DEFECTIVE HEARTBEAT DETECTION

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Bachelor of Technology

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WAKNAGHAT

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DECLARATION

We hereby declare that the work reported in the B-Tech thesis entitled "Defective Heart-Beat Detector" submitted at Jaypee University of Information Technology,Waknaghat India, is an authentic record of my work carried out under the supervision of Prof.(Dr.) Sunil V. Bhooshan. We have not submitted this work elsewhere for any other degree or diploma.

(Signature of the Students)

(Sakshi Singh-121013)

(Suryakiran Singh-121069)

Department of Electronics And Communication

Jaypee University of Information Technology, Waknaghat , India

26-05-2016

CERTIFICATE

This is to certify that the work reported in the B-Tech. thesis entitled "Defective Heartbeat Detector", submitted by Sakshi Singh(121013) and Suryakiran Singh(121069) at Jaypee University of Information Technology, Waknaghat , India is a bonafide record of his / her original work carried out under my supervision. This work has not been submitted elsewhere for any other degree or diploma.

(Signature of Supervisor)

Prof.(Dr.) Sunil V. Bhooshan

Department of Electronics and Communication

26-05-2016

ABSTRACT

In this project, the aim is to detect the defective heartbeat by a non-invasive method. Preliminary detection of the heartbeat can help in various stages afterwards and can lead to high performance heart diagnostics.

The Fast-Fourier transform of a defective ECG is found out and is compared against the FFT of a normal ECG. Time-domain analysis is observed by calculating the power spectral density after noise is removed from the ECG and then it is compared against a normal ECG with noise removed as well.

Similarly, Auto-correlation of both defective and normal ECG are also found out and then their cross-correlation helps in establishing relationships between the two wave-forms.

All the above mentioned parameters helps in establishing relationships between the defective and normal ECG. And such procedures with pre-processing techniques implemented can help in developing of a non-invasive tool for detecting a defective heart-beat.

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

When we talk of heart disease, it includes any disorder that affects the heart's ability to function normally. There are different types of heart diseases, for example, arrhythmias, prolapsed mitral valve, coronary artery disease, congenital heart disease, and so on. One of the most common causes of heart disease is narrowing of the arteries in the heart that supply blood to the heart muscle but some heart diseases are present at birth. Heart disease has been examined by various methods.One of them, the non invasive method, is highly used and is the most effective. This method refers to the diagnosis of heart without actually injecting something in the body. An electrocardiogram (ECG) signal for heart disease investigation is used, because it is a simple and noninvasive diagnostic tool. ECG can be easily obtained by placing the electrodes on the chest wall and attaching them to an ECG machine. In a conventional 12 lead ECG, ten electrodes are placed on the patient's limbs and on the surface of the chest. The overall magnitude of the heart's electrical potential is then measured from twelve different angles ("leads") and is recorded over a period of time (usually 10 seconds). In this way, the overall magnitude and direction of the heart's electrical depolarization is captured at each moment throughout the cardiac cycle. The graph of voltage versus time produced by this noninvasive medical procedure is referred to as an electrocardiogram (abbreviated ECG or EKG).

Reasons for performing electrocardiography include:

- Suspected heart attack
- Suspected pulmonary embolism
- A third heart sound, fourth heart sound, a cardiac murmur or other findings to suggest structural heart disease
- Perceived cardiac dysrhythmias
- Fainting or collapse
- Seizures
- Monitoring the effects of a heart medication
- Assessing severity of electrolyte abnormalities, such as hyperkalemia

The United States Preventive Services Task Force does not recommend electrocardiography for routine screening procedure in patients without symptoms and those at low risk for coronary heart disease. This is because an ECG may falsely indicate the existence of a problem, leading to misdiagnosis, the recommendation of invasive procedures, or overtreatment. However, persons employed in certain critical occupations, such as aircraft pilots, may be required to have an ECG as part of their routine health evaluations.

CHAPTER 2

ELECTROCARDIOGRAM (ECG)

An ECG is a representation of the heart muscle's electrical activityas it changes with time, printed on paper for easier analysis. Just like other muscles, muscle of the heart contracts in response to electrical depolarization of the muscle cells. Taking the sum of this electrical activity,we amplify and record it for a few seconds, which is known as an ECG.

Normal cardiac cycle begins with spontaneous depolarization of the sinus node, an area of specialized tissue situated in the high right atrium (RA). Then a wave of electrical depolarization spreads through the right atrium and across the inter-atrial septum into the left atrium (LA).

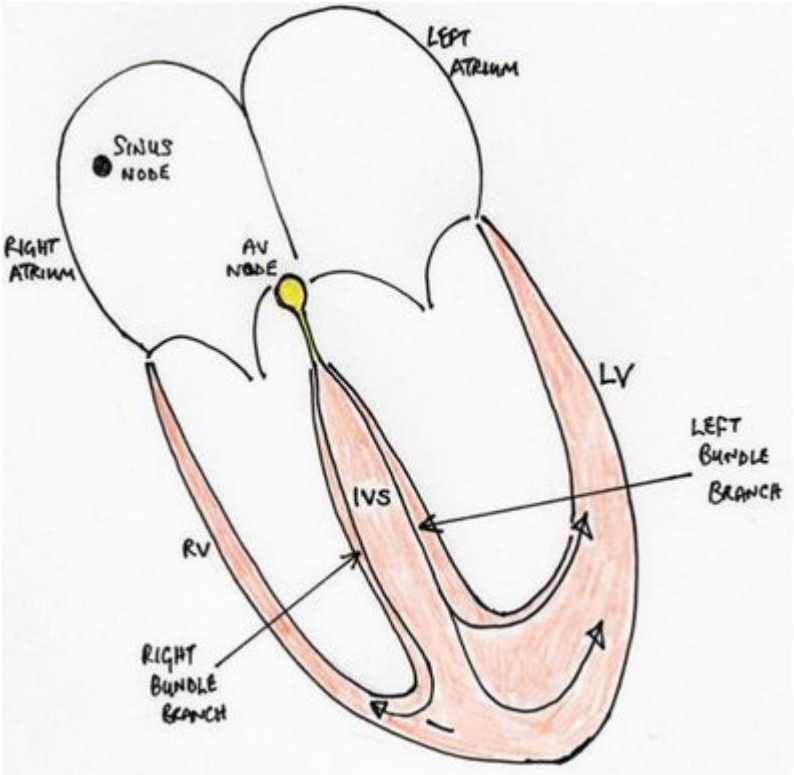

Figure 2.1 : Basic electrophysiology of the heart

Source http://www.southsudanmedicaljournal.com/archive/may-2010/how-to-read-an-electrocardiogram-ecg.-part-one-basic-principles-of-the-ecg.-the-normal-ecg.html

Atria are separated from the ventricles by an electrically inert fibrous ring, so that in the normal heart the only route of transmission of electrical depolarization from atria to ventricles is through the atrioventricular (AV) node. Thisatrioventricular node delays the electrical signal for a short time, and then the depolarization wave spreads down the interventricular septum (IVS). Therefore with normal conduction the two ventricles contract simultaneously, this is important in maximizing efficiency of the heart.

When complete depolarization of the heart has happened, the myocardium must then repolarize, before it can be ready to depolarize again for the next cardiac cycle.

2.1 VOLTAGE AND TIMING INTERVALS

In general, the ECG signal is recorded using standard measures for amplitude of the electrical signal and for the speed at which the paper moves during the recording. This allows:

- An easy appreciation of cardiac intervals and heart rates.
- A meaningful comparison to be made between ECGs recorded on different occasions or by different ECG machines.

The voltage, or amplitude, is expressed on an ECG in the vertical axis and is measured in millivolts (mV). Talking abouta standard ECG paper, 1mV is represented by 10 mm. An increase in the amount of muscle mass usually results in a larger electrical depolarization signal, and so a larger amplitude of vertical deflection on the ECG.

One of the most important features of the ECG is that the electrical activity of the heart is shown against with time. We can think of the ECG as a graph, where electrical activity is plotted on the vertical axis against time on the horizontal axis. Standard ECG paper moves at 25 mm per second during real-time recording. This means that when we look at the standard printed ECG a distance of 25 mm along the horizontal axis represents 1 second in time.

The ECG paper is marked with small and large squares which form a grid. Each small square represents 40 milliseconds (ms) in time along the horizontal axis and each larger square contains 5 small squares, therefore representing 200 ms. Standard ECG paper speeds and square markings allow easy measurement of cardiac timing intervals, thus enabling calculation of heart rates and identification of abnormal electrical conduction within the heart.

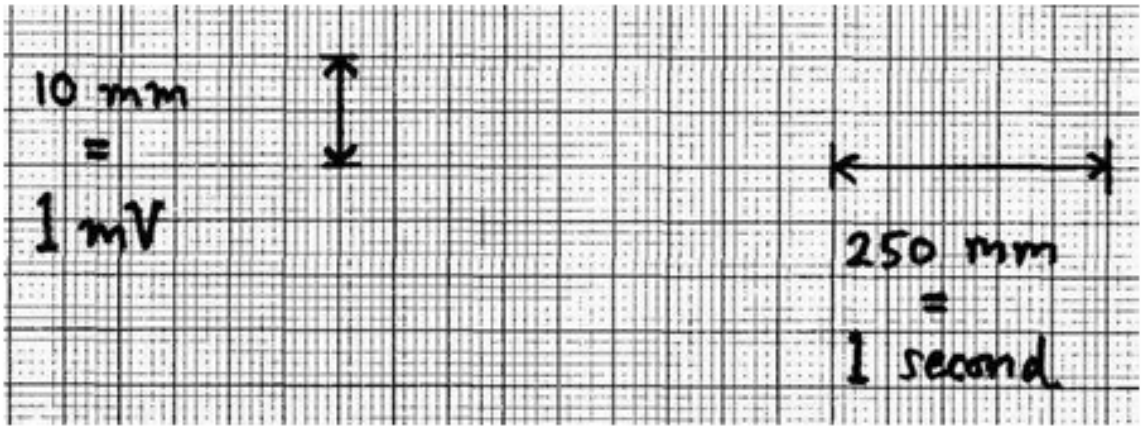

Figure 2.2 : Sample of standard ECG paper showing the scale of voltage, measured on the vertical axis, against time on the horizontal axis

Source: http://www.southsudanmedicaljournal.com/archive/may-2010/how-to-read-an-electrocardiogram-ecg.-part-one-basic-principles-of-the-ecg.-the-normal-ecg.html

2.2 THE NORMAL ECG

The first area in the heart to be depolarized is the right atrium, closely followed by the left atrium, and so the first electrical signal on a normal ECG originates from the atria and is known as the P wave. Usually there is only one P wave in most leads of an ECG, but the P wave is in fact the sum of the electrical signals from the two atria (right and left), which are usually superimposed.

After that there is a short, delay as the atrioventricular (AV) node slows the electrical depolarization before it proceeds to the ventricles. This is responsible for the PR interval, a short period where no electrical activity is seen on the ECG. It is represented by a straight horizontal, also called the 'isoelectric' line.

