CHAPTER 4 Methodology

4.1 Introduction

The methodology of the system is described in the block diagram as shown in Figure 4.1. The data sets consist of 24 patients' ECG signals. Each ECG signal was recorded for approximately 16.67 minutes in the MIT-BIH Database [13]. We subdivided these ECG signals into segments of 6.4 seconds, which consists of 1600 samples each, at a sampling rate of 250 Hertz. The number of samples in each segment was taken to be even for the Discrete Wavelet Transform (DWT) to reduce computational cost. 12 patients' ECG signals were used for training purposes while the others were reserved for the testing and simulation of the system.

The block diagram in Fig. 4.1 not only summarises our ECG classification method, but also provides us with the opportunity to review the structure of our thesis under a more functional/pragmatic light. The detection of R-R intervals was described in the previous chapter. The current chapter will be mainly concerned with discussing VPC Detection with the State Transition Model. In processing terms, the R-R Interval detection stage dealt with in Chapter 3, is followed by the Pattern Recognition stage, and this is dealt with in Chapter 5. The subsequent processing step, Fuzzy Decision Inference, is described in Chapter 6.

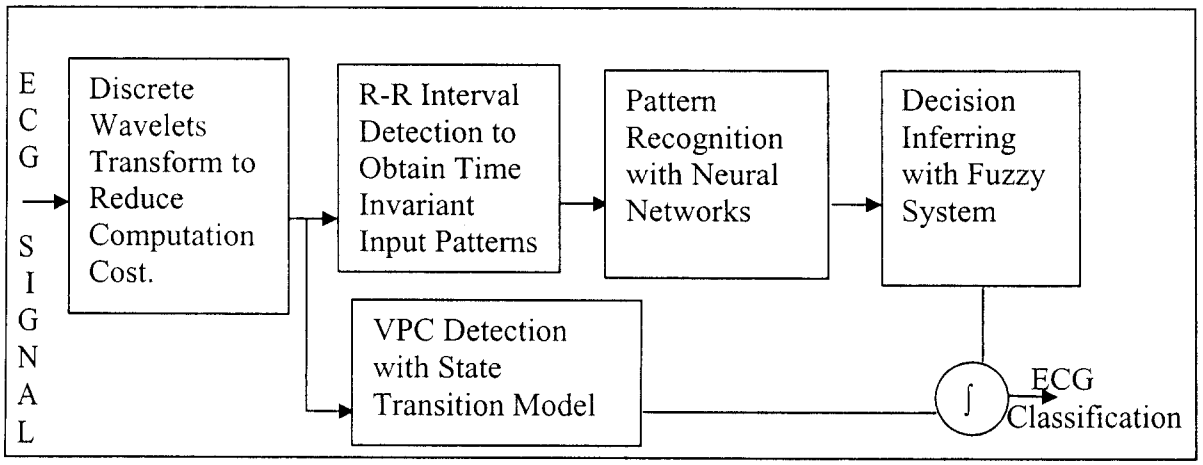

Figure 4.1: Block Diagrams of the ECG classification system.

Feature analysis is an essential and important step towards designing effective clustering and classification algorithms. Clustering looks for substructures present in a data set, i.e. it partitions the data set into homogeneous groups. A classifier, on the other hand, partitions the feature space so that any unlabeled data point can be assigned the appropriate class label.

Model:

1) Utilization of unconstrained optimisation method to detect the peak of QRS wave in an ECG cycle.

2) Detection of VPC based on the durations of two consecutive R-R intervals.

3) Generalisation of the ECG signals into homogenous groups using an ensemble of neural networks.

4) Application of Extended Kalman Filter (EKF) for the optimization of weight parameters in neural network.

5) Modelling of a hybrid neural fuzzy system as the principal classifier to yield decisions concerning the class membership of various ECG signals.

