9 Results and proposed direction for future work

Chapter 9
Results and proposed direction for future work

Chapter depicts the results obtained using GUI designed in Chapter 8, for sets of parameters for each network model and training algorithms. **Table 9.1** and **Table 9.2** in section indicates types of signals used for testing, network parameters, waveforms generated and figure of merit based on selected signal processing operations.

Table 9.1 Data files

Type	File name
signal	ECG1: N0001.adc..adc
	ECG2: N0029.adc..adc
Noise	EMG: EMG01.adc..adc

Table 9.2 Separated lead signals

File names(ECG as well as EMG)
L*.dat
R*.dat
C1*.dat
C2*.dat
C3*.dat
C4*.dat
C5*.dat
C6*.dat

*** = ECG or EMG**

9.1 Filtering

9.1.1 Hopfield Neural Network based filtering (LS/RLS Algorithm)

Parameters

R : input resistance
c : input capacitance
k1 : Constant multiplier of f(u)
k2 : Constant multiplier of g(u)
TRG : Number of training samples
TST : Number of test samples

Set I

Sr No.	Type of signal		Values of parameters					
	training	testing	r	c	K1	K2	TRG	TST
1	recg	c1ecg	1000	0.00001	1	1	1000	2000

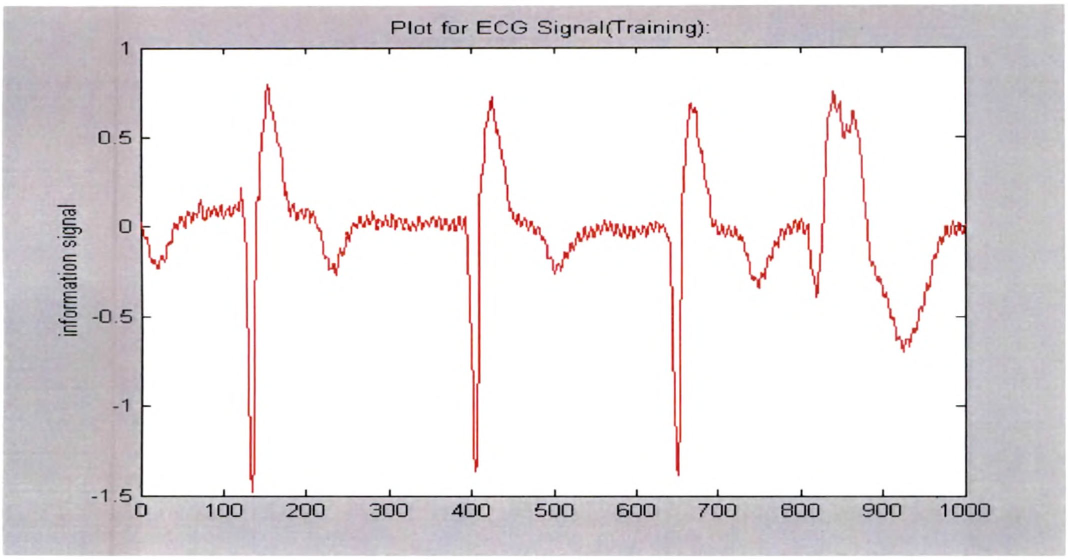

Figure 9.1(a) Plot of expected signal used for training(recg)

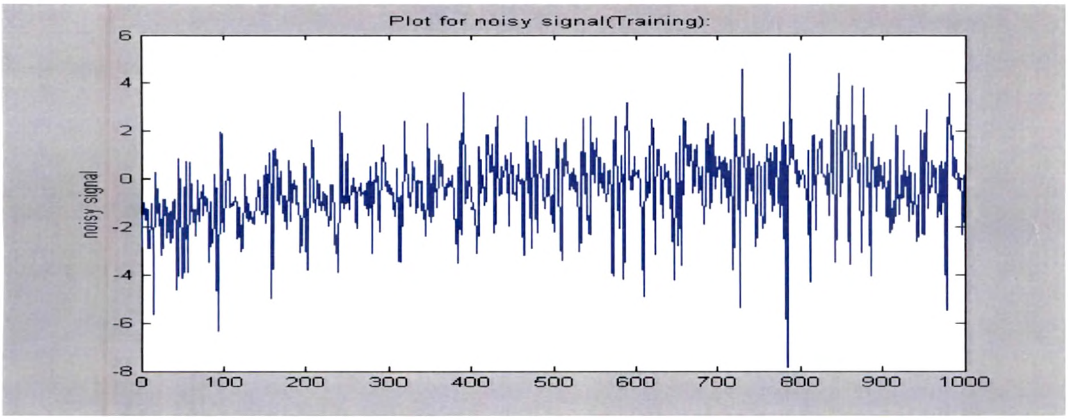

Figure 9.1 (b) Plot for noisy signal where originality of signal is lost(training)

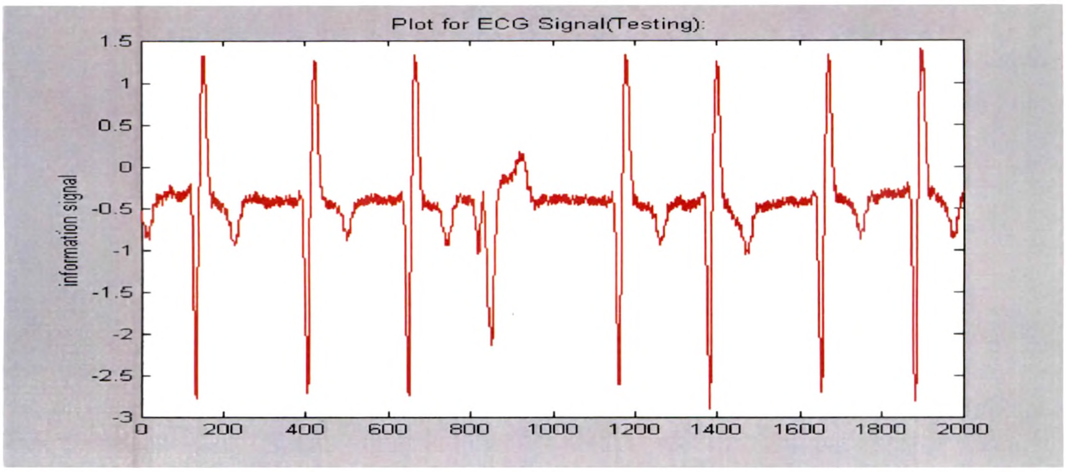

Figure 9.1 (c) Plot for ECG used for testing (c1ecg)

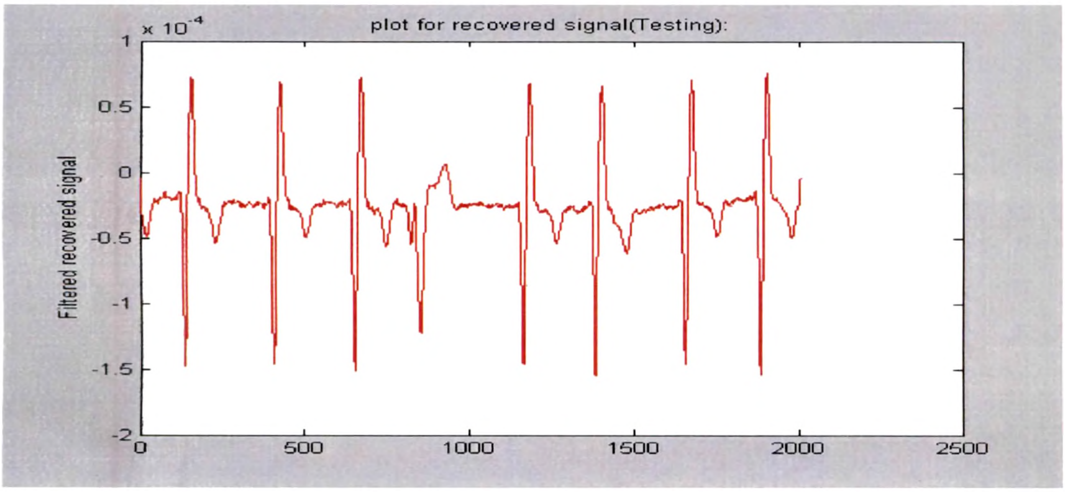

Figure 9.1 (d) Plot for recovered signal during testing

Figure 9.1 Waveforms showing related signals for filter using Hopfield NN

Recovered signal is very weak in aaamplitude. Hopfield NN insists on specific values of parameters. Hence does require careful selection of training sets.

