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Suppression of Electromagnetic Interference in ECG Signal Using Artificial Intelligent Algorithm

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Abstract: Electromagnetic interference produced by the incubator medical equipments may interrupt or degrade the premature infant Electrocardiography (ECG) signal. The premature infant ECG is always contaminated by an 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 an 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-Artificial Neural Network (PSO-ANN) feed forward algorithm is used for the Active Noise Control (ANC) of the fundamental electromagnetic interference in the incubators. The performance of the proposed noise cancellation approach is compared with gradient based algorithms and this proposed approach is successfully removing the noise.

Key words: Infant incubator, electromagnetic interferences, ECG signal, PSO, ANN, back propagation algorithm, active noise control

INTRODUCTION

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. 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 infant incubators motor creates Electromagnetic Interferences (EMI). While measuring the ECG in incubator babies, the infant ECG signals contaminated due to the electromagnetic interferences.

Thanigai *et al*. (2007) proposed a non-linear 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 eigenvalue 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. The Genetic Algorithm (GA) using adaptive infinite impulse response filter (Yim *et al*., 1999) is proposed for Active Noise Control (ANC) applications. Russo and Sicuranza (2006) investigates the performance of genetic optimization in a non-linear system for active noise control based on Volterra filters. Belgiannis *et al*. (2005) proposed a non-linear model

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structure identification of complex biomedical data using a GA (Beligiannis *et al*., 2005). Moreover, Russo and Sicuranza (2007) developed a genetic optimization of non-linear 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 in the year 1995 by Kennedy and Eberhart (1995). It is an exciting new methodology in evolutionary computation and a population-based optimization tool like GA. PSO is motivated from the simulation of the behavior of social systems such as fish schooling and birds flocking.

Adaptive noise canceller based on three-tier neural network trained by improving PSO algorithm is proposed by Xia *et al*. (2008). A PSO based adaptation of the weights of multilayer perceptron network as an ANC algorithm for nonlinear control problems has been proposed by Modares *et al*. (2006) and Rout *et al*. (2010). In Rout *et al*. (2012) presented the conditional reinitialized PSO algorithms for developing an efficient ANC without the use of secondary path estimation.

In this study, researchers develop a systematic algorithm for hybrid PSO based ANC System for the electromagnetic interference cancellation in infant incubator ECG signals. Using PSO algorithm the performance criterions, i.e., the mean squared error are minimized to its global value.

INCUBATOR ANC SYSTEM

Incubator is generally used to provide a closed, safe and controlled environment for newborn infants by circulating heated air over the skin of the premature infant. Some infants are nursed in incubators for weeks or many months after birth. The high noise levels in infant incubators should be considered a prenatal risk factor with may result in cochlear damage (Committee on Environmental Health, 1997).

In 1974, the American Academy of Pediatrics (AAP) suggested noise in the NICU is <45 dB (Quest Technology, 2002). The goal for NICUs is to provide an environment that promotes sleep but the noise disturbs sleep causes physiologic stress and leads to complications with hearing and comprehension The development of auditory visual and central nervous systems are occur in the last stages during the time the premature baby is in the incubator.

Electromagnetic interference is emitted by incubator devices that generate electromagnetic field which covers the area where the baby lies. In incubators unwanted reception of this electromagnetic radiation affect the premature infants (Bearer, 1994). All medical equipments generate some EMI.

Incubator noise is generated by equipment such as blowers, nebulizers, humidifiers, fans, pumps and heating machinery. Incubator noise is suggested as a possible contributive factor in the cause of deafness. The common NICU noise sources are pump alarms (70 dB), Oximeter alarm (85 dB), respiratory tubes (80 dB), finger tapping (72 dB) and loud voices (>100 dB) (Carvalho and Pedreira, 2005).

Canceling this broadband noise can be made effective by utilizing an ANC System. The feed forward ANC System with reference microphone is required to cancel the broadband incubator noise. A single channel ANC System uses one reference microphone, one secondary loud speaker and one error microphone. The primary noise from incubator noise source is picked up by the reference microphone, processed by the ANC System to generate the anti-noise which is sent to the secondary source of loud speaker for canceling the interference noise. The error microphone measures the residual noise which is used for updating coefficients of the neural network adaptive filter. The FXLMS algorithm is used to cancel the interference noise inside the incubator (Liu *et al*., 2008).

PROPOSED HYBRID PSO-ANN ALGORITHM FOR INTERFERENCE CANCELLATION IN INFANT INCUBATORS

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-ANN algorithm for minimizing the electromagnetic interference in incubators. The corrupted signal M(k) consists of desired infant ECG

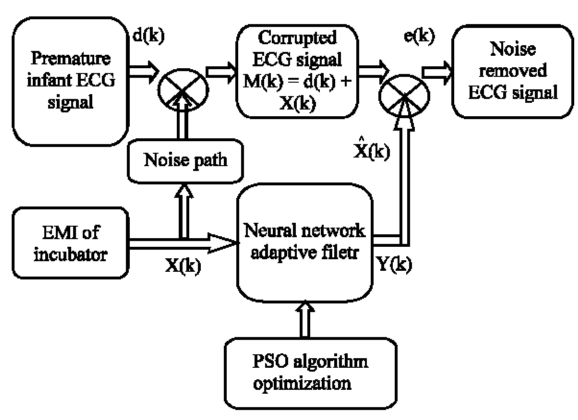

Fig. 1: ANC for infant incubator using hybrid PSO-ANN algorithm

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 $\hat{X}(k)$:

$$M(k) = d(k) + X(k) \tag{1}$$

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:

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

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

The output of this equation used as the input to the PSO algorithm for removing the interference signal. The objective of the PSO-ANN 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:

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

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

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

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 earlier position is represented as $Wpbest_i$ (personal best). The best among all the particles is represented by $Wgbest_i$ (global best). The PSO algorithm updates the particle velocity and position with respect it's $Wpbest_i$ and $Wgbest_i$ positions at each step according to the following update equations. Velocity updation:

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

Position updation:

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

Where:

V	=	The velocity of individual i
K	=	Pointer of iterations
ϖ	=	The inertia weight
C_1, C_2	=	The acceleration constant
r1, 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 earlier 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)

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

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,
- According to velocity update Eq. 8 update particle velocity
- According to position update Eq. 9 update particle position

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

Table 1: Control parameters of PSO

Parameters	Values
Population size (P)	100.0
Inertia factor (ϖ)	0.5
Cognitive factor (C_1)	2.0
Social factor (C_2)	2.0
W_{max}	0.9
W_{min}	0.4

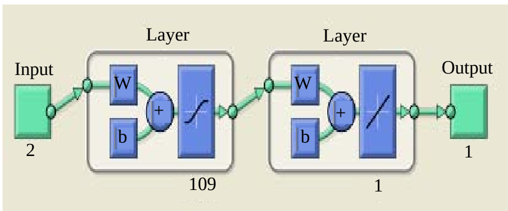

Fig. 2: Structure of ANN

The control parameter value of the PSO evolutional algorithm used in the simulation are shown in Table 1. The ANN learning algorithm takes the error signal as input and updates the filter coefficients based on the parameters. The adaptive filter the weight update equation is:

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

The simulated structure of the hidden layer and output layer activation function outputs of ANN are shown in Fig. 2. In which X [1] represent the inputs, Z {1} represents the hidden layer activation output is given to the input for the output layer. Y [1] represents the output layer activation output. The W and b represents the inter-connection weights and bias of the artificial neural network, respectively. The interference cancellation is performed with learning constant varied from 0-1, the momentum constant varied from 0-1 and the number of hidden neurons varied from 31-200. For this training of 100 training epochs are performed.

SIMULATION RESULTS

In this study, 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 0-1 and the best performance is obtained for 109 hidden neurons for which the mean square error is 0.007. For this training of 100 training epochs are performed. Using the proposed algorithm an ANN is achieved with Nh = 109, Lr = 0.6963 and Mc = 0.0802. Thus, the proposed

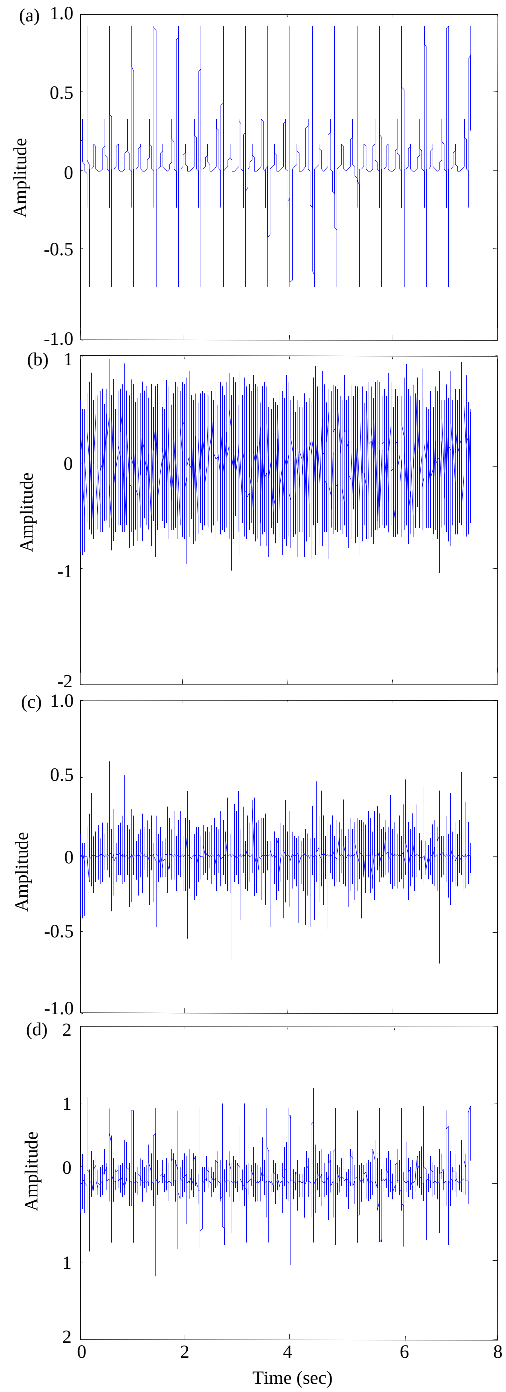

Fig. 3: Measured ECG signal from incubator; a) synthetic infant ECG; b) noise source; c) interference signal and d) Contaminated ECG

algorithm yields a compact network configuration in the architecture space algorithm automatically evolve a best solution and the residual error is 0.007.

