2012 Third FTRA International Conference on Mobile, Ubiquitous, and Intelligent Computing

The use of Artificial Neural Network in the Classification of EMG Signals

Md. R. Ahsan, Muhammad I. Ibrahimy, Othman O. Khalifa
Department of Electrical and Computer Engineering, Faculty of Engineering,
International Islamic University Malaysia, Kuala Lumpur
Kuala Lumpur 53100, Malaysia
e-mail: ibrahimy@iium.edu.my

***Abstract*— This paper presents the design, optimization and performance evaluation of artificial neural network for the efficient classification of Electromyography (EMG) signals. The EMG signals are collected for different types of volunteer hand motion which are processed to extract some predefined features as inputs to the neural network. The time and time-frequency based extracted feature sets are used to train the neural network. A back-propagation neural network with Levenberg-Marquardt training algorithm has been employed for the classification of EMG signals. The results show that the designed and optimized network able to classify single channel EMG signals with an average success rate of 88.4%.**

Keywords- Electromyography, Artificial Neural Network, Back-Propagation, Levenberg-Marquardt algorithm, EMG Signal Classifier etc.

I. Introduction

EMG signals can be used for a variety of applications including diagnoses of neuromuscular diseases, controlling assistive devices like prosthetic/orthotic devices, human-computer interfaces (HCI) [1] etc. During past couple of years, the research and development of EMG based control has got the focus because it would increase the social acceptance of the disabled and aged people in the society by improving their quality of life. However, in the development of myoelectric control based interfaces, it is quite challenging task to classify EMG signals according to the requirements of application area. This is basically due to the large variations in EMG signals characteristics with different signatures depending on age, muscles activity, motor unit patterns, skin-fat layer, and gesture style etc. Beside these, the EMG signal contains complicated types of noise compared to other biosignals. These noises are caused by inherent equipment and environment noise, electromagnetic radiation, motion artifacts, and the interaction of different tissues [2]. Sometimes it is difficult to extract useful features from the residual muscles of an amputee or disabled. Even more difficulties are added while resolving a multiclass classification problem [3]. Many researches have proposed and developed different types of EMG signal classification techniques with acceptable recognition performance.

EMG signals from a body's intact musculature have been used to identify motion commands for the controlling of an external peripherals or devices. For this purpose, the pattern signatures of the EMG signal have been extracted for each movement and then classify the EMG signal using a proper mapping method based on features. However, the extreme complexities involved in EMG signals make it difficult to have a precise structural or mathematical model that relates the measured signals to a motion command. There are many pattern recognition techniques are available to discriminate the functionality from the extracted features. Most of the research work has been done with multichannel EMG signals except the recent work of Kim *et. al.* [4]. The EMG signals from increased numbers of channels obviously will increase the classification efficiency. Some of the previous studies like [5] and [6] present that it is advantageous to use multiple channels. It has also found that though the average classification accuracy will increase with increased numbers of channels but a diminishing return may observed after the numbers of channels more than four [7]. It has been found that most of the researchers used Artificial Neural Network (ANN) for the processing of biosignals [8]. ANNs are formed of cells simulating the low-level functions of biological neurons are particularly useful for complex pattern recognition and classification tasks. The capability of learning from examples, the ability to reproduce arbitrary non-linear functions of input, and the highly parallel and regular structure of ANN make them especially suitable for pattern classification tasks [9]. On this account, integral absolute value (IAV) feature based feed-forward ANN used by Hiraiwa *et. al.* [10], independent component analysis (ICA) based ANN by Naik *et. al.* [11], different multi-layer perceptron (MLP) based neural network used by [12], [13], prominent researcher Hudgins *et. al.* [14] have used Hopfield and ART, and later FIRNN. Most of the ANN based research work has been carried out with MLP containing one hidden layer and back-propagation algorithm for training. Some other researchers have employed fusion of neural network with different fuzzy architecture. For example, fuzzy mean max neural network (FMMNN) [15], fuzzy clustering neural network (FCNN) [16], adaptive neuro-fuzzy inference system (ANFIS) [17], wavelet based neuro-fuzzy[18] classifier. Other classifiers used by researchers are different kinds of fuzzy classification techniques [19], kNN classifiers [20], linear discriminant analysis (LDA) classifier [21]. However, the computation time, classification rate of these methods is varying and needs more expertness. Although, LDA requires little computations and less memory compared to the other mentioned classifiers, it suffers from the problem of singularity [22].

