ECG Noise Removal using GA tuned Sign-Data Least Mean Square Algorithm

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Abstract— **Adaptive filter is a primary method to filter Electrocardiogram (ECG), because it does not need the signal statistical characteristics. In this paper, an adaptive filtering technique for denoising the ECG based on Genetic Algorithm (GA) tuned Sign-Data Least Mean Square (SD-LMS) algorithm is proposed. This technique minimizes the mean-squared error between the primary input, which is a noisy ECG, and a reference input which can be either noise that is correlated in some way with the noise in the primary input or a signal that is correlated only with ECG in the primary input. Noise is used as the reference signal in this work. The algorithm was applied to the records from the MIT-BIH Arrhythmia database for removing the baseline wander and 60Hz power line interference. The proposed algorithm gave an average signal to noise ratio improvement of 10.75 dB for baseline wander and 24.26 dB for power line interference which is better than the previous reported works.**

Keywords-Adaptive filter, Baseline wander, ECG, Genetic Algorithm, Power line interference, Sign Data LMS algorithm.

I. INTRODUCTION

ECG signal processing is a huge challenge since the actual signal is measured in a noisy environment. The main sources of noise are Baseline Wander (BW), Power line interference (PLI), Muscle noise and other electromagnetic interferences. Baseline wander is a low frequency component present in the ECG. This may be due to various reasons like offset voltages in the electrodes, respiration activity, patient movement, loose electrodes, etc during recording. Baseline noises occur in the frequency range of 0.05 to 0.5 Hz.

Several methods have been worked out for the removal of baseline wander. Filtering techniques reported include linear filters like Finite Impulse Response (FIR) filter and Infinite Impulse Response (IIR) filters, nonlinear filters, polynomial interpolation and wavelet filters [1]. Linear filters [2], [3] are used to remove baseline wander but their fixed cut off frequency may result in a loss of information from the ECG signal. Non linear filtering techniques can be used for BW removal. Yan Sun et.al. [4], used a modified morphological filtering (MMF) technique for signal conditioning in order to accomplish baseline correction and noise suppression with minimum signal distortion. MMF performs well in terms of the filtering characteristics, but its application may result in waveform distortion. Weituo Hao and Yu Chan [5] introduced a nonlinear mean-median filter that preserves the outline of the BW. It also avoids distortion caused by the median filter. The reported values are comparatively lower. Simple Adaptive Filters (AF) [6] can be used to filter the BW but it lacks a suitable reference signal. Kalman filters [7], [8] can effectively remove BW, but the SNR is relatively low. Mohamed Zia Ur Rahman et.al [9,10] uses a normalized sign-sign LMS algorithm for the removal of BW. Even though the method is less computationally complex, the SNR improvement and the waveform shape are inadequate. He has compared the performance of several signed Least Mean Square (LMS) based adaptive filters with the conventional adaptive LMS algorithm for the elimination of PLI, BW, muscle and motion artifacts.

In this paper we propose a modified adaptive filtering technique where the reference input is derived from the noisy ECG signal using a Kalman filter. This reference input is correlated with the noise in the ECG. In order to evaluate the performance of the filter an ECG record is selected from MIT/BIH Arrhythmia database [11]. This record is corrupted with real BW noise from MIT-BIH NSTDB database [12] and an artificial PLI. On application of this method to the five records from MIT/BIH Arrhythmia database [11], it gave an average SNR improvement of 10.75 dB for baseline wander and 24.26 dB for power line interference which is better than reported results [4,5,9,10].

The paper is organized as follows. Section II gives a brief description on the method used, section III describes the proposed algorithm, section IV gives the simulation results of the filtering technique and section V concludes the paper.

