

Optimization algorithms for adaptive filtering of interferences in corrupted signal

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Neural network adaptive filters are mainly used for the interference cancellation techniques. The gradient based design methods are well developed for the design of neural network adaptive filter but they converge to local minima. This paper describes the global optimization interference cancelling techniques for adaptive filtering of interferences in the corrupted signal. The system is designed using the adaptive filtering of the interferences in the corrupted signal using the Back Propagation Neural Network (BPNN) algorithm, Genetic Algorithm (GA), and Bee Colony (BC) algorithm. These optimization algorithms are used for initialization of weights, learning parameters, activation function and selection of network structure of the artificial neural network. The adaptive filtering system is designed using an adaptive learning ability of BPNN algorithm. This paper presents a comparison of evolutionary optimization algorithm such as hybrid GA-BPNN and BC-BPNN algorithm for the interference cancellation in corrupted signals.

Keywords: Adaptive filters, Bee colony algorithm, Back propagation algorithm, Genetic algorithm, Interferences

1 Introduction

In the recent years, intelligent based design methods are well developed for the design of adaptive filters and widely applied to interference cancellation applications. Adaptive filters play an important role in many control and signal processing applications such as prediction, function approximation, system identification and noise cancellation. For the adaptive noise cancellation, the corrupted signal passes through the adaptive filter that tends to eliminate the noise while leaving the original signal unchanged. Adaptive filters are used to separate the valid signal components from the interferences due to the self-optimization property.

The electrocardiography signal is an electrical signal which is generated from our heart beat. While acquisition of the electrocardiography, it gets corrupted due to different types of artifacts and interferences. Thakor and Zhu¹ have assessed Least Mean Square (LMS) adaptive recurrent filter structure for acquiring the impulse response of the normal QRS complex and this method is also applied to several arrhythmia detection problems. The adaptive filter essentially minimizes the mean-squared error between a primary input, which is the corrupted electrocardiogram

and a reference input, which is either noise that is correlated in some way with the noise in the primary input that is correlated only with electrocardiography in the primary input.

Hamilton investigated the relative performance of an adaptive and non adaptive 50/60-Hz notch filter applied to an electrocardiography signal and evaluated the performance of the adaptive and non adaptive filter implementations with respect to adaptation rate, signal distortion and electrocardiography data compression². Ngia and Sjoberg³ proposed the training of neural network for adaptive filtering which uses Levenberg-Marquardt algorithm in off-line applications. Regarding off-line application the Levenberg-Marquardt algorithm is superior for the purpose of non linear adaptive filtering. This analytical concept of Levenberg-Marquardt algorithm can be used to train the adaptive filter for interference cancellation in infant cardiograph signals.

Besides, Zhang⁴ has developed a Thresholding Neural Network (TNN) for adaptive noise reduction⁴. Gradient based learning algorithm is used for finding the mean square error. This algorithm includes supervised and unsupervised batch and stochastic learning. The TNN nonlinear adaptive filtering

performs the conventional linear adaptive filtering in both optimal solution and learning performance. A nonlinear adaptive electromagnetic interference filter is proposed by Ziarani for elimination of power line noise in electrocardiogram signals⁵. The proposed method employs, as its main building block, a recently developed signal processing algorithm capable of extracting a specified component of a signal tracking its variations over time.

Adaptive control as a three-part adaptive-filtering problem is proposed by Plett⁶. First of all, the dynamical system which is to be controlled is modeled using adaptive system identification techniques. Second, the dynamic response is controlled by adaptive feed-forward controller and the system output is used by an adaptive algorithm to adjust the parameters of the controller. Third, the interference canceling is performed using an additional adaptive filter.

The neural networks has been a predominant technology for intelligent control in many years. The cascaded correlation neural network algorithm has the powerful capabilities of learning and adaptation. Dheeba and Padma⁷ have been adopted an intelligent algorithm based on cascaded neural networks which is used to cancel the interference while measuring fetal electrocardiography.

