CHAPTER 3 Electrocardiogram Signal

3.1 Introduction

In this chapter, the ECG signal is analysed for three different types of abnormalities and also for the normal heart. A mathematical framework for the detection of the ECG cycle is then developed for use in the computerised analysis.

The ECG signals come in a wide variety. They vary in the number of leads used (one to twelve or more). A full ECG requires 12 sensors and is usually recorded for a relatively short time. However, continuous ECG monitoring using one or two sensors can observe cardiac variations over an extended period of time at the bedside or in ambulatory cases. This provides more information to doctors, increasing their understanding of the patient's circumstances and allows a more reliable diagnosis for some cardiac abnormalities. In this study, the ECG waveforms were taken from the MIT-BIH Database [13]. For each patient, there are one to two channels of ECG waveforms available in the database and comparison is made between using one channel of samples only.

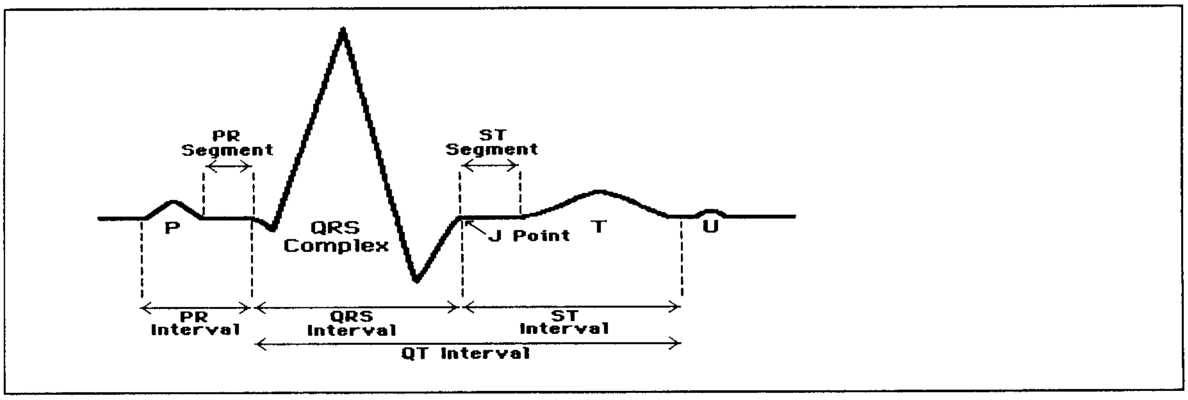

Figure 3.1: The ECG waves.

As the cardiac impulse passes through the heart, electrical currents spread into the tissues surrounding the heart, and a small proportion of these spreads all the way to the surface of the body. If electrodes are placed on the skin on opposite sides of the heart, electrical potentials generated by these currents can be recorded; the recording is known as an electrocardiogram. A normal ECG for single beat of the heart is illustrated in Figure 3.1. A normal ECG can be broken down into three primary components: the P-wave, QRS complex, and T-wave.

Below are a few examples of ECG, the first from a normal heart, the second from a heart undergoing STDP, the third from a heart undergoing TINV and the fourth from a heart undergoing SVT. The differences, while not extreme, indicate a significant change in the behaviour of the heart.

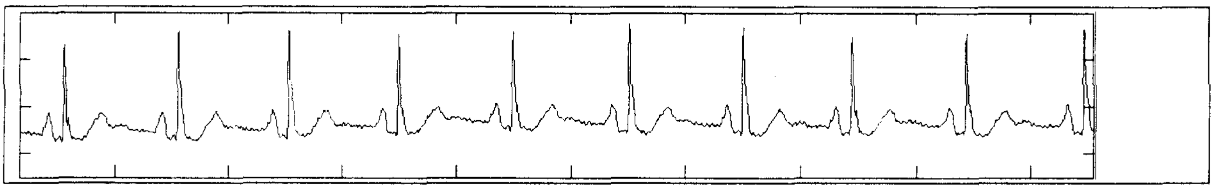
Figure 3.2: A typical normal sinus rhythm (NSR) signal.