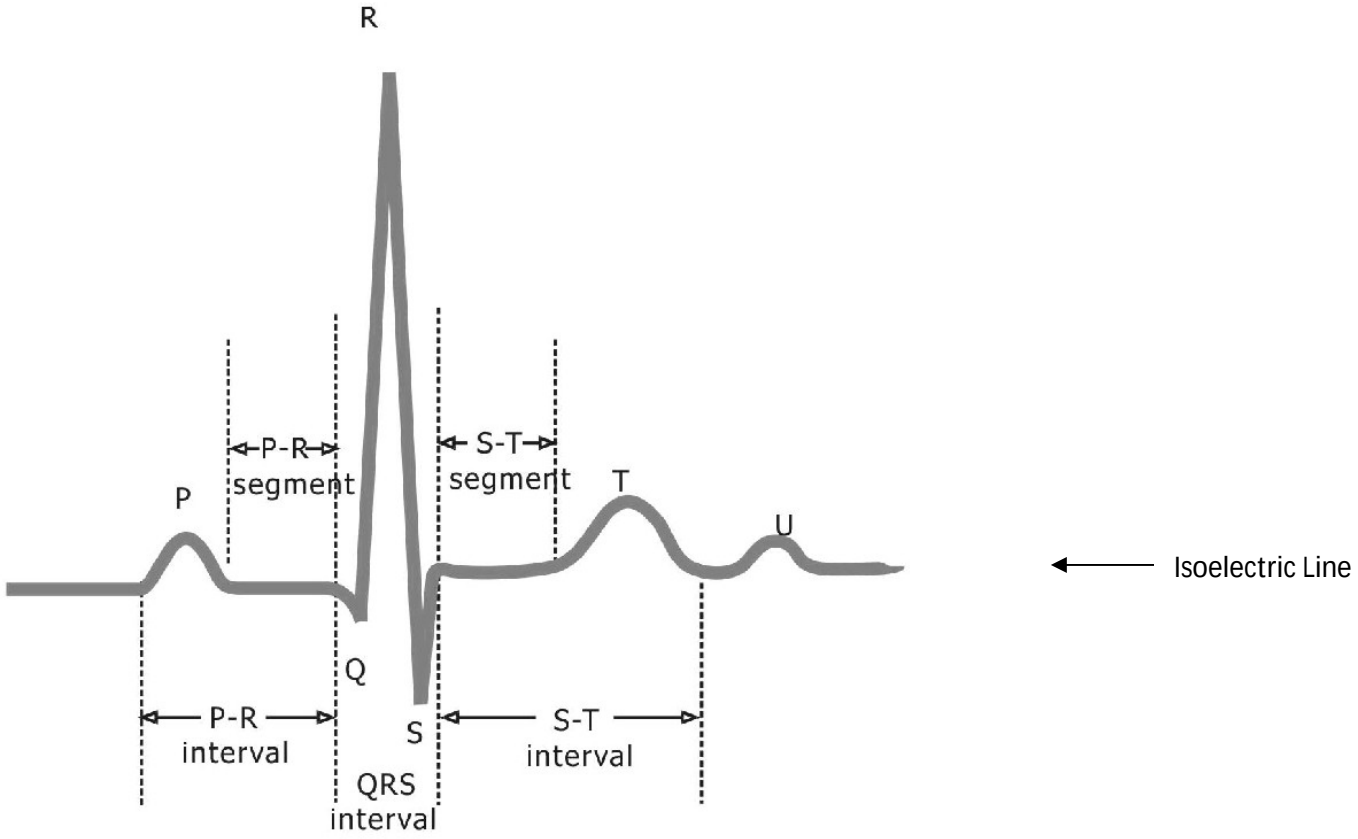

Figure 2.3 : The major waves of a single normal ECG pattern

Source: http://www.ni.com/tutorial/6349/en/

Now the ventricles are depolarized, and it results in usually the largest part of the ECG signal (because of the greater muscle mass in the ventricles) and this is known as the QRS complex.

- The Q wave is the first downward or 'negative' deflection
- The R wave is the next upward deflection (with a condition that it crosses the isoelectric line and becomes 'positive')
- The S wave is then the next deflection downwards, also with a condition that it crosses the isoelectric line to become negative for a short time before returning to the isoelectric baseline.

There is also an electrical signal reflecting repolarisation of the myocardium in the case of the ventricles. It is represented as the ST segment and the T wave. The ST segment is normally on the baseline, and the T wave is an upward deflection of variable amplitude and duration.

2.3 NORMAL INTERVALS

We can measure the time taken for the various phases of electrical depolarization with the help of the recording of an ECG on standard paper. Time is usually measured in milliseconds. There is a recognized normal range for such 'intervals':

- PR interval: It is measured from the beginning of the P wave to the first deflection of the QRS complex, or we can say when the Q wave begins. Normal range is 120 – 200 ms (3 – 5 small squares on ECG paper).
- QRS duration: It is measured from first deflection of QRS complex to end of QRS complex at isoelectric line, when the S wave ends. Normal range is up to 120 ms (3 small squares on ECG paper).
- QT interval: It is measured from first deflection of QRS complex, i.e. the start of the Q wave, to end of T wave at isoelectric line. Normal range is up to 440 ms (though it varies with heart rate and may be slightly longer in females).

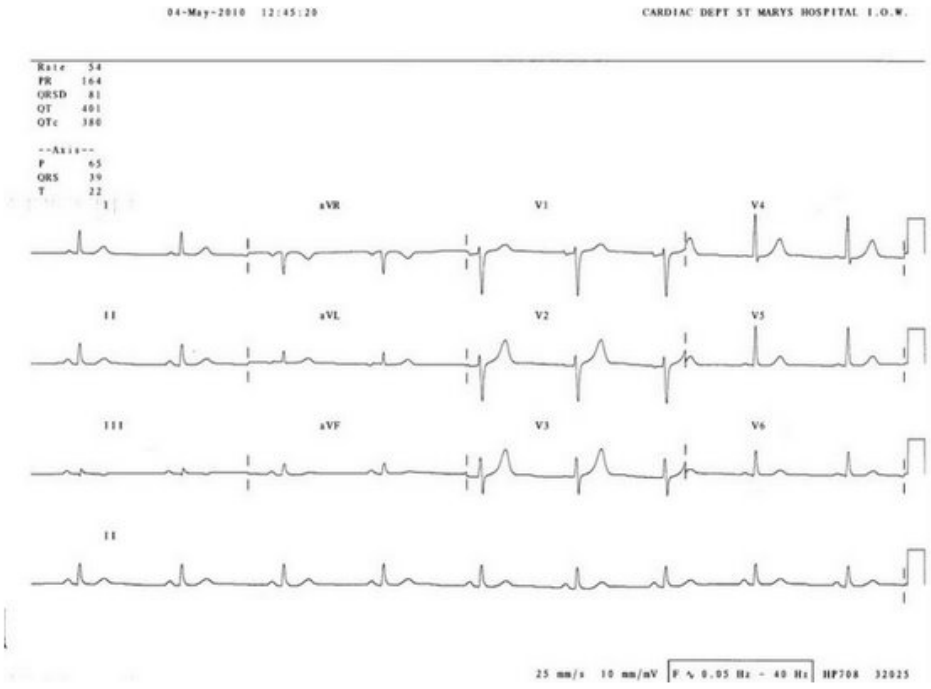

Figure 2.4 : Example of a normal 12 lead ECG; notice the downward deflection of all signals recorded from lead aVR. This is normal, as the electrical axis is directly away from that lead
Source:http://www.southsudanmedicaljournal.com/archive/may-2010/how-to-read-an-electrocardiogram-ecg.-part-one-basic-principles-of-the-ecg.-the-normal-ecg.html

2.4 HEART RATE ESTIMATION FROM THE ECG

Standard ECG paper allows an approximate estimation of the heart rate (HR) from an ECG recording. Each second of time is represented by 250 mm (5 large squares) along the horizontal axis. So if the number of large squares between each QRS complex is:

- 5 - The heart rate is 60 beats per minute.
- 3 - The heart rate is 100 beats per minute.
- 2 - The heart rate is 150 beats per minute.

CHAPTER 3

FAST FOURIER TRANSFORM AND MATLAB IMPLEMENTATION

A signal has one or more frequencies in it, and can be viewed from two different standpoints:

Time domain and Frequency domain

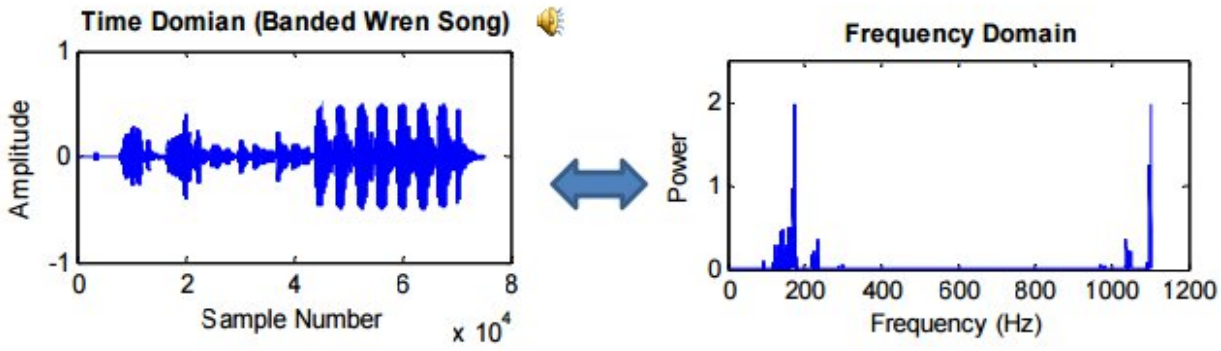

Fig 3.1 A sample signal in time domain and frequency domain

Frequency-domain figure: how much of the signal lies within each given frequency band over a range of frequencies

Why frequency domain analysis?

• To decompose a complex signal into simpler parts to facilitate analysis

• Differential and difference equations and convolution operations in the time domain become algebraic operations in the frequency domain

• Fast Algorithm (FFT)

A fast Fourier transform (FFT) algorithm computes the discrete Fourier transform (DFT) of a sequence, or it's inverse. Fourier analysis converts a signal from its original domain (often time or space) to a representation in the frequency domain and vice versa. An FFT rapidly computes such transformations byfactorizing the DFT matrix into a product of sparse (mostly zero) factors. As a result, it manages to reduce the complexity of computing the DFT from $O(n^2)$, which arises if one simply applies the definition of DFT, to $O(n \log n)$, where n is the data size.

Fast Fourier transforms are widely used for many applications in engineering, science, and mathematics.

3.1 USE OF FFT IN ELECTROCARDIOGRAM

ACCURATE NONINVASIVE DETECTION of patients at risk for development of sustained ventricular tachycardia (VT) is not yet possible. Recently, high gain amplification and signal-processing techniques in the time domain have detected low-amplitude, high frequency potentials in the terminal QRS complex and ST segment of signal-averaged electrocardiograms (ECGs) obtained during arrhythmia-free intervals from patients and experimental animals with sustained VT.' Results of studies in which endocardial and epicardial mapping were used suggest such potentials reflect either delayed or disorganized ventricular activation. Fast-Fourier transform analysis (FFTA) is a powerful analytic method for signal processing in the frequency domain that allows some of the inherent limitations of high-gain amplification and signal filtering required for analysis in the time domain to be avoided."1 Any periodic signal, such as the QRS complex, may be represented by the mathematical summation of a series of sine waves of differing frequencies and amplitudes. The sinusoidal component with the lowest frequency is called the fundamental and has a repetition rate equal to the repetition rate of the periodic signal under evaluation. All higher sinusoidal components, or harmonics, have frequencies that are integer multiples of the fundamental frequency. FFTA is a computer-based mathematical algorithm whereby the amplitudes of the various harmonic components that comprise a complex periodic waveform are determined. The Fourier transform is unique since for each time-domain signal there is one and only one frequency domain presentation and vice versa. To determine whether FFTA would facilitate objective identification and characterization of abnormal low-amplitude potentials in the surface ECG, procedures for FFTA of signal-averaged ECGs are developed, rigorously tested with both computer-generated mathematical functions and analog test voltages, and subsequently applied to patients.