Bershad proposed an affine combination of the outputs of two least mean square adaptive filters that simultaneously adapt using the same white Gaussian inputs⁸. The purpose of the combination is to obtain a LMS adaptive filter with fast convergence and small steady state mean square deviation. Rout *et al*⁹. presented the conditional reinitialized PSO algorithms for developing an efficient ANC without the use of secondary path estimation. Adaptive filtering is a primary method to filter noisy signal because it does not need the signal characteristics.

Krukowics approached the active noise control method based on a multi layer neural network algorithm and a nonlinear input-output system identification model with a nonlinear primary path¹⁰. Sowmya *et al*¹¹. proposed a novel Optimum Step Size Least Mean Square (OSSLMS) adaptive filtering technique for the removal of artifacts from cardiac signals.

El-Dahshan and El-Sayed¹² have adopted a hybrid scheme genetic algorithm and wavelet transform is used for denoising the electrocardiography signal corrupted by non-stationary noises. In this hybrid noise elimination method, the optimal wavelet

denoising parameters have been selected by genetic algorithm. The hybrid scheme performance is evaluated using percentage root mean square difference and signal to noise ratio.

Artificial bee colony algorithm has been used for the optimization of synaptic weights from artificial neural network architecture, and the transfer function of each neuron from an artificial neural network. Kumbhar and Krishnan¹³ presented an ABC based methodology, which maximizes its accuracy and minimizes the number of connections of an artificial neural network.

Artificial bee colony algorithm is a nature meta-heuristic algorithm, implemented in optimization applications. Nandy *et al*¹⁴. proposed an improved artificial bee colony algorithm based back-propagation neural network training method for fast and improved convergence rate of the hybrid neural network learning method.

George and Panda¹⁵ proposed a functional-link-artificial-neural-network-based (FLANN) multichannel nonlinear active noise control system trained using a PSO algorithm suitable for nonlinear noise processes. The use of PSO algorithm in a multichannel active noise control environment not only reduces the local minima problem but also removes the requirement of computationally expensive modeling of the secondary-path transfer functions.

Boroujeny and Eshghi¹⁶ proposed a new evolutionary algorithm known as bacterial foraging (BF) is used for optimising the adaptive controller. The proposed active noise control system using Bacterial Foraging Optimisation (BFO) has the ability to prevent falling into local minima. Moreover, using the BF algorithm to adapt the active noise control filter coefficients removes the need for the preliminary identification of the secondary path.

In the present paper, the hybrid GA-BPNN and hybrid BC-BPNN feed forward algorithm have been applied for the removal of the fundamental electromagnetic interference in contaminated signal and the simulations are realized for this problem. The performances of these proposed interference cancellation approach is compared with gradient based algorithms and evolutionary based algorithms.

2 Evolutionary Optimization Algorithms for Interference Cancellation

For the adaptive noise cancellation, the corrupted signal is passing through the neural network adaptive

filter that tends to eliminate the noise while leaving the original signal unchanged. Levenberg-Marquardt Back propagation Neural Network algorithm is basically a gradient based algorithm to minimize the error signal. The basic operation of this algorithm is select a pattern $X(f)$ form the training set T and compute the activations of input, hidden and output neurons. The error is computed by comparing the generated and desired outputs. Based on this error change, the input to hidden layer weights and hidden to output layer weights until the error gets reduced.

The two main phases in the operation of artificial neural network (ANN) is learning or training and testing. The aim of learning is to minimize the error signal or cost function with respect to weights, such that the actual response of each output neuron in the network approaches the desired response.

Figure 1 shows the block diagram of interference cancellation using Levenberg-Marquardt Back propagation neural network algorithm for minimizing the electromagnetic interference. The noise model is done for generating the electromagnetic signals in incubators. In incubator systems, the only parameter that cannot be eliminated completely is called noise. Noise limits the measurements, precision and signal detectability.

When doctors are analysing the incubator babies in on-line and want to review the Electrocardiography (ECG) of the premature babies in real time, the infant ECG signal has been contaminated by Electro Magnetic Interference (EMI). Adaptive filters are

used to eliminate the contaminated signal in order to obtain better signal and interpret the infant ECG data.

