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Optimization algorithm for Noise cancellation using Adaptive Estimator

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Abstract

Noise signals corrupt the information available in a channel. Most of the noise sources are additive. The signals are corrupted by the noises and it loses its quality. This paper presents the detail analysis of the adaptive estimator for noise cancellation in multichannel system using different optimization technique. Different noise cancellation techniques are available in the literature like matched filtering, wavelet transform and statistical analysis. This paper presents the evolutionary methodology approach using Artificial Bee Colony and Particle swarm optimization for the optimization of multichannel adaptive filter l. The investigation of the efficiency of the method was evaluated using a real time ECG data. The noise in the ECG signal is removed using the multichannel adaptive filter using evolutionary optimization technique.

Keywords:*PSO,ABC, LMS, Adaptive filter, Multichannel, Machine learning, Noise canceller, RLS*

I. INTRODUCTION

In the modern technology world information became the most valuable asset. The information is transmitted or received from different means. Different means of channels are used to communicate the information. The data varies from field to field. In medical field a channel is corrupted by various noises like Power line interference, Electrode contact noise, Motion artifacts, Muscle contraction, Base line drift and Instrumentation noise. In audio signal processing the noises are due to power line interference. Echo and harmonics and in embedded system the noise happens due to offset noises and electronics noises (Awwab, 2017). The noise reduction in the signal determines the level to which the information in the signal can be extracted effectively (Abbas 2011). The main problem and the major challenge is when the noise signal frequency range correlates with the information frequency. The challenges increase when the number of channels is more. Various methods are adopted in the past to remove the noises using adaptive filters (Abbas 2011). The methods are focused only on the removal of power line interference. There is an overlap between the signal processing and machine learning. The computer program learn from the data, experience and performance (Berrar 2003). It improves from the experience. The combinational of the inductive inference algorithm and statistical signal processing forms the basis for the new theory of adaptive filters(Martens 2006).. These nonliniear phenomenon will be suitable for adaptive filters which will work on the machine learning approach. The statistical signal processing methods like independent component analysis (ICA) , principle component analysis(PCA) are complex in implementation. Its very difficult to incorporate the machine learning approaches in statistical signal processing methods like ICA, PCA etc But if these complex systems found new hardware methodology to be implemented then Statistical Signal Processing (SSP) along with Machine Learning (ML) approach

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will be a platform for building new devices with effectiveness.

II. BACKGROUND METHODOLOGY

For Noise cancellation adaptive filters were used due to its self-learning process. Through iterations the filter coefficients are updated with respect to the noise strength. By adjusting the coefficients adaptively the error is minimized. The adaptive filters are implemented using gradient-based techniques. The Least Mean-Square (LMS), and Recursive Least-Square (RLS) belongs to the gradient based techniques. These LMS and RLS based algorithm plays a vital role in designing digital noise cancellers in various applications like speech processing (Greenberg, J.E. (1998), extraction (Ravindrakumar and Bommannaraja (2014)) and speech enhancement (Goswami et al, 2014). But in literature several other optimization algorithms are presented. The methods are based on the particle swarm optimization, Artificial Bee Colony (Gao et al, 2013, Karaboga, 2010)), etc. methods. These optimization techniques were more suitable for adaptive equalization (Cheded et al, 2011). Zhao et al (2013) used the bee colony algorithm to design the digital filter design. The method was suitable for DSP application. Real parameter optimization was done using the ABC algorithm(Akay, B. and Karaboga, D. 2012). The global optimization increases when these optimization is used. The block diagram of ANC filter with ABC is shown in Figure 1.

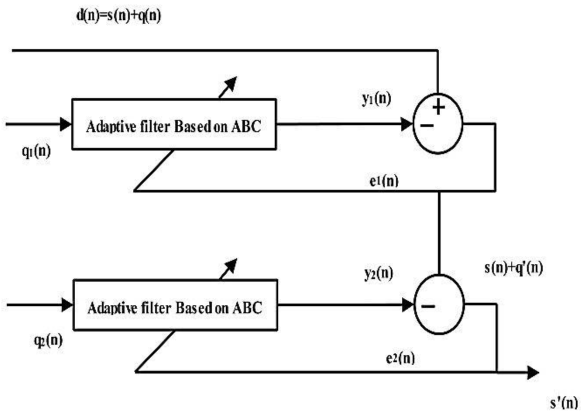

Figure 1. Adaptive filter using ABC

For evaluation of the efficiency an ECG signal is taken as example. The data is used from real time database consisting of 5 channels.