9.1.2 MLPANN based filtering

Parameters

DIFF/I: Phase difference in terms of number of samples/ Number of input layer nodes

H : Number of hidden nodes

TIME : Time epochs during training

ETA : Learning rate

TRG : Number of training samples

TST : Number of test samples

Set I

Sr No.	Type of signal		Values of parameters					
	training	testing	DIFF/I	H	TIME	ETA	TRG	TST
1	r	c2	0/3	2	100	0.01	1000	3000

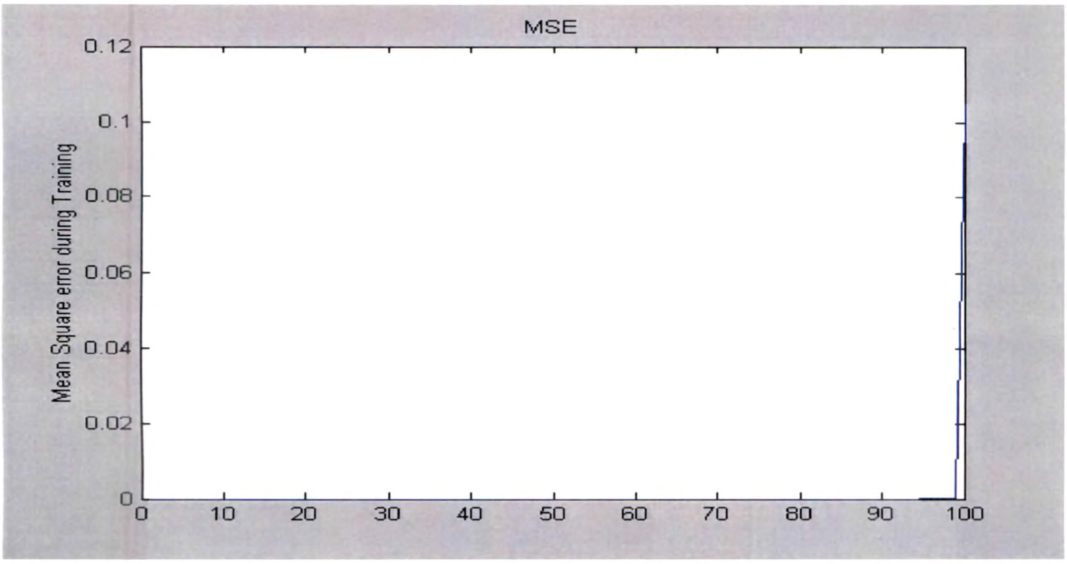

Figure 9. 2(a) Plot for mean square error during training for time epoch 100

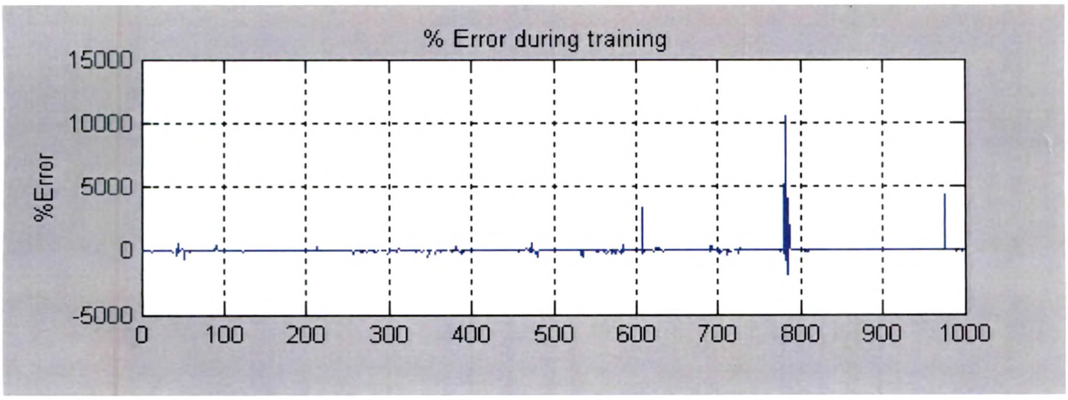

Figure 9.2 (b) Plot for % Error between original and reconstructed signal for training with 1000 samples

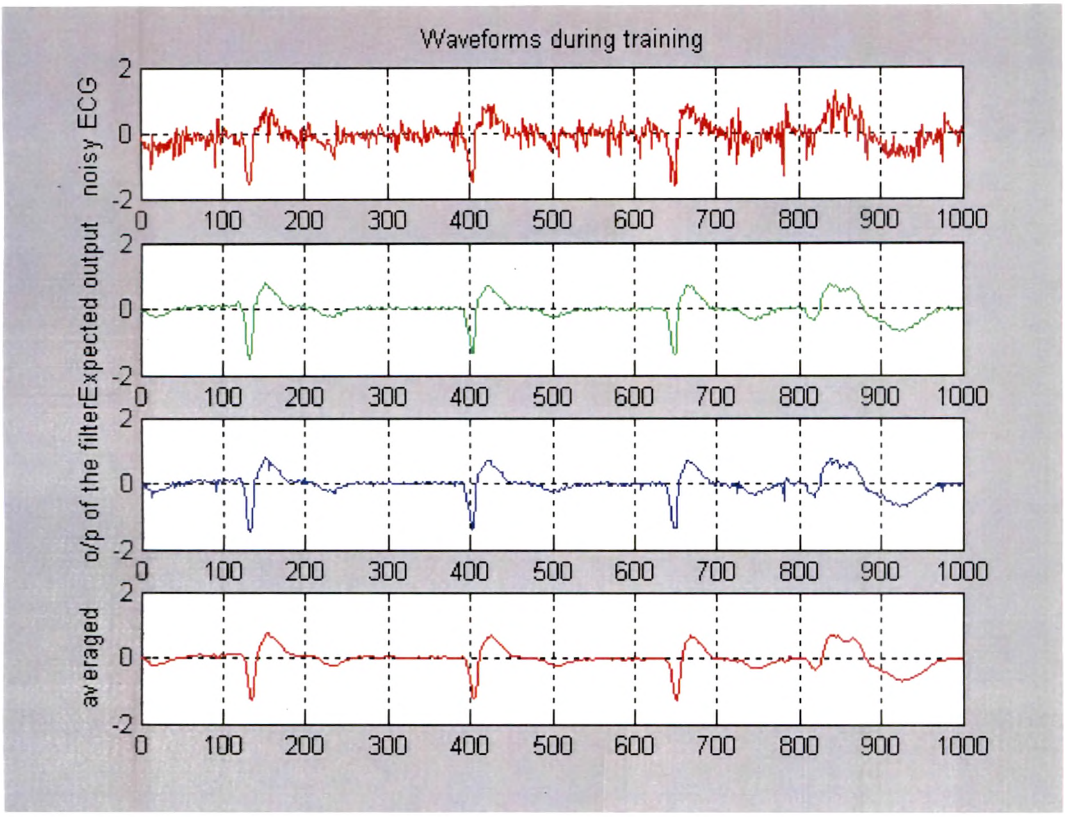

Figure 9.2 (c) Waveforms showing how effectively filtering is carried out during training

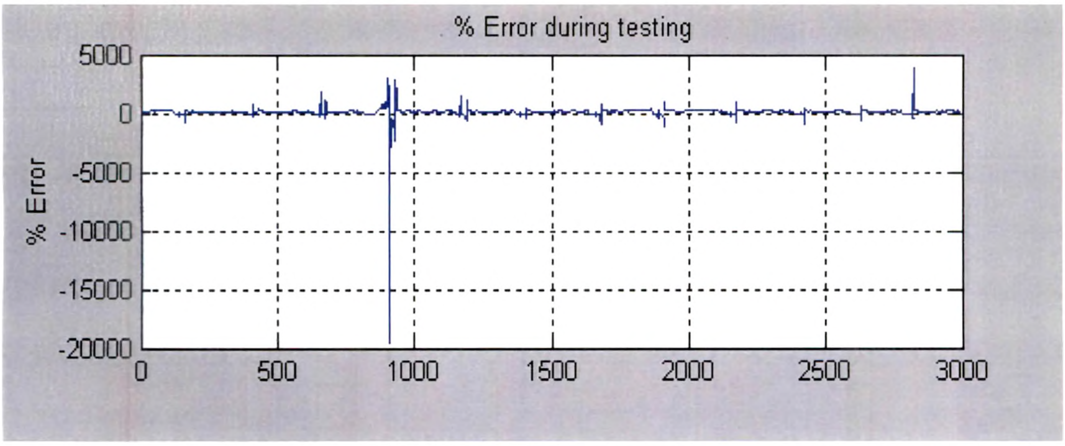

Figure 9.2 (d) Plot for % Error between original and reconstructed signal for testing with 3000 samples