The corrupted signal $C(k)$ consists of desired Infant ECG signal $d(k)$ is corrupted by uncorrelated additive incubator noise of Electro Magnetic Interference $S(k)$. The input to the adaptive filter is an incubator noise $X(k)$ modified by the environment. The contaminated signal $C(k)$ output is compared with the output of the adaptive filter $y(k)$. When this happens, the error signal approaches the desired signal $d(k)$. The overall output is the error signal $e(k)$ and not the adaptive filter output.

The Contaminated signal output is give

$$C(k) = d(k) + S(k) \quad \dots(1)$$

The secondary signal output of the adaptive:

$$Y(k) = W^T(k) X(k) \quad \dots(2)$$

where

$$W^T(k) = [W_0(k), W_1(k), \dots, W_{L-1}(K)]^T \quad \dots(3)$$

is the coefficient vector of the adaptive filter $W(z)$.

The reference signal vector is:

$$X(k) = [X(k), X(k-1), \dots, X(k-L+1)]^T \quad \dots(4)$$

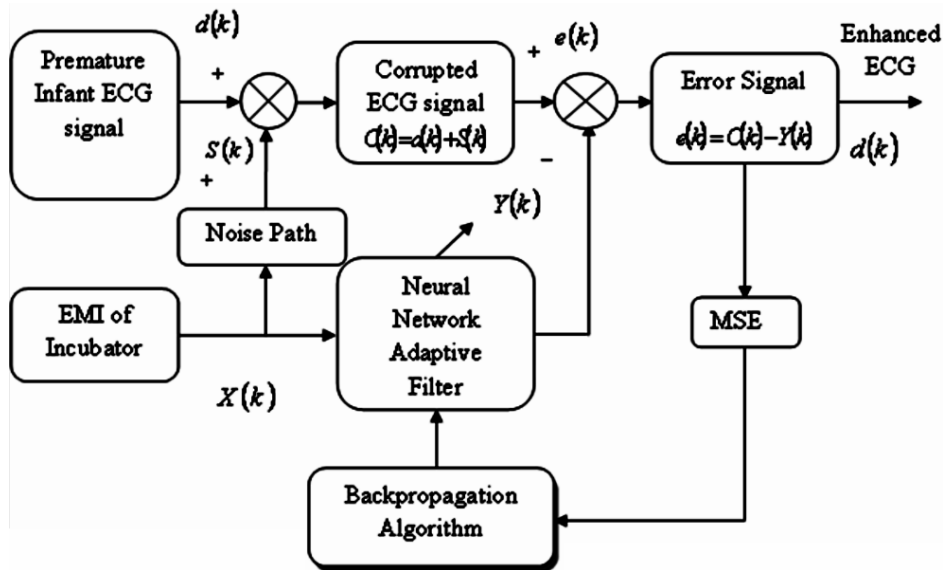


Fig. 1—Neural network adaptive filter for interference minimization

The residual error is:

$$e(k) = C(k) - y(k) \quad \dots(5)$$

$$e(k) = d(k) + S(k) - W^T(k)X(k) \quad \dots(6)$$

The output of this Eq. (6) is used as the input to the Levenberg-Marquardt back propagation algorithm for removing the interference signal. Minimizing the mean square of e , therefore, causes e to be a best least squares match to the primary infant ECG signal.

For the adaptive filter the weight update equation is:

$$W(k+1) = W(k) - [\nabla e^2(k)] \quad \dots(7)$$

$$W(k+1) = W(k) + 2e(k)X(k) \quad \dots(8)$$

The genetic algorithm and bee colony algorithm are used for initialization of weights, learning parameters, activation function and selection of network structure of the artificial neural network.

GA is a global searching and optimization procedure emulates biological evolution to solve optimization problems. GA is less vulnerable to local minima problem. Genetic adaptive algorithm has been developed to optimise the artificial neural network for active noise control applications. This genetic algorithm operates with three steps. First, the current evaluation is estimated using the fitness function. Second, the GAs selects “parents” from the current population. Third the GA produces “children” from

selected “parents” using crossover and mutation operations.

