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Fetal Heartbeat Signal Extraction using an Adaptive Noise Canceller implemented with an improved Simulated Annealing Algorithm

Mr. Kevin Mwongera [1], Dr. Kibet Langat[2], Dr. E. N. Ndung'u[3]
[1, 2, 3]*(Department of Telecommunication and Information Engineering, Jomo Kenyatta University of Agriculture and Technology, Nairobi, Kenya)*

Abstract: *Measured fetal heartbeat signals are usually contaminated by the corresponding mother's heartbeat signal and other random noise. Adaptive Noise Cancellation (ANC) is usually employed in extraction of fetal heartbeat signals from signal measurements taken at the mother's abdomen. A variety of algorithms can be utilized in ANC to yield minimal-noise fetal heartbeat signals. An ideal algorithm ought to generate an accurate result in as little time as possible. In this paper, an improved Simulated Annealing (SA) algorithm is utilized in ANC to yield a minimal-noise fetal electrocardiogram signal in MATLAB. A performance analysis between use of the improved SA algorithm and the standard SA algorithm (alongside Genetic, Least Mean Squares (LMS) and Normalized Least Mean Squares (NLMS) algorithms) is done. The improved SA algorithm is found to outperform the other algorithms.*

Keywords: *Adaptive Noise Cancellation, Genetic Algorithm, Least Mean Squares algorithm, Normalized Least Mean Squares algorithm, Simulated Annealing algorithm*

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I. Introduction

Fetal heartbeat signals are usually contaminated by the corresponding mother's heartbeat signal and other random noise in a measurement process. Noise arising in data transfer/ communication systems is usually eliminated at reception stages using filters. There are two main filter categories; fixed filters and adaptive filters. Fixed filters technically feature a predefined fixed response which cannot change in the course of the filter operation irrespective of changes in noise and/or the desired signal. Their operation is basically achieved by modeling the noise signal and subtracting it from the signal distorted by noise [1]. In randomly changing signal/ noise conditions, direct subtraction of the noise at the desired signal point results in a high likelihood of increasingly distorting the desired signal. This is due to the fact that the nature of the transmission channel/ the noise that exists along the transmission channel is not exactly known. It is imperative to note that for the noise signal to be eliminated the noise subtracted ought to be an exact replica of the noise present at the desired signal tapping point. This cannot be achieved without making use of a filter whose response can change in accordance to changing noise and signal conditions; hence the superiority of adaptive filters [1]. Adaptive filters are the major component of Adaptive Noise Cancellation (ANC) schemes. In data transfer/ communication systems, the term filter refers to a system that reshapes the frequency components of an input signal to generate an output signal with desirable features. Application of Artificial Intelligence (AI) based algorithms in ANC is an active research area.

II. Adaptive Noise Cancellation

ANC is ideal in extraction of fetal electrocardiogram from signal measurements taken at the mother's abdomen owing to time-changing noise conditions. Fetal heartbeat signals are typically contaminated by the corresponding mother's heartbeat signal and other random noise. A review of ANC can be found in [2].
Basically an Adaptive Noise Canceller would be of the nature illustrated in Fig. 1 [2], [3].

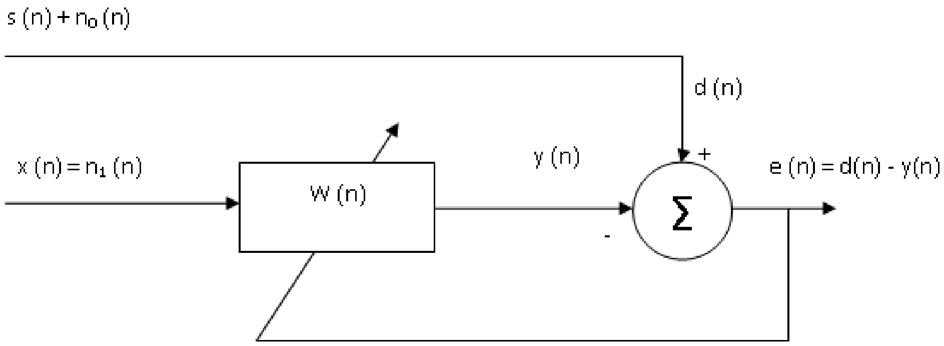

Fig. 1: Adaptive noise canceller

As per Fig. 1, an adaptive noise canceller has two inputs primary (represented by *d*) and reference (represented by *x*). The primary input is a signal s that is corrupted by the presence of noise n_0 that is uncorrelated with the signal. The reference input is a noise signal n_1 that is uncorrelated with the signal s but correlated in some way with the noise n_0. The noise n_1 passes through an adaptive filter to generate an output y that is a close estimate of the primary input noise n_0. This noise estimate is consequently subtracted from the corrupted signal to generate an estimate of the signal *e*, the ANC system output.