The VPC detection with state transition model is designed as a separate module, as shown in Figure 4.1. This module can be integrated qualitatively with the hybrid neural fuzzy system at the end of the recognition process. This is because VPC may be present in any of the ECG signals such as STDP, TINV and NSR. The detection of VPC requires measurement of two consecutive ECG cycles, as will be explained in Section 4.2, whereas the recognition of various ECG signals such as STDP, SVT, TINV and NSR is processed with an ECG cycle.

4.2 Detection of Ventricular Premature Cycle (VPC)

The absence of P wave is significant in a Ventricular Premature Cycle (VPC). The QRS wave of the VPC signal follows immediately from the ST segment of its previous cardiac cycle. The QRS wave is inverted in a VPC signal. The size of the QRS wave is also significantly greater than its neighbouring QRS waves. VPC may be present in both normal sinus rhythm ECG signal and abnormal ECG signals as shown in the Figure 4.2-4.4.

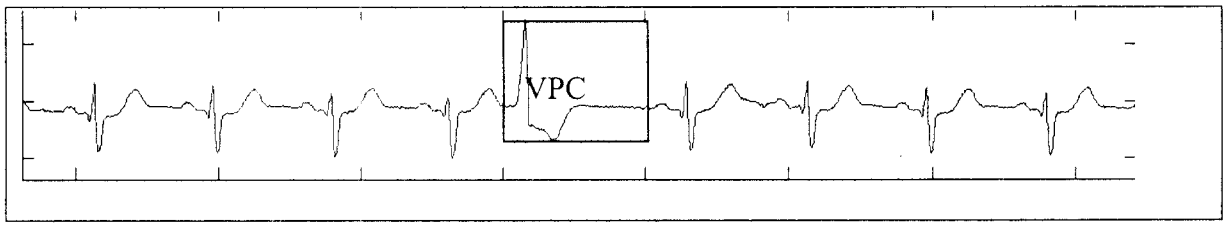

Figure 4.2: A typical normal sinus rhythm ECG with VPC.

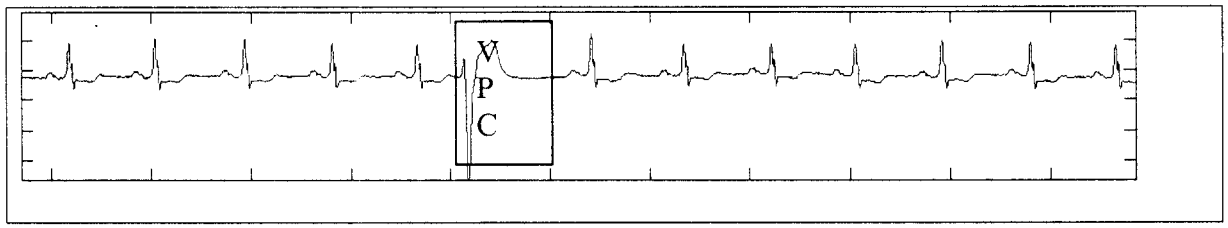

Figure 4.3: A typical ST-segment depression ECG with VPC.

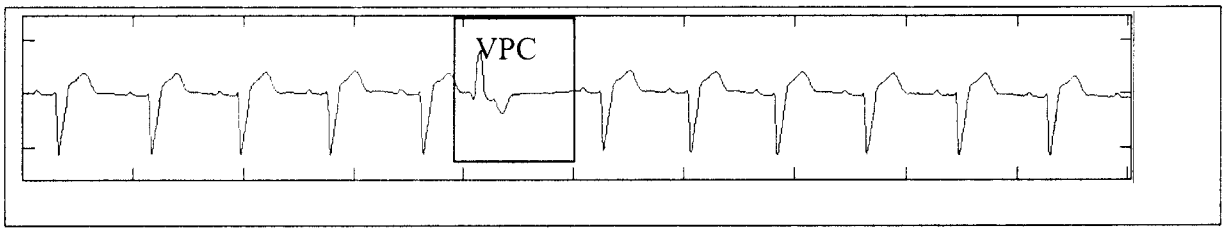

Figure 4.4: A typical ST-segment elevation ECG with VPC.

