



# **Removal of EMG Interference from Electrocardiogram Using Back Propagation**

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**Abstract:** In this paper a technique called back Propagation Network (BPN) is proposed to cancel electromyogram (EMG) interference in electrocardiogram (ECG). The performance evaluation of the proposed technique is done in terms of signal to noise ratio, mean square error and epochs. The paper presented also illustrates the effect of training algorithm for a given application. Electrocardiogram signals are used to detect heart diseases and also in recent clinical studies. These signals (ECG) are mixed with noise such as baseline drift, electrode motion artifacts, power line interference etc. Previous studies for ECG noise removal are not up on satisfactory marks due to the non stationary nature of the associated noise sources and their spectral overlap with desired ECG signals.

**Keywords:** Noise removal, Electrocardiogram (ECG), Electromyogram (EMG), Back propagation (BPN), Spectral overlap.

## **I. INTRODUCTION**

Electrocardiogram (ECG) signals have been widely used in clinical studies for the diagnosis of heart disorders. It is the electrical potential record produced by heart. Due to the movement of Na<sup>+</sup> and K<sup>+</sup> ions in blood the electrical wave is generated by depolarization and repolarization of certain cells. The ECG signal is in the range of 2mv and also require a recording bandwidth of 0.1 to 120 Hz [1]. To acquire ECG signal non invasive technique is used i.e. placing the electrodes at standard location on the skin of person [2]. The ECG signal and heart rate expose the cardiac health of human heart. Any disorder in heart rate or change in morphological pattern of ECG signal indicates cardiac arrhythmia. It is detected and identified by analysis of recorded ECG waveform. Information about the nature of disease related to heart is contained in amplitude and duration of the P-QRS-T-U wave. Generally the recorded ECG is often corrupted by different types of noises and these artifacts that can be with in the frequency band of ECG signal and may change characteristics of ECG signal. Hence it is very difficult to take out useful information of signal. The major noise that corrupt the ECG signal are Electromyography(EMG) noise, power line interference, noise due to random movement and respirational movements, electrode contact noise.

High pass, low pass, window based filter for the analysis of ECG are defined in[3]. In this rectangular, hamming, hanning, kaiser window are used for noise reduction in ECG. The rectangular window FIR has sharpe attenuation. The rectangular has linear phase and filter was found to be stable. Various modeling techniques are employed, such as the extended Kalman filters [4]. RLS based adaptive filter is presented [5]. In this paper performance characteristics of two adaptive filters LMS and RLS are given. The MSE increases and SNR decreases in RLS adaptive filter in comparison to LMS adaptive filter. The performance comparison of SRLMS, NSRLMS, LMS etc. is based on SNR is in [6]. Values of SNR in this paper shows that its value is less in basic algorithm like SRLMS as compared to NSRLMS. Same in case with LMS and NLMS, which means that normalizing improves SNR. Discrete wavelet transform and neural network is used for ECG signal noise reduction [7]. Neural network model for noise reduction is in [8]. In this paper neural network model is developed for noise reduction. Two different neural networks have been compared to minimize the effect of noise. Several other techniques have been also proposed to extract the ECG components contaminated with the background noise and allow the measurement of subtle features in the ECG signal.

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The rest of the paper is organized as follows: Section II is about problem formulation means what types of problems are in previous work. After that section III for algorithm description, in which steps regarding algorithm takes place. In section IV design methodology of network and the last Section V discuss the results and section VI concludes the paper.

## II. PROBLEM FORMULATION

- Electromyogram (EMG) artifacts often contaminate the electrocardiogram (ECG). They are more difficult to suppress or eliminate, compared for example to the Baseline wander etc. Electromyogram is a random signal. It varies from time to time and also from person to person. Due to their random character and to the considerable overlapping of the frequency spectra of ECG and EMG signals obtained from the same pair of electrodes.
- There are many methods have been implemented to eliminate the noise from noisy signal. High pass, low pass and notch filter are the basic method to pass the signal. The filters have the biggest disadvantage that these also remove important frequency components in the locality of cut off frequency. The usually applied low-pass filtering results in limited suppression of the EMG artifact and considerable reduction of sharp Q, R and S ECG wave amplitudes.
- ECG is a random signal. The coefficients of static filter are constant. Therefore design of static is not possible to cancel the interference in ECG.
- To overcome the limitation of static filters different adaptive filtering methods are developed. The design of fixed filter is not possible to cancel the interference in ECG. Hence, an adaptive mechanism called BPN is proposed in this paper. It explains the efficiency of BPN to cancel the EMG interference in ECG signal.