In typical noise cancellation systems, the objective is usually to produce a system output $e = s + n0 - y$ that is a best fit in the least squares sense to the signal of interest *s*. This objective is met through feeding back the system output *e* to the adaptive filter and consequently adjusting the filter through an adaptive algorithm with an aim of minimizing the total system output power. The system output is typically the error signal for the adaptive process.

In the following analysis, it is assumed that s, n_0 and n_1 are statistically stationary and have zero means; the signal s is uncorrelated with n_0 and n_1, and n_1 is correlated with n_0.

$$e = s + n_0 - y \tag{1}$$

$$e^2 = s^2 + (n_0 - y)^2 + 2s(n_0 - y) \tag{2}$$

Taking the expectation of both sides in (2) and realizing that s is uncorrelated with n_0 and y;

$$E[e^2] = E[s^2] + E[(n_0 - y)^2] + E[2s(n_0 - y)] \tag{3}$$

And consequently;

$$E[e^2] = E[s^2] + E[(n_0 - y)^2] \tag{4}$$

The signal power $E[s^2]$ is not affected since the filter is adjusted to minimize the total output power $E[e^2]$ as per (5).

$$min\, E[e^2] = E[s^2] + \min E[(n_0 - y)^2] \tag{5}$$

When the filter weights are adjusted with an aim towards minimizing the total output power $E[e^2]$, the output noise power $E[(n_0 - y)^2]$ is also minimized. Since the signal power in the output remains constant, minimizing the total output power maximizes the output Signal to Noise Ratio (SNR).

III. Least Mean Squares Algorithm

The Least Mean Squares (LMS) algorithm aims at minimizing some Mean Square Error (MSE) function as per (6) by iteratively by updating filter weights in a manner negative to the direction of the gradient of the MSE function [2].

$$J(n) = E[|e(n)|^2] \tag{6}$$

$$w(n+1) = w(n) + \frac{1}{2}\,\mu[-J\Delta(n)] \tag{7}$$

In (7), w (n) corresponds to the filter weighting at a given point in time. The constant μ is referred to as step-size. The step-size in general has a big bearing on converge rate alongside overall algorithm stability. Too small a step-size leads to high convergence time; the converse is true. However, too large a step size increases the asymptomatic error. Thus the selection of the step size value is largely a tradeoff between the application requirements, algorithm stability, convergence rate and accuracy [2].

A subclass of LMS algorithms that is very commonly used is the Normalized Least Mean Square (NLMS) algorithm. This algorithm is typically an upgrade to the standard LMS algorithm, and it is intended to increase convergence speed, and overall stability despite increased complexity. The NLMS algorithm largely removes performance dependence on the step size value. A scaling factor for the step size is utilized in order to constantly scale the step size with a focus towards increasing the algorithm's performance while increasing the stability. This is achieved by normalizing the step size with an estimate of the input signal power. The normalization factor, however, is made inversely proportional to the signal instantaneous power. This acts to increase stability and convergence speed by allowing for utilization of a larger step size [2].

IV. Genetic Algorithm

The Genetic Algorithm (GA) is based on the evolution process as per Charles Darwin's theory of natural evolution. Starting from an initial random solution to some optimization problem, poorly performing solutions are eliminated and good solutions kept and consequently mutated with an aim of yielding better and better solutions.

V. Simulated Annealing Algorithm

The Simulated Annealing (SA) algorithm is an optimization technique based on the way in which a metal cools and freezes into a minimum energy crystalline structure (the physical annealing process). This algorithm was proposed in 1983 by Kirk Patrick, Gelatt and Vecchi [4] as a probabilistic method for finding global minima or maxima of a cost function that may possess several local minima or maxima. A description of the SA algorithm can be found in the book be Aarts Emile, Korst Jan and Michiels Wil [5]. An implementation of SA algorithm in hardware is described in [6]. A classic optimization problem involving train scheduling is solved on the basis of the SA algorithm in [7].

SA algorithm approaches optimization problems in an analogous manner to a bouncing ball approach (a ball bouncing over mountains (function crests) and from valley (function troughs) to valley). It begins at a high "temperature" which enables the ball to make very high bounces (enables it to bounce over any mountain to access any valley). As the temperature declines, the ball cannot bounce very high and consequently it can be easily trapped in a relatively small range of valleys [8].