In order to detect these VPC signals, we need to extract the common features of the VPC signals. The absence of P wave will cause the R-R interval duration between the preceding normal cardiac cycle and the VPC becomes shorter and the R-R interval duration between the VPC signal and the following normal cardiac cycle becomes longer as shown in Figure 4.5.

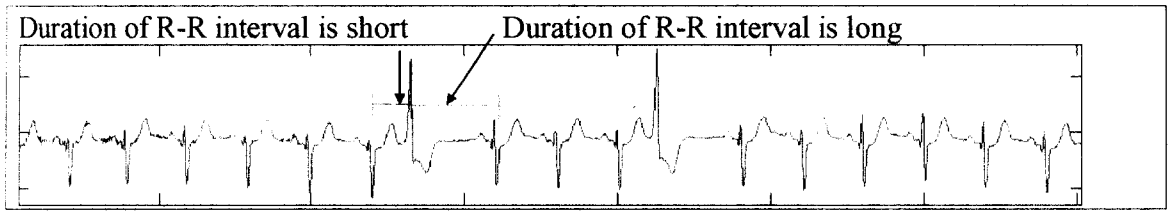

Figure 4.5: A typical normal sinus rhythm ECG with two VPC.

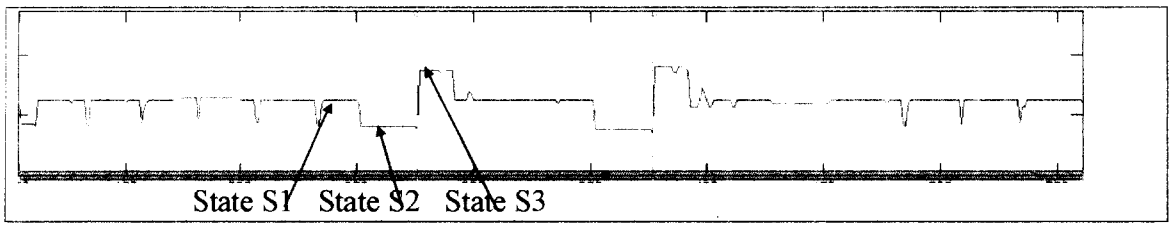

Figure 4.6: Detection of the VPC signal as shown in the above figure by measuring the distance of R-R intervals.

By plotting the duration of R-R intervals versus time as shown in Figure 4.6, the recognition of VPC signal is reduced down to merely recognition of the state transitions marked by the vertical lines in pink. We introduce a simple state model in Figure 4.7 for the recognition of VPC signal. Let S1, S2 and S3 represent the states of medium, low and high duration of R-R interval respectively. We therefore conclude that the transition from state S1 to S2 and then to S3 will result in VPC.