3.2 MATLAB CODES AND RESULTS

The database that is used for obtaining sample defective and normal ECG is a courtesy of Massachusetts institute of technology and Boston's Beth Israel Hospital. Sample of normal and defective ECG is taken for analysis and relationship is established using simple mathematical functions and operations in MATLAB.

3.3 COMPARISON OF FOURIER TRANSFORMS

In the following abstract, we will compare the Fourier transform of an ECG suffering from various heart diseases affected ECG with a normal ECG. Comparison of Fourier transform of various diseases such as arrhythmia and sudden cardiac arrest which can be judged very easily by analysing the Fourier transform which is a non-invasive tool.

A) Arrhythmia

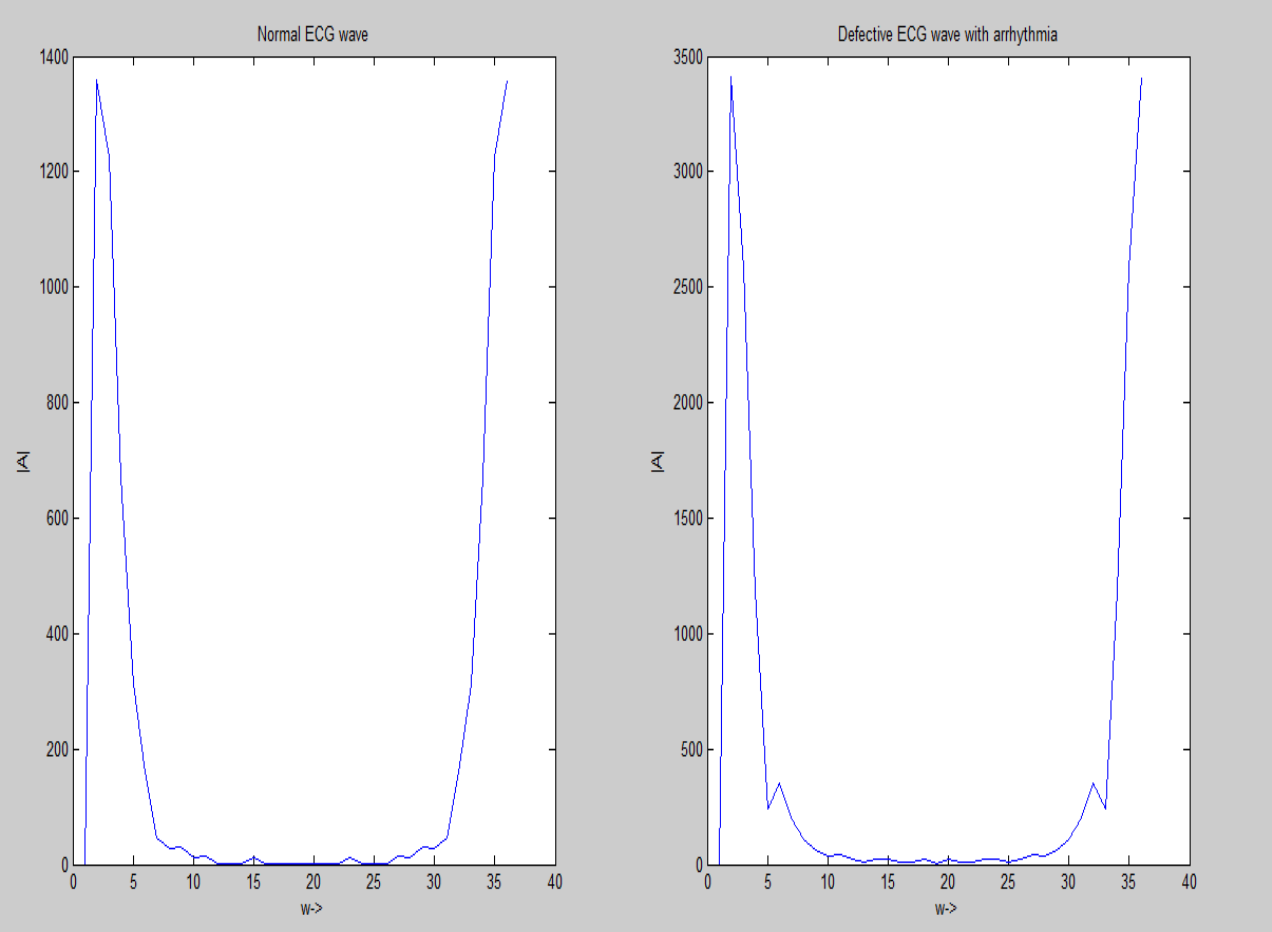

Fig 3.2 Comparison of Fourier Transform of defective and normal ECG wave(Arrhythmia)

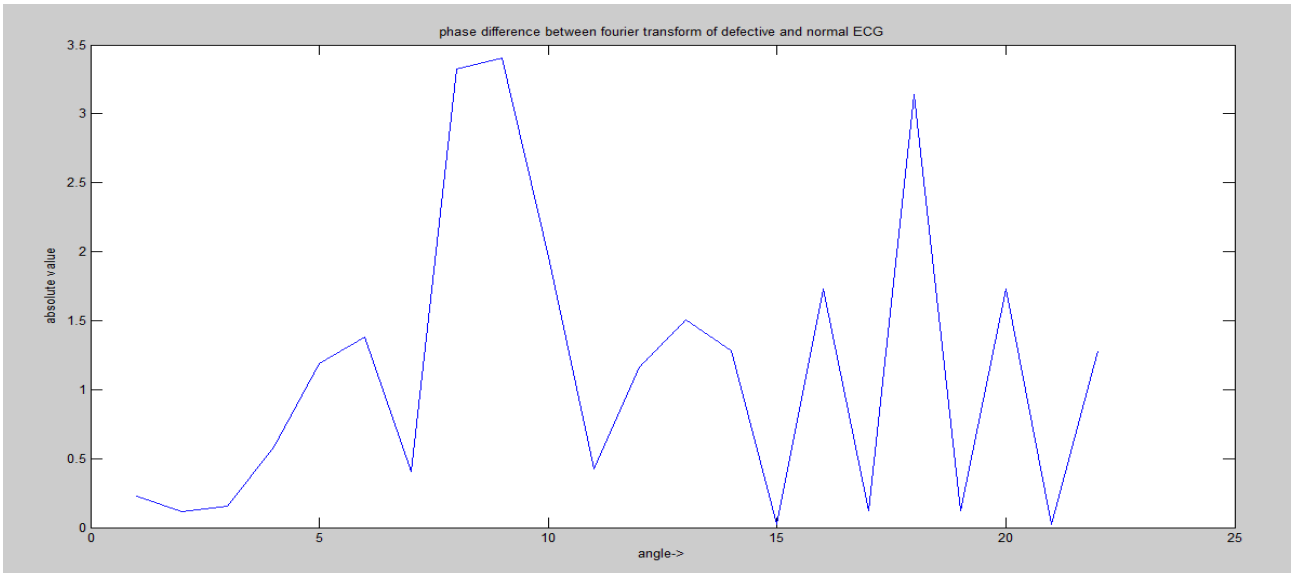

Fig 3.3 Phase Difference between the Fourier transform of defective and normal ECG

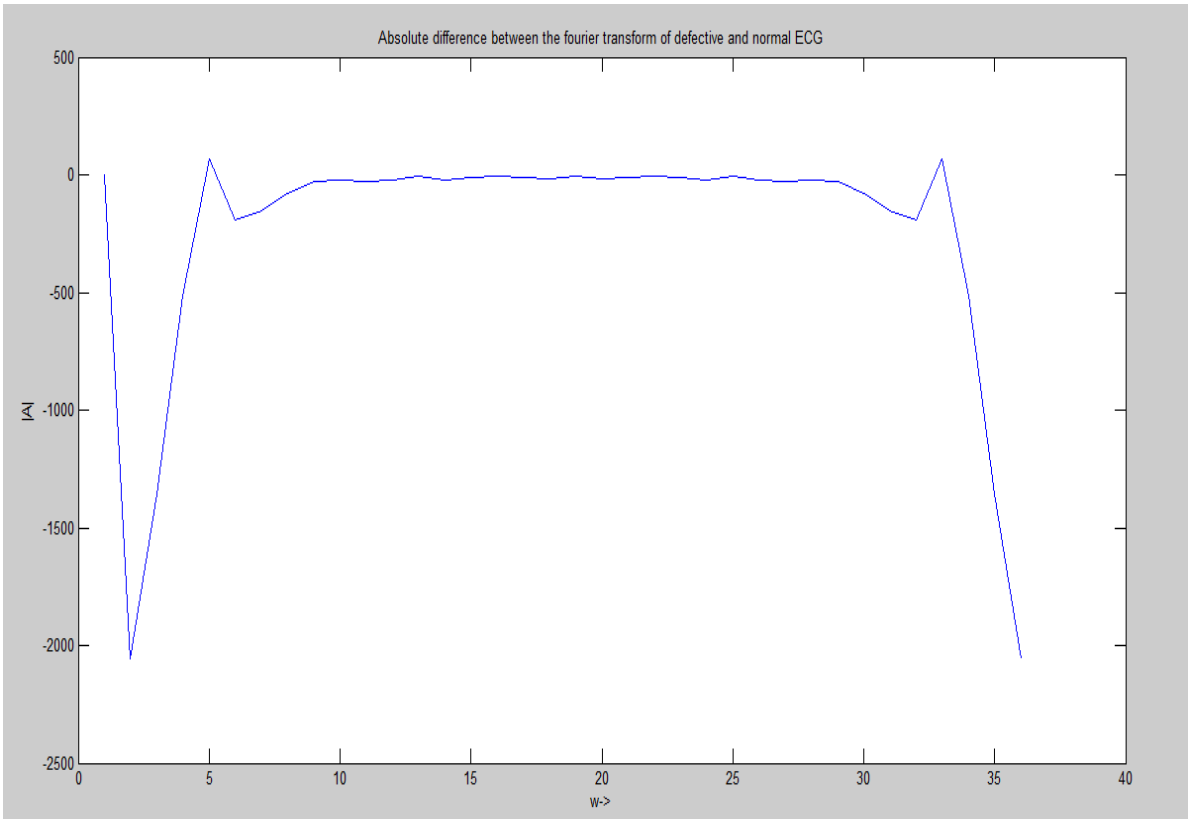

Fig 3.4 Absolute difference between the Fourier transform of defective and normal ECG