978-0-7695-4727-5/12 $26.00 © 2012 IEEE
DOI 10.1109/MUSIC.2012.46

It has found that different types of ANN structure have been used by many researchers because of its ability to adapt and learn from various arbitrary data to classify EMG signals. The capability of learning from examples, the ability to reproduce arbitrary non-linear functions of input, and the highly parallel and regular structure of ANNs make them especially suitable for pattern classification tasks. A back-propagation neural network has been designed and optimized in this research work to classify the pre-processed EMG signals which are obtained for different hand motion. Seven statistical time and time-frequency based features namely Moving Average (MAV), RMS (Root Mean Square), VAR (Variance), SD (Standard Deviation), ZC (Zero-crossing), SSC (Slope Sign Change) and WL (Waveform Length) are used as inputs to the neural network. The Levenberg-Marquardt algorithm is used to train the network.

II. MATERIALS AND METHODS

A. Architecture of ANN

The feed-forward back-propagation network architecture is shown in Figure 1. The designed ANN consists of 3-layers: input layer, tan-sigmoid hidden layer and linear output layer. Each layer except input layer has a weight matrix *W*, a bias vector *b* and an output vector *a*. The weight matrices connected to inputs called input weights (*IW*) and weight matrices coming from hidden layer outputs called layer weights (*LW*). Additionally, superscripts are used to denote the source (second index) and the destination (first index) for the various weights and other elements of the network. *p* is the input vector, *n* is the layer output before transfer function and *a* is the actual output vector of a layer.

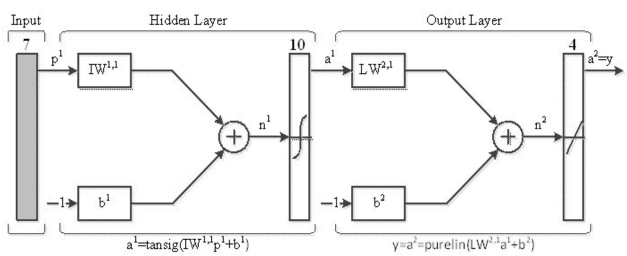

Figure 1. Architecture of ANN

The ANN has been designed with 7 (seven) inputs, 10 (ten) *tan-sigmoid* neurons in hidden layer which is in optimized condition and 4 (four) linear neurons in output layer. The Details are given in Fig. 2. The decision of selecting number of hidden neurons still remains a challenge. If numbers of neurons are large in hidden layer then the network requires more memory and the training becomes complicated. However, if the numbers of neurons are too small, the network cannot adjust the weight properly and there may be over fitting. Over fitting problem cannot make the network generalized when presented with slightly different inputs. Since there is no specific way to find out the numbers of hidden neurons, it has been determined using trial and error method. The input feature vectors are normalized in the range of [-1, +1] for the efficient and faster training of neural network.

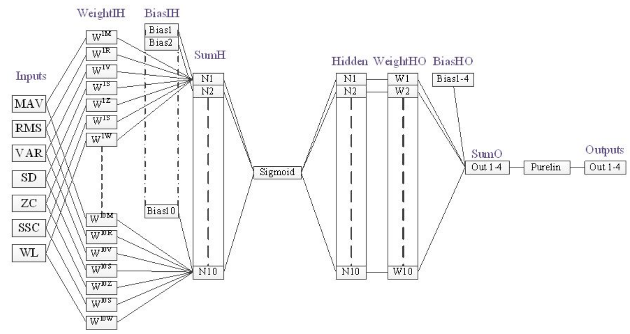

Figure 2. Detail Architectural View of ANN

The back-propagation algorithm is used for the training of feed-forward ANN. The algorithm determines how to adjust the weights to minimize performance (Mean Square Error - MSE) by using the gradient of the performance function. Levenberg-Marquardt (*trainlm*) algorithm was for back-propagation training. It is the fastest method for training of moderate-sized feed-forward neural networks and based on numerical optimization techniques. The network was also generalized to avoid over fitting. This is done by dividing the training input data; 70% for training, 15% for validation and 15% for testing. Furthermore, the number of data points in training set was more than sufficient to estimate the total number of parameters in the network. Early stopping method also applied to improve the generalization of the network. Two early stopping conditions were used: either total mean squared error, MSE <=0.001 or training stopped after 1000 epochs. The weights and bias of input layer and hidden layer were saved after each training session. When the simulation results are not satisfactory, the network is trained again with the last saved weight and bias values. This is done to improve the network performance and to reduce the number of time for training.

