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A new approach for Reducing Noise in ECG signal employing Gradient Descent Method by Artificial Neural Network

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Abstract: **ECG is the main tool used by the physicians for identifying and for interpretation of Heart condition. The ECG should be free from noise and of good quality for the correct diagnosis. In real time situations ECG are corrupted by many types of noises. The high frequency noise is one of them. In this thesis, analysis has been carried out the use of neural network for denoising the ECG signal. A multilayer artificial neural network (ANN) is designed. Here gradient descent method (GDM) is used for training of artificial neural network. The noisy ECG signal is given as input to the neural network. The output of neural network is compared with De-noised(original) ECG signal and value of Root Mean Square Error(RMSE) is computed. In training process the weights are updated until the value of RMSE is minimized. Several iteration has to be performed in order to find Minimum Mean Square Error(MMSE). At MMSE network weights are finalized. Subsequently, network parameters are used for Noise reduction. The comparison with other technique shows that the neural networks method is able to better preserve the signal waveform at system output with reduced noise. Our results shows better accuracy in terms of parameters root mean square error, signal to noise ratio and smoothness (RMSE,SNR and R) as compare to GOWT[18].The database has been collected from MIT-BIH arrhythmias database.**

Keywords: **ECG, ANN, GDM, RMSE, MMSE MIT-BIH.**

1. INTRODUCTION

The electrocardiogram [ECG] signal is generated by the rhythmic contractions of the heart. It represent the electrical activity of the heart muscles and is usually measured by the electrode placed on the body surface. The ECG works by detecting and amplifying the small electrical changes on the skin that are caused when the heart muscle "depolarizes" during each heartbeat. The ECG is a measurement of the effect of depolarization and repolarization for the entire heart on the skin surface[1]. The depolarization and repolarization of atria and ventricle are detected as small rises and falls in the voltage between two electrode placed either side of heart which displays a waveform. A typical ECG signal wave is give below in fig(1).

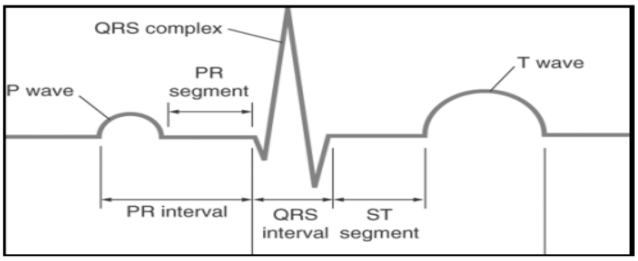

Fig.1: Typical ECG Waveform

It is noticed that even though the ECG signals from different patients have the similar forms, the ECG of each individual patient is different. To make appropriate medical diagnosis, doctors often need to compare the ECG signal of patient with own individual record[2]. In addition, ECG signal is often corrupted with noise, which makes an accurate diagnosis very difficult.

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ECG noise removal is complicated due to the time varying nature of ECG signal. Besides, since the spectral content of muscles noise over-laps that of the ECG, rectification of signal-to-noise ratio(SNR) merely by means of digital filtering is not possible without introducing adequate distortion in the ST-segment regions. Generally the almost shape of the component wave, expected to be present in noisy signal, may be known and the need is to calculate its time of occurrence and its precise shape. The two separate approaches used to solve this problem are those which appoint the structural features of the component wave and secondly the method that uses template matching techniques. Algorithms based on the first approach are of heuristic nature and are selective to the particular type of component wave being searched (e.g. the QRS complex). In the second method, the approximate knowledge on the shape of the component waves used to generate a template, which is defined by the previous information on the signal characteristics. The signal is then regularly simulate with the template by means of correlation, matched filtering, or other pattern recognition techniques. In this way, it would be possible to raise the diagnosis of some diseases of the heart and various pathologies [3]

A major number of algorithm for noise reduction in ECGs signal are like: Filter techniques [4],[5],[6] and wavelet transform approaches [7],[8],[9].problem of wavelet transform has low convergence rate and large mean square error. Also there are other application on empirical mode decomposition (EMD) method [10],[11],[12],[13],[14] that cancel the ECGs noise.

In this paper artificial neural network based on Gradient descent method is used, which noise the noise of electrocardiogram signal. Also it reshapes the ECG signal to some extent that physician can get desirable information. Computer simulation results demonstrate this proposed technique can successfully model the ECG signal and remove noise.