II. METHODOLOGY

A. *Sign-data LMS Algorithm*

Adaptive filters work on the principle of minimizing an error function, generally the mean squared difference, between the filter output signal and a target signal. These filters are advantageous because they do not require a prior knowledge of signal as in the case of fixed filters. An AF learns statistics of the input source and tracks them if they vary slowly. AF can thus be used efficiently for estimation and identification of non-stationary signals like ECG. Least Mean Squares (LMS) algorithm and Recursive Least Squares (RLS) algorithm and their variants can be used to solve this problem [13]. Compared to RLS algorithms, the LMS algorithms do not involve any matrix operations and hence require fewer computational resources and memory. The implementation of the LMS algorithms is easier than the RLS algorithms. To

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further reduce the amount of computation, signed LMS can be used, especially when the input data rate is high. These filters perform well when it is meant to be implemented on a cheaper processor.

The Sign Data LMS (SD-LMS) algorithm is a variant of LMS algorithm [14]. Using SD-LMS algorithm changes the mean square error calculation by using the sign of the input data to change the filter coefficients. In vector form, the SD-LMS algorithm is given by (1) and (2).

$$sgn(u) = \begin{cases} 1; & x > 0 \\ 0; & x = 0 \\ -1; & x < 0 \end{cases} \quad (1)$$

$$w(n+1) = w(n) + \mu . e(n) . sgn(u(n)) \quad (2)$$

with vector containing the weights applied to the filter coefficients and vector containing the input data. is the error at time and the quantity the SD-LMS algorithm seeks to minimize. The constant is a step size, which controls the amount of gradient information used to update each filter coefficient [14]. The step size directly affects how quickly the filter will converge towards the reference input. If is very small, then the coefficient will change only a small amount on each update, and the filter may converge very slowly. With a larger step size more gradient information may be included in each update and the filter may converge quickly, but if the step size is very large, the coefficients may change too quickly and the filter may diverge. So choosing a correct value of step size is important.

B. *ECG database*

The database chosen for this work was MIT-BIH Arrhythmia database [11]. In order to have a proper comparison with existing results, five records from this database were taken. Each record is nearly 30 minutes in length with a sampling frequency of 360 Hz. 4000 samples from Lead II of each record was selected for analysis. The real BW noise used to corrupt the ECG was taken from MIT-BIH NSTDB database [12]. The PLI used to corrupt the ECG was an artificial sine wave generated with a frequency of 60 Hz, amplitude of 1mV and a sampling frequency of 128 Hz.

III. PROPOSED ALGORITHM

The proposed method used for BW removal involves the following steps as shown in Fig. 1. The SD-LMS algorithm used here requires two datasets, one the primary input $x(n)$ which is the ECG with BW and the other a reference input containing the noise signal $d(n)$. Here $x(n)$ is obtained by adding the BW noise with the ECG record from MIT BIH database. The reference input for the adaptive filter is obtained by filtering the noisy ECG with a Kalman filter [8]. In Fig. 1 $e(n)$ is the error signal and $w(n)$ the weights applied to the filter coefficients. The filter length is set to 5. The step size μ was optimized with genetic algorithm. Since GA combines survival of the fittest among chromosomes with structured and randomized information [15], it has the ability to identify the optimum value of step size. Reproduction, Crossover and Mutation are the basic operators in GA which helps in the convergence of the solution. SNR improvement was taken as the fitness function. The number of generations was chosen as 500 and population size 50. The initial range of μ's was set in the range of 0.0001 to 0.1. Roulette wheel

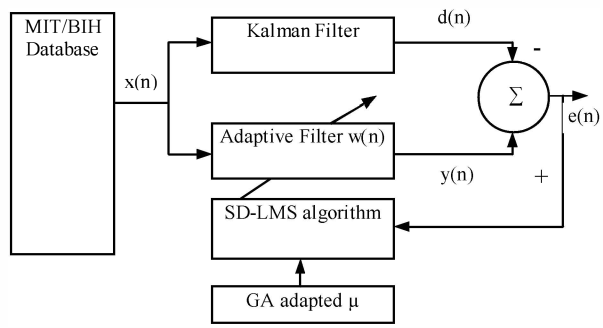

Fig. 1 The proposed SD-LMS configuration for BW removal.

selection technique has been used. Elite count was set as 2 and cross over fraction 0.8. The scale and shrink parameters which decide the standard deviation of the Gaussian distribution used in the Gaussian mutation function was set as 1. Record 105 was used for training. The optimum value of μ obtained was 0.00563. To ensure a good convergence rate and stability, theoretically μ should be within the practical bounds as given by (3)

$$0 < \mu < \frac{1}{N(Input\ Signal\ Power)} \quad (3)$$

where N is the number of samples in the signal. It is seen that the optimized value of μ satisfies this condition.