B) Ventricular Ectopy

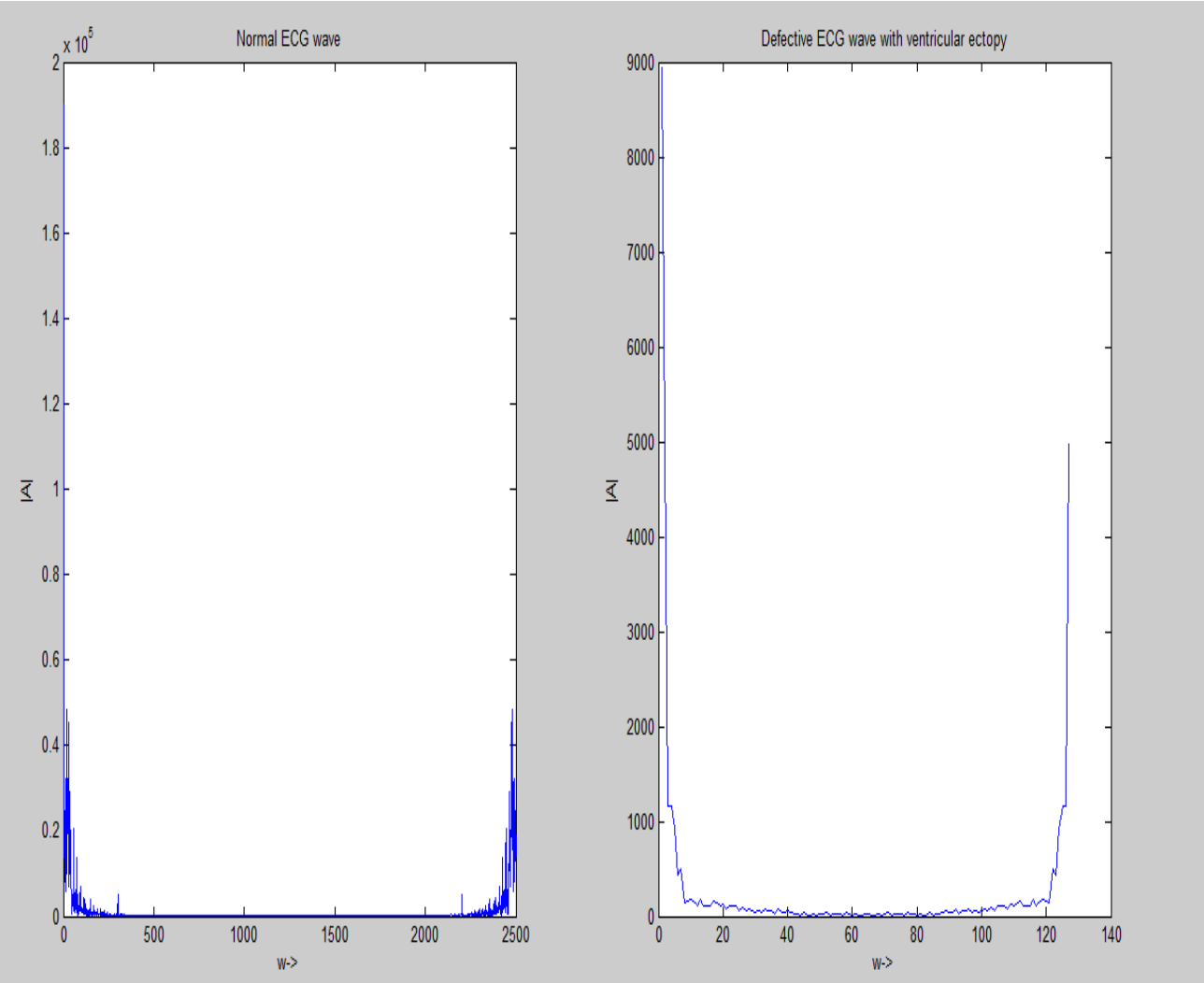

Fig 3.5 Comparison of Fourier Transform of defective and normal ECG wave(Ventricular Ectopy)

C) Supraventricular Arrhythmia

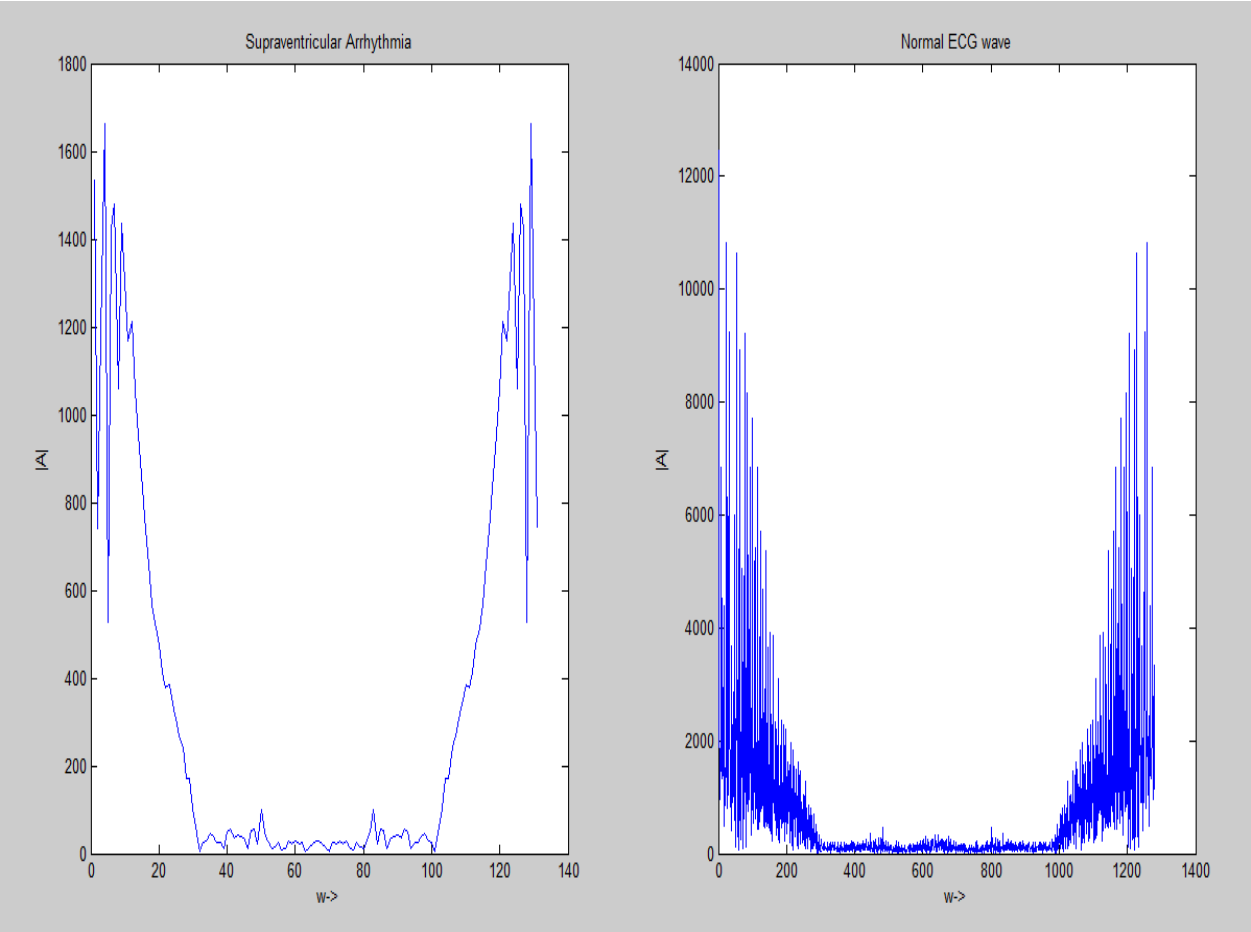

Fig 3.6 Comparison of Fourier Transform of defective and normal ECG wave(Supraventricular Arrhythmia)

D) Congestive Heart Failure

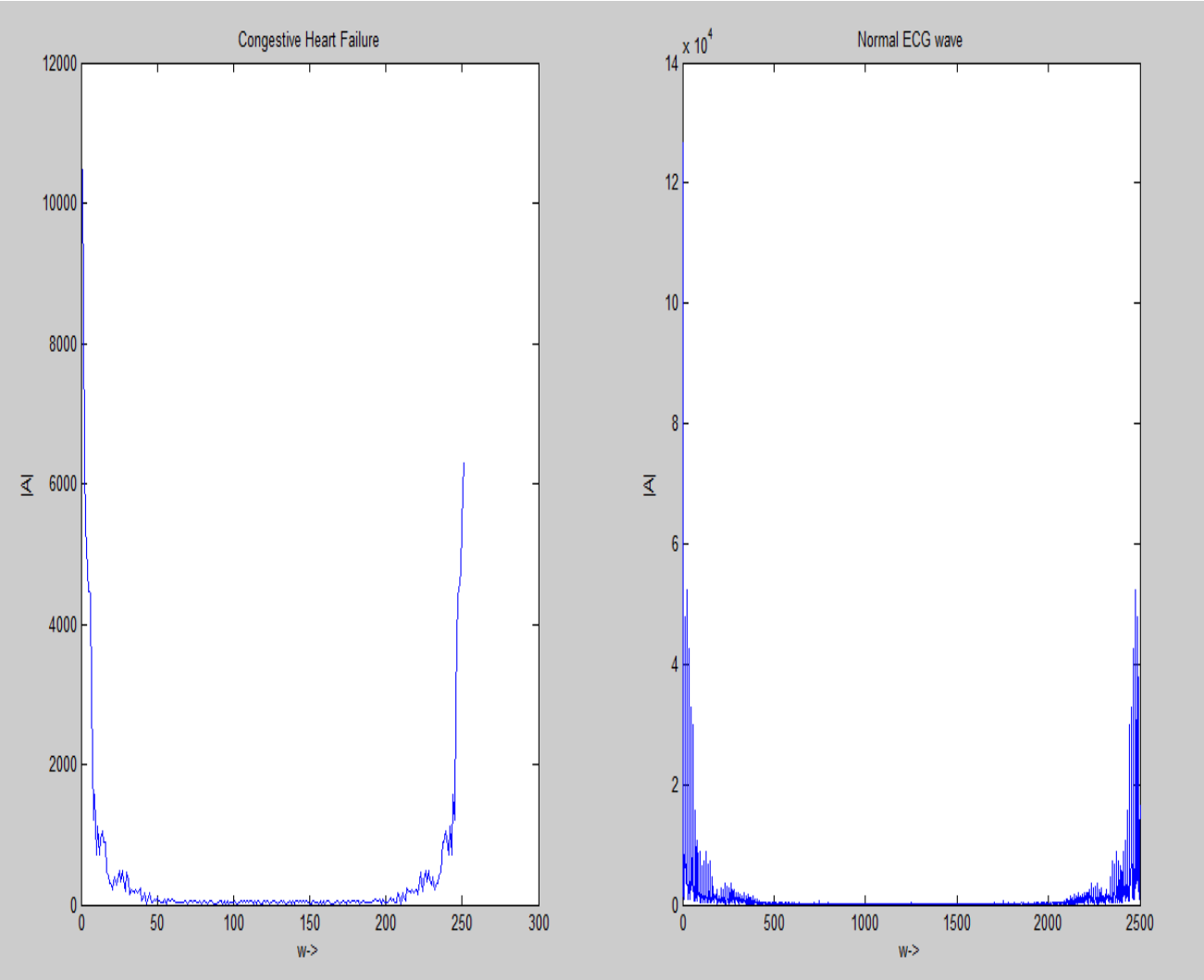

Fig 3.7 Comparison of Fourier Transform of defective and normal ECG wave (Congestive Heart Failure)

