CHAPTER-IV
DECISION SUPPORT SYSTEM FOR CONGENITAL HEART SEPTUM DEFECT DIAGNOSIS BASED ON ECG SIGNAL FEATURES USING NEURAL NETWORKS

4.1 Introduction

One of the clinical tests performed to diagnose Congenital Heart Septum Defect is through Electrocardiogram signals, which shows an electrical activity of the heart in terms of the waves. To diagnose Congenital Heart Septum Defect, a physician should obtain the features like amplitude values of the waves and the time interval between the waves from ECG signals. As an ECG signal may be of different lengths and an irregularity of the heart may be shown at any intervals of the signal, a physician has to analyze the signals completely to diagnose the disease. It causes the time delay of the diagnosis and also it is difficult for an inexperienced physician to take the decision about the diagnosis accurately. This makes the patient to enter into the severe condition. Therefore, in the present study, an algorithm is developed based on Discrete Wavelet Transformation to extract the features from ECG signals. Also, in this study, a Decision Support System is developed to perform Congenital Heart Septum Defect Diagnosis classification based on the ECG features using Backpropagation Neural Networks. The Network is trained by using a Delta

Learning Rule. The developed algorithm and Decision Support System are implemented in MATLAB 7.3with GUI features.

4.2 The Electrocardiogram (ECG)

4.2.1 Introduction

The *Electrocardiogram* (ECG or EKG) is a graphic record of the direction and magnitude of the electrical activity of the heart that is generated by depolarization and repolarization of the atria and ventricles [FHAT09].

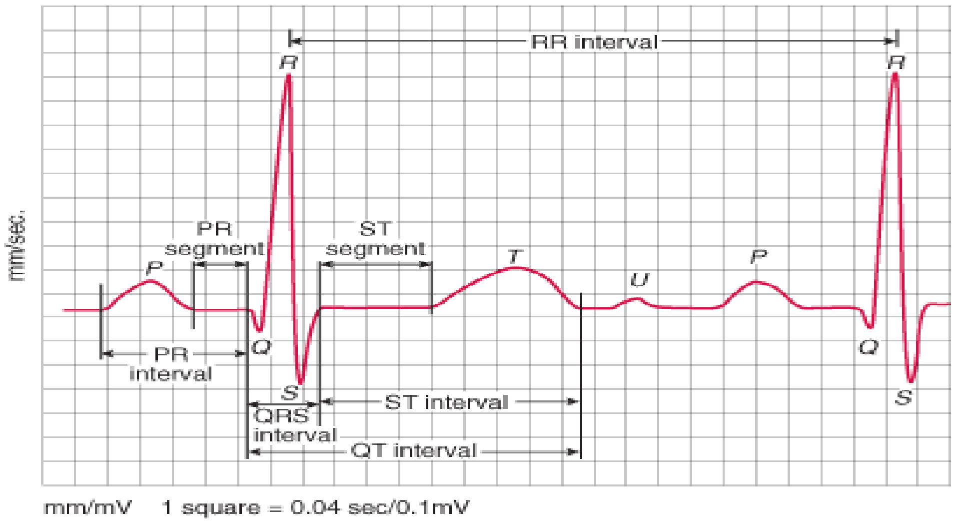

Fig 4.1: Normal ECG waves and corresponding intervals

Depolarization occurs when the cardiac cell, which are electrically polarized, lose their internal negativity. The spread of depolarization is, producing a wave of depolarization across the entire heart. This wave represents a flow of electricity that can be detected by electrodes placed on the surface of the body. Once depolarization is completed, the cardiac cells are restored to their resting potential. This process is called *repolarization*. This flow of energy takes in the form of ECG waves and is composed of P wave followed by QRS complex followed by T wave followed by U wave per cardiac cycle which is shown in fig 4.1. The amplitude values of the waves are represented in terms of mV and the time intervals between the waves are represented in terms of seconds.

Many of the heart related diseases can be diagnosed by using the Electrocardiogram signals. In order to diagnose these diseases, a physician analyzes the signal and extracts the features like amplitudes of the waves and the time interval between them [DPB07].

4.4.2 Heart Waves and Durations

P Wave

The P wave is a small low-voltage deflection away from the baseline caused by the depolarization of the atria prior to atria contraction. Generally, the amplitude of a P-wave is 0.25 mV and the duration of a P wave is 0.08 to 0.1 seconds (80-100 ms) [SSN08]. By using the time intervals between the P waves, atrial rate can be calculated. A Peaked P waves indicates right atrial hypertrophy e.g., pulmonary hypertension or tricuspid stenosis. Bifid broad P waves suggest left atrial hypertrophy e.g., mitral stenosis.

QRS Complex

The second wave is the QRS complex. Typically this complex has a series of 3 deflections that reflect the current associated with right and left ventricular depolarization. By convention the first deflection in the complex, if it is negative, is called a Q wave. The first positive deflection in the complex is called an R wave. A negative deflection after an R wave is called an S wave. A second positive deflection after the S wave, if there is one, is called the U wave. Some QRS complexes do not have all three deflections. But irrespective of the number of waves present, they are all QRS complexes. QRS-complex is the largest-amplitude portion of the ECG [KH04]. Generally the amplitude of R wave is 1.6mV and the amplitude of Q-wave is 25% of the R-wave. Ventricular rate can be calculated by determining the time interval between QRS complexes. The duration of the QRS complex is normally 0.06 to 0.1 seconds. This relatively short duration indicates that ventricular depolarization normally occurs very rapidly. A broad QRS complex with 'RSR' pattern in V1 represents right bundle branch block. A broad QRS with an 'M' pattern in lead I represents left bundle branch block. The first negative deflection of a QRS complex is the Q wave. If the Q wave is > 2mm, it is considered to be pathological.

T Wave

The T-wave is the result of ventricular repolarization and is longer in duration than depolarization. The polarity of this wave normally follows main QRS deflection in any lead. The ventricles are electrically unstable during the period of repolarization extending from the peak of the T wave to its initial downslope. A stimulus (e.g. a run away heart beat called a premature beat) falling on this vulnerable period has the potential to precipitate ventricular fibrillation- the so called R-on-T phenomenon. Generally the amplitude of a T-wave ranges from 0.1 to 0.5 mV. Sometimes a small positive U wave may be seen following the T wave, which is considered to be a representation of the Papillary Muscle or Purkinje Fibers. A tall tented T waves could represent hyperkalaemia. T wave inversion can represent coronary ischaemia, previous infraction or electrolyte abnormality such as hypokalaemia.

PR Interval

The period of time from the onset of the P wave to the beginning of the QRS complex is termed as the P-R interval, which normally ranges from 0.12 to 0.20 seconds in duration. This interval represents the time between the onset of atrial depolarization and the onset of ventricular depolarization. If the P-R interval is > 0.2 sec, there is an AV conduction block, which is also termed a first-degree heart block if the impulse is still able to be conducted into the ventricles. A short PR interval represents rapid conduction across the AV node, usually, through an accessory pathway. A long P-R interval but preceding every QRS complex by the same distance is first degree AV block. A P-R interval that lengthens with each consecutive QRS complex, followed by a P wave which has no QRS complex and then by a P wave with a short PR interval is 2nd degree AV block. If the P waves that are followed by a QRS complex have a normal PR interval with the occasional non conducted P wave i.e., a P wave with no subsequent QRS complex rhythm is said to be Mobitz type II 2nd degree AV block.

RR Interval

The time period between the R waves is called as R-R interval. Using this R-R interval [GM08] [TFS02] the heart beat rate (the number of R-R interval) and irregularity of a heart beat can be determined. A regular heart beat has uniform R-R interval values where as an irregular heart beat has variable R-R interval values. Generally a normal value of a heart rate may be in the range of 60-100 beats/min. A slower rate than this value is called as bradycardia and a higher rate is called as tachycardia. That is any change in the normal heart rate indicates arrhythmia.

ST Interval

The isoelectric period (ST segment) following the QRS is the time at which the entire ventricle is depolarized and roughly corresponds to the plateau phase of the ventricular action potential. The ST segment is important in the diagnosis of ventricular ischemia or hypoxia because under those conditions. The ST segment can become either depressed or elevated. There are basically three abnormalities seen in ST segment. A ST depression could signify cardiac ischaemia, a ST elevation could highly suggestive of infraction and a Saddle shaped concave ST segments usually seen across all the ECG suggesting a diagnosis of pericarditis. The period of time from the offset of the QRS complex wave to the offset of the T wave is termed as the S-T interval, which normally has a value less than 0.30 seconds in duration.