B. Optimation of ANN for the Classification of EMG Signals

The network was trained by using 204 sets of data for different movements. Each set consists of input feature vector obtained from specific type of hand movement and corresponding output vector. The training of network was done and then analyzed by both Levenberg-Marquardt (*trainlm*) and scale conjugate gradient (*trainscg*) algorithm as mentioned earlier. During the training, the weights and biases of the network were iteratively adjusted to minimize the MSE and hence it increased the rate of network performance. The utilization of back-propagation learning updates the networks weights and biases in the direction where the MSE decreases most rapidly. As mention before that the MSE was set to 0.001, maximum validation failure was set to 6 times, learning rate was set 0.05, training status will be displayed after single run of the algorithm and maximum number of epochs set to 1000. The training is stopped if any of the following condition fulfilled: the maximum number of epochs was reached or the performance gradient became less than the minimum gradient or validation performance increased more than the maximum fail times since the last decreased one. The network training is evaluated with MSE of the training data, correlation coefficient/regression (R) between the network outputs and corresponding target outputs and the characteristics of the training, validation, and testing errors. The networks with the best performance (lowest MSE, highest R) and almost similar error characteristics among the training, validation and testing are selected as the network for the respective network structure. It is clear that if the error for the training, validation and testing vary greatly during the training procedure, then the network structure is considered unsatisfactory even though the training MSE shows very low value. In this case, the network can be considered as not generalized and training is not acceptable. Hence, further tuning and training is performed for the network to achieve better performance. Different number of hidden neurons selected for both type of back-propagation training to find out optimized and best network structure through studying the MSE and R.

III. Result and Discussion

Then ANNs with different numbers of hidden neurons were tested and validated at training stage to sort out how accurately the newly designed network system could predict the output classes. By Simulating the network with different hidden neurons and both type of training algorithms, network responses and the function of the networks are verified with statistical analysis of MSE and R. For 10 times run of the designed networks simulation, the network performances (in terms of MSE and R) are collected and presented in a tabular form with mean and Standard Deviation (SD).

Fig. 2 presents the graphical view of the different network performance through error bars of mean and SD. According to the Fig. 2, the lowest mean (0.065401) and the lowest SD (0.013987) of the MSE are found for 10 numbers of hidden neurons during the training of the network with Levenberg-Marquardt algorithm. Comparing with other types of network structures and for both of the back-propagation training algorithm, the ANN with 10 neurons is clearly showing its outperformances.

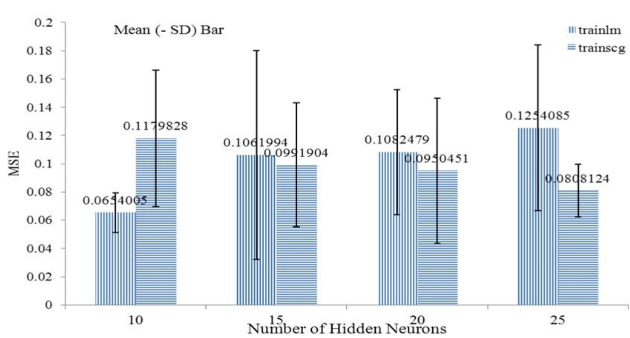

Figure 3. Comparison of MSE in between different ANN architecture

As with the reference of Fig. 4, it has been found that the highest correlation coefficient (0.87401) was achieved when the ANN was trained by Levenberg-Marquardt algorithm with10 hidden neurons. For this architecture of ANN also achieved the lowest mean and the lowest SD among all trainings for both types of learning algorithms. The graphical presentations (Fig. 4) of the regression analysis of the network responses (R) for different network structures and both types of back-propagation training is clearly promoting the ANN structure with 10 hidden neurons than others. Hence, it can be conclude that the optimal ANN structure for the classification of EMG signals is the ANN with the Levenberg-Marquardt algorithm for back-propagation training and using 10 neurons in its hidden layer.

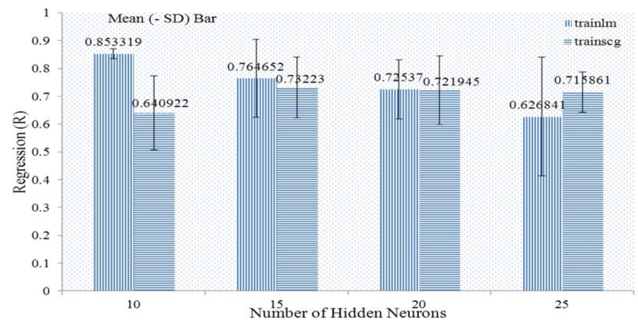

Figure 4. Comparison of R in between different ANN architecture

With the optimal ANN structure, different combinations of feature sets also studied. Figure 5 shows the error histogram for different combinations of feature sets. The Figure 5 (d) is clearly different than other combinations. It has been found that, if the optimized ANN structure fed with input vector of seven features then maximum instances (around 550) of MSE errors distributed near to zero line in the error histogram.