Figure 3.3: Example of an abnormal ECG called ST segment depression (STDP)


Figure 3.4: Example of an abnormal ECG called T-wave inversion (TINV).

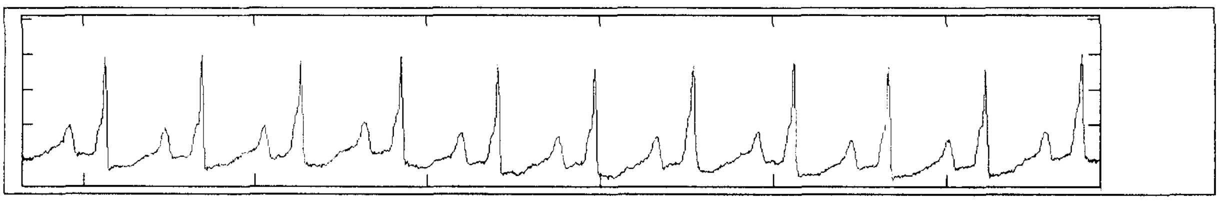
Figure 3.5: Example of an abnormal ECG called Supraventricular Tachycardia (SVT).

Heart rate sequences can be measured by determining the time interval between successive ECG R-waves that is called an R-R interval. The R-R interval detection in ECG cycle is very important in recognizing the signal parts. The QRS complexes detections in

ECG waveforms are also very useful quantitative measures of various functions of the heart. Reliable QRS detection is of fundamental importance, whether the purpose is to locate tentative QRS complexes for further morphological analysis [49-51] or to obtain a table of R-R intervals [52, 53]. Most recent detectors are intended for software implementation, which allows a more complex structure than realization in hardware. Since the R wave portion of the complex usually is easy to distinguish due to its relatively sharp peak, several algorithms incorporate simple slope criteria [54, 55]. Automated ECG beat classification was traditionally performed using a decision-tree-like approach, based on various features extracted from an ECG beat [56-60].

3.2 Detection of R-R Interval

The location in time of certain input information may vary over a class of inputs. Assuming that the time period of observation is larger than the event that is to be detected, the starting and ending times of the event may be random. One desirable characteristic of the recogniser is that the event be recognized independently of starting time. However, the neural network that we develop for the clustering of ECG signals, as will be explained in the next chapter, typifies the static multi layer (ML) feed forward (FF) structure. The fact that inputs are time-varying is, insofar as this network is concerned, irrelevant. The network has no memory of past inputs. Unless additional elements are incorporated into FF structure network design and training, the resulting network is shift sensitive. Thus, generalization to input shift invariance is not inherent in the FF structure network. In order to make SI recognition possible for the neural network, we introduced the R-R interval detection algorithm as described in the following:

A discrete-time ECG signal of length N is represented by $y(k)$ where $k = 0,1,2,\ldots,N-2,N-1,N$. We truncate the ECG signal into segments denoted by

$y_d = [y(d) \quad . \quad . \quad . \quad y(d+M-1)]$ with a moving rectangular window (Frame) of length M for $d = 0,1,2,3,\ldots,N-M-1,N-M,N-M+1$ as shown in Figure 3.6. In order to measure the R-R interval, we need to locate the peaks of two consecutive QRS waves. First, we make an initial guess of the appropriate length for R-R interval detection to be M' as shown in Figure 3.7. Since the 1^{st} and 2^{nd} peaks detected in this interval are located too near to each other, we conclude that the initial guess is incorrect. Hence, we make a second guess of the length of the interval of two cardiac cycles to be M''. The 1^{st} and 2^{nd} highest peaks of this interval are located some distance apart (threshold values are used for determining such a distance, these parameters have been search by trial and error and verification was done computationally). Therefore, we conclude that the appropriate length for R-R interval detection is M''. Since the peak R of an ECG cycle has the greatest absolute deviation and second derivative value, detection of the 1^{st} and 2^{nd} highest peaks in the interval of length M'' is described in the following:

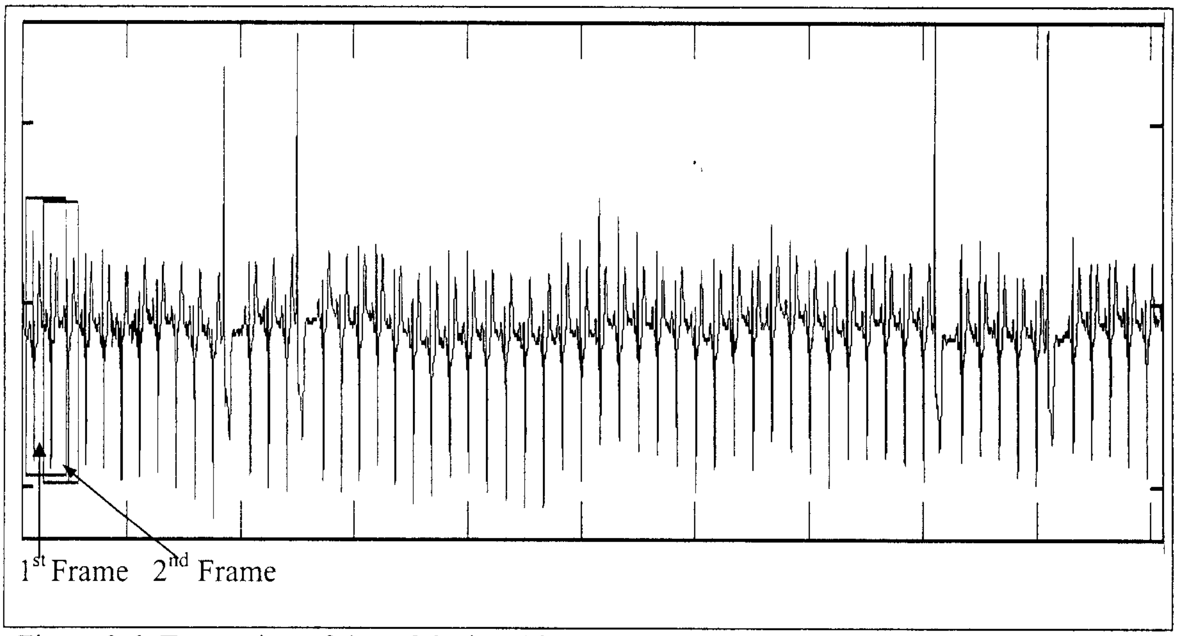

Figure 3.6: Truncation of the ECG signal into segments.

First, we calculate the mean value of y_d given by

$$\mu_d = \frac{1}{M}\sum_{i=0}^{M-1} y(d+i) \tag{3.1}$$

, and then we determine the absolute deviation of y_d as given by

$$|\sigma_d(k)| = | y_d(k) - \mu_d | \text{ for } k = 0,1,\ldots,M-2,M-1. \tag{3.2}$$

The absolute deviation of y_d, $|\sigma_d(k)|$ is shown as green stem in Figure 3.8(a). In order to increase the accuracy of the peak R detection, we also determine the absolute second derivative of y_d as given by

$$|a_d(k)| = | y_d(k-1) - 2[y_d(k)] + y_d(k+1) | \text{ for } k = 0,1,\ldots,M-2,M-1. \tag{3.3}$$

The absolute second derivative of y_d, $|a_d(k)|$ is plotted as red stem in Figure 3.9(a). The 1st and 2nd highest peaks are determined by taking the two largest values of the product of absolute deviation and second derivatives as shown in the following:

$$r_{d1} = \max\{|\sigma_d(k).a_d(k)|\} \text{ for } k = 0,1,\ldots,M-2,M-1. \tag{3.4}$$

&

$$r_{d2} = \max\{|\sigma_d(k).a_d(k)|\} \text{ for } k = 0,1,\ldots,M-2,M-1, \text{where } k \neq I_{rd1} \tag{3.5}$$

They are the precise locations of the 1st and 2nd peaks respectively as shown in red stems in Figure 3.8(c).

