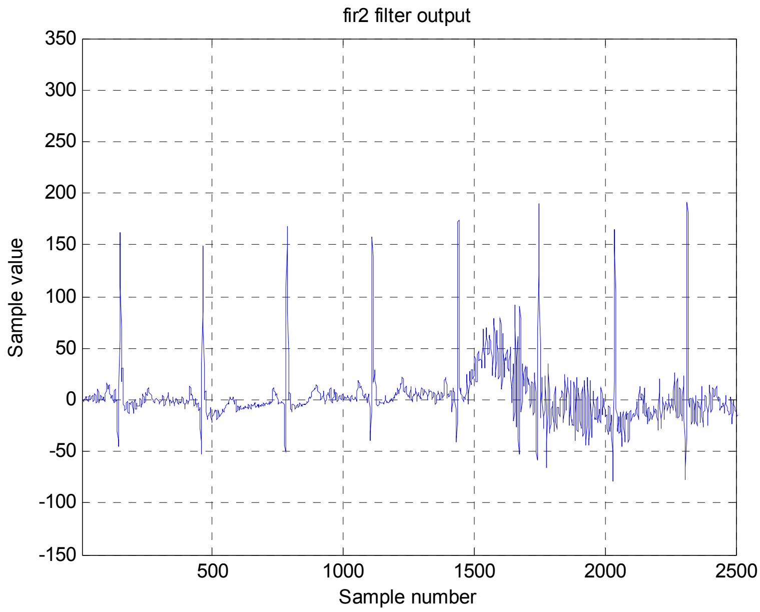

Figure 4.4 The result of signal de-noising by Fir2 filter.

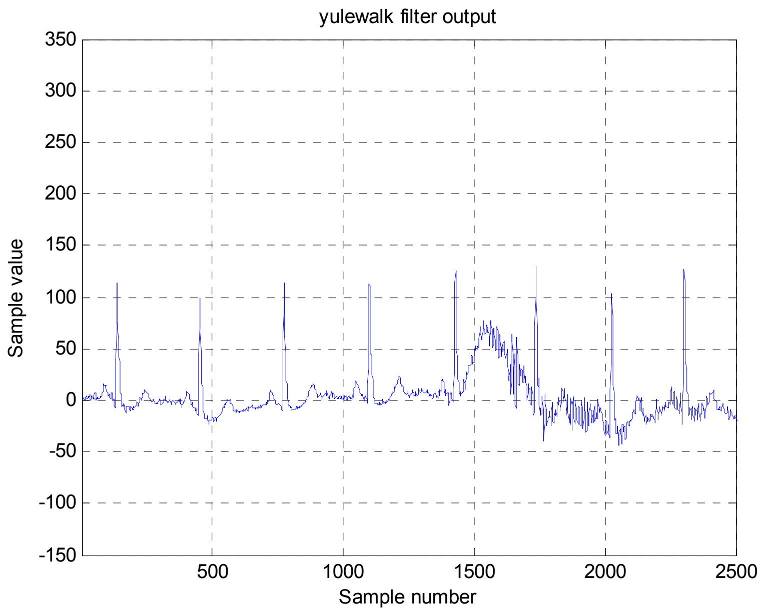

Figure 4.5 The result of signal de-noising by Yulewalk filter.

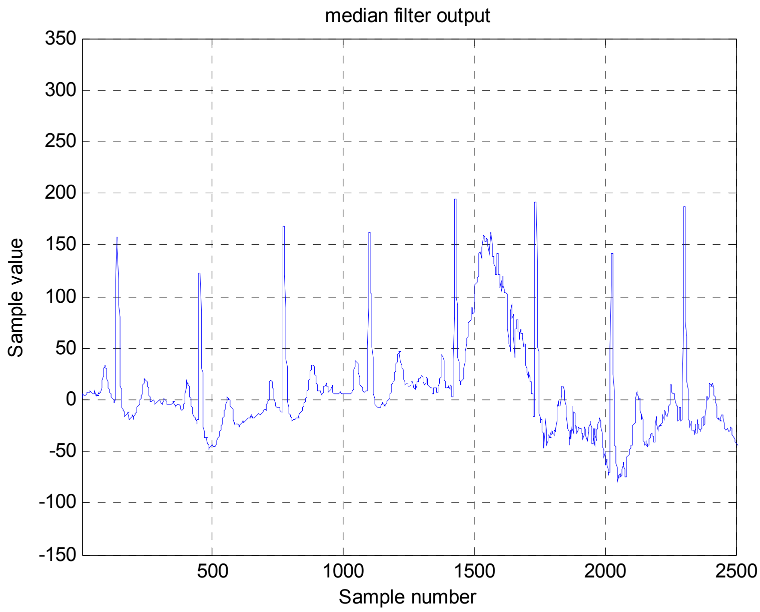

Figure 4.6 The result of signal de-noising by median filter.

Two types of filters, FIR and IIR, were investigated to remove noise from the ECG signal. The remez, fir1 and fir2 belongto FIR type and the Butterworth, elliptic, Chebyshev1, Chebyshev2 and Yulewalk belong to IIR filter, One median filter was also used. It was found that remez, Fir1, Fir2, Yulewalk and median filters had better performances in removing noise from the ECG signals.

Table 4.1 SNR(dB) Calculation for different filters with different noise level

Noise level / Filter Type	Noise with 5%	Noise with 10%	Noise with 20%	Noise with 30%
Without Filter	31.5301	25.4939	18.3468	14.5969
Parks-McClellan (remez)	52.1439	52.2261	52.0133	52.1905
Fir1	54.3288	52.4241	54.1614	54.3352
Fir2	54.3996	54.4942	54.2321	54.4054
Yulewalk	59.7589	59.8355	59.5208	59.5901
Median	66.8339	67.4839	65.7762	65.9782

Among the selected filters, Yulewalk had the best performance. Therefore Yulewalk filter will be used in signal processing period in this research.

The performance of the selected filters is compared not only by visual evaluation but also by the quantitative measurements. SNR were calculated for the quantitative measurement purposes which is shown in Table 4.1. Yulewalk and median filters had better visual results and provided a larger signal to noise ratio. Table 4.1 gives the examples of better filters quantitative measurement. SNR can be enhanced from 14 dB to 59 dB and 65 dB with the signal de-noising result of Yulewalk and median filter. In this project, Yulewalk filter was chosen because its implementation is much easier than median filter. For most analysis done using Matlab and the signal processing toolbox, IIR filters are the best choice because they give better performance with lower filter order. This is confirming the visual performance results we found in signal pre-processing.

The advantage of the IIR filters is that they have very small coefficient compared with FIR filters. Analogue filters can be readily transformed into equivalent IIR digital filters meeting similar specifications. This is impossible with FIR filters as they have no analogue counterpart. The disadvantage to IIR filters is that their stability cannot be guaranteed(Ifeachor E. C. and Jervis B. W., 1993).

The disadvantage of FIR filters is that they often require a much higher filter order than IIR filter to achieve a given level of performance. Correspondingly, the delay of these filters is often much greater than for an equal performance IIR filter. FIR filters is algebraically more difficult to synthesise.

But FIR filters also have some primary advantages which are as follows:

- They can have exactly linear phase.
- They are always stable.
- The design methods are generally linear.
- They can be realised efficiently in hardware.
- The filter start up transients has finite duration.

The main difference between FIR and IIR filter is that for FIR filters, the output depends only on the current and past input values, whereas for IIR filters, the output depends not only on the current and past input values but also on the past output values. Among them Yulewalk possessed the best performances in the experiment. This is an IIR filter, so in this research IIR filters have better results than FIR filters(Little J. N. and Shure L., 2001).

Median filter is also another good choice filter for this application and its performance is even better than Yulewalk filter according to the result of SNR calculation.

4.2 Results and Discussions of Experiment2 (QRS complex detection)

The input signals in QRS detection were tested with two ECG signals containing 8 and 40 heartbeats to verify the experimental results. Different algorithms were used in the QRS detection. The performance of QRS detection algorithms depends on the threshold parameter. The proposed algorithm can detect all of the QRS components correctly by selecting a proper threshold value. The graphical results of applying FS1, AF1, AF2, AF3, FD1, FD2, FS2 and median algorithms to the QRS detection are illustrated in Figures 4.7, 4.8, 4.9 4.10, 4.11, 4.12, 4.13, 4.14.

Based on the experimental results of different algorithms it was found that AF1, FD1, FD2 and median algorithms had better performance in QRS detection from the ECG signal. Figures 4.8, 4.9, 4.12, and 4.13 illustrate the results of the above-mentioned algorithms. It was found that FS1, FS2 and AF3 algorithms had poor performance in QRS detection of the selected ECG signal. The results are shown in Figures 4.7, 4.13, 4.10.