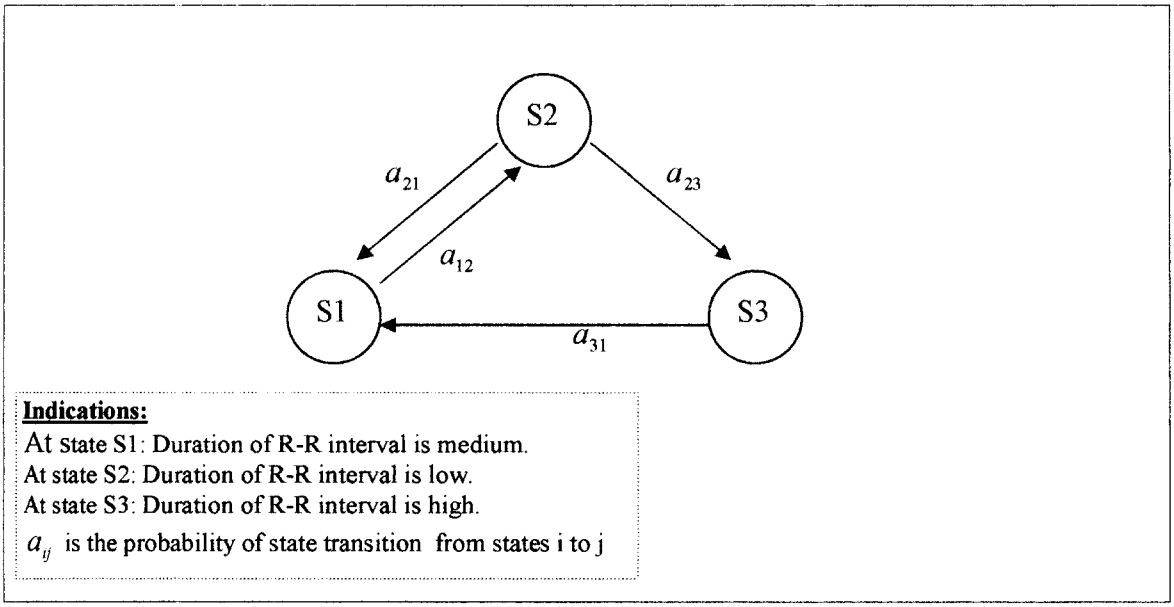

Figure 4.7: State model for the recognition of VPC.

However, there are other premature signals such as Atrial Premature Cycle (APC) that will produce the same state transitions as the VPC signal, Figure 4.8 and 4.9. The absence of P wave will cause the R-R interval duration between the preceding normal cardiac cycle and the APC becomes shorter and the R-R interval duration between the APC signal and the subsequent normal cardiac cycle becomes longer as shown in Figure 4.8 and 4.9.

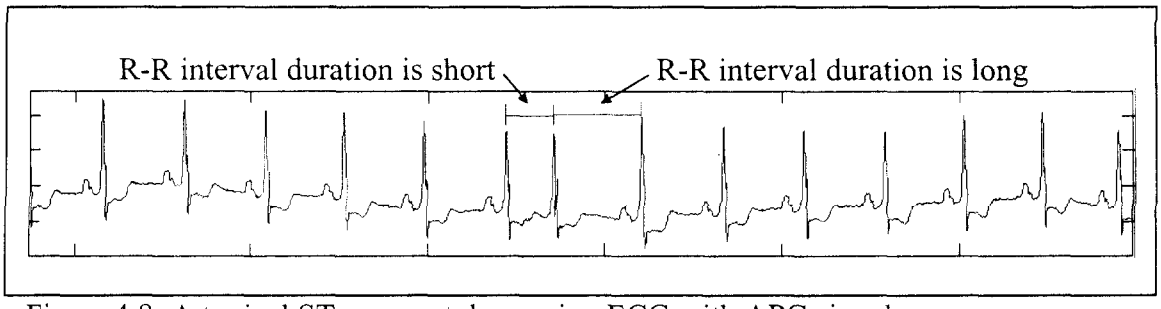

Figure 4.8: A typical ST-segment depression ECG with APC signal.

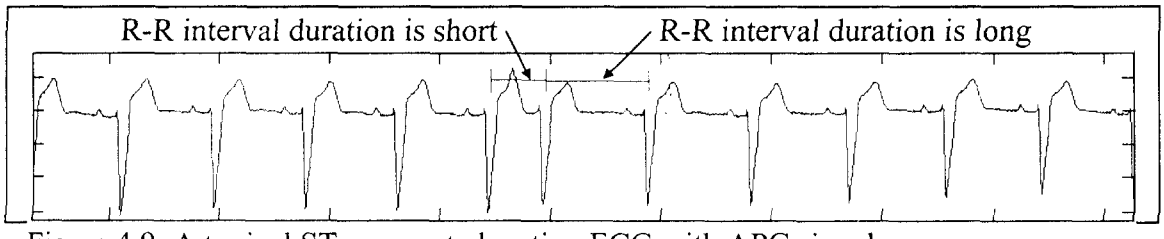

Figure 4.9: A typical ST-segment elevation ECG with APC signal.