The input patterns constructed by the single shifted-input neural units are time varying as shown in Figure 3.9(a). Recognition of input patterns often requires a mechanism that is invariant or insensitive to some variation in the inputs. In this case, the variation is the one dimension translation of signal. We applied the R-R interval detection

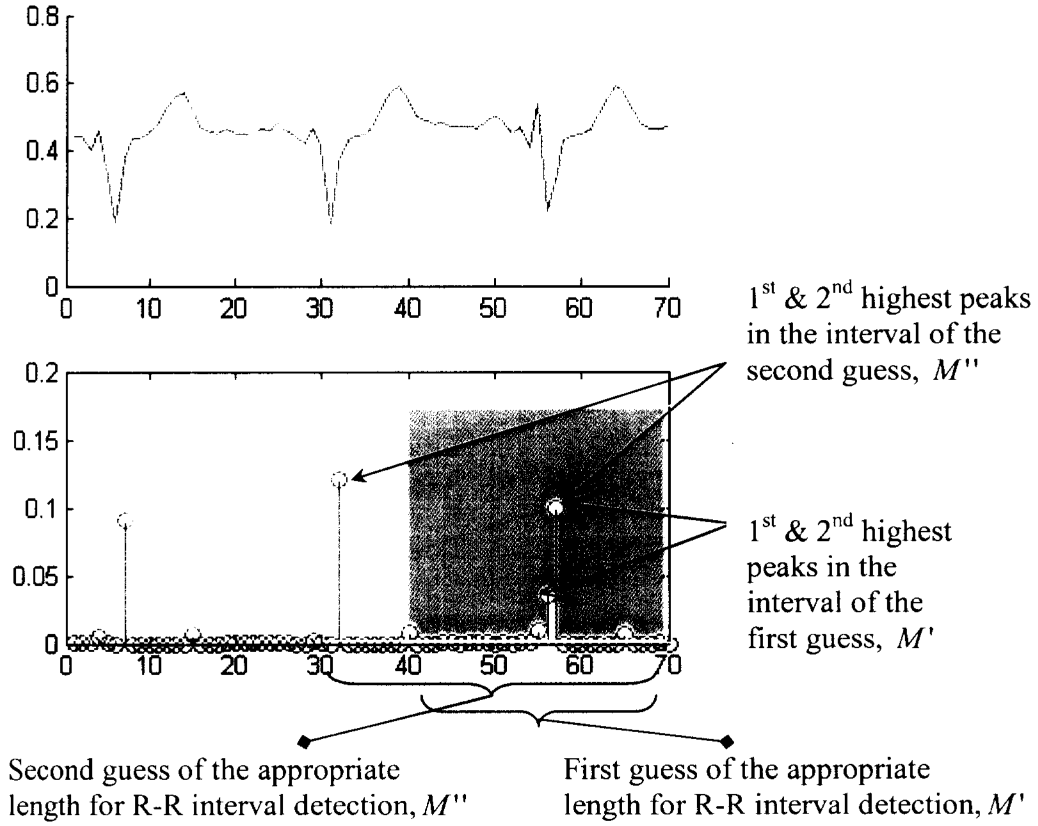

Figure 3.7: The guessing of the appropriate length for R-R interval detection. The bottom graph is the plot of second derivative values of the ECG signal as shown on the top graph. The second derivative values are evaluated at stationary points only to save computational cost as we know that the peaks only occur at these points.

The Figure 3.7 shows that the ECG cycle has two stationary points extremely close together. Therefore, when approximating the R-R interval, if we assume that the distance between the first two local highest peaks will always be the length of the R-R interval, then this might lead to the error of estimating an R-R interval with the length of one time step. This is illustrated in Figure 3.7 where we have taken the first two local highest peaks in the blue region. This error can occur because the first two local highest peaks can be exactly next to each other. So the blue region needs to be extended further to cover the actual R-R interval length which is indicated by the yellow lines. The threshold value for the minimum distance between the first two local highest peaks was arbitrarily set to five time steps. This threshold value was computationally verified to give a detection success rate of 100%.