2. METHODOLOGY

Neural Network- Artificial Neural Network (ANN) is generally called neural network is a computational model which is motivated by the structure of biological neural network. A neural network (NN) combines an interconnected group of artificial neuron. This paper explains the use of neural network in noise removal of ECG signal, where the input units represents the noisy input ECG signal and the output unit represent noise free ECG signal. Every input vector is given to the input layer. Each hidden units computes the weighted sum of its input to outline its scalar a net activation. Net activation is the inner product of the inputs and weight vector at the hidden unit [15].

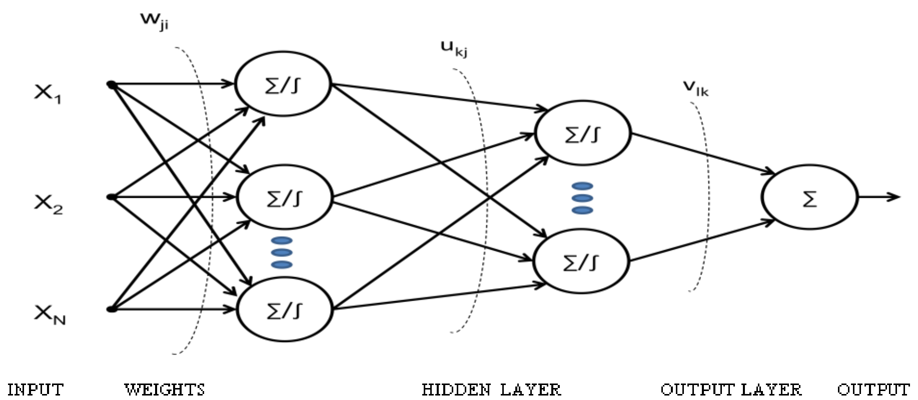

Fig. 2: Neural Network Model

Model Description-

Inputs: proposed model is using three noisy inputs X1 , X2.......,Xn which are the shifted version of original signals,which are matrix with a number of samples of each of the input signal.

Weights: this model is using weights at three levels W_{ji} , U_{kj} and V_{lk}

W_{ji} is a input vector

U_{kj} is a hidden vector

V_{lk} is a output vector

Neuron nodes:

Aggregation function- simple perceptron

Activation function- tan sigmoid function(tan h(x))

Weight updation: weights are updated by Gradient Descent Method

Let we have a feed forward neural network, which have three inputs and the weights at three levels which are given below.

Input layer weights:

$$W_{ji} = \begin{bmatrix} w_{11} & w_{12} & w_{1I} \\ w_{21} & w_{22} \ddots & \vdots \\ w_{J1} & \cdots & w_{JI} \end{bmatrix} \tag{1}$$

First Hidden layer weights:

$$U_{kj} = \begin{bmatrix} u_{11} u_{12} \dots u_{ij} \\ u_{21}\, u_{22} \ddots \vdots \\ u_{k1} \dots \dots . u_{kj} \end{bmatrix} \tag{2}$$

Output layer weights:

$$V_{lk} = [v_1 \quad v_{2 \dots\dots\dots} v_k] \tag{3}$$

The algorithm used to adopt a neural network is the backpropagation algorithm. Nevertheless this one requires the compute of 1st derived from the function of quadratic error with respect to all the weights of the network. That implies the use of the "Chain rule" since the exit error is not an explicit function of the weights in the input layer, which represents a high computational complexity due to the operations, numbers and the evaluation of the tansigmoidal functions in each node [16]. So, it is necessary to develop mechanisms that allow the estimation of derived from the average quadratic error with respect to the weights of the network required in the training phase of the neural networks with a computational complexity. To solve two important problems in the multilayer perceptron (optimization of the number of nodes in the hidden layer and reduction the computational complexity) this article proposes an increasing neuronal network in which the number of the nodes in the hidden layer and the network weights are reduced. In the proposed system the number of nodes of the network is optimized adding a node in the hidden layer after several iterations, and not changing the estimated weights initially the connect the input layer with the hidden layer.

