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Effect of Adaptive Line Enhancement Filters on Noise Cancellation in ECG Signals

George Karraz[1]

Abstract: Power line interference is the main noise source that contaminates Electrocardiogram (ECG) signals and measurements. In recent years, adaptive filters with different approaches have been investigated to eliminate power line interference in ECG waveforms. Adaptive line enhancement filter is a special type of adaptive filter that, unlike other adaptive filters, does not require a reference signal and has potential application in ECG signal filtering. In this paper, a self-learning filter based on an adaptive line enhancement (ALE) filter is proposed to remove power line interference in ECG signals. We simulate the adaptive filter in MATLAB with a noisy ECG signal and analyze the performance of algorithms in terms of signal-to-noise ratio (SNR) improvement. The proposed algorithm is validated with Physikalisch-Technische Bundesanstalt (PTB) ECG signals database. Additive white gaussian noise is added to the raw ECG signal. Influential parameters on the ALE filter performance such as filter delay, the convergence factor, and the filter length are analyzed and discussed.

Keywords: Adaptive filter, Adaptive Line Enhancement, ECG, Power Line Interference.

1 Introduction

For many decades, Electrocardiography (ECG) has been one of the most gold standard techniques in Cardiology. ECG is a routinely used method for monitoring and recording electrical heart activity. Thus, ECG plays a key role in monitoring and diagnosing cardiovascular diseases [1]. It is well known that ECG signal is recorded in a limited frequency range that is between 0.05 Hz and 0.1 kHz. In addition, ECG recordings feature low aptitude in nature and thus, some characteristic peaks in the ECG waveform are remarkably small. This makes the recording of such weak signals highly vulnerable to ambient noise and motion artifacts [2, 3]. More specifically, recorded ECG signals are contaminated by power line interference with a considerable amplitude approaching nearly up to half of the largest amplitude in ECG recorded signals. Moreover, there exist a number of potential sources of noise and artifacts that can distort the

[1a]Faculty of Informatics Engineering, Al-Sham Private University, Damascus, Syria
[1b]Faculty of Information Technology, Damascus University, Damascus, Syria; E-mail: dean.foit@aspu.edu.sy

morphological features of ECG waveforms and in particular low amplitude waves such as P, T, and U waves. These sources are to a large extent, power line interference, radio frequency noise, improper electrode contact, motion artifacts, breathing oscillations, and the signal baseline drift [4]. These sources of interference and noises may adversely affect all of the waves comprising the ECG signal. Furthermore, these sources may in turn lead to inaccurate diagnostic information extracted from ECG signal post-processing. For instance, errors in arrhythmia detection and consequently inaccurate cardiovascular disorders diagnosis can take place.

A common filter to eliminate power line interference is to use a notch filter but the notch frequency can change and, thus, the notch filter cannot attenuate noise with frequency shift. This makes the notch filter unsuitable for cleaning ECG signals [5]. Widening the notch filter can eliminate the noise shift However, this approach is not practical as it attenuates frequencies in the signal of interest.

Recently, more advanced filters particularly, adaptive filters with different approaches have been investigated to remove the power line interference at 50/60Hz in the ECG signal. In particular, the design of an adaptive filter with a dynamic structure for ECG signal conditioning [6]. ECG denoising using adaptive filter algorithms has also been pursued by prior works [7].

Investigation of adaptive filtering technique for noise cancellation in ECG signals [8], design and implementation of algorithms using MATLAB for adaptive noise cancellation from ECG recordings were conducted as well. However, much of the previous work concentrated on Least Mean Square (LMS) or Normalized Least Mean Square algorithms (NLMS) for their adaptive filters.

These algorithms can modify filter coefficients quickly and effectively. Nonetheless, when the power line noise is as high as half of the amplitude of the highest peak of the ECG signal, these algorithms cannot provide effective outcomes, and as a consequence, the filtered signal still contains a considerable amount of noise that may complicate the further analysis of ECG signal.

Accordingly, several studies have focused on improving these adaptive filters. Of more interest, Qureshi R et. al., [9] devised a multistage adaptive filter to eliminate multiple noise and artifact sources that may affect the ECG signal.

