Chapter 5
Ventricular arrhythmia detection and classification

5.1 Introduction

Ventricular arrhythmia detection is vital to help the patients facing death or recover them from worst situation. This is done by acquiring the signal, preprocessed according to the requirement. The signal is decomposed and delineated for QRS points and the detection and classification of ECG arrhythmia is carried out by energy variation in different scales of wavelets. It differs from normal to arrhythmia patient. The variations are showed here for normal and arrhythmia patients.

5.2 Working methodology

The signal is acquired from ECG device and it is preprocessed for noise of base line wandering and other noises. Delineation stage detects and delineates different constituent parts of the ECG, i.e. the QRS complex, the P/T-wave etc. The wavelet transform, due to its apt ability to process non-stationary signals, also finds its application in detection and delineation of different waves and segments in the inherently non-stationary ECG.

The information extracted during the delineation phase along with different features extracted from the ECG itself can be used. Frequency based techniques for classification of
cardiac rhythms offer more promising prospects as they are more robust to noise in comparison to time domain techniques and present a more effective model of the QRS complex. However, use of
time-frequency decomposition of the ECG signal using the wavelet transform offers a better alternative than the application of Fourier transform for beat classification due to the non-stationary nature of the ECG signal. Wavelet Transform provides a higher classification accuracy for ten types of beats from the MIT-BIH Arrhythmia database [86].

Figure 5.1 shows the overall detection algorithm of ventricular arrhythmia. The ECG signal is decomposed into low pass and high pass signals, the detailed signal of the stage $2^4$, $2^6$, and $2^7$ stages are used to analyze the arrhythmias. The system checks for QRS. If QRS is not available in the signal there may be chance for ventricular fibrillation (VFIB) or ventricular Flutter (VFL). If QRS is available then checks for VT and SVT by energy variations in different scales, through that it identifies the VT and SVT.

5.2.1 Acquisitions

In general the ECG data is acquired from patients. For this analysis the data are acquired from MIT – BIH arrhythmia data base with the sampling rate of 250 Hz. The signal is resampled at 360 Hz for further wavelet preprocessing and analyzing.

5.2.2 Preprocessing

One of the first stages applied in the preprocessing of ECG signals is the removal of baseline wandering. This interference appears in the acquisition stage due to different reasons: patient movement, breathing, physical exercise, etc. The baseline wandering can make the inspection of ECG difficult. Moreover, in automatic inspection systems, other processing tasks such as wave detection signal classification, etc. can be affected by it. Therefore, it is of great importance to reduce its effect as much as possible. The field of ECG signal preprocessing can be divided into three major areas: removal of baseline wandering, Denoising and Detection of the waveforms
5.2.3 Removal of baseline wandering

The best level depends on the amplitude and main spectrum distribution of the baseline interference. This method is based on measures of the resulting signal variance and on spectrum energy dispersion of the approximation. In order to eliminate or reduce the baseline wandering, the approximations must have a narrow spectrum, as such interferences are usually almost pure sinusoids. Besides, the variance of the resulting signal needs to be as low as possible, because the approximations should not have high frequency components such as peaks following R peaks, and so, the final signal must be flat. Once the level is obtained, the wavelet approximation is calculated, and then, it is subtracted from the signal. So, the baseline wander of this signal is greatly reduced.

5.2.4 ECG denoising

Wavelet denoising method or nonlinear wavelet filtering is based on taking DWT of a signal, passing transform through a threshold, which removes the coefficients below a certain value, then taking the inverse DWT, as illustrated in Figure 5.2. This method is able to remove noise and achieve high compression ratios because of the “concentrating” ability of the wavelet transform. The DWT localizes the most important spatial and frequential features of a regular signal in a limited number of wavelet coefficients.
This means that the expected noise energy is the same with all coefficients. If this energy is not too large, noise has a relatively small influence on the important large signal coefficients. These observations suggest that the small coefficients should be replaced by zero, because they are dominated by noise and carry only a small amount of information. Noise is removed by incorporating wavelet shrinkage via soft thresholding. Universal threshold, a threshold value $\sigma \sqrt{2 \log N}$, $\sigma$ the standard deviation of noise and N number of samples i.e. number of wavelet coefficients at each decomposition level [126].

### 5.2.4.1 Denoising

Let us consider the discrete noisy signal [127]

$$y(n) = f(n) + \sigma e(n) \quad n = 1 \ldots N$$

The vector $y$ represents noisy signal and $f$ is unknown, deterministic signal, $e$ is Gaussian white noise $N(\mu, \sigma^2) = N(0,1)$

Wavelet transform is used to construct the original data. Here simple non redundant, orthogonal, discrete wavelet transform is used. The operation can be represented by an orthogonal matrix $W$.

$$w = W_y$$

$$v = W_f$$
\[ s = W \]  \hspace{1cm} (5.2)

donoho’s soft thresholding or shrinking function is used, a wavelet coefficient \( W \) between \(-\delta\) to \(+\delta\) is set to zero, while the others are shrunk in absolute value.