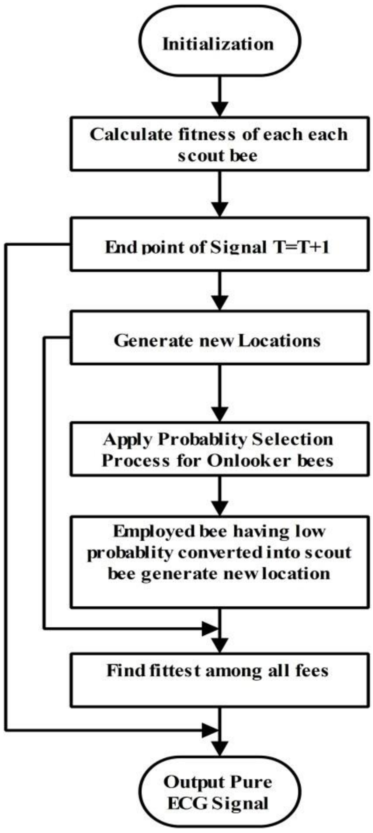

Figure 2. Block diagram of ABC algorithm for ECG denoising.

The block diagram of the ABC algorithm is shown in figure 2. The position of the bee is equavated to the coefficient of the adaptive filter.

The initial random population or the filter co-efficients are generated according to equation below

$$x_{ij} = x_{min,j} + rand(a) * (x_{max,j} - x_{min,j}) \quad (1)$$

‘ a’ takes the value between -1 to +1.’ i’ is the colony size and j is the dimension value in the colony which represent the filter coefficient of the adaptive filter. The probability of optimized position or coefficient value is determined by the equation

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \quad (2)$$

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Once new location are generated probability selection process is carried out with the fitness value fit and SN choosen index value.

To optimize the coefficient value the ABC algorithm uses a scaling factor(sf) which produces the minimum or zero error function. The best filter coefficient is found using the equation

$$x_{i,j} = \begin{cases} x_{min,j} + \phi_{i,j} * (x_{max,j} - x_{min,j}) & \text{for} \quad sf \\ x_{min,j} & \text{otherwise} \end{cases} \tag{3}$$

The magnitude of perturbation is controlled by the scaling factor.

III. PROPOSED METHODOLOGY

In the proposed methodology the optimization of the adaptive filter updating is extended towards multichannel system using the evolutionary methods. Five channels were chosen for the same. The optimization of the LMS algorithm uses instantaneous estimation of vectors based on sample values of input d (n) and error e(n) using the below equation.

$$\nabla(n) = -2e(n)[d(n)] \tag{4}$$

In conventional methods the filter coefficients are updated along the direction of gradient vector estimate as

$$[h(n+1)] = [h(n)] + \mu e(n)[d(n)] \tag{5}$$

The estimation requires the knowledge of data x(n) alone and not the knowledge of cross correlation.

$$e(n) = [h(n)] + \mu e(n)[d(n)] \tag{6}$$

In gradient vector estimate for multichannel system can be coined by the equation

$$d(n) = q_1(n)[F(n) + M(n) + q_2(n)] \tag{7}$$

Where d is the input and N is the noise representing low and high frequency component. The coefficient of the filter is estimated based on the data input and previous stage output. In our example the input is the noisy ECG signal (d) contains the pure ECG signal and noise ($q(n)$). The high frequency components are the power line noise and low frequency components are muscle noise which are additive and uncorrelated with $s(n)$. Referring figure 1, $q1(n)$ and $q2(n)$ are high and low frequency noises, respectively, The error signal ($e1(n)$) is computed as the difference of $d(n)$ and $y1(n)$, which is fed back to ANC filter in each iteration. The iteration process will continue till $e1(n)$ or the high frequency noise is minimised in first stage. The output signal containing low frequency noise is given to second stage of ANC filter where the error signal ($e2(n)$) is computed as the difference of $s(n) + q1(n)$ and $y2(n)$. The $e2(n)$ is fed back to ANC filter in each iteration till $e2(n)$ is minimised. The final output signal ($s(n)$) is nearly equal to $s(n)$. The error function for $e1(n)$ and $e2(n)$ is represented by

$$\text{error function} = \frac{1}{N}\sum_{i=1}^{N}\left(e_{ij}(n)\right)^2 \tag{8}$$

Where,$eij(n)$ is jth error of ith sample for nth iteration and N is the total number ofsamples of applied input signal.

For multichannel system the ABC algorithm is framed as

$$x_{cij} = x_{c,min,j} + rand(a) * (x_{c,max,j} - x_{c,min,j}) \tag{9}$$

Where c denotes the multichannel system and the error function is given by

$$\text{error function}_c = \frac{1}{N}\sum_{i=1}^{N}\left(e_{c,ij}(n)\right)^2 \tag{10}$$

$$\text{error}_{cum} = \frac{1}{c}\sum_{k=1}^{k=c} \frac{1}{N}\sum_{i=1}^{N}\left(e_{k,ij}(n)\right)^2 \tag{11}$$

The cumulative error function is the reduction of error in all channels as a collective optimization. In conventional adaptive filters the optimization is done only after each iteration with one possible solution, but in using ABC algorithm the optimization has n number of solutions with faster convergence rate (Rodrigo et al, 2017). The other algorithms like particle swarm optimization to be discussed in next section also provide faster convergence rate and strong global search. The ABC and PSO are easy to implement.