Kose et. al. [10] used descendant adaptive filters to clean ECG signals contaminated with different sources of noise. They used their adaptive filter for LMS and RLS structures but their work was limited by the need for a reference signal.

In addition, Martinek, R et. al., [11] presented in their work a new method for optimizing the control parameters including step size and filter order of both LMS and RLS adaptive filters aiming to improve the filtering process in noninvasive ECG based fetal monitoring.

To alleviate this problem and further enhance the performance of the adaptive filter, we propose in this work an optimized adaptive filter algorithm based on Adaptive Line enhancement (ALE). This algorithm was validated with the ECG database from the PTB ECG database [12, 13].

Therefore, the main objective of this paper is to investigate the applicability of the ALE adaptive filtering technique and to realize its efficiency in terms of signal-to-noise ratio (SNR). The effect of the most influential parameters on the performance of the ALE filter for ECG signals is discussed as well.

2 Materials and Methods

In general, the computational requirements for signal processing strategies particularly in medical applications have been increased dramatically in the last two decades. More importantly, filters that are used in preprocessing stages are key elements in producing clean and informative signals. Therefore, devising an algorithm with the ability to filter out noise from signals efficiently, with automatic performance adaptation, and at the same time offering a good trade-off between performance and computational requirements, has become an interesting motivation to pursue.

Adaptive signal processing techniques are one of the most important solutions towards that aim. That is to say, in contrast to classical commonly used digital filters such as Finite Impulse Response filters (FIR) and Infinite Impulse Response filters (IIR), adaptive filters automatically change their characteristics, by optimizing their controlling coefficients [14].

Since adaptive filters are widely used in several areas including the preprocessing of biomedical signals, they have been integrated into ECG devices. However, biomedical signals such as ECG, Electromyography (EMG) signals can have remarkably small amplitudes. As mentioned earlier, these tiny peaks and signals are commonly affected and suppressed by overwhelming noise. Consequently, it can be extremely difficult to discern and filter out this noise from these signals, and errors resulting from filtering may distort the morphology of their waveforms. Therefore, adaptive filters can provide a workable solution to filter out these artifacts and certain frequencies related to power line interference.

Fig. 1 presents a typical configuration of an adaptive filter scheme. The filter coefficients are updated through a feedback process designed to make the output of the filter as equal to some desired target response denoted by d[n], as possible, which can be attained by minimizing the error signal that is denoted by e[n].

Linear filter block predicts the output of the adaptive filter by updating the filter coefficient through a feedback process (adapted from [15]).

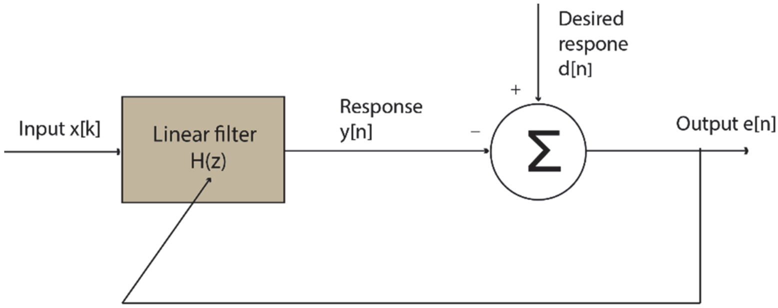


Fig. 1 – *Basic schematic diagram showing the structure of an adaptive filter.*

The adaptive filter can be represented by a set of FIR filter coefficients, b[k]. The FIR filter equation can be given by the following expression

$$y[n]=\sum_{k=0}^{L-1} b_n[k]x[n-k]. \tag{1}$$

Basically, the operation of the adaptive filter can be characterized by frequently modifying its coefficients, $b_n[k]$, based on some signal characteristics. In order to reach the optimal filtering, the squared error is to be minimized. In other words, the filter coefficients are adjusted as shown in Fig. 1. The difference between the filter output and the desired output is used to change the filter coefficients so that the error difference is greatly reduced [16].