The shrinking (soft thresholding) operations can be represented as

\[
s(j,k) = \begin{cases} 
\text{sgn}(c_{j,k})(|c_{j,k}| - \delta) & \text{if } |c_{j,k}| \geq \delta \\
0 & \text{if } |c_{j,k}| < \delta 
\end{cases}
\]  \hspace{1cm} (5.3)

or matrix notation

\[ w_\delta = D_\delta w \]  \hspace{1cm} (5.4)

Where

\[ D_\delta = \text{diag}(d_\delta) \]  \hspace{1cm} (5.5)

\[
d_\delta \begin{cases} 
0 & \text{if } |w_i| < \delta \\
1 - \frac{\delta}{|w_i|} & \text{otherwise}
\end{cases}
\]

the elements of the matrix \( D_\delta \) depends on the signal \( w \).

the other possible thresholding function \( S \) hard function, which can be described as the usual process of setting to zero the elements whose absolute value are lower that the threshold.
the inverse transforms give the result:

\[ y_\delta = w^{-1} y \]  \hspace{1cm} (5.6)

The overall operation can then be represented by

\[ y_\delta = A_d y \]  \hspace{1cm} (5.7)

Where

\[ A_d = w^{-1} D_d w \]  \hspace{1cm} (5.8)

\( A_d \) is the influence matrix, through \( D_d \), it depends on the threshold value but also on the input signal \( y \).

### 5.2.4.2 Choice of Threshold

This choice of threshold should be optimal in a certain way. If \( y_\delta \) is the result of applying the threshold procedure to the wavelet coefficients of a signal \( y \), and \( e_\delta \equiv y_\delta - f \) is the noise of this result, then an often used criterion to measure the quality of this result is its *signal-to-noise* (SNR) ratio:

\[ SNR = 10 \log_{10} \frac{\sum_i f_i^2}{\sum_i e_{\delta_i}^2} \]  \hspace{1cm} (5.9)

An optimal choice of \( \delta \) should maximize SNR. This is equivalent to minimizing the
mean square error $R(\delta)$, or in the literature is used the risk function as well:

$$R(\delta) = \frac{1}{N} \sum_{i}^{N} (y_{\delta_i} - f_i)^2 = \frac{1}{N} \|y_\delta - f\|^2 = \frac{1}{N} \|e_\delta\|^2$$  \hspace{1cm} (5.10)

$$\text{Risk}(\delta) = \frac{1}{N} E (\|y_\delta - f\|^2)$$

where classical Euclidean vector norm is used.

Because of the orthogonality of $W$, $R(\delta)$ can be computed from the wavelet coefficients as:

$$R(\delta) = \frac{1}{N} \|S_\delta\|^2$$  \hspace{1cm} (5.11)

Where

$$S_\delta = w_\delta - v = W e_\delta$$  \hspace{1cm} (5.12)

is the noise after the operation in the wavelet domain.

However, because $f$ is unknown the function $R(\delta)$ is not computable and hence it cannot be used to find an optimal $\delta$. The optimal threshold has to be estimated.
5.2.4.3 Visu Shrink

Donoho and Johnstone [127] propose to use the “universal threshold” estimation:

$$ \delta = \sqrt{2\log(N)\bar{\sigma}} $$

(5.13)

where $\bar{\sigma}$ is estimation of the noise variance $\sigma^2$ given by:

$$ \bar{\sigma} = \frac{\text{median}(|c(j,k)|)}{0.6745} $$

(5.14)

They called the method VisuShrink in reference to the good visual quality of reconstruction obtained by the simple “shrinkage” of wavelet coefficients. The resulting estimation $y_0$ is with high probability tending to 1 (as $N \to \infty$) at least as smooth as $f$.

5.2.4.4 Sure Shrink

In the other paper [128] Donoho and Johnstone proposed estimation of threshold based on Stein’s Unbiased Estimate of Risk (SURE). The scheme is level dependent, this means that the shrinking function is applied at each scale $j, j=1,...,J$. Then the estimated coefficients $w_{\delta,j}$ are obtained based on the selected threshold $\delta = [\delta_1, \delta_2, \ldots, \delta_J]$.
Note $\delta_j$ is the threshold for wavelet coefficients as scale $j$.