Initially, a random possible solution is considered. An acceptance scheme is also defined. The acceptance scheme depends on the difference between the function value of the solution to be explored and the last obtained best solution (initially a random solution). The acceptance scheme decides probabilistically whether to move to a new solution or stay in some current solution. The acceptance scheme depends on some "temperature" parameter. By carefully controlling the rate of "temperature" reduction, SA can easily obtain a global solution . The acceptance probability scheme is given in (8), where δ_f is the increase in objective function value and T is the system "temperature".

$$p = e^{\frac{-\delta_f}{T}} \tag{8}$$

Temperature reduction involves a linear decrement as given in (9).

$$t_i = \alpha t_{i-1} \tag{9}$$

VI. Methodology

1. SA ALGORITHM IMPROVEMENT

1.1 Acceptance Probability

During SA algorithm run, not only better solutions are accepted but also worse solutions (to avoid convergence to a local minimum) but with a decreasing probability as execution progresses.

In the standard SA algorithm, the probability of accepting a worse move is based on an exponential calculation as per Equation 4. Such calculations are computationally intensive and consequently this slows down algorithm execution speed. Use of simpler but efficient functions would result in increased algorithm convergence rate.

An efficient acceptance probability scheme is hereby defined as per (10).

$$p = 1 - \frac{\delta(t)}{T} \tag{10}$$

This approximates the exponential calculation utilized in the standard SA algorithm. Figs. 2 and 3 illustrate the developed scheme.

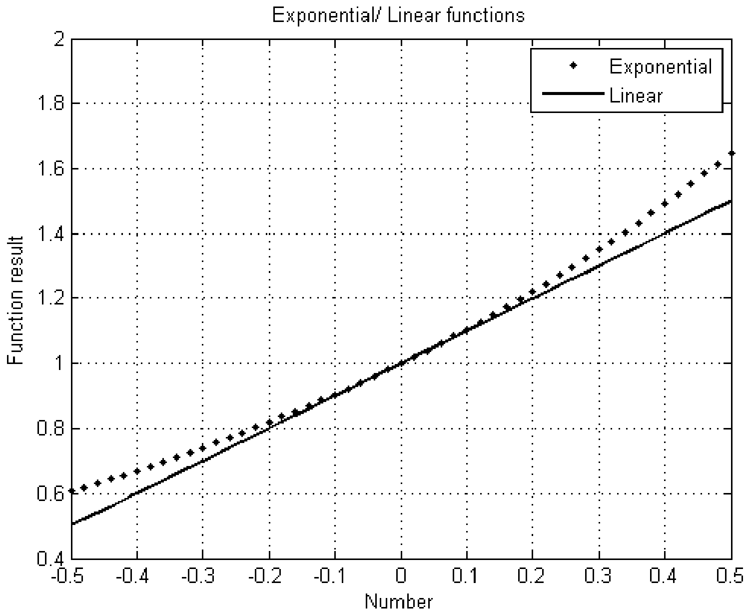

Fig. 2: Exponential function/ linear function comparison

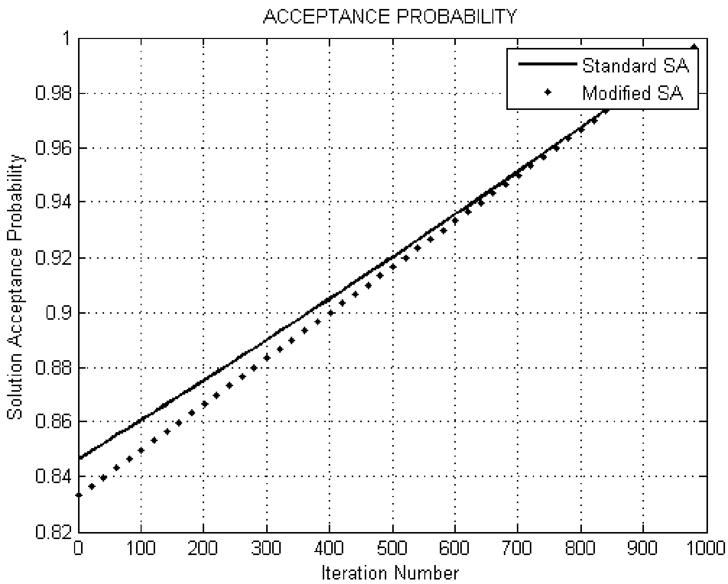

Fig. 3: Developed acceptance probability scheme

1.2 Cooling scheme

In the standard SA, at high temperatures, the probability of accepting worse solutions is high (seemingly a random search process). As the temperature decreases, the probability of accepting worse solutions decreases. Generally, SA algorithm does most of its work during the middle stages of the cooling schedule. This seemingly suggests that annealing at a roughly constant temperature in the middle stages is a viable idea.