QT Interval

The Q-T interval represents the time for both ventricular depolarization and repolarization to occur and therefore roughly estimates the duration of an average ventricular action potential. This interval can range from 0.2 to 0.4 seconds depending upon heart rate. At high heart rates, ventricular action potentials shorten in duration, which decreases the Q-T interval. Because prolonged Q-T intervals can be diagnostic for susceptibility to certain types of tachyarrhythmias, it is important to determine if a given Q-T interval is excessively long. In practice, the Q-T interval is expressed as a corrected Q-T (QTc) by taking the Q-T interval and dividing it by the square root of the R-R interval (interval between ventricular depolarizations). This allows an assessment of the Q-T interval that is independent of heart rate. Normal corrected Q-T intervals are less than 0.44 seconds. A prolongation can lead to serious ventricular arrhythmia such as torsades de pointes.

4.3 The Wavelet Transformation

4.3.1 Introduction

In signal analysis, there are number of different functions one can perform on that signal in order to translate it into different forms that are more suitable for different applications. The most popular function is the *Fourier* *transform* that breaks down a signal into constituent sinusoids of different frequencies. That is, it transforms the signal from time based to frequency based. For many signals (stationary signal), Fourier transform is extremely useful because the signals frequency content is of great important. But the serious drawback with this approach is the time information is lost in transforming to frequency domain. So, it is not possible to tell when a particular event occurred through this approach. This drawback can be overcome by using *Short Time Fourier Transformation* (STFT). In a Short Time Fourier Transformation a signal is mapped in both frequency and time dimensions using a technique called Widowing. Though the time and frequency information is obtained at a time using this approach, it has a drawback that the size of the time window must be fixed for all frequencies. To overcome this drawback a most common method called *Wavelet Transformation* (WT) is used which it has a time window of variable size [LM07].

A *Wave* is an oscillating function of time or space. *Wavelets* are localized waves and they have their energy concentrated in time or space. The Transform of a signal is another form of representing the signal. It does not change the information content present in the signal. A *Wavelet Transformation* involves convolving the signal against particular instances of the wavelet at various time scales and positions. Since changes in frequency can be modeled by changing the time scales and changes in time can be modeled by shifting the position of the wavelet, both frequency and location of frequency can be modeled by using the Wavelet Transformation. That is a Wavelet transformation uses multi resolution technique by which different frequencies are analyzed with different resolutions. A Wavelet Transform at high frequencies gives good time resolution and poor frequency resolution, while at low frequencies the Wavelet Transform gives good frequency resolution and poor time resolutions. The most frequently and commonly used types of Wavelet Transformations are *Continuous Wavelet Transformation (CWT)* and the *Discrete Wavelet Transformation (DWT).*

4.3.2 The Continuous Wavelet Transform (CWT)

The Continuous Wavelet Transform was developed as an alternative approach to the Short Time Fourier transform, to overcome the resolution problem. The wavelet analysis is done in a similar way to the STFT analysis, in the sense that the signal is multiplied with a function similar to the window function in the STFT and the transform is computed separately for different segments of the time-domain signal. However, there are two main differences between the STFT and the CWT.

- The Fourier Transforms of the windowed signals are not taken and therefore single peak will be seen corresponding to a sinusoid, i.e., negative frequencies are not computed.

- The width of the window is changed as the transform and is computed for every single spectral component, which is probably the most significant characteristic of the wavelet transform.

The Continuous Wavelet Transform (CWT) is provided by equation 4.1, where $x(t)$ is the signal to be analyzed, ψ (t) is the mother wavelet or the basis function. All the wavelet functions used in the transform are derived from the mother wavelet through wavelet translation (shifting) and scaling (dilation or compression).

$$X_w(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\, \psi^* \left(\frac{t-b}{a}\right) dt \qquad \ldots 4.1$$

The mother wavelet used to generate all the basis functions is designed based on some desired characteristics associated with that function. The translation parameter *b* relates to the location of the wavelet function as it is shifted through the signal. Thus, it corresponds to the time information in the wavelet transform. The scale parameter *a* defined as |1/frequency| and corresponds to frequency information. The Scaling either dilates or compresses a signal. Large scales (low frequencies) dilate the signal and provide detailed information hidden in the signal, while small scales (high frequencies) compress the signal and provide global information about the signal. The Wavelet Transform merely performs the convolution operation of the signal and the basis function. The above analysis becomes very useful in most practical applications.

The high frequencies (low scales) do not last for a long duration, but instead, appear as short bursts, while low frequencies (high scales) usually last for entire duration of the signal.

In order to recover the original signal *x*(*t*) from the transformed Continuous Wavelet Transformation, the following Inverse Continuous Wavelet Transform (ICWT) can be used.

$$x(t) = \int_0^{\infty} \int_{-\infty}^{\infty} \frac{1}{a^2} X_w(a,b) \frac{1}{\sqrt{|(a)|}} \tilde{\psi} \left(\frac{t-b}{a} \right) db \; da \qquad \text{... 4.2}$$

$\tilde{\psi}(t)$ is the dual function of ψ(*t*). And the dual function should satisfy

$$\int_0^{\infty} \int_{-\infty}^{\infty} \frac{1}{|a^3|} \psi \left(\frac{t_1-b}{a} \right) \tilde{\psi} \left(\frac{t-b}{a} \right) db \; da = \delta(t-t_1) \qquad \text{... 4.3}$$

Sometimes, $\tilde{\psi}(t) = C_{\psi}^{-1} \psi(t)$, where

$$C_{\psi} = \frac{1}{2} \int_{-\infty}^{+\infty} \frac{\left|\hat{\psi}(\zeta)\right|^2}{|\zeta|} d\zeta \qquad \text{... 4.4}$$

is called the admissibility constant and $\hat{\psi}$ is the Fourier transform of ψ. For a successful inverse transform, the admissibility constant has to satisfy the admissibility condition:

$$0 < C_{\psi} < +\infty \qquad \text{... 4.5}$$

It is possible to show that the admissibility condition implies that $\hat{\psi}(0) = 0$, so that a wavelet must integrate to zero.

For practical implementation of Continuous Wavelet Transformation, it is computed over a finely discretized time-frequency grid. This dicretization involves an approximation of the transform integral (summation) computed on a discrete grid of *a* scales and *b* locations. In general, the wavelet transform is approximated in this way over each time step for a range of wavelet scales. Therefore, there is a heavy computational burden involved in the generation of the CWT and a vast amount of repeated information is contained within this redundant representation of the Continuous Wavelet Transform T(a,b).

4.3.3 The Discrete Wavelet Transform (DWT)

The discretization of Continuous Wavelet Transform is called as *Discrete Wavelet Transform (DWT)*. The Discrete Wavelet Transform employs a dyadic grid (integer power of two scaling in *a* and *b*), orthonormal wavelet basis functions and exhibits zero redundancy. Mathematically, a Discrete Wavelet Transformation can be computed in the following way. A general way to sample the parameters *a*, *b* is to use a logarithmic discretization of scale *a* and location *b*. To link *b* to *a*, we move in discrete steps to each location *b*, which proportional to *a* scale. This kind of discretization of the wavelet has the form

$$\psi_{m,n}(\mathrm{t}) = \frac{1}{\sqrt{\mathrm{a}_0^{\mathrm{m}}}}\psi\left(\frac{t - nb_0\mathrm{a}_0^{\mathrm{m}}}{\mathrm{a}_0^{\mathrm{m}}}\right) \quad \ldots$$

where the integers *m* and *n* control the wavelet dilation and translation respectively, a_0 is a specified fixed dilation step parameter set at a value greater than 1 and b_0 is the location parameter which must be greater than zero. A common choice for discrete wavelet parameters a_0 and b_0 are 2 and 1 respectively. This power-of-two logarithmic scaling of both the dilation and translation steps is known as the dyadic grid arrangement. The dyadic grid is perhaps the simplest and most efficient discretization for practical purposes and lends itself to the construction of an orthonormal wavelet basis. Bu substituting a_0=2 and b_0 =1 into equation 4.6, the dyadic grid wavelet can be written compactly as

$$\psi_{m,n}(\mathrm{t}) = 2^{-\mathrm{m}/2}\psi(2^{-\mathrm{m}}\mathrm{t} - \mathrm{n}) \qquad \text{... 4.7}$$