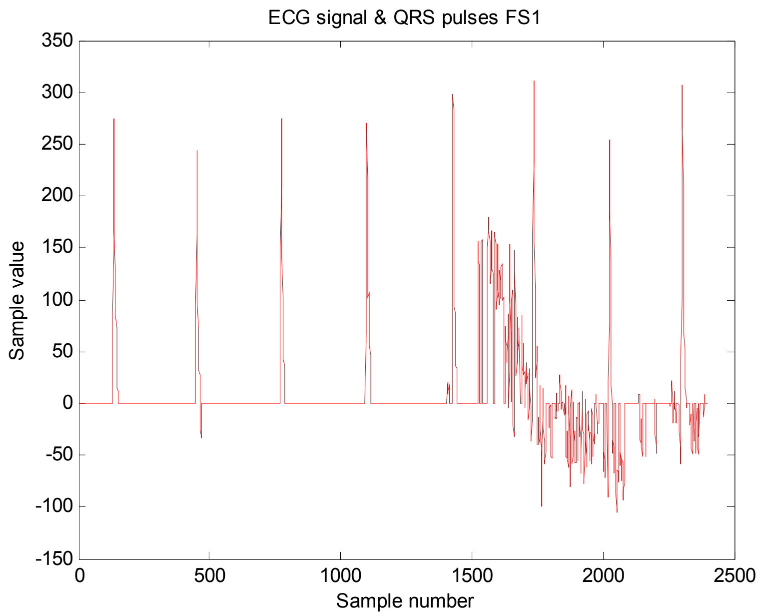

Figure 4.7 The result of QRS detection using FS1 algorithm.

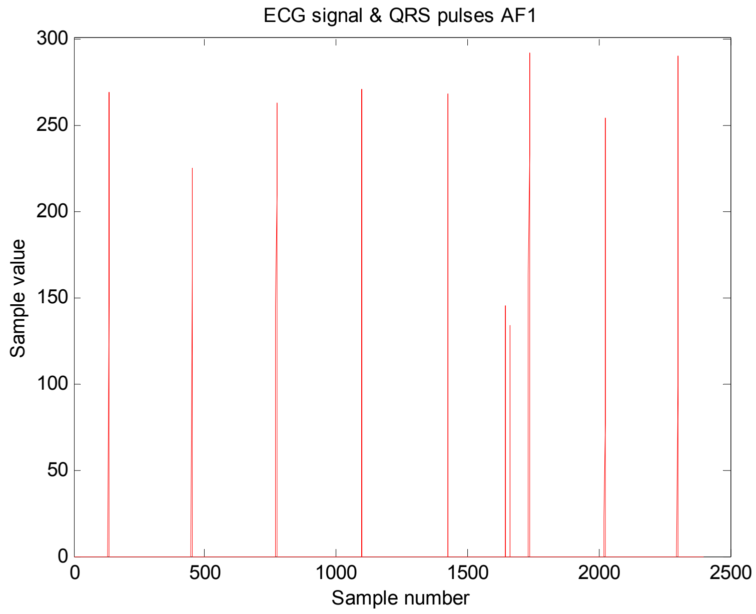

Figure 4.8 The result of QRS detection using AF1 algorithm.

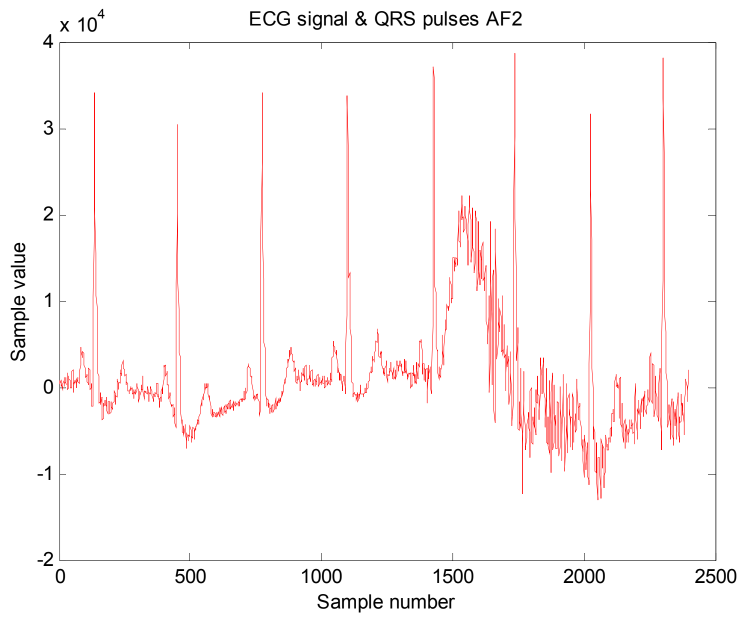

Figure 4.9 The result of QRS detection using AF2 algorithm.

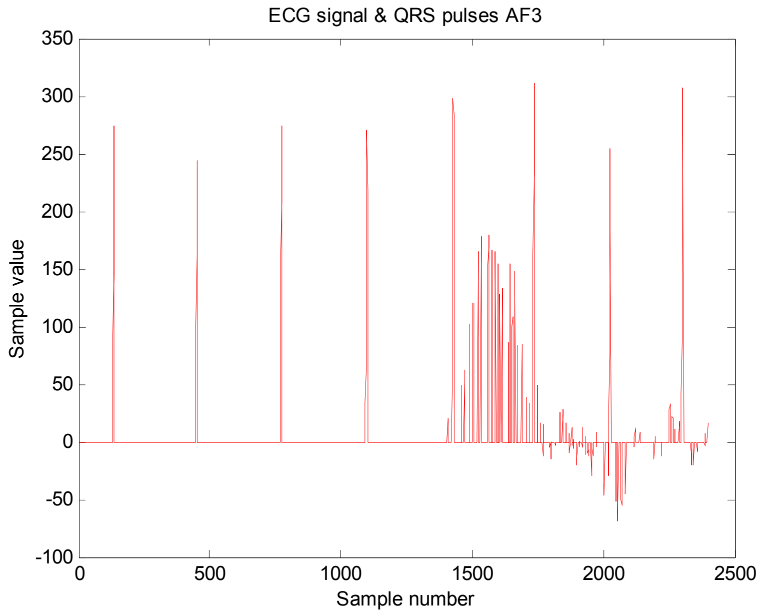

Figure 4.10 The result of QRS detection using AF3 algorithm.

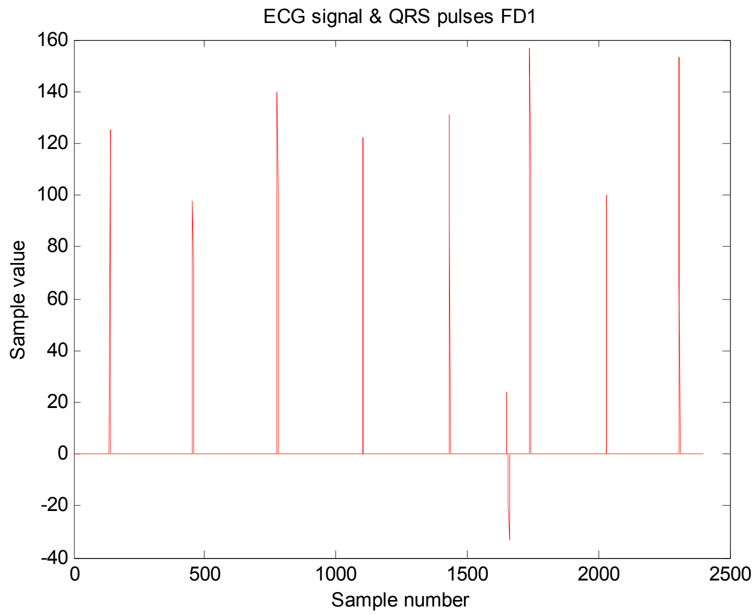

Figure 4.11 The result of QRS detection using FD1 algorithm.

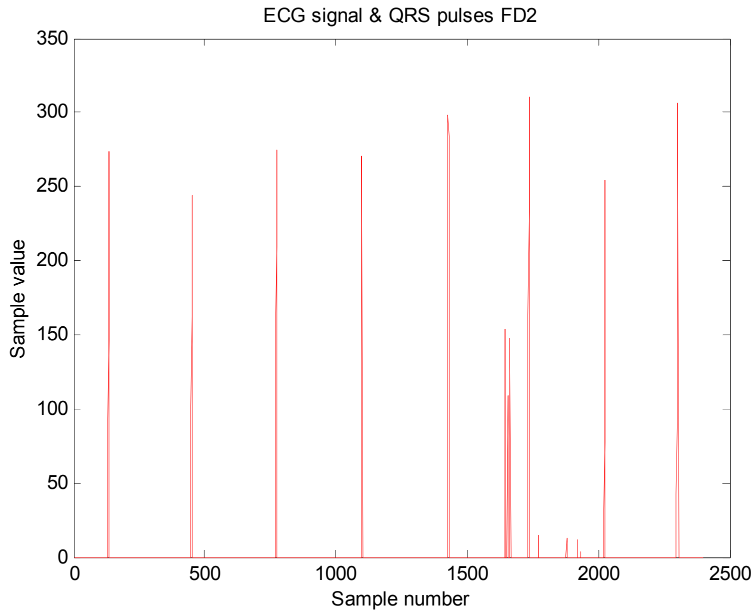

Figure 4.12 The result of QRS detection using FD2 algorithm.

