USE OF RBF NEURAL NETWORK IN EMG SIGNAL NOISE REMOVAL

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***Abstract**:-* The bioelectric potentials associated with muscle activity constitute the electromyogram (EMG). EMG signal is used in biomedical applications to detect abnormal muscle electrical activity that occur in many diseases and conditions like muscular dystrophy, inflammation of muscles, pinched nerves, peripheral nerve damages, amyotrophic lateral sclerosis, disc herniation, myasthenia gravis and others. In this paper, it is depicted that an RBF neural network as compared with other types of neural networks can be effectively used for EMG signal noise removal, which is a typical nonlinear multivariable regression problem. The performance parameters i.e. MSE and correlation coefficient are found to be in the expected range of values.

***Key Words*:** EMG, RBF, MSE, MLP, PE, Correlation Coefficient, NN.

1 Introduction

The bioelectric potentials associated with muscle activity constitute the **Electromyogram**, which is abbreviated as **EMG.** These potentials may be measured at the surface of the body near a muscle of interest or directly from the muscle by penetrating the skin with needle electrodes. Since most EMG measurements are intended to obtain an indication of the amount of activity of a given muscle, or group of muscles, rather than of an individual muscle fiber, the pattern is usually a summation of the individual action potentials from the fibers constituting the muscle or muscles being measured. EMG electrodes pick up potentials from all muscles within the range of the electrodes, hence potentials from nearby large muscles may interfere with attempts to measure the EMG from smaller muscles, even though the electrodes are placed directly over the small muscles. Where this problem arises, needle electrodes are inserted directly into the muscle are required.[1],[2]

The action potential of a given muscle (or nerve fiber) has a fixed magnitude, regardless of the intensity of the stimulus that generates the response. Thus, in a muscle, the intensity with which the muscle acts, does not increase the net height of the action potential pulse, but increases the rate with which each muscle fiber fires and the number of fibers that are activated at any given time. The amplitude of the measured EMG waveform is the instantaneous sum of all the action potentials generated at any given time. Because these action potentials occur in both positive and negative polarities at a given pair of electrodes, they sometimes add and sometimes cancel. Thus, the EMG waveform appears very much like a random-noise waveform, with the energy of the signal as a function of the amount of muscle activity and electrode placement. Typical EMG waveform is as shown in Figure 1.

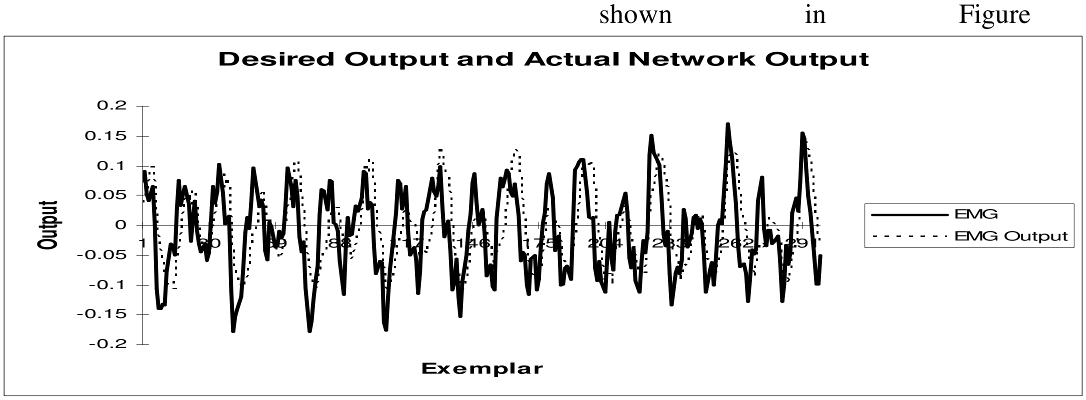


Fig 1**:** Typical electromygram waveform. (Waveform obtained from Simulation at Sr. No.3 in Table 2)

