Research Journal of Applied Sciences, Engineering and Technology 6(16): 2931-2935, 2013
ISSN: 2040-7459; e-ISSN: 2040-7467
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Submitted: December 15, 2012 Accepted: January 23, 2013 Published: September 10, 2013

Hybrid Swarm Algorithm for the Suppression of Incubator Interference in Premature Infants ECG

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Abstract: The premature infant Electrocardiography (ECG) is always contaminated by an electromagnetic interference caused by the incubator devices. This study describes the interference noise cancelling techniques for filtering of the corrupted infant ECG signal using the biological inspired Particle Swarm Optimization (PSO) algorithm. The active noise control system is designed using a adaptive learning ability of artificial neural network Back propagation algorithm. The neural weights are adapted based in PSO in an adaptive manner. In this study, the hybrid Particle Swarm Optimization-Back Propagation Neural Network (PSO-BPNN) feed forward algorithm is used for the Active Noise Control (ANC) of the fundamental electromagnetic interference in the incubators. The results showed the incubator noise can be significantly reduced using the developed hybrid PSO-BPNN algorithm. To implement this process of noise cancellation, the software used is MATLAB 7.10 with the help of neural network toolbox.

Keywords: Active noise control, back propagation algorithm, ECG signal, electromagnetic interferences, neural network, PSO

INTRODUCTION

One of the leading causes of death in infants around the world is cardiovascular disease. Early diagnosis of heart diseases can prevent sudden death of infants. In NICU premature infants kept in incubator. The problems associated with noise in medical instrument inside the Neo Natal Intensive Care Unit (NICU) creates number of harmful health effects on Infant's health and hence their control has been an important for the present day research. The infant incubators motor creates Electromagnetic Interferences (EMI). While measuring the ECG in incubator babies, the infant ECG signals contaminated due to the electromagnetic interferences.

Priya *et al*. (2007) proposed a nonlinear Filtered-X Least Mean Square (FXLMS) algorithm for achieving the active noise control for reducing impulse interference in incubators. Das *et al*. (2006) proposed Filtered-S Least Mean Square (FSLMS) algorithm for nonlinear multichannel active noise control. The filtered-*x* partial-error affine projection algorithm suitable for multichannel active noise control (Das and Panda, 2004).

The FXLMS algorithms have some limitations; it uses gradient method to update the coefficient of the adaptive filter of the ANC. The FXLMS algorithm may also lead to local minima problem and large eigen value disparity of input signal's autocorrelation matrix To overcome such limitations investigators have adopted intelligent control strategies such as fuzzy and neural network.

Neural network is the best structures for dealing with nonlinear behavior (Plett, 2003). Krukowicz (2010) proposed the active noise control algorithm based on a neural network algorithm. Salmasi *et al*. (2011) designed the multi layer perceptron and generalized regression neural network and trained with acoustic noise signals. Ngia and Sjoberg (2000) proposed the training of neural network for adaptive filtering using Levenberg-Marquardt algorithm. Zhang (2001) proposed a thresholding neural network for adaptive noise reduction.

The genetic algorithms have been used as a powerful optimizer to develop an ANC (Tang *et al*., 1996). Chang and Chen (2010) designed the Adaptive Genetic Algorithms (AGA) have been used as an alternative learning algorithm to develop an ANC without the use of secondary path estimation. Russo and Sicuranza (2006) investigates the performance of genetic optimization in a nonlinear system for active noise control based on Volterra filters. Beligiannis *et al*. (2005) proposed a nonlinear model structure identification of complex biomedical data using a GA.

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Moreover, Russo and Sicuranza (2007) developed a genetic optimization of nonlinear systems for active noise control.

Recently, PSO have been proposed as a powerful optimizer alternative to GA and has been applied to many practical applications. Particle swarm optimization was first proposed Kennedy and Eberhart (1995). Nirmal Kumar *et al*. (2012) presented the conditional reinitialized PSO algorithms for developing an efficient ANC without the use of secondary path estimation.

This study describes a systematic hybrid PSO-BPNN algorithm for the electromagnetic interference cancellation in infant incubator ECG signals. Using PSO-BPNN algorithm the mean squared error is minimized to its global value and the presented computed simulation result shows the proposed method gives the better performance than the conventional methods. The results showed the incubator noise can be significantly reduced using the developed hybrid PSO-BPNN algorithm. To implement this process of noise cancellation, the software used is MATLAB 7.10

HYBRID PSO-BPNN ALGORITHM FOR INTERFERENCE CANCELLATION

Particle Swarm optimization algorithm is basically a robust stochastic based algorithm to minimize the error signals. The hybrid PSO-ANN algorithm uses a combination of neural network, adaptive filtering techniques and optimization algorithm.