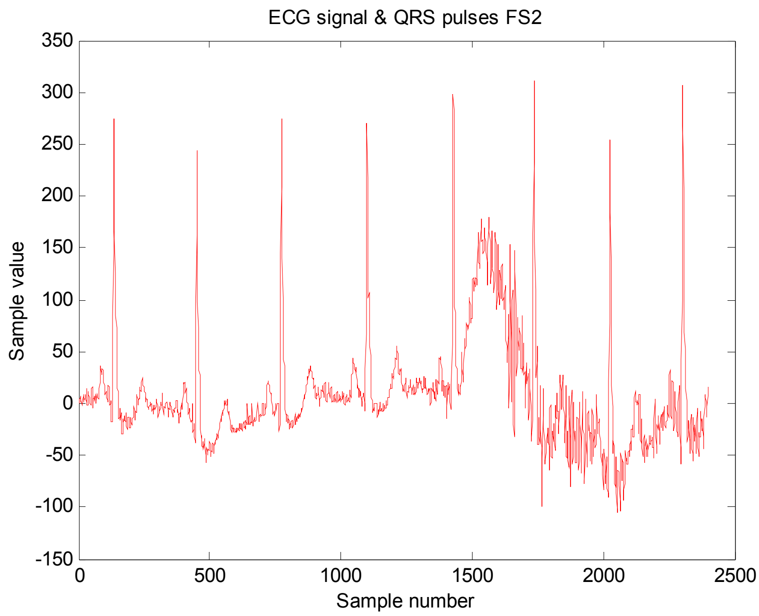

Figure 4.13 The result of QRS detection using FS2 algorithm.

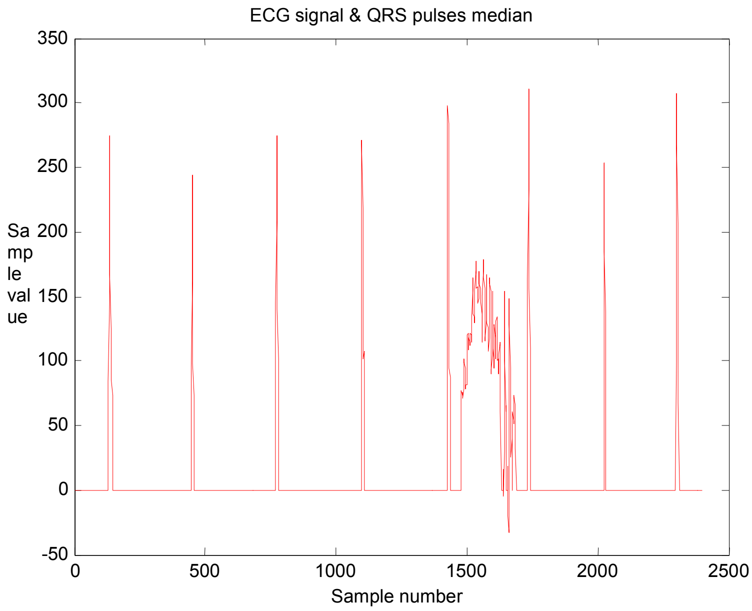

Figure 4.14 The result of QRS detection using median algorithm.

However, FD1 possesses the best performance among the algorithms. The performance of QRS detection algorithms also depends on the threshold parameter. Another way of thinking improvement of the result is to change the threshold of FD1 algorithm. In order to improve the performance of the FD1 algorithm, different thresholds were tried to find the best threshold. The initial value of the threshold was 1, but when the threshold was enhanced to 1.2, a better result was achieved which can be seen from the Figure 4.15.

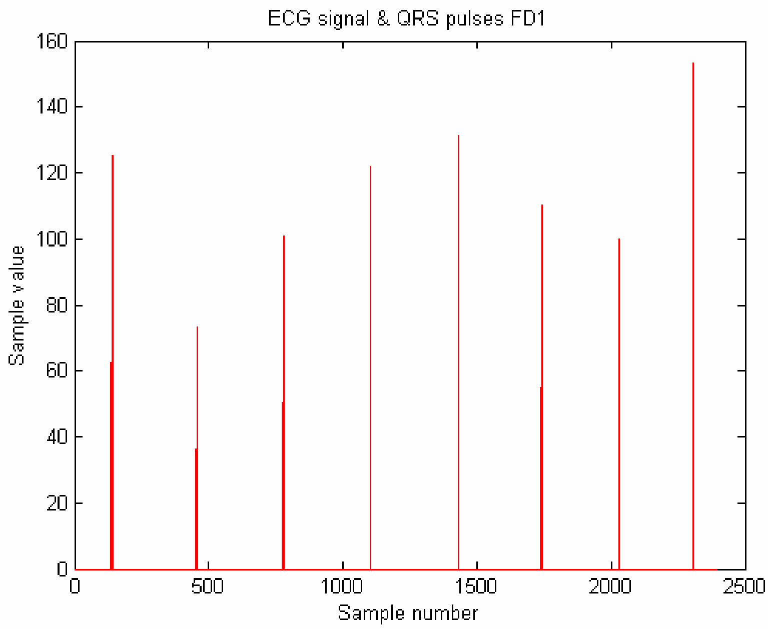

Figure 4.15 The result of QRS detection using improved FS1 algorithm.

The QRS detection algorithms were tested with two ECG signals containing 8 and 40 heartbeats. The QRS pulses were counted correctly with the same number of the input of heartbeats. Figure 4.16, 4.17 and 4.18 are the experiment result of the conclusion.