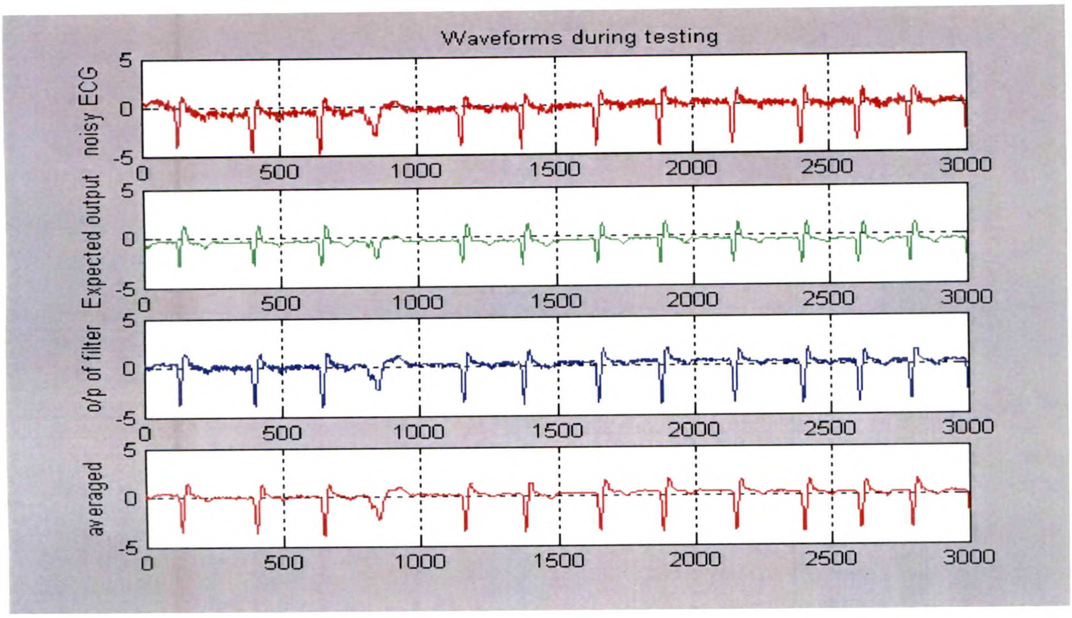

Figure 9.2 (e) plots for showing how effectively filtering is carried out during testing

Figure 9.2 Waveforms for MLPANN based filtering for parameter set I

Set II

Sr No.	Type of signal		Values of parameters					
	training	testing	DIFF/I	H	TIME	ETA	TRG	TST
2	r	1	0/4	2	100	0.01	1000	3000

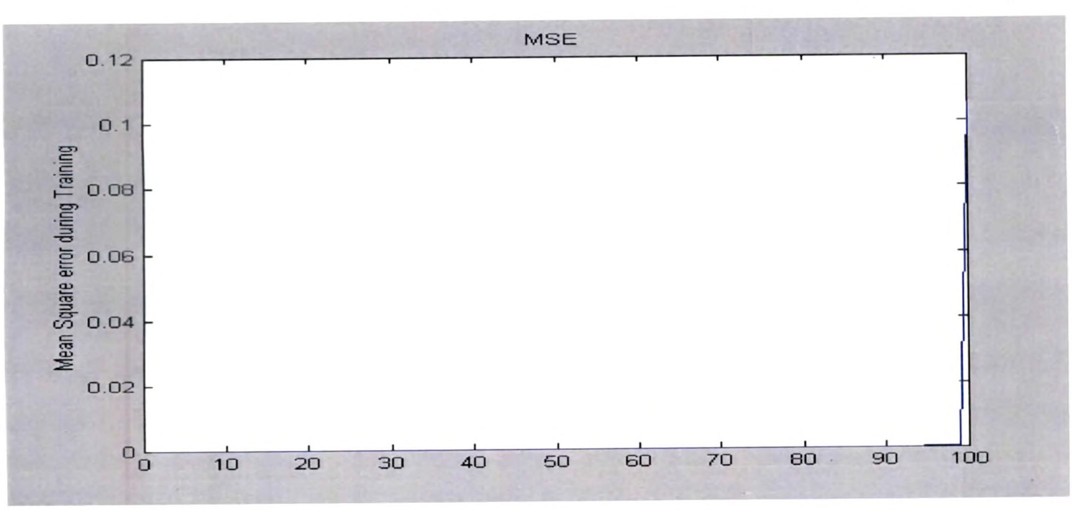

Figure 9.3 (a) Plot for mean square error during training for time epoch 100

With same line of arguments, even for significant value of % Error during training and testing at some points, desired signal is recovered satisfactorily with all clinical visibility.

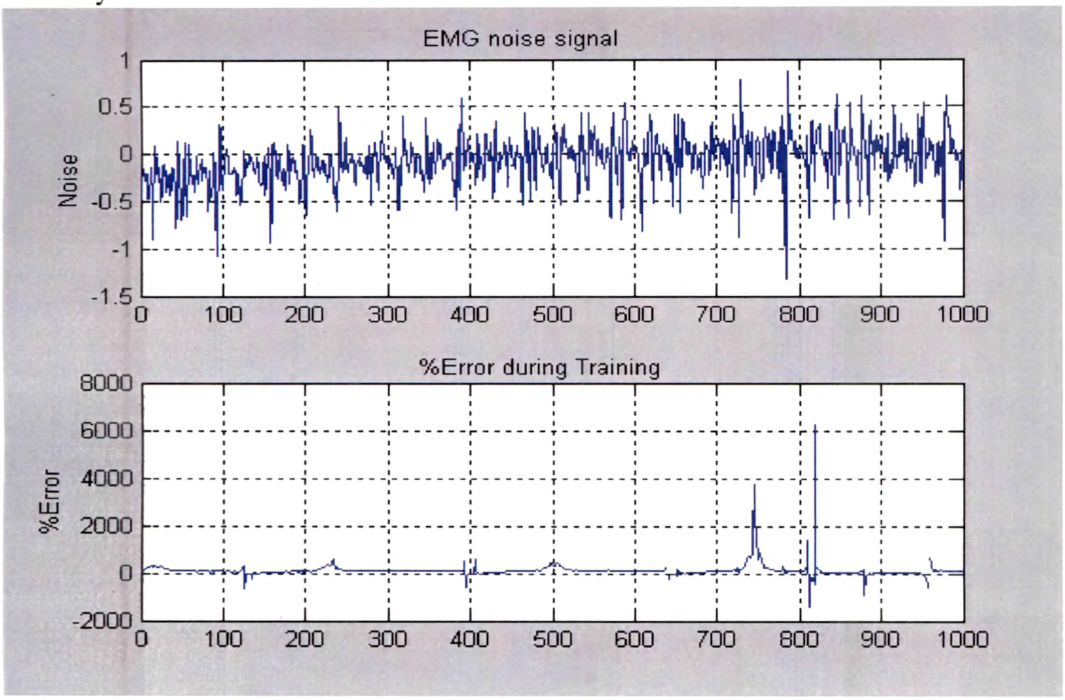

Figure 9.3 (b) Plot for % Error between original and reconstructed signal for training with 1000 samples

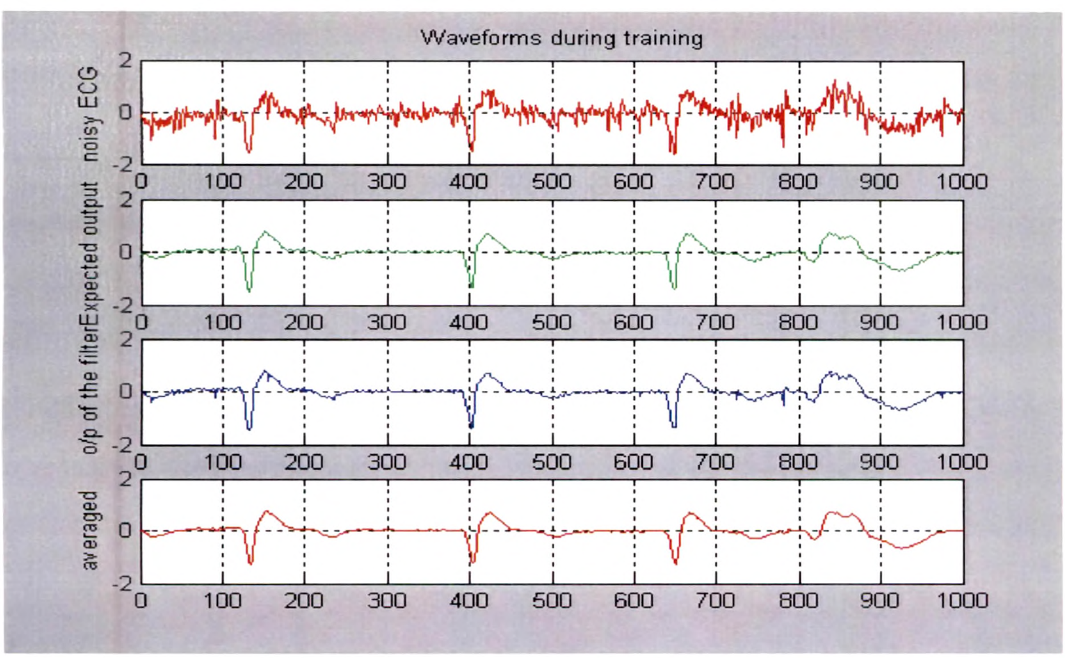

Figure 9.3 (c) Waveforms showing how effectively filtering is carried out during training