Figure 1 shows the block diagram of Active Noise Control (ANC) for infant incubators using hybrid PSO-BPNN algorithm for minimizing the electromagnetic interference in incubators. The corrupted signal *C* (*k*) consists of desired Infant ECG signal d (k) is corrupted by incubator noise of Electro Magnetic Interference X (k) is given in Eq. (1). The electromagnetic interference noise in incubator is fed to the neural network adaptive filter which produces the output Y (k) and generate the anti noise signal $\hat{X}$ (k):

$$C(k) = d(k) + S(k) \tag{1}$$

The adaptive filter produces the output:

$$Y(k) = W^T(k)X(k) \tag{2}$$

The anti-noise output is:

$$Y(k) = \hat{X}(k) \tag{3}$$

The contaminated signal M (k) output is compared with the output of the adaptive filter y (k).
The error signal e (k) is:

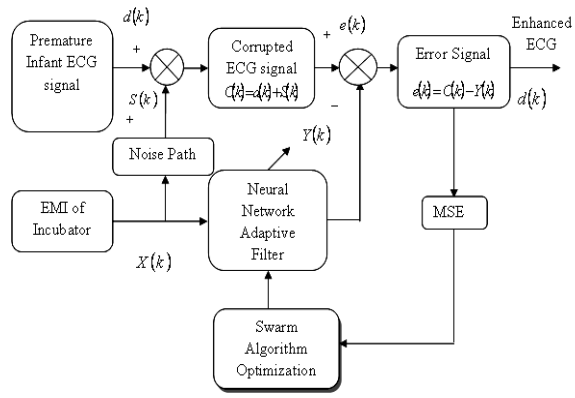

Fig. 1: Block diagram for interference cancellation using hybrid PSO-BPNN algorithm

$$e(k) = C(k) - y(k) \tag{4}$$

$$e(k) = d(k) + X(k) - \hat{X}(k) \tag{5}$$

The output of this equation used as the input to the PSO algorithm for removing the interference signal. The objective of the PSO-BPNN algorithm is to minimize the mean square error which represents the fitness of each particle. The swarm initially has a randomly generated population. Each potential solution, called a particle has a position represented by a position vector and given a moving velocity represented by a velocity vector and is flown through the problem space. At each time step, a new velocity for particle is updated by using the individual best position and global best position.

The coefficient vectors of the adaptive filters are represented as:

$$W^T(k) = [W_0(k), W_1(k), \cdots W_{L-1}(K)]^T \tag{6}$$

The initial random solutions of the coefficient vectors of the adaptive filters are called particles.
A set of residual error signals as:

$$e(k) = [e(k), e(k-1), \cdots e(k-L+1)] \tag{7}$$

The position of the ith particle is denoted by W_i (k) and the velocity of the ith particle is denoted by V_i (k). The smallest fitness function in the previous position is represented as $Wpbest_i$ (personal best). The best among all the particles is represented by Wpbesti (global best). The PSO algorithm updates the particle velocity and position with respect it's $Wpbest_i$ and $Wpbest_i$ positions at each step according to the following update equations.
Velocity updation:

$$Vi(k) = \varpi.Vi(K-1) + C_1 r1 \begin{bmatrix} Wpbest_i - \\ Wi(K) \end{bmatrix} + C_2 r2[Wgbest_i - Wi(K)] \tag{8}$$

Table 1: Control parameters of PSO

Parameter	Value
Population size P	100
Inertia factor ϖ	0.5
Cognitive factor C_1	2
Social factor C_2	2
W max	0.9
W min	0.4

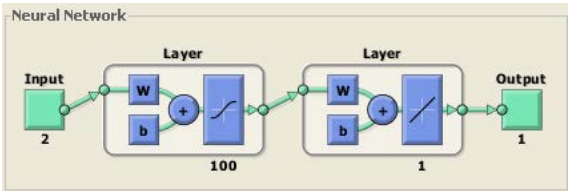

Fig. 2: Structure of ANN

Position updation:

$$Wi(k) = Wi(K-1) + Vi(K) \tag{9}$$

where,

V = The velocity of individual i
K = Pointer of iterations
ϖ = The inertia weight
C_1, C_2 = The acceleration constant
1r, r2 = The random numbers between 0 and 1
Pbest = The positional best position of individual of the particle i
gbest = The global best position of the swarm of the particles

Equation (8) updates a new velocity for each particle and its previous velocity Vi (K - 1) Eq. (9) updates each particle's position.