## III. ALGORITHM DESCRIPTION

Artificial Neural Network (ANN) has been the successfully used classifier in numerous fields. So, it is of interest to use it for ECG analysis. The basic processing unit of brain is neuron which works identically in ANN [9]. The neural network is formed by a set of neurons interconnected with each other through the synaptic weights. It is used to acquire knowledge in the learning phase. The number of neurons and synaptic weights can be changed according to desired design perspective. The basic neural network consists of 3 layers input layer, hidden layer, output layer.

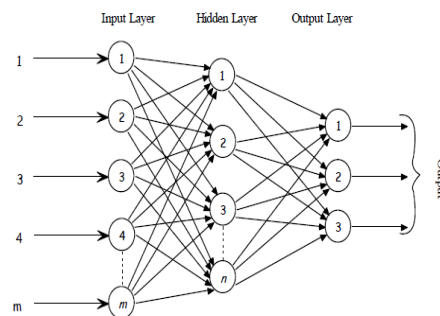


Fig. 1 General Structure of a Neural Network

### 3.1 Back propagation network

The back propagation training with generalized delta learning rule is an iterative gradient algorithm designed to minimize the root mean square error between the actual output of a multilayered feed-forward NN and a desired output. Each layer is fully connected to the previous layer, and has no other connection.

The Back Propagation Algorithm is explained in the following steps:

Step: 1 Initialization

Set all the weights and biases are set to small real random values between 0 and 1.

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Step: 2 Presentation of input and desired output

Present the input vector  $x(1), x(2), \dots, x(N)$  from the measured ECG signal and corresponding desired response  $d(1), d(2), \dots, d(N)$  from original ECG signal, where  $N$  is the number of training patterns.

Step: 3 Calculation of actual outputs

Equation (1) below is used to calculate the output signals  $y_1, y_2, \dots, y_{NM}$

$$y_i = \varphi \left( \sum_{j=1}^{N_{M-1}} w_{ij}^{(M-1)} x_j^{(M-1)} + b_i^{(M-1)} \right), i = 1, \dots, N_{M-1}$$

(1)

Where

$w_{ij}$  are the weights and  $b_i$  are the biases.

Step: 4 Adaptation of weights ( $w_{ij}$ ) and biases ( $b_i$ )

The weights and biases are changed as per equation (2)

$$\Delta w_{ij}^{(l-1)}(n) = \mu x_j(n) \delta_i^{(l-1)}(n),$$

(2)

$$\Delta b_i^{(l-1)}(n) = \mu \delta_i^{(l-1)}(n),$$

(3)

Where

$$\delta_i^{l-1}(n) = \begin{cases} \varphi(\text{net}_i^{l-1})[d_i - y_i(n)], l = M, \\ \varphi(\text{net}_i^{l-1}) \sum_k w_{ki} \delta_k^l(n), 1 \leq l \leq M, \end{cases} \quad (4)$$

in which  $x_j(n)$  = output of node  $j$  at iteration  $n$ ,  $l$  is layer,  $k$  is the number of output nodes of neural network,  $M$  is output layer,  $\varphi$  is activation function. The learning rate is represented by  $\mu$ . There are two phases of data flow. First, the input pattern is propagated from the input layer to the output layer and, as a result of this forward flow of data, it produces an actual output. Then the error signals resulting are back propagated from the output layer to the previous layers to update their weights. Different training algorithms use the gradient of the performance function to determine how to adjust the weights to minimize performance (i.e., MSE), these algorithms are Gradient descent with adaptive lr (learning rate) back propagation (traingda), gradient descent momentum and adaptive lr back propagation (traingdx), Leverberg Marquardt back propagation (trainlm) and Scaled conjugate gradient back propagation(traingcg) [9].