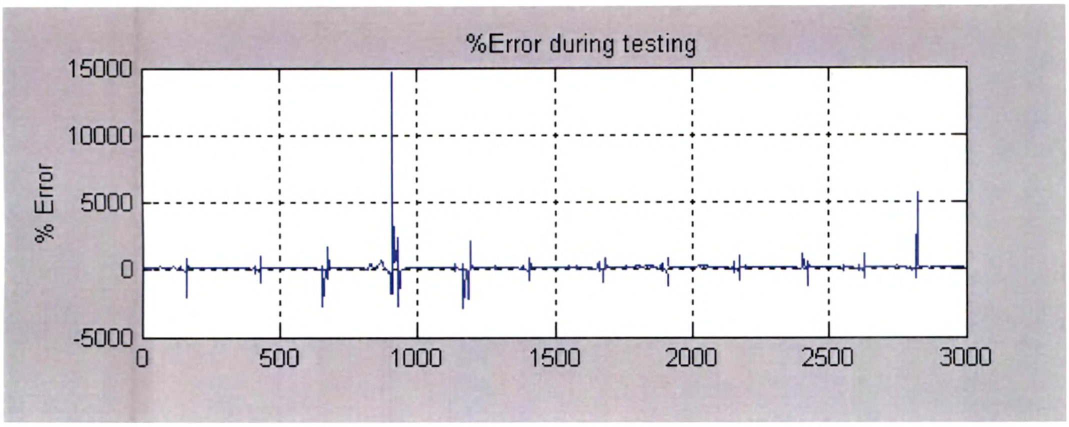

Figure 9.3 (d) Plot for % Error between original and reconstructed signal for testing with 3000 samples in set II

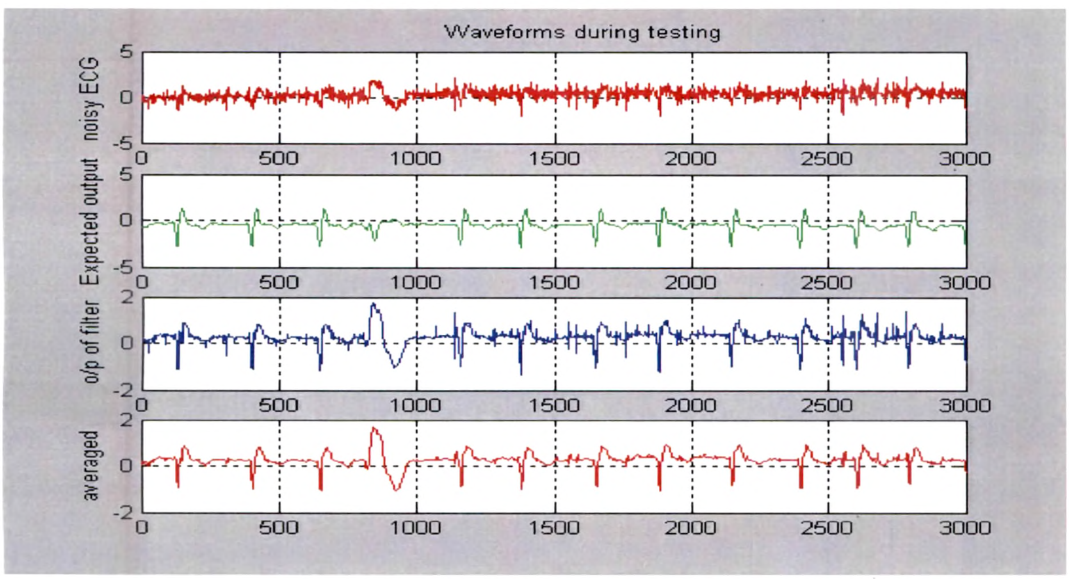

Figure 9.3 (e) plots for showing how effectively filtering is carried out during testing

Figure 9.3 Waveforms for MLPANN based filtering for parameter set II

9.1.3 RBFNN based filtering

Parameters

eg :	Phase difference in terms of number of samples
sc :	Number of hidden nodes
DIFF/I:	Phase difference in terms of number of samples/ Number of input layer nodes
TRG :	Number of training samples
TST :	Number of test samples

Set I

Sr No.	signal		Values of parameters				
	training	testing	eg	sc	DIFF	TRG	TST
1	c2	c3	0.01	800	0/4	300	3000

Following waveforms in **Figure 9.4** clearly show how noise with D.C. offset is filtered out very effectively and original ECG is restored.

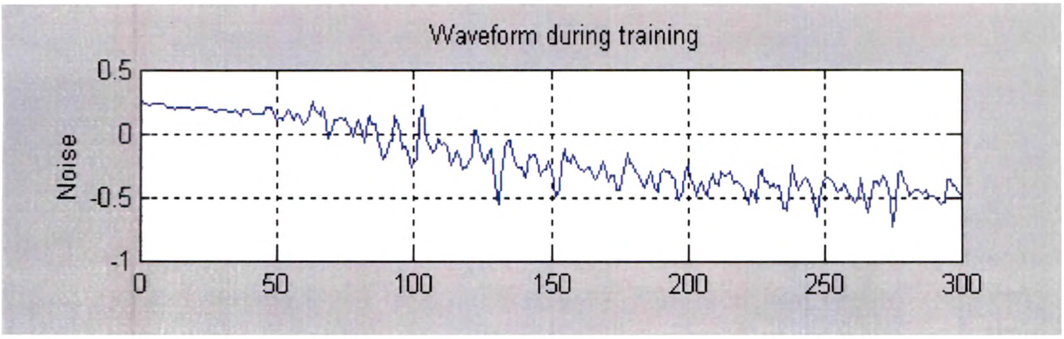

Figure 9.4 (a) Plot for noise waveform for 300 training samples.