3.4 COUNT OF NUMBER OF PEAKS

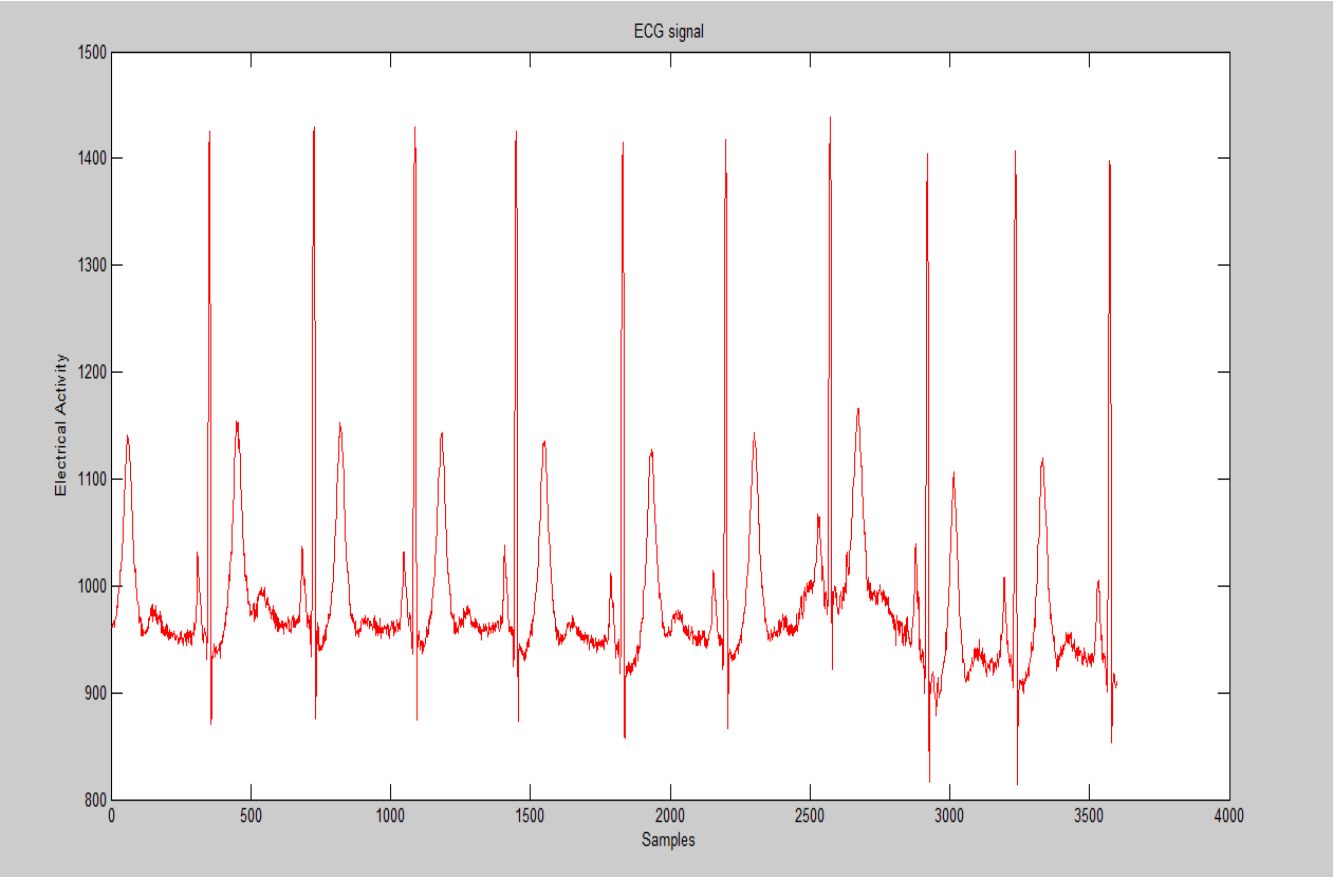

Fig 3.8 A defective ECG wave for a period of 10 seconds.

Matlab code:

```
clear all;
close all;
clc;
load('106m.mat');
sig=val;

plot(sig);
xlabel('Samples')
ylabel('Electrical Activity');
title('ECG signal');
hold on;
plot(sig,'r');
% Counting the dominant peaks in the signal
%they correspond to heartbeat
% Peaks are defined to be samples greater then their two nearest neighbors
% and greater then 1397
beat_count=0;
for k= 2 :length(sig)-1
if sig(k)>sig(k-1) && sig(k)>sig(k-1) && sig(k)>1397
        k
```

```
        disp('prominent peak found');
        beat_count=beat_count+1;
end
end
```

3.5 OUTPUT

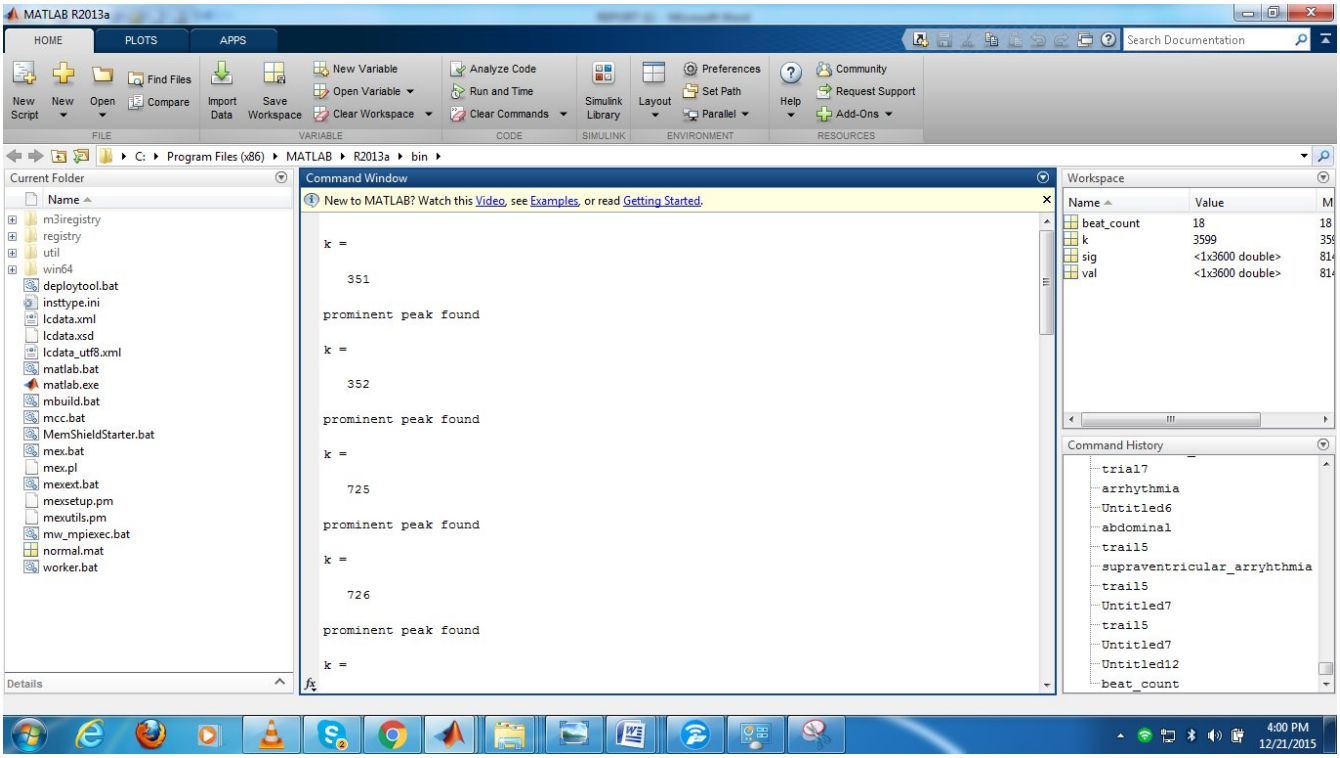

Fig 4.8: Command window snapshot of peek detector program

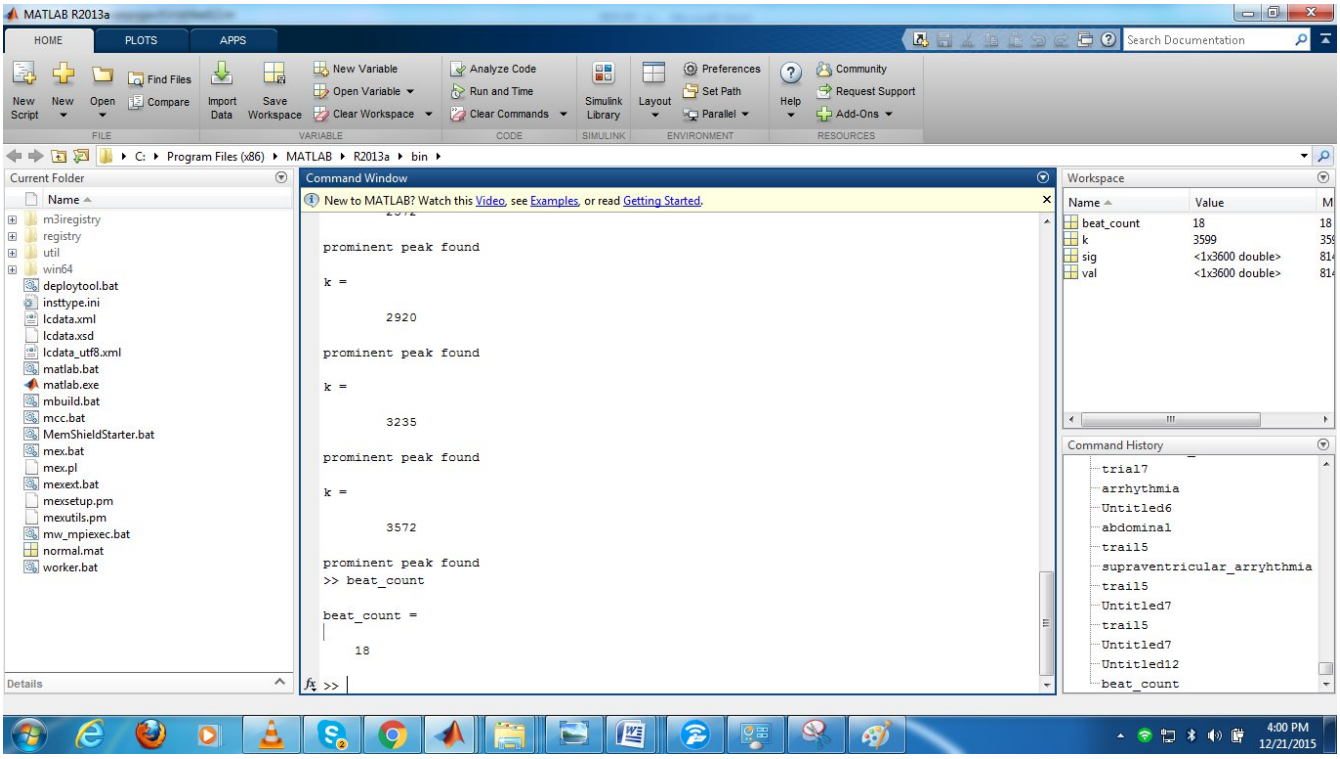

Fig 3.10 Command window snapshot of peek detector program showing final beat count.

