DEFECTIVE HEARTBEAT DETECTION

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CERTIFICATE

This is to certify that project report entitled "**DEFECTIVE HEARTBEAT DETECTION**", submitted by Shubhangi Maheshwari (111006), Yamini Sharma (111096), Shubham Tayal (111102) in partial fulfillment for the award of degree of Bachelor of Technology in Electronics and Communication Engineering to Jaypee University of Information Technology, Waknaghat, Solan has been carried out under my supervision.

This work has not been submitted partially or fully to any other University or Institute for the award of this or any other degree or diploma.

Date: 25 May 2015

Supervisor's Name: Prof. Dr. S. V. Bhooshan

Designation: HOD, Dept. of ECE

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It is said that gratitude is a virtue. This part is dedicated to special thanks that we would like to deliver to the people who helped to make possible the fulfillment of this project.

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We would also like to thank Mohan Sir for helping us in the lab. Thank you for allowing us to work in your lab and sparing your precious time for us.

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 first subsystem is based on the relationship between the electrocardiogram (ECG) and phonocardiogram (PCG) signals. The relationship between both signals is determined as an impulse response (*h(n)*) of a system, where the decision is made based on the linear predictive coding coefficients of a heart's impulse response. The other subsystem uses a phase space approach, in which the mean squared error between the distance vectors of the phase space of the normal heart and abnormal heart is judged by the likelihood ratio test (Λ) value, on which the decision is made.

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Date : 25 May 2015

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Date : 25 May 2015

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. Besides an ECG signal, a phonocardiogram (PCG) signal is also used for heart disease diagnosis. A PCG signal is the recorded heart sound using a microphone placed on the chest wall. Both ECG and PCG signals play important roles in heart abnormality detection; however, diagnosis based on ECG signal or PCG signal alone cannot detect all cases of heart symptoms; you need a combination of both to accurately detect a heart abnormality. For example, an ECG signal can reveal various physiological and abnormal behaviors of the heart. But some symptoms like heart murmurs often caused by defective heart valves cannot be detected from an ECG signal. Therefore, heart defect diagnosis is based on the relationship between ECG and PCG signals which can lead to high performance heart diagnostics.

Both ECG and PCG signals can be used together for preliminary detection of heart disease. Early detection of heart disease is important because it can provide for the ease of treatment given thereafter and also save people's lives. In this report, the proposed system is composed of two decision-making subsystems. First subsystem is based on the system's impulse response and the other subsystem is based on phase space. Impulse response-based subsystem uses the relationship between an ECG signal and an envelope of a PCG signal (EPCG) of a heart. Envelope of PCG signal is used because the PCG signal is easily corrupted by noise due to murmurs and other organs. In this technique, a human heart is defined as a system that has an ECG signal as an input and an EPCG signal as an output. The impulse response $h(n)$ of the system can be used to show whether the heart is functioning normally or not. The ratio between discrete Fourier transform (DFT) of the ECG signal and DFT of the EPCG signal is

determined and the inverse discrete Fourier transform (IDFT) of the result is the impulse response of the system, in this case the heart. If we want to make an automated system, a neural network has to be used for learning and justifying the output. However, rather than providing the impulse response to a neural network, linear predictive coding (LPC) coefficients of *h(n)* are used. Now, the trained neural network with LPC coefficients as inputs can be used to determine whether the heart has an abnormality or not.

For the second subsystem, i.e. the phase space approach, the chaos method is used as an additional decision-making technique. The chaos method has recently been applied to describe the behavior of ECG signals and PCG signals. In this report, a phase space of an ECG signal and of an EPCG signal is used to show the behavior of an ECG signal and an EPCG signal. Mean squared error (MSE) between the distance vector of the target ECG or EPCG signal and the distance vector of the reference signal (from which we compare the signal of the person under consideration) is calculated. The distance vector is a vector whose element is the distance from an origin point to each point on the phase space. The MSE data set of each case is applied to form the probability density functions. The obtained MSE probability density functions are used to determine a likelihood ratio test value. This value is a threshold for making a decision that whether the heart is normal or not.

CHAPTER 2

ELECTROCARDIOGRAM (ECG)

An ECG is a representation of the heart muscle's electrical activity as 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).

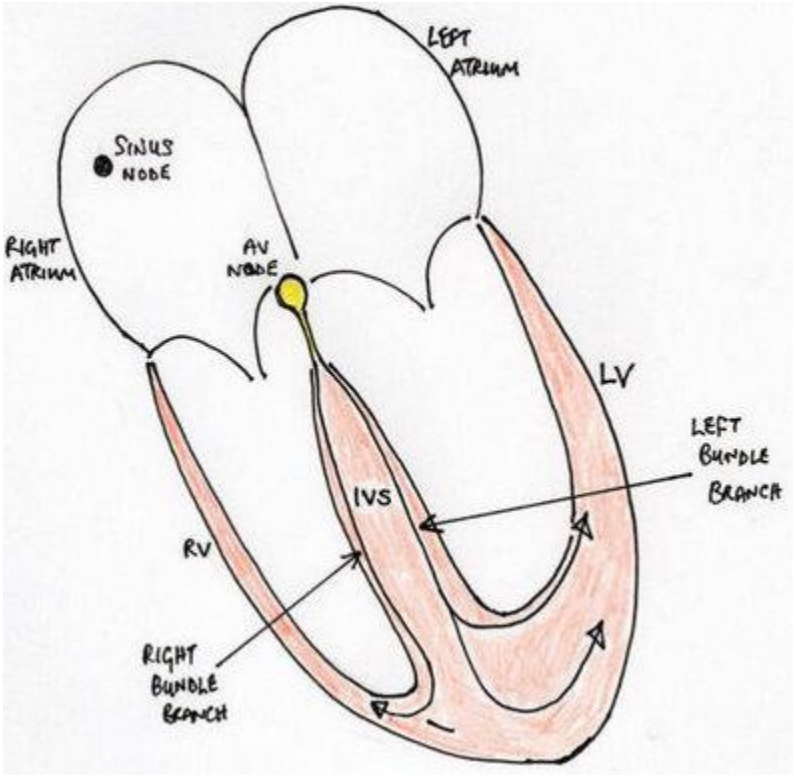

Figure 2.1 : Basic electrophysiology of the heart

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. This atrioventricular 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 about a 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.