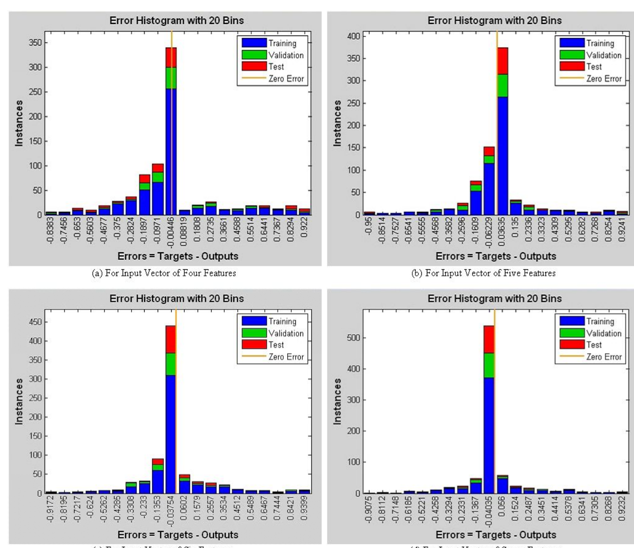

Figure 5. Error histogram for input vector of (a) four features, (b) five features, (c) six features and (d) seven features.

Finally, the optimized ANN structure by using the Levenberg-Marquardt algorithm with input feature vector of seven features and 10 hidden neurons is simulated for several times. For a single trial, the training is stopped after 10 epochs because the validation error increased for more than six times as shown in Figure 6. The training, validation, and testing errors were in fairly good agreement with the characteristics during training. The summery of classification performance of the ANN is shown in Table I. It is found that Levenberg-Marquardt algorithm based neural network with 10 hidden neurons yields the best classification rate and required time is minimum. This network outperforms over other network structures regarding the number of iterations required, time elapsed and classification rate. The average of best overall classification rate during training is 88.4%.

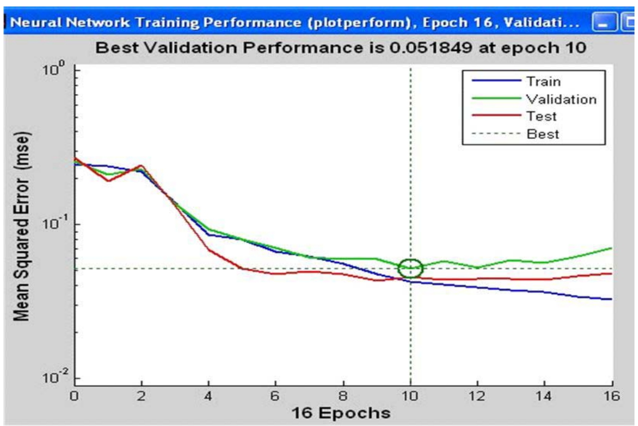

Figure 6. Training Validation and Test errors during training with Levenberg-Marquardt algorithm

The trained network has also been tested on completely unknown EMG signals. The feature vectors are fed into the network without the corresponding targets. The expected output is 1 in its index position for a specific type of movement. The sample input feature vectors (p1, p2... p10) from test EMG signal and its corresponding output are shown in Table II. The classified movements are presented in bold numbers which are the largest than the others and closer to 1. The test output shows that the trained network successfully classified all types of movements.

IV. CONCLUSION

After analyzing the performance comparison for different types of architecture, it has been found that the optimized ANN structure consists of 10 neurons in its hidden layer. The result shows that the optimized ANN architecture can successfully classify EMG signals with correct and average classification rate of 88.4%. Nevertheless, in a single trial the best overall performance has been found 89.2%. It should be note that the classification performance has been obtained with single channel EMG signals which is outstanding compared to previous research works where multiple channels were utilized. This is one of the key contributions of the research where a better classification rate can be achieved without prior training to the subject and by using available laboratory facilities. However, the designed ANN structure has not been tested with the EMG signals from disable or aged people. They could have different muscle natures and different ways to move hand muscles. Hence, huge noise and poor EMG signals from them may deteriorate the performance of designed ANN. In that situation, it should be required to redesign the network through trial and error which may improve the classification performance.