Application of the steepest descent, can be done using the partial derivative of the squared error signal [15] with respect to the coefficients, as given in (2)

$$\nabla_n = \frac{\partial e_n^2}{\partial b_n[k]} = 2e[n]\frac{\partial\left(d[n]-y[n]\right)}{\partial b[k]}. \tag{2}$$

Equation (2) can be rewritten and expressed in terms of the product of both the error signal and the input signal as follows

$$\nabla_n = -2e[n]x[n-k]. \tag{3}$$

For every input sample, a new error signal can be computed followed by the determination of the new filter coefficients as follows

$$b_n[k] = b_{n-1}[k] + \Delta e[n]x[n-k], \tag{4}$$

where Δ is the convergence factor. This parameter must be chosen with great caution. In other words, a large value of Δ will lead to large alterations in the filter coefficients that will affect convergence, but they can also lead to other undesired effects such as instability and oscillations. Conversely, a small value will result in slow convergence of the filter coefficients to their desired optimal values.

Therefore, it has been suggested that the value of this parameter has to be given in the range governed by the following condition [15]

$$0 < \Delta < \frac{1}{10LP_x}, \tag{5}$$

where L is the length of the FIR filter and P_x is the power of the input signal.

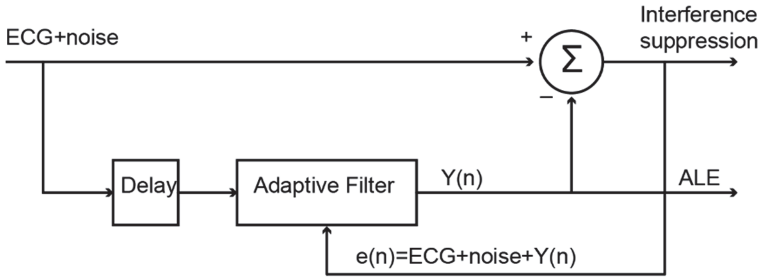


Fig. 2 – *A block diagram of the ALE filter for noise suppression in ECG recordings* (*adapted from* [15]).

The adaptive filter component is used to predict ALE output based on error signal and delayed input signal. For adaptive line enhancement, ECG [n] is the noise, and noise[n] is the signal. The desired signal, the ALE output, is subtracted from the input signal to filter out the ECG signal.

Fig. 2 presents the block diagram of the ALE filter used for ECG interference suppression. This ALE filter is a special type of adaptive noise filter that is designed to remove the broadband noise component from the input signal while passing the narrowband signal component of interest with minimal attenuation. In this ALE filter, the narrowband signal, noise[n], is the signal and the broadband signal, ECG[n], is the noise. Thus, the desired narrowband signal is the ALE filter's output (see Fig. 2).

Also, ALE presented in Fig. 2 consists of a delay component and a linear predictor. The input signal is a combination of the desired signal and the disturbing noise. Then, the adaptive filter output is subtracted from the input signal to produce the estimation error signal. This estimation error is, in turn, used to adaptively control the predictor of the adaptive filter. The predictor input is the input signal delayed with Δ samples.

3 Results and Discussion

The adaptive line enhancement filter was applied to two different ECG signals. The first one was taken from the PTB database, and the second one was taken from a simulated ECG. Both signals were contaminated with white noise.

The reason for contaminating with white noise was to simulate the electrical activity of muscles or EMG artifacts and power line noise with a possible frequency oscillation.

