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Noise Reduction of Biomedical Signal using Artificial Neural Network Model

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ABSTRACT

The Electromyography (EMG) is a very important biomedical signal and can be used for verity of applications in clinical or biomedical field. This signal is used to detect abnormal muscle activities like impaired nourishment of an organ or part of body, inflammation of muscles, pinched nerves and peripheral nerve damages etc. The EMG signal is controlled by nervous system and is dependent on the anatomical and physiological properties of muscles and is affected due to artifacts. Therefore the EMG signal is complicated signal and noise-prone. This noise signal reduces the performance of EMG signal. During signal processing, the system picks up noise signal along with desired signal. In this paper, Artificial Intelligent model using Focused Time Lagged Recurrent Neural Network with a single hidden layer has been developed. From the implication of findings, FTLRNN reduces noise intelligently from the EMG signal. The difference between EMG with noise and desired EMG signal is computed from the performance measures MSE, NMSE and r.

Key words*: Artificial Neural Network, Biomedical Signal, FTLRNN*

I. INTRODUCTION

Biomedical signal means a collective electrical signal acquired from any organ that represents a physical variable of interest. This signal is normally a function of time and is describable in terms of its amplitude, frequency, and phase. The Electromyography (EMG) is a very important biomedical signal and can be used for verity of applications in clinical or biomedical field. This signal is used to detect abnormal muscle activities like impaired nourishment of an organ or part of body, inflammation of muscles, pinched nerves and peripheral nerve damages etc. The EMG signal is controlled by nervous system and is dependent on the anatomical and physiological properties of muscles and is affected due to artifacts. Therefore the EMG signal is complicated signal and noise-prone. This noise signal reduces the performance of EMG signal. During signal processing, the system picks up noise signal along with desired signal. The EMG potentials from the muscle or group of muscles produce a noisy waveform that varies in amplitude with the amount of muscular activities. Peak amplitudes vary from 25uV to about 5mV, depending on the location of the measuring electrodes with respect to muscle and the activity of the muscle. The frequency responses from about 5 Hz to well over 5000 Hz is required for faithful reproduction. Using an amplifier with high gain, high input impedance and differential input with good common mode rejection could reduce the EMG noise. Now various mathematical techniques and Artificial Intelligence approaches are being used for noise reduction. Literature survey shows that in nonlinear system identification, a mathematical model includes wavelet transform, time frequency approaches, Fourier transforms, Wegner-Villie Distribution, statistical measures and higher order statistics. AI includes artificial neural network, dynamic recurrent neural network, Fuzzy logic system and genetic algorithm. Measuring and accurately representing the surface EMG signal depends on the properties of electrodes and their interaction with skin, amplifier design and the conversion and subsequent storage of the EMG signal from analog to digital form. EMG signal is affected by electrical noise and some other factors. Electrical noise included inherent noise in Electronic equipments, ambient equipments, ambient noise, motion artifacts and inherent instability of signal. By using conventional method, it is difficult to reduce noise from EMG signal.

Biomedical applications using signal processing techniques is a major area of interest that has been investigated by a large number of scientific researchers (Penzel & Conradt 2000; Hassanpour *et al.*, 2004). On the other hand, Shimada *et al.* (2000) in an experiment, implemented neural networks for the purpose of characteristic waves detection of sleep EEG. For instance, Paul et al. (1999) presented a method known as the cepstrally transformed discrete cosine transform (CTDCT) to analyze electrocardiography data with wide QRS deflection. Another proposed procedure by Sivannaryana *et al*. (1999) is to estimate the ECG parameters using the multi-scale analysis of the biorthogonal wavelet transforms. Maglaveras *et al*. (1998) discussed a number of ECG recognition and classification methods including non-linear transformation, neural networks (NN), and non-linear principle component analysis (NLCPA).Chen-Ning Huang *et al* (2004) introduces the measurement of facial EMG including the electrode selection, electrode position and noise reduction. Band stop filters for eliminating the power line noise and simple pass filter to reduce motion artifact. H. N. Suresh (2008) presents removal of noise signal, which can be EMG, ECG or a combination of these two artifacts from the corrupted EEG, signal and also signal enhancement both using recurrent learning technique. For this purpose, they have implemented the RTRL (Real Time Recurrent Learning) algorithm, which is the most recent and sophisticated real time neural network algorithm. This algorithm is coded using C language and is executed on the DSP processor TMS320CV5402. The obtained result is verified using MATLAB. Mohammed A *et.al* (2010), used deconvolution approach based on time frequency representation (TFR) methods for the estimation and analysis of biomedical signals. Chosen as examples are electroencephalogram (EEG) as well as the Electrocardiogram (ECG) signals for normal and abnormal patients. Viktor Owall *et.al* (2008) discussed the mechanisms of energy dissipation and presented some specific solutions regarding implementation of signal processing in implantable cardiac devices. Cuiwei Li *et.al* (1995), has developed an algorithm based on wavelet transforms (WT's) for detecting ECG characteristic points. Kale S.N. *et al*. (2009), proposed Focussed Time Lagged Recurrent Neural Network for removal of biomedical signal noise. Anca Daniela Ionita (2004) discussed the simulation technique for cleaning electromyographic and electroneurographic signals covered by Gaussian noise and periodic electromagnetic interference with low frequencies.