The Hybrid GA-BPNN algorithm uses a combination of neural network, adaptive filtering techniques and genetic algorithm. Figure 2 shows the block diagram of active noise control for infant incubators using optimization algorithm (Genetic Algorithm). With the method of GA, the best numbers of hidden layer neurons, learning rate and momentum factor for training the neural network are selected. Initial population is made of binary chromosomes. The population size is set to p . After passing cross over and mutation, new chromosomes are developed by the algorithm. In the stage of ‘evaluation’ less Mean Square Error (MSE) calculated will save the next iteration and continue this process until error minimum. By using the Genetic Algorithm, the best parameters for training the neural network are selected, therefore, adaptive filter output convergence into global extreme.

GA starts randomly by selecting an initial population of likely problem solutions. At each generation, each element of the current solution space (chromosomes) is evaluated and assigned a measure of its fitness. Based on the fitness value, the chromosomes are selected for further genetic operations – selection, crossover and mutation. In modified genetic Algorithm an improved evolutionary direction operator and also a modified mutation scheme are introduced which improves the solution search and also increase the solution diversity.

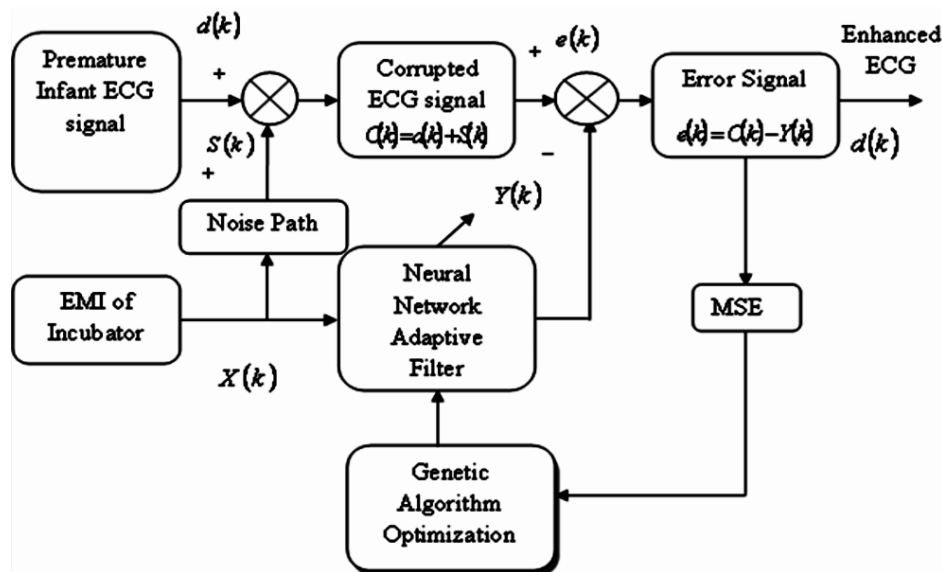


Fig. 2—Neural network adaptive filter for interference minimization using Genetic Algorithm optimization