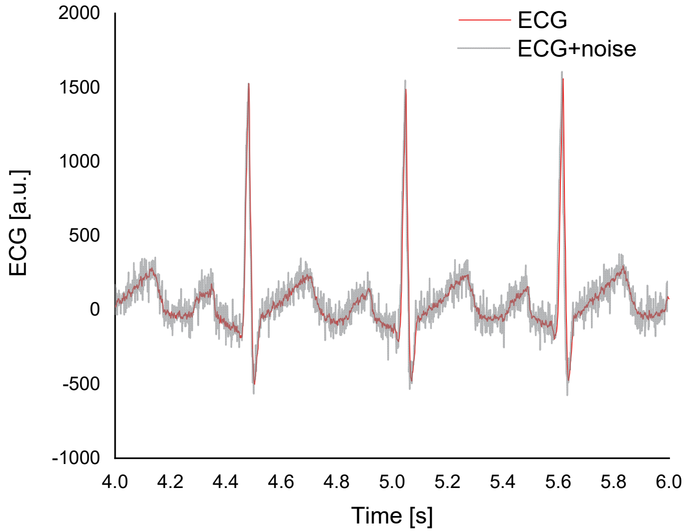
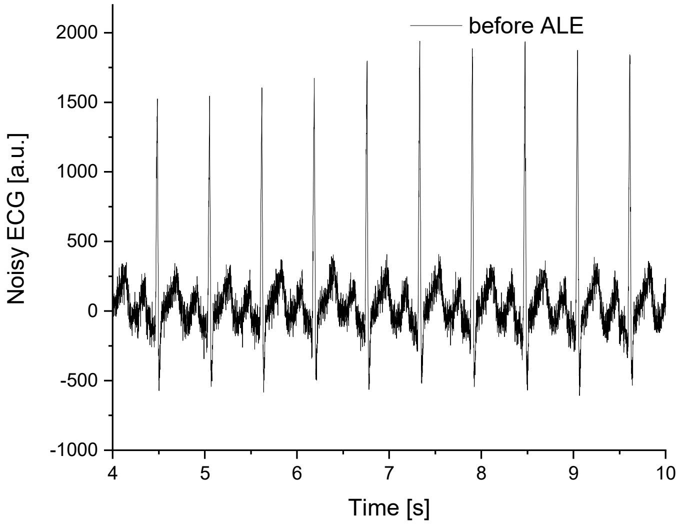


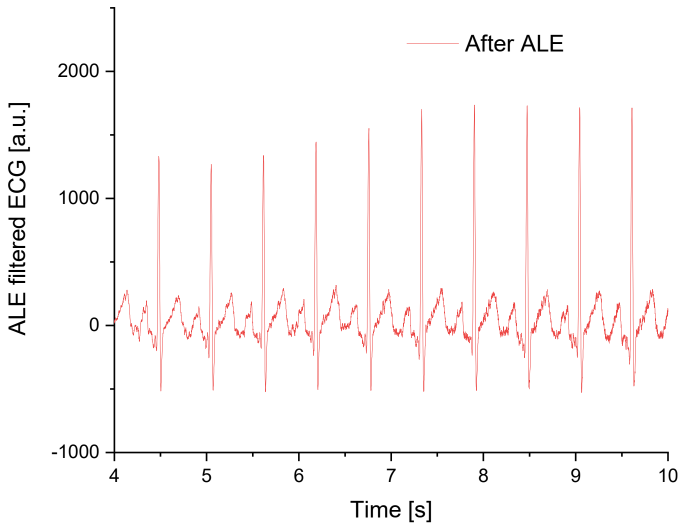
Fig. 3 – *ECG signal with added white Gaussian noise before filtering, the noise amplitude can be as high as the amplitude of small peaks in the ECG signal.*

White noise was created in the MATLAB environment. The effect of step size of the adaptive filter on its performance, in particular, its signal-to-noise ratio SNR was investigated. The implementation of the algorithms was done in MATLAB (MathWorks Inc. version 2016). Fig. 3 shows a sample of real ECG signal contaminated with white Gaussian noise with a signal-to-noise ratio of 20 dB. Fig. 4, on the other hand, demonstrates the performance of the ALE filter whereas the lower graph shows the ECG signal after ALE filtering with an improved signal-to-noise ratio in comparison to the original ECG signal in the upper graph.

Fig. 4 illustrates the performance of the proposed ALE adaptive filter in filtering out the white noise from simulated ECG signal. Similarly, elimination of white noise from real human ECG signals retrieved from the PTB database (see Fig. 4a) is displayed in Fig. 4b. Furthermore, to quantify the effect of the ALE filter on the noisy signal, the power spectrum based on Fast Fourier Transform (FFT) was determined for the noisy ECG signal before and after the application of the ALE filter as shown in Fig. 5.