The proposed PSO-based ANC consists of the following steps:

Step 1: For each particle
Initialize the particle and velocity with feasible random values
End

Step 2: Calculate the fitness value (mean square error):

$$F = 1 \Big/ \sum_{k=0}^{W-1} e_i^2(n)$$

If the mean square error value is better than the pbest:

$$F > pbest_i$$

Then Current value = pbest:
$pbest_i = F$
End

Step 3: The particle with best fitness value in the population is chosen as the gbest.
If $F > gbest_i$
Then
$gbest_i = F$

Step 4: For each particle
1. According to velocity update Eq. (8) update particle velocity
2. According to position update Eq. (9) update particle position

End

Step 5: Continue
Until a stopping criterion (good gbest fitness) is met.

The control parameter value of the PSO evolutional algorithm used in the simulation are given in Table 1.

The ANN learning algorithm takes the error signal as input and updates the filter coefficients based on the parameters (Fig. 2). The adaptive filter the weight update equation is:

$$W(k+1) = W(K) + \mu e(k) x(k) \tag{10}$$

The interference cancellation is performed with learning constant varied from 0 to 1, the momentum constant varied from 0 to 1 and the number of hidden neurons varied from 31 to 200. For this training of 100 training epochs are performed.

SIMULATION RESULTS

In this section, the proposed hybrid PSO-ANN algorithm is applied to interference cancellation in infant incubator ECG signal. The hybrid PSO-ANN algorithm has been designed in a framework of MATLAB 7.10, which aims at developing electromagnetic interference cancellation when measuring ECG for premature infants in Incubators.

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 100 hidden neurons for which the mean square error is 0.009. For this training of 100 training epochs are performed. Using the proposed algorithm an ANN is achieved with Nh = 100, Lr = 0.7963 and Mc = 0.0902. Thus, the proposed algorithm yields a compact network configuration in the architecture space algorithm automatically evolve a best solution and the residual error is 0.009.

The synthetic premature infant input ECG signal shown in Fig. 3a is corrupted by the electromagnetic interference signal produced from the noise source is shown in Fig. 3b to d shows the contaminated ECG signal consists of premature infant ECG signal and the electromagnetic interference signal. The neural network is trained using noisy interference as its input, with infant ECG signal is the desired output. The interference produced by the incubator devices is estimated using the proposed hybrid PSO-ANN algorithm. The estimated interference from the output of the proposed neural network is shown in Fig. 4a.

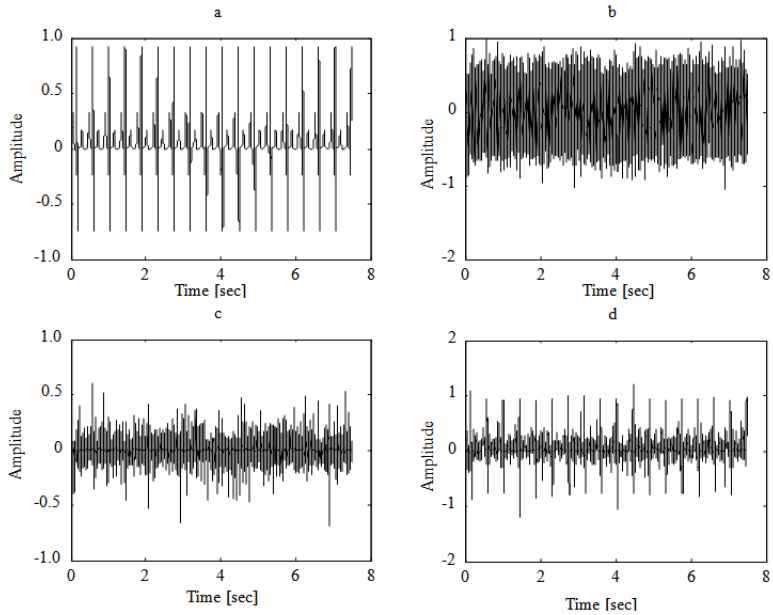

Fig. 3: Measured ECG signal from incubator, (a) synthetic infant ECG, (b) noise source, (c) interference signal, (d) contaminated ECG

