CHAPTER 7

DETECTION OF VENTRICULAR LATE POTENTIALS

7.1 INTRODUCTION

Ventricular Late Potentials are microvolt level high frequency low amplitude signals appearing at the terminal portion of the QRS complex and the beginning of the ST segment. VLP’s represent slow or delayed conduction signals passing through the ventricular myocardium. They can be thought of as small action potentials from myocytes isolated by fibrosis that depolarize at latter instant, after the majority of myocytes that constitute the QRS complex has depolarized. The VLP’s have been shown by many researchers as powerful indicators of ventricular tachycardia, which is one of the leading causes of sudden cardiac deaths in patients who have suffered Myocardial Infarction (MI) (Simson 1981). Hence the detection of VLP’s has become a topic of interest in clinical cardiology for over three decades. Early diagnosis of heart disease by detecting VLP’s might save a large number of lives.

The recording of VLP’s is usually done on the body surface by signal averaging techniques applied to ST segment. Ventricular late potentials are obtained from Signal Averaged Electrocardiograms (SAECGs). The algorithm presented here investigates the application of the wavelet transform for the detection of VLP’s. The wavelet transform is a powerful tool which is able to characterize the ECG signals both in time and in frequency domains.
thus allowing a better insight in the pathological phenomenon of VLP’s. The feed forward neural network is then designed for the recognition of VLP’s.

### 7.2 ECG SIGNALS AND VENTRICULAR LATE POTENTIALS

The frequency distributions of ECG signals are classified as lower frequency P and T waves, middle to high frequency QRS complex and high frequency late potentials when they exist. The P and T waves are medium amplitude low frequency signals. The QRS complex is high amplitude medium frequency signal and the VLP is a low amplitude high frequency signal. Figure 7.1 shows the different frequency components of ECG presented against their respective amplitudes.

![Figure 7.1 Frequency distribution of different ECG components](image)

**Figure 7.1 Frequency distribution of different ECG components**

Characteristic changes in these waves are indication of possible abnormalities. Late in the ECG cycle, when high frequency events occur, these low amplitude signals are identified as late potentials. VLP’s have been shown to be a predictive of arrhythmia of the heart. When arrhythmias, such as ventricular tachycardia do occur, the QRS undergoes important morphological changes. These changes may be in the form of widening of the QRS complex. As the QRS widens, its power spectra shows diminished contributions at higher frequencies and these are spread out over a wider body
of the signal. This empirical description of time domain features of the ECG signal lends itself particularly well to analyse it by time frequency and time scale methods.

In previous studies, low amplitude, high frequency signal in the last 40ms of the filtered QRS and a prolonged QRS duration have been shown to identify patients with ventricular tachycardia. A late potential is defined as a low amplitude signal of 20 μV in the last 40 ms of the filtered QRS complex and a long filtered QRS complex is defined as total filtered QRS duration greater than 120 ms where filtering is carried out using the wavelet transform (Mallat 1989).

7.3 SIGNAL AVERAGED ECG (SAECG)

7.3.1 Lead systems

For recording VLP’s from the surface of the body most investigators use an XYZ lead system formed by three orthogonal bipolar electrode combinations. Signals from the three bipolar electrodes can be combined into a spatial Vector Magnitude (VM) which is given by Equation (7.1), yielding a composite waveform. Others have used a variety of precordial lead systems to achieve closer proximity to the left ventricle.

\[ VM = \sqrt{X^2 + Y^2 + Z^2} \]  

(7.1)

Some have suggested that a precordial lead system has advantages (Steinberg et al 1996); others have shown there is no advantage (Goldberger et al 1980). Most current systems use orthogonal, bipolar XYZ ECG leads, which are recorded, averaged, filtered, and combined into a vector magnitude called the filtered QRS complex.
7.3.2 Analog to Digital Conversion of signals

ECG electrode signals are initially amplified 10 to 100 times with a wide frequency band pass amplifier before analog to digital conversion. Some investigators further amplify the signals after analog to digital conversion. The original continuous analog ECG signal is converted into a digital signal of voltages sampled at frequent, fixed intervals. As with all digitized signals, resolution is governed largely by sampling interval. Sampling rates for VLP evaluations vary from 1000 samples to 10,000 samples per second, whereas standard computerized ECG equipment is limited to 250 to 500 samples per second.