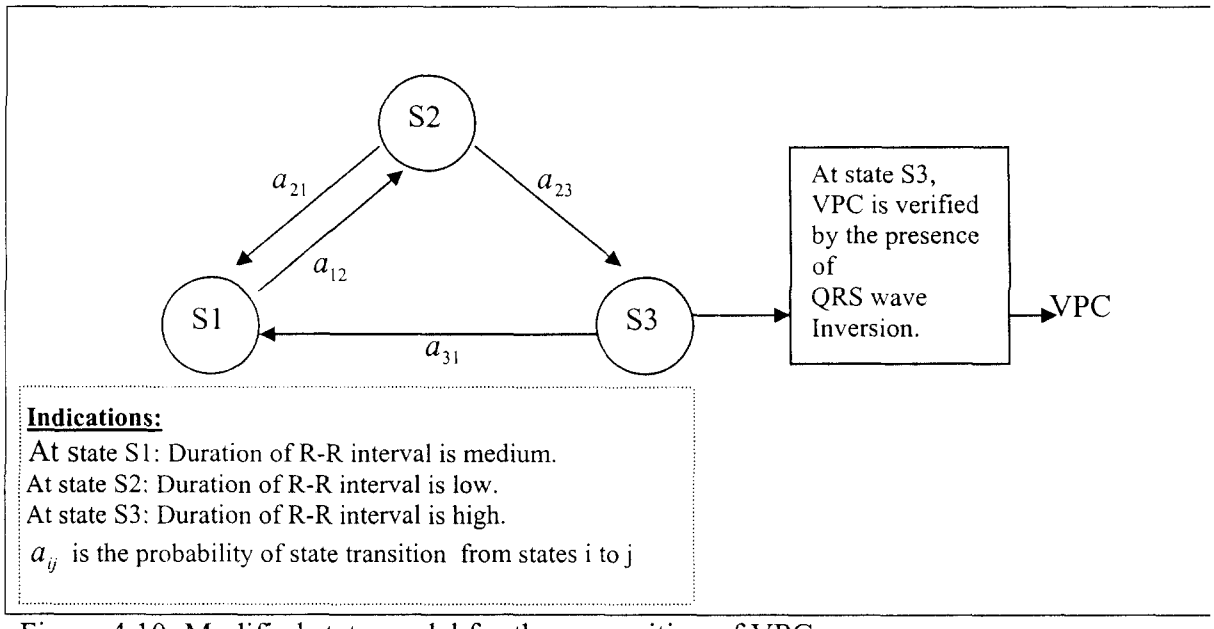

Figure 4.10: Modified state model for the recognition of VPC.

In such cases, the state model described in Figure 4.7 alone could not distinguish VPC signal from APC signal. Hence, we need to modify the model such that it includes detection of QRS wave inversion that is present in VPC signal only as shown in Figure 4.10.

In Section 3.2, we denote the 1st and 2nd highest peaks of two consecutive QRS waves as, r_{d1} and r_{d2}, and their indices as I_{rd1} and I_{rd2}. The second derivative of the 1st and 2nd highest peaks, $a_d(I_{rd1})$ and $a_d(I_{rd2})$ are plotted as blue line and red line respectively in Figure 4.11(a) for $d = 0,1,2,3,...,N-M-1, N-M, N-M+1$. In the presence of QRS wave inversion that is common in VPC signal, the second derivative values of the two consecutive peaks R will be different in sign. This is because for a stationary point, the second derivative of this point is negative if it is a maximum point whereas the second derivative of this point is positive if it is a minimum point, as explained in Appendix A. The presence of QRS wave inversion is obvious from Figure 4.11(a) and is indicated in Figure 4.11(b) by each pair of green lines. Figure 4.11(c) is the plot of R-R interval duration versus time as discussed previously. The VPC signals are as shown in Figure 4.11(d).