This has the same notation as the general discrete wavelet transformation. Here, $\psi_{m,n}(t)$ will be used only to denote dyadic grid scaling with a_0=2 and b_0 =1. Discrete dyadic grid wavelets are usually chosen to be orthonormal. That is, they are both orthogonal to each other and are normalized to have unit energy. This is expressed as

$$\int_{-\infty}^{\infty} \psi_{m,n}(\mathrm{t})\psi_{m',n'}(\mathrm{t})\ dt = \begin{cases} 1 & \text{If m=m}' \text{ and n=n}' \\ 0 & \text{Otherwise.} \end{cases} \qquad \text{... 4.8}$$

This means that the information stored in a wavelet coefficient $T_{m,n}$ obtained from the wavelet transform is not repeated elsewhere and allows for the complete regeneration of the original signal without redundancy. The corresponding family of orthonormal wavelets is an orthonormal basis. Using the dyadic grid wavelet of equation 4.8**,** the Discrete Wavelet Transform DWT can be written as:

$$T_{m,n} = \int_{-\infty}^{\infty} x(\mathrm{t})\, \psi_{m,n}(\mathrm{t})\, dt \qquad \text{... 4.9}$$

where $T_{m,n}$ is known as the wavelet (or detail) coefficient at scale and location indices (m, n). The distinct difference between the DWT and discretized approximations of the CWT is the discretization of the CWT required for its practical implementation involves a discrete approximation of the transform integral computed on a discrete grid of *a* scales *b* locations. The inverse Continuous Wavelet Transform is also computed as a discrete approximation. How close an approximation to the original signal is recovered depends mainly on the resolution of the dicretization used and with care usually a very good approximation can be recovered. On the otherhand, DWT defined in equation 4.9 transforms integral remains continuous but is determined only on a discretized grid of *a* scales and *b* locations. We can then sum the DWT coefficients infinity over *m* and *n* to get the original signal back exactly. Orthonormal dyadic discrete wavelets are associated with scaling functions and their dilation equations. The scaling function is associated with the smoothing of the signal and has the form as wavelet, given by

$$\phi_{m,n}(\mathrm{t}) = 2^{-\mathrm{m}/2}\phi(2^{-\mathrm{m}}\mathrm{t} - \mathrm{n}) \qquad \text{... 4.10}$$

They have the property

$$\int_{-\infty}^{\infty} \phi_{0,0}(\mathrm{t})\, dt = 1 \qquad \text{... 4.11}$$

where □$_{0,0}$(t)=□(t) is sometimes referred to as the father scaling function or father wavelet (cf mother wavelet). The scaling function is orthogonal to translations of itself, but not to dilations of itself. The scaling function can be convolved with the signal to produce approximation coefficients as follows.

$$S_{m,n} = \int_{-\infty}^{\infty} x(\mathrm{t})\, \phi_{m,n}(\mathrm{t})\, dt \qquad \text{... 4. 12}$$

From the above, we can see that the approximation coefficients are simply weighted averages of the continuous signal factored by $2^{m/2}$. The approximation coefficients at a specific scale *m* are collectively known as discrete approximation of the signal at that scale. A continuous approximation of the signal at scale *m* can be generated by summing a sequence of scaling functions at this scale factor by the approximation coefficients as follows

$$x_m(\mathrm{t}) = \sum_{\mathrm{n}=-\infty}^{\infty} S_{m,n}\phi_{m,n}(\mathrm{t}) \qquad \text{...}$$

where x_m(t) is a smooth, scaling-function-dependent version of the signal x(t) at scale index *m*. This continuous approximation approaches x(t) at small scales, i.e. as $m \to -\infty$. A signal x(t) can then be represented using a combined series expansion using both the approximation coefficients and the wavelet (detail) coefficients as follows

$$x(\mathrm{t}) = \sum_{\mathrm{n}=-\infty}^{\infty} S_{m_0,n}\phi_{m_0,n}(\mathrm{t}) + \sum_{\mathrm{m}=-\infty}^{m_0} \sum_{\mathrm{n}=-\infty}^{\infty} T_{m,n}\psi_{m,n}(\mathrm{t}) \qquad \text{... 4.14}$$

This equation shows that the original continuous signal is expressed as a combination of an approximation of itself at arbitrary scale index m_0 added to a succession of signal details from scales m_0 down to negative infinity. The signal details at scale *m* is defined as

$$d_m(\mathrm{t}) = \sum_{\mathrm{n}=-\infty}^{\infty} T_{m,n}\psi_{m,n}(\mathrm{t}) \qquad \text{... 4.15}$$

Hence, this equation can be written as

$$x(\mathrm{t}) = x_{m_0}(\mathrm{t}) + \sum_{\mathrm{m}=-\infty}^{m_0} d_m(\mathrm{t}) \qquad \text{... 4.16}$$

From this equation, it is easy to show that

$$x_{m-1}(\mathrm{t}) = x_m(\mathrm{t}) + d_m(\mathrm{t}) \qquad \text{... 4.17}$$

which tells that the addition of signal detail at an arbitrary scale (index m) to the approximation at that scale gives the signal approximation at an increased resolution (i.e. at a smaller scale, index m-1). This is called a multiresolution representation [Mal89].

Multi-Resolution Analysis using Filter Banks Theory: Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations and the scale is determined by upsampling and downsampling (subsampling) operations.

The Discrete Wavelet Transform of a signal can be computed by passing it through the lowpass and highpass filters as shown in fig 4.2**.** This is called the Mallat algorithm or Mallat-tree decomposition [Mal89]. In the fig 4.2**,** X[n] represents the original signal to be filtered, where n is an integer, G_0 represents the lowpass filer and H_0 represents the highpass filter. At each level, the highpass filters produces detail information, d[n], while the lowpass filters associated with scaling function produces coarse approximations, a[n].

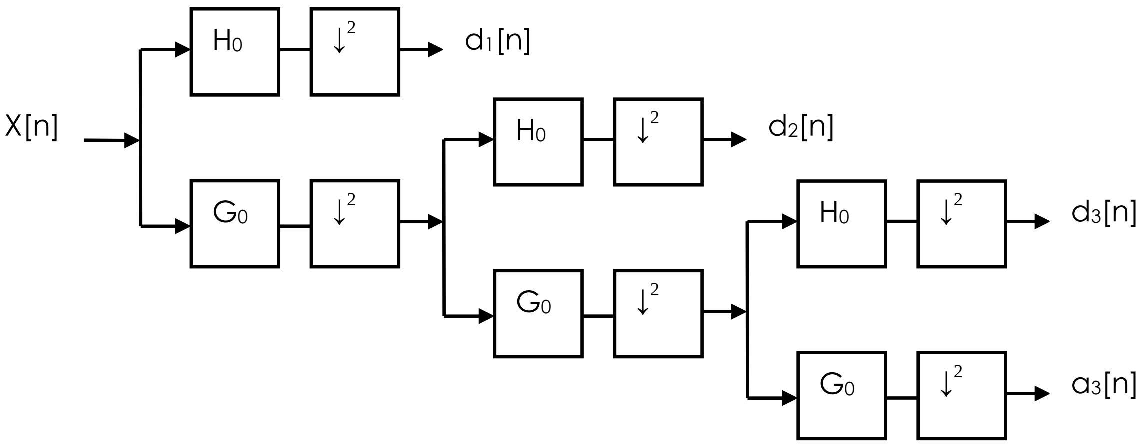

Fig 4.2: Three-level Wavelet Decomposition Tree

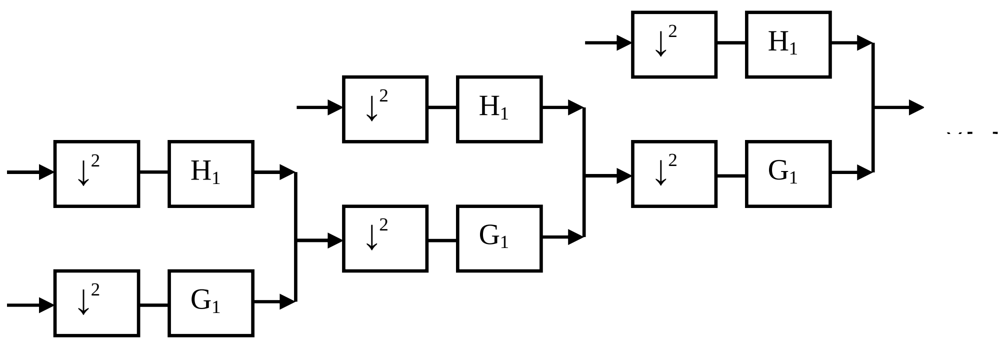

Fig 4.3: Three-level Wavelet Reconstruction Tree

With this approach, the time resolution becomes arbitrary good at high frequencies, while the frequency resolution becomes arbitrary good at low frequencies. The filtering of the decimation process is continued until the desired level is reached. The maximum number of levels depends on the length of the signal. The DWT of the original signal is then obtained by concatenating all the coefficients, a[n] and d[n], starting from the last level of decomposition.

