CHAPTER 7 Results and Discussions

7.1 Introduction

In this chapter, we compare the convergence and generalization capabilities of the EKF and other training algorithms. We tested the algorithms, in terms of dynamic training (pattern by pattern), for the ability to improve generalization as more and more new input patterns become available for training. Finally, we compare the classification results of the neural fuzzy system for various ECG signals.

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.

7.2 Comparative Results of Training Algorithms

Figure 7.1 illustrates the comparative results on the convergence and generalization capabilities of the EKF and other training algorithms. The y-axis corresponds to the classification rate relative to the whole training set. The x-axis represents distinct sub-data-sets used for training, where each sub-data-set consists of 4 distinct patterns. The training sequence goes as follows: first a distinct sub-data-set with four patterns is selected for training; then different neural networks with the same architecture are trained on that sub-data-set using different training algorithms until an acceptable classification rate relative to the four patterns has been achieved; subsequently the error rates relative to the whole training-set and for all the networks are calculated and plotted; finally a new sub-data-set of four patterns is chosen and the process is repeated until 60 sub-data-sets have been used.

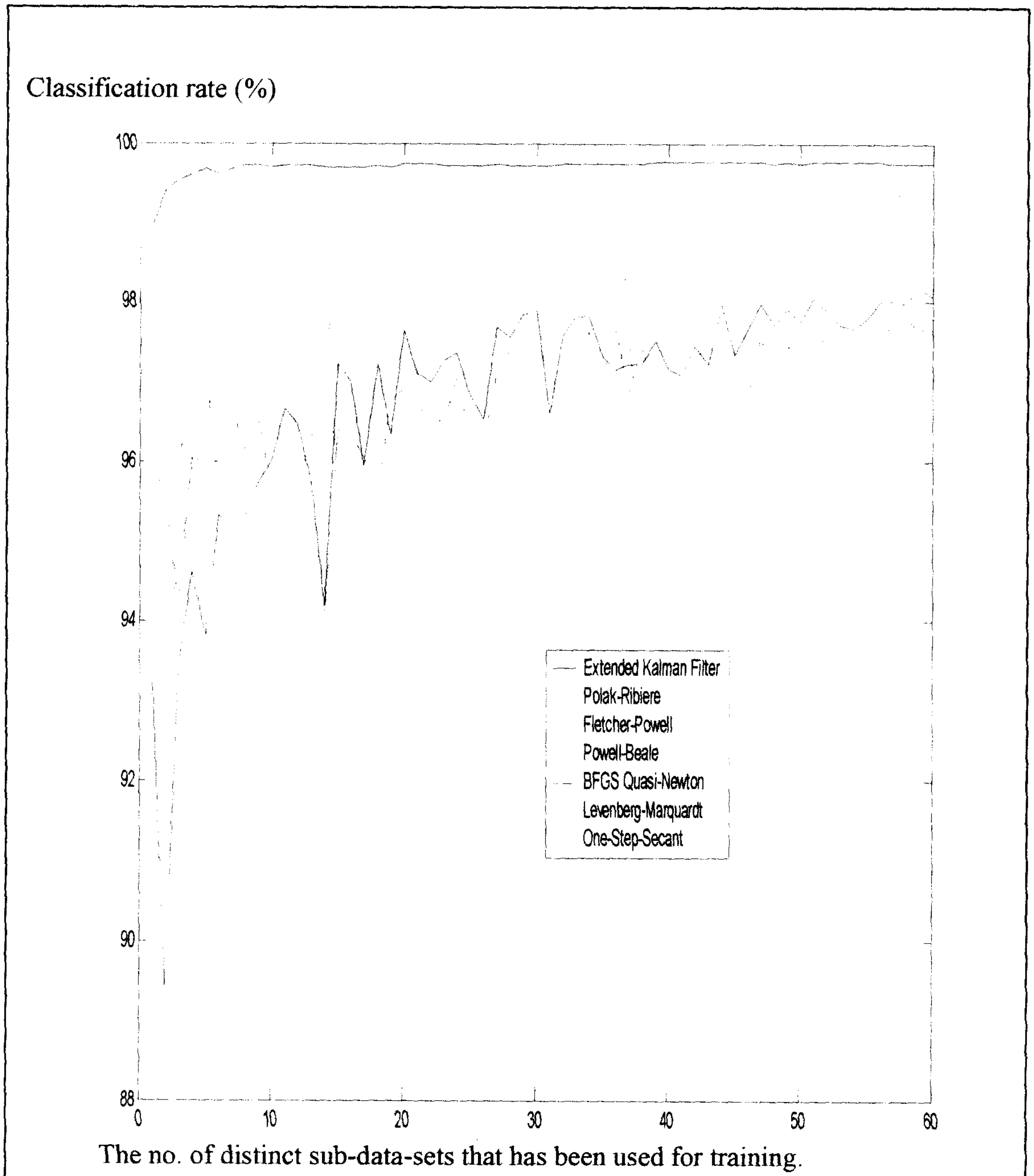


Figure 7.1: Comparison between various training algorithms for the MLPN.

Two significant observations can be made on immediate inspection of the plots in Figure 7.1, one regarding convergence and the other generalization. One can see that the EKF algorithm converges very fast as compared to other training algorithms: the classification rate relative to the whole training-set is already significantly high after training on only the first sub-data-set. Secondly, whereas the overall classification rate of other training algorithms can deteriorate significantly for some sub-data-sets, the EKF algorithm shows no significant dip in its classification rate, which seems to indicate that it has generalized adequately from the very beginning (i.e. it's ability to remember, or not forget, previously learned patterns, is most likely due to the fact that it has learnt to make a correct generalization of the patterns).

We also compare the classification results of the ECG signals using various training algorithms. In this comparative study, the patient population is divided into two groups i.e. Normal and Abnormal. There are 8 cases in the normal group and 8 cases in the abnormal group. Each case contains 16640 ECG cycles. We divide the ECG cycles into training and testing data-sets. The testing data-sets consist of 5 cases from each group and the training data-sets consist of 3 cases from each group. The training data-sets are then divided into three sub-data-sets. We first train the MLPN using the 1st sub-data-set according to the one step secant method (performed by the Matlab function 'trainoss'). We then calculate the classification rate using the testing data-sets. This training and testing process is repeated for the same MLPN using the 2nd and 3rd sub-data-set. We then compute the average classification rate for each training algorithm, e.g. Powell-Beale ('traincgb'), scaled conjugate gradient ('trainscg'), Polak-Ribiere ('traincgp'), resilient backpropagation ('trainrp'), gradient descent with both momentum and adaptive learning rate ('traingdx'), gradient descent with adaptive learning rate only ('traingda'), gradient descent with momentum only ('traingdm'), Levenberg-Marquardt ('trainlm'), quasi-Newton ('trainbfg') and Fletcher-Reeves ('traincgf') using the Matlab functions.

Training Algorithms	Error Rates (%) (trained with 1st sub-data-set)	Error Rates (%) (trained with 2nd sub-data-set)	Error Rates (%) (trained with 3rd sub-data-set)	Averages of Error Rates (%)
Trainoss	10.7206	12.1835	14.5078	12.4706
Traincgb	11.7864	8.8968	9.6090	10.0974
Trainscg	19.4395	9.3858	10.3647	13.0633
Traincgp	12.2995	11.3256	11.7804	11.8018
Trainrp	12.0027	10.6138	12.1150	11.5772
Traingdx	16.2549	16.2549	16.2549	16.2549
Traingda	10.2344	9.8706	9.5975	9.9008
Traingdm	16.2549	16.2549	16.2549	16.2549
Trainlm	11.4162	8.7272	11.9191	10.6875
Trainbfg	16.2549	16.2549	16.2549	16.2549
Traincgf	11.6464	9.4394	11.5262	10.8707
EKF	9.5738	10.7578	10.6540	10.3285

Table 7.1: Comparison between various training algorithms for the MLPN.

The classification results of the training algorithms are listed in Table 7.1. There are only two algorithms that have lower error rate than EKF i.e. Powell-Beale ('Traincgb') and gradient descent with adaptive learning rate ('Traingda'). The Powell-Beale algorithm has lower error rate than the EKF learning algorithm but the latter converges much faster than the former. Although the gradient descent with adaptive learning rate has the minimum error rate, it is impractical for clinical use due to its slow convergence rate as illustrated in Table 7.2.