A decreasing temperature is defined as per Fig. 4. The temperature reduction rate is kept low in the middle stages of algorithm run. This is a move from the standard SA algorithm in which temperature reduction is linear.

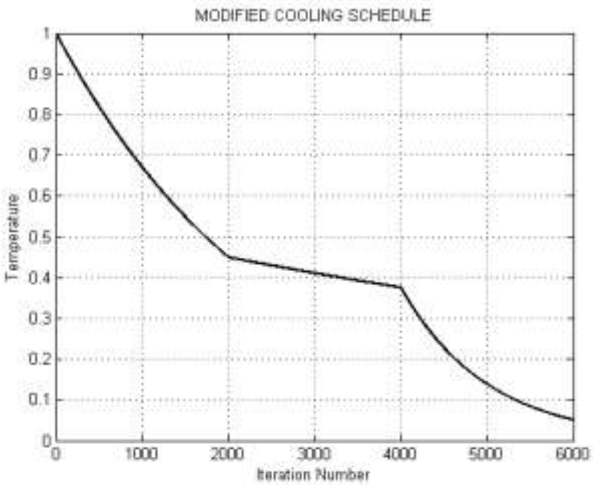

Fig. 4: Developed cooling schedule

2. COST FUNCTION DESIGN

The cost function developed is on the basis of (6).

$$error\ signal = noise\ contaminated\ signal - weighted\ noise\ estimate \tag{6}$$

Let (7) be some *M X* 1 tap-weight vector.

$$\mathbf{w}^T = [w_1, w_2, \ldots, w_M] \tag{7}$$

Let (8) be some *M X* 1 input vector.

$$\mathbf{X}^T(n) = [x(n), x(n-1), \ldots, x(n-M+1)] \tag{8}$$

Then the filter output can be framed as per (9).

$$y(n|\mathbf{X}_n) = \mathbf{w}^{\mathrm{H}}\mathbf{X}(\mathrm{n}) \tag{9}$$

Consequently, (6) be written as per (10), where *e*(*n*) is the filter output, *d*(*n*) the noise contaminated signal, *w*(*n*) a set of filter weights and *x*(*n*) an estimate of the noise signal.

$$e(n) = d(n) - \mathbf{w}^{\mathrm{H}}\mathbf{X}(\mathrm{n}) \tag{10}$$

The mean squared error (cost function) *J*(**w**) can consequently be expressed as E[e(n)e*(n)] (expanded in (11)).

$$J(\mathbf{w}) = \mathrm{E}[\big(d(n) - \mathbf{w}^{\mathrm{H}}\mathbf{X}(n)\big)(d^*(n) - \mathbf{X}^{\mathrm{H}}(n)\mathbf{w})] \tag{11}$$

The optimal solution (obtained by minimizing the cost function as per (11) through filter weights optimization) is ideally a noise free signal.

3. EUCLIDEAN DISTANCE PERFORMANCE MEASURE

In the performance evaluation comparison, Euclidean distances play a pivotal role in the analysis of final solution convergence for different optimization algorithms studied in this thesis. Euclidean distance is a measure of similarity or dissimilarity that can be used to compare two sets of vectors and compute a single number which evaluates the similarity/dissimilarity. Given two points in a two dimensional space, Euclidean distance is the length of the path connecting them in the plane. The distance between say two points (x_1, y_1) and (x_2, y_2,) is given by (12).

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (12)$$

In general, for any set of points in a Euclidean space R_N, the distance between points x and y is given by (13).

$$d = \sqrt{\sum_{i=1}^{N} |x_i - y_i|^2} \quad (12)$$

VII. Performance Of The Improved Simulated Annealing Algorithm In Fetal Heartbeat Extraction

1. OVERVIEW

Comparisons are hereby done between the performance of SA, its improved version, GA, LMS and NLMS algorithms in fetal heartbeat extraction.
The electrocardiogram signal depicted in Fig. 5 is utilized as the desired signal in the simulations.

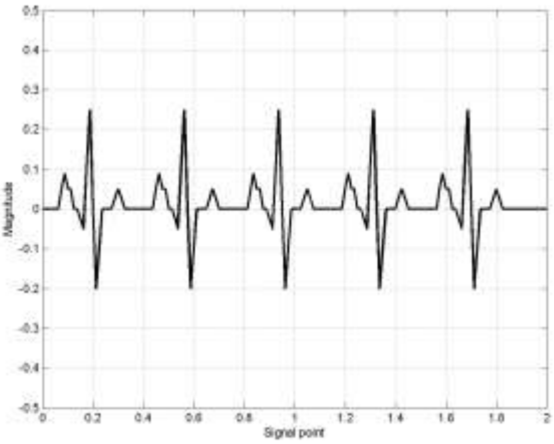

Fig. 5: Desired signal

The noise corrupted signal is depicted in Fig. 6. Noise is simulated as the maternal heartbeat and some randomly generated noise. The fetal heartbeat is indecipherable from the noise-corrupted form as per Fig. 6.