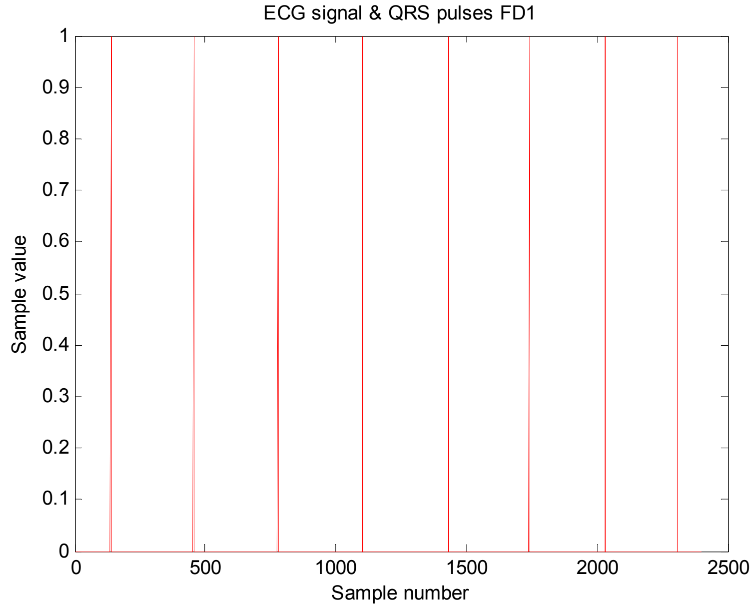

Figure 4.16 QRS pulses of FD1 algorithm

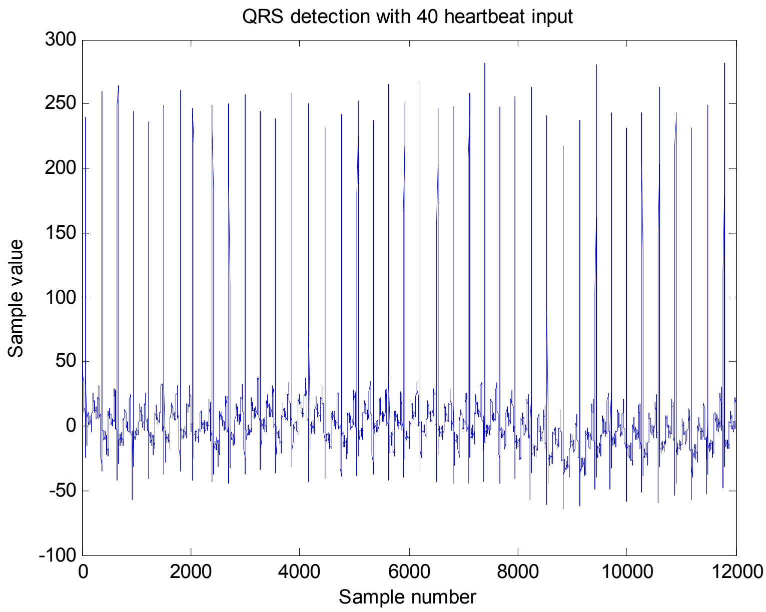

Figure 4.17 40 ECG cycles for QRS detection

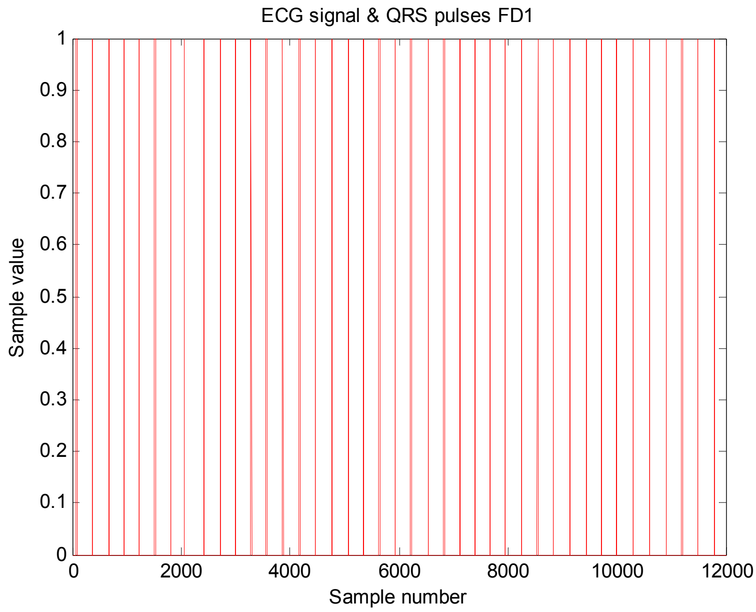

Figure 4.18 FD1 algorithm QRS detection using 40 ECG cycles

4.3 Results and Discussions of Experiment 3 (ECG feature extraction)

ECG signal classifier becomes more complex as the number of signal abnormalities increase. To overcome this problem, a feature vector containing the following features was employed as the input vector for the classifier. This experiment is based on the existing feature extraction algorithm (Hosseini, 1999). A total of 12 features were extracted as follow:

Eight Morphology features:

ST segment area, ST slope, the R-S interval, the R-T interval, the QRS area, QT interval, R wave amplitude, and HBR

Four Statistic features

QRS energy, mean of PSD, auto-correlation coefficient, and signal histogram.

13 Compression of the ECG samples

A fixed 52-sample interval centred at the QRS complex was selected for compression purposes. These samples were obtained by applying a fixed-width window to the output of the R-wave detection algorithm. A two-stage compression process based on turning point (TP) algorithm was chosen to achieve a CR of 4:1. The TP algorithm compresses the ECG signal with a fixed CR of 2:1 without diminishing the elevation of large amplitude QRSs.

The set of 12 extracted features and 13 compressed ECG samples formed the input vector with N=25 elements will be used for each heartbeat in this research. Arranging the input vector using this small number of features for each heartbeat instead of using the whole raw samples dramatically decreased the complexity of the classifier. In other words, instead of using a raw ECG sample (about 360 sample per heartbeat), 25 samples were employed for each ECG waveform to minimise the structural complexity of the network.

The extracted features, which were used in this research, obtained from applying existing feature extraction algorithms as applied to the selected signals from the MIT/BIH database. This research focuses on the ECG classification, which is finding a suitable neural network structure for the classification

The extracted features were devised to automatically detect and classify ECG signal abnormalities. Thus the combination of compressed ECG samples and the extracted features was an effective method of classifying the cardiac abnormalities that are mainly reflected in the QRS complex. With the extracted features from the ST segment, ischaemia can be recognised. In fact, pre-processing steps are necessary for removing noise from the ECG signal before extracting the morphological parameters.

The accuracy of the ECG data classifiers using the statistical features is highly dependent on the number of classes present in the input data. With only two classes, each feature is able to provide correct classification. However, as the number of classes increases more features should be employed. The advantage of the ANN classifier using the proposed feature vector is its simplicity and ease of implementation.

4.4 Results and discussions of Experiment 4 (ANN classification)

In experiment 4, NET1, 2, 3 and 4 networks were trained and tested in the same way in order to compare their performances. Nguyen-Widrow initialisation algorithm was used to initialise all networks. The Log sigmoid transfer function and the Gradient Descent with Momentum and Bias Adjust Learning Function as well as the Gradient Descent with Momentum and Adaptive Learning Rate backpropagation training function were also used for all network architectures

4.4.1 The training results

The training data set was selected from the most common ECG waveforms in the MIT/BIH database. Five cases with 100 samples each were selected to train the networks. The samples for training NET1 and NET2 contain 12 features of the ECG waveforms. The samples for training NET3 and NET4 consist of 12 features plus 13-compressed components of the signal in each waveform.

Figure 4.19 and Table 4.2 show the training process and performance of NET1 with 12 inputs and 3 neurons in its output for different choices of the number of neurons in hidden layer.

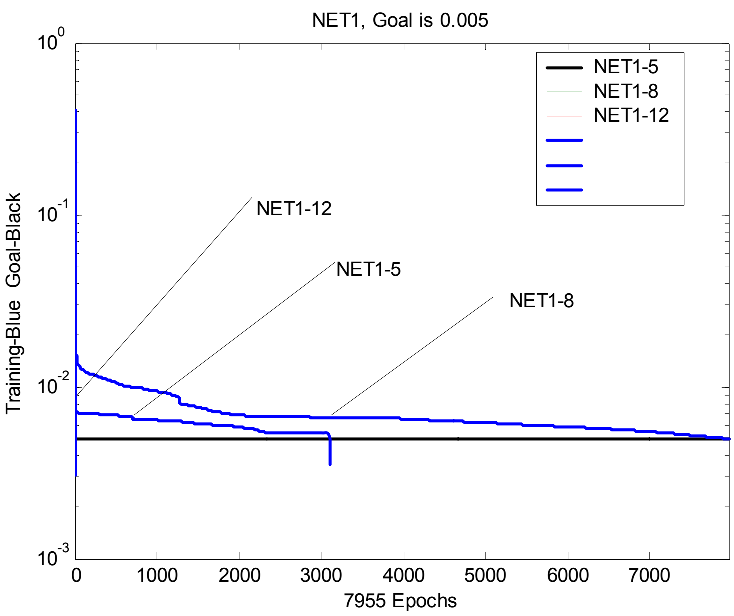

Figure 4.19 The training performance of NET1

Table 4.2 The training performance of NET1

Network	Input layer	Output Layer	Hidden layer	Epoch	Escape Time (sec.)	MSE
NET1_5	12	3	5	3099	454.42	0.00351134
NET1_8			8	7995	2240.9	0.00499969
NET1_12			12	16	9.7640	0.00305856

It can be observed that the behaviour of the three networks in terms of training speed were different. The NET1_12 trained with the least number of epochs and the CPU time employed was also lowest under the same goal. The NET1_8 trained with the most epochs and the CPU time employed was also highest under the same condition.

Figure 4.20 and Table 4.3 display the training process and performance of NET2 with 12 inputs and 5 neurons in its output for different choices of number neurons in hidden layer. It can be seen that NET2_12 and NET2_5 took the same epochs but NET2_5 took the smallest CPU time employed for training. NET2_12 is little more than for training NET2_8. NET2_12 trained with the most number of epochs and the CPU time employed was also highest.

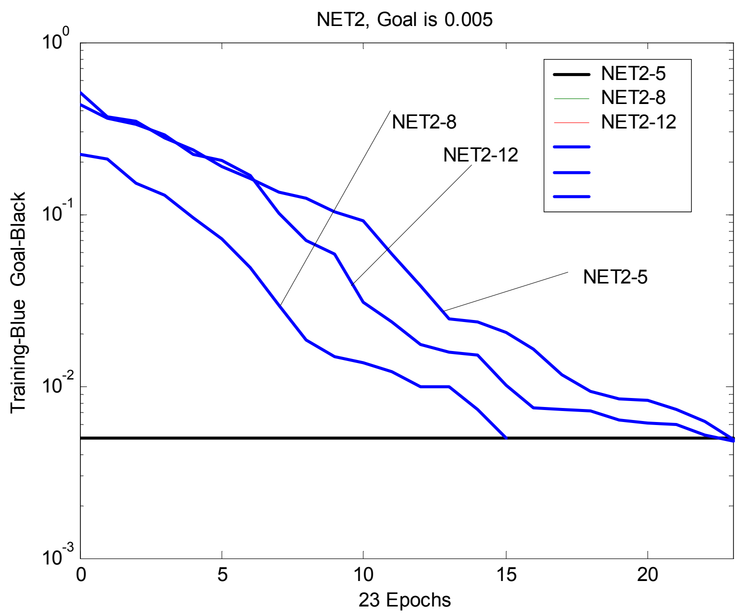

Figure 4.20 The training performance of NET2

Table 4.3 The training performance of NET2

Network	Input layer	Output layer	Hidden layer	Epoch	Escape Time (sec.)	MSE
NET2_5	12	5	5	23	7.48	0.00492607
NET2_8			8	15	9.29	0.00499643
NET2_12			12	23	23.013	0.00474518

It can be seen from the above results that NET2_8 and NET2_5 have better training behaviour with the least epoch and escape time.