Mathematical Analysis of Gradient Descent Method- The total mean error in a network is given by the following equation.Mean Square Error between desired output value and actual output value is equal to:

$$\mathrm{E} = \frac{1}{\mathrm{P}} \sum_{\mathrm{p}=1}^{\mathrm{P}} \left(\mathrm{y}_\mathrm{p}^\mathrm{d} - \mathrm{y}_\mathrm{p}^\mathrm{a}\right)^2 \tag{4}$$

Weight updation rule for different layers:

Weight updation rule for input layer:

$$\frac{\mathrm{dE}}{\mathrm{dw_{ji}}} = \frac{\mathrm{dE}}{\mathrm{d}\left(\mathrm{y}_\mathrm{p}^\mathrm{d} - \mathrm{y}_\mathrm{p}^\mathrm{a}\right)} \times \frac{\mathrm{d}\left(\mathrm{y}_\mathrm{p}^\mathrm{d} - \mathrm{y}_\mathrm{p}^\mathrm{a}\right)}{\mathrm{dy}_\mathrm{p}^\mathrm{a}} \times \frac{\mathrm{dy}_\mathrm{p}^\mathrm{a}}{\mathrm{d(net\ Y)}} \times \frac{\mathrm{d(net\ Y)}}{\mathrm{dt}_\mathrm{p}^\mathrm{a}} \times \frac{\mathrm{dt}_\mathrm{p}^\mathrm{a}}{\mathrm{d(net\ T)}} \times \frac{\mathrm{d(net\ T)}}{\mathrm{dz}} \times \frac{\mathrm{dz^a}}{\mathrm{d(net\ Z)}} \times \frac{\mathrm{d(net\ Z)}}{\mathrm{dw}}$$

$$= \frac{1}{\mathrm{P}} \sum_{\mathrm{p}=1}^{\mathrm{P}} \left(\mathrm{y}_\mathrm{p}^\mathrm{d} - \mathrm{y}_\mathrm{p}^\mathrm{a}\right) \times \left(1 - \mathrm{y}_\mathrm{p}^{\mathrm{a}^2}\right) \times \left(1 - \mathrm{z}_\mathrm{p}^{\mathrm{a}^2}\right) \times \mathrm{v_{lk}} \times \left(1 - \mathrm{t}_\mathrm{p}^{\mathrm{a}^2}\right) \times \mathrm{u_{kj}} \times \mathrm{x_i} \tag{5}$$

Weight updation rule for hidden layer weight:

$$\frac{\mathrm{dE}}{\mathrm{du_{kj}}} = \frac{\mathrm{dE}}{\mathrm{d}\left(\mathrm{y}_\mathrm{p}^\mathrm{d} - \mathrm{y}_\mathrm{p}^\mathrm{a}\right)} \times \frac{\mathrm{d}\left(\mathrm{y}_\mathrm{p}^\mathrm{d} - \mathrm{y}_\mathrm{p}^\mathrm{a}\right)}{\mathrm{dy}_\mathrm{p}^\mathrm{a}} \times \frac{\mathrm{dy}_\mathrm{p}^\mathrm{a}}{\mathrm{d(net\ Y)}} \times \frac{\mathrm{d(net\ Y)}}{\mathrm{dt}_\mathrm{p}^\mathrm{a}} \times \frac{\mathrm{dt}_\mathrm{p}^\mathrm{a}}{\mathrm{d}\left(\mathrm{u_{kj}}\right)}$$

$$= \frac{1}{\mathrm{P}} \sum_{\mathrm{p}=1}^{\mathrm{P}} \left(\mathrm{y}_\mathrm{p}^\mathrm{d} - \mathrm{y}_\mathrm{p}^\mathrm{a}\right) \times \left(1 - \mathrm{y}_\mathrm{p}^{\mathrm{a}^2}\right) \times \mathrm{v_{lk}} \times \mathrm{z_j} \tag{6}$$

Weight updation rule for output layer:

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$$\frac{dE}{du_{kj}} = \frac{dE}{d(y_p^d - y_p^a)} \times \frac{d(y_p^d - y_p^a)}{dy_p^a} \times \frac{dy_p^a}{d(\text{net } Y)} \times \frac{d(\text{net } Y)}{dv_{lk}}$$

$$= \frac{1}{P}\sum_{p=1}^{P}(y_p^d - y_p^a) \times (1 - y_p^{a^2}) \times t_k \tag{7}$$