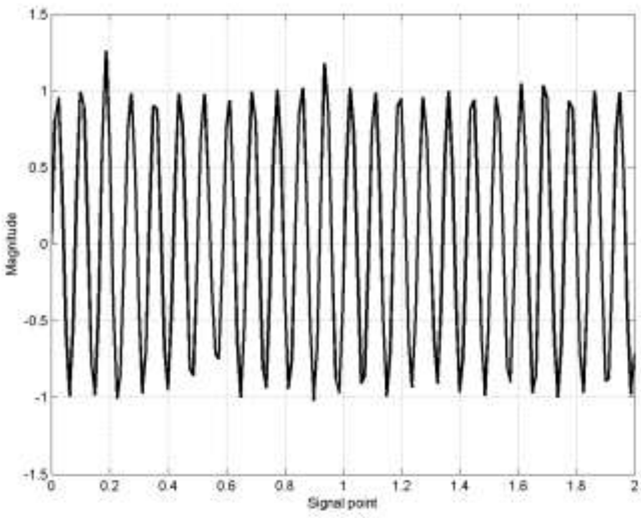

Fig. 6: Corrupted signal

A close replica of the total noise (maternal heartbeat and some randomly generated noise) is taken as the reference signal in the adaptation process (in line with Fig. 1). The adaptive noise canceller is designed to filter out noise, yielding an output highly correlated with the desired fetal signal.

2. RESULTS

The result obtained using the improved SA algorithm is depicted in Fig. 7. This is a close replica of the desired fetal heartbeat signal as per Fig. 5.

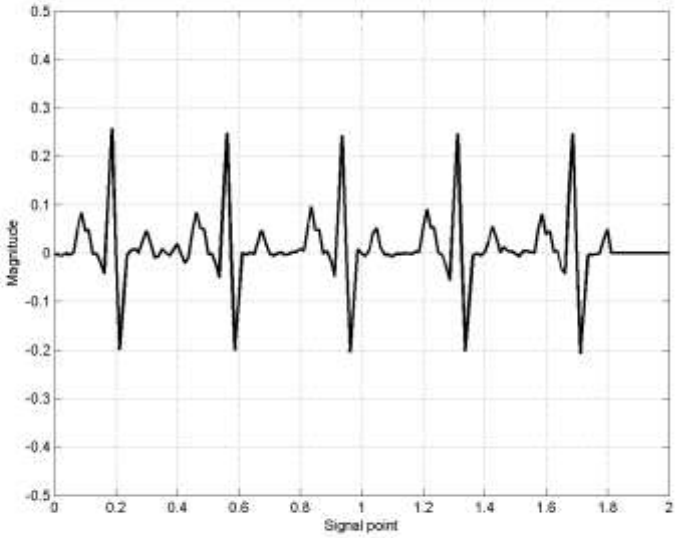

Fig. 7: Improved SA algorithm result

The result obtained using the standard SA algorithm is depicted in Fig. 8. This is a close replica of the desired fetal heartbeat signal as per Fig. 5.

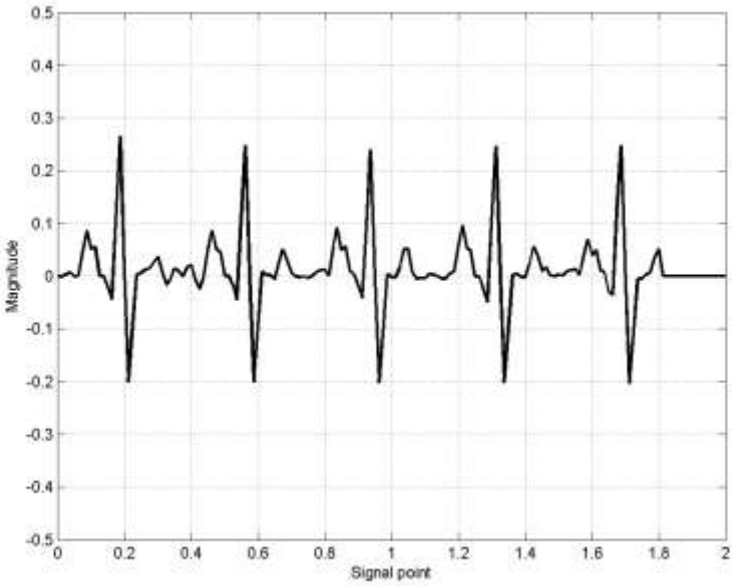

Fig. 8: Standard SA algorithm result

The result obtained using the standard GA algorithm is depicted in Fig. 9. This is a close replica of the desired fetal heartbeat signal as per Fig. 5.