Figure 4.21 and Table 4.4 show the training performance of NET3 with 25 inputs and 3 neurons in its output for 5, 8 and 12 neurons in hidden layer.

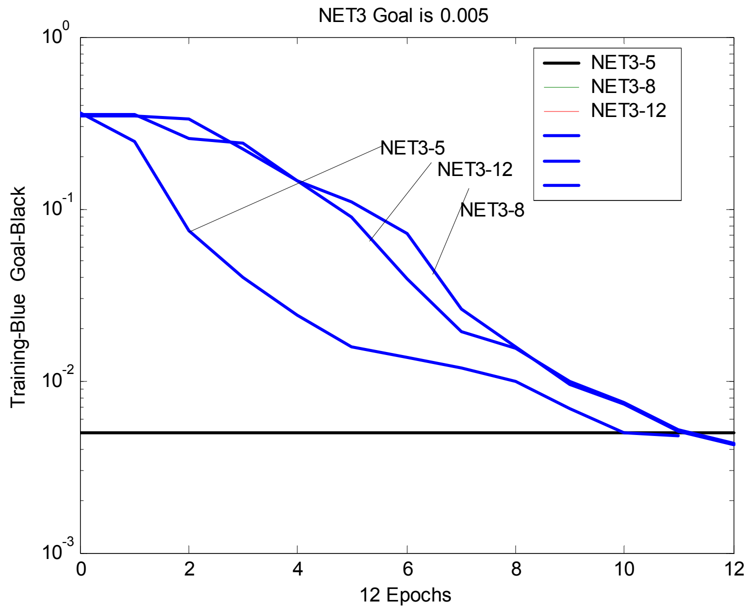

Figure 4.21 The training performance of NET3

Table 4.4 The training performance of NET3

Network	Input layer	Output layer	Hidden layer	Epoch	Escape Time (sec.)	MSE
NET3_5	25	3	5	11	5.3980	0.0047
NET3_8			8	12	10.0380	0.00436
NET3_12			12	12	20.8410	0.0042

The training behaviours of the three network architectures were different. The CPU time employed by NET3_12 was the lowest under the same goal. NET3_8 has the most number of epochs and the CPU time employed was also highest under the same condition.

Figure 4.22 and Table 4.5 display the training performance of neural network architecture 4 with 25 inputs and 5 neurons in its output for 5, 8 and 12 neurons in hidden layer.

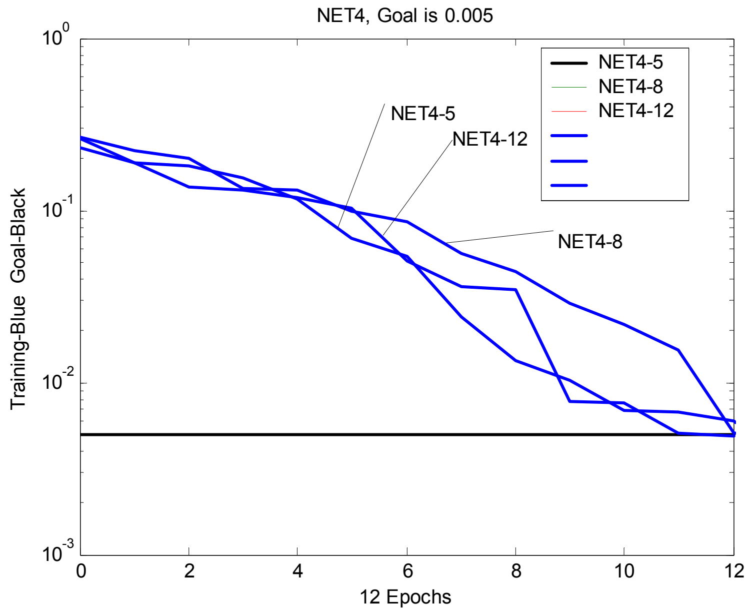

Figure 4.22 The training performance of NET4 (25-x-5)

Table 4.5 The training performance of NET4

Network	Input layer	Output layer	Hidden layer	Epoch	Escape Time (sec.)	MSE
NET4_5	25	5	5	12	9.0650	0.00484
NET4_8			8	13	10.755	0.00428
NET4_12			12	13	25.9900	0.00412

The NET4_8 networks trained with the least number of epochs and the CPU time employed was also lowest under the same goal. The NET4_12 trained with the most epochs and the CPU time employed was also the highest under the same condition.

4.4.2 The testing results:

By definition the output result of a Boolean matrix, the classification results gave a one hundred result of a Boolean matrix can judge the classification result and counts the recognition rate of the diagnostic results.

Table 4.6 reports on the performance of NET1 and NET2 with 12 basic features from 5 ECG classes. NET1 and NET2 with 12 neurones in the hidden layer had respectively the lowest average classification rate of 33.34% and highest average classification rate of 44%. NET2 with 8 neurones in the hidden layer had the highest average classification rate of 44% and with 5 neurones in the hidden layer had the lowest average classification rate of 33.4% respectively. It also was conclude that the NET2 had better classification rate than NET1. The best result achieved was with NET2_8 with 12 input, 8 neurons in the hidden layer and 5 neurons in its output layer. But this result was also too low in the practical applications, which cannot be accepted in the diagnostic area. This means that the training result with 12 features input was not satisfactory and caused the testing result to be unacceptable. More features will be used in the next test using NET3 and NET4.

Table 4.6 Different structures of ECG classifiers with 12 inputs

Training Samples: 100
Testing Samples: 100

Network Structure	Input layer	Output layer	Hidden layer	Heart problem	Recognition rate %	Average rate%
NET1_5	12	3	5	Nw	43	34
				Aw	46	
				Pw	14	
				Rw	1	
				Fw	66	
NET1_8	12	3	8	Nw	8	36.4
				Aw	57	
				Pw	7	
				Rw	50	
				Fw	60	
NET1_12	12	3	12	Nw	20	38
				Aw	69	
				Pw	4	
				Rw	21	
				Fw	76	
NET2_5	12	5	5	Nw	11	33.4
				Aw	51	
				Pw	25	
				Rw	0	
				Fw	80	
NET2_8	12	5	8	Nw	11	44
				Aw	42	
				Pw	22	
				Rw	61	
				Fw	84	
NET2_12	12	5	12	Nw	10	38.2
				Aw	42	
				Pw	1	
				Rw	72	
				Fw	66	

Table 4.7 reports on the testing results performed by NET3 and NET4 using test signals consist of 12 basic features plus 13 compressed samples. It shows that NET4_5 with 12

and 5 neurones in the hidden layer had almost the same average correct recognition rate around 91.8%. NET4_8 had 87.4% recognition rate. This result is general a good result in the experiment. Table 4.7 indicates that the NET4 with 5 neurones in the output layer has better classification rate than NET3 with 5 neurones in the output layer. So, it can be concluded that the best architecture was NET4_5 with 25 input, 5 neurons in hidden layer and 5 neurones in output layer.

Table 4.7 Different structure ECG classification with 25 inputs

Training Samples: 100
Testing Samples: 100

Network Structure	Input layer	Output layer	Hidden layer	Heart problem	Recognition rate %	Average rate
NET3_5	25	3	5	Nw	77	85
				Aw	83	
				Pw	100	
				Rw	83	
				Fw	82	
NET3_8	25	3	8	Nw	81	82.2
				Aw	43	
				Pw	98	
				Rw	99	
				Fw	90	
NET3_12	25	3	12	Nw	64	83
				Aw	79	
				Pw	92	
				Rw	85	
				Fw	95	
NET4_5	25	5	5	Nw	88	91.8
				Aw	99	
				Pw	91	
				Rw	100	
				Fw	81	
NET4_8	25	5	8	Nw	76	87.4
				Aw	98	
				Pw	100	
				Rw	81	
				Fw	82	
NET4_12	25	5	12	Nw	14	75.6
				Aw	96	
				Pw	100	
				Rw	94	
				Fw	74	

4.4.3 Discussions and analysis results of experiment4

ECG signal from MIT/BIH database is pre-processed to form input vectors of the neural networks. The train and test data sets used in the experiment contain 5 classes of ECG waveforms with 100 sample beats in each.