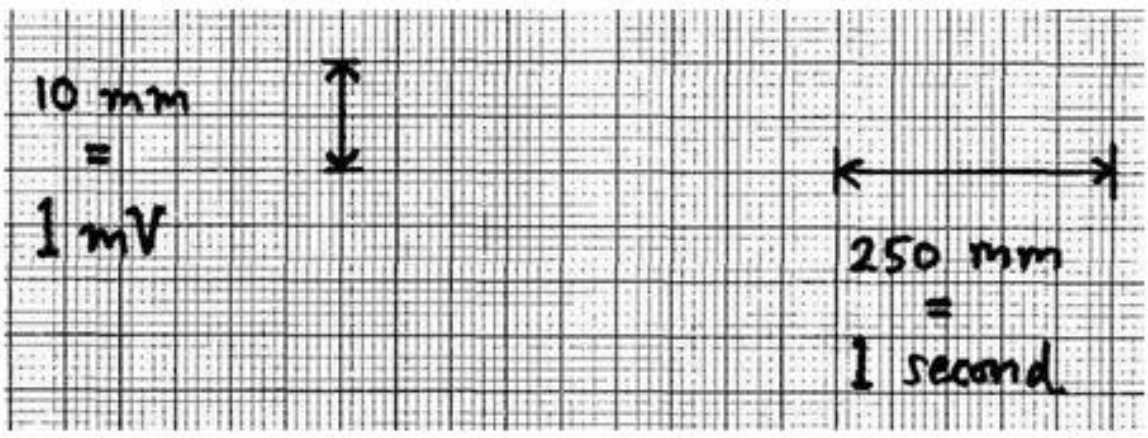

Figure 2.2 : Sample of standard ECG paper showing the scale of voltage, measured on the vertical axis, against time on the horizontal axis

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.

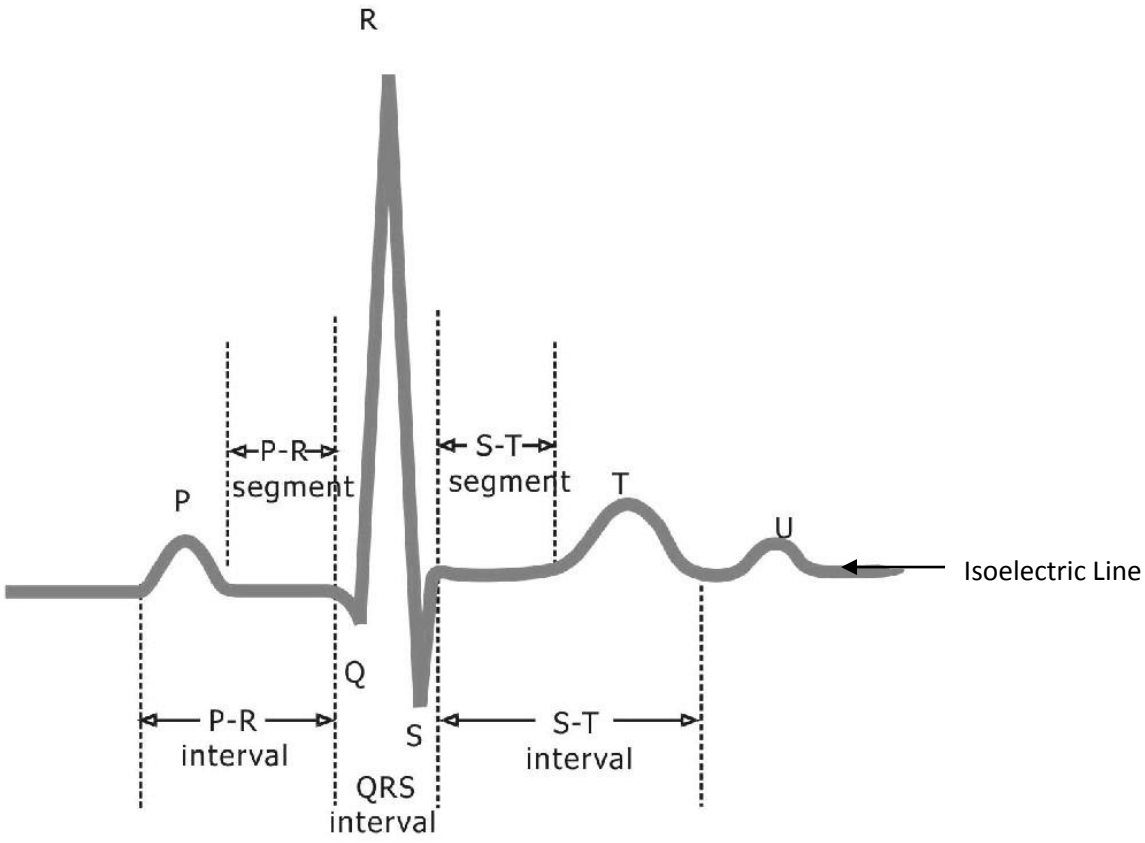

Figure 2.3 : The major waves of a single normal ECG pattern

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).

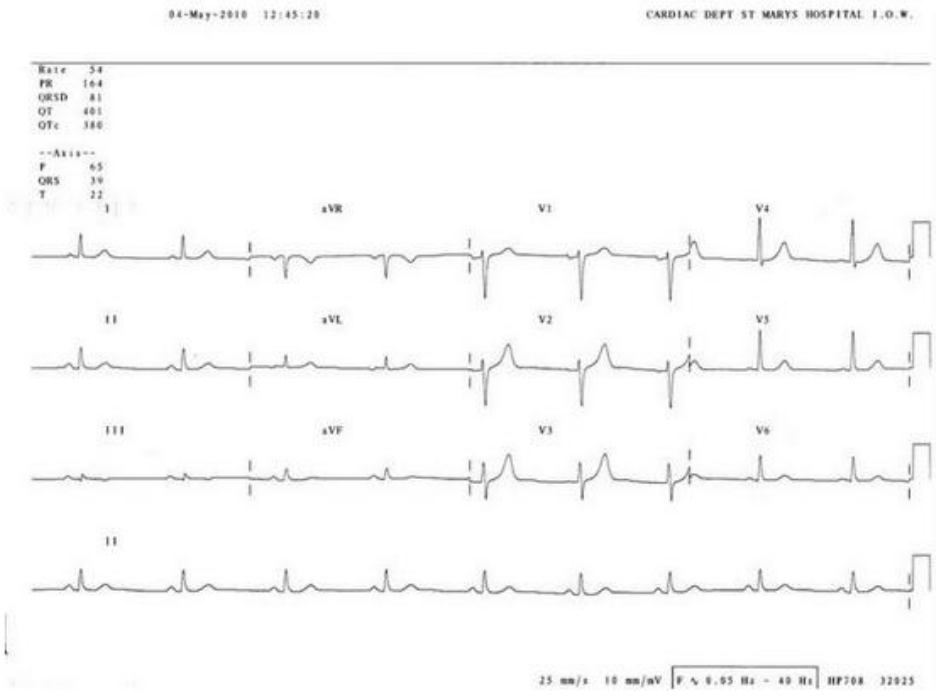

Figure 2.4 : Example of a normal 12 lead ECG; notice the downward deflection of all signals recorded from lead aVR. This is normal, as the electrical axis is directly away from that lead

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

PHONOCARDIOGRAM

A **Phonocardiogram** or **PCG** is a plot of recording of the sounds and murmurs made by the heart with the help of a machine called phonocardiograph. These sounds result from vibrations created by closure of the heart valves. There are at least two closures that generate these sounds: the first occurs when the atrioventricular valves close at the beginning of systole and the second occurs when the aortic valve and pulmonary valve close at the end of systole.