II. SOFTWARE SPECIFICATION REQUIREMENT & IMPLEMENTATION DETAILS

To design a Neural Network, we need a sufficiently large amount of data for training, testing and cross validation. The data is get available from Benchmark data sets source from Principe. The data stored in Excel sheet arranged in column vectors so that it can be supplied to the Neural Network. Tagged input data EMG with noise as 'Column as Input' and EMG data as 'Column as output' and select the percentage of data for training, cross validation and testing are as given in Table-1.

Table 1: Data Partition for Training, C.V. and Testing

Total Dataset = 1499	**Data Partition**	**Number of Data samples**
Training	60 %	899
Cross Validation	15 %	225
Testing	25 %	375

The performance of NN is assessed on the basis of performance parameters such as MSE, NMSE, r and visual inspection of desired EMG signal and the Network EMG signal. The Network has been trained at least 3 times, starting from different random initial weights so as to avoid local minima. Neuro Solutions (Version 5) is specially used for obtaining results. Various Neural Network are designed and compared the performance measures, it is observed the best result is obtained at FTLR Neural Network which remove noise intelligently from EMG signal.

III. SIMULATION RESULTS

The results are obtained on Neuro Solutions Software and accordingly, simulations are carried out on EMG with noise as input and EMG only as desired output. The EMG with noise signal was inputted to MLP Neural Network with one hidden layer. The parameters like processing elements, transfer function, learning rule, step size and momentum of hidden layer and output layer of MLPs were tested with maximum epoch 5000

Multilayer Perceptron

1) Selection of Transfer Function and Learning Rule for Hidden Layer:

Various learning rules such as momentum, CG, LM, QP and DBD are used for training and best performance parameters are observed. Results are observed for various Transfer Functions like Linear Tanh Axon, Linear Sigmoid Axon, Bias Axon, Linear Axon and Axon only as shown in the Table 2.

a. Transfer Function-Tanh Axon

The neural network is built for transfer function Tanh Axon. The training report for various learning rule like momentum, CG, LM, QP and DBD is as shown in the Figures 1-5.

