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PERFORMANCE COMPARISON OF BACK PROPAGATION AND RADIAL BASIS FUNCTION WITH MOVING AVERAGE FILTERING AND WAVELET DENOISING ON FETAL ECG EXTRACTION

M. Pradeepa* and K. Helenprabha**

Abstract: Fetal ECG is an obligatory signal to recognize the physical conditions of the fetus but the fetal ECG extraction is a taxing task for the signal researchers for the reason that the intrusion present in the recorded signal is more. The signal is actually recorded from abdomen of the mother, hence the interference is more, and mainly the predominant source of hindrance is the maternal ECG present in abdomen signal. The maternal ECG present in the abdomen is identified by a mapping the maternal ECG to abdomen ECG. The feed forward back propagation network perform this mapping and have the potential of error minimization using Levenberg-Marquardt back propagation method which updates weight and bias values of the network training function. The radial basis function uses local receptive fields to perform mapping. This article evaluates the performances of back propagation network and radial basis function network on fetal ECG extraction. The result of the extraction is further improved by moving average filtering and wavelet denoising techniques. The extraction of both the methods is compared with variance parameter, where the radial basis function provide 14.06% less variance than the back propagation method and similarly the clarity of extraction is better than the back propagation network.

Keywords: back propagation, radial basis function, mother ECG, abdomen ECG, fetal ECG

1. INTRODUCTION

Many applications of signal processing in biomedicine involve signal enhancement or the extraction of features of clinical interest. The need for signal extraction arises from the problem of artifacts or signal contamination which is pervasive in biomedicine. Artifacts are caused by both external (main supply and other medical equipment) and internal (head and body movements, muscle and cardiac activities and eye movements) sources to the recording system. These shrink the clinical effectiveness of the recorded signals and make psychoanalysis difficult [1]. Signal extraction tasks are often characterized by the problem of low signal levels compared to the noise interference, and overlap between the signal and noise spectra. Thus a great deal of care is often required to minimize the distortion by the signal extraction process. The recoding of ECG for an adult is an easy process but for a fetus, it's a more challenging task because the non invasive method of recording the fetal ECG. In this method the ECG of the fetus is recorded at abdomen of the mother and the maternal ECG is recorded at thorax. The abdominal ECG is a composite of maternal ECG and fetal ECG [2]. Many signal processing based techniques for FECG extraction have been developed with different level of achievement and restrictions. This article compares the performance of Back Propagation and Radial Basis Function with moving average filtering and wavelet denoising techniques.

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2. MATERIAL AND METHODS

2.2 Back Propagation network

Back propagation was formed by using the Widrow-Hoff learning rule and a nonlinear transfer function which is used minimizes the error in multiple layer networks. The back propagation network is trained with input and target vectors until the desired goals are obtained. The network with sigmoidal transfer function, bias value and a linear output layer performs this function approximation. Back propagation is a gradient descent algorithm and the gradient is calculated to minimize the error in nonlinear multilayer networks. If the network is trained properly the back propagation networks provide realistic outcome when accessible with inputs that they have not trained [3].

Feed Forward Network

Each neuron in feed forward network has R inputs, and each input to the neuron is weighted with a weight value. The input to the transfer function is the sum of the weighted inputs and the bias. The differentiable transfer function is used by the neurons to produce the output. Log-sigmoid, tan-sigmoid and purelin transfer functions are generally used transfer functions for back propagation network. The last layer of a multilayer network either uses sigmoid neurons or linear output neurons. The sigmoid neurons are used to a small output ranges. The linear output neurons are used to any ranges. Normally the linear output neuron is used at the last layer. The derivatives of any transfer functions are calculated to back propagate the error [3].

The network architecture of multilayer feed forward network is shown below.