CHAPTER 4

POWER SPECTRAL DENSITY AND MATLAB IMPLEMENTATION

4.1 INTRODUCTION

Electrocardiogram or ECG is a very popular and usefulbiosignal which has been used by doctors and physicians for the purpose of diagnosis of heart diseases. Some reasons for its popularity are that the method to obtain ECG iscompletely non-invasive and free of any dangers unlike x-rays or other diagnostic tools. However, ECG that is normally used showing the PQRST waveforms is the time and amplitude representation. The signal is obtained from patients by placing electrodes on the body and real-time recordings of the amplitudes are continuously plotted on the screen of the electrocardiograph. A brief discussion about ECG waveform is beneficial to know about the relation between the different parts of the waveform like P, Q, R, S and T and the parts of the heart which are involved in generating those. This wave consists of certain parts named as the P wave, PR interval, QRS complex, ST segment, T wave, QT interval and then the infrequent presence of U wave. The sino- atrial node or the SA node is positioned on the left atrium and this initiates the electrical signal causing atrial depolarisation. Although the atrium is anatomically divided into two parts, electrically they function as one part. Atria have very little muscle and produce a wave of small amplitude called the P wave. The PR segment is the subsequent part after the P wave and occurs as the electrical impulse is conducted through the atrio-ventricular node or the AV node, bundle of His and Purkinje fibres. The PR interval can be defined as the time between the onset of atrial depolarisation and the onset of ventricular depolarisation. After the PR interval, QRS complex occurs. This complex is generated by thedepolarisation wave which travels through theinterventricular septum via the bundle of His and bundle branches and reaches the ventricular myocardium via the Purkinje fibre network. The impulse first depolarises the left side of the septum, and then spreads towards the right. The left ventricle has larger muscle mass and thus its depolarisation dominates the ECG wave. The QRS complex ends at the J point and from here starts the ST segment. The ST segment which lies between the J point and the onset ofthe T wave, represents the period between the end of ventricular depolarisation and

repolarisation. The T wave is the result of ventricular repolarisation. This wave in a normal ECG is asymmetrical as the first part of this wave is more gradual than the subsequent part. The QT interval is measured from the beginning of the QRS complex to the endof the T wave. Measurement of this interval is done by taking into account the heart rate as this interval elongates as heartrate decreases. The last part of the ECG is the U wave which is found just after the T wave ends. It is a small deflection and generally upright . The heart diseases that have been taken for this paper are
normal sinus beats from a normal person, ventricular tachyarrhythmic beats, atrial fibrillation beats and ventricular or supraventricular beats. For each of the datasets ten data have been used. All the diseased ECG data have been taken from PhysioNet. The ventricular tachyarrythmic beats contain ventricular tachycardia, ventricular flutter and fibrillation. Ventricular fibrillation is a serious condition of the heart which may lead to stoppage of the heart if untreated. Precursor of fibrillation
is often ventricular tachycardia or flutter. So it is important to detect flutter and tachycardia in the ECG. Ventricular tachycardia is defined as three or more ventricular extrasystoles in succession at a rate of more than 120 beats per minute. The tachycardia may be self terminating but is described as "sustained" if it lasts longer than 30 seconds. This kind of tachycardia falls under broad category
tachycardia which maybe of ventricular or supraventricular in origin but is mostly ventricular. In ventricular tachycardia the sequence of cardiac activation is altered, and the impulse no
longer follows the normal intraventricular conduction pathway. As a consequence, the morphology of the QRS complex is bizarre, and the duration of the complex is
prolonged. This data from PhysioNet isnamed have sampled at 250 samples per second.

4.2 HEART RATE NORMALIZATION

Suppose*x(n)* be a period under consideration, whose length is *M*samples, of an ECG/ PCG signal at an random heart rate. The discrete Fourier components of *x(n)* can be expressed as

$$X(k) = \sum_{? ? ?}^{? ? ?} x(n)\mathrm{e}^{\frac{? ?? ? ??}{?}}$$

where k is the frequency index corresponding to digital frequency for $0 \le k \le M - 1$.

This corresponds to $k?_?/M$ in Hertz (Hz), where $?_?$ is a sampling frequency. At the normal heart rate (80 beats per minute), a period (time of one heartbeat) is considered to be (60/80) =0.75 seconds. Let sampling frequency be 10000 Hz, one period of 80 beats per minute heart rate ECG/PCG signal must contain 7500 samples (N) (Sampling frequency x time period of one heartbeat). The rate of the ECG/PCG of heart at the recording time may not be at such rate, one period of the obtained signal (M) may be longer or shorter than 7500 samples. At this point, α is defined as the ratio of the standard length N(corresponding to 80 beats per minute)and the obtained length M (corresponding to the random heart rate).

Consider the parameter α. $\alpha > 1$ implies that the heart rate of the ECG signal under consideration is higher than the standard rate.$\alpha < 1$ implies it is lower than the standard rate. To make $\alpha = 1$ or to normalize the length of the obtained signal to N samples in one period, the obtained signal must be sampled by using a frequency lower or higher than 10000 Hz for $\alpha > 1$ or $\alpha < 1$, respectively. Since the signal has readily been obtained at fs = 10000 Hz, the alternative method can be achieved by synthesizing the normalized heart rate signal with the following relationship

$$x_? (n) = \sum_{???}^{?} |X(k)| \cos\left(\frac{2\pi kn}{\alpha N} + \angle X(k)\right)$$

where $0 \le n \le N - 1$ and $|X(k)|$, $\angle X(k)$ are magnitude and phase component of DFT coefficients $X(k)$, respectively.k represents the frequency index corresponding to the highest digital frequency which is present in the spectrum of ECG and PCG bandwidth.

In this report, the normalized heart rate technique for pre-processing is proposed. The parameter alpha is used to adjust the time period scale. We can choose any alpha value to obtain the normalized heart rate and it will not affect heart defect detection. The normalized heart rate technique is used to adjust time period scale (α) of the ECG and PCG signals but it is not used to adjust the waveform characteristics of the ECG and PCG signals and so the normalized heart rate technique does not affect heart defect detection, which is analyzed by using the waveform characteristics of the ECG and PCG signals. However, the parameter alpha value must be the same for each normalized heart rate because the signal scale is adjusted to be the same in each period of data length.

4.3 ENVELOPE DETECTION

The concept is similar to the envelope detection used in amplitude demodulation.We require the envelope of the PCG signal because the PCG signal is easily corrupted by noise made my other organs in the body. Envelope of a PCG signal contains information which is carried by the PCG carrier signal. To determine the envelop of a PCG signal the positive level of the PCG signal is first obtained, and then the signal is passed through a low pass filter to obtain the envelope.

4.4 MATLAB CODES AND RESULTS

a) DEFECTIVE ECG:

```
% filter1=[0.0 0.037828455507264 04 -0.023849465019556843 -
0.11062440441843718 0.37740285561283066 0.8526986790088938
0.37740285561283066 -0.11062440441843718 -0.023849465019556843
0.037828455507264 04];
load('106m.mat'); %Defective ECG
filter1=[0.125 0.375 0.375 0.125];
xy = wgn (1, 3600, 1);
xyz2 = (xy + val);
xyz1 = mean (xyz2);
xyz = xyz2 - xyz1;

a=imfilter(xyz,filter1);
% filter2=[0.0 -0.06453888262869706 0.04068941760916406
0.41809227322161724 -0.7884856164055829 0.41809227322161724
0.04068941760916406 -0.06453888262869706 0.0 0.0];
filter2=[-2 2];
```

```
b=imfilter(xyz,filter2);
c=imresize(a, [1 1800]);
w=imresize(b, [1 1800]);

d=imfilter(c,filter1);
e=imfilter(c,filter2);
f=imresize(d, [1 900]);
x=imresize(e, [1 900]);

g=imfilter(f,filter1);
h=imfilter(f,filter2);
i=imresize(g, [1 450]);
y=imresize(h, [1 450]);

j=imfilter(i,filter2);
z=imresize(j, [1 225]);
y1=imresize(y, [1 225]);
multiply=z.*y1;
y2=abs(multiply);

figure
subplot(2,3,1);
plot(val);
title('ECG input 100')
```

```
subplot(2,3,2)
plot(xy);
title('AWGN noise')

subplot(2,3,3);
plot(xyz);
title('Normalized ECG')

%subplot(3,3,4);
%plot(w);
%title('Filter Bank 1')
```

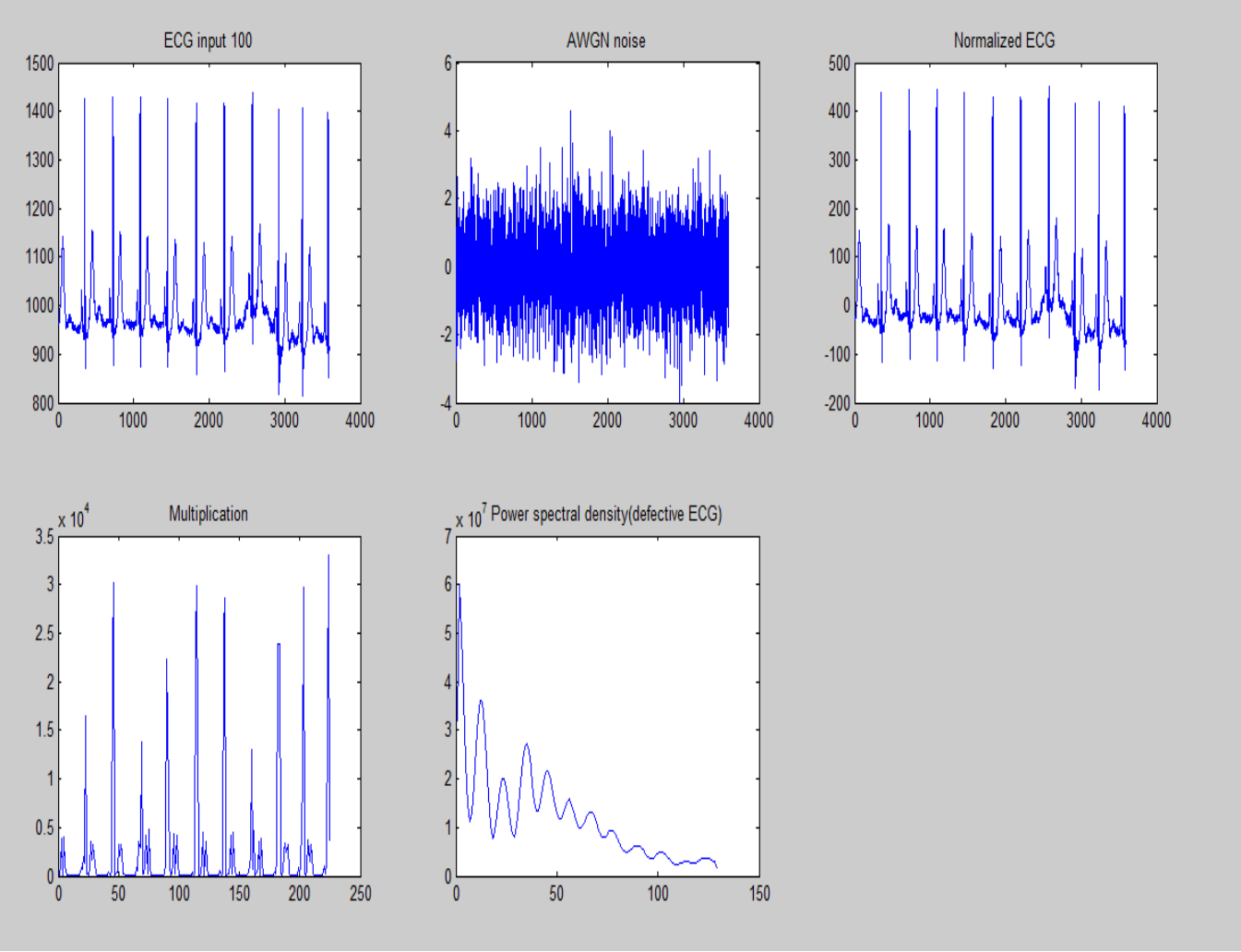

Fig 4.1 Power spectral density of a defective ECG wave obtained after normalization.