Fig 4.3 shows the reconstruction of the original signal from wavelet coefficients. Basically, the reconstruction is the reverse process of decomposition. The approximation and detail coefficients at every level are upsampled by two passes through the lowpass and highpass synthesis filters and then added. This process is continued through the same number of levels in the decomposition process to obtain the original signal. The Mallat algorithm works equally well if the analysis filters, G_0 and H_0, are exchanged with synthesis filters, G_1 and H_1.

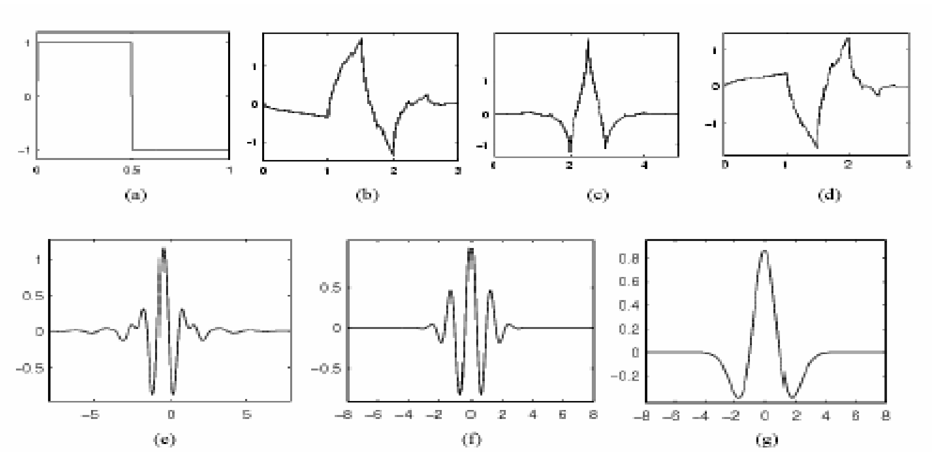

Fig 4.4: Wavelet Families (a) Haar (b)Daubachies4 (c)Coiflet1 (d)Symlet2 (e) Mayer (f) Morlet (g)Mexican Hat

There are a number of basis functions that can be used as the mother wavelet for Wavelet Transformation. Since the mother wavelets produces all the wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting Wavelet Transform. Fig 4.4 illustrates some of the commonly used wavelet functions. The Haar wavelet is one of the oldest and simples wavelet. Daubaches wavelets are the most popular wavelets. The Haar, Daubeches, Symlets and Coiflets are compactly supported orthogonal wavelets. The wavelets are chosen based on their shape and their ability to analyze the signal in a particular application.

4.4 Automatic Extraction of ECG Features using Discrete Wavelet Transform

4.4.1 Introduction

One of the clinical tests performed to diagnose Congenital Heart Septum Defect is through Electrocardiogram signals. In order to diagnose Congenital Heart Septum Defect based on ECG signals, a physician analyzes and extracts the features like the amplitudes of P wave, QRS complex and T waves and the time intervals between P-R, R-R S-T and Q-T of the waves. Since an ECG may have different lengths and being a non-stationary signal and the irregularity may not be periodic instead it can be shown up at any interval of the signal, it is difficult for a physician to analyze and to extract the features from ECG signal manually. In this module, an algorithm is developed to automatically analyze and to extract the features from ECG signals based on Discrete Wavelet Transform. The developed algorithm initially performs preprocessing of a signal in order to remove baseline drift (De-trending) and noise (De-noising) from the signal and then it uses the preprocessed signal for extracting the features from the ECG signal automatically. By using developed algorithm, the accuracy of the analysis can increased and the analysis time of an ECG signal can be reduced.

4.4.2 Material and Methods

Dataset used

The data set used for the present study is the Electrocardiogram signals, which are obtained from the MIT-BIH database via Physionet website [Phy] and stored in a text format. The MIT-BIH database contains many types of Electrocardiogram signals including both abnormal or unhealthy Electrocardiograms and normal Electrocardiograms, which are sampled at different rates. For example record 16272 is originally sampled at 128 Hz, record 30 was sampled at 250 Hz and record 113 was sampled at 360 Hz. Therefore, to process all the signals uniquely, all the samples must be resampled at 360 Hz before processing the ECG signal. ECG signals of length 30 minutes duration are selected for the present study. But while processing only 10 seconds of the data is used.

Method

In the present module, to automatically extract ECG features, an algorithm is developed based on the Discrete Wavelet Transform. The processing steps involved in the developed algorithm are as follows:

- Initially the original ECG signal is decomposed into 8 levels using Discrete Wavelet Transform and Dabachies6 (db6) as the mother wavelet. Then by using the Inverse Discrete Wavelet Transform, the individual decomposed components are reconstructed. Now based on these individual reconstructed components of the ECG signal, the features are extracted.
- Before extraction of ECG features, the signal must be preprocessed in order to have signal without baseline drift and noise.
- Since the low frequency components causes for a baseline drift, low frequency reconstructed components must be deducted from the original ECG signal to remove baseline drift.
- Similarly, in order to remove noise, the high frequency reconstructed components (which causes for noise) must be deducted from the de-trended ECG signal.
- Now, the preprocessed ECG signal is used for extracting ECG features.

The detailed description of the developed algorithm along with the experimental results is shown in the following section.

4.4.3 Extraction of ECG Features

In order to extract ECG features, the developed algorithm decomposes the obtained original ECG signal into corresponding Approximation and Detail coefficients up to 8 levels using *Discrete Wavelet Transformation*. The mother wavelet or basis function that is used in the decomposition is *Dabachies6* (db6) [MAA05]. The decomposed approximation and detail coefficients of the signal are cA1, cA2 . . . , cA8 and cD1, cD2. . . ,cD8 . The decomposed signal is then reconstructed to get original ECG signal components by using I*nverse Discrete Wavelet Transformation* (IDWT). The reconstructed approximation and detail coefficients of the signal are A1, A2 . . . ., A8 and D1, D2, … D8. Among these components, the components A8 and D8 have the lowest frequencies, the components A1 and D1 have the highest frequencies and between of these components have from lower to higher frequencies. Now, the obtained individual reconstructed ECG components are used for both preprocessing and extracting ECG features. The developed algorithm is implemented in *MATLAB 7.3* using GUI feature. In the present module, in order to test the developed algorithm a *Record No 103 of MIT-BIH Arrhythmia* is selected. The original ECG signal of length 800 samples for Record No 103 of MIT-BIH Arrhythmia is shown in fig 4.5**.**

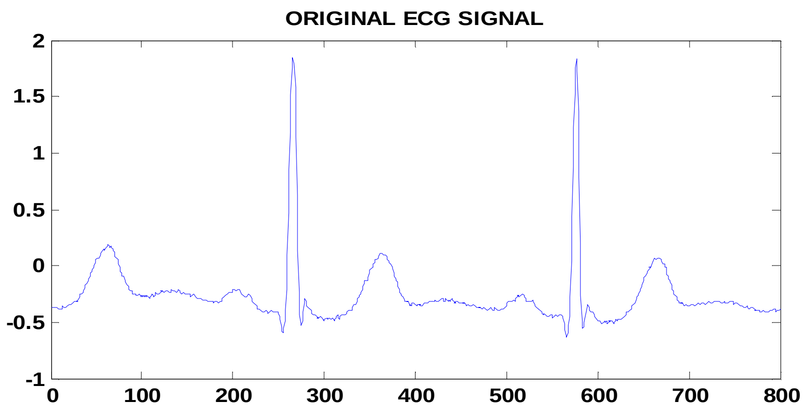

Fig 4.5: The original ECG signal of Record No 103 of MIT-BIH Arrhythmia

After decomposition, the individual reconstructed components of the ECG signal of length 3600 samples are shown in fig 4.6. Now the obtained components are used for both preprocessing and extracting the features from the ECG signal.