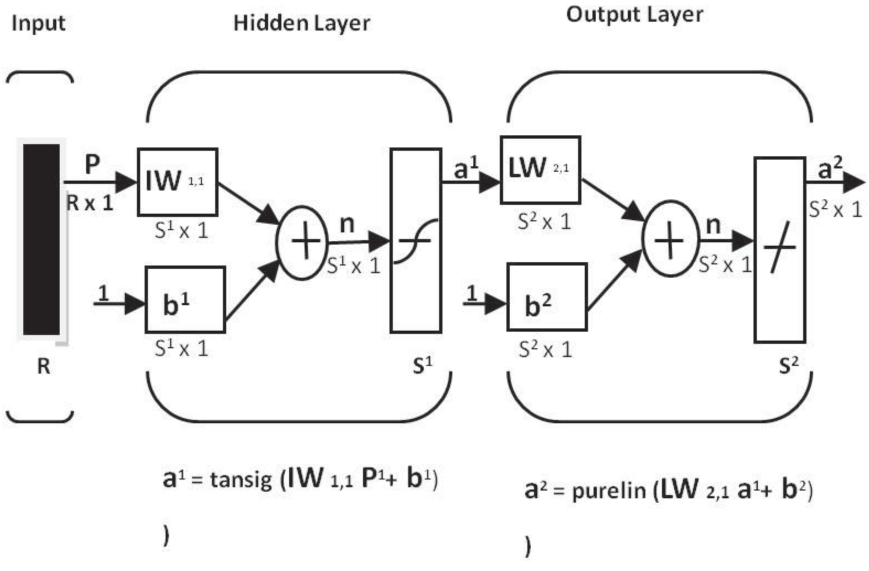

Figure 1 Architecture of multilayer feed forward network

Feed forward networks contain one or more hidden layers with sigmoid neurons and an output layer with linear neurons. Neurons in the layers with nonlinear transfer functions make the network to approximate the nonlinear and linear interaction between input and output vectors. This network can be used to perform any function approximation. Initially the network weights and biases are initialized, and then the set of input and target values are presented to train the network to perform function approximation. The weight and bias values are adjusted to minimize the network performance function during training process of each iteration. The performance function is the mean square error for feed forward networks. A number of different training algorithms are available for feed forward networks but all the algorithms calculate the gradient of the performance function to update the weights and biases to minimize the error. The weights are moved in the direction of the negative gradient for the back propagation algorithm [3].

Back Propagation Algorithm

Many variations of the back propagation algorithms are available but the simplest back propagation learning method modifies the network weights and biases in the track in which the mean square error decreases most quickly. The kth iteration of the algorithm is

$$X(k+1) = X_k - \alpha_k g_k \tag{1}$$

where is a vector of current weights and biases, is the current gradient, and is the learning rate. The gradient descent algorithm can be implemented in either incremental mode or batch mode. The gradient is calculated after each input is presented to the network and the weights are updated in the incremental mode. All the inputs are simultaneously applied to the network for the updating of weights in the batch mode [3].

Levenberg-Marquardt Algorithm

The network training function uses Levenberg-Marquardt algorithm to update weight and bias values. This algorithm is the fastest back propagation algorithm but need larger memory than the other algorithms. The Levenberg-Marquardt algorithm was designed to move toward second-order training speed without calculating the Hessian matrix. The Hessian matrix can be written as

$$H_m = J_m^T J_m \tag{2}$$

and the gradient can be computed as

$$g = Jm^T e \tag{3}$$

where is the Jacobian matrix, which specifies first order derivatives of the network errors, and **e** is a vector of network errors. Through a standard back propagation technique, the Jacobian matrix can be computed with fewer difficult than calculating the Hessian matrix. The Levenberg-Marquardt algorithm uses the following update rule

$$X(k+1) = X_k - [J^T J + \mu I]^{-1} J^T e \tag{4}$$

If μ is zero, it is Newton's method of update rule, if μ is large it is the gradient descent method of with a smaller step size [3] [4].

2.3 Radial Basis Function

Radial basis networks need more neurons compared to standard feed-forward back propagation networks, but this network takes fraction of time to learn the network. This network provides best results when trained with more training vectors [4]. A radial basis network with N inputs and neuron in the network uses radial bias transfer function and the net input to this neuron is completely different compared with back propagation network. The vector distance between its weight and the input vector, multiplied by the bias is the net input to the transfer function [3] [4].

The transfer function of a radial basis neuron is,

$$\text{radbas}(n) = e^{-n2} \tag{5}$$

The function attains maximum value 1 if its input is 0. When the vector distance decreases, the output of the function increases. When the input is identical to its weight vector, radial basis neuron produces 1, hence a radial basis neuron function as a detector [3] [4].