7.3.3 Noise

Numerous sources of noise are encountered in highly amplified recordings. Artifact from respiratory muscles is independent of electrical activity arising from the heart, and cancels out with signal averaging. Electronic noise arising from the electrodes is lessened with proper skin preparation. Electrical power lines and other nearby electronic equipment can create noise, which can be reduced by using shielding or filters. The effective reduction of noise is achieved by increasing the number of cycles averaged.

7.3.4 Filtering

Filters have a great effect on the recognition and measurement of VLP’s. Most studies use high band pass filters (cutoff ranging from 25 to 100 Hz), which enable higher frequency signals derived from the depolarization phase of the action potential to pass without attenuation while reducing the low frequency large amplitude signals originating from the plateau or repolarization phase of the action potential. Most current systems
also use a bidirectional digital filter to reduce artifact, but differing results are still reported with the various filters as pointed by Nollo et al (2000).

7.3.5 Averaging

After analog to digital conversion, the signals are averaged. To use signal averaging techniques the waveforms must be periodic and have a specific feature, like the R wave, which can be used as a reference point so that each waveform can be appropriately aligned (Watenabe et al 1980). Computer template recognition is currently used to align QRS complexes and to reject ectopic and noisy beats. A frequent sampling interval produces a relatively smooth and continuous waveform. The net effect after averaging is an increase in the signal to noise ratio. Most systems include 100 to 400 beats on average, although some average up to 1000 beats.

7.4 COMPARISON OF EXISTING ALGORITHMS

The VLP’s were first reported by Berberi et al (1978) and Simson et al (1981) from ECGs recorded on the chest wall in dogs. They were subsequently demonstrated in human beings by Breithardt et al (1981) and Simson (1981). Over the last 25 years several signal processing techniques for examining the region around the terminal portion of the QRS complex have been developed. The SAECG is a noninvasive, inexpensive ECG recorder that incorporates high gain amplification, high frequency digital sampling rates, and signal averaging techniques. From ECG recordings on the surface of the human body, the SAECG can detect low amplitude high frequency signals in or near the terminal portion of the QRS complex.

Many investigators including Gardner et al (1985) have used direct epicardial and endocardial mapping techniques to record delayed, fragmented electrical activity in patients and animals with ventricular
Several investigators like Simson et al (1981) and Schwarzmaie et al (1990) have used both the body surface SAECG and endocardial catheter techniques to record delayed potentials in human beings and animals with ventricular tachyarrhythmias. They found a close temporal correlation between the delayed potentials recorded by the invasive techniques and the SAECG.

The standard method for detecting VLP’s was proposed by Simson et al (1981). This method computes the parameter measurements obtained from the filtered signal averaged ECG in the time domain. Many attempts have been made to study VLPs using time frequency domain techniques, for example the wigner distribution and the short time fourier transform. The limitation of the wigner distribution is that it produces unwanted inference terms that do not reflect the original signal whereas the short time fourier transform has fixed time frequency resolution that is not optimal for the analysis of non stationary signals. VLP’s are assumed to be non stationary signals. The wavelet transform is proposed as an alternative technique and it can solve some of the limitations encountered in the wigner distribution and short time fourier transform.

Fast Fourier transform analysis of the SAECG is another method used to quantify VLP activity. It is a powerful computer based mathematical algorithm that can determine the amplitudes and frequencies of the various harmonic components that comprise a complex periodic signal such as the ECG. The area ratio is expressed as the area under the curve for frequencies between 20 and 50Hz divided by the area under the curve for frequencies between 0 and 20Hz. This has the advantage over time domain systems of being less filter dependent, while yielding more quantitative information. Other methods of estimating the spectra of short ECG segments that have been used include moving time window techniques, such as spectrotemporal
mapping (Lander et al 1990), spectral turbulence analysis (Kelen et al 1991), and autoregressive methods (Schels et al 1991).

