Background Noise Cancellation Using Adaptive LMS Algorithm in Medical Applications

A.K.M Fazlul Haque⁺, M Shamim Kaiser++, S.K Aditya+++  
*Dept. of Electronics and Telecommunication Engineering, Daffodil International University  
++ Telecommunication Engineering, TID, University Grants Commission, +++ Department of Applied Physics, 
Electronics and Communication Engineering, University of Dhaka.

Abstract

In this paper, the implementation of an adaptive least-mean-square (LMS) algorithm has been proposed to remove the 50/60Hz noise from an electrocardiogram (ECG) signal. The simulation is performed using Matlab. The ECG signal together with noise has been generated by writing a program. There is noticeable improvement in the filtered ECG in comparison to the unfiltered ECG signal in terms of power spectral density and harmonic distortion suggesting that adaptive filtering achieves accurate filtering without substantial signal degradation.

Keywords: Least Mean Square (LMS), Electrocardiogram (ECG), Adaptive filter, Savitzky Golay Filter.

1. INTRODUCTION

Adaptive Noise Cancelling is a technique used, within an electronic system, to remove an unwanted noise affecting a desired signal carried out from the human body, especially Electrocardiogram (ECG). Peak detection is first employed to locate the general ECG complexes, referred to as candidate events. Each stage automatically generates a template of a source from the candidate events in the initialization period, and thereafter performs classification of the remaining candidate events based on a template matching technique. The detected events of the stronger signal are subtracted from the composite ECG signal prior to initialization and classification of the weaker signal. Once ECG complexes are successfully detected and separated, a counting mechanism is utilized to derive the corresponding heart rates. Matlab simulation results on offline ECG data demonstrate the effectiveness of the adaptive LMS algorithm. Signal degradation by 50/60Hz noise is the main problem with ECG signals. This noise can be regarded as the result of electromagnetic compatibility issue- background electromagnetic field interference from surrounding equipment and from building power conduits corrupt the ECG signal. When recording an ECG signal, the signal’s path from patient to machine cannot be completely shielded from this background EMF and other measures must be considered to either preserve or improve the ECG signals quality. An alternative to shielding would be to filter the signal after it has been sampled and digitized and before it has been displayed on the ECG output unit. This solution is possible because the ECG signal and the 50/60Hz noise are uncorrelated signals.50/60 Hz noise could be removed from the ECG signal through bandpass filtering or through the use of very narrow notch filter[1]. However, each of these solutions has its drawbacks. Most of the information contained in an ECG signal is found below 100 Hz and substantial indiscriminate filtering could not be tolerated in terms of preserving signal clarity. In the case of the notch filter, the frequency of the electric power of the ECG would have to remain relatively constant in order to remain with in the notch of the filter. This is a problem since ECG signals have very small voltage and signal power is at a premium.

Bioelectrical signals are typically very small in amplitude (mV) and an amplifier is required to accurately depending on the hardware and software used, the biological amplifier serves to amplify the signal. It is also known that the frequency of heart signals is very low, approximately 5 to 10 Hz. During the amplification, a range of filtering options is required for the removal of unwanted signal artifacts due to additive white noise or random noise. In this paper, the use of adaptive noise canceller [2] has been investigated to address the problem of source separation from instantaneous noisy mixtures. In particular, focus has been given on the
ECG extraction problem, which is computed by the fact that ECGs are generally non-stationary. The combined Savitzky Golay filter [3] and LMS method has been used to smooth the recovered ECG signal.

2. ADAPTIVE LMS ALGORITHM

Adaptive noise cancellation requires noise to be subtracted from a received signal using an adaptive process. The desired result is a minimized signal to noise ratio. There are two main signals involved in adaptive noise cancellation: a primary signal and a reference signal. The primary signal, denoted by $d(n)$, is the sum of a desired signal $s(n)$ corrupted by a noise signal $v_0(n)$

$$d(n) = s(n) + v_0(n) \quad (1)$$

The two signals are uncorrelated. That is, the expected value is:

$$E[s(n)v_0(n-k)] = 0 \quad \text{for all } k \quad (2)$$

The reference noise signal, $v_r(n)$, is uncorrelated with the ECG signal, but correlated with the noise corrupting the signal. The correlation of the reference noise with the ECG signal is:

$$E[s(n)v_r(n-k)] = 0 \quad \text{for all } k \quad (3)$$

and with the noise corrupting the ECG signal is:

$$E[s(n)v_r(n-k)] = p(k) \quad (4)$$

Given a set of N points of the input signal and the reference signal, the optimum impulse response can be found. If given another set of N points, there is no guarantee that the optimum response will be close or even related to the first impulse response [4,5].