### 3.2 Implementation of BPN

The software used for the implementation of BPN is MATLAB. The basic procedure for implementing BPN algorithm is as follow:

- Specifying the inputs and targets to the BPN.
- Specifying the number of layers. Repeated experiments were performed to determine the size of the hidden layer.
- Mentioning the activation functions for each layer:  
TANSIG is a hyperbolic tangent sigmoid transfer function for hidden layer.  
PURELIN is a linear transfer function which is used as the activation function for the output layer.
- Creating a feed forward back propagation network.
- Training the network using the training function called TRAINLM, TRAINSCG, TRAINGDA, and TRAINGDX.

## IV. DESIGN METHODOLOGY

Various steps used for removal of noise from ECG are as follow:

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- First collect the ECG and EMG signal.
- Corrupted signal in which EMG and ECG signals interfered.
- Calculate Estimated Signal ECG signal.
- Then apply back propagation with different training algorithms.
- Compare the performance of training algorithms.
- Get estimated Desired Signal.

## V. RESULTS AND DISCUSSION

The proposed system was evaluated using ECG signals with muscle noise (EMG). In fig. 2 original ECG signal is the target in the training process and fig. 3 shows EMG signal. In fig. 4 corrupted signal is shown in which EMG and ECG signals interfered. The training stops as soon as the performance goal (mean square value of the estimated ECG) reaches a minimum. Mean Squared Error is the average squared difference between outputs and targets. Lower values of (MSE) indicate better performance of the network and zero means no error.

$$MSE = \frac{1}{N} \sum_{i=1}^N (e_i)^2 = \frac{1}{N} \sum_{i=1}^N (t_i - a_i)^2$$

(5)

Where,  $t$  - Target  
 $a$  - Actual output  
 $e$  - Error,  
 $N$  - Number of exemplars

Here target is to achieve the original ECG signal .which is given as a target to the network. The input to the signal is measured signal which is contaminated with EMG signal noise. This is caused by the contraction of other muscles besides the heart.

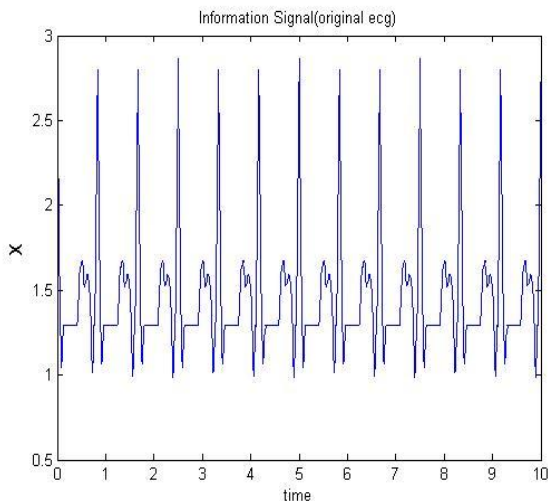


Fig.2 Information signal (Original ECG)

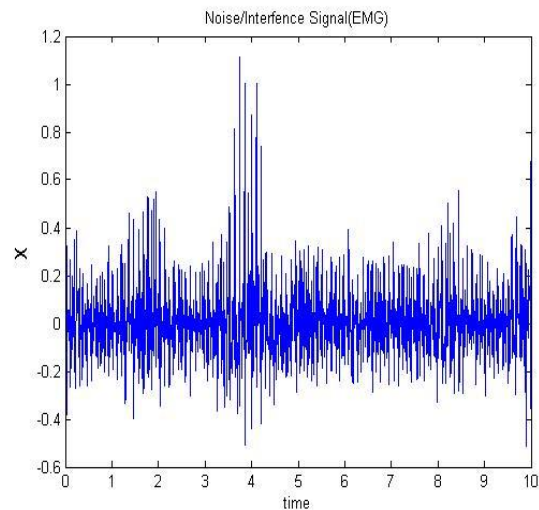


Fig.3 Noise signal (EMG)