REFERENCES

[1] M. R. Ahsan, M. I. Ibrahimy, and O. O. Khalifa, “EMG signal classification for human computer interaction: A review,” European Journal of Scientific Research, vol. 33, no. 3, pp. 480-501, 2009.

[2] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin, “Techniques of EMG signal analysis: detection, processing, classification and applications,” Biological procedures online, vol. 8, no. 1, pp. 11–35, 2006.

[3] M. R. Ahsan, M. I. Ibrahimy, and O. O. Khalifa, “Hand motion detection from EMG signals by using ANN based classifier for human computer interaction,” in Modeling, Simulation and Applied Optimization (ICMSAO), 2011 4th International Conference on, 2011, pp. 1-6.

[4] J. Kim, S. Mastnik, and E. André, “EMG-based hand gesture recognition for realtime biosignal interfacing,” in Proceedings of the 13th international conference on Intelligent user interfaces, 2008, pp. 30–39.

[5] K. Englehart and B. Hudgins, “A robust, real-time control scheme for multifunction myoelectric control,” Biomedical Engineering, IEEE Transactions on, vol. 50, no. 7, pp. 848–854, 2003.

[6] J. Lyman, A. Freedy, and M. Solomonow, “System integration of pattern recognition, adaptive aided, upper limb prostheses,” Mechanism and Machine Theory, vol. 12, no. 5, pp. 503–514, 1977.

[7] G. Tsenov, A. H. Zeghbib, F. Palis, N. Shoylev, and V. Mladenov, “Neural networks for online classification of hand and finger movements using surface EMG signals,” in Neural Network Applications in Electrical Engineering, 2006. NEUREL 2006. 8th Seminar on, 2007, pp. 167–171.

[8] M. R. Ahsan, M. I. Ibrahimy, and O. O. Khalifa, “Advances in electromyogram signal classification to improve the quality of life for the disabled and aged people,” Journal of Computer Science, vol. 6, no. 7, pp. 706-715, 2010.

[9] A. Subasi, M. Yilmaz, and H. R. Ozcalik, “Classification of EMG signals using wavelet neural network,” Journal of neuroscience methods, vol. 156, no. 1-2, pp. 360–367, 2006.

[10] A. Hiraiwa, K. Shimohara, and Y. Tokunaga, “EMG pattern analysis and classification by neural network,” in Systems, Man and Cybernetics, 1989. Conference Proceedings., IEEE International Conference on, 2002, pp. 1113–1115.

[11] G. R. Naik, D. K. Kumar, V. P. Singh, and M. Palaniswami, “Hand gestures for HCI using ICA of EMG,” in Proceedings of the HCSNet workshop on Use of vision in human-computer interaction-Volume 56, 2006, pp. 67–72.

[12] K. Englehart, B. Hudgins, M. Stevenson, and P. A. Parker, “A dynamic feedforward neural network for subset classification of myoelectric signal patterns,” in Engineering in Medicine and Biology Society, 1995., IEEE 17th Annual Conference, 2002, vol. 1, pp. 819–820.

[13] M. F. Kelly, P. A. Parker, and R. N. Scott, “The application of neural networks to myoelectric signal analysis: a preliminary study,” Biomedical Engineering, IEEE Transactions on, vol. 37, no. 3, pp. 221–230, 2002.

[14] B. Hudgins, P. Parker, and R. N. Scott, “A new strategy for multifunction myoelectric control,” Biomedical Engineering, IEEE Transactions on, vol. 40, no. 1, pp. 82-94, 1993.

[15] Jong-Sung Kim, Huyk Jeong, and Wookho Son, “A new means of HCI: EMG-MOUSE,” in Systems, Man and Cybernetics, 2004 IEEE International Conference on, 2004, vol. 1, pp. 100-104 vol.1.

[16] B. Karlik, O. Tokhi, and M. Alci, “A Novel Technique for Classification of Myoelectric Signals for Prosthesis,” International Federation of Automatic Control, Jul. 2002.

[17] M. Khezri, M. Jahed, and N. Sadati, “Neuro-fuzzy surface EMG pattern recognition for multifunctional hand prosthesis control,” in Industrial Electronics, 2007. ISIE 2007. IEEE International Symposium on, 2007, pp. 269–274.