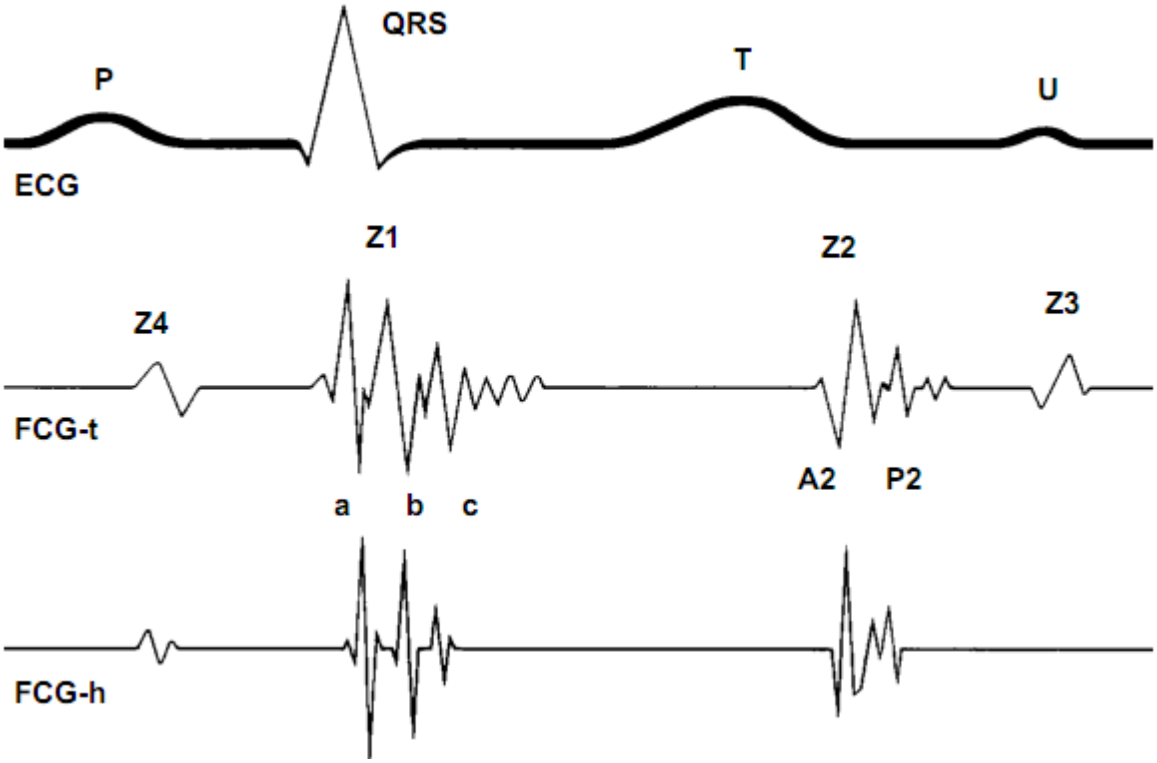

Figure 3.1 : A normal PCG pattern comparing the murmurs with the corresponding ECG waves

Source: Google

Phonocardiogram allows the detection of faint sounds and murmurs, which could not be identified with a stethoscope, and makes a permanent record of these events. The ordinary stethoscope cannot detect such feeble sounds or murmurs, and provides no record of their occurrence. This ability to quantify the

sounds made by the heart helps in getting information which is not available from more sophisticated tests, and provides vital information about the effects of certain drugs upon the heart. It is also an effective method for tracking the progress of the patient's disease.

Heart sounds are produced by a sum of series of mechanical events, such as:

- **Valvular events:** These vibrations are caused mostly by the closing of the heart valves; opening of the valves produces a vibration of lesser intensity.
- **Muscular events:** These are the vibrations of the myocardium during contraction.
- **Vascular events:** These vibrations are produced by the sudden dilation of the arterial walls during ejection.
- Vibrations caused by the **acceleration/deceleration of the blood flow.**

The most important component of the sound from the heart is the closure of the valves.

CHAPTER 4

THEORETICAL BACKGROUND

Generally, the ECG and PCG signals are in synchronization with each other, in which the ECG is the electrical signal while the PCG is the mechanical signal. The ECG and PCG signals are related to each other related because the PCG signal is obtained by the mechanical operation of the heart, which relies on the electrical operation of the heart. Therefore to activate the mechanical heart operation that generates the PCG signal, the ECG and PCG signals are used. The ECG and EPCG (envelope of PCG) impulse response signals have shown a linear relationship and time-invariance. So we consider the human heart as a linear system in order to find the impulse response. The concept of defective heartbeat detection can be illustrated as a block diagram as shown in Figure 4.1. It is composed of two subsystems, the impulse response and the phase space subsystems. They are described in detail later in this report.