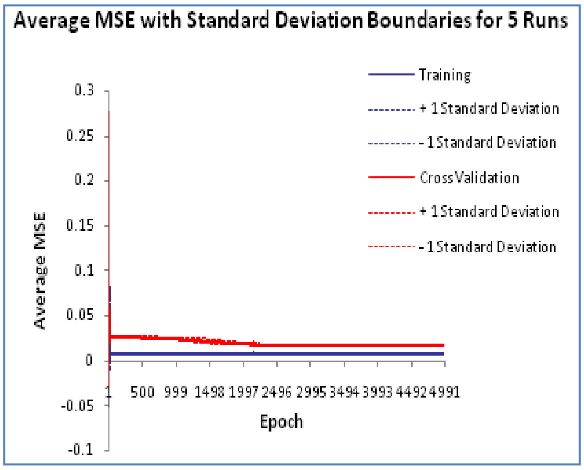

Fig. 1: Avg. Min MSE Vs Epochs for learning rule Momentum

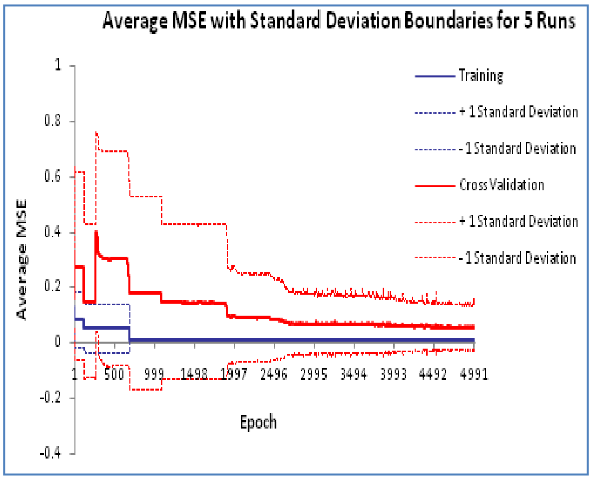

Fig. 2: Avg. Min MSE Vs Epochs for learning rule CG

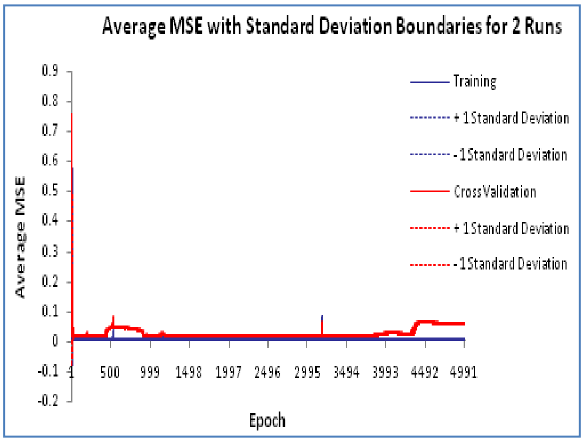

Fig. 3: Avg. Min MSE Vs Epochs for learning rule LM

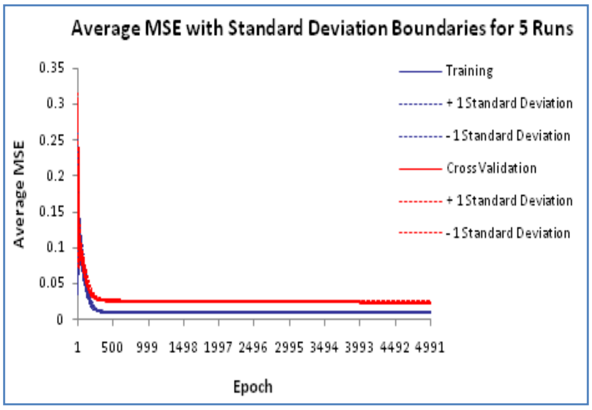

Fig. 4: Avg. Min MSE Vs Epochs for learning rule QP

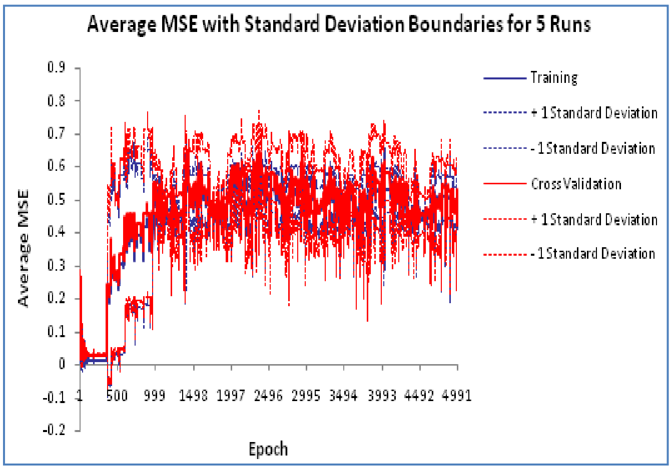

Fig 5: Avg. Min MSE Vs Epochs for learning rule DBD

b. Transfer Function -Sigmoid DBD

The neural network is built for transfer function Sigmoid Axon. Train the network by varying learning rules. The training report for various learning rule like momentum, CG, LM, QP and DBD is as shown in the following Figures 6 -9.