Convergence speed \ Average error rate	Above 10.5 %	10 %-10.5 %	Below 10 %
Slow (Above 5 batches of iterations)	Traingdx, Traingdm		Traingda
Medium (3 to 5 batches of iterations)	Trainscg, Traincgp, Trainrp, Trainbfg, Traincgf	Traincgb	
Fast (below 3 batches of iterations)	Trainlm	EKF	

Table 7.2: Summary of comparison between various training algorithms for the MLPN.

7.3 ECG Classification Results

Each ECG signal has been simulated for approximately 16.67 minutes. The output value for each of the neural network is plotted in different colours (MLPN1 is in red, MLPN2 is in green and MLPN3 is in blue).

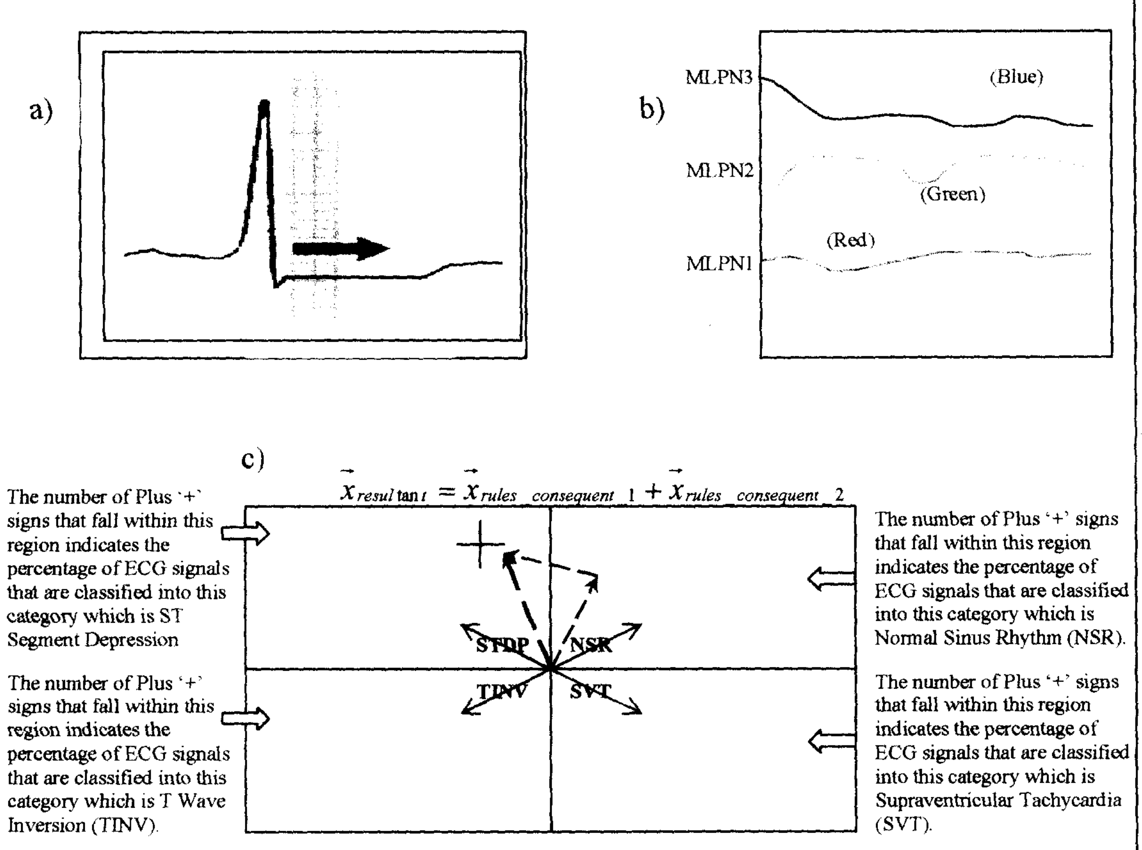
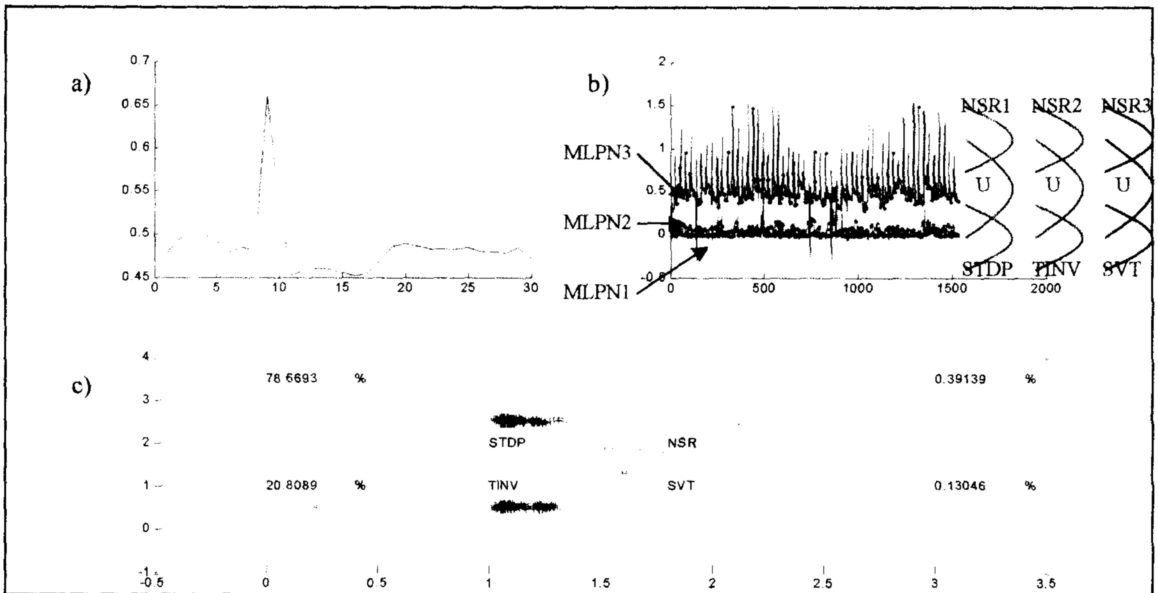


Figure 7.2: Classification of heart diseases using vector addition of rule consequent.

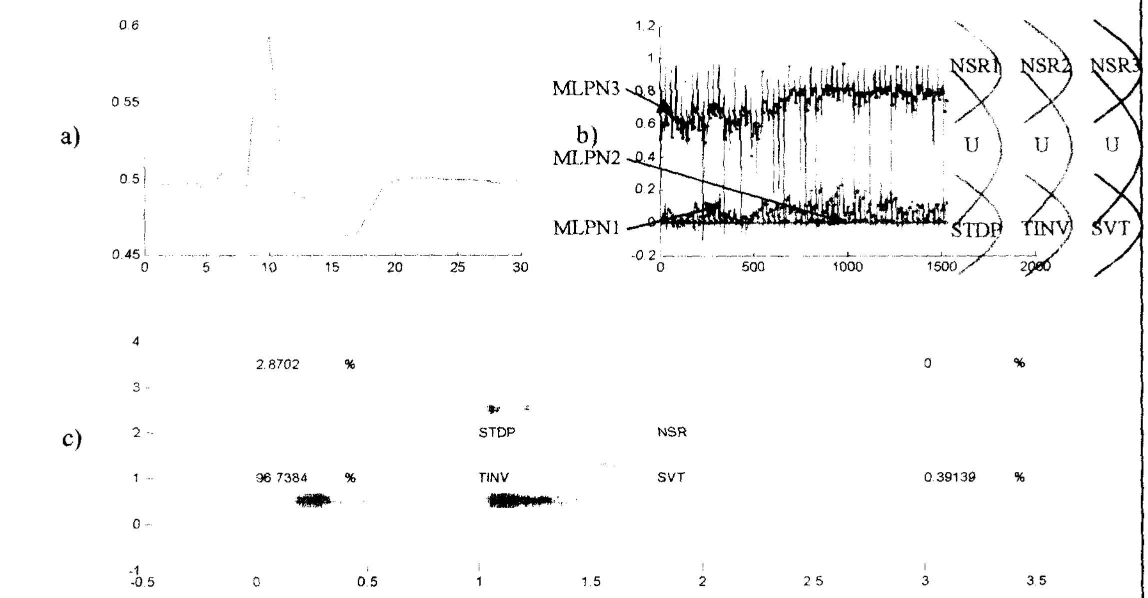
Before we present the simulation results for the classification of various ECG signals, we first illustrate the visual display of the classification results as shown in Figure 7.2 (a), (b) & (c). The visual display of the ECG signal is shown in Figure 7.2(a), as the output value of each neural network is plotted in 3 different colours (red, green, blue) as shown in Figure 7.2(b). Decision inference with the output values from the ensemble of MLPN gives the crisp result of the classification as shown in Figure 7.2(c). In the fuzzy system, each rule consequent (vector) will indicate the degree of vagueness that a certain heart disease may or may not be present. Vector summation of all rule consequents divided by the total number of rules will give the crisp classification result.