(a)



(b)

Fig. 4 – (a) *The original ECG signal contaminated with noise before applying the ALE filter;* (b) *Filtered ECG signal after the application of the ALE filter.*

This demonstrates the capability of the ALE filter in suppressing the noise contaminating the ECG signal over a range of frequencies. The importance of the ALE filter lies in its ability to attenuating the frequencies of the noise signal while preserving the frequencies of the ECG signal as shown in Fig. 5.

To further investigate the signal-to-noise ratio of the ALE filter, three parameters were considered. That is a delay, delta, and the length of the ALE FIR filter. First, the delay parameter was varied in the range from 0 and 200, and the SNR was calculated accordingly.

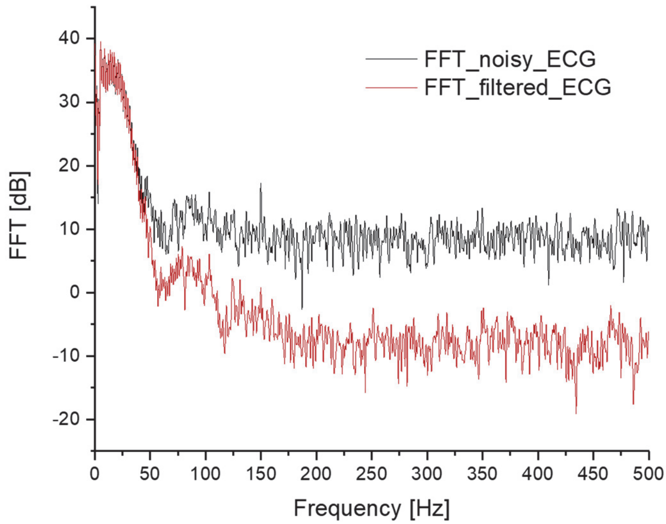


Fig. 5 – *Power spectrum of the noise ECG signal represented with the black spectrum and the power spectrum of the filtered ECG signal after applying the ALE filter represented with red spectrum.*

Fig. 6 shows the trend of SNR as a function of the delay of the ALE filter. The data were fitted to sigmoid function with (R2 = 0.99).

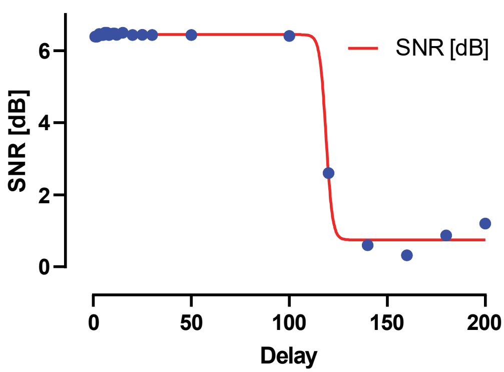


Fig. 6 – *Signal to noise ratio of the ALE filter as a function of the delay parameter. Blue dots represent the calculated SNR and the red line represents the fitted line.*

It is clear that the SNR of the studied filter remains stable for all values of delay in the range from 0 to 100. For larger values, the SNR decreases rapidly down to nearly 2 dB for values of delay around 150.

Second, the effect of the convergence parameter, delta, on the SNR of the ALE filter has also been investigated. To that end, a set of values of the convergence factor ranged from 0 to 1 were considered and consequently, the corresponding SNR values were determined. The relationship between the convergence parameter and the SNR is plotted in Fig. 7.

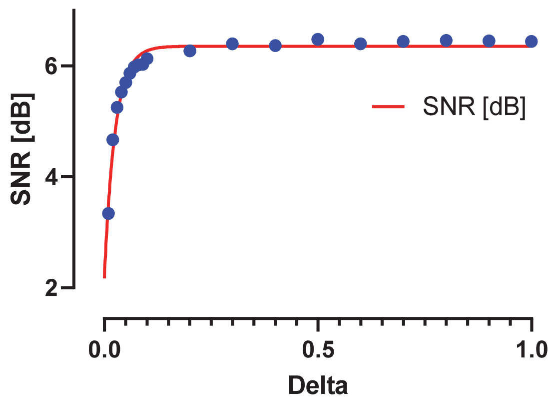


Fig. 7 – *Signal to noise ratio of the ALE filter as a function of delta parameter. Blue dots represent the calculated SNR and the red line represents the fitted line.*