[18] X. Zhang, Y. Yang, X. Xu, and M. Zhang, “Wavelet based neuro-fuzzy classification for emg control,” in Communications, Circuits and Systems and West Sino Expositions, IEEE 2002 International Conference on, 2003, vol. 2, pp. 1087–1089.

[19] A. B. Ajiboye and R. F. Weir, “A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthesis control,” Neural Systems and Rehabilitation Engineering, IEEE Transactions on, vol. 13, no. 3, pp. 280–291, 2005.

[20] J. Kim, S. Mastnik, and E. André, “EMG-based hand gesture recognition for realtime biosignal interfacing,” in Proceedings of the 13th international conference on Intelligent user interfaces, 2008, pp. 30-39.

[21] A. Phinyomark, C. Limsakul, and P. Phukpattaranont, “A novel feature extraction for robust EMG pattern recognition,” Journal of Computing, vol. 1, no. 1, pp. 71–80, 2009.

[22] R. N. Khushaba, A. Al-Jumaily, and A. Al-Ani, “Evolutionary fuzzy discriminant analysis feature projection technique in myoelectric control,” Pattern Recognition Letters, vol. 30, no. 7, pp. 699–707, 2009.

TABLE I. CLASSIFICATION RESULT FOR DIFFERENT ANN ARCHITECTURE

Training Function	**Hidden Neurons**	**Stop Epochs**	**Regre-ssion**	**Time Elapsed (s)**	**Classification Rate**			
					Training	***Validation***	***Test***	***Overall***
trainlm (Levenberg-Marquardt Algorithm)	10	15	0.8597	1.047	88.6	83.3	90	88
		18	0.87251	0.921	94.3	66.7	80	88
		16	0.87401	0.8721	88.7	90.3	90.3	89.2
		Avg	**0.86874**	**0.9467**	**90.5333**	**80.1**	**86.76667**	**88.4**
	20	33	0.85706	2.797	91.4	70	83.3	87
		14	0.85508	1.218	90	80	86.7	88
		12	0.84772	1.094	92.9	76.7	83.3	89
		Avg	0.853287	1.703	91.4333	75.5667	84.43333	88
	30	16	0.86112	2.36	92.1	80	76.7	88
		11	0.85018	1.703	91.4	90	73.3	88.5
		14	0.85102	2.125	89.3	76.7	83.3	86.5
		Avg	0.854107	2.06267	90.9333	82.2333	77.76667	87.6667

TABLE II. SAMPLE TEST DATA WITH CORRESPONDING CLASSIFICATION OUTPUT

Input>	**p1**	**p2**	**p3**	**p4**	**p5**	**p6**	**p7**	**p8**	**p9**	**p10**
Feature vector from Test EMG	-0.12863	-0.61608	0.37114	0.20342	-0.13348	-0.75516	0.22405	0.33569	-0.24777	-0.79584
	-0.12208	-0.66515	0.34085	0.16422	-0.22866	-0.77763	0.09469	0.32470	-0.34035	-0.81355
	-0.51192	-0.88580	-0.00891	-0.22084	-0.60371	-0.93406	-0.29750	-0.02931	-0.69024	-0.94736
	-0.12391	-0.66707	0.33959	0.16281	-0.23027	-0.77885	0.09339	0.32338	-0.34266	-0.81470
	-0.17617	-0.64118	0.19024	0.32336	-0.13286	-0.75488	0.09132	0.46075	-0.34527	-0.78546
	-0.29730	0.40541	0.10811	-0.78378	-0.05405	0.45946	0.29730	-0.56757	0.08108	0.00000
	-0.42105	-0.55263	-0.65789	0.31579	-0.23684	0.02632	-0.52632	0.50000	-0.55263	-0.50000
Expected Output	0	0	1	0	0	0	1	0	0	0
	0	0	0	1	0	0	0	1	0	0
	1	0	0	0	1	0	0	0	1	0
	0	1	0	0	0	1	0	0	0	1
Simulation Output	0.0036	0.0004	**0.6597**	0.0081	0.0447	0.0024	**0.6676**	0.0273	0.0063	0
	0.0085	0.0036	0.0032	**0.955**	0.0021	0	0.0017	**0.8774**	0.0003	0.0133
	0.9928	0.0001	0.3271	0.091	**0.7688**	0.0018	0.5993	0.1906	**0.8913**	0.0008
	0.0548	**0.9991**	0.02	0	0.1496	**0.998**	0.0093	0	0.288	**0.9995**