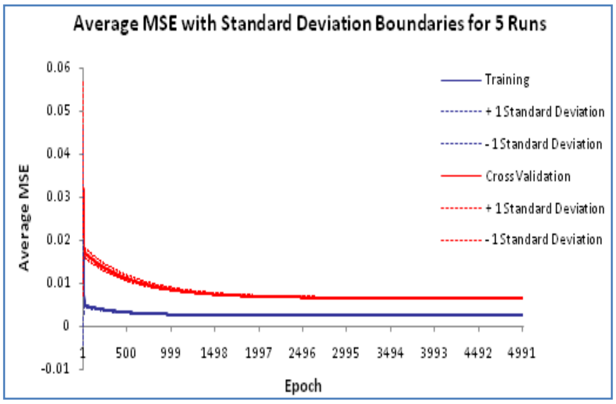

Fig. 6: Avg. Min MSE Vs Epochs for learning rule Momentum

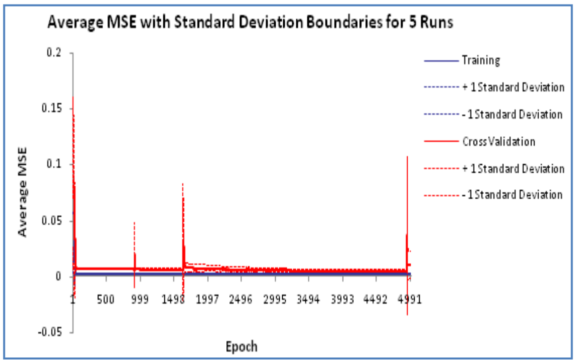

Fig. 7: Avg. Min MSE Vs Epochs for learning rule CG

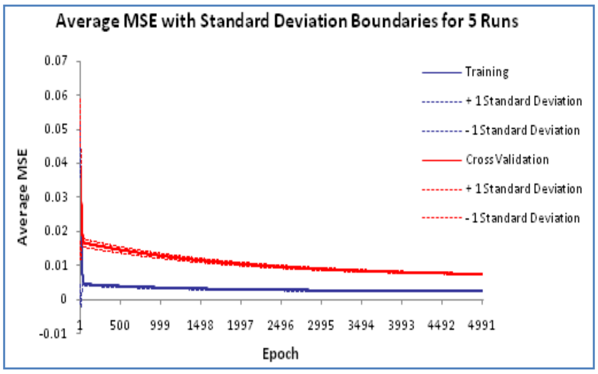

Fig. 7: Avg. Min MSE Vs Epochs for learning rule CG

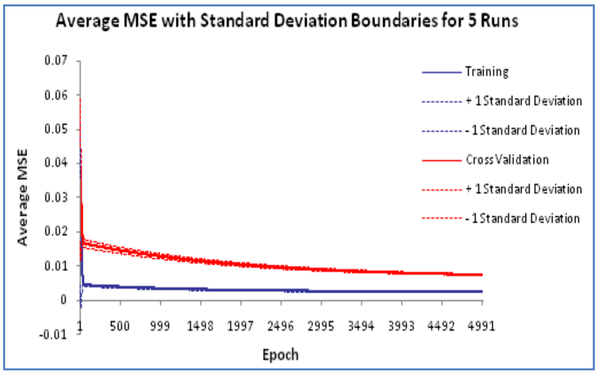

Fig. 8: Avg. Min MSE Vs Epochs for learning rule QP

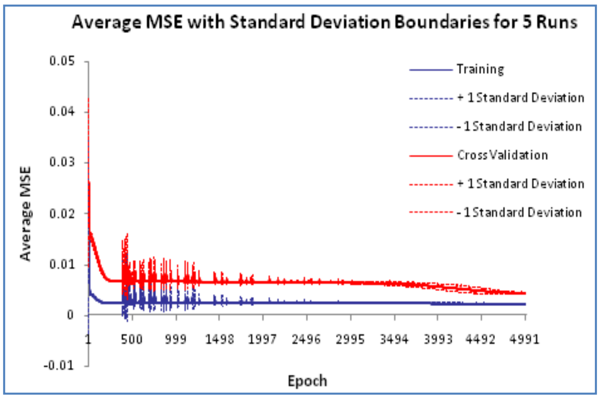

Fig. 9 : Avg. Min MSE Vs Epochs for learning rule DBD

c. Transfer Function-Linear Tanh Axon

The neural network is built for transfer function Linear Tanh Axon. Train the network by varying learning rules. The training report for various learning rule like momentum, CG, LM, QP and DBD is as shown in the Figures 10-13.