Indications U: Unknown ECG signals. NSR1, 2, 3: The 1st, 2nd and 3rd Type of Normal Sinus Rhythm Signals
STDP: ST Segment Depression Signals TINV: T Wave Inversion Signals

Figure 7.3: a) an abnormal ECG signal of ST segment depression (STDP) b) Output of the 1st MLPN (in red line) & Output of the 2nd MLPN (in green line) & Output of the 3rd MLPN (in blue line) c) Output of the Hybrid Fuzzy Neural System, as an abnormal ECG signal of ST segment depression (STDP) is simulated with the classification system.

We tested the classification system with 12 ECG signals consisting of various heart diseases as shown in Figures 7.3-7.14. In Figure 7.3, the classification system was tested with a STDP signal. The output values from the 1st, 2nd and 3rd MLPN are plotted in red, green and blue line respectively as shown in Figure 7.3(b). These output values from the 1st, 2nd and 3rd MLPN are partitioned into fuzzy regions and the corresponding membership functions are sketched in red, green and blue parabolic curves respectively as shown in Figure 7.3(b). The output value from the 1st MLPN (in red) has the highest density in the region of STDP signal. The output value from the 2nd MLPN (in green) has the highest density in the region of TINV signal. The output value from the 3rd MLPN (in blue) has the highest density in the region of Unknown signal. By referring to Table 6.2, when x_1(the output value from the 1st MLPN), x_2(the output value from the 2nd MLPN) and x_3(the output value from the 3rd MLPN) is clustered as STDP, TINV and Unknown signal respectively, the crisp classification result is STDP. As a result of the fluctuations in both the 2nd and 3rd MLPN output values, the classification rate for this STDP signal is only 78.6693% as shown in the upper left corner of Figure 7.3(c). The total misclassification rate is 22.3307% which consists of 20.8089% in the lower left corner (TINV), 0.39139% in the upper right corner (NSR) and 0.13046% in the lower right corner (SVT) of Figure 7.3(c).

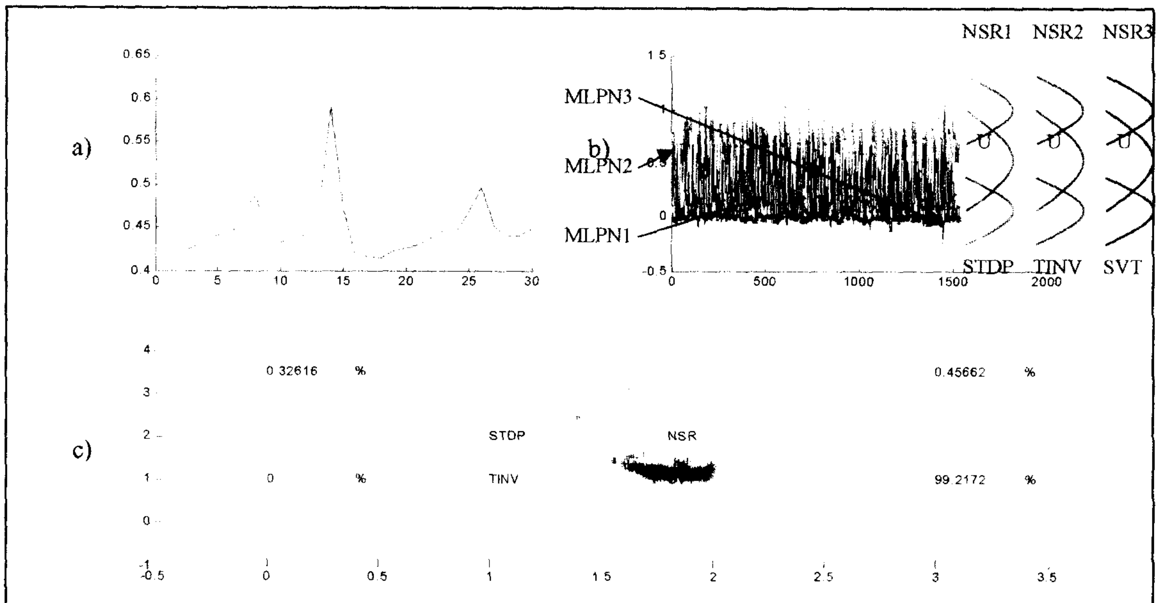


Indications U: Unknown ECG signals. NSR1, 2, 3: The 1st, 2nd and 3rd Type of Normal Sinus Rhythm Signals
STDP: ST Segment Depression Signals TINV: T Wave Inversion Signals

Figure 7.4: a) an abnormal ECG signal of T wave inversion (TINV) b) Output of the 1st MLPN (in red line) & Output of the 2nd MLPN (in green line) & Output of the 3rd MLPN (in blue line) c) Output of the Hybrid Fuzzy Neural System, as an abnormal ECG signal of T wave inversion (TINV) is simulated with the classification system.

In Figure 7.4, the classification system was tested with a TINV signal. The output values from the 1st, 2nd and 3rd MLPN are plotted in red, green and blue line respectively as shown in Figure 7.4(b). These output values from the 1st, 2nd and 3rd MLPN are partitioned into fuzzy regions and the corresponding membership functions are sketched in red, green and blue parabolic curves respectively as shown in Figure 7.4(b). The output value from the 1st MLPN (in red) has the highest density in the region of Unknown signal. The output value from the 2nd MLPN (in green) has the highest density in the region of TINV signal.

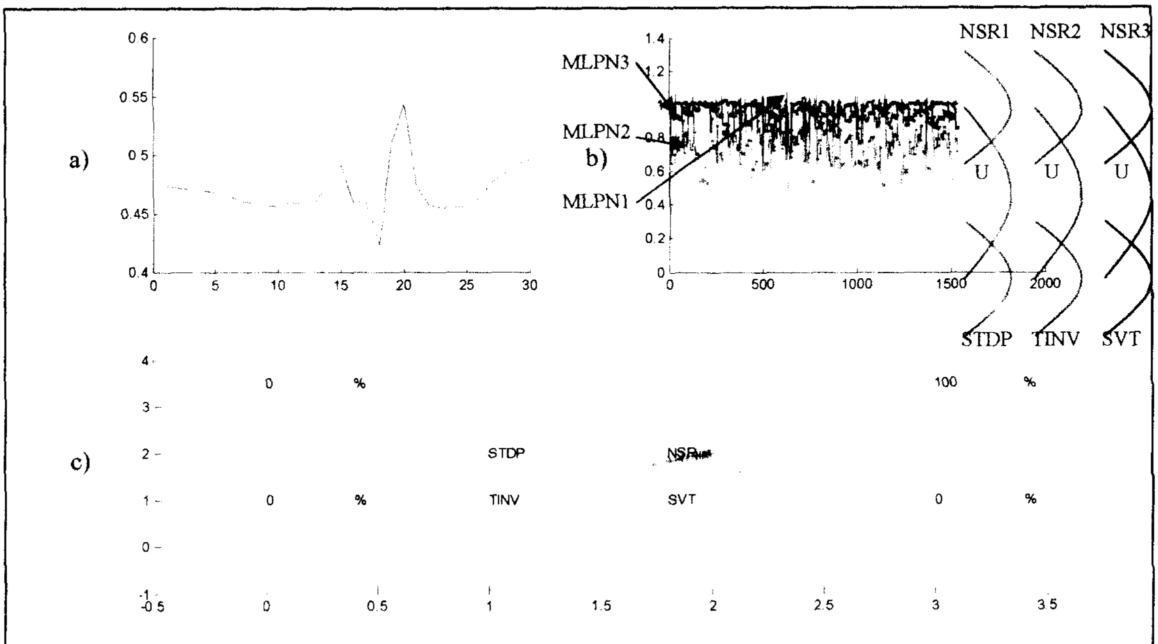
The output value from the 3rd MLPN (in blue) has the highest density in the region of Unknown signal. By referring to Table 6.2, when x_1 (the output value from the 1st MLPN), x_2 (the output value from the 2nd MLPN) and x_3 (the output value from the 3rd MLPN) is clustered as Unknown, TINV and Unknown signal respectively, the crisp classification result is TINV. As a result of the consistency in the 2nd MLPN output value, the classification rate for this TINV signal is 96.7384% as shown in the lower left corner of Figure 7.4(c). The total misclassification rate is only 3.2616% which consists of 2.8702% in the upper left corner (STDP), 0% in the upper right corner (NSR) and 0.39139% in the lower right corner (SVT) of Figure 7.4(c).