Change in weights after every iteration are given below:

$$\Delta w_{ji} = \eta \times \frac{dE}{dw_{ji}} \tag{8}$$

$$\Delta u_{kj} = \eta \times \frac{dE}{du_{kj}} \tag{9}$$

$$\Delta v_{lk} = \eta \times \frac{dE}{dv_{lk}} \tag{10}$$

Value of the updated weights:

$$w_{ji}^{new} = w_{ji}^{old} + \Delta w_{ji} \tag{11}$$

$$u_{kj}^{new} = u_{kj}^{old} + \Delta u_{kj} \tag{12}$$

$$v_{lk}^{new} = v_{lk}^{old} + \Delta v_{lk} \tag{13}$$

We stops the training until we find Minimum mean square error. Several iteration has to be performed in order to find Minimum Mean Square Error(MMSE).At MMSE network weights are finalized. Subsequently, these network parameters are used for to denoises ECG signal. Figure 3 demonstrates the algorithm via flow chart.

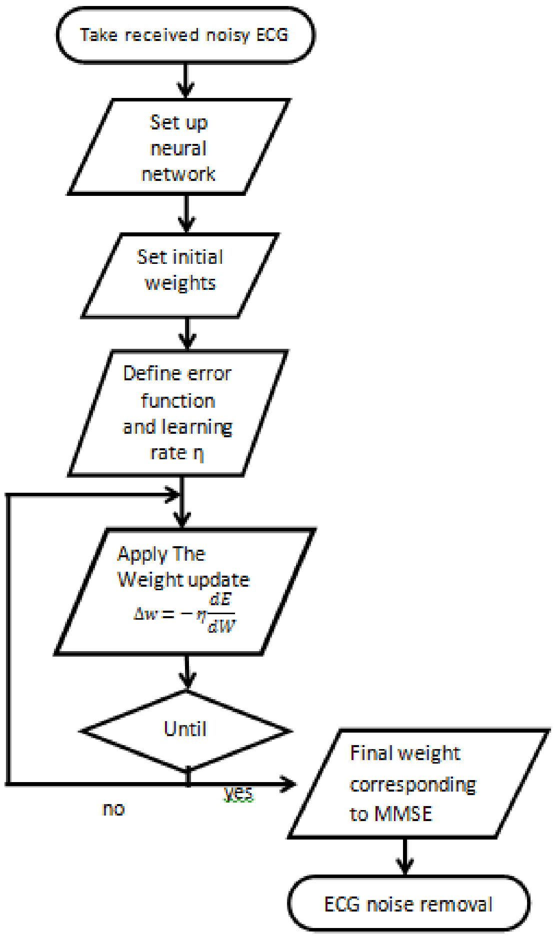

Fig.3: Flow Chart of Gradient Descent Algorithm

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3. DATABASE COLLECTION

The ECG signals from MIT-BIH Arrhythmia Database[17] were chosen to evaluate the performance of our work. It contains 48 half-hour excerpts of two channel ambulatory ECG recordings. The database comprises approximately 230 samples. The recordings of the database were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. The first 60s sampling data of ECG signal were adopted from the 30 minutes length of recording for offline de-noising evaluation.

4. RESULT AND COMPARISON

In this portion we have studied de-noising of signal of using sample no. 118 from MIT-BIH database by using Gradient descent method(ANN). In this method we take all the ECG signal of MIT-BIH database. After signal reconstruction the estimated signal to noise ratio(SNR), root mean square error(RMSE) and smoothness (r) are used as evaluation index for filtering comparison.

The SNR is a measure of signal strength relative to background noise after wavelet threshold denoising[18]. It can be defined as below:

$$SNR = 10log_{10}\frac{\sum_{i=1}^{N}\hat{S}^2(i)}{\sum_{i=1}^{N}|\hat{S}(i)-\hat{S}(i)|^2} \qquad (14)$$

The smoothness and distortion are two interrelated indexs for signal filtering.The signal filtering method should remove the undesirable fluctuation of useful signal caused by the noise. The RMSE is the root mean square error of the signal S(i) and denoised signal Ŝ(i).It can be expressed as equation

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{n-1}[S(i)-\hat{S}(i)]^2} \qquad (15)$$

The r is the smoothness of denoised of denoised signal Ŝ(i) after filtering.It can be described as:

$$r=\frac{\sum_{i=1}^{n-1}[\hat{S}(i+1)-\hat{S}(i)]^2}{\sum_{i=1}^{n-1}[S(i+1)-S(i)]^2} \qquad (16)$$