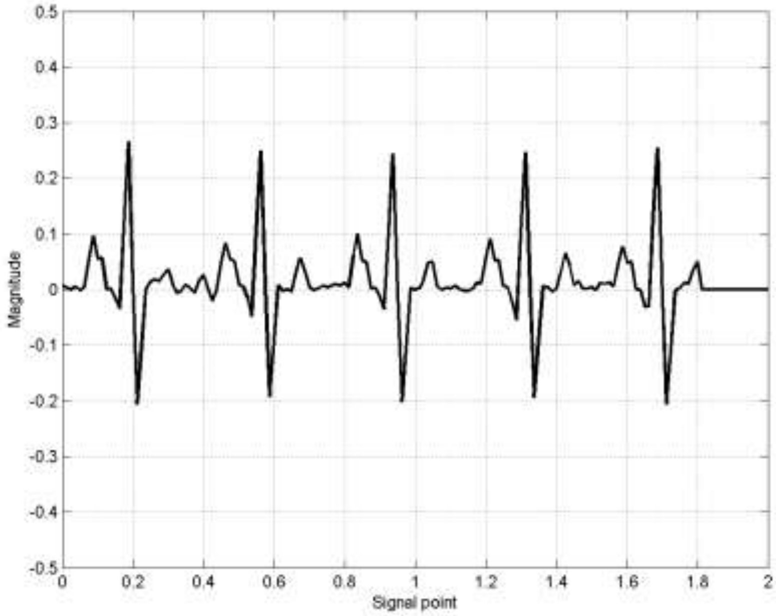

Fig. 9: Standard GA algorithm result

The result obtained using NLMS algorithm is depicted in Fig. 10. This is a close replica of the desired fetal heartbeat signal as per Fig. 5.

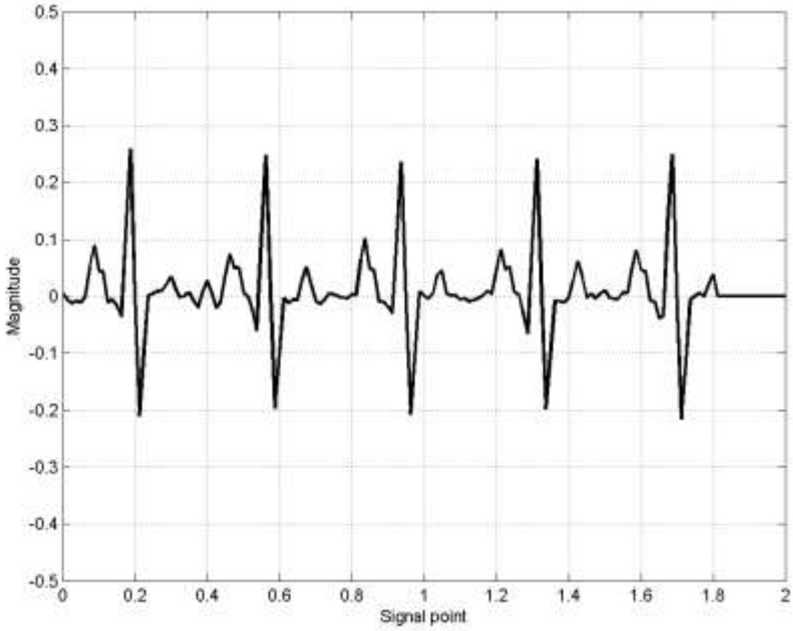

Fig. 10: NLMS algorithm result

The result obtained using the LMS algorithm is depicted in Fig. 11. This is a close replica of the desired fetal heartbeat signal as per Fig. 5.