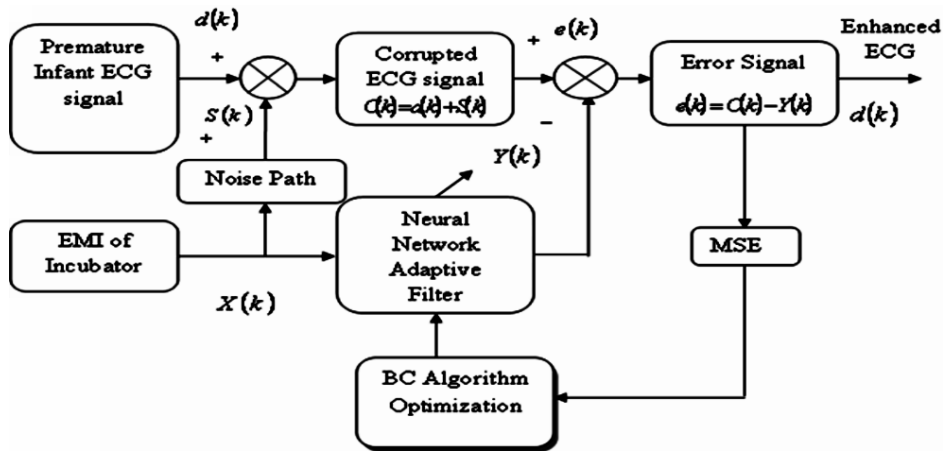


Fig. 3—Neural network adaptive filter for interference minimization using BC algorithm optimization

BC based back-propagation algorithm is the newly proposed algorithm to optimize the back-propagation neural network training. Conventional BC algorithm is modified in terms of movement of employed bee to the food source and the movement of employed bee is used to modify the weight and bias of each solution towards optimum solution. The involvement of scout bee in each iteration of back-propagation optimization phase is decided according to the average performance of solutions and thus the process of exploitation is maintained in the proposed method.

The proposed method in this work includes an improved BC algorithm based back-propagation neural network training method for fast and improved convergence rate of the hybrid neural network learning method. The BC is basically a nature inspired heuristic optimization algorithm to minimize the error signals. The hybrid BC-BPNN algorithm uses a combination of neural network, adaptive filtering techniques, and heuristic optimization algorithm. Figure 3 shows the block diagram of Adaptive filtering for infant incubator interference using optimization (BC) algorithm for minimizing the electromagnetic interference in incubators.

The error signal $e(k)$ is the difference between the noisy signal and the adaptive filter output. The error is computed and fed back to the ABC adaptation algorithm to adjust the adaptive filter coefficients in order to minimize a given cost function. The mean squared error (MSE) to be minimized as:

$$P(k) = E \left[|e(k)|^2 \right] \quad \dots(9)$$

Table 1 — Control parameters of ABC

Parameter	Value
Colony size p	30
Limit value	180
W_{max}	1
W_{min}	-1

The objective of the ABC-ANN algorithm is to minimize the mean square error which represents the fitness of each particle.

$$F(i) = \frac{1}{1 + P_i(k)} \quad \dots(10)$$

where $\Psi_i(\omega)$ is the cost function. At each time step, the cost function is calculated.

The sum of squared error is:

$$P_l(k) = \sum e(k)^T e(k) \quad \dots(11)$$

$$P_l(k) = \sum [c(k) - y(k)]^T [c(k) - y(k)] \quad \dots(12)$$

The ANN learning algorithm takes the error signal as input and updates the filter coefficients based on the parameters. The control parameter values of the BC evolutionary algorithm used in the simulation are presented in Table 1.

The population for the proposed modified BC based back-propagation optimization needs to be adjusted to get a good convergence rate for every problem. Most of the experiment, 30 numbers of populations are used. At the time of initialization, one

of the best solutions among other evaluated solutions is considered as a best solution, and that is found by the scout bee. It is only considered to initialize the proposed algorithmic procedure, and then the number of food source available to be selected by the onlooker bee depends on the correct classification rate.

3 Simulation and Comparison of Results

The proposed hybrid algorithm is applied to ECG interference cancellation. The infant ECG signal generated is shown in Fig. 4.

The electromagnetic signal in incubator devises which got accumulated with the infant ECG. The infant ECG signal is corrupted by the noise source. The signal obtained from noisy signal as is shown below (Fig. 5).

The contaminated ECG signal consists of premature infant ECG signal and the electromagnetic

interference signal. The contaminated signal is shown in Fig. 6. This contains much noise in addition to the infant ECG signal which is to be filtered by adaptive noise canceller trained by various algorithms.

The neural network is trained using noisy interference as its input, with clear ECG signal is the desired target. The interference caused by the incubator is estimated using the ANN algorithm. Fig. 7 shows the estimated interference from the output of the proposed neural network.

Adaptive filter is used to extract a desired signal from a noise corrupted signal by canceling the noise. Fig. 8 shows the noise eliminated ECG signal of the infant in the incubator.