In the next, Stein estimator is briefly introduced. Let $f = (f_i: i = 1, \ldots N)$ be a $N$ dimensional vector, and let $y_i = N (f_i, 1)$ be multivariate normal observation with that meanvector. Let $\hat{f} = \hat{f}(y)$ be a particular fixed estimator of $f$. Stein (Stein) introduced a method for estimating the loss $\|\hat{f} - f\|^2$

in an unbiased fashion. $\hat{f}(y) = y + g(y)$ where

$$g = [g_1, g_2, \ldots, g_N]$$

is a function from $\mathbb{R}^N$ to $\mathbb{R}^N$. Stein showed that when $g(y)$ is weakly differentiable, then:

$$E_\delta = \|\hat{f}(y) - f\|^2 = N + E_f\{\|g(y)\|^2 + 2\nabla y g(y)\} \quad (5.15)$$

Where

$$\nabla y g(y) = \sum^N_i \frac{\partial g_i}{\partial y_i} \quad (5.16)$$

SURE is an unbiased estimator of the above risk (5.15), defined as:
If we now consider equitation, can apply the result in the wavelet domain,

where the \( \hat{f}(y) \approx w_\delta(y), f(y) \approx v(y) \)

and soft threshold function \( w_\delta = D_\delta w \) yields

\[
SURE(\delta,w) = N - 2\{i: |w_i| \leq \delta\} + \sum_{i=1}^{N} (|w_i|\delta)^2
\]  

(5.18)

We can select a threshold \( \delta \) as:

\[
\delta^* = \argmin SURE(\delta,w)
\]  

(5.19)

Notice, that it is not required to minimalize equalization, the optimisation problem (5.18) is computationally straightforward. Suppose, without any loss of generality, that the \( w_i \) have been reordered in order of increasing \( w_i \). Then on intervals of \( \delta \) which lie between two values of \( |w_i| \), SURE (5.18) is strictly increasing. Therefore the minimum value \( \delta^* \) is one of the data values \( |w_i| \). 
5.2.4.5 Comparison of denoising methods

In order to gain the best performance of algorithm proposed in next section we tested the combination of VisuShrink and SureShrink along with soft and hard thresholding. The results can be seen in table 5.2.

<table>
<thead>
<tr>
<th>Noisy Signal</th>
<th>VisuShrink Hard</th>
<th>VisuShrink Soft</th>
<th>SureShrink Hard</th>
<th>SureShrink Soft</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.18</td>
<td>+5.74</td>
<td>+6.77</td>
<td>+2.73</td>
<td>+4.34</td>
</tr>
<tr>
<td>5.54</td>
<td>+4.5</td>
<td>+5.56</td>
<td>+0.27</td>
<td>+3.91</td>
</tr>
<tr>
<td>9.21</td>
<td>+3.28</td>
<td>+4.36</td>
<td>-2.86</td>
<td>+2.45</td>
</tr>
<tr>
<td>14.49</td>
<td>+3.27</td>
<td>+2.53</td>
<td>-7.77</td>
<td>+1.24</td>
</tr>
</tbody>
</table>

In the first column is SNR of noisy signal, in the second one is gain of denoising
defined as:

\[ \text{Gain} = \text{SNR(denoised signal)} - \text{SNR(noisy signal)} \]

It is clear from the result that the combination of VisuShrink along soft-thresholding approach yields the best performance among others. Since this denoising technique is used.

5.2.5 Detection of Ventricular Fibrillation

5.2.5.1 Detection of QRS Point

Initially 1024 samples were selected randomly and used as first window. By àtrous algorithm the signal is decomposed into six levels 21, 22, …, 26. The QRS signal is having maximum energy in level 24 (0.1 – 30 Hz) [69]. This algorithm searches for maximum modulus lines exceeding some threshold at scales from 21 to 24. After eliminating all redundant maximum points, the zero crossing of wavelet transform at level 21 between the positive maximum and negative minimum pair is marked as QRS [27], [38] with a predefined threshold values. Q and S points are identified. The threshold point will be varied according to the signal variation. This threshold point variation is obtained from QRS point through adaptive threshold variation technique [122].

5.2.5.2 Detection and Classification of Ventricular Fibrillation

If QRS is not available in the signal there may be chance for ventricular fibrillation (VFIB) or ventricular Flutter (VFL). The peak value of VFIB and VFL are much lower than VT, SVT and
normal one in the $2^4$ level as shown in Figure 5.3. Both ventricular flutter (VFL) and ventricular fibrillation (VFIB) have dominant frequencies in the 2-5 Hz band [61],[129], and the major portion of this range is contained in D5 (2.875-5.75 Hz). The VFIB and VFL consist of several continuous cycles. By energy distribution in the frequency domain, VFIB and VFL can be easily identified [61,130]. The energy ratio of D4 to D6 for VFL is larger than VFIB. By this energy variation, VFIB and VFL can be classified. Frequency response and energy distribution for each scale is as shown in table 5.2.