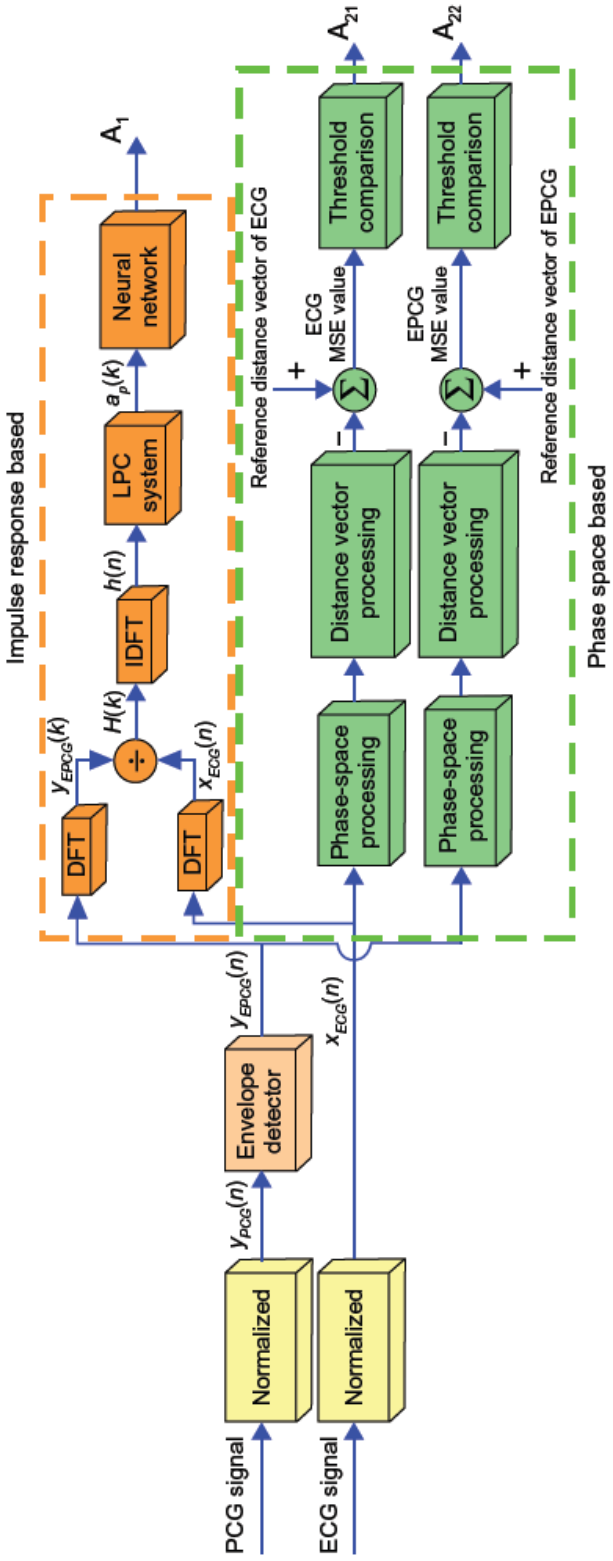

Figure 4.1: Block diagram for the system proposed for defective heartbeat detection

Source: http://www.dovepress.com/heart-detection-and-diagnosis-based-on-ecg-and-epcg-relationships-peer-reviewed-article-MDER

CHAPTER 5

SIGNAL PRE-PROCESSING

The ECG and EPCG signals employed are normalized to be the signals at a standard heart rate, which for an adult whose heart is healthy (normal) in relaxing state is around 80 beats per minute. Pre-processing the signal is necessary because the recorded ECG/PCG signals of each person will have different heart rates. Even the signals recorded from the same person but at different times can have different heart rates. So one period of different signals may have different number of signal samples. Therefore, the ECG and PCG signals are pre-processed by frequency normalization. With this pre-processing, the signals will be the same during each period of data collection.

5.1 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

$$X(k) = \sum_{n=0}^{M-1} x(n)\, \mathrm{e}^{\frac{-\mathrm{j}2\pi \mathrm{kn}}{\mathrm{M}}}$$

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

This corresponds to kf_s/M in Hertz (Hz), where f_s 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

$$x_n(n) = \sum_{x=0}^{K} |X(k)| \cos\left(\frac{2\pi kn}{\alpha N} + \angle X(k)\right)$$

where $0 \leq n \leq N - 1$ 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.

5.2 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.

CHAPTER 6

IMPULSE RESPONSE BASED SUBSYSTEM

The impulse response based subsystem for defective heartbeat detection can be depicted by a block diagram (Figure 4.1). In this system, the human heart is considered as a linear system where an ECG signal ($x_{ECG}(n)$) is the input and an EPCG signal (y_{EPCG} (n)) is an output of the system. It can be shown that the output of the heart is determined by the convolution between the ECG input and the impulse response of the system

$$y_{EPCG}(n) = \sum_{k=-\infty}^{\infty} x_{ECG}(k)\, h(n-k)$$

By taking z-transform on both sides of the above equation, it yields

$$Y_{EPCG}(z) = X_{ECG}(z)\, H(z)$$

Hence, the transfer function of a system ($H(z)$) can be determined by

$$H(z) = \frac{Y_{EPCG}(z)}{X_{ECG}(z)}$$

From the above equation, the DFT ($H(k)$) of the system is obtained by the following relationship

$$H(k) = H(z)\Big|_{z=e^{j2\pi k/N}}, \qquad k = 0,1, \ldots N-1$$

$$= \frac{Y_{EPCG}(z)}{X_{ECG}(z)}\Big|_{z=e^{j2\pi k/N}}$$

$$= \frac{\sum_{n=-\infty}^{\infty} y_{EPCG} e^{-j2\pi nk/N}}{\sum_{n=-\infty}^{\infty} x_{ECG} e^{-j2\pi nk/N}} = \frac{Y_{EPCG}(k)}{X_{ECG}(k)}$$

where $y_{EPCG}(k)$ is the DFT of y_{EPCG} (n) and $x_{ECG}(k)$ is the DFT of $x_{ECG}(n)$. To obtain the impulse response ($h(n)$) of a system, the IDFT is applied on both sides of above equation, which is

$$h(n) = \frac{1}{N}\sum_{k=0}^{N-1} H(k) e^{j2\pi kn/N}$$

$$= \frac{1}{N}\sum_{k=0}^{N-1}\left(\frac{Y_{EPCG}(k)}{X_{ECG}(k)}\right) e^{j2\pi kn/N}$$

As shown in the above equation, the impulse response of a system can be determined by using the IDFT of the ratio between the DFT of an EPCG signal and the DFT of an ECG signal.

6.1 LINEAR PREDICTIVE CODING

The Linear Predictive Coding (LPC) technique is used to extract the features of the impulse response in the form of LPC coefficients. It's basic idea is that each signal sample $x(n)$ is approximated as a linear combination of previous p samples as described in the following equation:

$$x'(n) = \sum_{k=1}^{p} a_p(k)\, x(n-k)$$

where $x(n)$ is a signal sample, $x'(n)$ is the predicted signal, p is the order of LPC and, $a_p(k)$ s are LPC coefficients.