Indications U: Unknown ECG signals. NSR1, 2, 3: The 1st, 2nd and 3rd Type of Normal Sinus Rhythm Signals
STDP: ST Segment Depression Signals TINV: T Wave Inversion Signals

Figure 7.5: a) an abnormal ECG signal of Supraventricular Tachycardia (SVT) b) Output of the 1st MLPN (in red line) & Output of the 2nd MLPN (in green line) & Output of the 3rd MLPN (in blue line) c) Output of the Hybrid Fuzzy Neural System, as an abnormal ECG signal of Supraventricular Tachycardia (SVT) is simulated with the classification system.

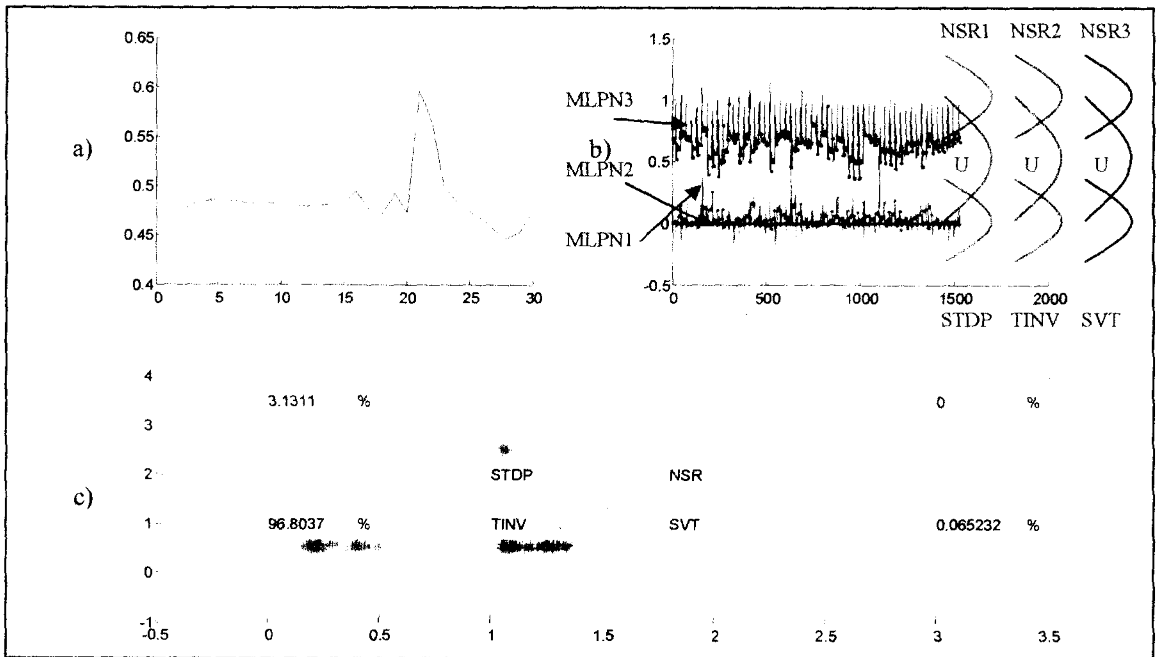
In Figure 7.5, the classification system was tested with a SVT signal. The output values from the 1st, 2nd and 3rd MLPN are plotted in red, green and blue line respectively as shown in Figure 7.5(b). These output values from the 1st, 2nd and 3rd MLPN are partitioned nto fuzzy regions and the corresponding membership functions are sketched in red, green ınd blue parabolic curves respectively as shown in Figure 7.5(b). The output value from the 1st MLPN (in red) has the highest density in the region of Unknown signal. The output value from the 2nd MLPN (in green) has the highest density in the region of Unknown signal. The output value from the 3rd MLPN (in blue) has the highest density in the region of SVT signal. By referring to Table 6.1, when x_1 (the output value from the 1st MLPN), x_2 (the output value from the 2nd MLPN) and x_3 (the output value from the 3rd MLPN) is clustered as Unknown, Unknown and SVT signal respectively, the crisp classification result is SVT. As a result of the consistency in the 3rd MLPN output value, the classification rate for this SVT signal is 99.2172% as shown in the lower right corner of Figure 7.5(c). The total misclassification rate is only 0.7828% which consists of 0% in the lower left corner (TINV), 0.45662% in the upper right corner (NSR) and 0.32616% in the upper left corner (STDP) of Figure 7.5(c).



Indications U: Unknown ECG signals. NSR1, 2, 3: The 1st, 2nd and 3rd Type of Normal Sinus Rhythm Signals
STDP: ST Segment Depression Signals TINV: T Wave Inversion Signals

Figure 7.6: a) a normal ECG signal of Normal Sinus Rhythm (NSR) b) Output of the 1st MLPN (in red line) & Output of the 2nd MLPN (in green line) & Output of the 3rd MLPN (in blue line) c) Output of the Hybrid Fuzzy Neural System, as a normal ECG signal of Normal Sinus Rhythm (NSR) is simulated with the classification system.

In Figure 7.6, the classification system was tested with a NSR signal. The output values from the 1st, 2nd and 3rd MLPN are plotted in red, green and blue line respectively as shown in Figure 7.6(b). These output values from the 1st, 2nd and 3rd MLPN are partitioned into fuzzy regions and the corresponding membership functions are sketched in red, green and blue parabolic curves respectively as shown in Figure 7.6(b). The output value from the 1st MLPN (in red) has the highest density in the region of NSR signal. The output value from the 2nd MLPN (in green) has the highest density in the region of Unknown signal. The output value from the 3rd MLPN (in blue) has the highest density in the region of NSR signal. By referring to Table 6.3, when x_1(the output value from the 1st MLPN), x_2(the output value from the 2nd MLPN) and x_3(the output value from the 3rd MLPN) is clustered as NSR, Unknown and NSR signal respectively, the crisp classification result is NSR. As a result of the consistencies in both the 1st and 3rd MLPN output values, the classification rate for this NSR signal is 100% as shown in the upper right corner of Figure 7.6(c).