### TABLE 5.2:
FREQUENCY RESPONSE AND ENERGY DISTRIBUTION AMONG THE SCALES

<table>
<thead>
<tr>
<th>Scale (a)</th>
<th>Lower 3 db Frequency (Hz)</th>
<th>Upper 3 db Frequency (Hz)</th>
<th>QRS</th>
<th>VFIB, VFL</th>
<th>VFIB classify</th>
<th>VT</th>
<th>SVT</th>
</tr>
</thead>
<tbody>
<tr>
<td>$2^1$</td>
<td>62.5</td>
<td>125</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$2^2$</td>
<td>18.0</td>
<td>58.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$2^3$</td>
<td>8.0</td>
<td>27</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$2^4$</td>
<td>4.0</td>
<td>13.5</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$2^5$</td>
<td>2.0</td>
<td>6.5</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$2^6$</td>
<td>1.2</td>
<td>2.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>√</td>
</tr>
</tbody>
</table>

Decomposed ECG signal with VFL (422), VFIB (419), VT (605) are shown in Figure 5.3, Figure 5.4, and Figure 5.5 respectively. The number in the parenthesis specifies the annotation reference in
5.2.5.3 Detection and Classification of Ventricular Flutter

The VFIB and VFL episodes comprise several cycles, it checks for VFIB or VFL episodes by determining how many cycles occur within a certain time interval. Based on energy distributions in the frequency domain we are able to observe a difference between VFIB and VFL. The energy ratio
of D4 to D6 for VFL episodes is larger than for VFIB episodes. Therefore we compared the energy ratio of D4 to D6 in an episode in order to classify it as either VFIB or VFL, to determine whether a signal contains a VFIB or a VFL rhythm, the algorithm detects valley points where the amplitude of D6 is lower than a fixed threshold and checks on whether there is a signal above a different fixed threshold level in D4 within a prescribed interval. By this process, we isolated VFIB and VFL events.

5.2.6 Detection and Classification of Ventricular Tachycardia and Supra Ventricular Tachycardia

5.2.6.1 Detection and Classification of Ventricular Tachycardia
Major characteristics of the ventricular tachycardia (VT) signals in our wavelet decomposition method are a very low amplitude S wave and a very fast heart rate. The low amplitude S wave is located in D6 or D7 in our experiment. In order to detect a VT beat, our algorithm checks to see if there is a signal below a predefined threshold in D6 or a different threshold in D7 within a certain interval following the R wave. The algorithm declares a VT episode based on the interval between adjacent detected VT beats.

5.2.6.2 Detection And Classification of Supra Ventricular Tachycardia
Each ECG signal is analyzed for QRS detection, if QRS is not available then algorithm will check for ventricular fibrillation (VFIB) or ventricular flutter (VF), if QRS is available then it will check for ventricular tachycardia (VT) or supra ventricular tachycardia (SVT).

To detect VT and SVT scales $2^5$ and $2^6$ are used. The VT can be identified by low amplitude S wave and fast heart rate. The low amplitude S value is available in the level 5 or 6. Algorithm checks if there is a signal after R wave with a predefined threshold value for level 5 and level 6.
Supra ventricular Tachycardia can be identified by higher heart rate and no P wave in RR interval. When R-R interval is shorter than the normal rhythm, then T and P wave may appear in level 6. To detect a SVT beat, the algorithm calculates the R-R interval and counts the number of peaks within the R-R interval in D6 when the R-R interval is shorter than a set criterion. Algorithm declares after detecting continuous cycle of SVT beats.

Energy contained in wavelet coefficients at each scale is given by

$$E_m = \sum_n |W_{m,n}|^2$$  \hspace{1cm} (5.20)

Table 5.3 shows the normal ECG signal energy variations for different scales, it differs from the cardiac arrhythmias patients.

<table>
<thead>
<tr>
<th>scale</th>
<th>3db bandwidth</th>
<th>Energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>S=2^7</td>
<td>62.5~125Hz</td>
<td>50.2±25.6</td>
</tr>
<tr>
<td>S=2^6</td>
<td>18~58.5 Hz</td>
<td>350.2±215.2</td>
</tr>
<tr>
<td>S=2^5</td>
<td>8~27 Hz</td>
<td>740.7±426.3</td>
</tr>
<tr>
<td>S=2^4</td>
<td>4~13 Hz</td>
<td>1060.2±595.1</td>
</tr>
<tr>
<td>S=2^3</td>
<td>2~6.5 Hz</td>
<td>1075.3±850.4</td>
</tr>
<tr>
<td>S=2^2</td>
<td>1~3.3 Hz</td>
<td>1030.7±790.8</td>
</tr>
<tr>
<td>S=2^1</td>
<td>0.5~1.5 Hz</td>
<td>970.4±659.8</td>
</tr>
</tbody>
</table>

### 5.2.7 Reporting

The ECG signal is processed, all noises are removed, and QRS wave is detected. The R-R interval is measured and the classification of different arrhythmias is identified by the wavelet energy variation
technique. The energy variations are different for each scales, if arrhythmias are present, the values of energies differ from normal sinus rhythm.