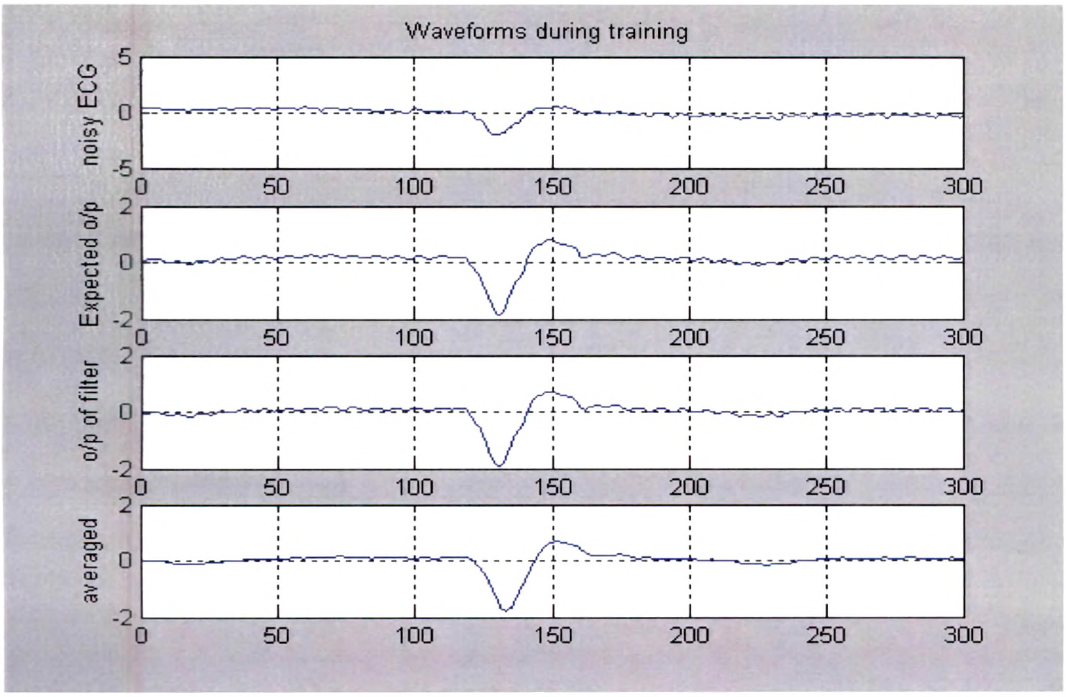

Figure 9.4 (b) Plot for waveforms during training

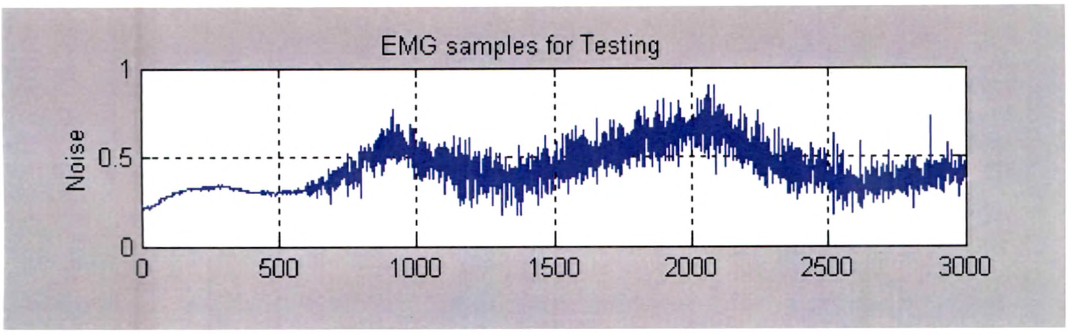

Figure 9.4 (c) Plot representing amount of noise that corrupts ECG

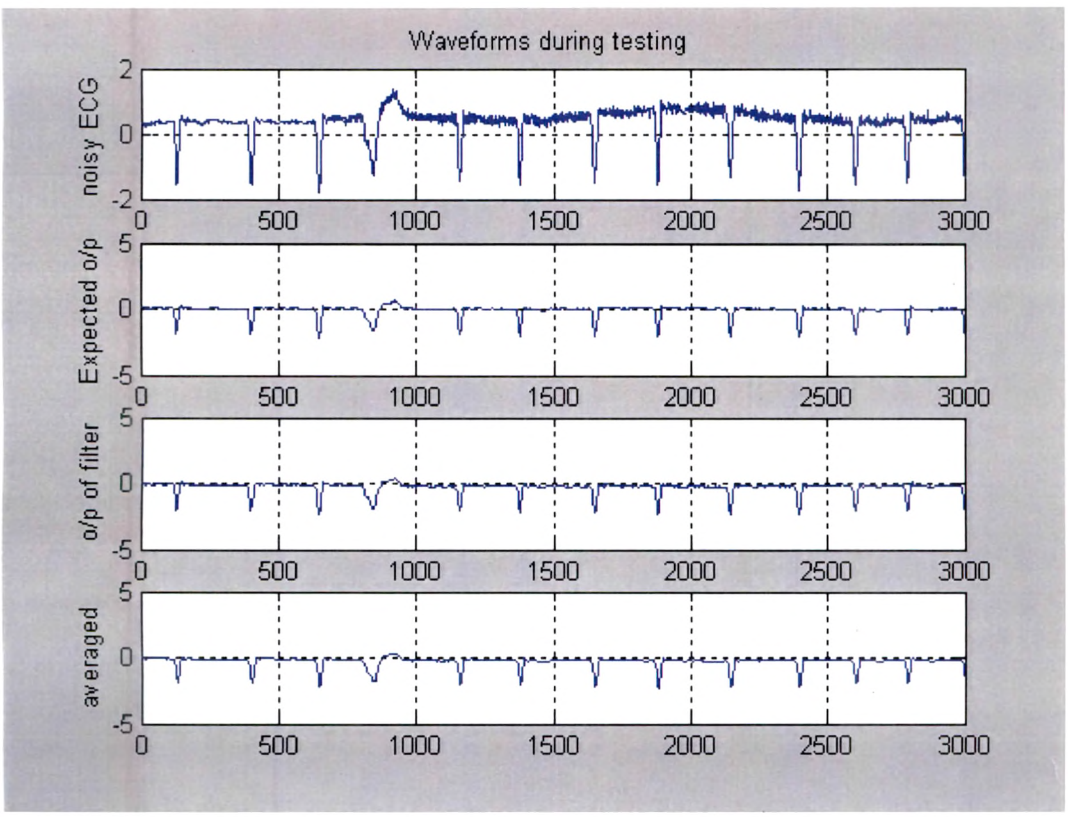

Figure 9.4 (d) Plot for waveforms during testing including recovered waveform as exact replica of desired ECG

Figure 9.4 Waveforms showing role of RBFNN in removing noise

Set II

Sr No.	Type of signal		Values of parameters				
	training	testing	eg	sc	DIFF/I	TRG	TST
1	c2	c3	0.01	800	2/3	300	3000

Exactly same output as with DIFF =0 **(Figure 9.4).**

9.2 Compression

9.2.1 MLPANN Based Compression

Parameters

I : No. of input layer nodes
H : No. of hidden layer nodes
O : No. of output layer nodes
eta : Learning rate
TIME : Number of time epoches
TRG : Number of training sets
TST : Number of test sets

Set I

Sr	Type of signal		Values of parameters					
No.	training	testing	I=O	H	eta	TIME	TRG	TST
1	r	C3	6	3	0.1	5	500	500

Results obtained:

CR	PRD during training	PRD During testing
2	31.1814	25.7546

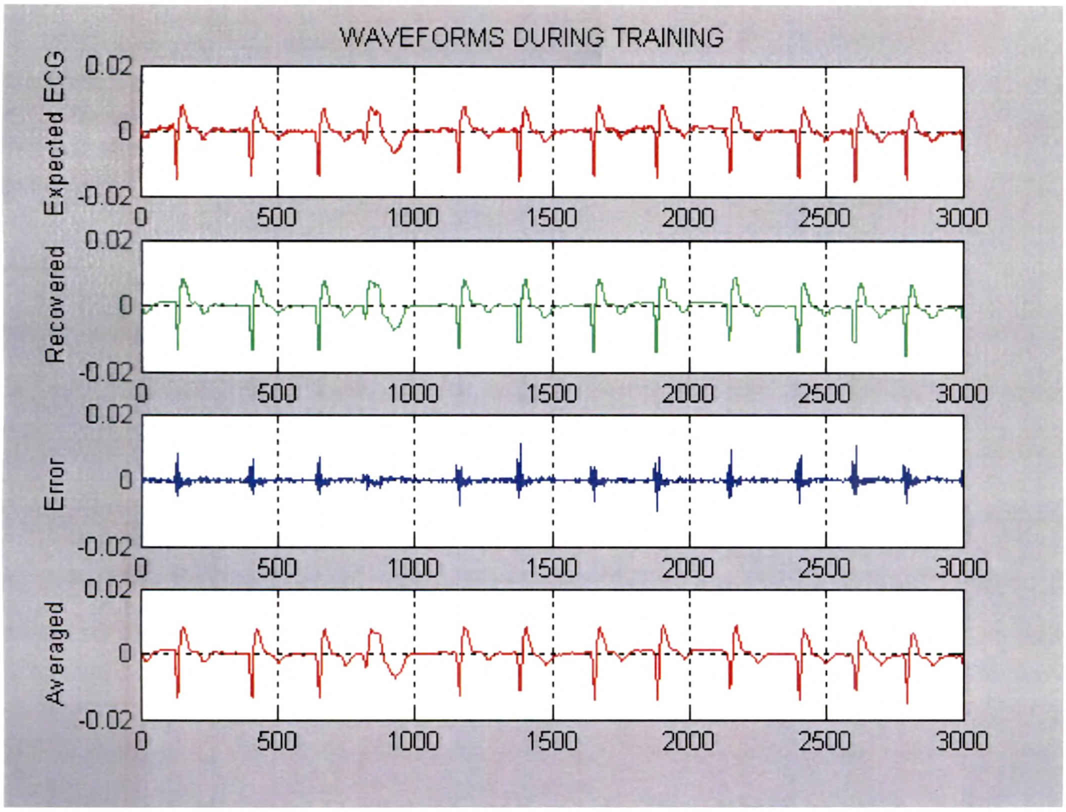

Figure 9.5 (a) Waveforms during training phase for compression using MLPANN

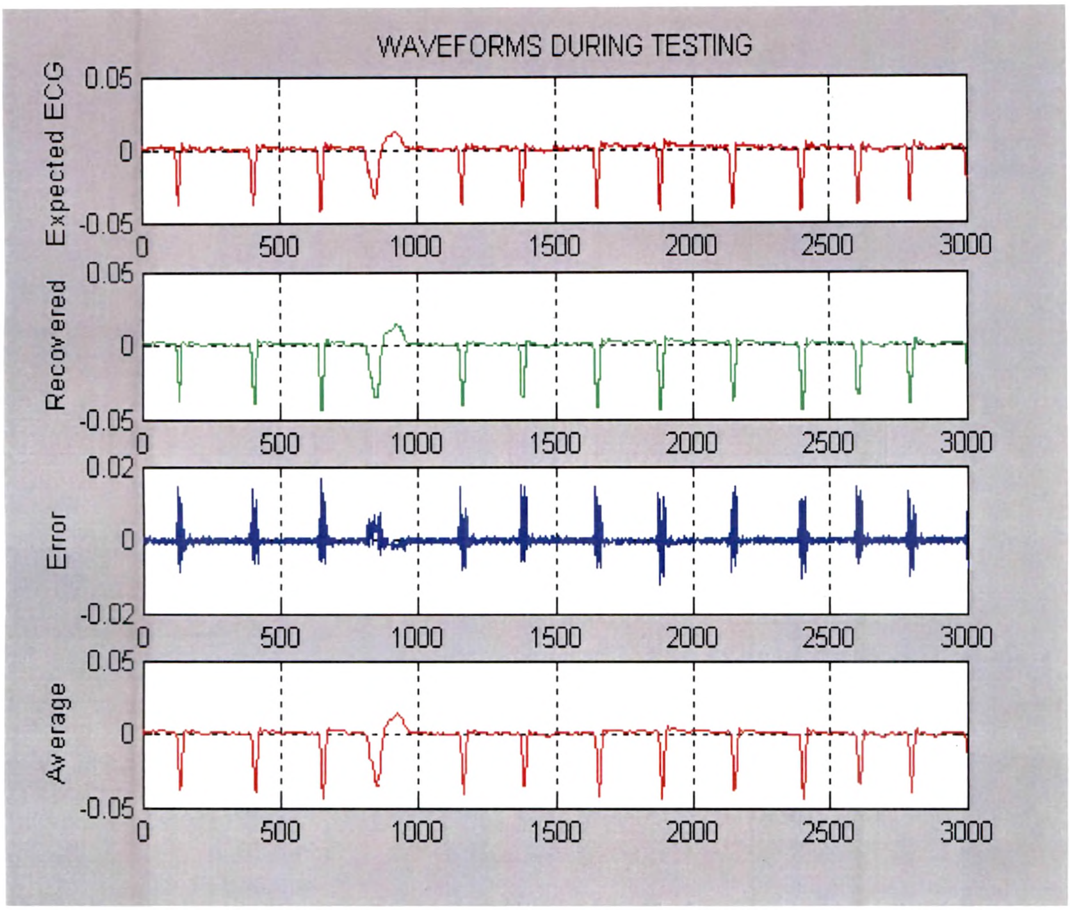

Figure 9.5 (b) Waveforms during training phase for compression using MLPANN

Figure 9.5 Waveforms for compression using MLPANN for set I

Set II

Sr No.	Type of signal		Values of parameters					
	training	testing	I=O	H	eta	TIME	TRG	TST
2	r	C3	6	3	0.1	500	500	500

Results obtained:

CR	PRD during training	PRD During testing
2	29.8005	24.0542

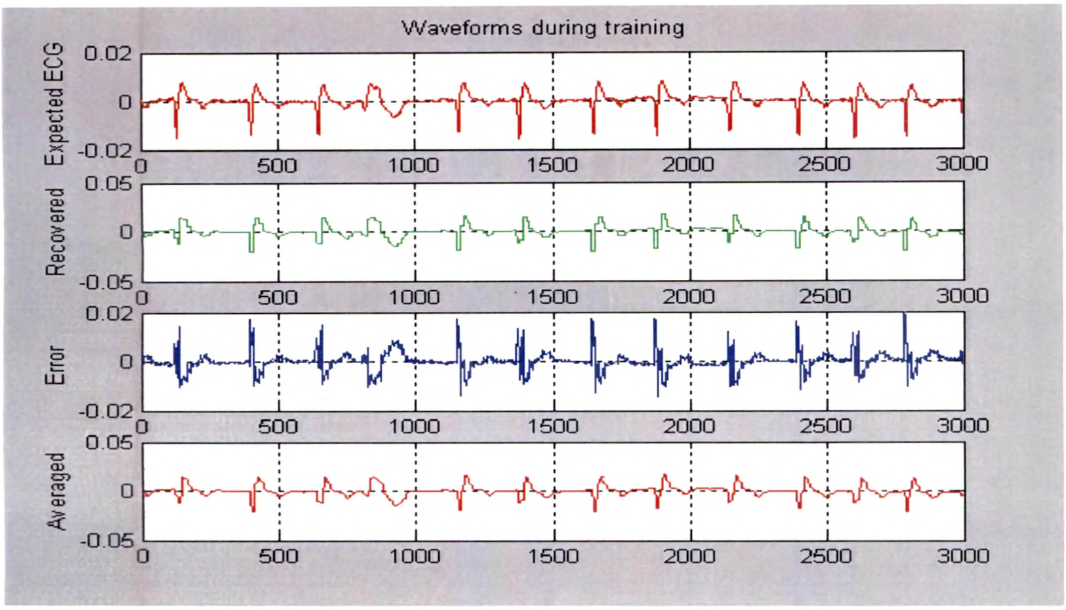

Figure 9.6 (a) Waveforms during training phase for compression using MLPANN

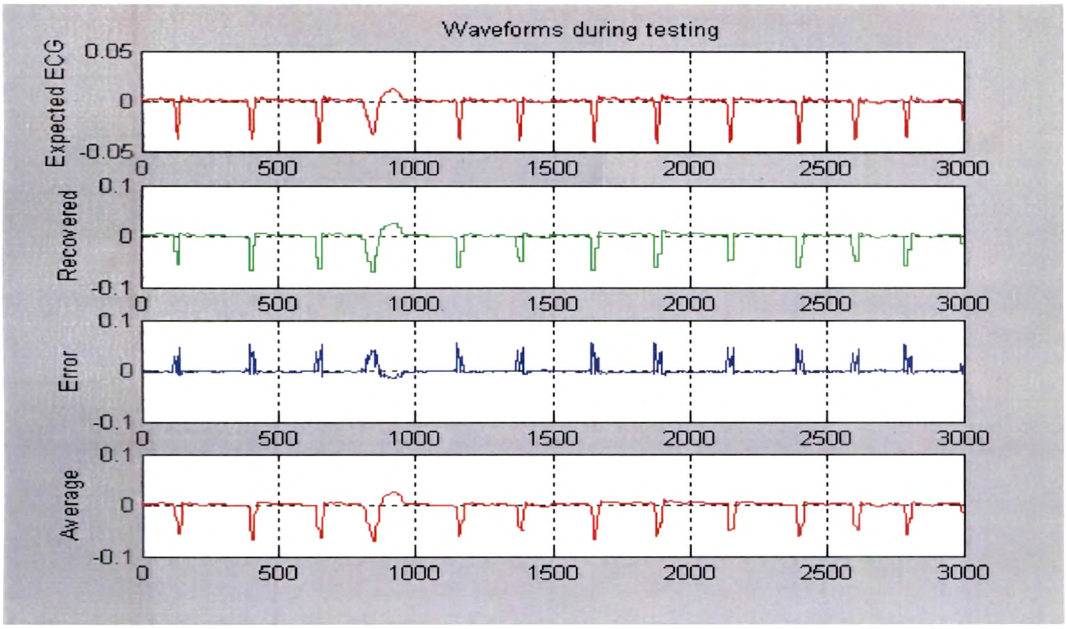

Figure 9.6 (b) Waveforms during training phase for compression using MLPANN

Figure 9.6 Waveforms for compression using MLPANN for set II

Set III

Sr No.	Type of signal		Values of parameters					
	training	testing	I=O	H	eta	TIME	TRG	TST
3	r	c3	6	3	0.1	1000	500	500

Results obtained:

CR	PRD during training	PRD During testing
2	28.7406	22.7858

Set IV

Sr No.	Type of signal		Value of parameters					
	training	testing	I=O	H	eta	TIME	TRG	TST
4	c2	c4	12	3	0.1	1000	250	250

Results obtained:

CR	PRD during training	PRD During testing
4	47.0833	47.7726

Higher and higher value of TIME improves PRD.