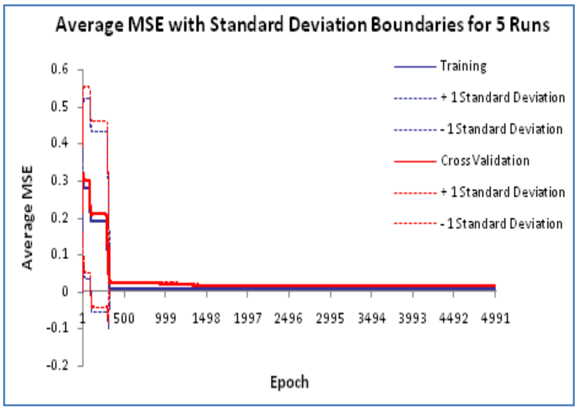

Fig. 10: Avg. Min MSE Vs Epochs for learning rule Momentum

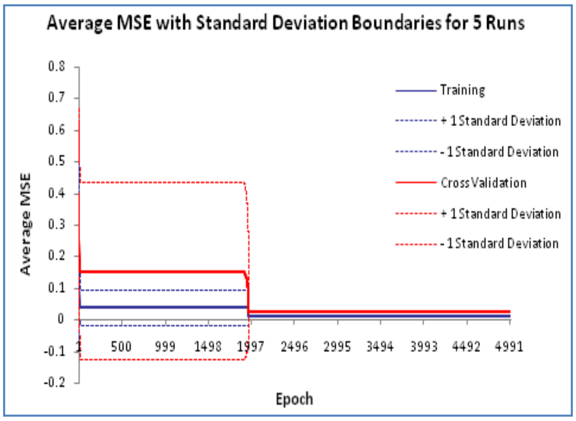

Fig. 11: Avg. Min MSE Vs Epochs for learning rule CG

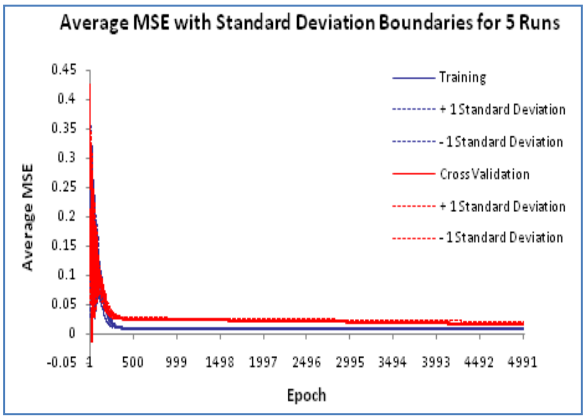

Fig. 12 : Avg. Min MSE Vs Epochs for learning rule QP

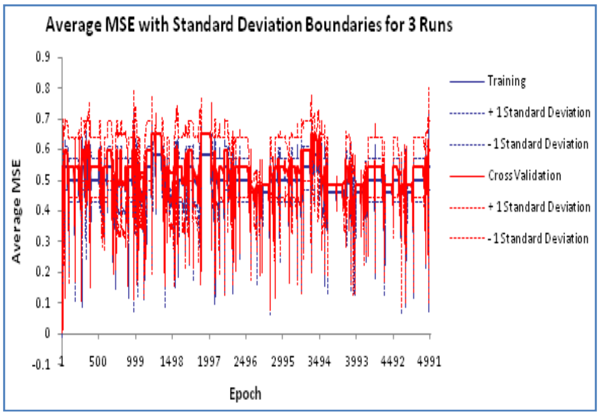

Fig.13: Avg. Min MSE Vs Epochs for learning rule DBD

d. Transfer Function- Linear Sigmoid Axon

The neural network is built for transfer function Linear Sigmoid Axon. Train the network by varying learning rules. The training report for various learning rule like momentum, CG, LM, QP and DBD is as shown in the Figures 14-18.