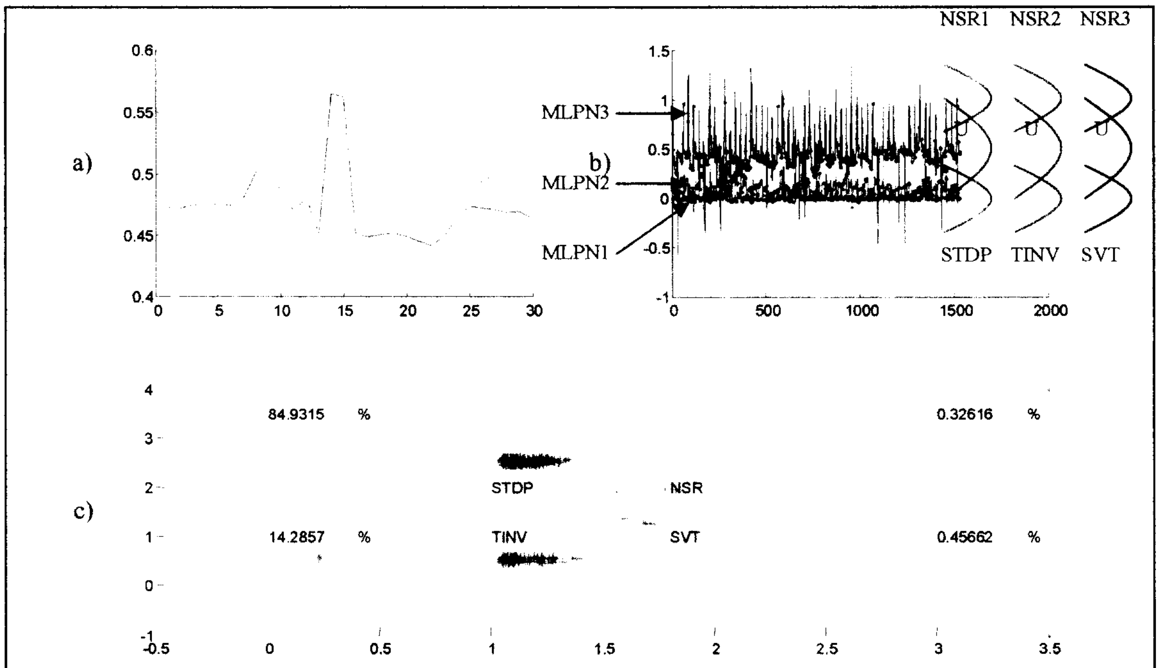


Indications U: Unknown ECG signals. NSR1, 2, 3: The 1st, 2nd and 3rd Type of Normal Sinus Rhythm Signals
STDP: ST Segment Depression Signals TINV: T Wave Inversion Signals

Figure 7.7: a) an abnormal ECG signal of T wave inversion (TINV) b) Output of the 1st MLPN (in red line) & Output of the 2nd MLPN (in green line) & Output of the 3rd MLPN (in blue line) c) Output of the Hybrid Fuzzy Neural System, as an abnormal ECG signal of T wave inversion (TINV) is simulated with the classification system.

In Figure 7.7, the classification system was tested with a TINV signal. The output values from the 1st, 2nd and 3rd MLPN are plotted in red, green and blue line respectively as shown in Figure 7.7(b). These output values from the 1st, 2nd and 3rd MLPN are partitioned into fuzzy regions and the corresponding membership functions are sketched in red, green and blue parabolic curves respectively as shown in Figure 7.7(b). The output value from the 1st MLPN (in red) has the highest density in the region of Unknown signal. The output value from the 2nd MLPN (in green) has the highest density in the region of TINV signal. The output value from the 3rd MLPN (in blue) has the highest density in the region of Unknown signal. By referring to Table 6.2, when x_1 (the output value from the 1st MLPN),

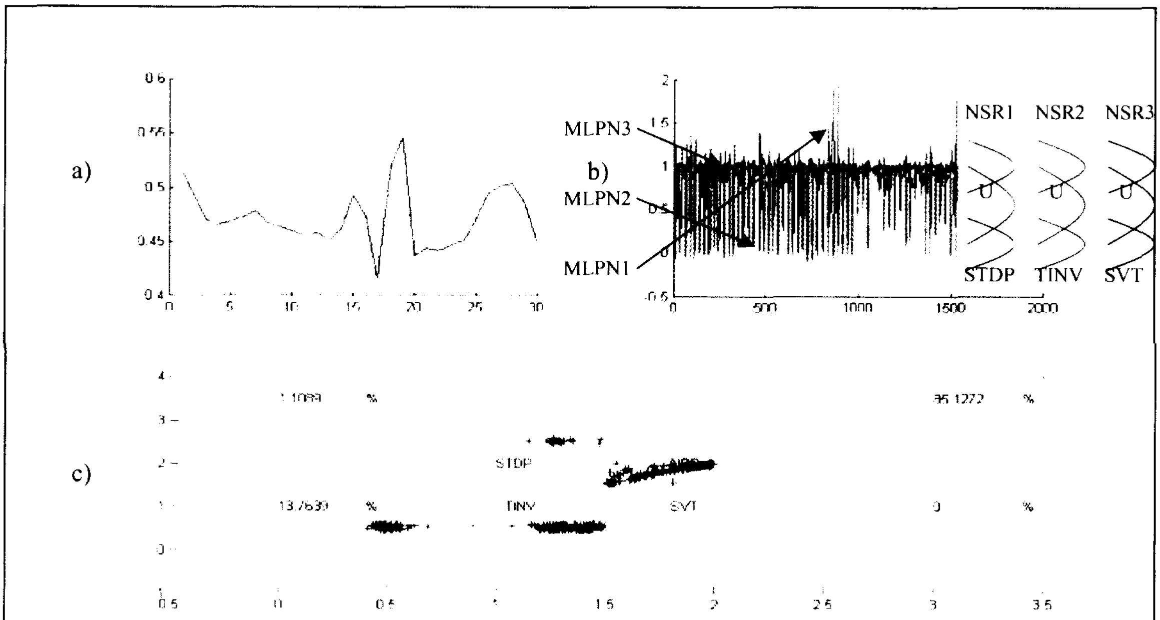
x_2(the output value from the 2nd MLPN) and x_3(the output value from the 3rd MLPN) is clustered as Unknown, TINV and Unknown signal respectively, the crisp classification result is TINV. As a result of the consistency in the 2nd MLPN output value, the classification rate for this TINV signal is 96.8037% as shown in the lower left corner of Figure 7.7(c). The total misclassification rate is only 3.1963% which consists of 3.1311% in the upper left corner (STDP), 0% in the upper right corner (NSR) and 0.065232% in the lower right corner (SVT) of Figure 7.7(c).



Indications U: Unknown ECG signals. NSR1, 2, 3: The 1st, 2nd and 3rd Type of Normal Sinus Rhythm Signals
STDP: ST Segment Depression Signals TINV: T Wave Inversion Signals

Figure 7.8: a) an abnormal ECG signal of ST segment depression (STDP) b) Output of the 1st MLPN (in red line) & Output of the 2nd MLPN (in green line) & Output of the 3rd MLPN (in blue line) c) Output of the Hybrid Fuzzy Neural System, as an abnormal ECG signal of ST segment depression (STDP) is simulated with the classification system.

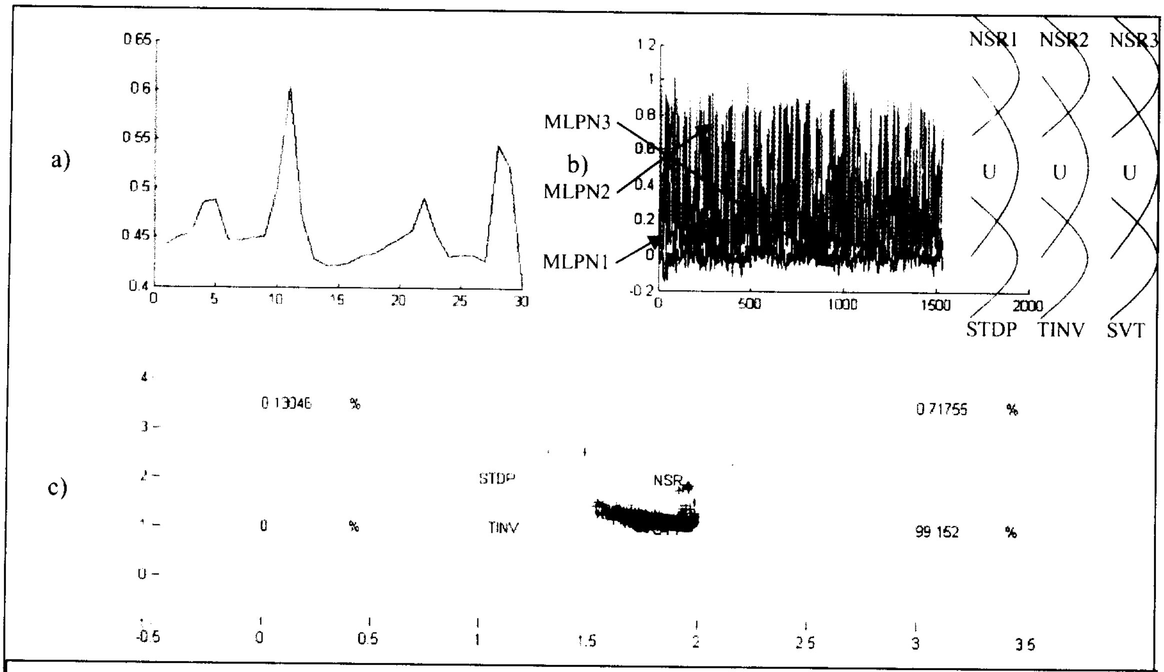
In Figure 7.8, the classification system was tested with a STDP signal. The output values from the 1st, 2nd and 3rd MLPN are plotted in red, green and blue line respectively as shown in Figure 7.8(b). These output values from the 1st, 2nd and 3rd MLPN are partitioned into fuzzy regions and the corresponding membership functions are sketched in red, green and blue parabolic curves respectively as shown in Figure 7.8(b). The output value from the 1st MLPN (in red) has the highest density in the region of STDP signal. The output value from the 2nd MLPN (in green) has the highest density in the region of TINV signal. The output value from the 3rd MLPN (in blue) has the highest density in the region of Unknown signal. By referring to Table 6.2, when x_1(the output value from the 1st MLPN), x_2(the output value from the 2nd MLPN) and x_3(the output value from the 3rd MLPN) is clustered as STDP, TINV and Unknown signal respectively, the crisp classification result is STDP. As a result of the fluctuations in both the 2nd and 3rd MLPN output values, the classification rate for this STDP signal is only 84.9315% as shown in the upper left corner of Figure 7.8(c). The total misclassification rate is 15.0685% which consists of 14.2857% in the lower left corner (TINV), 0.32616% in the upper right corner (NSR) and 0.45662% in the lower right corner (SVT) of Figure 7.8(c).