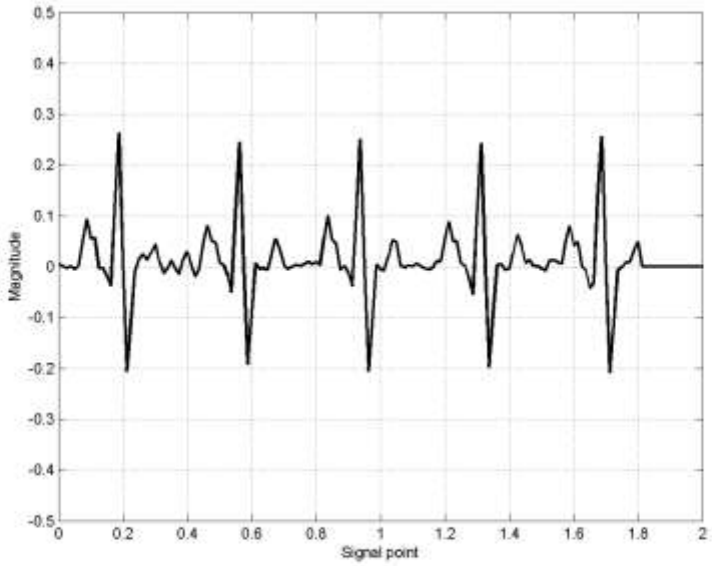

Fig. 11: LMS algorithm result

Fig. 12 illustrates a comparison between the results obtained by each algorithm.

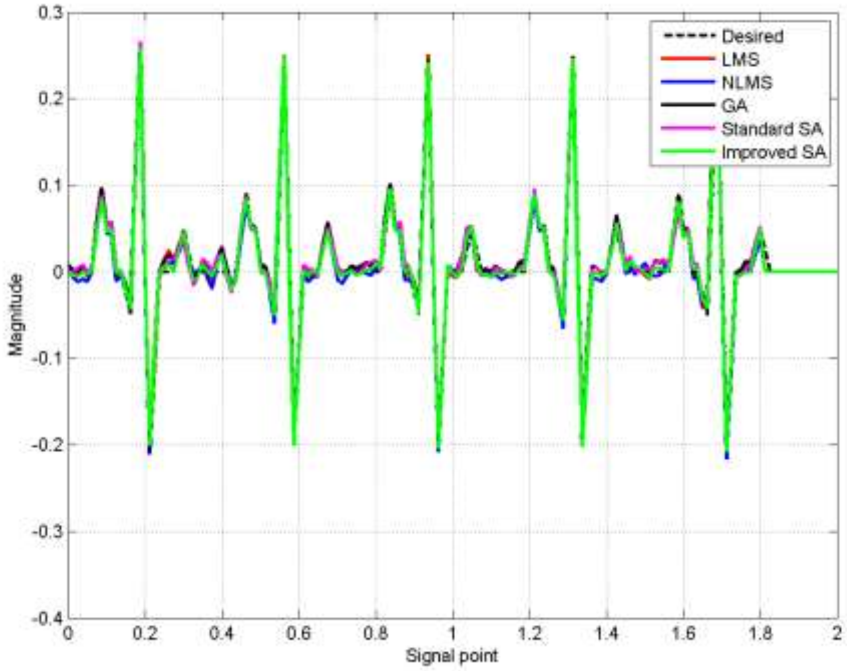

Fig. 12: LMS, NLMS, SA and improved SA algorithm results comparison

Fig. 13 illustrates a Euclidean distance comparison between the results obtained by each algorithm.

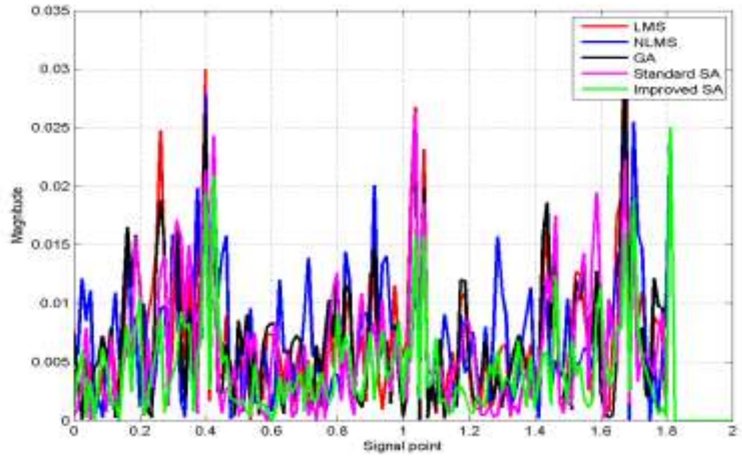

Fig. 13: Point by point Euclidean distances comparison

Fig. 14 illustrates an overall Euclidean distance comparison between the results obtained by each algorithm.