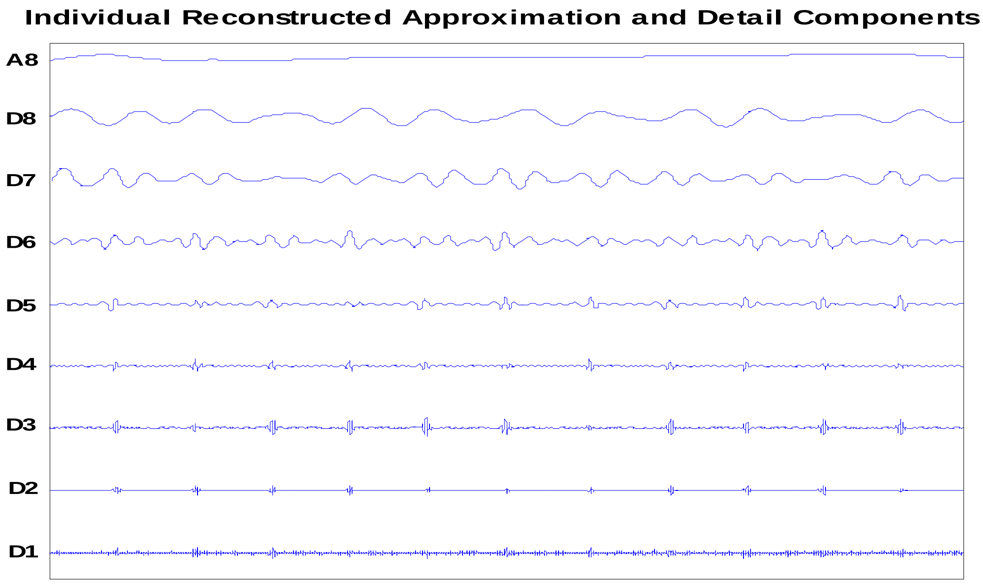

Fig 4.6 : Reconstructed Approximation and Detail Components of the ECG signal

4.4.3.1 ECG Preprocessing

When an Electrocardiogram is recorded many kinds of noises are also be recorded due to very low and high frequencies [VRAP06] , which causes an ECG to have baseline drift and noise in the signal and is very difficult to clinical diagnosis. For proper diagnosis of ECG, it is necessary to remove noise from the signal [AK10]. A process of removing the baseline drift of a signal [Daq05] is called de-trending and a process of removing the noise [UMV09] of a signal is called de-noising. Both of these processes come under the preprocessing of an

ECG signal. Once the signal is preprocessed then it can be used for feature extraction.

ECG Baseline Drift Removal

Since the low frequency components cause the signal for baseline shifting, these components must be deducted to have a signal without baseline drift. In this study, the low frequency components of a decomposed signal are A8 and D8.

Therefore, to remove the baseline drift, the developed algorithm removes these components from the original ECG signal. Thus, the problem of baseline shifting is solved. The original and de-trended ECG signal of length 800 samples is shown fig 4.7.

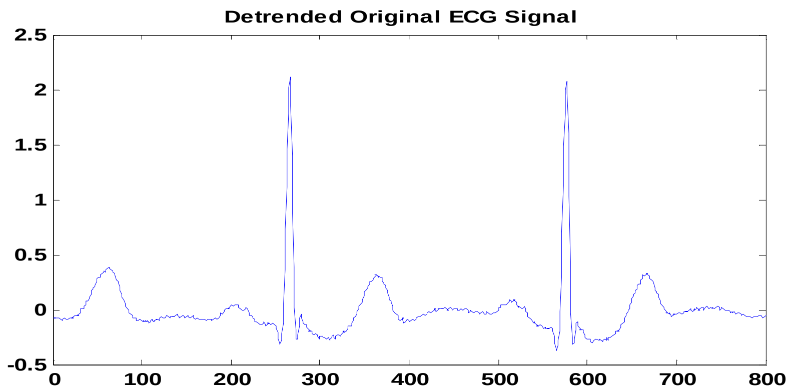

Fig 4.7: The De-trended ECG Signal

ECG De-noising

Though the low frequency components are removed from the original signal, still it may have noise due to high frequency components. In order to remove the noise from ECG signal, it is required to identify which components contain the noise and then these identified components are removed from the de-trended signal. When a signal is decompose by DWT, the successive approximations becomes less and less noisy as more and more high frequency information is filtered out of the signal. But, in discarding all the high frequency information many of the original signal's sharpest features are lost. Optimal de-noising requires a more subtle approach called *thresholding* [MK08]. This involves discarding only the portions of the details that exceed a certain limit. The developed algorithm uses global thresholding option, which is derived from Donoho-Johnstone fixed form thresholding strategy for an un-scaled white noise. By using the developed algorithm, the identified high frequency components are D1, D2. These components must be filtered by applying a threshold. Then the thresholded components are removed from the de-trended signal. The de-noised ECG signal of length 800 samples is shown in fig 4.8.

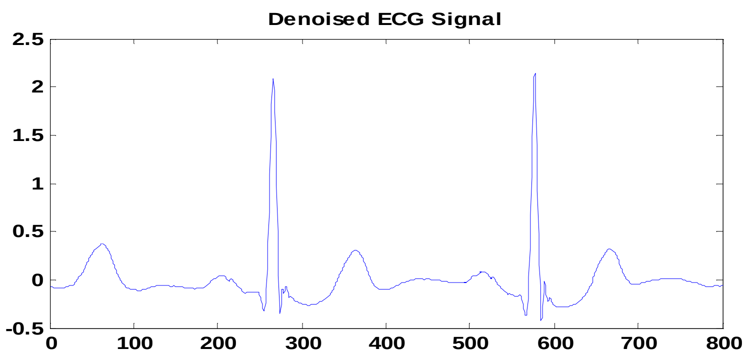

Fig 4.8: De-noised ECG signal

4.4.3.2 Extraction of ECG Features

QRS complex

Since the peaks of R waves in the ECG signal have the largest amplitude values among the other waves, identifying the QRS complexes of an ECG signal by using the developed algorithm is an easy task. To detect the R waves, the developed algorithm removes the very low and very high frequency components from the ECG signal. In this study, the detail components of D3, D4 and D5 show the QRS complex more clearly comparing with other components. Therefore, the algorithm keeps these components and removes the other low frequency and high frequency components. The R waves of ECG signals are shown in fig 4.9.

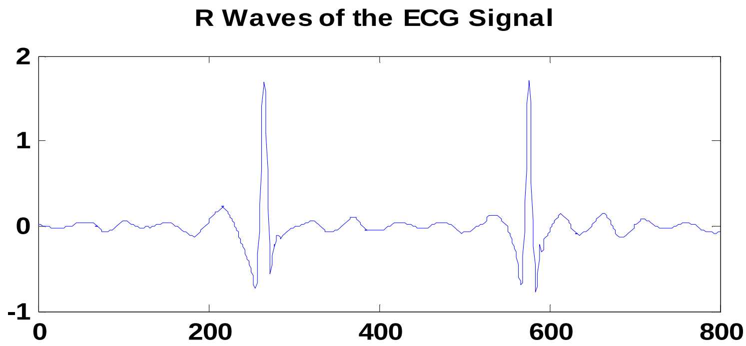

Fig 4.9: R-waves of the ECG Signal

To make the R wave more noticeable, the obtained signal is squared, which is shown in fig 4.10. Since the obtained signal has pseudo peaks, a lower limit is applied to remove these pseudo peaks (thresholding), which is shown in fig 4.11. Once the R-peaks are identified then it can be used by the developed algorithm to automatically calculate the amplitude values of R waves and the time intervals between them. The amplitude values of R waves for ECG record 103 of arrhythmia, determined by the developed algorithm are 1.694, 1.7132, 1.7914, 1.6916, 1.7963, 1.6179, 1.8395, 1.8736, 1.7154, 1.6519 and 1.7910.