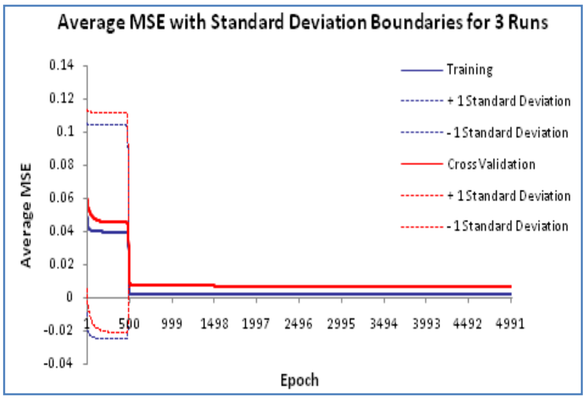

Fig. 14: Avg. Min MSE Vs Epochs for learning rule Momentum

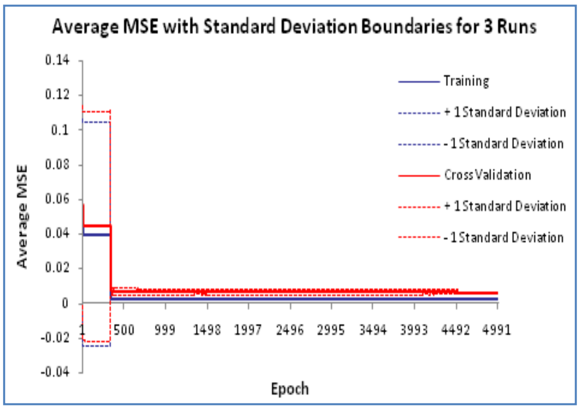

Fig. 15: Avg. Min MSE Vs Epochs for learning rule CG

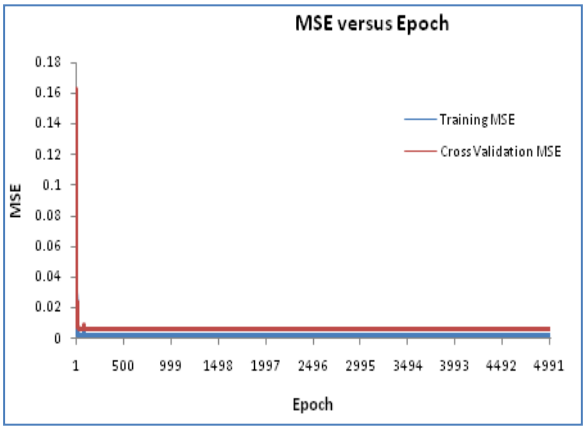

Fig. 16: Avg. Min MSE Vs Epochs for learning rule LM

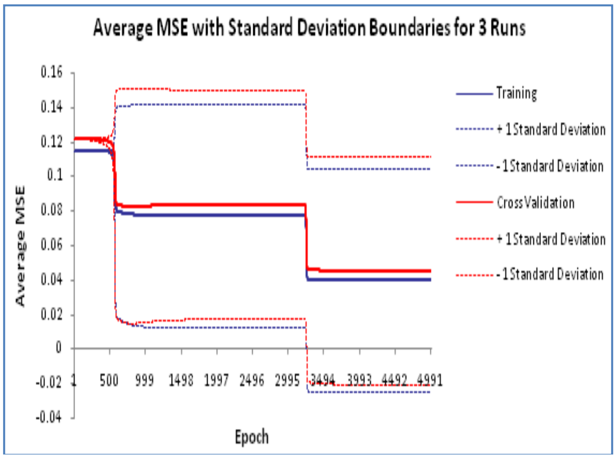

Fig. 17: Avg. Min MSE Vs Epochs for learning rule QP

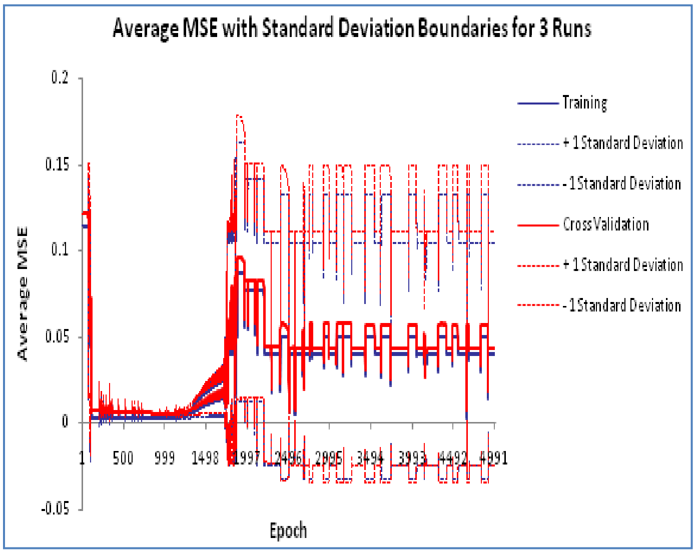

Fig. 18: Avg. Min MSE Vs Epochs for learning rule DBD

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Table 2: Values of MSE, NMSE and r for Transfer functions and Learning Rules in hidden layer