Needle electrodes for EMG consist merely of fine insulated wires, and are placed so that their tips, which are bare, in contact with the nerve, muscle, or other tissue from which the measurement is made. The remainder of the wire is covered with some form of insulation to prevent shorting. Wire electrodes of copper or platinum are often used for EMG pickup from specific muscles. The wires are either surgically implanted or introduced by means of a hypodermic needle that is later withdrawn, leaving the wire electrode in place. With this type of electrode, the metal-electrolyte interface takes place between the uninsulated tip of the wire and the electrolytes of the body, although the wire is dipped into an electrolyte paste before insertion in some cases. The hypodermic needle is sometimes a part of the electrode configuration and is not withdrawn. Instead, the wires forming the electrodes are carried inside the needle, which creates the hole necessary for insertion, protects the wires, and acts as a grounded shield. A single wire inside the needle serves as a unipolar electrode, which measure the potentials at the point of contact with respect to some indifferent reference. If two wires are placed inside the needle, the measurement is called bipolar and provides very localized measurement between the two wire tips.

Surface, needle, and fine-wire electrodes are all used for different types of EMG measurement. Surface electrodes are generally used where gross indications are suitable, but where localized measurement of specific muscles is required, needle or wire electrodes that penetrate the skin and contact the muscle to be measured are needed. As in neuronal firing measurements, both the unipolar and bipolar measurements of EMG are used.[3],[4]

2 EMG Measurement

Although action potentials from individual muscle fibers can be recorded under special conditions, it is the electrical activity of the entire muscle that is of primary interest. In this case, the signal is a summation of all the action potentials within the range of the electrodes, each weighted by its distance from the electrodes. Since the overall strength of muscular contraction depends on the number of fibers energized and the time of contraction, there is a correlation between the overall amount of EMG activity for the whole muscle and the strength of muscular contraction. In fact, under certain conditions of isometric contraction, the voltage-time integral of the EMG signal has a linear relationship to the isometric voluntary tension in a muscle. There are also characteristic EMG patterns associated with special conditions, such as fatigue and tremor.[7]

The EMG potentials from a muscle or group of muscles produce a noisy waveform that vary in amplitude with the amount of muscular activity. Peak amplitudes vary from 25 μV to about 5 mV, depending on the location of the measuring electrodes with respect to the muscle and the activity of the muscle. A frequency response from about 5 Hz to well over 5000 Hz is required for faithful reproduction.[5],[6],[12] The amplifier for EMG measurements, like that for ECG and EEG, must have high gain, high input impedance and a differential input with good common-mode rejection. However, the EMG amplifier must accommodate the higher frequency band. In many commercial electromyographs, the upper-frequency response can be varied by use of switchable lowpass filters. Unlike ECG or EEG equipment, the typical electromyograph has an oscilloscope readout instead of a graphic pen recorder. The reason is the higher frequency response required. Sometimes a storage cathode-ray tube is provided for retention of data, or an oscilloscope camera is used to obtain a permanent visual record of data from the oscilloscope screen.

The EMG signal can be quantified in several ways. The simplest method is measurement of the amplitude alone. In this case, the maximum amplitude achieved for a given type of muscle activity is recorded. Unfortunately the amplitude is only a rough indication of the amount of muscle activity and is dependent on the location of the measuring electrodes with respect to the muscle. Another method of quantifying EMG is a count of the number of spikes or, in some cases, zero crossings, that occur over a given time interval. A modification of this method is a count of the number of times a given amplitude threshold is exceeded. Although these counts vary with the amount of muscle activity, they do not provide an accurate means of quantification, for the measured waveform is a summation of a large number of action potentials that cannot be distinguished individually. The most meaningful method of quantifying the EMG utilizes the time integral of the EMG waveform.[18] With this technique, the integrated value of the EMG over a given time interval, such as 0.1 second, is measured and recorded or plotted. As indicated above, this time integral has a linear relationship to the tension of a muscle under certain conditions of isometric contraction, as well as a relationship to the activity of a muscle under isotonic contraction. As with the amplitude measurement, the integrated EMG is greatly affected by electrode placement, but with a given electrode location, these values provide a good indication of muscle activity.[9]

In another technique that is sometimes used in research, the EMG signal is rectified and filtered to produce a voltage that follows the envelope or contour of the EMG. This envelop, which is related to the activity of the muscle, has a much lower frequency content and can be recorded on a pen recorder, frequently in conjunction with some measurement of the movement of a limb or the force of the muscle activity.