4.4.3.1 The training result discussions

The training data included a total of 641 N, 248 P, 270 R, 158 A, and 120 F waveforms. The first 100 of the training data were used for training to test the performance of different network structure.

Table 4.8 shows the training process performance of NET1 –NET4. The behaviours of the proposed networks in terms of training time are different. The samples for training NET1 and NET2 contain 12 basic features of the ECG signal. The samples for training NET3, NET4 consisted of 12 features plus 13 compressed samples of the signal. Firstly, the same training parameters were delicately optioned for all networks and they were chosen including maximum epoch of 20000, minimum gradient limited of 0.0001, and a goal was 0.005. However, it was hard to train NET1 and NET2 with the goal 0.005 comparing with NET3 and NET4.

Table 4.8 shows all the results of the performance of NET1-NET4. From Table 4.7 NET1_8 take the most epoch (7995) and training time (2240.9s) and also the most MSE even when it reached the goal of training. NET_5 is also very slow but the MSE is pretty good. , There were the least epochs (12) for all networks with 12 neurons in the hidden layer in NET1. The epoch and training time is also acceptable in NET2 and NET2_8 use and least epoch (15) and NET2_5 use the least training time (7.48s).

All the training results of NET3 and NET4 are desirable. All of the network structures use almost the same epoch and training which means this kind of 25 input enhanced the training performance of the network a lot compared with the 12 input.

The 12 input networks NET1, NET2 were more difficult to train than the 25 input network NET3 and NET4. This means that 12 feature input network cannot achieve a desirable result in training. It also means that 12 input features is not enough for training the network.

Table 4.8 The training performance of NET1-NET4 for discussion

Network	Input layer	Output layer	Hidden layer	Epoch	Escape Time (sec.)	MSE
NET1	12	3	5	3099	454.42	0.00351134
			8	7995	2240.9	0.00499969
			12	16	9.7640	0.00305856
NET2	12	5	5	23	7.48	0.00492607
			8	15	9.29	0.00499643
			12	23	23.013	0.00474518
NET3	25	3	5	11	5.3980	0.0047
			8	12	10.0380	0.00436
			12	12	20.8410	0.0042
NET4	25	5	5	12	9.0650	0.00484
			8	13	10.755	0.00428
			12	13	25.9900	0.00412

4.4.3.2 The testing results discussions

In order to compare the recognition behaviour of the networks for 5 ECG classes, the recognition rate can be defined and used to evaluate the performance of the classifiers. This factor is equal to one when all real events in a specific subgroup are detected correctly. In the case of missing some true events during classification, the recognition rate value would fall below one. The corresponding recognition rates for the selected ECG waveforms were assigned as; Nr for Normal, Pr for Paced, Rr for R, Ar for A, and Fr for F beat. The test data set contains a total of 104 N, 236 P, 115 R, 104 A, and 101 F waveforms and the first 100 samples were selected as the testing data for testing the ability of classifiers.

The first test was performed using NET1 and NET2 with 12 basic features from 5 ECG classes and the results were shown Table4.8. NET1 and NET2 with 5 neurones in the hidden layer had respectively the lowest average classification rate of 33.4% and 34%. NET1 and NET2 with 8 neurones in the hidden layer had the highest average classification rate of 36.4% and 44% respectively. It also was seen that NET2 had better classification rate than NET1. The best performance was achieved by NET2_8 with 12 input, 8 neurons in hidden layer and 5 neurons in output layer, which can get the recognition rate of 44%.

Generally, the average recognition rate of NET1 and NET2, which had 12 input features, was only 36.13% recognition rate. This kind of result was too low to be accepted in the application. The reason for this result was that 12 features input was not enough for training and testing in the ECG diagnostic applications. So in NET3 and NET4 testing 12 basic ECG features plus 13-compressed ECG signal would be used to find the improvement of the classification result.

Table 4.9 NET1 and NET2 classification for discussion

Input layer	**Output layer**	**Hidden layer**	**Nr (%)**	**Pr (%)**	**Rr (%)**	**Ar (%)**	**Fr (%)**	**Avr (%)**
12	3	5	43	14	1	46	66	34
		8	8	7	50	57	60	36.4
		12	20	4	21	69	76	38
Avr(%)			23.67	8.33	24	57.33	67.33	36.13
12	5	5	11	25	0	51	80	33.4
		8	11	22	61	42	84	44
		12	10	1	72	42	66	38.2
Avr(%)			10.67	16	44.33	45	76.67	38.53

Table 4.10 reports on the second testing results performed by NET3 and NET4 using test signals consisting of 12 basic features plus 13 compressed samples which were 25 features input. It shows that NET4 with 12 neurones and with 8 neurones in the hidden layer had classification rate 75.6% and 87.4% and the result generally indicated that the NET4_5 with 5 neurones in the output layer had the highest classification rate 91.8% but NET4_12 had the lowest rate 75.6%.

The result NET3_5, NET3_8 and NET3_12 had almost the same average correct recognition rate around 83.4%. Also the recognition rate of NET4 was much different from that of NET3. The average recognition rate of NET4 was 84.93%, which was also better than NET3. This means 5-output layer is also better than that of 3 outputs. It could be also observed that the best result was network with 25 input, 5 neurons in hidden layer and 5 neurons in output layer.

Table 4.10 NET3 and NET4 classification for discussion

Input layer	Output layer	Hidden layer	Nr (%)	Pr (%)	Rr (%)	Ar (%)	Fr (%)	Avr (%)
25	3	5	77	100	83	83	82	85
		8	81	98	99	43	90	82.2
		12	64	92	85	79	95	83
Avr (%)			74	96.67	89	68.33	89	83.4
25	5	5	88	91	100	99	81	91.8
		8	76	100	81	98	82	87.4
		12	14	100	94	96	74	75.6
Avr (%)			59.33	97	91.67	97.67	79	84.93

4.5 General Discussions

Based on the above-mentioned discussion we can give the general discussion as follows:

- Based on the result of the signal processing experiment, different types of signal processing algorithm were used with Matlab toolbox and found that the IIR filters are better than FIR filters. Some FIR filters are also accepted but not as good as IIR filter. FIR filters often require much higher order than IIR filter to achieve a given level of performance. The delay of FIR filter is often much greater than for an equal performance IIR filter. Median filter is also as good as the Yulewalk filter.

- Eight kinds of QRS detection algorithm were tested in the experiment. FD1 was found to give the best result. In order to improve the performance of the FD1 algorithm, thresholds could be enhanced to a proper number, which gets the best result. In this experiment threshold 1.2 was found to get best result.

- The extracted features were devised to automatically detect and classify ECG signal abnormalities. The combination of compressed ECG samples and the extracted features was an effective method in classifying the cardiac abnormalities, which are mainly reflected in the QRS complex. The advantage of the ANN classifier using the proposed feature vector is its simplicity and ease of implementation. Even though the 12 proposed basic features are the most important for ANN classifier, the other 13-compressed ECG signal are also important for the classification. The total 25 element input features for the ANN classifier minimised the complexity of the network, but also could keep the recognition rate of the classification.

- Training performance: In the experiment of ANN signal classification, the NET3 and NET4 training performance is better than NET1 and NET2.This is because the 12 features input is not enough for training the neural network but the 12 feature plus 13 compressed signals can efficiently enhance the training performance of the neural network.

- Testing result: The testing results of NET3 and NET4 are much better than NET1 and NET2. The recognition rates of NET1 and NET2 are so low that they cannot be used in the application. It also means that 12 basic ECG features are not enough in real usage. The recognition rates of NET3 and NET4 are better than and NET4 structure has the best testing result, which can be used in the real application. It also means 12 ECG features plus 13 compressed ECG signals, which formed a 25 input vector, are desirable in the experiment and real application.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

Computerised detection and classification of cardiac conditions is an active area of research worldwide. The methods developed for automatic cardiac classification have a vast number of applications and may provide significant contributions to the implementation of other intelligent diagnostic system. This research provides a complete description of the procedure required in a system that categorises the ECG signals into five cardiac conditions.

The ECG signal classification using the proposed neural network architecture was satisfactory. Good result were achieved with an average recognition rates of 84.93% Different methods of signal pre-processing and QRS detection algorithm were tested Different structures of neural networks were employed utilising MIT/BIH database and existing feature extraction algorithm to determine the most suitable one.