Indications U: Unknown ECG signals. NSR1, 2, 3: The 1st, 2nd and 3rd Type of Normal Sinus Rhythm Signals
STDP: ST Segment Depression Signals TINV: T Wave Inversion Signals

Figure 7.9: a) a normal ECG signal of Normal Sinus Rhythm (NSR) b) Output of the 1st MLPN (in red line) & Output of the 2nd MLPN (in green line) & Output of the 3rd MLPN (in blue line) c) Output of the Hybrid Fuzzy Neural System, as a normal ECG signal of Normal Sinus Rhythm (NSR) is simulated with the classification system.

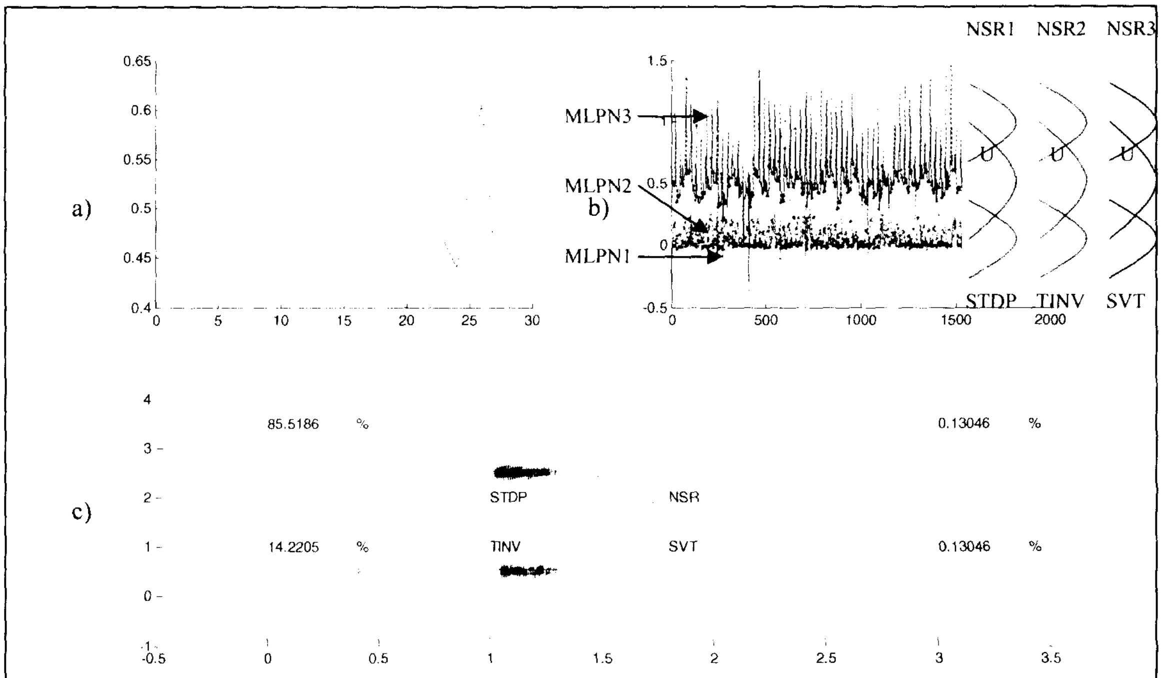
In Figure 7.9, the classification system was tested with a NSR signal. The output values from the 1st, 2nd and 3rd MLPN are plotted in red, green and blue line respectively as shown in Figure 7.9(b). These output values from the 1st, 2nd and 3rd MLPN are partitioned into fuzzy regions and the corresponding membership functions are sketched in red, green and blue parabolic curves respectively as shown in Figure 7.9(b). The output value from the 1st MLPN (in red) has the highest density in the region of Unknown signal. The output value from the 2nd MLPN (in green) has the highest density in the region of Unknown signal. The output value from the 3rd MLPN (in blue) has the highest density in the region of NSR signal. By referring to Table 6.3, when x_1 (the output value from the 1st MLPN), x_2 (the output value from the 2nd MLPN) and x_3 (the output value from the 3rd MLPN) is clustered as Unknown, Unknown and NSR signal respectively, the crisp classification result is NSR. As a result of the fluctuations in both the 1st and 2nd MLPN output values, the classification rate for this NSR signal is only 85.1272% as shown in the upper right corner of Figure 7.9(c). The total misclassification rate is 14.8728% which consists of 1.1089% in the upper left corner (STDP), 13.7639% in the lower left corner (TINV) and 0% in the lower right corner (SVT) of Figure 7.9(c).



Indications U: Unknown ECG signals. NSR1, 2, 3: The 1st, 2nd and 3rd Type of Normal Sinus Rhythm Signals
STDP: ST Segment Depression Signals TINV: T Wave Inversion Signals

Figure 7.10: a) an abnormal ECG signal of Supraventricular Tachycardia (SVT) b) Output of the 1st MLPN (in red line) & Output of the 2nd MLPN (in green line) & Output of the 3rd MLPN (in blue line) c) Output of the Hybrid Fuzzy Neural System, as an abnormal ECG signal of Supraventricular Tachycardia (SVT) is simulated with the classification system.

In Figure 7.10, the classification system was tested with a SVT signal. The output values from the 1st, 2nd and 3rd MLPN are plotted in red, green and blue line respectively as shown in Figure 7.10(b). These output values from the 1st, 2nd and 3rd MLPN are partitioned into fuzzy regions and the corresponding membership functions are sketched in red, green and blue parabolic curves respectively as shown in Figure 7.10(b). The output value from the 1st MLPN (in red) has the highest density in the region of Unknown signal. The output value from the 2nd MLPN (in green) has the highest density in the region of Unknown signal. The output value from the 3rd MLPN (in blue) has the highest density in the region of SVT signal. By referring to Table 6.1, when x_1(the output value from the 1st MLPN), x_2(the output value from the 2nd MLPN) and x_3(the output value from the 3rd MLPN) is clustered as Unknown, Unknown and SVT signal respectively, the crisp classification result is SVT. As a result of the consistency in the 3rd MLPN output value, the classification rate for this SVT signal is 99.152% as shown in the lower right corner of Figure 7.10(c). The total misclassification rate is only 0.848% which consists of 0.13046% in the upper left corner (STDP), 0% in the lower left corner (TINV) and 0.71755% in the upper right corner (NSR) of Figure 7.10(c).