The same setup with new initial parameters was used to remove power line interference. The adaptive filter length was 5 and the optimized value for μ is 0.008564. The reference input was the artificial sine wave.

IV. RESULTS AND DISCUSSION

Implementation of the above filters and applying it to the MIT-BIH database yielded promising results (Fig. 2). The signal to noise ratio was calculated by using (4).

$$SNR = 10 log_{10}\left(\frac{S_p}{N_p}\right) \quad (4)$$

where S_p and N_p denotes the power of the signal and noise respectively. Table I shows the SNR improvement obtained for BW removal on five records from MIT-BIH Arrhythmia database. The average SNR improvement obtained is 10.75 dB. This is better than the results mentioned in reference [9,10]. To visually compare the results, the output of the Kalman filter and the proposed algorithm for record 105 [11] is plotted in Fig. 3. It is clearly visible that the proposed algorithm removes

BW more efficiently. The disturbances arising in the output of Kalman filter is visible in the plot. To make sure that the filtered output is similar to the original ECG, another parameter, the correlation coefficient has been computed and is given in Table I. Values close to 1 suggest that there is a positive linear relationship between the original and filtered ECG signals.

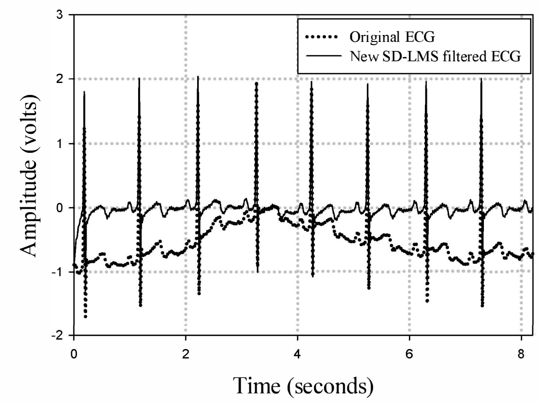

Fig. 2. Results obtained for the removal of BW with the new SD-LMS

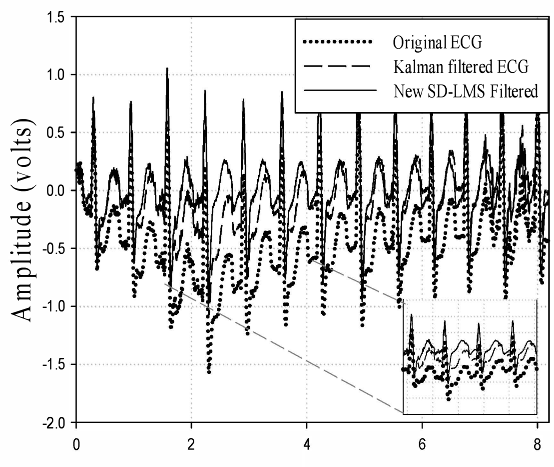

TABLE I: SNR improvement and correlation coefficient for BW

Record	SNR before filtering (dB)	SNR after filtering (dB)	SNR improvement (dB)	Correlation coefficient
100	0.8218	11.2061	10.3843	0.9626
105	2.5370	15.4090	12.8719	0.9863
108	1.1365	11.2618	10.1253	0.9651
203	2.3729	13.5545	11.1816	0.9791
228	3.6689	12.8811	9.2122	0.9768
Average	2.10742	12.8625	10.7551	0.9739

In addition to the above, the power line interference has been removed using the same filtering technique. An artificially generated sine wave was used as the reference input. The results obtained are given in Table II. An average SNR improvement of 24.26 dB is achieved which is better than the previously reported results [10]. Fig. 4 shows the ECG with PLI and Fig. 5 gives the filtered output. The peridogram power spectral density estimate with and without PLI are shown in Fig.6 and Fig.7. It can be seen from Fig.7 that the peak corresponding to the 60 Hz has been removed. From these plots it is evident that PLI can also be eliminated successfully.