Let *x(n)* in the above equation be the impulse response *(h(n))* of the heart, then the error between the original signal and the signal under consideration is given by

$$e(n) = h(n) - h'(n) = h(n) - \sum_{k=1}^{p} a_p(k)\, h(n-k)$$

The LPC coefficients (a_k) are defined by minimizing the mean squared error (MSE). The procedure for minimizing the MSE is obtained by setting the partial differential MSE with respect to all of the parameters a_k to be zero. The LPC coefficients are found to be

$$\underline{a}_p = R_{hh}^{-1} r_{hh}(m)$$

where R_{hh} is a $p \times p$ autocorrelation matrix, $r_{hh}(m)$ is the autocorrelation of the sequence $h(n)$, and a_p is a $p \times 1$ vector of model parameters.

Now two sets of the LPC coefficients, one set for a normal heart and another for an abnormal heart, are provided to the input of an artificial neural network for learning and making decisions.

6.2 DECISION MAKING USING A NEURAL NETWORK

Artificial Neural Networks are used very often to classify the data. Artificial Neural Network is inspired by the biological nervous system and it is designed for a specific application, such as pattern recognition or data classification. Here, the ANN is employed to distinguish between a normal and an abnormal heart. The ANN used for defective heartbeat detection is a feed-forward back propagation (BP) neural network. The Back Propagation algorithm is a supervised learning algorithm (where target output values are provided and error is calculated as the difference between the target value and the actual output of the system) using feed-forward networks. It is basically a gradient descent method and its objective is to minimize the MSE between the target values and the actual output of the network.

The ANN employed in this work is demonstrated in Figure 6.2. The structure is composed of the input layer, the hidden layer of neurons with a tangent sigmoid transfer function, and the output layer of neurons with linear transfer function. The set of LPC coefficients that are impulse response signals of the heart system are fed to the input of the ANN. The ANN output target values are 0 for an abnormal heart and 1 for a normal heart.

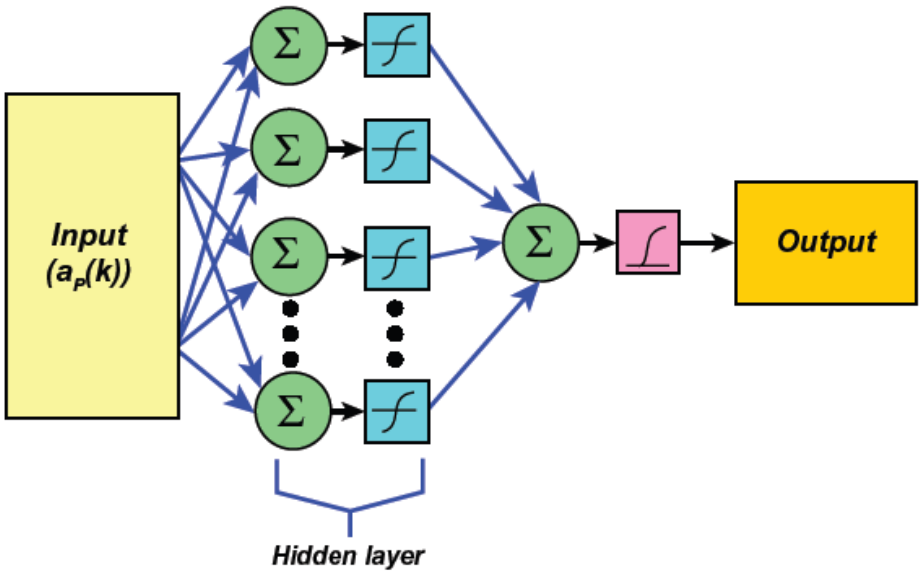

Figure 6.2 : Structure of the Artificial Neural Network employed in this project

The output obtained from the neural network can be one of four cases: TP, the value of true positive; FP, the value of false positive; TN, the value of true negative; and FN, the value of false negative.

Suppose a person is being checked for a medical condition. Then the above values can be defined as:

- True positive: The individual has the condition and tests positive for the condition.
- True negative: The individual does not have the condition and tests negative for the condition.
- False positive: The individual does not have the condition but tests positive for the condition.
- False negative: The individual has the condition but tests negative for the condition.

The decision on whether a heart is normal or abnormal is determined by positive predictive value (PPV) and negative predictive value (NPV), respectively. These values are evaluated, respectively, by

$$PPV(\%) = \left(\frac{TP}{FP+TP}\right) \times 100$$

$$NPV(\%) = \left(\frac{TN}{FN+TN}\right) \times 100$$

CHAPTER 7

PHASE SPACE BASED SUBSYSTEM

Any data sequence measured in time domain can be converted into a geometric figure in space, which is called the phase space, using the phase space approach. This can help us study some features that cannot be observed in a time domain. To construct a phase space, the procedure starts from raw data and builds vector by iteration of time delay. For a discrete time signal, scalar time $s(n)$, (where n = 1,2,…, N) can be converted into a multidimensional phase space using time delay coordinates. The delay coordinate construction approach, based on the Taken theorem, is applied to a series of data such as

$$S(n) = s(n), s(n+\tau), \ldots, s(n+(m-1)\tau)$$

Here, τ is a delay time, n is the number of samples used for phase space construction, m is the dimension into which we are embedding the time domain signal.

A reconstructed phase space matrix Y of dimension m and lag τ, called a trajectory matrix, is defined by

$$Y = \begin{bmatrix} S(1) \\ S(2) \\ \cdot \\ \cdot \\ \cdot \\ S(M) \end{bmatrix} = \begin{bmatrix} s(1) & s(1+\tau) & \cdots & s(1+(m-1)\tau) \\ s(2) & s(2+\tau) & \cdots & s(2+(m-1)\tau) \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ s(M) & s(M+\tau) & \cdots & s(M+(m-1)\tau) \end{bmatrix}$$

where row vectors *S(n)*, with $n = 1, 2, \ldots, M$ represent individual points in the reconstructed phase space. The number of points is $M = N - (m - 1)\tau$. The features of the constructed phase space plot depend on the value of the time delay parameter, τ. For a two-dimensional phase space (such that m=2), the trajectory matrix becomes

$$Y = \begin{bmatrix} S(1) \\ S(2) \\ . \\ . \\ . \\ S(M) \end{bmatrix} = \begin{bmatrix} s(1) & s(1+\tau) \\ s(2) & s(2+\tau) \\ . & . \\ . & . \\ . & . \\ s(M) & s(M+\tau) \end{bmatrix}$$

But it will be very difficult to discriminate between the normal and defective heartbeat because the spread characteristics of both the curves will be very similar to each other in the phase space. To handle this problem and see noticeable differences in the spread characteristics of both the curves, the phase space is the plotting coordinates $(s(n), s(n+1) - s(n))$, where $s(n + 1) - s(n)$ is the tangent vector. The reconstructed phase space matrix employed in this research thus is given by

$$Y = \begin{bmatrix} S(1) \\ S(2) \\ . \\ . \\ . \\ S(M) \end{bmatrix} = \begin{bmatrix} s(1) & s(1+\tau) - s(1) \\ s(2) & s(2+\tau) - s(2) \\ . & . \\ . & . \\ . & . \\ s(M) & s(M+\tau) - s(M) \end{bmatrix}$$

The block diagram of the subsystem for defective heartbeat detection based on phase space of ECG and EPCG signals is shown in Figure 4.1.