Radial basis networks consist of a hidden radial basis layer and an output linear layer.

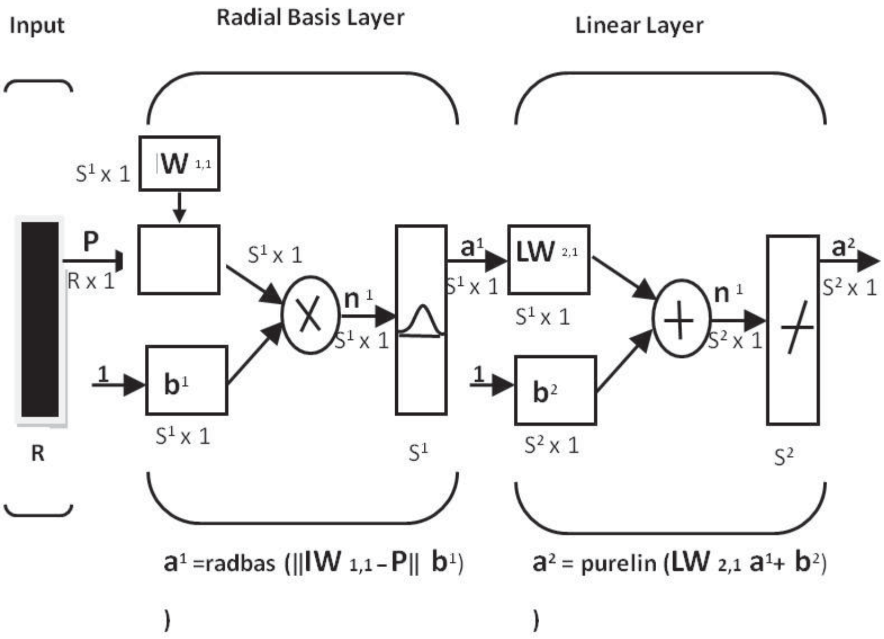

Figure 2. Architecture of Radial Basis Network

The function receives the input vector and the input weight matrix and produces an output vector which contains the distances between the input vector and weight matrix.

Radial basis networks are designed with the function newrbe. This function produces a network with zero error when presented with training vectors. The input vectors, target vectors and a spread constant are given to the function and the function returns a network with weight and bias values. The condition to get zero error when presented with training inputs is that spread constant is large then only the input regions of the neurons overlap which makes the network function smoother and results in better when new input vectors are presented. However, the spread constant should not be too large then only the neuron is responding in time [3] [4].

3. MOVING AVERAGE FILTERING AND WAVELET DENOISING

3.1 Moving Average filtering

The baseline wander is a superfluous and low-frequency motion in the ECG signal which interferes with the signal and making the clinical interpretation inaccurate. Baseline wander is produced by many sources such as perspiration, respiration, body movements and poor electrode contact. The frequency range of the baseline wander exists between 0.05-1Hz. This kind of noise can be removed by, the method to estimate the baseline wander and the method based on high-pass filtering. The baseline wander is estimated using a polynomial and it is subtracted from the noisy signal. By high-pass filtering, a signal distortion may occur due to the overlapping of signal and noise spectrum. Hence the linear high pass filtering may produce the distorted results [5]. The best way to estimate of baseline wander is a sample mean in the moving window. Baseline wander removal is achieved by high-pass filtering based on a moving average (MA) filter. It can be implemented with one-weight adaptive filter. The moving average filter function by taking average from each point in the input signal and produce each point in the output signal. It is represented as

$$y[i] = \frac{1}{\mathrm{N}} \sum_{j=0}^{j=M-1} x[i+j] \tag{6}$$

where x is the input signal, y is the output signal and N is the number of points in the average [6].

Wavelet denoising

Wavelet transform represent the signal characteristics in both time and frequency field [7]. Wavelet basis function comprises of many families such as Haar, Daubechies, symlet, biorthogonal and reverses biorthogonal wavelets. The wavelet transform produces a good performance on denoising the ECG signal. But the selection of appropriate wavelet family and decomposition level determines the quality of the denoised signal [7].