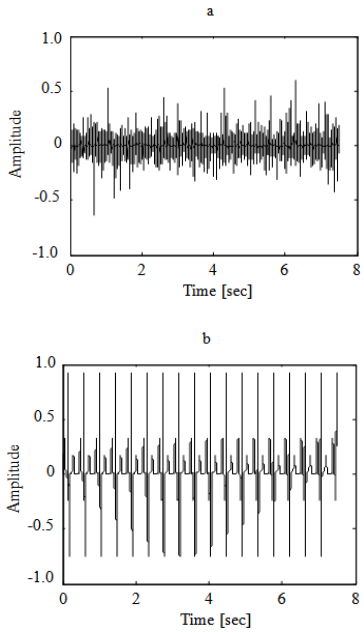

Fig. 4: Output results, (a) estimated interference, (b) noise eliminated ECG signal

The infant ECG is extracted by subtracting the estimated interference from the measured contaminated ECG signal shown in Fig. 4b. Mean Squared Error gives average squared difference between outputs and targets. Figure 5 shows the residual error signal using Back propagation ANN algorithm. Figure 6 shows the error between the generated premature infant ECG signal and the output of the interference eliminated network and is concluded from the output that the proposed hybrid PSO-BPNN algorithm effectively

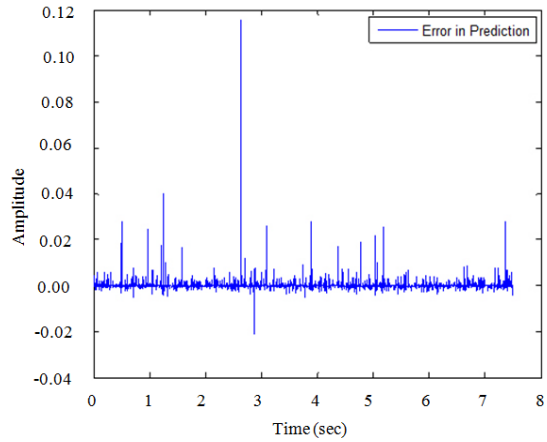

Fig. 5: Residual error signal (BP algorithm)

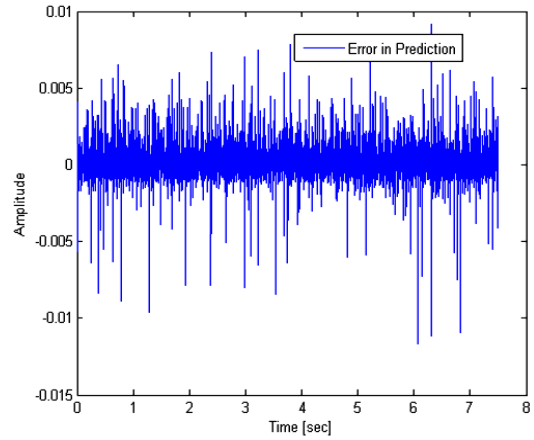

Fig. 6: Residual error signal (hybrid PSO-BPNN algorithm)

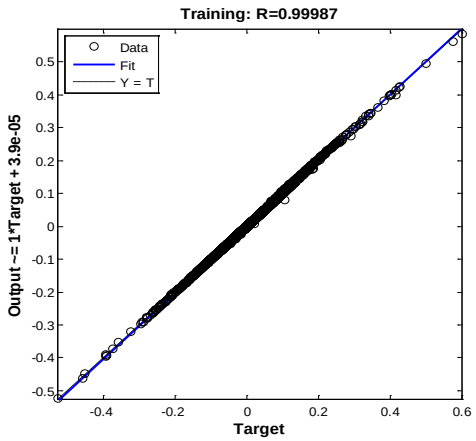

Fig. 7: Regression plot of the neural network

Table 2: Performance analysis

Algorithm	ANN	PSO-BPNN
RMSE	0.118	0.009

cancels the interference minimum mean square error 0.009.

Figure 7 shows the regression plot of the neural network training. Regression R Values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship. In the proposed algorithm R value is 0.99987 this shows that a very close relation between the output and target values.

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

CONCLUSION

In this study the problem of interference cancellation from incubator using hybrid PSO-BPNN algorithm is proposed. The system proposes in this study plays an important role in reducing the incubator ECG interference signals. The results show the computation efficiency and convergence property of the proposed method for obtaining the target values with minimum mean square error 0.009. The results showed the incubator noise can be significantly reduced using the developed hybrid PSO-BPNN algorithm. To implement this process of noise cancellation, the software used is MATLAB 7.10 with the help of neural network toolbox.

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