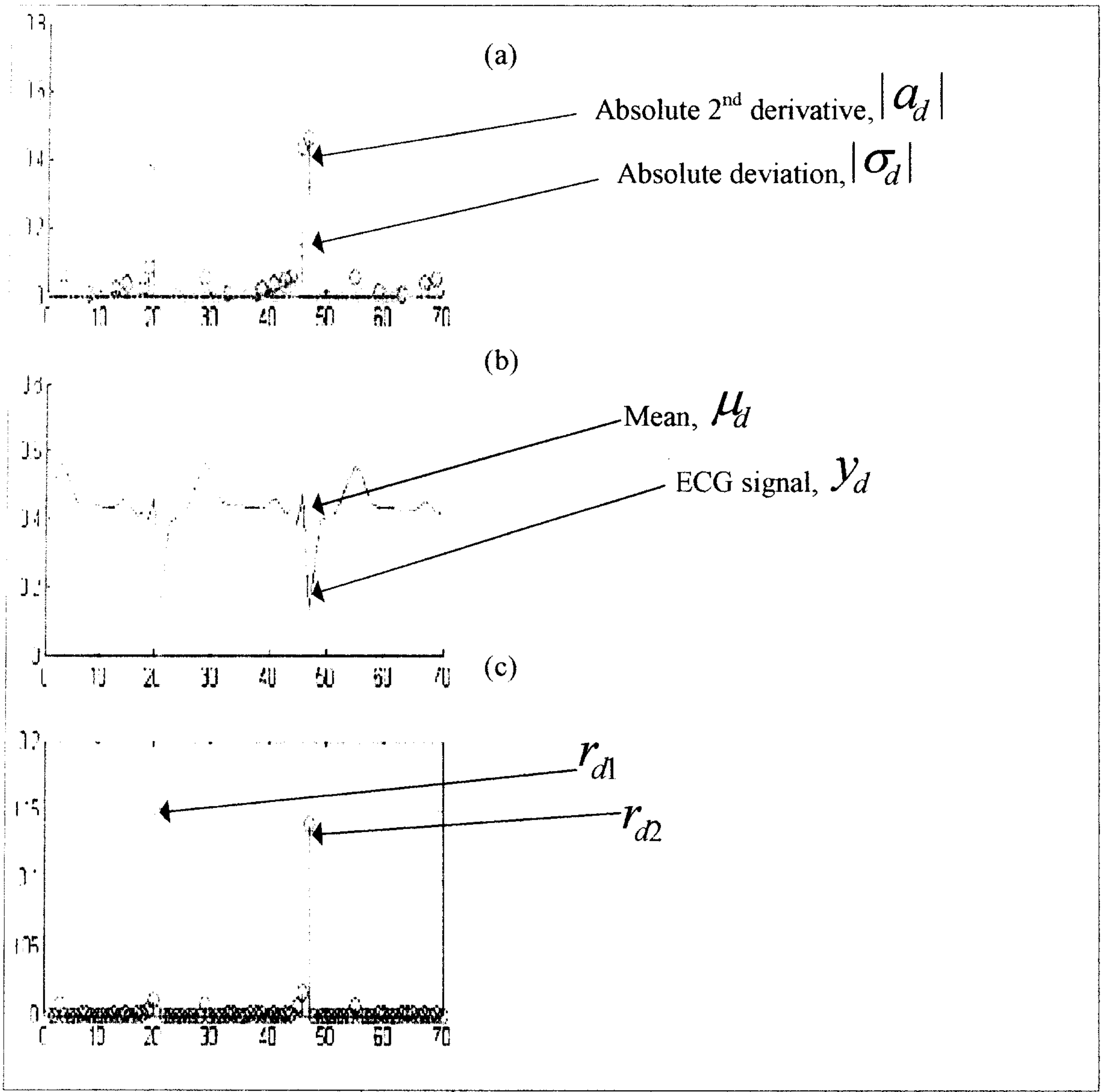

Figure 3.8: Detection of the 1st and 2nd highest peaks of two consecutive QRS waves.