9.2.2 VQNN based compression (difference of samples)

Parameters

I : No. of input layer nodes
H : No. of hidden layer /competing nodes
eta : Learning rate
TIME : Number of time epoches
TRG : Number of training sets
TST : Number of test sets

Set I

Sr No.	Type of signal		Values of parameters					
	training	testing	I	H	eta	TIME	TRG	TST
1	r	r	300	100	0.1	2000	50	100

Results obtained:

CR (As per Equation 6.4)	PRD during training	PRD During testing
1200	149.0223	152.5699

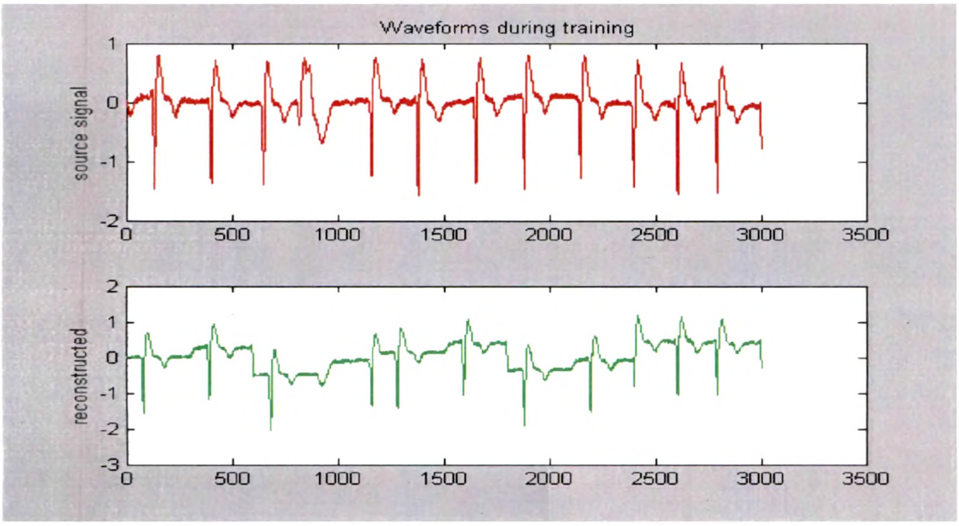

Figure 9.7 (a) Plot for original and reconstructed signals during training

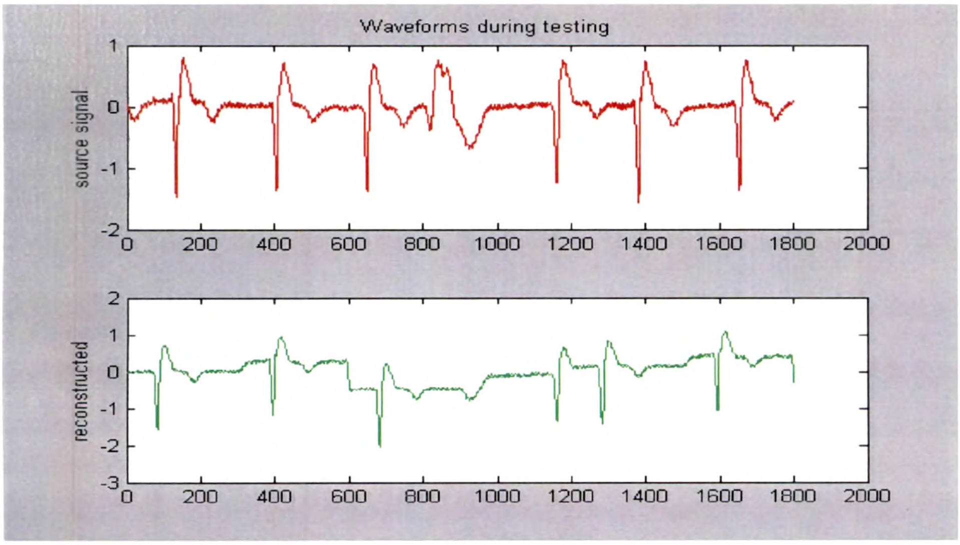

Figure 9.7 (b) Plot for original and reconstructed signals during testing

Figure 9.7 Waveforms for compression using VQANN (difference of samples)

As can be seen, this method can give better CR but can give faithful reproduction only if heavy training is imparted and large number of test patterns are used for training.

9.2.3 VQNN based compression (absolute samples)

Parameters

I	:	No. of input layer nodes
H	:	No. of hidden layer /competing nodes
eta	:	Learning rate
TIME	:	Number of time epoches
TRG	:	Number of training sets
TST	:	Number of test sets

Set I

Sr No.	Type of signal		Value of parameters					
	training	**testing**	**I**	**H**	**eta**	**TIME**	**TRG**	**TST**
1	r	l	4	128	0.05	8	128	500

Results obtained:

CR (As per Equation 6.4)	PRD during training	PRD During testing
6.85	2.3498	13.8434

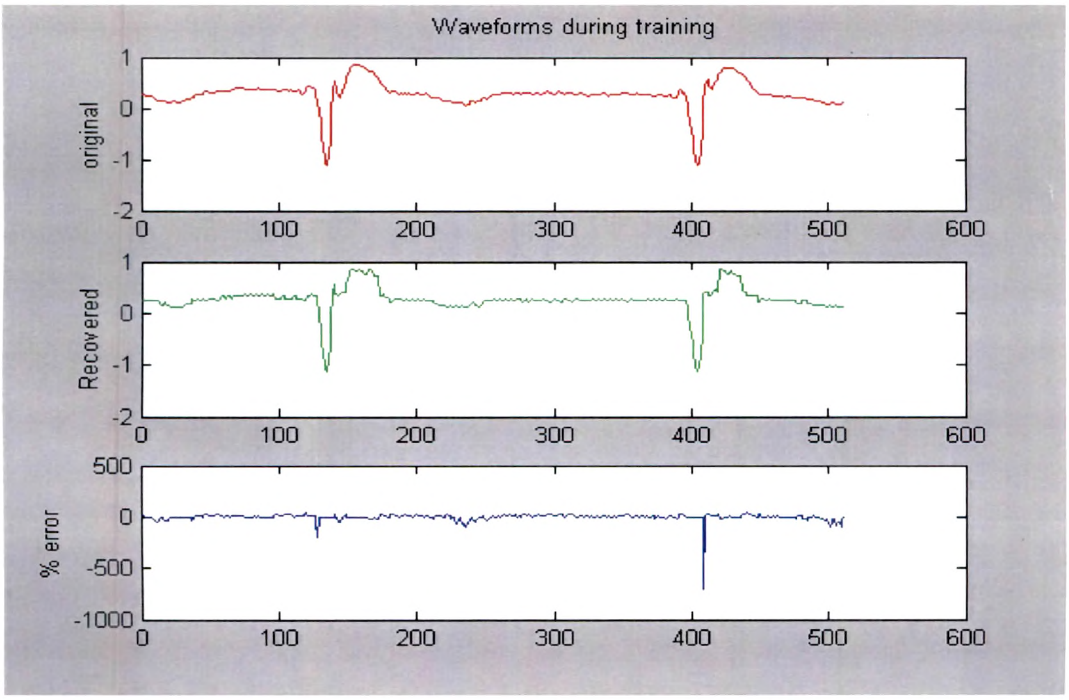

Figure 9.8 (a) Plot for original and reconstructed signals during training

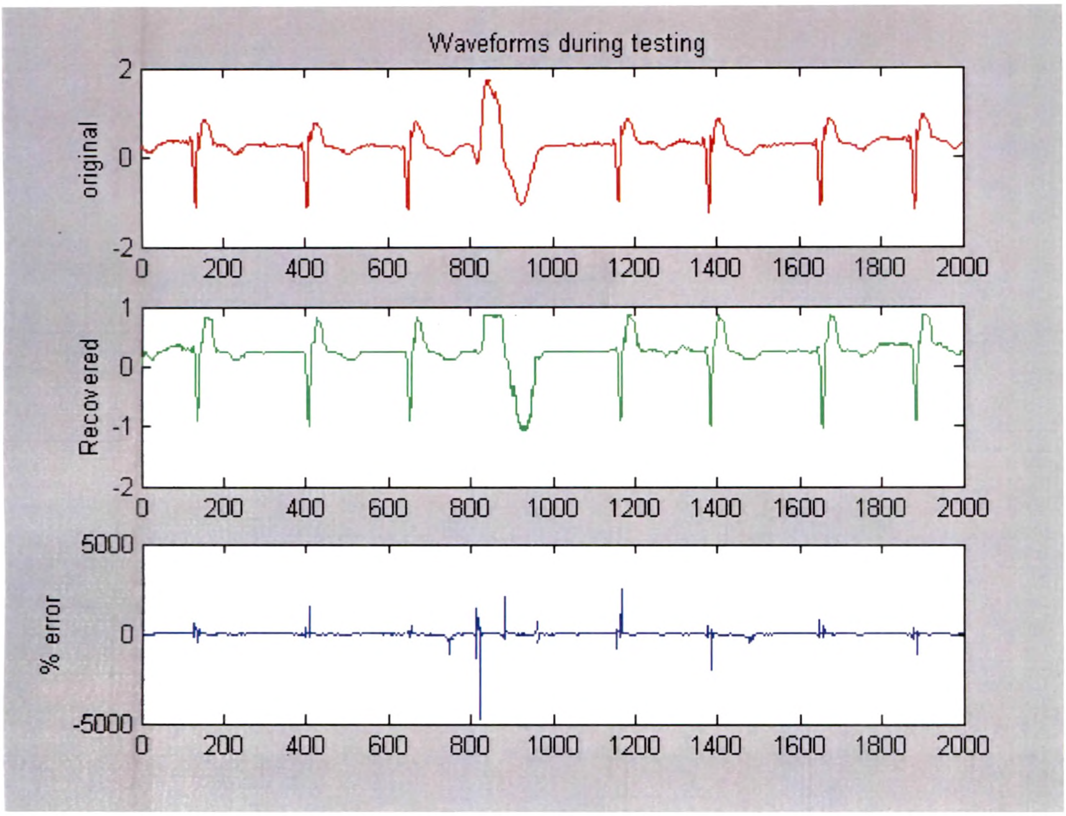

Figure 9.8 (b) Plot for Original and reconstructed signals during training

Figure 9.8 Waveforms for compression using VQANN (absolute samples)