Based on the experimental results the conclusions of different experiments can be presented as follows:

5.1.1 Conclusion of experiment1 (Signal pre-processing)

In experiment 1, some pre-processing algorithms (including: Remez, Fir1, Fir2, Butterworth, ellip, Chebyshev1, Chebyshev2, Yulewalk and median filters) for ECG noise cancellation were implemented in Matlab. It was shown that Yulewalk and median filters perform quite successfully in removing most of the noise types.

Based on the result of the experiment 1, it was concluded that IIR filters perform better than FIR filters for this application. The performance of the selected filters is compared not only by visual evaluation but also by the quantitative measurements. SNR were calculated for the quantitative measurement purposes. Yulewalk and median filters had better visual results and provided a larger signal to noise ratio.

5.1.2 Conclusion of experiment 2 (QRS complex detection)

In experiment 2, eight QRS detection algorithms were tested to find a suitable one for QRS detection. This stage plays a fundamental role in automatic ECG signal diagnostic. It was found that FD1 algorithm provides a better result. Moreover, the performance of QRS detection depends on the selected threshold parameter. FD1 algorithm can detect the QRS components very well by selecting a proper threshold value. Different thresholds were also tested and the best threshold for this experiment was found.

The QRS detection algorithms were tested with two ECG signals containing 8 and 40 heartbeats. The QRS pulses were counted correctly with the same number of the input of heartbeats.

5.1.3 Conclusion of experiment 3 (ECG feature extraction)

In experiment 3, a number of features applicable to the ECG signal analysis and classification were presented. This experiment showed that important ECG features could be extracted from both morphological and statistical characteristics of the ECG signal. The problem of ECG signal variations among patients with the same cardiological conditions affects the performance of cardiac arrhythmia classifiers. The patient independent extracted ECG features in this experiment were employed as one part of the classifier input vector. These extracted features can enhance the performance of an ANN-based classifier.

The compressed form of the ECG waveform was also used instead of the raw data as the second part of the input vector to improve the speed, noise immunity, simplicity and recognition rate of the classifier. A computerised ECG signal classifier can be developed by employing the extracted features and compressed signal for detection of a vast range of cardiac arrhythmias.

The extracted features were devised to automatically detect and classify ECG signal abnormalities. The combination of compressed ECG samples and the extracted features was an effective method in classifying the cardiac abnormalities, which are mainly reflected in the ECG waveforms characters.

The advantage of the ANN classifier using the proposed feature vector is its simplicity and ease of implementation. It was found that not only the 12 proposed basic features play an important role in ANN classifier but also the other 13-compressed ECG signal are also very important. Using a 25-element input features for the ANN classifier minimised the complexity of the network and improved its recognition rate of the classification. This conclusion was tested and verified by experiment 4.

25 features used in the ANN classifications were: eight morphological features, four Statistic features and 13 Compressed ECG signals

5.1.4 Conclusion of experiment 4 (ANN classification)

In experiment4, four selected network architectures were used which can categorise into two basic types of feed forward neural networks.

In NET1 and NET2, 12 ECG features have been extracted from ECG signal as input. In NET3, NET4 the same features plus 13-compressed ECG samples were used to form an input vector with 25 elements. Different hidden layers including 5, 8, and 12 neurons have been tested for each network to investigate the effect of neurons in the network hidden-layer.

The training performance and recognition rate depended on the number of elements in input vector. The 25 input networks were more easy to train than the 12 input networks. This is because 12 input elements still cannot include enough characteristics of the ECG signal for training and classification. It needs more input features to enhance the efficient and speed of the network.

The 25 input networks had better test results than the 12 input networks classifiers. This proved that the 13 compressed ECG samples vectors, which formed the second part of input vectors of the neural networks, had significantly contributed to enhance the correct classification rate for ECG diagnosis.

In testing the training performance of ANN signal classifiers, NET3 and NET4 were performed better than NET1 and NET2.

The recognition rate results of NET3 and NET4 were much better than NET1 and NET2. It was found that NET4 had the best testing result, which can be used in the real application. It also means 12 ECG features plus 13-compressed ECG signal that formed a 25 input vector are desirable in the experiment and real application. This network improves the accuracy of diagnosis where the network deals with a large group of inputs and decreases the structure complexity of the networks.

5.2 General Conclusion

The most important step in ECG diagnostic is to detect and measure different waves, which form the entire ECG cycle, to extract efficient features and to find suitable structure and algorithm for ANN ECG signal classifications. Different methods of ECG signal processing and analysis were tested to achieve in this purpose. The selected features were suitable for diagnosis of five cardiac conditions and enhanced the efficiency, simplicity and recognition rate of the neural network.

Based on the above discussion a general conclusion can be summarised as follows:

- The performances of Yulewalk filter and median filter were better than other selected filters based on the results of visual and quantitative evaluation.

- FD1 QRS detection algorithm was a suitable one in this application and a good threshold was also found. The FD1 algorithm was verified not only with eight heartbeats but also with 40 heartbeats.

- The extracted features were devised to automatically detect and classify ECG signal abnormalities. The combination of compressed ECG samples and the extracted features was an effective method in classifying the cardiac abnormalities. The advantage of the ANN classifier using the proposed feature vector is its simplicity and ease of implementation.

- In testing of the ANN signal classification, it was found that NET3 and NET4 training performance and testing results were much better than NET1 and NET2. The best performance of network was NET4 which achieve in a highest recognition rate of 91.8% and an average recognition rate of 87.4%. This result means that 12 feature input is not enough for training and testing the neural network but 12 feature plus 13 compressed ECG signals can efficiently enhanced the training performance of the neural network and decrease the complexity of the network structure. It also means that 12 ECG features plus 13 compressed ECG signals, which formed a 25 input vector, are desirable in this experiment and real application for five cardiac conditions.

- Matlab is a good tool for this research. The use of Matlab reduced the programming demands and allowed us to focus more on algorithm development rather than programming.

The developed filters and neural networks are applicable to other types of cardiac conditions. However, there are some limitations on the experiments. For example, the proposed one-stage neural network is suitable for those five cardiac conditions listed in section1.3. This one-stage network is not suitable for classifying a large number of the ECG signal abnormalities because the training and testing speed maybe unacceptable. To solve this problem a multi-stage neural network should be designed to improve the speed. The selected 25 features are also more suitable for five cardiac conditions. Some of the features maybe changed if other cardiac conditions are selected.

5.3 Future work

Computerised ECG diagnostic system is an important tool used in clinical practice today. Analysis of ECG signal is a difficult task but with the help of Matlab, signal processing and neural network toolboxes, it is possible to automate this process. There is still a lot of works to do in the future:

- In the signal processing stage, other techniques should be tested such as: adaptive filters, filter bank and neural network.

- In the QRS detection stage, the techniques such as: singularity detection based approaches, Neural network approaches, wavelet based QRS detection and zero crossing based QRS detection etc should also be tested in the future.

- In the feature extraction stage, other features related to other cardiac condition should be found. There are more than hundred ECG features introduced in the literature. The selected features in this research are suitable for five cardiac conditions but for more cardiac abnormalities more features are required as each abnormality related with different features.

- In signal classification stage, other structures and algorithms of the neural network should be tested. One stage network can perform very well with the present application, but there are more cardiac abnormalities than were covered in this project and a multi-layer and muti-stage classifier should be designed to separate them. This multi-stage neural network can use suitable algorithms in each stage and diagnostic part of the cardiac conditions which can minimise the whole complexity of network structure. In this way, the classifier can deal with more cardiac conditions while using a simple network structure at each stage.

- This research can be applied to telemedicine application area. Remote access to ECG diagnoses is a very useful service for both medical community and patients. This service has been used actively in the last decade. The remote clinical session uses multimedia tools to transmit ECG information from one clinic to a remote site. This service can facilitate the training of specialists, researchers and doctors. This medical service is primarily dedicated to chronic patients. The patient's ECG data are stored in the computer server in the form of personal electronic medical record. The patient send his medical data to hospital by using standard computer equipment and telephone line or by specially designed hardware. The explosive growth of the technology in the last decade allows us to utilise different devices and services. Generally, tele-ECG diagnosis research is a promising area in the future.

The extension of this research should be under further work in the future. The overall objects of this research is to design and implement an intelligent, interactive ECG analyser with some specification as listed below (Hosseini H. G., 2002):

- A versatile, cost effective, reliable and intelligent ECG signal analyser using an ordinary personal computer.
- Ability to collect and detect a wide range of abnormalities of the ECG signal form different patient body. Then the final analysing report will be based on this collected signal database
- On-line monitoring to improve management of signal abnormalities

- Ability to save and display a range of different data about the function of the human body as well as some other patient information for further analysis.

Bibliography

Ahlstrom M. L. and Tompkins W. J. (1983). Automated high speed analysis of holter tapes with microcomputers. *IEEE Transactions on Biomedical Engineering, BME-30*, 651-657.

Balda R.A. et al. (1977). *The HP ECG analysis program*. North Holland.