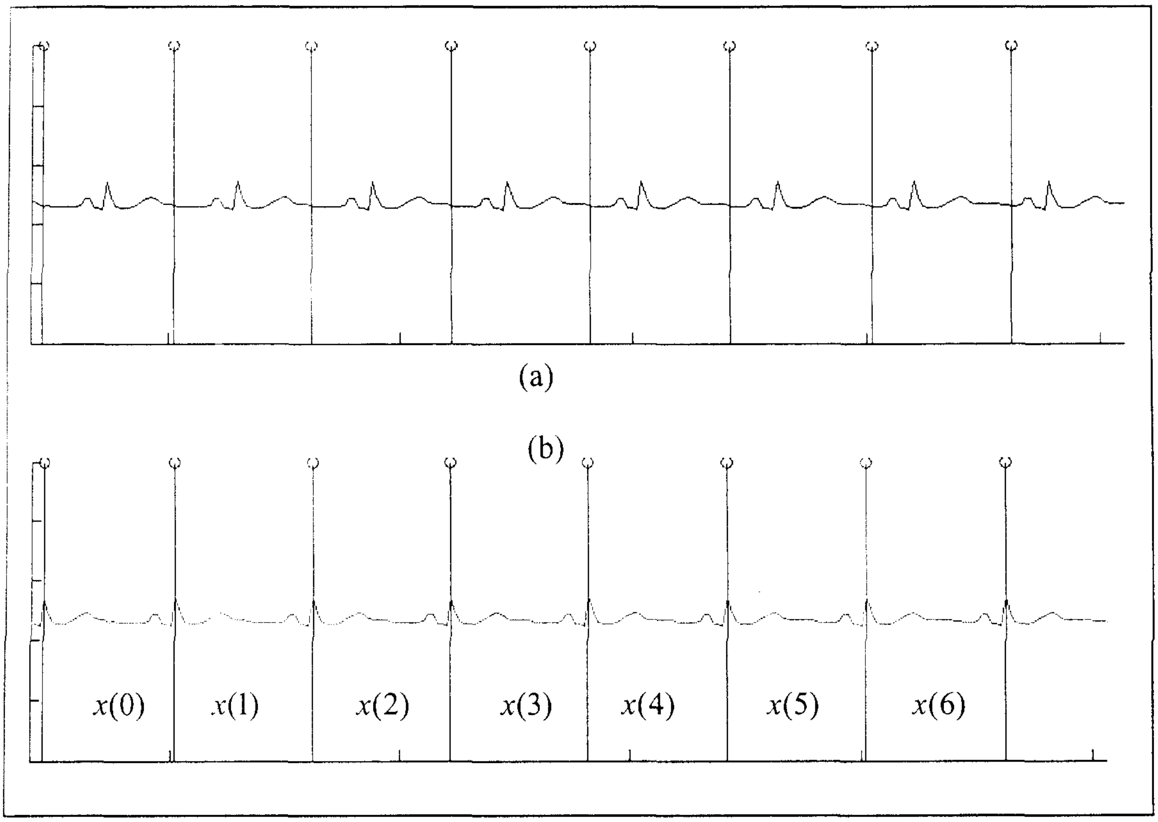

Figure 3.9: (a) The time varying spatial input patterns, (b) The time invariant spatial input patterns.

3.3 *Conclusions*

An ECG is a measurement of the heart electrical activity that allows physicians to accurately diagnose a wide range of heart disorders. Hence, ECG can assist in the diagnosis of cardiac diseases. The feature detection method divides an ECG signal into elements of R-R interval. The use of elements, rather than a continuous signal, provides a much better framework for recognition of irregularly shaped signals.