### 7.5 SIMSON METHOD

The conventional time domain method of VLP detection, developed by Simson (1981), is based on feature extraction from the filtered SAECG (Spaargaren et al 1999 and Taboada-Crispi et al 1999). Simson (1981) employed a high pass filter (cutoff frequency of 25 or 40 Hz) to attenuate low frequency components of averaged XYZ signals (SAECG). To avoid the filter ringing effect in the terminal parts of QRS complex, Simson proposed a bidirectional four pole Butterworth high pass filter (Spaargaren et al 1999). After high pass filtering of the averaged XYZ signals, these signals are combined into a Vector Magnitude (VM) waveform defined by Equation (7.1).

After estimating the onset and offset of the filtered QRS complex (the QRS complex in the VM signal), three conventional time domain features can be measured to detect VLP’s (Baykal et al 2001 and Wu et al 2001):

- **QRS_T**: Duration of the filtered QRS complex (from the onset to the offset)
- **D_{40}**: Low-amplitude signal duration (from the offset backward to the point where VM reaches the 40 μV and remains at or above this voltage for atleast 3 ms)
- **V_{40}**: Root-mean-square value of the last 40ms of the filtered QRS as shown in Figure 7.2.
Figure 7.2  A ventricular SAECG with the three parameters $\text{QRS}_T$, $D_{40}$ and $V_{40}$ that characterize the filtered QRS complex

The criteria to define a VLP positive test are $\text{QRS}_T > 114\text{ms}$, $D_{40} > 38\text{ms}$ and $V_{40} < 20\mu\text{V}$ (Wu et al 2001). In Figure 7.2, a plot of a typical filtered QRS complex and the definition of the conventional time domain features, introduced above, can be viewed. Then the CWT is applied to the terminal part of the QRS complex in the $VM$ signal and the features are extracted from the resulted time scale plot.

7.6  PROPOSED ALGORITHM FOR THE DETECTION OF VLP’s USING WAVELET NEURAL APPROACH

The detection of VLP’s in the ECG signals is carried out in two stages. First, the features are extracted from the ECG by applying the wavelet transform. Secondly, the recognition of VLPs is done using feed forward neural network.
7.6.1 Feature Extraction using Wavelet Transform

In recent years, the wavelet analysis has been used widely in biomedical researches (Mousa et al 2001, Chen 2002). The wavelet transform is a linear time frequency transform which is based on decomposition of a signal using a set of basis functions. These basis functions are scaled and shifted versions of a prototype mother wavelet (Mousa et al 2001 and Wu et al 2001). The wavelet transform produces a time frequency representation of the signal which is a function of time ‘b’ and scale ‘a’. The scale can be considered as the inverse of the frequency (Taboada-Crispi et al 1999). The smaller scales bring about a higher resolution in time which is useful to detect VLP’s as they are high frequency, short duration signals. In this study, the DWT is adopted, using the MATLAB wavelet toolbox.

In this study, a set of data containing records for both VT and nonVT myocardial infarction patients is used. Each record is decomposed into a number of time signals with different frequency contents using DWT techniques. The DWT level containing the frequency range of interest in each signal is then used in the analysis.

Since the DWT uses circular convolution during decomposition and reconstruction, edge effects become apparent whenever the detail coefficients are manipulated. To avoid this effect, the baseline of each lead is corrected. This ensures that the end points of the signal meet at the same level without altering the content of the signal. Another possible solution to this problem can be to apply the DWT to a mirror signal, which does not affect the resolution of the coefficient sets.