2.1 Sources of Errors

Errors can occur in a multitude of ways. These errors need to be considered, although may not be always present simultaneously:

- Errors due to tolerance of electronic components.
- Mechanical errors in meter movements.
- Component errors due to drift or temperature variation.
- Errors due to poor frequency response.
- In certain types of instruments, errors due to change in atmospheric pressure or temperature.
- Reading errors due to parallax, inadequate illumination, or excessively wide ink traces on a pen recording.

2.2 Noise

All semiconductor junctions generate noise, which limits the detection of small signals. Op Amps have transistor input junctions, which generate both noise-voltage sources and noise-current sources. These are depicted in Figure 2.

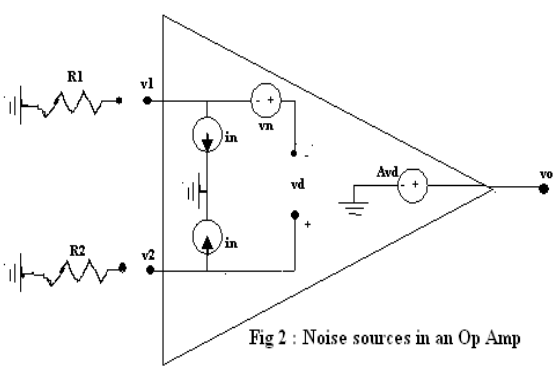


Fig 2 : Noise sources in an Op Amp

For low source impedance, only the noise voltage v_n is important; it is large compared with the i_nR drop caused by the current noise i_n. The noise is random, but the amplitude varies with frequency. For example, at low frequencies the noise power density varies as 1/f (flicker noise), so a large amount of noise is present at low frequencies. At the infrequencies, the noise is lower and can be specified in rms units of $V.Hz^{-1/2}$. In addition, some silicon planar-diffused bipolar integrated-circuit op amps exhibit bursts of noise[2]. The noise currents flow through the external equivalent resistances so that the total rms noise voltage is

$$v_t = \{[v_n^2 + (i_nR_1)^2 + (i_nR_2)^2 + 4kTR_1 + 4kTR_2]BW\}^{1/2}$$

where R_1 and R_2 = equivalent source resistances

v_n = mean value of the rms noise voltage, in $V.Hz^{-1/2}$, across the frequency range of interest.

i_n = mean value of the rms noise current, in $A\ Hz^{-1/2}$, across the frequency range of interest.

k = Boltzmann's constant.

T = temperature, K

BW = noise bandwidth, Hz.

3 Performance Measures

3.1 MSE (Mean Square Error)

The formula for the mean square error is

$$MSE = \sum_{j=0}^{p} \sum_{i=0}^{n} (d_{ij} - y_{ij})^2 / NP$$

where P = number of output processing elements, N= number of exemplars in the data set, y_{ij} = network output for exemplar i at processing element j, d_{ij} = desired output for exemplar i at processing element j.[10]

3.2 r (Correlation Coefficient)

The size of the mean square error (MSE) can be used to determine how well the network output fits the desired output, but it doesn't necessarily reflect whether the two sets of data move in the same direction. For instance, by simply scaling the network output, the MSE can be changed without changing the directionality of the data. The correlation coefficient (r) solves this problem. By definition, the correlation coefficient between a network output x and a desired output d is:

$$r = \frac{\dfrac{\sum_i (x_1 - \overline{x})(d_i - \overline{d})}{N}}{\sqrt{\dfrac{\sum_i (d_i - \overline{d})^2}{N}}\sqrt{\dfrac{\sum_i (x_1 - \overline{x})^2}{N}}}$$

The numerator is the covariance of the two variables and the denominator is the product of the corresponding standard deviation. The correlation coefficient is confined to the range [-1,1]. When r = 1, there is a perfect positive linear correlation between x and d, that is, they co-vary, which means that they vary by the same amount.