Here in our example as shown in figure 3 the number of samples are 3600 with sampling frequency of 360Hz. Totally 10 epoch were used for testing. The step size µ was 0.1 which in the next example it was kept 0.5. In figure 4 the number of samples are 6000 with sampling frequency of 360Hz. In the figure 3 all the channels are affected by nearly equal amount of noises. But in figure 4 it can be observed that the channel 3 is affected by more noise than the other channel and the ANC designed is hard to remove the noises. From this investigation it can be observed that if the noise level is very high the ANC using any methods will fail to remove the noise. So in real time most input cables, wires and electrodes are coupled with EMC system to remove the noises at the input end itself. The noise happening in the acquisition is reduced means the rest of the noises are from the processing circuits which the noise can be easily removed.

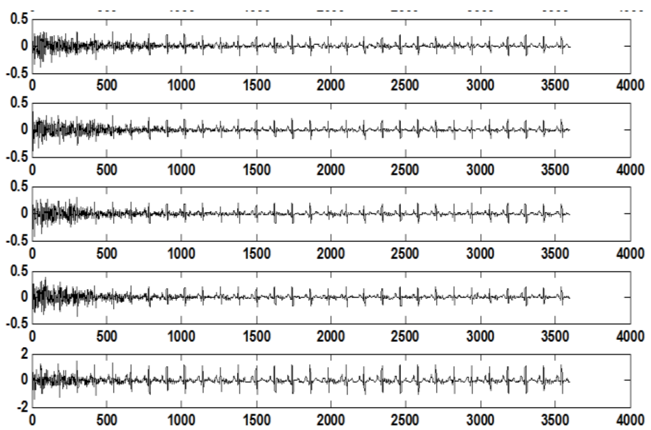

Figure 3.output of the LMS algorithm for multichannel system-high SNR

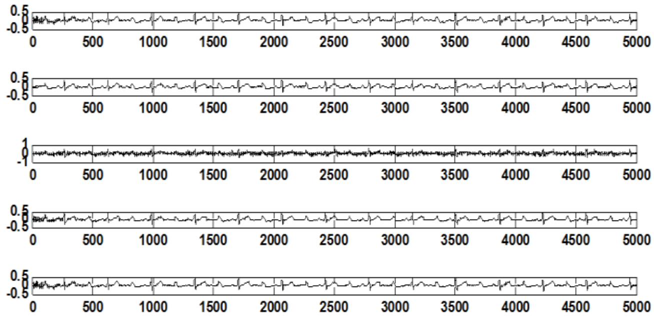

Figure 4.output of the LMS algorithm for multichannel system- low SNR

3.1. PSO Algorithm for multichannel system

The PSO algorithm can be used to solve any nonlinear equations. Here a random swarm is initiated, velocity and position updates are made. The particle fitness is evaluated based on selected fitness function. The position is updated in each training update. Figure 5(a) shows an example of PSO for adaptive filter used in ECG signal analysis. Figure 5(b) shows the PSO with inertia weight. The inertia weight parameters provides better efficiency and convergence.

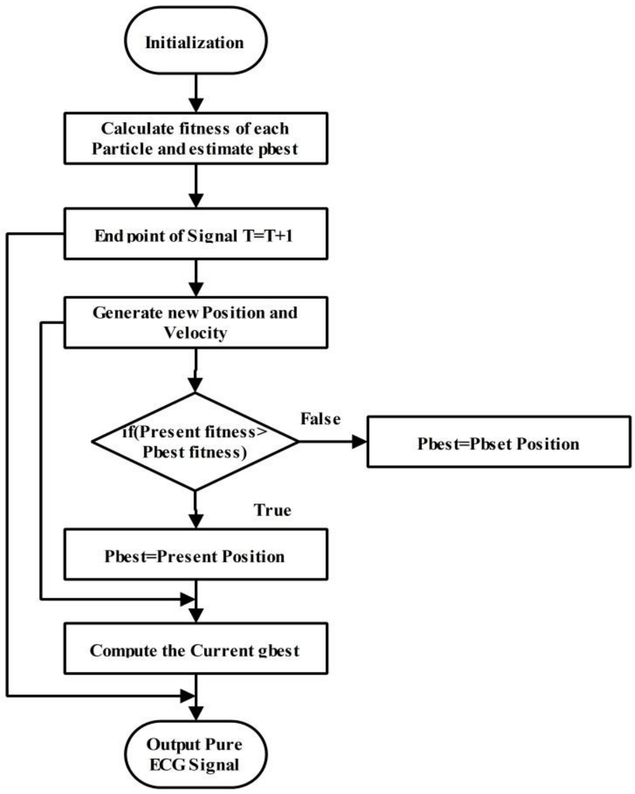

Figure 5(a) shows the PSO for adaptive filter

In this method, for the best possible positions with least swarm is optimized.