The error signal is the difference between the generated premature infant ECG signal and the output of the interference eliminated. The training of neural network is accomplished out by Levenberg-Marquardt Back propagation algorithm. A considerable number of samples are used to calculate the mean square error

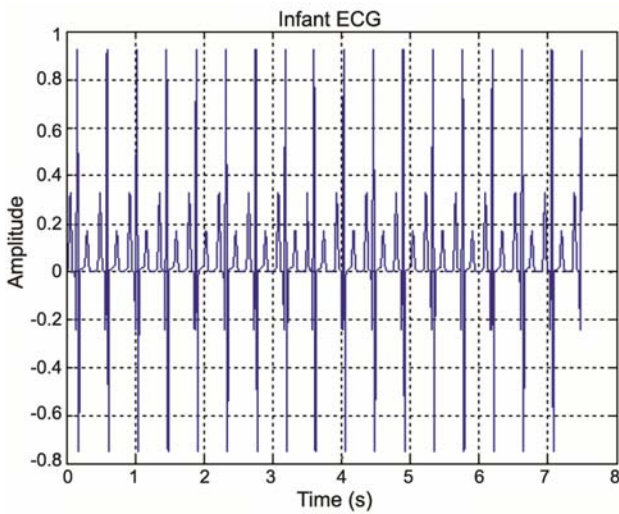


Fig. 4 — Infant ECG signal

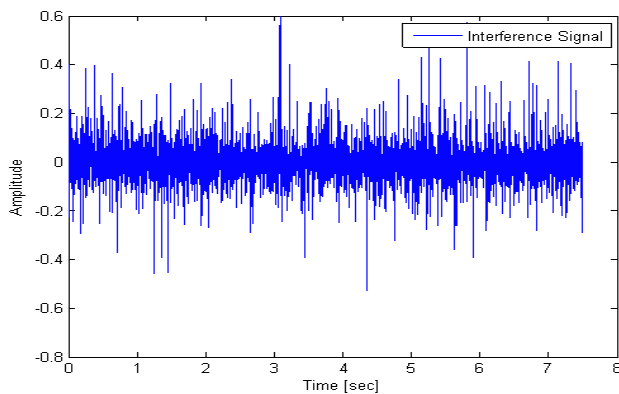


Fig. 5—Noise source

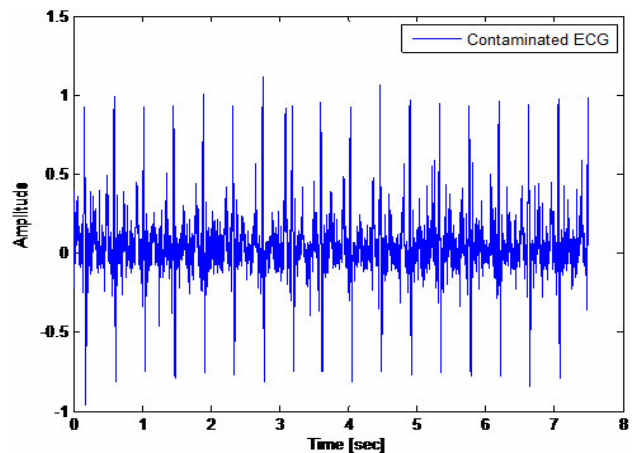


Fig. 6 — Corrupted ECG signal

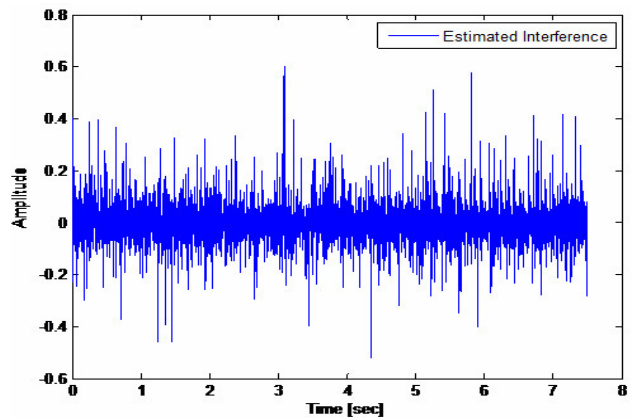


Fig. 7 — Estimated interference

The ANN interference canceller is performed with the learning rate and the momentum constant varied from 0 to 1 and the hidden neurons varied from 31 to 150. For this training of 100 training epochs are performed. Using the proposed algorithm an ANN is achieved with $N_h = 100$, $L_r = 0.01$ and $M_c = 0.9$. Thus, the proposed algorithm yields a compact network configuration in the architecture space algorithm automatically evolve a best solution and the residual error is 0.12. Fig. 9 shows the residual error signal using ANN-BP algorithm.

By using the Genetic Algorithm, the best parameters for training the neural network are selected, therefore adaptive filter output convergence into global extreme. Figure 10 shows the residual error signal using hybrid GA-BPNN algorithm. Using the proposed algorithm, an optimized ANN is achieved with $N_h = 193$, $L_r = 0.3731$ and $M_c = 0.3743$. Thus, the proposed algorithm yields a compact network configuration in the architecture space algorithm automatically evolve a best solution and the residual error is 0.01.