4 Neural Network Approach

There are numerous real life situations where the exactness of the measurements is required. In Biomedical applications, due to complicated situations, the measurements are often error prone and hence, are noisy. Neural networks can be used to obtain reasonably good accuracy in removal of noise or elegantly filtering out the desired signals. At a high level, the filtering problem is a special class of function approximation problem in which the function values are represented using time series. A time series is a sequence of values measured over time in the discrete or continuous time units. Neural Networks can also be used for solving the nonlinear multivariable regression problem.

Signal filtering from present observations is a basic signal processing operation by use of filters. Conventional parametric approaches to this problem involve mathematical modeling of the signal characteristics, which is then used to accomplish the filtering. In a general case, this is relatively a complex task containing many steps for instance model hypothesis, identification and estimation of model parameters and their verification. However, using a Neural Network, the modeling phase can be bypassed and nonlinear and nonparametric signal filtering can be performed. As the thresholds of all neurons are set to zeros, unknown variables for one step ahead filtering are only the connection weights between the output neurons and the j^{th} neuron in the second layer, which can be trained by available sample set. [8]

In the last decade, NN, have given rise to high expectations for model free statistical estimation from a finite number of sample. The goal of predictive learning is to estimate or learn an unknown functional mapping between the input variables and the output variables, from the training set of known input output samples. The mapping is typically implemented as a computational procedure in software. Once the mapping is obtained from the training data, it can be used for predicting the output value, given only the values of the input variables.[11]

Literature survey revealed that the Neural Networks can be effectively used for nonlinear regression problem.[13],[14],[15] Also, there is a wide scope for designing an exact Neural Network with the performance indices approaching to their ideal values, i.e. MSE = 0, and correlation coefficient = 1. In the previous research work [16], the effects of EMG signal sampling frequency and the pass band frequency on neuromuscular signal recognition have been studied. The classification of the EMG signal is done using two intelligent computational methods: RBF and Fuzzy subtractive clustering network. Also, in the work referred in [17], the EMG signal were recorded during isometric contraction for calculating the characteristic features of EMG signals like the median frequencies and temporal and spectral moments.

A typical nonlinear regression problem of removing noise from an EMG signal has been considered in this paper using a Radial Basis Function Neural Network. Radial Basis Function (RBF) networks are nonlinear hybrid networks typically containing a single hidden layer of processing elements (PEs). This layer uses Gaussian transfer functions, rather than the standard sigmoidal functions employed by MLPs. The centers and widths of the Gaussians are set by unsupervised learning rules, and supervised learning is applied to the output layer. These networks tend to learn much faster than MLPs. The Training data is used to train the RBF neural network for removing the noise in the EMG signal. This contains 1500 data samples in two variables.

5 Simulation

The results are obtained on Neuro Solutions platform and accordingly, simulations are carried out on noisy EMG input and desired EMG signal. The noisy EMG input was inputted to an RBF Neural Network with number of hidden layers varying from 3 to 5. RBF Neural Network with input, hidden and output layer with varying parameters like processing elements, transfer function, learning rule, step size and momentum were tested in supervised learning mode with maximum epoch value, 1000.

After training the RBF Neural Network on a noisy input and desired output data values with 1500 samples and under different test condition, the expected results were obtained with minimum MSE values around the estimated values as shown below. The EMG signal under consideration, having a total 1500 samples was divided into various tags i.e. 60% sample for training, 15% for cross validation and 25% for testing. The numbers of hidden layers were varied from 2 to 5 for experimentation. The other parameters like cluster center, competitive rule, metric method, processing element per hidden layer, transfer function, learning rule were also varied. The results for optimum parameters are given in the following tables.