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 and c. Figure 3d 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.

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-ANN algorithm effectively cancels the interference minimum mean square error 0.007.

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 0.99962 this shows that a very close relation between the output and target values. The performance analysis of the proposed hybrid PSO-ANN based noise cancellation algorithm is compared with that of conventional ANN algorithm in terms of Root Mean Square Error (RMSE) and the hybrid PSO-ANN shows better performance as shown in Table 2.

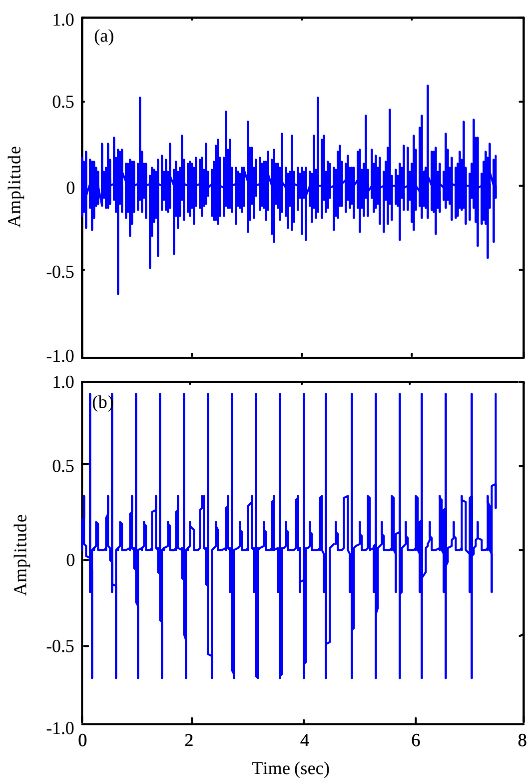

Fig. 4: Output results; a) estimated interference and b) noise eliminated ECG signal

Table 2: Performance analysis

Algorithm	ANN	PSO-ANN
RMSE	0.118	0.007

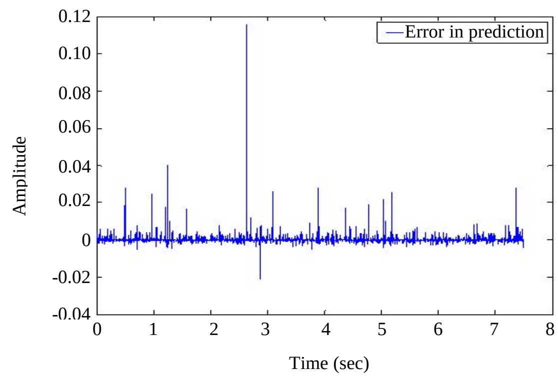

Fig. 5: Residual error signal (ANN algorithm)

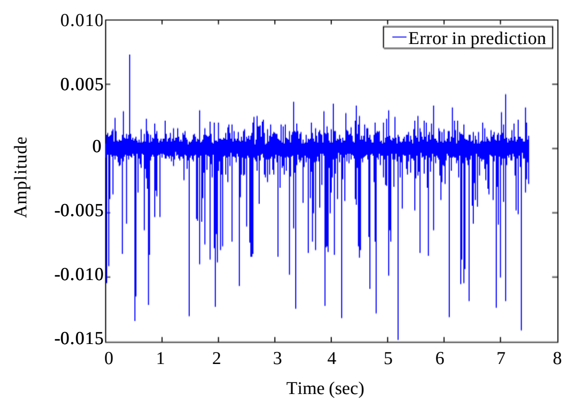

Fig. 6: Residual error signal (hybrid PSO-ANN algorithm)

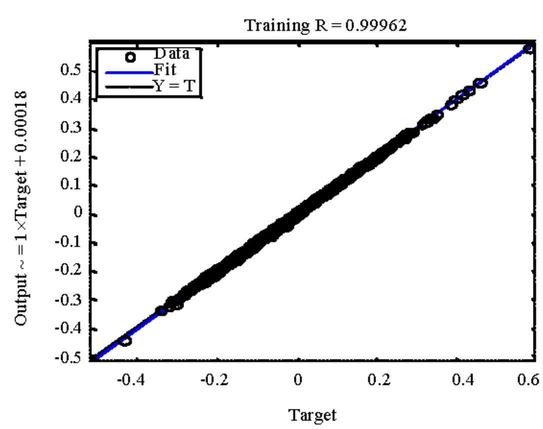

Fig. 7: Regression plot of the neural network

CONCLUSION

In this study, the problem of interference cancellation from incubator using hybrid PSO-ANN 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 0.007. The results showed the incubator noise can be significantly reduced using the developed hybrid PSO-ANN 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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