The wavelet transform is a scaled and shifted version of time. The mother wavelet of DWT is expressed by:

$$ø_{a,b}(t) = \frac{1}{a} ø\left(\frac{t-a}{a}\right)_{a,b} \in \mathrm{S},\ a > 0 \tag{7}$$

where, a is a scaling factor and b is a shifting factor and S is the wavelet space. The mother wavelet must satisfy the condition

$$\mathrm{C}\psi = \int_{-\infty}^{+\infty} \frac{|\psi(\omega)|^2}{\omega} d\omega < \infty \tag{8}$$

where, ψ (ω) is the Fourier transform of the mother wavelet function [8].

2.4 Methods on fetal ECG extraction

For back propagation network and radial basis function network, the input vector is maternal ECG and the target vector is abdomen ECG. The network will perform mapping from input space to output space. The network is trained and the function parameters are updated according to their learning procedure and minimize the mean square error. The network function estimates the maternal component present in the abdomen signal. Then this component is removed from the abdomen ECG signal and the resultant is the extracted fetal ECG. But the extracted fetal ECG contains more noise which is removed using moving average filtering and wavelet denoising with reverse biorthogonal wavelet rbio6.8.

Back Propagation Network Algorithm:

The method proposed to implement the back propagation network algorithm is shown below.

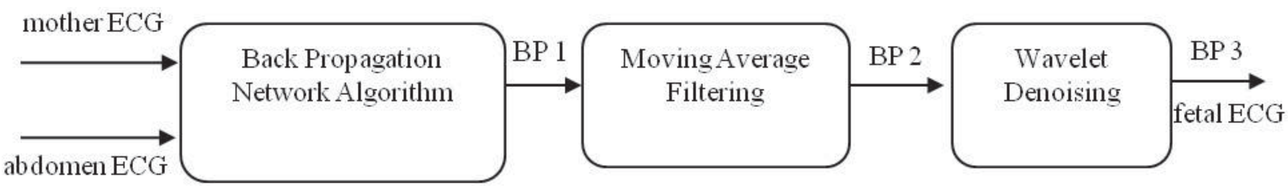

Figure 3. Proposed method using Back Propagation Network algorithm

In back propagation network algorithm, a feed-forward back propagation network is created with Hyperbolic tangent sigmoid transfer function where the training function that revise its weight and bias values according to Levenberg-Marquardt optimization. The Maximum number of epochs used to train the network is chosen as 2500 and minimum performance gradient is chosen as. Mother ECG given as input and abdomen ECG is given as target, where the error of the back propagation network is the extracted fetal ECG. Then the base line noise is removed using moving average filtering and the other interferences are removed by using wavelet denoising using reverse biorthogonal wavelet rbio6.8.

Radial Basis Function Network

The method proposed to implement the radial basis function network algorithm is shown below.

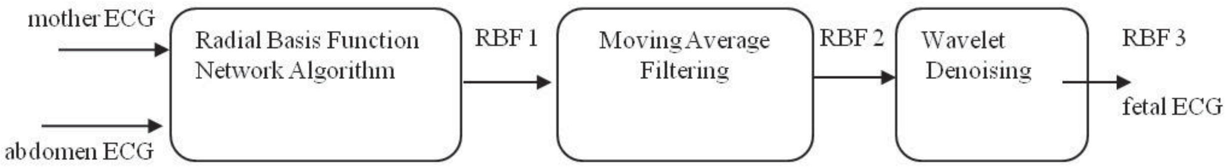

Figure 4. Proposed method using Radial Basis Function Network algorithm

Radial basis networks can be used to approximate functions. The spread of radial basis function is chosen as 1.5. The larger the spread is, the smoother the function approximation will be. Mother ECG given as input and abdomen ECG is given as target, where the error of the radial basis function network is the extracted fetal ECG. Then the base line noise is removed using moving average filtering and the other interferences are removed by using wavelet denoising using reverse biorthogonal wavelet rbio6.8.

3. RESULTS AND DISCUSSION

The proposed algorithm is tested with data provided by De Moor, DaISy: Database for the Identification of Systems. The database contains a record measured over 10 sec, and sampled at 250 Hz. It includes five abdominal ECG recordings measured at abdomen and three maternal ECG measured at thorax of the pregnant women [9].

The results of the proposed method under all stages are listed below.