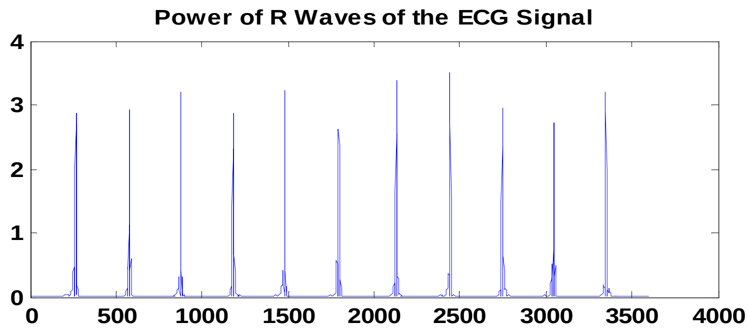

Fig 4.10: The Power of R-waves of the ECG Signal

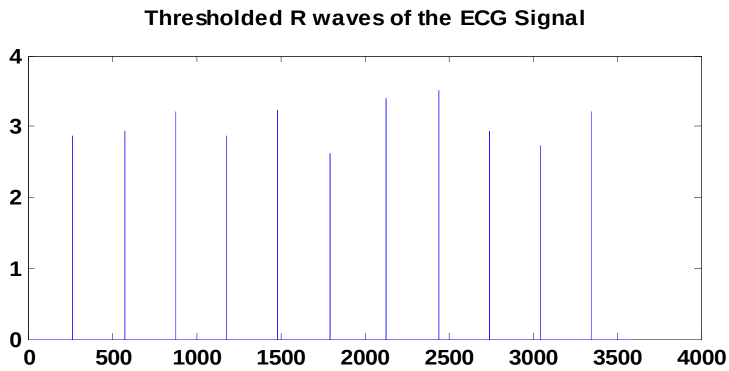

Fig 4.11: Thresholded R-waves of the ECG Signal

Once the R peaks are determined then based on these peaks the Q and S peaks are detected. Generally, the Q and S peaks occurs about the R peak within 0.1 second. Therefore, to make the peaks more noticeable, the developed algorithm removes all the detail components of the signal up to D5 from the signal. The approximation signal is remained same. The first negative deflection to the left of the R-peak is denoted as Q-peak and the first negative deflection to the right of the R peak is denoted as S peak. In the fig 4.12, the left point about the R peak denotes the Q-peak and the right point about the R peak denotes the S peak. Once the R-peaks are identified then it can be used by the developed algorithm to calculate the amplitude values of Q and S waves automatically. The amplitude values of the Q waves and S waves for ECG record 103 of arrhythmia are -0.3206, -0.3694, -0.3083, -0.3087, -0.3643, -0.3314, -0.3235,-0.3095, -0.3495, -0.3456, -0.2884 and -0.3493, -0.4266, -0.4398, -0.4697, -0.281, -0.3296, -0.4012, -0.3836, -0.4458, -0.4190, -0.3620.

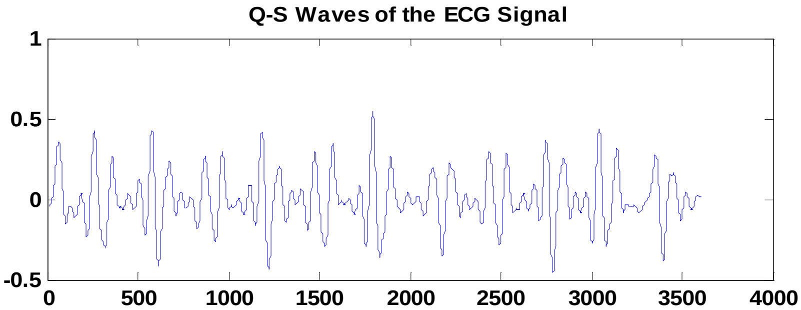

Fig 4.12: The Q and S-waves of the ECG Signal

P and T-waves

The extreme of the signal before and after zero crossings about QRS complex denotes the P and T waves. The detected zero crossings of the signal about the P and T peaks are the onset and offset points of the waves respectively. To make the P and T peaks more noticeable, the developed algorithm keeps the details D4 to D8, which are shown in fig 4.13. Once the P and Q peaks are identified then it can be used by the developed algorithm to calculate the amplitude values of P and T waves automatically.

The amplitude values of the Q waves and S waves for ECG record 103 of arrhythmia are 0.0448, 0.0873, 0.0188, 0.0795, 0.0607, 0.0369, 0.0700, 0.0453, 0.0864, 0.0171, 0.0493 and 0.3083, 0.3220, 0.3032, 0.3009, 0.3582, 0.3067, 0.3313, 0.2967, 0.3400, 0.3324, 0.2821.

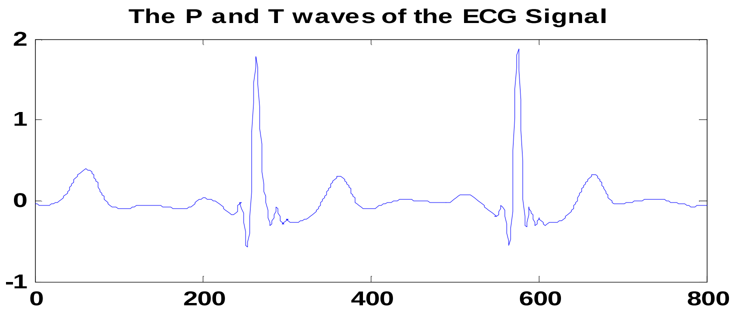

Fig 4.13: The P and T waves of ECG Signal

RR-Interval

The R-R interval of an ECG signal is the time interval between the R-waves. In order to determine the R-R interval of a signal, the developed algorithm determines the difference between the two consecutive R wave locations based on the identified R waves. The R-R interval values in terms of the seconds obtained through the developed algorithm for the Record No 103 are 0.8639, 0.8333, 0.8444, 0.8417, 0.8667, 0.9250, 0.8778, 0.8333, 0.8333 and 0.8417. Since these interval values are not constant throughout the signal, it indicates the abnormality of a heart rate. Also the number of heart beats per minute calculated (number of R-R intervals) by the developed algorithm is 60.

P-R Interval

Once the P and R waves are identified, it can be used by the developed algorithm to determine P-R intervals. In order to determine P-R interval, the developed algorithm determines the interval between the onset of P waves and onset of Q waves. The P-R intervals determined by the developed algorithm for record no 103 of arrhythmia are 0.1833, 0.1833, 0.1250, 0.1278, 0.1722, 0.1833, 0.1778, 0.1139, 0.1806, 0.1139 and 0.1806.

S-T Interval

Once the S and T waves are identified, it can be used by the developed algorithm to determine S-T intervals. In order to determine S-T interval, the developed algorithm determines the interval between the onset of S waves and offset of T waves. The S-T intervals determined by the developed algorithm for record no 103 of arrhythmia are 0.3222, 0.3028, 0.3250, 0.3194, 0.3306, 0.3611, 0.3278, 0.3222, 0.3194, 0.3472 and 0.3472.

Q-T Interval

Once the Q and T waves are identified, it can be used by the developed algorithm to determine Q-T intervals. In order to determine Q-T interval, the developed algorithm determines the interval between the onset of Q waves and offset of T waves. The Q-T intervals determined by the developed algorithm for record no 103 of arrhythmia are 0.4167, 0.3778, 0.4750, 0.4528, 0.4278, 0.4556, 0.4361, 0.4639, 0.4167, 0.5000 and 0.4417

Missing of Waves

Missing of the waves can be determined by the developed algorithm based the wave intervals. The missing of QRS complexes can be determined based the R-R interval values by checking whether there is any value with twice the value of R-R interval. Similarly the missing of P wave can be determined based the P-R interval values by checking whether there is any value with zero as P-R interval and the missing of T wave can be determined based on Q-T interval by checking whether there is any value with zero as Q-T interval. There are no missing waves determined by the developed algorithm in record No. 103 arrhythmia.

Inversion of waves

The inversion of the waves can be determined by the developed algorithm based on the amplitude values of waves. An inversion in a QRS complex is determined by checking the sign of the R wave maximum amplitude values. A positive amplitude value indicates that the R wave is located above the zero crossings and has no inversion. A negative amplitude value indicates that the R wave is located below the zero crossings and has inversion. Similarly the sign of the P wave and T wave amplitudes are determined to check the inversion of the P wave and T waves. There is no inversion of the waves determined by the developed algorithm in record no 103 arrhythmia.

Therefore, the developed feature extraction algorithm can be used by a physician to automatically analyze and to extract the features from ECG signals. The developed algorithm reduces the analysis time of a physician and also increases the accuracy of the ECG analysis. The proposed system is not only used for ECG analysis, instead it can also be used to store and view the results of the ECG analysis for future reference.