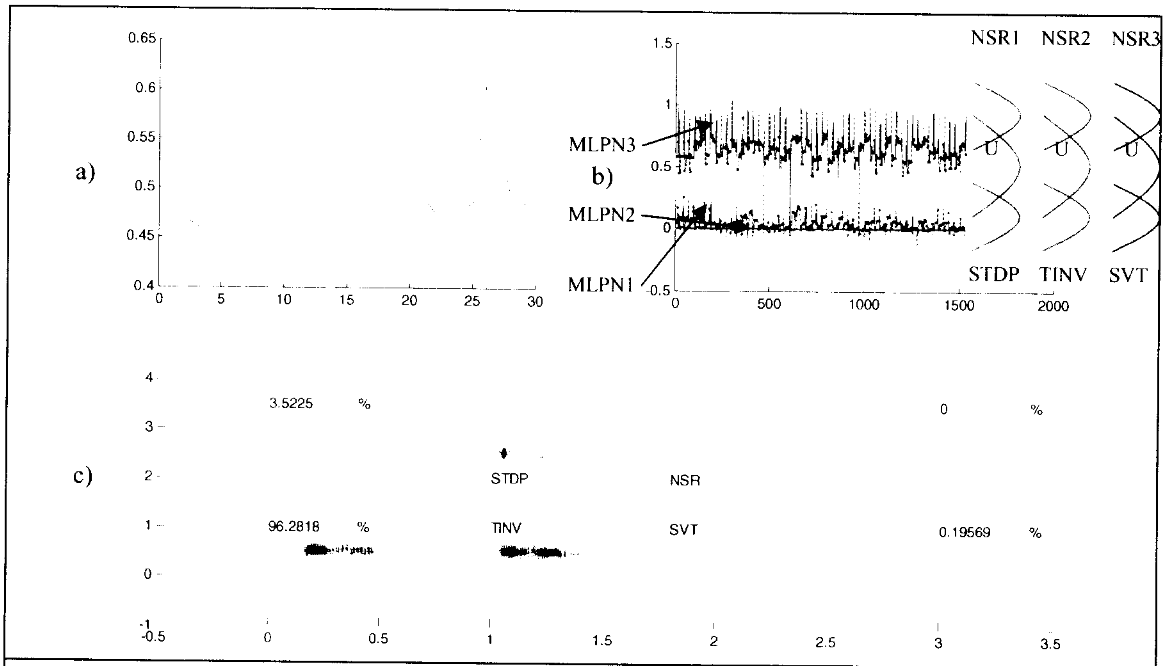


Indications U: Unknown ECG signals. NSR1, 2, 3: The 1st, 2nd and 3rd Type of Normal Sinus Rhythm Signals
STDP: ST Segment Depression Signals TINV: T Wave Inversion Signals

Figure 7.11: a) an abnormal ECG signal of ST segment depression (STDP) b) Output of the 1st MLPN (in red line) & Output of the 2nd MLPN (in green line) & Output of the 3rd MLPN (in blue line) c) Output of the Hybrid Fuzzy Neural System, as an abnormal ECG signal of ST segment depression (STDP) is simulated with the classification system.

In Figure 7.11, the classification system was tested with a STDP signal. The output values from the 1st, 2nd and 3rd MLPN are plotted in red, green and blue line respectively as shown in Figure 7.11(b). These output values from the 1st, 2nd and 3rd MLPN are partitioned into fuzzy regions and the corresponding membership functions are sketched in red, green and blue parabolic curves respectively as shown in Figure 7.11(b). The output value from the 1st MLPN (in red) has the highest density in the region of STDP signal. The output value from the 2nd MLPN (in green) has the highest density in the region of TINV signal.

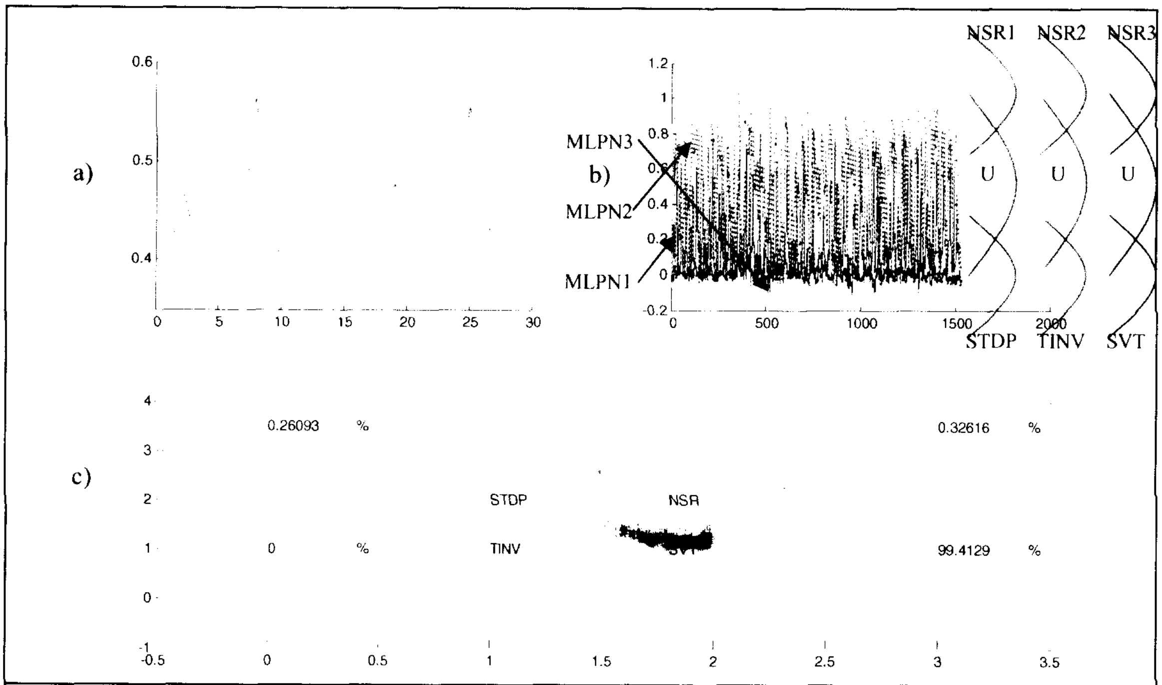
The output value from the 3rd MLPN (in blue) has the highest density in the region of Unknown signal. By referring to Table 6.2, when x_1 (the output value from the 1st MLPN), x_2 (the output value from the 2nd MLPN) and x_3 (the output value from the 3rd MLPN) is clustered as STDP, TINV and Unknown signal respectively, the crisp classification result is STDP. As a result of the high level of fluctuation in the 3rd MLPN output value, the classification rate for this STDP signal is only 85.5186% as shown in the lower right corner of Figure 7.11(c). The total misclassification rate is 14.4814% which consists of 0.13046% in the upper right corner (NSR), 14.2205% in the lower left corner (TINV) and 0.13046% in the lower right corner (SVT) of Figure 7.11(c).



Indications U: Unknown ECG signals. NSR1, 2, 3: The 1st, 2nd and 3rd Type of Normal Sinus Rhythm Signals
STDP: ST Segment Depression Signals TINV: T Wave Inversion Signals

Figure 7.12: a) an abnormal ECG signal of T wave inversion (TINV) b) Output of the 1st MLPN (in red line) & Output of the 2nd MLPN (in green line) & Output of the 3rd MLPN (in blue line) c) Output of the Hybrid Fuzzy Neural System, as an abnormal ECG signal of T wave inversion (TINV) is simulated with the classification system.