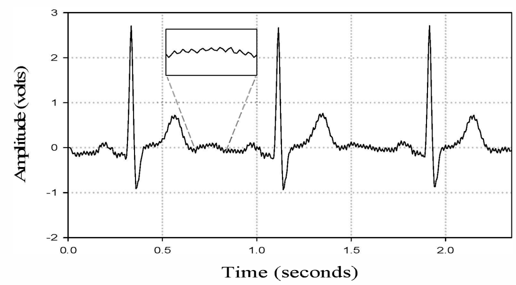

Fig 4. ECG Corrupted with 60Hz PLI

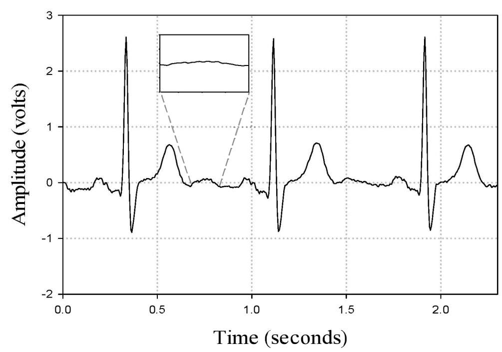

Fig. 5. ECG filtered for PLI with the new SD-LMS filter

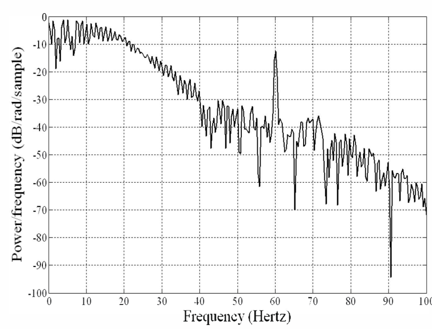

Fig. 6. Peridogram PSD of ECG with 60 Hz interference

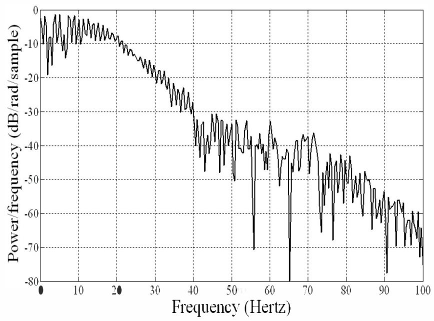

Fig. 7. Peridogram PSD estimate of PLI filtered ECG

TABLE II: SNR improvement and correlation coefficient for PLI

Record	SNR before filtering (dB)	SNR after filtering (dB)	SNR improvement (dB)	Correlation coefficient
100	15.4858	40.4888	25.0030	1.0000
105	8.1129	31.8853	23.7724	0.9997
108	14.9415	38.6769	23.7354	0.9999
203	8.6042	31.9102	23.3060	0.9997
228	13.0096	38.4940	25.4844	0.9999
Average	12.0308	36.2910	24.2602	0.9998

V. CONCLUSION

This paper presents a new adaptive filter that uses the SD-LMS algorithm for the removal of baseline wander and power line interference from ECG signals. As already discussed the adaptive filter requires a reference input that is uncorrelated with the signal of interest, but closely correlated with the interference or noise in some manner. The reference signal generated by Kalman filter, is highly correlated with the noise in the ECG and hence yields a good result. This setup removes PLI as well. It is seen that the step size μ optimized with GA helps in obtaining a better SNR value. The results show that the useful information in the ECG is not altered by the application of the algorithm. The weights of the AF coefficients together with the Kalman coefficients can be further optimized to obtain much better results.

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