b) NORMAL ECG

```
% filter1=[0.0 0.037828455507264 04 -0.023849465019556843 -0.11062440441843718 0.37740285561283066 0.8526986790088938 0.37740285561283066 -0.11062440441843718 -0.023849465019556843 0.037828455507264 04];
load('100m.mat'); %normal ECG
filter1=[0.125 0.375 0.375 0.125];
xy = wgn (1, 3600, 1);
xyz2 = (xy + val);
xyz1 = mean (xyz2);
xyz = xyz2 - xyz1;

a=imfilter(xyz,filter1);
% filter2=[0.0 -0.06453888262869706 0.04068941760916406 0.41809227322161724 -0.7884856164055829 0.41809227322161724 0.04068941760916406 -0.06453888262869706 0.0 0.0];
filter2=[-2 2];
b=imfilter(xyz,filter2);
c=imresize(a, [1 1800]);
w=imresize(b, [1 1800]);

d=imfilter(c,filter1);
e=imfilter(c,filter2);
```

```
f=imresize(d, [1 900]);
x=imresize(e, [1 900]);

g=imfilter(f,filter1);
h=imfilter(f,filter2);
i=imresize(g, [1 450]);
y=imresize(h, [1 450]);

j=imfilter(i,filter2);
z=imresize(j, [1 225]);
y1=imresize(y, [1 225]);
multiply=z.*y1;
y2=abs(multiply);

figure
subplot(2,3,1);
plot(val);
title('ECG input 100')

subplot(2,3,2)
plot(xy);
title('AWGN noise')

subplot(2,3,3);
```

```
plot(xyz);
title('Normalized ECG')

%subplot(3,3,4);
%plot(w);
%title('Filter Bank 1')

%subplot(3,3,5);
%plot(x);
%title('Filter Bank 2')

%subplot(3,3,6)
%plot(y);
%title('Filter Bank 3')

%subplot(3,3,7)
%plot(z);
%title('Filter Bank 4')

subplot(2,3,4)
plot(y2);
title('Multiplication')

subplot(2,3,5)
```

```
c=pwelch(y2);
plot(c);
title('Power spectral density(normal ECG)');

% figure, plot(w), figure, plot(x), figure, plot(y),figure, plot(z);
```

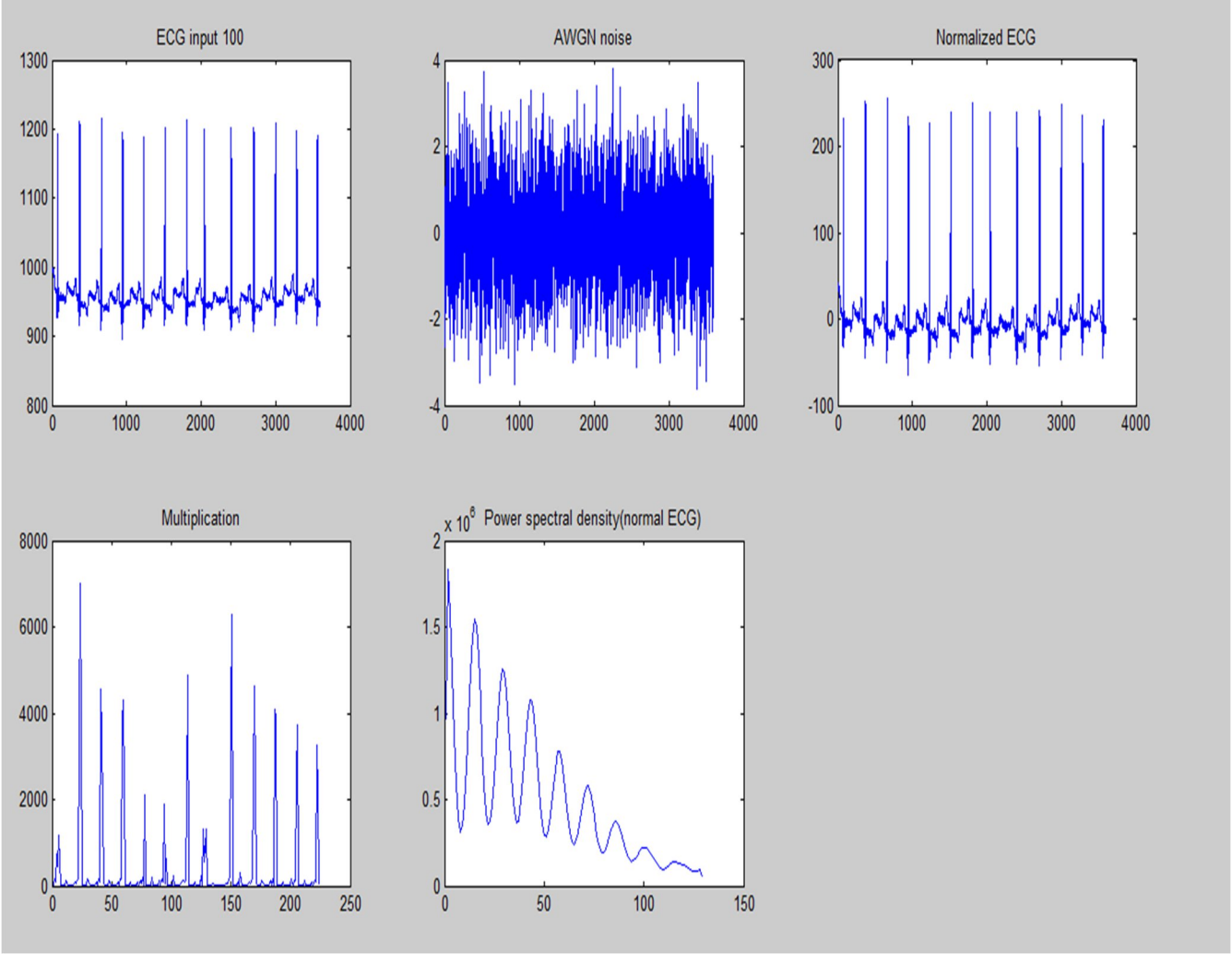

Fig 4.2 Power spectral density of a defective ECG wave obtained after normalization.

```
clear all
clc
load('normal.mat')
load('defective.mat')

a=mean(normal);
nor=normal-a;
b=mean(defective);
def=defective-b;

subplot(2,2,1);
plot(nor);
title('Normal ECG wave');
xlabel('t->');
ylabel('A');

subplot(2,2,2);
plot(def);
title('Defective ECG wave with arrhythmia');
xlabel('t->');
ylabel('A');

c=pwelch(nor);
d=pwelch(def);
```

```
subplot(2,2,3);
plot(c);
title('Normal ECG wave( Power Spectral Density)');
xlabel('w->');
ylabel('P');

subplot(2,2,4);
plot(d);
title('Defective ECG wave( Power Spectral Density)');
xlabel('w->');
ylabel('P');
```

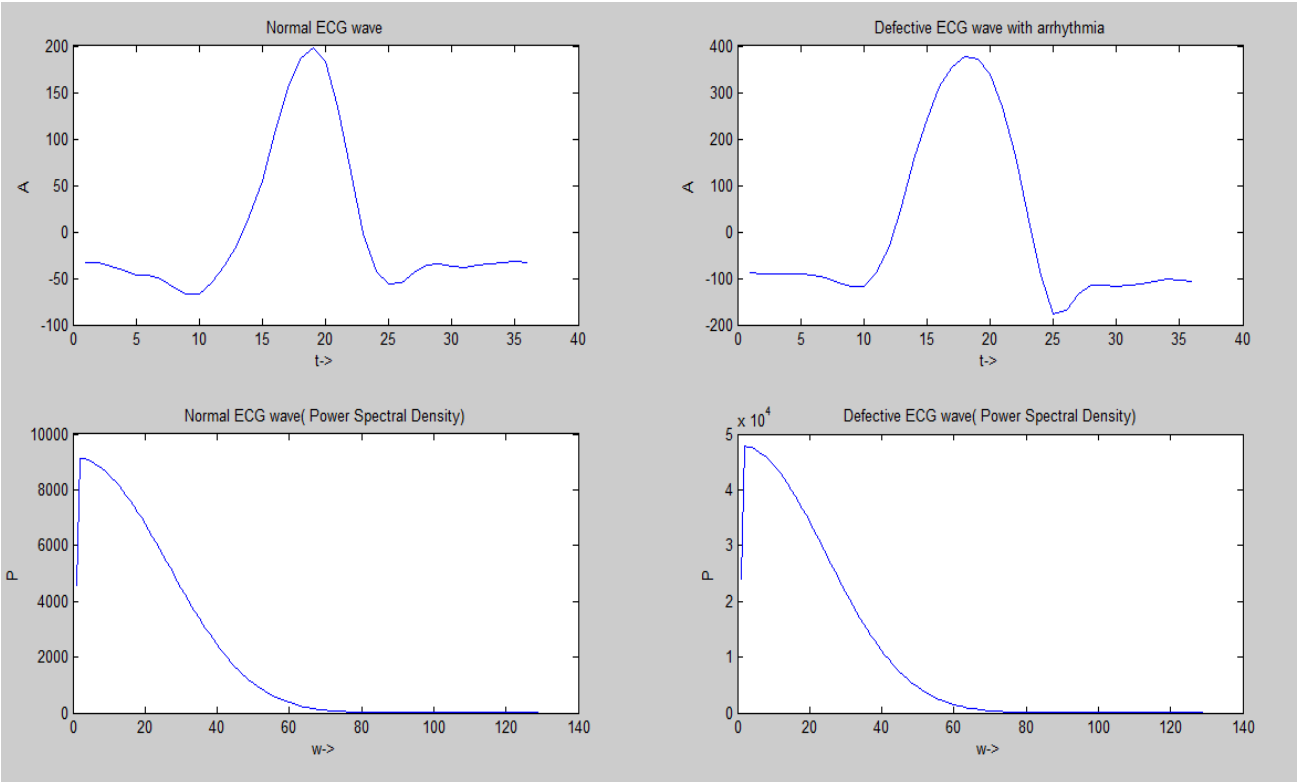

Fig 4.3 Power spectral density of single isolated waves of both defective and normal ECG.