The RMSE reflects the distortion of filtering. The smaller the RMSE is, the closer the denoised signal is to the original signal and less deforming of the denoised signal after filtering. The RMSE should not be so large to avoid serious filtering distortion. Controversially, the smaller the r is, the more smooth the denoised signal reveals and more data of the original signal is modified. Too large value of r usually indicates that some noise still remain in the signal[18]. The RMSE and the r are two complementary indexes that are essential to the execution of filtering methods. In proposed method the comparison of genetic optimize wavelet thresholding (GOWT) and proposed method carried out in paper. It is noticed that the problem of GOWT is the convergence and large mean square error to denoise the ECG signal whereas Neural network based gradient descent method overcomes this problem to precise value of all parameters shown in table(1):

Table 1 : Filtering Result Of Sample No. 118 Through Hard Thresholding, Soft Thresholding, GOWT and Proposed Method

Methods	RMSE	R	SNR
Hard threshoding	14.5143	0.8681	28.2976
Soft thresholding	25.0662	0.5166	25.0662
GOWT	19.9805	0.6442	27.1066
Proposed method	0.0031	0.6070	35.8188

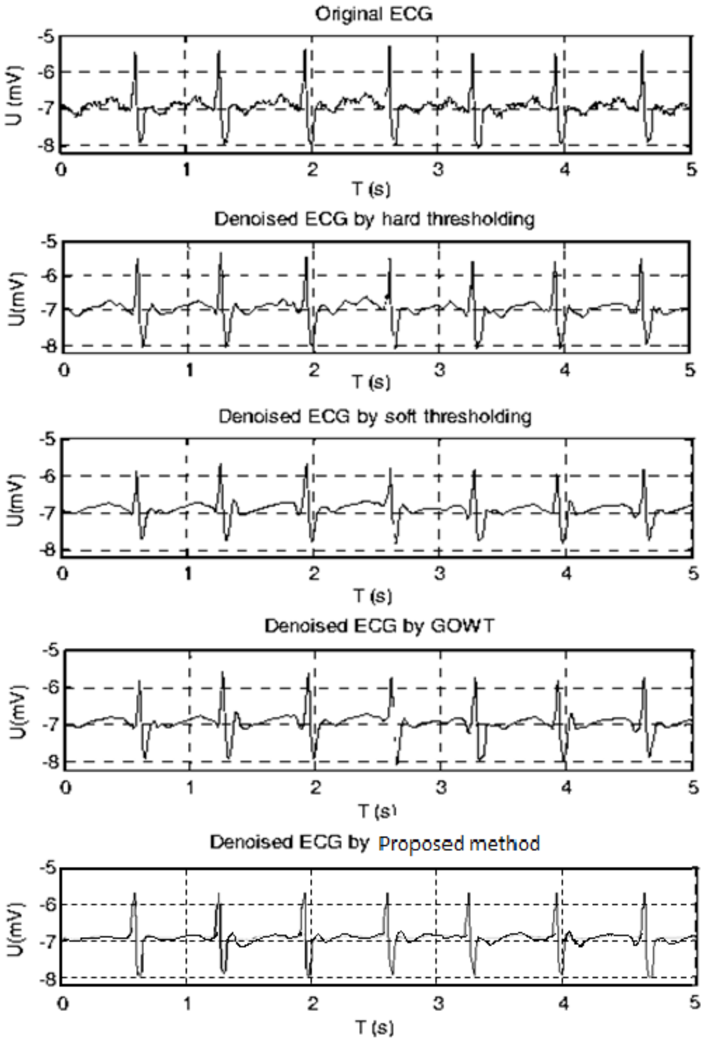

Fig.4: Reconstructed Signal Comparison Of Sample Number 118 Through Four Thresholding Method

5. CONCLUSION

De-noising and filtering of ECG signal is important for the medical diagnosis of cardiovascular diseases. Vital step encountered in data processing of exercise ECGs involves the suppression of noise. Since neural networks have the ability to learn by example, which makes them very powerful and flexible. The problem of GOWT, low convergence and large mean square is overcome by proposed method. The parameters results are self explanatory. The work presented in this paper focused on application of system is based on neural network using gradient descent method rule for updation of weights, for ECG denoising. The three parameters are root mean square error, signal to noise ratio and smoothness (RMSE, SNR, R) are computed to check the accuracy of the proposed method. Final result are compared with[18] and proposed method is found most accurate in terms of denoised parameters. MIT-BIH database is applied using proposed algorithm to denoise ECG signal.

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