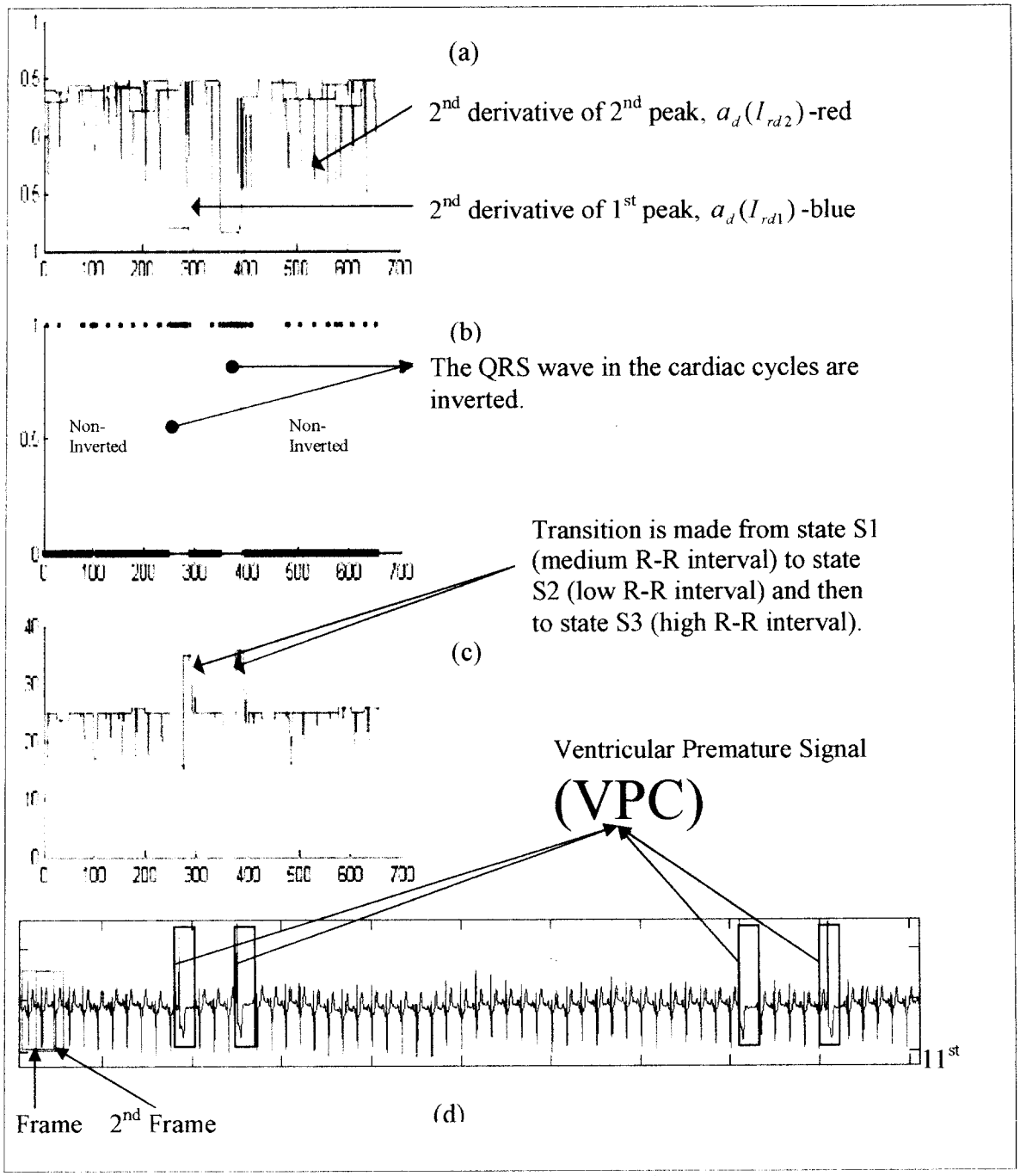

Figure 4.11: Detection of the presence of QRS wave inversion.

4.3 Conclusions

There exist classification systems that are able to localise pathological changes in ECG records such as detecting the QRS complex [61] and ST segment [62, 63], locating the R-R interval and individual waves [64-67]. But we are more comfortable with the proposed feature detection algorithms since it is customized to our online learning scheme.