The DWT of each lead is performed prior to calculating the vector magnitude, which ensures the elimination of undesirable cross terms resulting from the multiplication of different frequency components contained in the
signals. These undesirable terms result when calculating the vector magnitude using X, Y and Z leads directly. In this method, level-6 of the DWT of each lead is chosen, since it contains the range of frequencies of interest. The chosen levels are used in the Equation 7.1, which are defined as the filtered QRS used in the analysis. The aim is to identify VLP’s in the different ECG signals which require a good identification of the QRS complex and its end points. In order to find the onset and offset points of the QRS complex, the algorithm estimates the noise level in the signal. The highest levels in the DWT of the three leads are combined to form the noise estimate. A threshold of this noise in the beginning and end of the signal is calculated and used in the determination of the end points. The duration of the QRS is obtained from the difference between the onset and offset points. A forward and backward search for a 5ms segment (~ 11 samples) is carried out and when the average exceeds mean + 3 standard deviation of noise is performed. For best determination, the noise samples are different for onset and offset values. For onset, a 20ms (~ 44 samples) segment is used that begins at about 50ms before QRS onset (110 samples). For offset point, a 40ms (88 samples) segment which begins at 60ms after QRS (132 samples) is used.

Previous studies have set standards that are followed in this work. A three parameter criterion is established which are 1) QRS_T, 2) D_{40} and 3) V_{40} as mentioned earlier. These values are based on a 40Hz filter. As pointed out by Simson (1981), the QRS duration for MI patients with no VT, who are referred to as normal subjects, is found as 95 ± 10 ms and 139 ± 26 ms for MI patients with VT, who are referred to as abnormal subjects. The amplitude of the signal in the last 40ms in normal subjects is 73.8 ± 47.7 μV and 14.9 ± 14.4 μV for abnormal subjects with VT.

As can be seen, the type of the filter used affects the resultant values. In this work, there is no specific filter applied but rather a bank of
filters, which provide an added flexibility in the analysis. The desired cutoff frequency is determined by the sampling rate and the combination of levels or the chosen level by itself. The sampling rate is 22 kHz, which gives a Nyquist frequency of 1.1 kHz as the highest frequency in the signal. Table 7.1 lists the frequency bands associated with the wavelet decomposition at this sampling frequency and a signal length of 512 samples. The chosen level is level-6 that contained the frequency range from 68.75 to 137.5 Hz with a bandwidth of 68.75 Hz, which is equivalent to using a highpass filter with cutoff frequency of approximately 70 Hz.

This choice of filter cutoff provides an automatic elimination of the 50 or 60 Hz line frequencies used in USA and the rest of the world. The QRS duration is found as 101.25 ± 14.64 ms for normal subjects and 142.14 ± 29.33 ms for subjects with VT. The low amplitude signal in the last 40 ms is 25.93 ± 6.32 μV for normal subjects and 38.86 ± 3.75 μV for subjects with VT. Figure 7.3 shows a normal ventricular signal averaged ECG, SAECG of patients with mild and severe heart failures.

Table 7.1  Frequency bands and Bandwidth associated with various levels of wavelet decomposition

<table>
<thead>
<tr>
<th>Levels of wavelet Decomposition</th>
<th>Frequency Content (Hz)</th>
<th>Bandwidth (Hz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.296 - 0</td>
<td>1.074</td>
</tr>
<tr>
<td>2</td>
<td>8.593 - 4.296</td>
<td>4.296</td>
</tr>
<tr>
<td>3</td>
<td>17.1875 - 8.593</td>
<td>8.593</td>
</tr>
<tr>
<td>4</td>
<td>34.375 - 17.1875</td>
<td>17.1875</td>
</tr>
<tr>
<td>5</td>
<td>68.75 - 34.375</td>
<td>34.375</td>
</tr>
<tr>
<td>6</td>
<td>137.5 - 68.75</td>
<td>68.75</td>
</tr>
<tr>
<td>7</td>
<td>275 - 137.5</td>
<td>137.5</td>
</tr>
<tr>
<td>8</td>
<td>550 - 275</td>
<td>275</td>
</tr>
<tr>
<td>9</td>
<td>1100 - 550</td>
<td>550</td>
</tr>
</tbody>
</table>
Figure 7.3  a) Normal ventricular signal averaged ECG, b) SAECG recorded in a 67 year old man with mild heart failure and no history of arrhythmias, c) A clearly abnormal SAECG recorded in a man with severe heart failure.