4.5 Decision Support System for Congenital Heart Septum Defect Diagnosis using Neural Networks based on ECG analysis

4.5.1 Introduction

Though the developed algorithm analyzes and extracts features automatically from the Electrocardiogram signals, still it may be difficult for a physician to diagnose Congenital Heart Septum Defect due to lack of subjectivity of a physician (clinician) or inexperience with the previous cases of the physicians. This may cause the inaccuracy of the diagnosis and may increases the time delay of the diagnosis.

Therefore, in order to improve the diagnosis accuracy and to reduce the diagnosis time, it has become a demanding issue to develop an efficient and reliable medical Decision Support System to support complicated diagnosis decision process. Since the Neural Networks have shown great potential to be applied in the development of medical Decision Support System for diagnosis of Heart Diseases in the present study also, a Decision Support System is developed to perform the Congenital Heart Septum Defect Diagnosis classification based on the ECG features.

4.5.2 Materials and Methods

Parameters used

#No	Attribute Name	Description	Allowed Values
1	Age	Patients age	Continuous
2	Gender	Patients gender	Continuous
3	Systolic B.P	Systolic Blood Pleasure	Continuous
4	Diastolic B.P	Diastolic Blood Pleasure	Continuous
5	Heart Rate	Number of heart beats (bpm)	Continuous
6	P wave missing	Missing of P waves in the ECG signal	Binary
7	QRS complex missing	Missing of QRS complex in the ECG signal	Binary
8	T wave missing	Missing of T wave in the ECG signal	Binary
9	P wave inversion	Inverse of P waves in the ECG signal	Binary
10	QRS complex inversion	Inverse of QRS complex in the ECG signal	Binary
11	T wave inversion	Inverse of T wave in the ECG signal	Binary
12	P wave amplitude	Amplitude of the P wave	Continuous
13	Q wave amplitude	Amplitude of the Q wave	Continuous
14	R wave amplitude	Amplitude of the R wave	Continuous
15	S wave amplitude	Amplitude of the S wave	Continuous
16	T wave amplitude	Amplitude of the T wave	Continuous
17	RR interval	Interval between the two R waves	Continuous
18	Irregular Heart Beat	Indicates the irregularity of the heart beat	Binary
19	PR interval	Interval between the P wave and R wave	Continuous
20	ST interval	Interval between the S wave and T wave	Continuous
21	QT interval	Interval between the P wave and R wave	Continuous

Table 4.1: Parameter Names, Description and their allowed Values of DSS for CHSD Diagnosis based on ECG Signal features

The parameters that are used to perform Congenital Heart Septum Defect Diagnosis classification based on ECG features are the amplitude values of P, QRS complex and T waves and the times interval values of P-R, R-R, S-T and Q-T. In the present study a total of 200 samples are used, each sample is having a set of 13 input parameters and one output parameter. The parameter names along with the description and their allowed values are represented in table 4.1.

Method

In the present study, in order to develop a Decision Support System for Congenital Heart Septum Defect Diagnosis based on ECG Signal, at first, the ECG features are extracted from the obtained ECG signal by applying the developed ECG feature extraction algorithm. Then a Backpropgation Neural Network (discussed in section 2.2.7) is built based on the extracted ECG features along with the basic information of a patient as input nodes. The network is trained using a supervised Delta Learning Rule. The activation function used in this model is the sigmoid function. Once the network is trained, then it can be used to perform the diagnosis classification automatically for a new pattern. The user friendly Decision Support Systems are designed and implemented in MATLAB 7.3 with GUI features. The Decision Support System is developed not only for the diagnosis classification, but it can also be used to store and view the diagnosis result. The architecture of a Decision Support System for Congenital Heart Septum Defect Diagnosis based on ECG signal is shown in fig 4.14.

From the architecture, it shows that when the ECG signal of a patient is given as input by the user, the developed Decision Support System automatically analyzes, extracts features and performs the diagnosis classification automatically and displays the result. The developed Decision Support System also stores the diagnosis result automatically, which can be used to view for future reference.

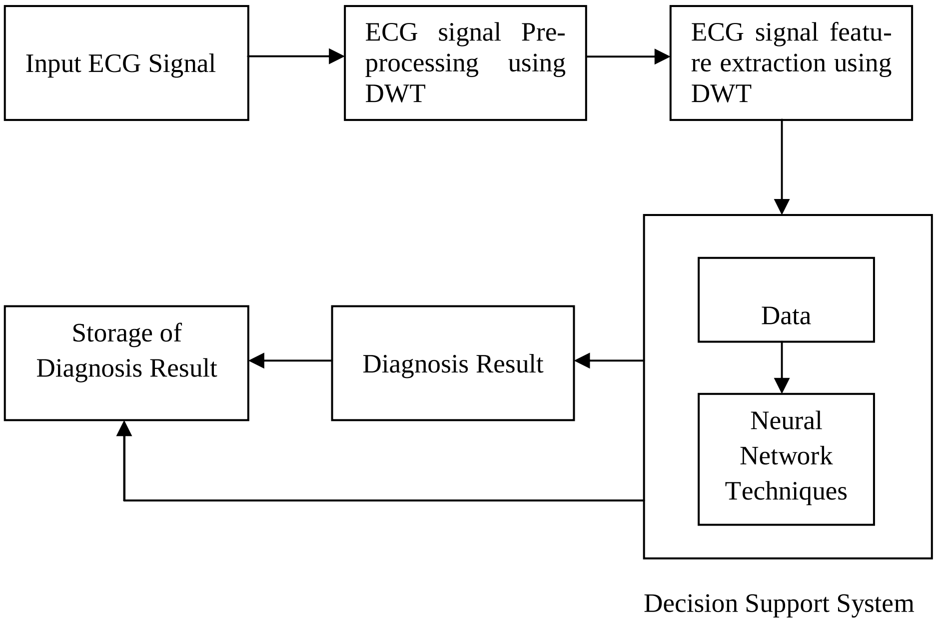

Fig 4.14: Architecture of DSS for CHSD Diagnosis based on ECG signal features

4.5.3 Experiments and results

Experiment:

The Decision Support System for Congenital Heart Septum Defect Diagnosis is designed and implemented in MATLAB 7.3 with GUI feature by using the Backpropagation Neural Network Model.

In order to implement Backpropagation Network Model, initially a Feed Forward Neural Network is built with 13 input nodes, 4 hidden nodes and one output node. The input parameters used in this system are the age, gender, B.P, heart rate and the features extracted from the ECG by using the developed algorithm. The output parameter used in this system is to indicate result of the diagnosis in terms of either normal or abnormal. Once the network is built, then it can be trained by using a Delta Learning Rule. The activation function used in this model is the sigmoid function. 200 samples are collected and used to train network and test the network. Among these samples, 85% of the data are used for training and 15% of the data are used for testing purposes. Once the Network is trained using these samples then the developed Decision Support System does the classification automatically for a new case. The Error performance (Mean Squared Error) of the training network is shown in fig 4.15.

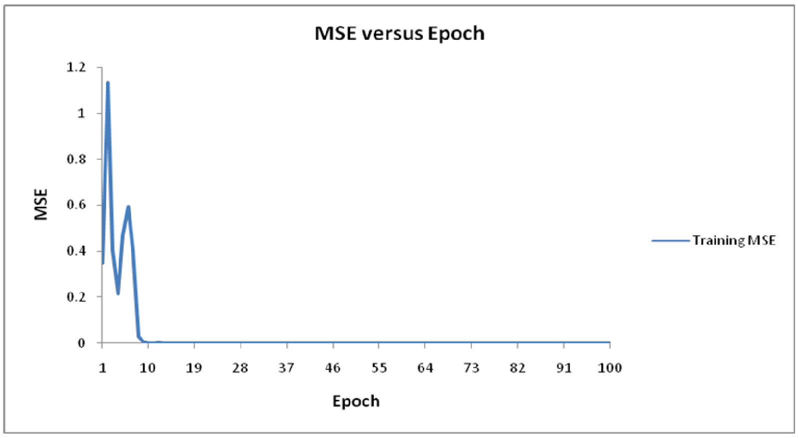

Fig 4.15: The Error Performance of a training network of DSS for CHSD Diagnosis based on ECG Signal features

The least MSE value for the present experiment is 0.0132**.** Since the Neural Network solutions will not depends on algorithmic solution instead it depends on examples of the previous cases, it gives more accurate results than the human diagnosis.