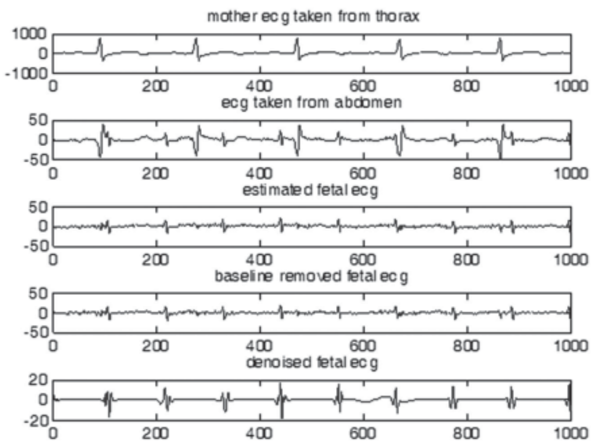

Figure 5. Results of Back Propagation network

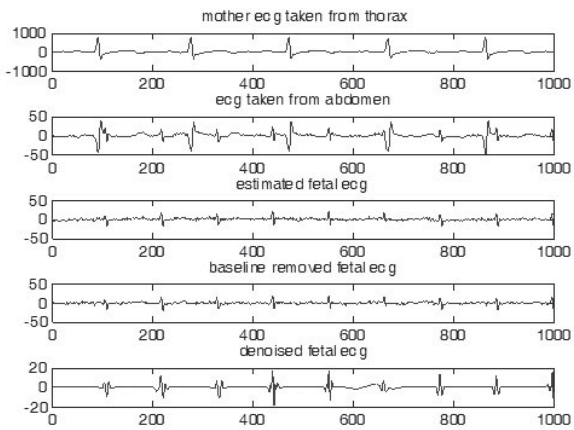

Figure 6. Results of Radial Basis Function network

The result shows that at each stage the clarity is improved which is ensured by visual comparison as wells as reduction in variance parameter. The variance parameter computed at output of each stage of the proposed methods and presented in Table 1 and the corresponding graph is shown Figure 7.

Table 1.
Comparison of Back Propagation Network and Radial Basis Function Network.

Back Propagation Network Algorithm / Stage	**BP1**	**BP2**	**BP3**
Variance	16.9221	15.6011	8.2920
Radial Basis Function Network Algorithm / Stage	**RBF1**	**RBF2**	**RBF3**
Variance	15.0824	13.9747	7.1255

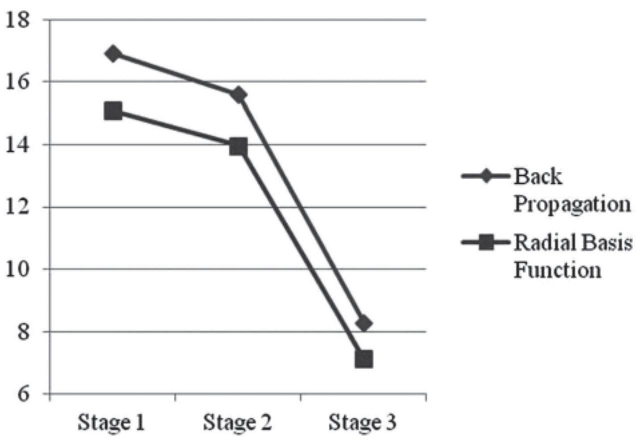

Figure 7. Variance of Back Propagation Network and Radial Basis Function Network.

The variance parameter at each stage proves that, the radial basis function performs better than the back propagation method. Even the variance is reduced from initial stage to final stage of both the proposed methods, when compared to back propagation method the radial basis function extracts fetal ECG more clearly.

4. CONCLUSION

The methods proposed to extract the fetal ECG are back propagation network and radial basis function along with moving average filtering and wavelet denoising. The baseline removal and denoising process is not to be done at the initial stages of the fetal ECG extraction process, because these noise reduction techniques removes the actual information of fetal ECG. Hence after extracting fetal ECG these techniques are applied to get clear fetal ECG without any loss of information. The proposed methods are able to extract the fetal ECG where the radial basis function provide 14.06% less variance than the back propagation method and similarly the clarity of extraction is better than the back propagation network.

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