For better classification of ECG signals, two more parameters are computed by the wavelet transform analysis, in addition to the three standard parameters. These parameters are helpful to improve the performance of the classification. The two new parameters are the area (power) under the WT calculated vector magnitude and the norm of the cross terms component resulting from the product of level-6 and level-5. These two parameters can be called as Wavelet Transform Parameters (WTP). The first of these has a value of $87.31 \pm 14.95$ and the second, $64.94 \pm 42.40$ for normal ECG signals. For VT subjects, the values of these parameters are $117.5 \pm 33.05$ and $43.5 \pm 43.14$ respectively.
7.6.2 Recognition of VLP’s with Feed Forward Neural Network

A neural network has a parallel distributed architecture that contains a large number of simple neurons which act like processing elements and a large number of weighted connections between the elements. The weights on the connections encode the knowledge of a network. The intelligence of a neural network emerges from the collective behavior of neurons, each of which performs only very limited operation. The topology of a neural network refers to its framework as well as its interconnection scheme. The number of input layers, hidden layers, output layers and the number of nodes per layer often specify the framework. A Multi layer Perceptron, which is a feed forward network, is chosen as a neural network structure for this study.

A network containing two hidden layers with three neurons for each layer is designed and trained using the back propagation learning algorithm. The network is trained for a number of times and the best result for the data set is chosen. A total number of 38 ECG signals are selected as data set with 17 numbers of normal ECG signals and 21 signals with VT which have VLPs. Five signals from each category are used as training set for the network with the remaining signals used for testing. The network is simulated with 50, 100, 150 and 200 epochs. The first layer has its weights coming from the three inputs and the last layer consists of a single neuron and represents the output. The hyperbolic tangent function is used as the nonlinear activation function.

7.7 RESULTS AND CONCLUSION

As the first step, the WTP parameters are given as input to the neural network. The result of this part is presented in Figure 7.4. The next step is the application of the three standard parameters as the inputs to the
neural network; the output is shown in Figure 7.5. The results of the first two steps are close with a slight advantage with the use of WTP.

Finally all five parameters are applied to the neural network. The combination of the three standard parameters with the WTP gives best classification performance. The results of this part gives a maximum value of 94.68% classification of ECG signals in the data set with only two exceptions, the dividing region is from -0.2 to +0.2 level as indicated in Figure 7.6. The symbol (o) represents signal for normal subjects, while (+) represents those with VLP in their ECG recordings.

![Figure 7.4 Classification using only WTP](image)

**Figure 7.4 Classification using only WTP**
Figure 7.5 Classification using three standard parameters

Figure 7.6 Classification using both WTP and three standard parameters
In this work an attempt is made to improve the ability to classify the ECG signals originated from different categories of patients. Table 7.2 summarizes the result obtained. The performance is assessed by the sensitivity and positive predictivity, given by Equations (5.3) and (5.4).

Table 7.2  Results of the classification of VLPs using neural network classifier

<table>
<thead>
<tr>
<th></th>
<th>WTP</th>
<th>3 Standard Parameters</th>
<th>WTP + 3 Standard Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TP</td>
<td>FP</td>
<td>FN</td>
</tr>
<tr>
<td>Normal</td>
<td>15</td>
<td>03</td>
<td>02</td>
</tr>
<tr>
<td>VT</td>
<td>18</td>
<td>02</td>
<td>03</td>
</tr>
<tr>
<td>Total</td>
<td>86.98</td>
<td>86.67</td>
<td></td>
</tr>
</tbody>
</table>

The results clearly show that the combination of WTP and the three standard parameters yields best results for the classification of ECG signals with VLP’s. Also the joint use of wavelet transform and the neural networks gives an extended capability into the analysis of ventricular late potentials.