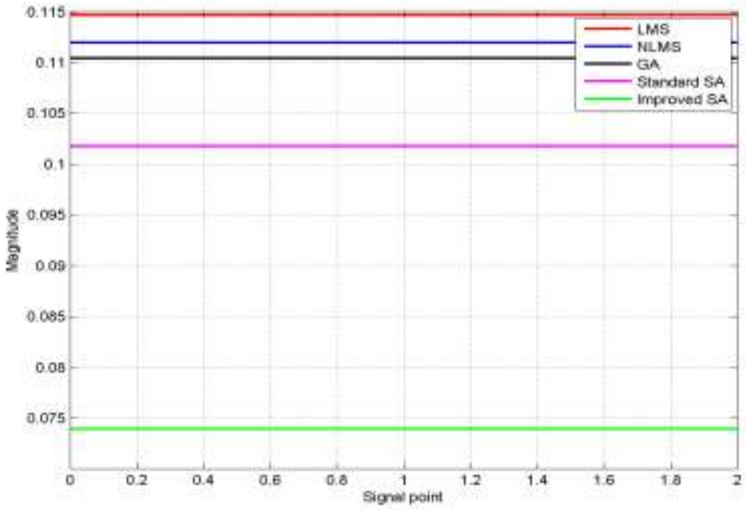

Fig. 14: Overall Euclidean distances comparison

Fig. 15 illustrates algorithm performance comparison. The improved SA algorithm converges faster than the other algorithms as per the Fig..

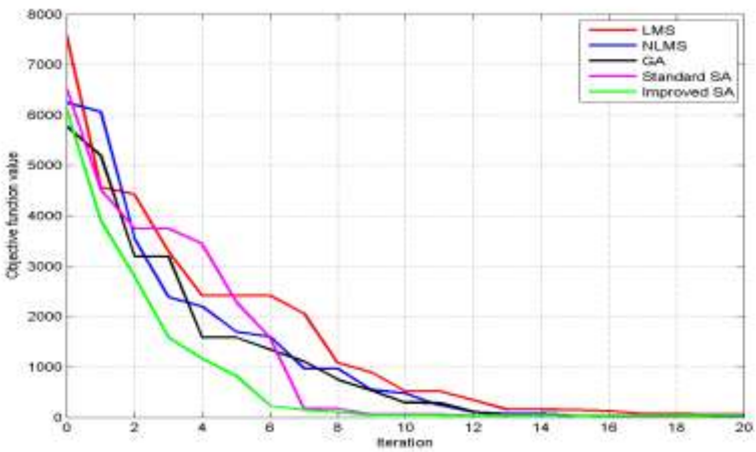

Fig. 15: Evolution of objective function with iterations

3. Discussion

The corrupted waveform and the desired waveform correlation value is -0.0640. The improved SA result and the desired waveform correlation value is 0.9961. The standard SA result and the desired waveform correlation value is 0.9923. The GA result and the desired waveform correlation value is 0.9912. The NLMS result and the desired waveform correlation value is 0.9909. The LMS result and the desired waveform correlation value is 0.9906. These figures depict the superiority of the improved SA algorithm.

The results obtained using the LMS, NLMS, GA, SA and improved SA algorithms are compared in Fig. 12. Fig. 13 shows a point by point Euclidean distance comparison between the utilized algorithm results. Fig. 14 shows an overall Euclidean distance comparison between the improved SA result (0.0740), the standard SA result (0.1018), the GA result (0.1104), the NLMS result (0.1119) and the LMS result (0.1146). Going by Figs. 14 and 15, the performance of the improved SA algorithm is better than that of the standard algorithm.

The improved SA algorithm is found to generate better results than the standard SA algorithm, GA, NLMS algorithm and LMS algorithm in the simulated scenarios. Generated signal graphs and the corresponding correlation values show that the improved SA algorithm yields a less noise corrupted signal.

VIII. Conclusion

Adaptive noise cancellers play a pivotal role in data transfer systems. A case in point is in the extraction of contaminated fetal heartbeat signals (Measured fetal heartbeat signals are usually contaminated by the corresponding mother's heartbeat signal and other random noise). The role of efficient adaptation algorithms for use in adaptive noise cancellers cannot be underestimated. An ideal algorithm ought to generate an accurate result in as little time as possible. In this paper, an improved Simulated Annealing (SA) algorithm is utilized in ANC to yield a minimal-noise fetal electrocardiogram signal in MATLAB. A performance analysis between use of the improved SA algorithm and the standard SA algorithm (alongside Genetic, Least Mean Squares (LMS) and Normalized Least Mean Squares (NLMS) algorithms) is done. Generally the improved SA algorithm performance is found to outweigh that of the standard SA algorithm, GA and also that of LMS and NLMS algorithms.

As the research into more efficient techniques continues, it would be viable to look into better variants of the SA algorithm in fetal heartbeat signal extraction. A real time implementation of the MATLAB simulation would also be worthwhile in an attempt at validating the viability of the developed SA algorithm improvements in ANC.

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