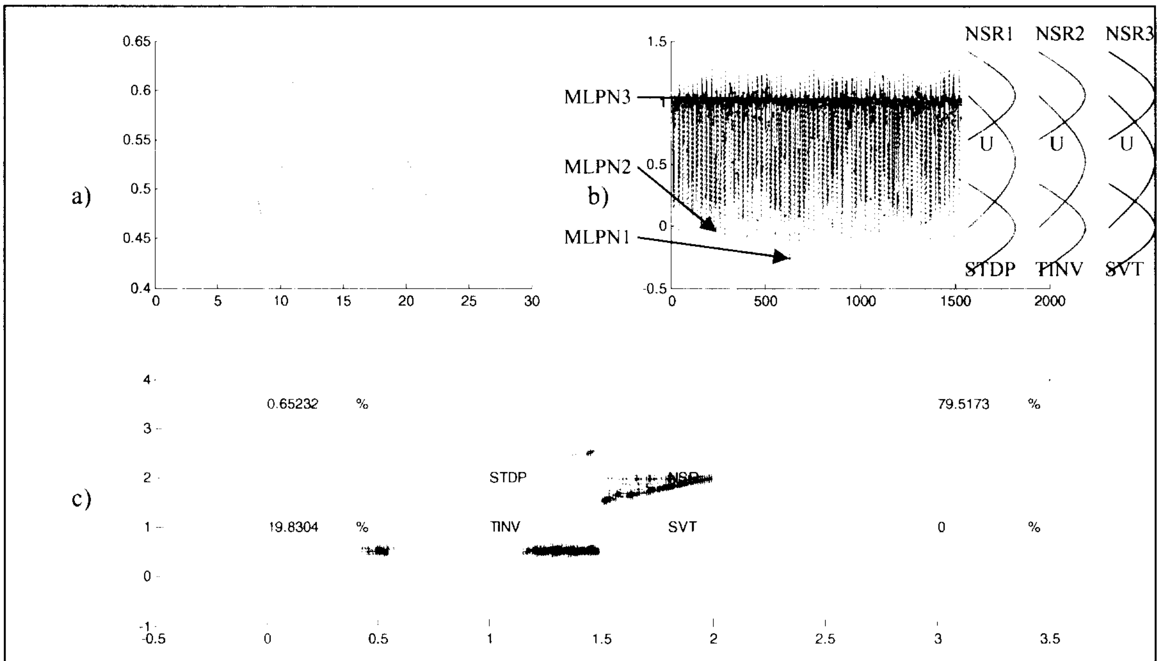
In Figure 7.12, the classification system was tested with a TINV signal. The output values from the 1st, 2nd and 3rd MLPN are plotted in red, green and blue line respectively as shown in Figure 7.12(b). These output values from the 1st, 2nd and 3rd MLPN are partitioned into fuzzy regions and the corresponding membership functions are sketched in red, green and blue parabolic curves respectively as shown in Figure 7.12(b). The output value from the 1st MLPN (in red) has the highest density in the region of Unknown signal. The output value from the 2nd MLPN (in green) has the highest density in the region of TINV signal. The output value from the 3rd MLPN (in blue) has the highest density in the region of Unknown signal. By referring to Table 6.3, when x_1 (the output value from the 1st MLPN), x_2 (the output value from the 2nd MLPN) and x_3 (the output value from the 3rd MLPN) is clustered as Unknown, TINV and Unknown signal respectively, the crisp classification result is TINV. As a result of the consistency in the 2nd MLPN output value, the classification rate for this TINV signal is 96.2818% as shown in the lower left corner of Figure 7.12(c). The total misclassification rate is only 3.7182% which consists of 3.5225%in the upper left corner (STDP), 0% in the upper right corner (NSR) and 0.19569% in the lower right corner (SVT) of Figure 7.12(c).



Indications U: Unknown ECG signals. NSR1, 2, 3: The 1st, 2nd and 3rd Type of Normal Sinus Rhythm Signals
STDP: ST Segment Depression Signals TINV: T Wave Inversion Signals

Figure 7.13: a) an abnormal ECG signal of Supraventricular Tachycardia (SVT) b) Output of the 1st MLPN (in red line) & Output of the 2nd MLPN (in green line) & Output of the 3rd MLPN (in blue line) c) Output of the Hybrid Fuzzy Neural System, as an abnormal ECG signal of Supraventricular Tachycardia (SVT) is simulated with the classification system.

In Figure 7.13, the classification system was tested with a SVT signal. The output values from the 1st, 2nd and 3rd MLPN are plotted in red, green and blue line respectively as shown in Figure 7.13(b). These output values from the 1st, 2nd and 3rd MLPN are partitioned into fuzzy regions and the corresponding membership functions are sketched in red, green and blue parabolic curves respectively as shown in Figure 7.13(b). The output value from the 1st MLPN (in red) has the highest density in the region of Unknown signal. The output value from the 2nd MLPN (in green) has the highest density in the region of Unknown signal. The output value from the 3rd MLPN (in blue) has the highest density in the region of SVT signal. By referring to Table 6.1, when x_1(the output value from the 1st MLPN), x_2(the output value from the 2nd MLPN) and x_3(the output value from the 3rd MLPN) is clustered as Unknown, Unknown and SVT signal respectively, the crisp classification result is SVT. As a result of the consistency in the 3rd MLPN output value, the classification rate for this SVT signal is 99.4129% as shown in the lower left corner of Figure 7.13(c). The total misclassification rate is only 0.5871% which consists of 0.26093% in the upper left corner (STDP), 0% in the lower left corner (TINV) and 0.32616% in the upper right corner (NSR) of Figure 7.13(c).



Indications U: Unknown ECG signals. NSR1, 2, 3: The 1st, 2nd and 3rd Type of Normal Sinus Rhythm Signals
STDP: ST Segment Depression Signals TINV: T Wave Inversion Signals

Figure 7.14: a) a normal ECG signal of Normal Sinus Rhythm (NSR) b) Output of the 1st MLPN (in red line) & Output of the 2nd MLPN (in green line) & Output of the 3rd MLPN (in blue line) c) Output of the Hybrid Fuzzy Neural System, as a normal ECG signal of Normal Sinus Rhythm (NSR) is simulated with the classification system.

In Figure 7.14, the classification system was tested with a SVT signal. The output values from the 1st, 2nd and 3rd MLPN are plotted in red, green and blue line respectively as shown in Figure 7.14(b). These output values from the 1st, 2nd and 3rd MLPN are partitioned into fuzzy regions and the corresponding membership functions are sketched in red, green and blue parabolic curves respectively as shown in Figure 7.14(b). The output value from the 1st MLPN (in red) has the highest density in the region of Unknown signal. The output value from the 2nd MLPN (in green) has the highest density in the region of Unknown signal. The output value from the 3rd MLPN (in blue) has the highest density in the region of NSR signal. By referring to Table 6.3, when x_1 (the output value from the 1st MLPN), x_2 (the output value from the 2nd MLPN) and x_3 (the output value from the 3rd MLPN) is clustered as Unknown, Unknown and NSR signal respectively, the crisp classification result is NSR. As a result of the fluctuations in both the 1st and 2nd MLPN output values, the classification rate for this NSR signal is only 79.5173% as shown in the lower left corner of Figure 7.14(c). The total misclassification rate is 20.4827% which consists of 0.65232% in the upper left corner (STDP), 19.8304% in the lower left corner (TINV) and 0% in the lower right corner (SVT) of Figure 7.14(c).

Category / Classification Rate in Percentage	STDP	TINV	NSR	SVT
1st Sample	78.67	96.74	100.00	99.22
2nd Sample	84.93	96.80	85.13	99.15
3rd Sample	85.52	96.28	79.52	99.41
Average	83.0	96.6	88.2	99.3

Table 7.3: The classification results of ECG signals.

The classification rates for the various types of ECG (12 test signals) are listed in Table 7.3. The overall average classification rate for the ECG signal is 91.8%. Referring to this table, the results of STDP and NSR are below 90% while those of TINV and SVT are above 95%. The major characteristic of the STDP signal lies in the ST wave which only constitutes one quarter of the signal cycle. Hence with the fixed number of inputs for the MLPN, it is not possible to capture a good view of this feature. The NSR signals also pose a great deal of challenge in terms of neural network generalization because of their high variability in waveform characteristics. Conversely the TINV signal has an inverted ST wave which provides a feature which is easy to recognise by the neural networks. The SVT signal, which has much higher frequency than the other signals, is most often detected with twin QRS peaks by the fixed number of inputs for the neural networks, and thus gives the best result for the ECG classification system.

7.4 Conclusions

The original intention of this study was to implement an offline-learning algorithm, and therefore most of the work reflects that. However, there were certain disadvantages of the offline-learning algorithm, mainly regarding the speed and consistence of learning, which would have made it unacceptable in a practical setting. Therefore the EKF online-learning algorithm was implemented, since this algorithm exhibited favourable properties such as fast and consistent convergence. This EKF online-learning approach was applied specifically to the neural side of the architecture since that was where it produced the best results. However, the benefit of EKF online-learning algorithm has not been fully demonstrated in the entire neuro-fuzzy system. This is due to the table-lookup scheme applied in the fuzzy inference system which requires each output from the ensemble of the neural networks to converge fully before the training procedure can be performed successfully in the fuzzy side of the architecture.