Using the hybrid ABC-BP algorithm, the ANN interference canceller is performed with the learning

rate and the momentum constant varied from 0 to 1 and the best performance is obtained for 109 hidden neurons for which the mean square error is 0.005. For this training of 100 training epochs are performed. Using the proposed algorithm, an ANN is achieved with $N_h = 150$, $L_r = 0.7413$ and $M_c = 0.9947$. Figure 11 shows the residual error signal using hybrid ABC-BPNN algorithm.

The Performance Analysis of the proposed hybrid BC-BP based noise cancellation algorithm is compared with that of conventional ANN algorithm in terms of Root Mean Square Error (RMSE) and the hybrid BC-BP shows better performance as presented in Table 2.

The BPNN leads to failure in finding a global optimal solution. The back propagation algorithm evolved the best solution and the residual error obtained was 0.118. The hybrid GA-BPNN uses the strong global searching ability of genetic algorithm. But it takes large time for convergence. The hybrid GA-BPNN algorithm evolved the best solution and the residual error obtained was 0.01.

The hybrid BC-BPNN based algorithm is used to find the optimal number of the hidden layer neurons.

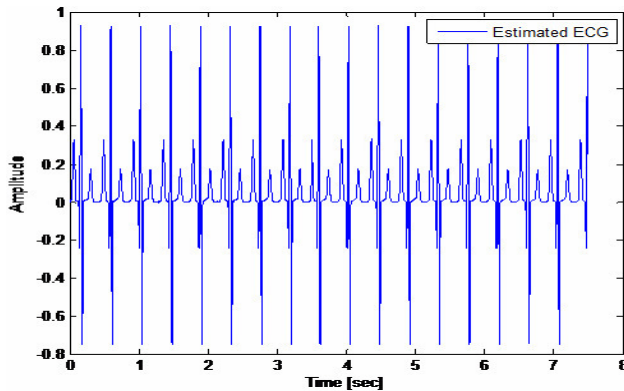


Fig. 8 — Estimated ECG signal using BPN algorithm

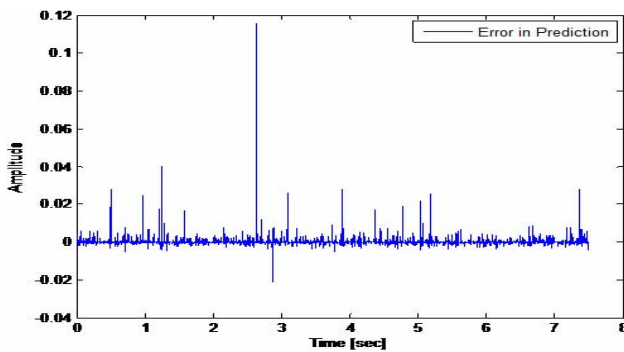


Fig. 9 — Residual error signal (ANN-BP algorithm)