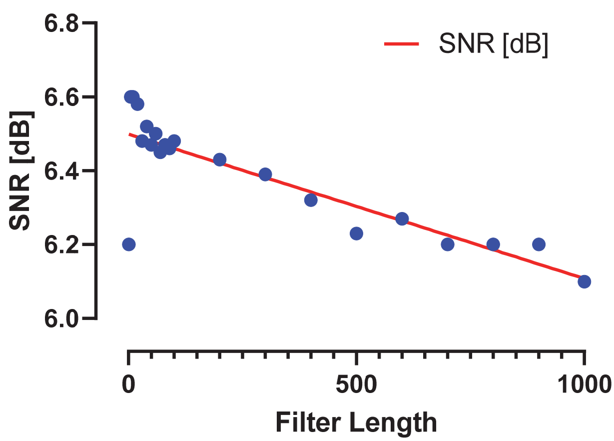


Fig. 8 – *Signal to noise ratio of the ALE filter as a function of FIR filter length parameter. Blue dots represent the calculated SNR and the red line represents the fitted line.*

The data were also fitted to an exponential function (R2 = 0.97). It can be observed that the SNR of the ALE filter increases with increased delta. For values of the convergence factor that is larger than 0.5, the SNR is stable and almost constant. This indicates that the optimal value of the convergence factor lies in the range from 0.5 to 1.

Third, the influence of the filter length on the SNR of the ALE adaptive filter has been studied. As a result, Fig. 8. displays the SNR as a function of the FIR filter length. The linear fitting curve was investigated and the corresponding value of R squared was 0.72. It is evident that SNR is inversely proportional to the filter length. However, this decline in SNR with increased values in FIR length does not seem to be significant. In other words, the decline in the SNR value is less than 5% for all values of FIR filter length that ranged from 0 to 1000. Thus, it can be said that the effect of the FIR ALE filter length on the SNR is negligible.

These results are in accordance with previous works [17, 18]. It can also be noted that ALE filters exhibit several advantages over other adaptive filters, namely, the ALE filter does not require any reference signal compared to other adaptive filters.

Ren. et al., [19] attained enhanced signal to noise ratio by as high as nearly 23% with their (LMS) algorithm based on symbolic functions and block-processing concepts. However, one limitation in their study is that their adaptive filter requires a reference signal. Thus, removing the interference noise in ECG signal using the presented tuned ALE adaptive filter without the need for a reference signal can be of paramount importance in practice where the hardware requirements are minimal and the noise source is less effective.

While Joshi. et. al*,* [20] were able to enhance the performance of their optimized adaptive filter, their filter used a complex algorithm, However, it was tested only on simulated data. Similarly, optimal performance of the developed adaptive filters for ECG denoising was investigated by Farzad et. Al [21].

Additionally, even though, LMS adaptive filter was used in this study, RLS can be used likewise. RLS algorithm should be preferred over the LMS for adaptive noise cancellation unless the computation time is of great concern as found by Islam et. al. [22]. It is highly anticipated that adaptive line enhancer filter will continue to have a potential application in biomedical signal processing as demonstrated recently by Hegde et. al. [23]. As future work, the results of this study can be extended by applying the ALE FIR filter to eliminate the undesired noise from other biomedical signals such as EMG, Electroencephalogram (EEG), and many others.

4 Conclusion

This paper attempted to explore the feasibility of applying Advanced Line enhancement for adaptive filtering of ECG signals from background noise. ALE-based algorithm filter was implemented and validated on real-life recorded ECG signals. Fine-tuning of ALE filter parameters can be optimized to enhance the overall performance of the filter in terms of noise suppression. Delta and delay parameters of the ALE adaptive filter, if not selected properly, can have a considerable effect on the performance and effectiveness of the filtering outcome. As a result, it can be said that ALE adaptive filters show a potential application in the preprocessing of ECG recordings. This may pave the way for further research on the effectiveness of these filters on other physiological signals that are buried in noise and power line interference.

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