7.1 DISTANCE VECTOR

The distance of the vector from the origin to the *P* point is equal to that of the displacement vector ($\vec{r}$) which is given by

$$d = |\vec{r}| = \sqrt{(x-0)^2 + (y-0)^2}$$

After constructing the phase space, with the help of the distance of the vector, the distance from the origin to each point on the phase space is calculated in a form of vector. When the distance vectors of the objective signal are determined, the error between these vectors and that of the reference normal heart is calculated. MSE of the error vector is then given by

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(d_{ref}(i) - d_{obj}(i)\right)^2$$

where *N* is the number of samples, d_{ref} is the reference distance vector, either of ECG signal or EPCG signal, for a normal heart, and d_{obj} is the distance vector of the signal under consideration, either ECG signal or EPCG signal.

The reference distance vector (d_{ref}) is derived from the phase space of a normal heart. To obtain the reference phase space, many ECG/ PCG data sequences of a normal heart are used to find their phase spaces. Then all these phase spaces are averaged to obtain the reference phase space based on ECG or EPCG. Averaging helps because even if there is some error or abnormality in the otherwise perfect heartbeat, averaging a lot of heartbeats will eliminate that effect of abnormality.

7.2 LIKELIHOOD RATIO TEST

The MSE value as previously discussed can be used to make a decision about whether the objective signal is normal or abnormal. To achieve a definite decision, a threshold value of MSE must be defined. In this research, this threshold is obtained by using a likelihood ratio test (Λ). The likelihood ratio test is a statistical test of the goodness-of-fit between two models. It provides one objective criterion for selecting among possible models.

In general, the likelihood ratio test can be thought of as a reversed version of conditional probability. The conditional probability of x is $P(\omega|x)$ for a given parameter ω that is formalized in Bayes theorem. The likelihood ratio test is calculated to find the threshold value between probability density functions of MSE values derived by equation (18) for a normal case and an abnormal case through ECG signals or EPCG signals. The decision rule therefore is

$$Decision = \begin{cases} \omega_1, & if\ P(\omega_1|x) > P(\omega_2|x) \\ \omega_2, & elsewhere \end{cases}$$

Where $P[\omega_1|x]$ is conditional probability of MSE values of a normal case and $P[\omega_2|x]$ is conditional probability of MSE values of an abnormal case.

By applying Bayes theorem in equation (19), it is

$$\frac{P(x|\omega_1)P(\omega_1)}{P(x)} \underset{\omega_2}{\overset{\omega_1}{>}} \frac{P(x|\omega_2)P(\omega_2)}{P(x)}$$

From equation (20), *P(x)* does not affect the decision rule so it can be neglected. Hence, the likelihood ratio test $\Lambda(x)$ is redefined as

$$\underbrace{\Lambda(x) = \frac{P(x|\omega_1)}{P(x|\omega_2)}}_{likelihood\ ratio\ test(\Lambda(x))} \underset{\omega_2}{\overset{\omega_1}{>}} \frac{P(\omega_2)}{P(\omega_1)}$$

where $P[x|\omega_1]$ is a conditional probability density function (likelihood) of MSE values of a normal case, and $P[x|\omega_2]$ is a conditional probability density function (likelihood) of MSE values of an abnormal case.

It is noted that $P[x|\omega_1]$ and $P[x|\omega_2]$ is defined by using a Gaussian distribution function as given by

$$P\left(x\middle|\omega_i\right) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}, \qquad i = 1,2$$

where μ is the mean value of distribution and σ^2 is the variance of distribution. In addition, the ratio $P(\omega_2)/P(\omega_1)$, which is the maximum likelihood ratio test, is initially set to 1. The obtained likelihood ratio test is employed to make judgment on the given MSE value of the distance vector of the objective signal. As previously described, the proposed system is performed in a computer with the results of each subsystem discussed in the following sections.

CHAPTER 8

WORKING AND CODES

MAIN CODE

```
filter1=[0.035226291882100656 -0.08544127388224149 -0.13501102001039084
0.4598775021193313 0.8068915093133388 0.3326705529509569]
xy = wgn (1, 3600, 1);
xyz2 = (xy + val);
xyz1 = mean (xyz2);
xyz = xyz2 - xyz1;
a=imfilter(xyz,filter1);
filter2=[-0.3326705529509569 0.8068915093133388 -0.4598775021193313 -0.13501102001039084
0.08544127388224149 0.035226291882100656]
b=imfilter(xyz,filter2);
% c=imresize(a, [1 1800]);
% w=imresize(b, [1 1800]);
c = ecg_down(a,'down');
w = ecg_down(b,'down');
d=imfilter(c,filter1);
e=imfilter(c,filter2);
% f=imresize(d, [1 900]);
% x=imresize(e, [1 900]);
f = ecg_down(d,'down');
x = ecg_down(e,'down');
g=imfilter(f,filter1);
h=imfilter(f,filter2);
% i=imresize(g, [1 450]);
% y=imresize(h, [1 450]);
i = ecg_down(g,'down');
```

```
y = ecg_down(h,'down');
z=imfilter(i,filter2);
% z=imresize(j, [1 225]);
% z = ecg_down(j,'down');
z1=y.*z;
z2=abs(z1);

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

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

subplot(3,3,3);
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(3,3,8)
plot(z1);
title('multi')

subplot(3,3,9)
plot(z2);
title('absolute')



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

ECG_DOWN FUNCTION

```
function c = ecg_down(a,q);

f = strcmpi(q,'down');
if f == 1
xy=size(a,2);
even = mod(xy,2);
for i=1:fix(xy/2)
    c(i)=(a(2*i-1) + a(2*i))/2;
end

c(i+even) = a(end);

else
```

```
a = [a, a(end)];
xy=size(a,2);
for i = 1:xy-1
   c(2*i-1) = a(i);
   c(2*i) = (a(i)+a(i+1))/2;
end
   c(i+2) = a(fix((i+2)/2)+1);
end
```

PEAK FUNCTION CODE

```
% z11=abs(z8);
len = length(y);
thresh = abs(max(y)/4);
% thresh1 = min(y)/2;
count = 0;
% count1= 0;
for i = 2:len - 1
      if y(i+1) - y(i-1) > thresh ;
         count =  count + 1;