These values of CR and PRD are comparable to such values by various methods listed in **table 6.2.**

9.3 VQNN based QRS detection

Parameters used:

I : No. of input layer nodes
H : No. of hidden layer /competing nodes
eta : Learning rate
TIME : Number of time epoches
TRG : Number of training sets
TST : Number of test sets

Set I

Sr No.	Type of signal	Value of parameters					
	training as well as testing	I	H	eta	TIME	TRG	TST
1	c1	40	128	0.05	5	200	2000

Output = 8 (Count/repeat for the selected pattern)

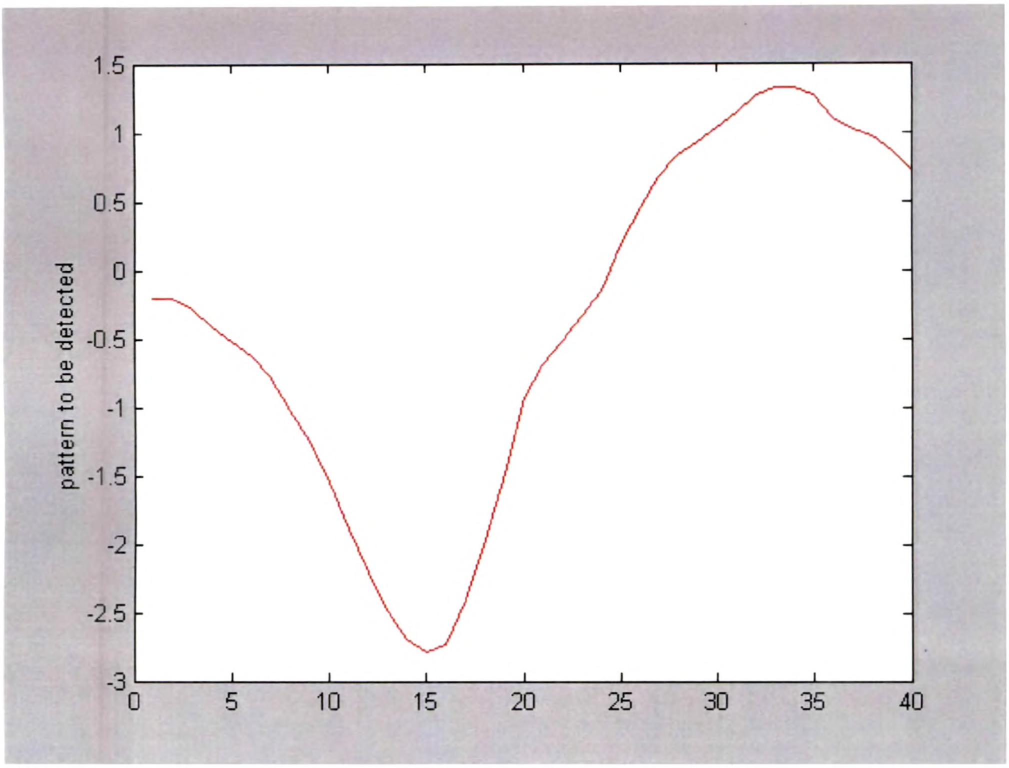

Figure 9.9 (a) Template of QRS complex to be detected for its occurrence

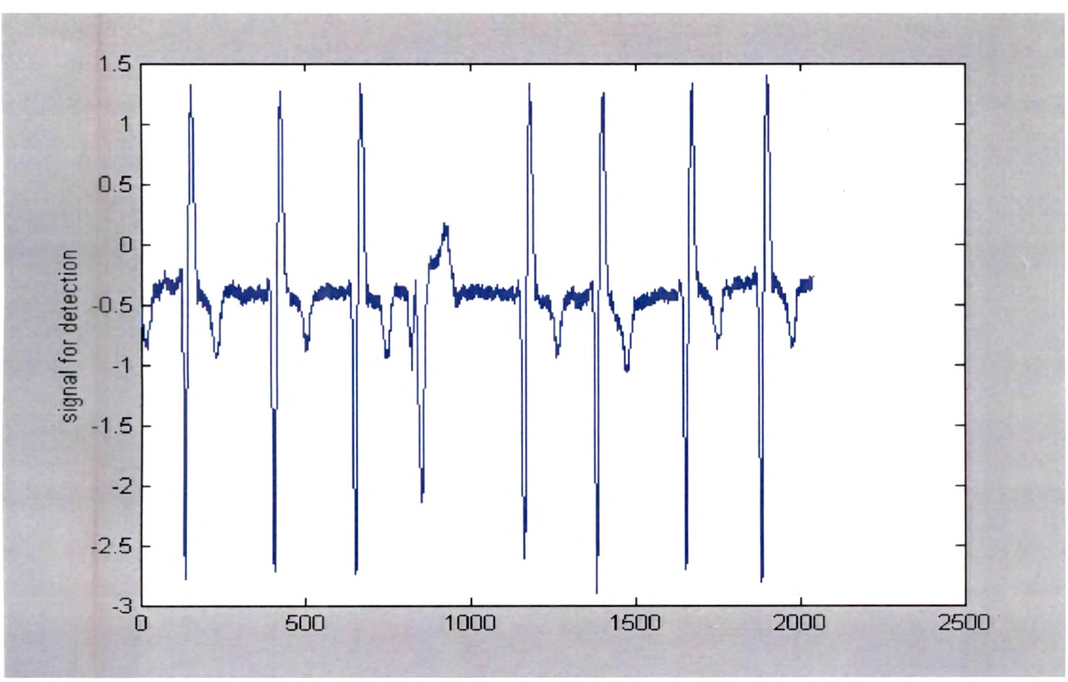

Figure 9.9 (b) Waveform from which QRS complex is to be detected

Figure 9.9 Waveforms for detection using VQANN

Algorithm works with 100% efficiency with correct detection upto any length as there is correct assignment of each pattern to each of 128 competing nodes.

9.4 Future scope

The environment developed helps user to carry out signal processing in a specified format. It is possible to extend the use of real time or on line signal processing. A hypothetical setup is shown in **Figure 9.10**.

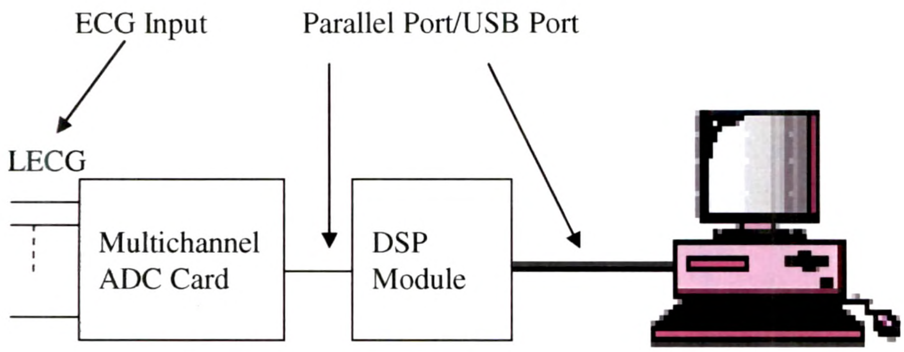

Figure 9.10 ECG Signal Processing Environment

The ECG input data can be received from eight leads through ADC Channels. A code using Plug-ins can be developed to create digital file online through DSP, using ccslink provided by "MATH WORKS" with MATLAB. This file can be used by the developed environment for online/ real time signal processing.

The software environment can be extended to carry out analysis and diagnosis of filtered or pure ECG signal. The compressed signal can be communicated through serial port to device at other end for experts' advice.

Currently advanced Neuro Fuzzy systems are also being developed. The software algorithms using Neuro Fuzzy and genetic algorithms can be developed and more flexible environment can be developed.