The developed Decision Support System performs five types of operations. These are represented in terms of NEW, ANALYSIS, DECISION, STORE and VIEW pushbuttons. Pushbutton NEW is used to clear the screen (for entering new patient information), the pushbutton ANALYSIS is used to automatically extract the ECG features based on the developed algorithm and to display the results, the pushbutton DECISION is used to perform diagnosis classification automatically based on the selected parameters and to display the result, the pushbutton STORE is used to store the patient information along with the resultant value in terms of text format and the pushbutton VIEW is used to view the stored text file.

The developed Decision Support System can be used by a physician to automatically diagnose Congenital Heart Septum Defect based on ECG signal features by giving the patient's ECG signal as input (in terms of patient number) along with the basic information of a patient i.e., systolic B.P, diastolic B.P etc of a patient. The developed system reduces the diagnosis time of a physician and also increases the accuracy of the diagnosis. In addition to the diagnosis, the proposed system also stores and retrieves the resultant values for future reference.

Results:

The developed Decision Support System is tested to diagnose record No 103 of Arrhythmia Database. The original ECG signal of record No 103 viewed through the developed Decision Support System is shown in fig 4.16. In the figure 4.16, it shows that once the patient number is entered then by pressing the VIEW ORIGINAL ECG SIGNAL pushbutton, it automatically shows the corresponding original ECG signal. Now, to automatically analyze and to perform the diagnosis classification, the ANALYZE ECG SIGNAL pushbutton should be pressed as shown in fig 4.17. By using this System, once the patient number is entered then it automatically extracts the features from the ECG signal and displays the results by pressing the ANALYZE button. Finally, to perform the diagnosis classification automatically and to display the results, the pushbutton DECISION should be pressed. The results obtained through the developed Decision Support System for record No 103 Arrhythmia Database is shown in fig 4.17.

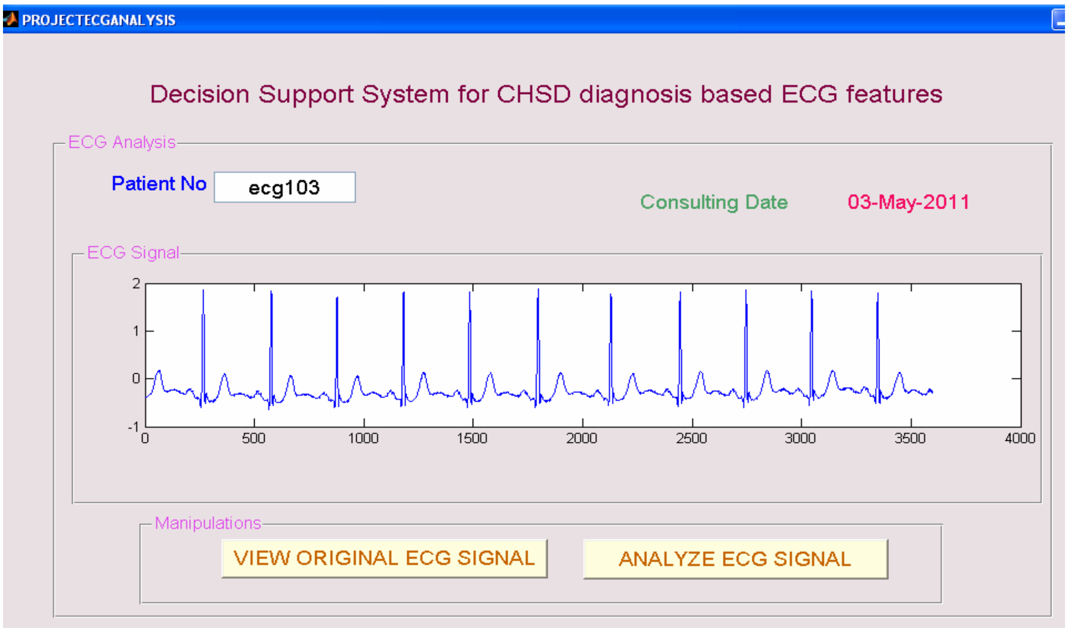

Fig 4.16: Viewing the Original ECG signal of Record No 103 of MIT-BIH Arrhythmia Database using developed Decision Support System

The developed Decision Support System gives an accuracy of 100%, which is shown fig 4.18. The classification result of the experiment in terms of the confusion matrix is shown in table 4.2.

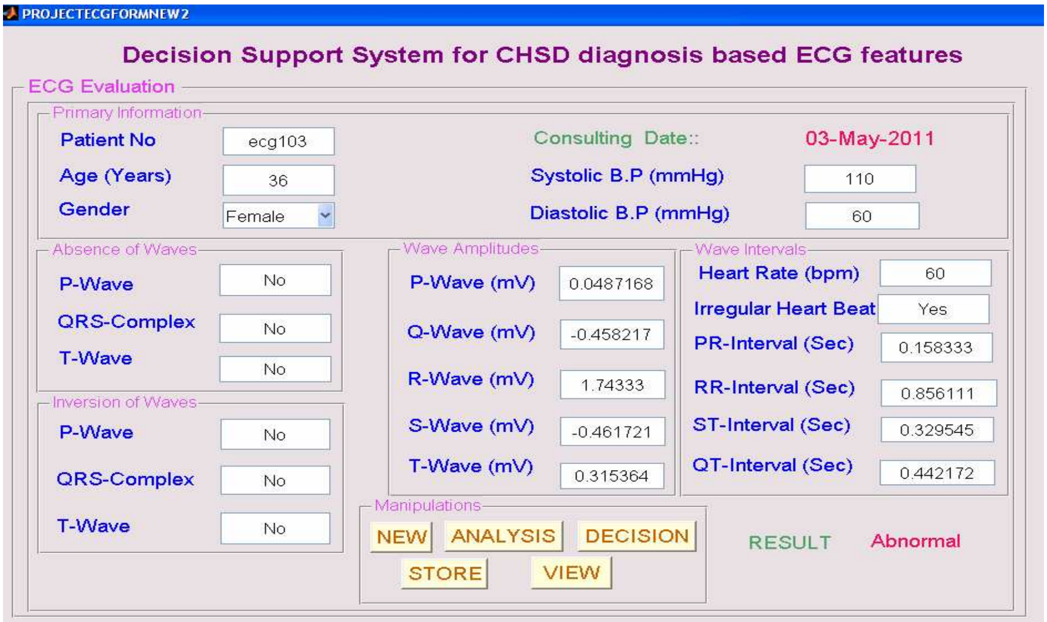

Fig 4.17: The diagnosis result of an abnormal person using developed DSS for CHSD based on ECG signal features

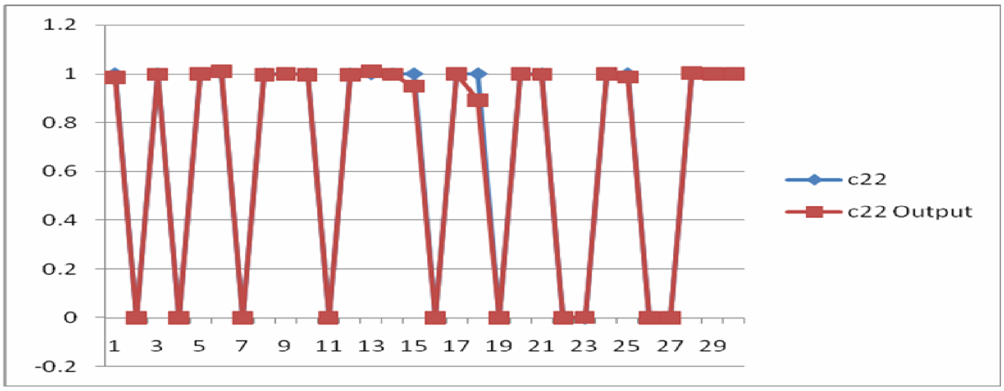

Fig 4.18: A chart representing the classification accuracy of the DSS for CHSD based on ECG features

Output / Desired	***0***	***1***
0	10	0
1	0	20

Table 4.2: Confusion Matrix of DSS for CHSD Diagnosis based on ECG features classification

4.6 Conclusion

Since an ECG signal may be of various lengths and the abnormality of a heart can be shown at interval of the signal, it is difficult for physicians to analyze and to extract the features automatically. Also it is a time consuming process. Therefore, the developed ECG feature extraction algorithm can be used by the physician to automatically analyze and to extract the ECG features. Also, the developed Decision Support System can be used to automatically diagnose Congenital Heart Septum Defect based on ECG features. The developed system reduces the diagnosis time and increases the accuracy of the diagnosis. Thus the performance of the developed system is increased.