%       if    y(i+1) - y(i) <  -thresh/2 ;
%           count1 =  count1 + 1;
% %          i=i+24;
%       end
      end
end
disp(count)
% disp(count1)
```

RESULTS

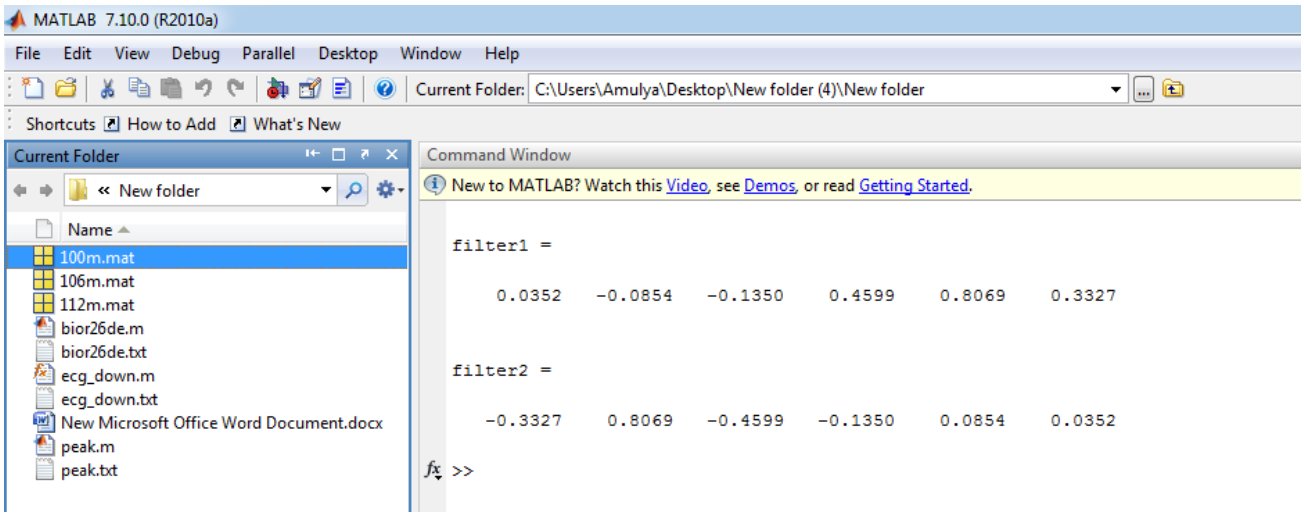

Figure Ra : Values of the orthogonal filter coefficients

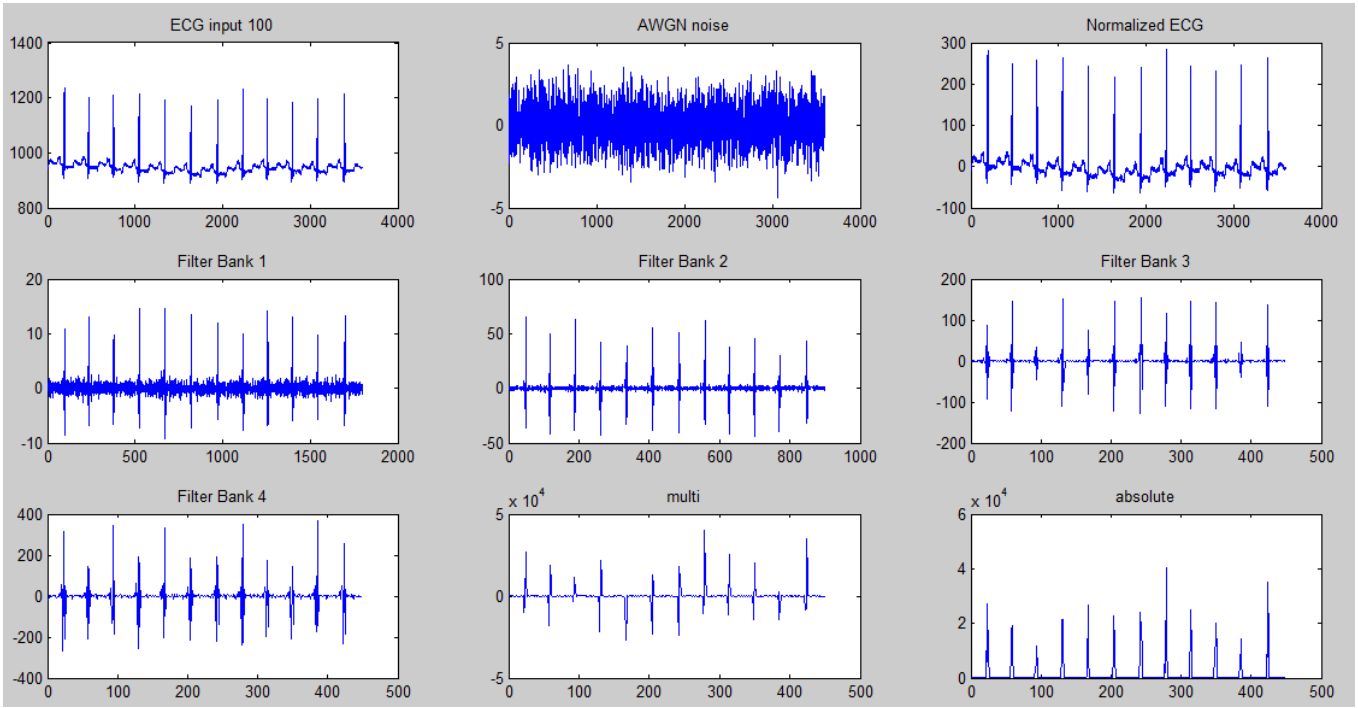

Figure Rb : Results of filtering when we use a perfect ECG signal

Peak=35 in this case.

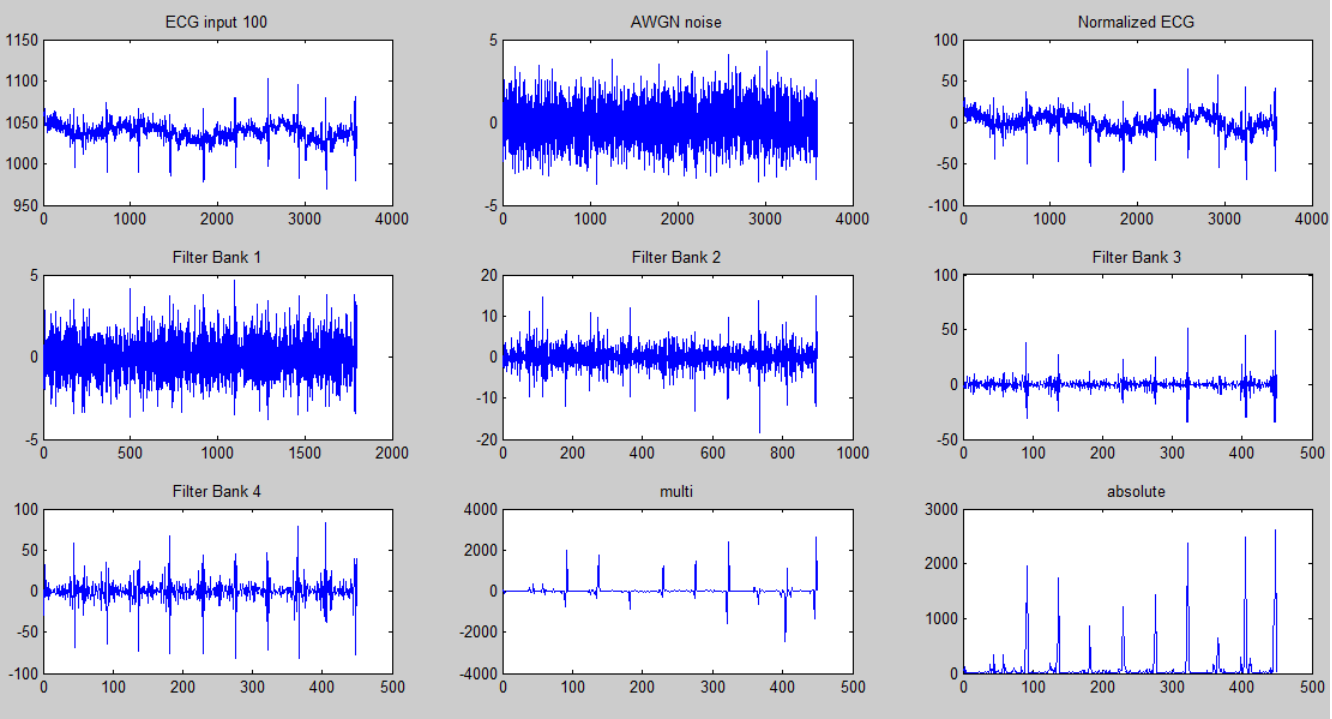

Figure Rc : Results of filtering when we use a very noisy/defective ECG signal

Peak=20 in this case

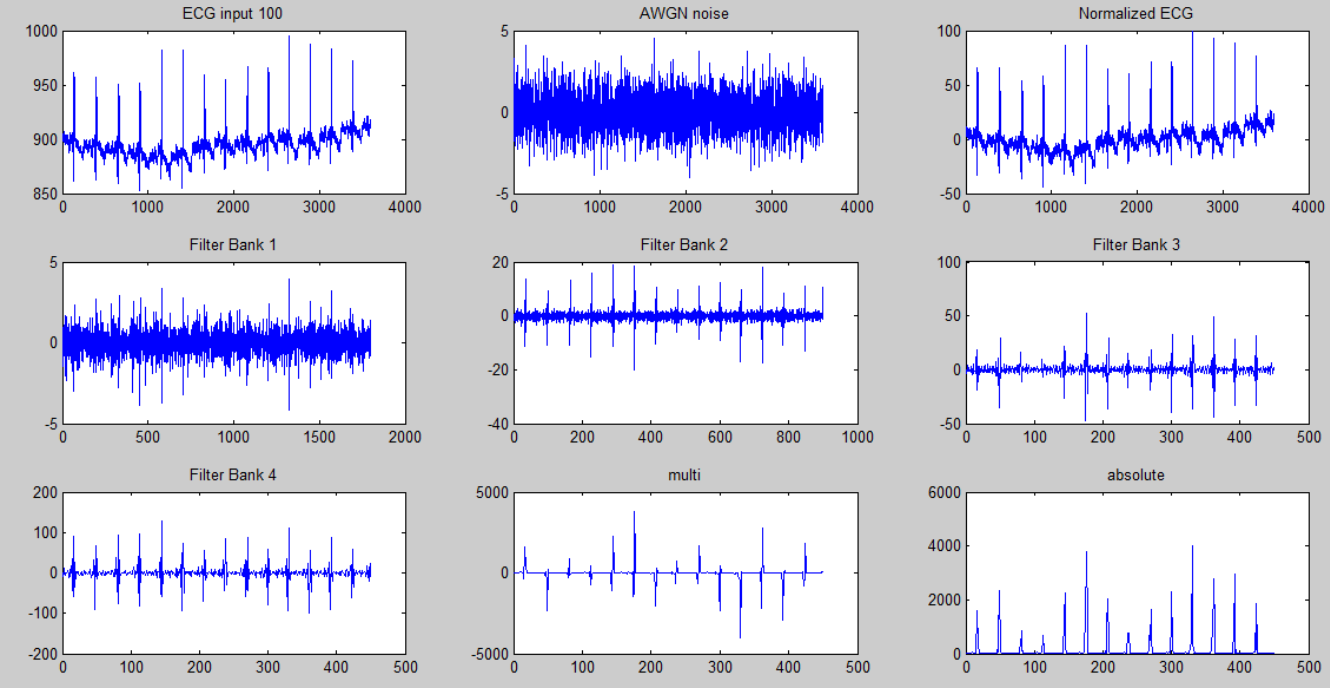

Figure Rd : Results of filtering when we use a perfect ECG signal

Peak = 32 in this case

CONCLUSION AND FUTURE SCOPE

A non-invasive system for detecting defective heartbeat is presented. The system consists of two subsystems. One is based on the impulse response of a heart system derived from the relationship between an ECG signal and the envelope of a PCG signal (EPCG). The decision is made by the back propagation neural network from the impulse response signal.

The other subsystem is based on phase space of the signal (ECG or EPCG). The MSE value obtained by comparing the distance vector of the testing signal with the reference distance vector is judged by the likelihood ratio test result. This technique provides 100% accuracy for decision making.

The results from both techniques show that the impulse response-based method can be used primarily to detect a heart abnormality, whereas the phase space-based approach can be used to indicate whether the heart defect is caused from the abnormal ECG signal and/or abnormal PCG signal. This proposed preliminary automated heart defect detection technique can provide the opportunity to help patients in rural areas.

Preliminary heart defect detection is important so that the treatment given thereafter can be efficient and according to the results derived when the heart is tested for abnormalities.

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