6 Simulation Results

Table 1: (For Hidden layers = 3, Cluster Center = 5, Competitive rule = Consciencefull, Metric Euclidean, Transfer function = Tanh Axan, Learning rule = Momentum and in supervised learning mode)

Sr. No.	Type of ANN	Hidden Layer Variation H1H2H3	Correlation Coefficient	Minimum MSE Criterion		
				Training	Cross validation	Testing
01	RBF network	**05**,05,05	0.631570498	0.009987406	0.025815334	0.003361018
02	RBF network	05,**05,**05	0.627446384	0.009985864	0.025917992	0.003333662
03	RBF network	**05,**05,07	**0.634935685**	**0.009961887**	0.025991453	0.003341636
04	RBF network	05,**05**,07	0.629228299	0.009990185	0.025742	0.003343127
05	RBF network	**05**,05,08	0.631092725	0.009978593	0.025897124	0.00330958
06	RBF network	05,**05**,08	0.633598594	0.009989789	0.025921768	0.003395086

Table 2: (For Hidden layers = 4, Cluster Center = 5, Competitive rule = Consciencefull, Metric= Euclidean, Transfer function = Tanh Axon, Learning rule = Momentum and in supervised learning mode)

Sr. No.	Type of ANN	Hidden Layer Variation H1H2H3H4	Correlation Coefficient	Minimum MSE Criterion		
				Training	Cross validation	Testing
01	RBF network	**15**,20,10,05	0.613085209	0.009986136	0.032334619	0.003398408
02	RBF network	15,**20,**10,05	0.615536256	0.009913111	0.032262425	0.003401639
03	RBF network	**05**,05,10,05	0.626473069	0.009995618	0.033206785	0.003238444
04	RBF network	05,**05,**10,05	0.624123099	0.009994416	0.032949311	0.003251107
05	RBF network	**02**,05,10,05	0.624981107	0.009973827	0.032576782	0.003404298
06	RBF network	02,**05**,10,05	0.0622015847	0.009996404	0.033318484	0.003297185

Table 3: (For Hidden layers = 5, Cluster Center = 5, Competitive rule = Consciencefull, Metric= Euclidean, Transfer function = Tanh Axan, Learning rule = Momentum and in supervised learning mode)

Sr. No.	Type of ANN	Hidden layer Variation H1H2H3H4H5	Correlation Coefficient	Minimum MSE Criterion		
				Training	Cross validation	Testing
01	RBF network	**4**,5,6,5,4	0.633913126	0.010163736	0.027555747	0.003257741
02	RBF network	4,**5**,6,5,4	0.634937464	0.00999774	0.026372377	0.00330488
03	RBF network	**5**,6,7,6,5	0.626702431	0.010075801	0.02649354	0.003324189
04	RBF network	5,**6**,7,6,5	0.633145836	0.0101425	0.027102996	0.003259303
05	RBF network	**4,**5,5,5,3	0.615242831	0.010863202	0.031167117	0.003347065
06	RBF network	4,**5**,5,5,3	0.595180751	0.012657307	0.038079664	0.003411631

Fig 3: Figure 3 depicts the variation of average of min MSE for 5 runs versus the number of PEs in first hidden layer (Simulation at Sr. No.3 in Table 1)