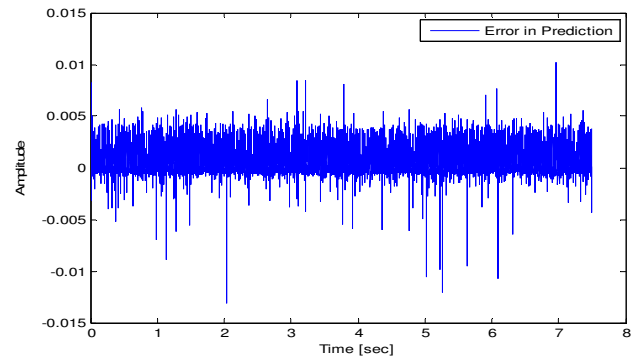


Fig. 10—Residual error signal (GA-BPNN algorithm)

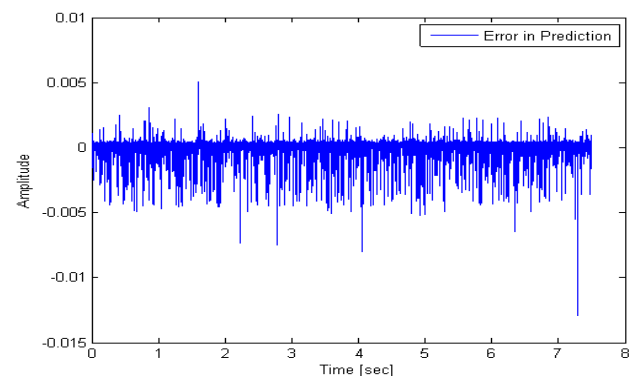


Fig. 11 — Residual error signal (hybrid BC-BPNN algorithm)

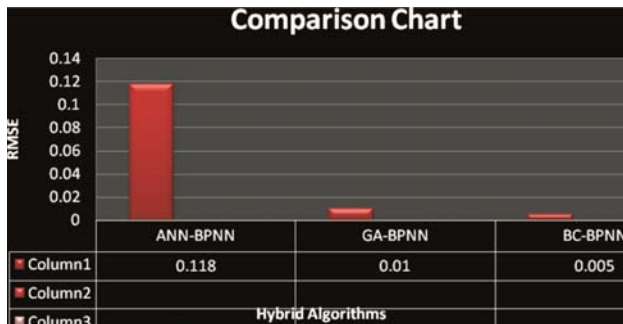


Fig. 12 — Comparison chart

Table 2—Performance analysis

Algorithm	ANN-BPNN	GA-BPNN	BC-BPNN
RMSE	0.118	0.01	0.005

The hybrid BC-BPNN algorithm includes two stages. At the first stage, ABC is employed to search for the optimum. At the second stage, BPNN algorithm is used to search around the global optimum according to this heuristic knowledge.

Apart from the maximum evaluation number and population size, a standard GA has three more control parameters (crossover rate, mutation rate, generation gap), a and the BC algorithm has only one control parameter (limit) apart from Colony Size and Maximum Cycle Number. The hybrid BC-BP algorithm evolved the global best solution and the residual error obtained was 0.005.

Figure 12 shows the comparison chart. simulations are realized for the electromagnetic interference problem and the performance analysis of the hybrid optimization interference cancellation algorithms were compared with that of conventional artificial neural network algorithm in terms of root mean square error and the hybrid bee colony algorithm showed better performance with global mean square error 0.005.

4 Conclusions

In the present paper, the suppression of interference cancellation from corrupted signal using evolutionary based optimization algorithm is proposed using artificial neural network back propagation, hybrid GA-BPNN and hybrid BC-BPNN, techniques. The results show the computation efficiency and convergence property of the proposed method for obtaining the target values with minimum mean square error 0.005. From the results obtained in this work, it can be concluded that the performance of BC algorithm is better than or similar to that of these algorithms although it uses less control parameters, simple, fast convergence and less mean square error value and it can be efficiently used for infant ECG interference minimization.

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