Barro S. M. and Delgado F. (1998). Classifying multi-channel ECG patterns with an adaptive neural network. *Engineering In Medicine And Biology*.

Berbari, E. J. (2000). Principles of Electrocardiography. In Josephd.Bronzino (Ed.), *The Biomedical Engineering Handbook* (Vol. 1, pp. 13-11): IEEE Press.

Berbari J. E. (2000). Principles of Electrocardiography. In Josephd.Bronzino (Ed.), *The Biomedical Engineering Handbook* (Vol. 1, pp. 13-11): IEEE Press.

Bronzino D. J. et al. (2000). *The Biomedical Engineering Handbook* (2nd ed. Vol. 1): IEEE Publisher.

Bruce N. E. (2001). *Biomedical Signal processing and Signal Modeling*: A Wiley Interscience Publication.

Camps G., M. M. a. S. E. (2001). Fetal ECG extraction using an FIR neural network. *IEEE Computer in Cardiology*.

Carr J. J. and John M.Brown J. M. (1998). *Introduction to Biomedical Equipment Technology* (3rd ed.): Prentice Hall, Inc.

Chazal D. P. (1998). *Automatic Classification of the Frank Lead Electrocardiogram.* Unpublished PHD, University of New South Wales.

Conde T. (1994). Automatic Neural Detection of Anomalies in ECG Signals. *IEEE Computer in Cardiology*.

D.Bronzino, J. (2000). *The Biomedical Engineering Handbook* (2nd ed. Vol. 1): IEEE Publisher.

Demuth H. and Beale M. (2001). *Neural network Toolbox For Use With Matlab*: The MathWorks, Inc.

Dubowik K. (1999). *Automated Arrhythmia Analysis-An Expert System for An Intensive Care Unit.* Lund University, Sweden, Lund.

Fraden J. and Neuman M. R. (1980). QRS wave detection. *Medical & Biological Engineering & Computing, 18*, 125-132.

Friesen G. M. and Jannett C. T. et al. (1990). A compareison of the Noise Sensitivety of Nine QRS Detection Algorithm. *IEEE Transactions on Biomedical Engineering, 37*.

Furno G. S. and Tompkins W. J. (1983). A learning filter for reducing noise interference. *IEEE Transactions on Biomedical Engineering, BME-30*, pp.234-235.

Gonzalez R. and Fernadez R. et al. (2000, July 23-28). *Real-time QT interval Measurement.* Paper presented at the 22nd Annual EMBS International Conference, Chicago.

Granit R. (2003). *ECG Analysis-Biomedical Engineering Laboratory Lecture*: Ragnar Granit Institute.

Gustafson D. et al. (1977). *Automated VCG interpretation studies using signal analysis techniques*. Cambridge, MA,: R-1044 Charles Stark Draper Lab.,.

Hamilton P. et al. (1991). Compression of the Ambulatory ECG by Average Beat Subtraction and Residual Differencing. *IEEE Transactions on Biomedical Engineering, 38*, 253-259.

Harris N. D. and Ireland R. H. et al. (2001). Can changes in QT interval used to predict the onset of hypoglycemia in type1 diabetes. *IEEE Computer in Cardiology*.

Hasnain S. K. U. and Asim S. M. (1999). Artificial Neural network in Cardiology-ECG Wave Analysis and Diagnosis Using Backpropagation Neural network.

Haynes J. R. (1936). *Heated Stylus for use with waxed recording paper*: Rev Sci Instrum.

Holsinger W. P. et al. (1971). A QRS preprocessor based on digital differentitation. *IEEE Transactions on Biomedical Engineering, BME-18*, 212-217.

Hosseini H. G. (2002). An Intelligent and Interactive Biosignal Analyser.

Hosseini H. G. et al. (1998a). *Detection and Extraction of The ECG Signal Parameters.* Paper presented at the Processings of the 20th Annual EMBS International Conference, Hong Kong.

Hosseini H. G. et al. (1998b). *ECG Noise Cancellation Using Digital Filters.* Paper presented at the The 2nd International Conference On Bioelectromagnetism, Melbourne.

Hosseini H. G. et al. (1999). *Efficient Features for ANN-based ECG Classifiers.* Paper presented at the IEEE/EMBS'99 Conference, Monash University, Australia.

Hosseini H.G. (2001). *Computer-aided Diagnosis of Cardiac Events.* Flinders University, Australia.

Hosseini, H. G. a. N. H. (1999). *Computer-aided Diagnosis of Cardiac Events.* Flinders University, Australia.

Howard Demuth, M. B. (2001). *Neural network Toolbox For Use With Matlab*: The MathWorks, Inc.

Hutchens G. et al. (1990). ECG Data Compression Techniques: A Unified Approach. *IEEE Transactions on Biomedical Engineering, 37*, 329-343.

Ifeachor E. C. and Jervis B. W. (1993). *Digital Signal Processing-A Practical Approach*: Addison Wesley Publishers Ltd.

Jadvar H. et al. (1989). *Computer ST segment Measurement during Transesophageal Atrial Pacing Stress*. Chicago, USA: Research and Development Arzco Medical Electronics, Inc.

Jamal R. and Pichlik H. (1998). *Labview Application and Solution*.

Jardins T. D. (2002). *Cardioopulmonary Anatomy Physiology* (4th ed.).

Jenkins J. M. (1981). *Computerized electrocardiography* (Vol. Crit Rev Bioeng): CRC.

Kohler B.U. et al. (2002). The Priciples of Software QRS Detction. *IEEE Engineering In Medicine And Biology*, 42-55.

Kung S. Y. and Taur J. S. (1995). Decision based neural network with signal/image classification application. *IEEE Transactions on Neural Network, 6*.

Laguna P. et al. (1990). New algorithm for QT interval analysis in 24-hour holter ECG: Performance and Application. *Medical & Biological Engineering & Computing*.

Little J. N. and Shure L. (2001). *Signal Processing Toolbox for use with Matlab*: The Mathworks Inc.

Lo T. Y. and Tang P. C. (1982). *A Fast Bandpass Filter for ECG Processing.* Paper presented at the IEEE Engineering In Medicine And Biology Society.

Mahoudeaux P. M. et al. (1981). Simple microprocessor based system for on-line ECG analysis. *Medical & Biological Engineering & Computing, 19*, 497-500.

Mark, R. (Ed.). (1992). *MIT-BIH Arrhythmia Database Directory*: Massachusetts Institute of Technology.

Menrad A. et al. (1981). *Dual microprocessor system for cardiovascular data acquisition, processing and recording.* Paper presented at the IEEE Int. Conf. Industrial Elect. Contr. Instrument.,.

Miller A. S. Blott B. H. and Hames T. K. (1992). Review of neural network application in medical imaging and signal processing. *Medical and Biological Engineering and Computing*, 449-464.

Moody G. and Mark R. (1992). *MIT-BIH Arrhymia Database Directory*: MIT-BIH database distribution.

Nashash H. A. (1995). A Dynamic Fourier Series for the Compression of ECG using FFT and Adaptive Coefficient Estimation. *Med. Eng. Phys., 17*, 197-203.

Nave G. and Cohen A. (1993). ECG Data Compression Using Long-Term Prediction. *IEEE Transactions on Biomedical Engineering, 40*, 877-886.

Nollo G. and Speranza G. et al. (1990). Dynamic measurement of the QT interval. *IEEE Computer in Cardiology*.

Paul J. S. et al. (1998). *Eigen Filter Based Extraction of ST-segment Waveform from Surface ECG's.* Paper presented at the Proceeding of the 20th Annual International Conference of the IEEE Engineering in Medicine and Bioology Socicty.

Pretorius L.C. et al. (1992). *Feature Extraction From ECG for Classification By Artificial Neural Network*. Pretoria, South Africa: University of Pretoria.

Pryor T. A. et al. (1980). Computer Systems for the Processing of diagnostic electrocardiograms. *IEEE Computer Society Press*.

R.Mark, G. M. a. (1992). *MIT-BIH Arrhymia Database Directory*: MIT-BIH database distribution.

Sahambi J. S. and Tandon S. N. et al. (2000). An Automated Approach to Beat-by-Beat QT-Interval Analysis. *IEEE Engineering In Medicine And Biology*.

Silipo R. and Marchesi C. (1998). Artificial neural network for automatic ECG analysis. *IEEE Transactions on Signal Processing, 46*.

Waller A. D. (1889). *One of the electromotive changes connected with the beat of mammalian heart, and the human heart in particular*: Phil Trans B.

Wartak J. (Ed.). (1978). *Electrocardiogram Interpretation*.

Yu H. H. and Tompkins W. J. (1997). A patient adaptable ECG beat classifier using a mixture of experts approach. *IEEE Transactions on Biomedical Engineering, 44*.