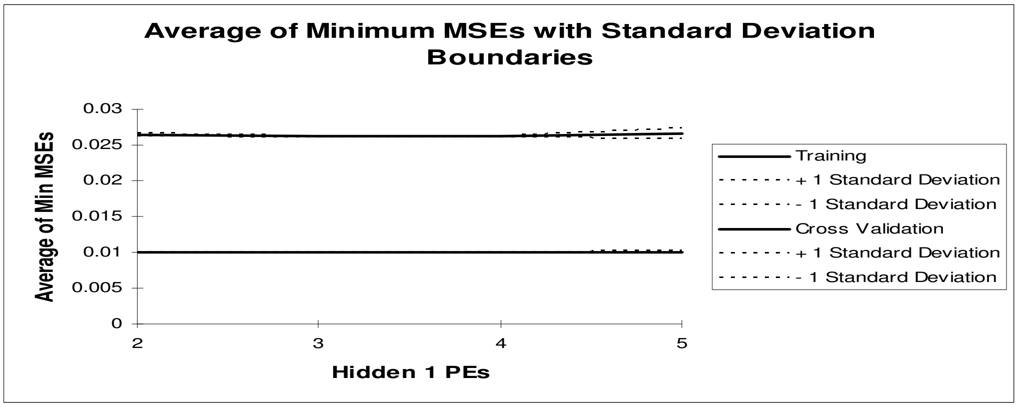
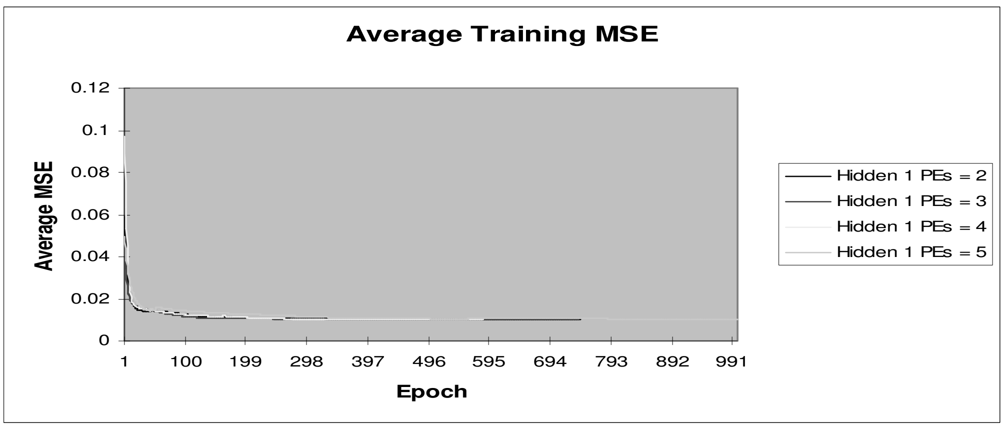


Fig 4: Figure 4 depicts the variation of average training MSE versus the number of epochs (Simulation at Sr. No.3 in Table 1)



Simulations were carried out for neural networks like Multi-Layer Perceptron NN (MLP), Generalized Feed Forward NN, Modular NN, Jordan/Elman NN and Recurrent NN with other parameters similar to RBF neural network and following results were obtained with maximum r (Correlation Coefficient) value, as indicated below in Table 4 with the optimal hidden layer configuration of RBF NN, i.e. **05**,05,07.

Table 4:

Sr. No.	Type of ANN	Hidden Layer Variation H1H2H3	Correlation Coefficient r	Minimum MSE Criterion		
				Training	Cross validation	Testing
01	MLP	**05**,05,07	0.627751035	0.010085787	0.024683456	0.003365081
02	Gen FF	**05**,05,07	**0.636240018**	**0.009501057**	0.018979003	0.004679485
03	Mod NN	**05**,05,07	0.636114324	0.011539849	0.026384025	0.002992898
04	Jor/elman NN	**05**,05,07	0.627025792	0.009949056	0.025520535	0.003213602
05	Recurrent N/W	**05**,05,07	0.616395357	0.009974084	0.024154242	0.003366557

7 Conclusion

EMG signal is an important biomedical signal that depicts muscle activity, thus revealing useful information about nerve system. Removal of noise using an RBF Neural Network and other Neural Networks, as indicated in table 4 have been studied in this paper. It is demonstrated that RBF NN elegantly reduces the noise from the EMG signal as compared to other neural networks. The difference between the noisy EMG signal and the desired EMG signal is computed as a performance measure (MSE) and is found to be in the expected range approaching to 0.01. The minimum MSE criterion is found satisfactory (0.0099-0.01) in trained RBF Neural Network and found to perform better during testing phase (0.003). Also, the correlation coefficient (r) is found to be in the desired range so that the network output and the desired output co-varies, i.e. varying by the same amount.

This work could be the basis for the development of neural networks with optimal performance and their realization in hardware for VLSI implementation.

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