Transfer Function →	Linear Tanh	Linear Sigmoid	Linear Axon	Bias Axon	Axon
Learning Rule →	**Mom**	Mom	QP	QP	LM
MSE →	**0.00282114**	0.0029092	0.003005	0.003005	0.0045501
NMSE →	**0.66993289**	0.6908521	0.7135911	0.7135911	1.0805147
r →	**0.63486465**	0.6323588	0.6300477	0.6300477	0.6300477

From Table 2, it is inferred that the optimal values are obtained for Transfer function- Linear Tanh Axon and Learning Rule- Momentum, in the hidden layer and output layer. The valves of r = 0.63486495, MSE = 0.00282112 and NMSE = 0.63486465 which are optimal values as compared to the results obtained for other transfer function.

2) Selection of Transfer Function in the output Layer:

Using Transfer function- Linear Tanh Axon and Learning Rule- Momentum in the hidden layer, the Neural Network was built for different Transfer Function with Learning Rule- Momentum at the output layer.

Table 3: optimal values for Transfer function- Axon and Learning Rule- momentum at output layer

Sr. No.	Different Parameters	In the Hidden Layer, Transfer Function- Linear Tanh Axon and Learning Rule- Momentum In the Output Layer, Learning Rule- Momentum No of Epochs-5000						
		Sigmoid Axon	Lin Tanh Axon	Tanh Axon	Lin Sigmoid	Bias Axon	Linear Axon	**Axon**
1	MSE	0.00295	0.00655	0.00755	0.00615	0.00274	0.00273	**0.00269**
2	NMSE	0.70053	1.55632	1.79216	1.45933	0.65178	0.64781	**0.63796**
3	r	0.62996	0.63005	0.62946	0.63005	0.63209	0.63315	**0.6346**

Table 3 shows that optimal values for Transfer function- Axon and Learning Rule- momentum at output layer, the values of r = **0.6346**, MSE = **0.00269**and NMSE = **0.63796**.

3) Selection of Step Size and Momentum Rate for output Layer:

MLP is also called Back Propagation. During training, iteration of back propagation NN, the weights at the output layer are modified and by proceeding backwards through the hidden layers one by one until it reach the input layer. It is the method of proceeding backwards. Therefore weights and biases are back propagating to the previous layer.
The network was trained for 5 times by varying Step Size and Momentum Rate individually. It was noticed from Table 4 that the optimal values are obtained at **Step Size = 0.5**.

Table 4: Step Size Vs Different Parameters for Output Layer

Step Size	0.1	0.2	0.3	0.4	**0.5**
Performance	***EMG only***	***EMG only***	***EMG only***	***EMG only***	***EMG only***
MSE	0.002677317	0.002676102	0.005935332	0.00267821	**0.00267549**
NMSE	0.635779687	0.635491075	1.409457111	0.63599194	**0.63534573**
r	0.634639669	0.634608943	0.630047669	0.63478499	**0.6345962**

IV. CONCLUSION

By using conventional method, it is difficult to reduce noise from EMG signal. The major task of neural network is to learn the model in which it is embedded and maintain the model sufficiently consistent with the real world problem. This model implies the faster improvement so as to achieve the specified goals of the application of interest. From the implication of findings, FTLRNN reduces noise intelligently from the EMG signal. The difference between EMG with noise and desired EMG signal is computed from the performance measures MSE, NMSE and r. These values are found optimal. The maximum value of **r = 0.941898667,** minimum values of **MSE = 0.000536187** and **NMSE = 0.12732776** is obtained. The Correlation Coefficient 'r' is found to be **0.941898667,** shows that desired output and network output is co- varied in the same direction.Proposed FTLRNN based model with time delay memory (TDNN) is able to filter noise from a typical EMG signal contaminated by noise. From the simulation study it is cleared that FTLR Neural Network Model gives best performance as compared to the Multilayer Perceptron.

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