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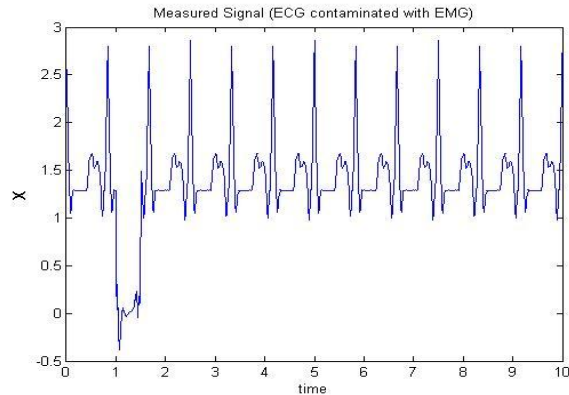


Fig.4 Corrupted signal (measured signal)

The estimated ECG using BPN is shown in fig 5. Table 1 summarizes the results of NN's training by comparing the Elapsed time, Epochs, SNR and the MSE with four training algorithms. These algorithms are Gradient descent with adaptive lr (learning rate) back propagation (traingda), gradient descent momentum and adaptive lr back propagation (traingdx), Leverberg Marquardt back propagation (trainlm), Scaled conjugate gradient back propagation (trainscg). All of these algorithms use the gradient of the performance function to determine how to adjust the weights to minimize performance (i.e., MSE).

**Table 1. Performance of network with four training algorithms**

Algorithm	SNR	MSE	Epoch
traingda	15.73	0.00289	247
traingdx	18.07	0.00238	126
trainscg	20.48	0.00116	56
trainlm	22.34	0.000783	12

As can be seen in Tables 1, NN trained with TRAINLM back propagation function results in a fastest algorithm implementation (12 epochs) with a best performance (MSE equals 0.000783). The estimated ECG signal using BPN and performance during the training process with trainlm algorithm is shown in fig. 6.

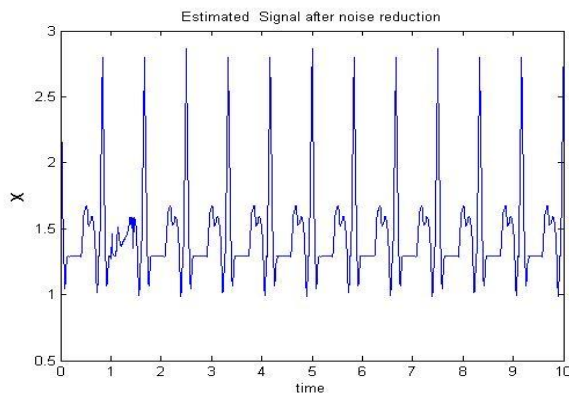


Fig. 5 Estimated signal using BPN

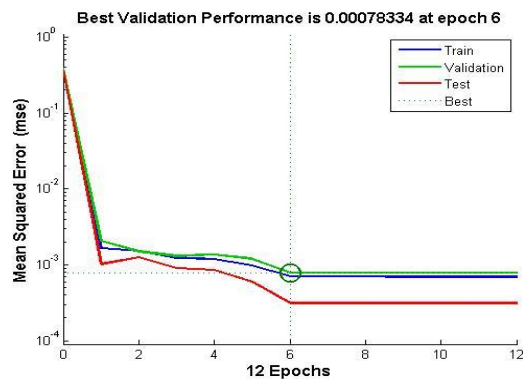


Fig.6 Performance during the training process



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## VI. CONCLUSION

The ECG signal is contaminated by various noises such as electrode noise, power line interference, and EMG. Conventional methods are used to remove the non physiological noises. Since some of the characteristics of ECG signal are similar to EMG signal. BPN technique is employed to cancel the EMG interference in ECG signal. The results obtained indicate that BPN is a useful technique to cancel the nonlinear interference from the ECG signal even if the frequency content of the interference overlaps with each other. From the above graph it is evident that the performance goal given to the various neural network learning algorithm that works on the back propagation with highest accuracy in term of fitting the to the pure ECG signal (original) from the noisy signal (measured). Leverberg Marquardt back propagation (trainlm) has value of MSE is very less and take less time.

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