CHAPTER 5

AUTO-CORRELATION AND MATLAB IMPLEMENTATION

5.1 INTRODUCTION:

The state of cardiac heart is generally reflected in the shape of ECG waveform and heart rate. ECG, if properly analyzed, can provide information regarding various diseases related to heart. However, ECG being a non-stationary signal, the irregularities may not be periodic and may not show up all the time, but would manifest at certain irregular intervals during the day. Clinical observation of ECG can hence take long hours and can be very tedious. Moreover, visual analysis cannot be relied upon and the possibility of the analyst missing the vital information is high. Hence, computer based analysis and classification of diseases can be very helpful in 16 diagnosis. Various contributions have been made in literature regarding beat detection and classification of ECG signal. Most of them use either time or frequency domain representation of the ECG waveforms, on the basis of which many specific features are defined, allowing the recognition between the beats belonging to different classes. The most difficult problem faced by today's automatic ECG analysis is the large variation in the morphologies of ECG waveforms. Moreover, we have to consider the time constraints as well. Thus our basic objective is to come up with a simple method having less computational time without compromising with the efficiency. This objective has motivated me to search and experiment with various techniques. In this thesis, R-peak detection of ECG signal is implemented using the properties of autocorrelation and Hilbert transform and classification has been done using multilayer perceptron (MLP) and radial basis function (RBF), taking the features as temporal features, heart beat interval features and ECG morphological features.

5.2 ATRIOVENTRICULAR BLOCKS

It is the normal propagation of the electrical impulse along the conduction pathways to the ventricles, but the block may delay or completely prevent propagation of the impulse to the rest of the conduction system. A first-degree AV block is occurred when all the P-waves are conducted to the ventricles, but the PR-interval is prolonged. Second-degree AV blocks are occurred when some of the Pwaves fail to conduct to the ventricles. In third-degree AV block, the rhythm of the P-waves is completely

dissociated from the rhythm of the QRS-complexes. Each beat at their own rate [1]. Fig. 0.12 Atrioventricular Blocks (A) first degree AV block, (B) Second degree AV block, (C) Third degree AV blocks. 1.6.6 Bundle Branch blocks Bundle branch block, cease in the conduction of the impulse from the AV-node to the whole conduction system. Due to this block there may occur myocardial infarction or cardiac surgery [1]. Fig. 1.13 Bundle Branch blocks. 14 The bundle branch block beat is categories into two types. These are Left bundle branch block beat (LBBB) and Right bundle branch block beat (RBBB). In LBBB the left bundle branch will prevent the electrical impulses from the A-V node from depolarising the left ventricular myocardium in the normal way. When the right bundle branch is blocked, the electrical impulse from the AV node is not able propagate to the conduction network to depolarise the right ventricular myocardium.

5.3 MATLAB CODES AND RESULTS

```
clear all
clc
load('normal.mat')
load('defective.mat')

a=mean(normal);
nor=normal-a;
b=mean(defective);
def=defective-b;

subplot(3,3,1);
plot(nor);
title('Normal ECG wave');
xlabel('t->');
ylabel('A');
```

```
subplot(3,3,2);
plot(def);
title('Defective ECG wave with arrhythmia');
xlabel('t->');
ylabel('A');
c=pwelch(nor);
d=pwelch(def);
subplot(3,3,3);
plot(c);
title('Normal ECG wave( Power Spectral Density)');
xlabel('w->');
ylabel('P');

subplot(3,3,4);
plot(d);
title('Defective ECG wave( Power Spectral Density)');
xlabel('w->');
ylabel('P');

acf1=autocorr(nor);
subplot(3,3,5);
plot(acf1);
title('Defective ECG wave( autocorrelation)');
```

```
xlabel('t->');
ylabel('acf');

acf2=autocorr(def);
subplot(3,3,6);
plot(acf2);
title('Normal ECG wave( autocorrelation)');
xlabel('t->');
ylabel('acf');


ccf=xcorr(nor,def);
subplot(3,3,7);
plot(ccf);
title('Crosscorrelation');
xlabel('t->');
ylabel('ccf');

subplot(3,3,8);
diff=c-d;
plot(diff);
title('Difference of Power Spectral Density');
xlabel('t->');
ylabel('Diff');
```

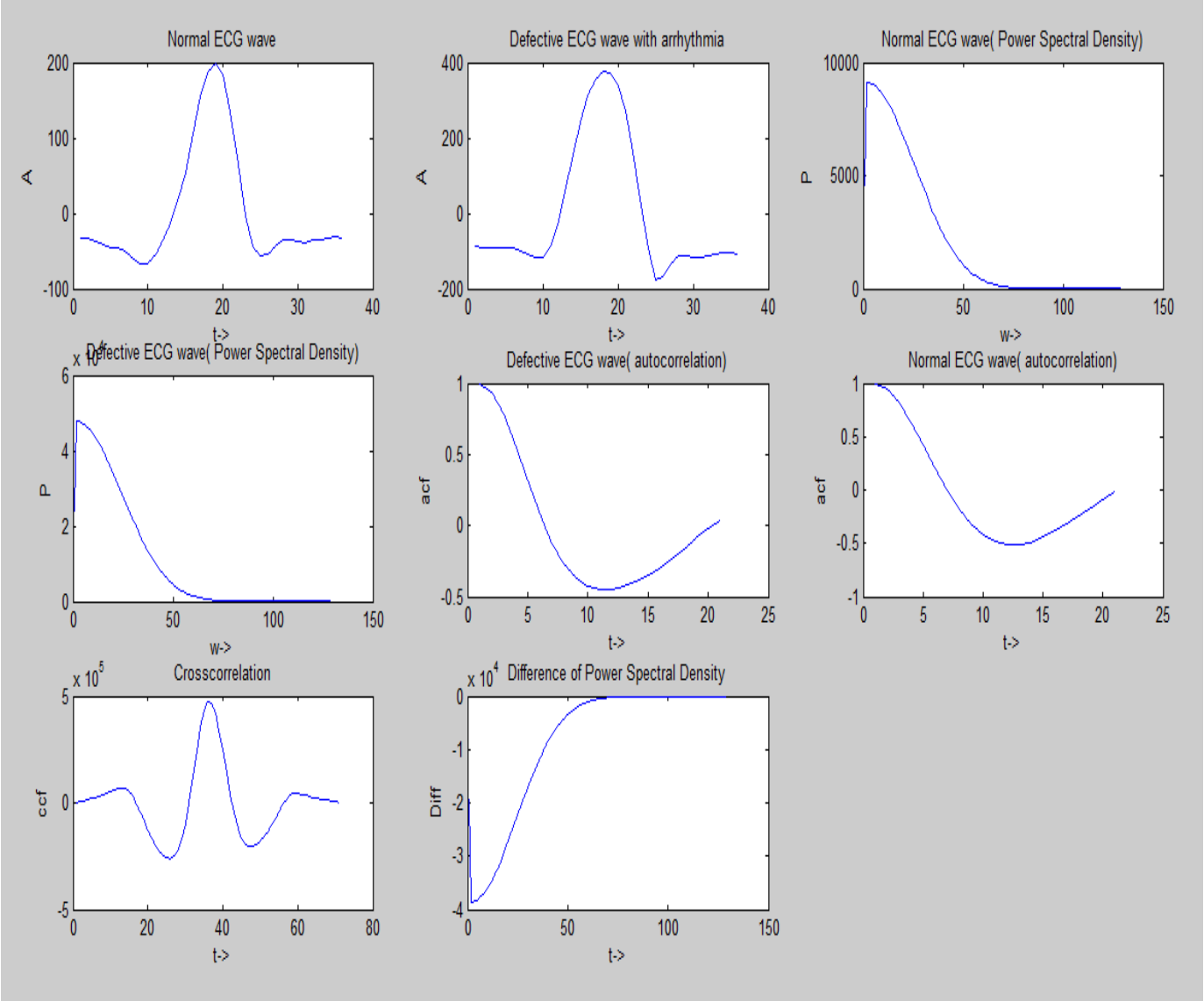

Fig 5.1 Auto-correlation and cross-correlation of normal and defective ECG wave obtained, Difference in the power spectral density of normal and defective ECG waves measured.

CHAPTER 6

ECG DATABASE

5.1 MIT-BIH ARRHYTHMIA DATABASE

The MIT/BIH arrhythmia database is used in the study for performance evaluation. The database contains 48 records, each containing two-channel ECG signals for 30 min duration selected from 24-hr recordings of 47 individuals. There are 116,137 numbers of QRS complexes in the database.The subjects were taken from, 25 men aged 32 to 89 years, and 22 women aged 23 to 89 years and the records 201 and 202 came from the same male subject. Each recording includes two leads; the modified limb lead II and one of the modified leads V1, V2, V4 or V5. Continuous ECG signals are band pass-filtered at 0.1–100 Hz and then digitized at 360 Hz. Twenty-three of the recordings (numbered in the range of 100–124) are intended to serve as a representative sample of routine clinical recordings and 25 recordings (numbered in the range of 200–234) contain complex ventricular, junctional, and supraventricular arrhythmias. The database contains annotation for both timing information and beat class information verified by independent experts.

5.2 AAMI STANDARD

MIT-BIH heartbeat types are combined according to Association for the Advancement of Medical Instrumentation (AAMI) recommendation. AAMI standard emphasize the problem of classifying ventricular ectopic beats (VEBs) from the non- ventricular ectopic beats. AAMI also recommends that each ECG beat can be classified into the following five heartbeat

1.(Normal beat)

2. S (supraventricular ectopic beats (SVEBs))

3. V (ventricular ectopic beats (VEBs)) 15

4. F(fusion beats)

5. Q (unclassifiable beats)

Each class includes heartbeats of one or more types as shown in Table 1.2. Class N contains normal and bundle branch block beat types and escape beat, class S contains supraventricular ectopic beats (SVEBs), class V contain Premature ventricular contraction beats and ventricular escape beat, class F

contains beats that result from fusing normal and VEBs, and class Q contains unknown beats including paced beats.

Thesis Outline

The Chapter 1 of the thesis explains the basic of ECG and ECG morphology.

In Chapter 2 Different modes of lead placement and the MIT-BIH arrhythmias database are discussed. This chapter also explains the different types of arrhythmias in ECG signal.

In Chapter 3 a method is developed by which Fast Fourier Transform of various heart-beats defected by various heart abnormalities is compared beside fast Fourier transform of a normal heart-beat.

In Chapter 4using some basic MATLAB commands, The power spectra of the two different types of heart-beats. Defective and normal ECG signals are compared. The spectra signifies certain qualities of the two heart-beats and helps in developing a sense of analysis.

In Chapter 5 autocorrelation and Hilbert transform for detection of QRS complex in ECG signal which is the first step of ECG signal analysis. The various characteristics features of ECG are extracted, which contains both temporal and morphological features of each heart beat.

In Chapter 6 MIT-BIH databases are extracted. ECG arrhythmias beat classification using multilayer perceptron (MLP) neural network and Radial basis function neural network (RBF) are discussed.

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