$$p(n+1) = W(n) + \mu(n).O(error_c(n), d(n), \phi(n)) \quad (12)$$

Similar to the ABC algorithm the PSO algorithm is applied to the real time data (Physionet.org) and the results are obtained. The ABC and PSO methods are compared with the conventional LMS, NLMS and RLS algorithm. The results are obtained using MATLAB (Table 1).

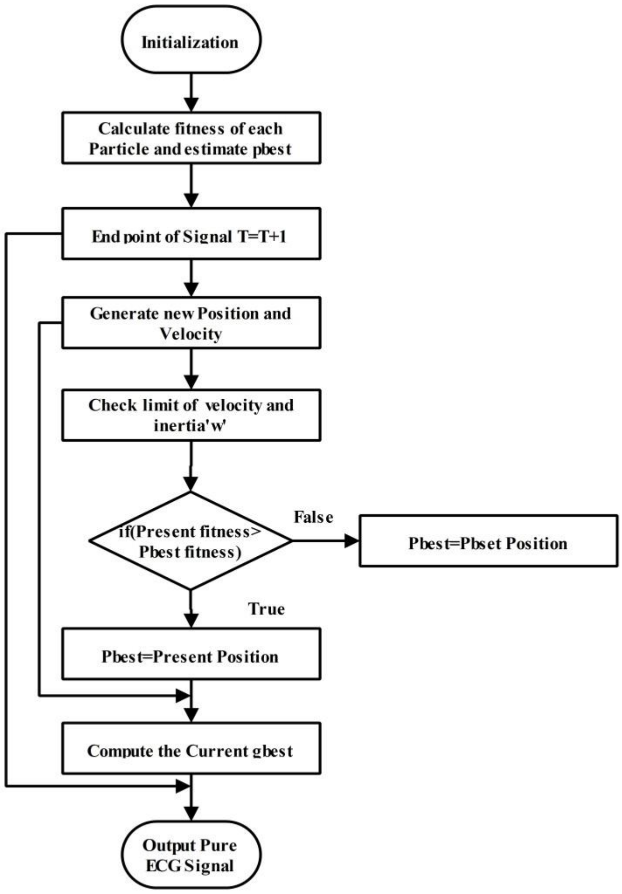

Figure 5() shows the PSO for adaptive filter and (b) with inertia weight

The MSE can be described as the mean of the square of the differences between the de-noised ECG signal and the original fetal ECG signal.

$$MSE = \frac{\sum_{I=1}^{N}(s-s_e)i^2}{n} \quad (13)$$

Where ' n' denotes the length of the signal in this work n=6000, ' s' represents the original signal and se is the estimated signal. Lower the values of MSE of the signal, higher the accuracy and efficiency of the output. The PSNR is defined as the ratio between the maximum signal power and the noise power.

$$PSNR = \frac{10\log_{10} n}{MSE} \quad (14)$$

Higher the values of PSNR of the extracted signal, higher the accuracy and efficiency of the output. This is the evaluation strategy used throughout the work. the maximum absolute error (MAXERR) and the energy ratio between original signal and approximation/extracted value are measured.

Table 1. Performance of Various Methods

PARAMETERS /METHODS	LMS	NLMS	RLS	ABC	PSO	PSOI
PSNR	78.89	78.82	77.19	79.55	79.52	79.47
MSE	8.3E-04	8.5E-04	1.2E-03	1.8E-04	1.40E-04	1.20E-04
MAXERR	0.232	0.297	0.395	0.262	0.252	0.243
L2RAT	1.364	1.356	1.203	1.311	1.307	1.280

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CONCLUSION AND FUTURE WORK

The removal of noises using evolutionary algorithm is addressed in this paper. The adaptive estimator using methods like ABC and PSO are investigated and implemented. The adaptive estimation was extended to the multichannel signal inputs. The evolutionary methodology approach using Artificial Bee Colony and Particle swarm optimization for the optimization of multichannel adaptive was reported. The investigation of the efficiency of the method was evaluated and found that the method has high PSNR and lowest mean square error. The methods are compared with the conventional LMS, RLS and NLMS algorithm using a real time ECG data. The proposed method gives nearly a 2% increase in SNR when compared to the existing methods. The mean square value obtained is nearly one order times better when compared to existing methods. The noise in the ECG signal is removed using the multichannel adaptive filter using evolutionary optimization technique. In future the methods will be implemented in hardware. This will enable into the creation of new portable devices.

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