The LMS algorithm is a linear algorithm composed of a filtering process and an adaptive process shown in figure 1. The filtering process, which is linear and non-recursive, performs the computation of the filter output determined by a set of tap inputs as well as estimates the desired response. The adaptive process, which is non-linear and recursive, automatically adjusts the tap weights of the filter. The filtering is accomplished using a transversal filter. An adaptive weight-control mechanism is required to perform the adaptive process. Refer to Figure 1 for a block diagram of the algorithm[6].

![Figure 1 Block diagram of the algorithm](image)

An M-by-1 tap input vector $u(n)$ consists of the elements $u(n)$, $u(n-1)$, ..., $u(nM+1)$ that span a multidimensional space, $U_n$. The value of $M$ is the filter order. The tap-weight vector $w(n)$ is composed of the elements $w_0(n)$, $w_1(n)$, ..., $w_{M-1}(n)$. The tap-weight vector must be initialized. A common practice is to set the initial vector $w(0) = 0$. Thus the filter output begins at zero and gradually approaches the optimal solution.
order for the filtering to take place, the desired response $d(n)$ as well as the tap-input vector must be available. The error is

$$c(n) = d(n) - y(n)$$  \hspace{1cm} (5)

which is the difference between the desired response, $d(n)$, and the filter output, denoted $y(n)$. This is the overall system output. The filter produces an output an output $d(n|U_n)$, which is an estimate of the desired response. The adaptive weight-control mechanism requires the error and the tap-input vector to be supplied to close the feedback loops around the tap weights. The feedback loop behaves like a low-pass filter. "The average constant is proportional to the step-size parameter, $\mu$" [6]. The step-size parameter is a convergence factor that controls stability as well as the rate of adaptation. The adaptive process progresses slowly when a small step-size parameter is used and the "effects of gradient noise on the tap weights are largely filtered" [7]. Figure 2 shows the details of the transversal filter.

![Transversal structure of FIR digital filter](image)

**Figure 2** Transversal structure of FIR digital filter

The adaptive process adapts the weights until the correlation between the noise in the signal and the reference noise is cancelled from the output [8]. In order to determine the correction $\delta w_k(n)$ that is applied to the tap weight $w_k(n)$ for the following iteration, the product of $e(n)$ and $u(n-k)$ is calculated for $k=0,1,2,...M-2,M-1$ and is scaled by $\mu$. This update of the tap-weights can be described by the equation

$$w(n + 1) = w(n) + 2\mu u(n)e(n)$$  \hspace{1cm} (6)

The filter response at each iteration is the sum of the previous filter response and the correction factor. As the step-size increases the speed of convergence increases proportionally. Details of the adaptive weight-control mechanism are shown in Figure 3.
3. METHODOLOGY

ECG signal is generated by writing a function. This function generates a wave similar to a sine function which representative of a true ECG waveform. Since the generated ECG signal is not smooth enough, Savitzky Golay Filter is used for smoothing the wave shape of ECG signal.

An ECG signal is the superposition of action potentials that occur throughout the heart. A typical ECG signal for one heartbeat is shown in Figure 4. An ECG signal is characterized by the P wave, the QRS complex wave and the T wave, with each wave created by specific heart activities. "The P wave is produced by atrial depolarization, the QRS complex primarily by ventricular depolarization and the T wave by ventricular repolarization" [9]. Some ECG signals also contain a small amplitude U wave following the T wave; U waves are common in slow heart rates but a prominent U wave may reflect a heart abnormality. An ECG signal can also be broken down into three main intervals: the P-R interval, the Q-T interval and the S-T interval. The P-R interval is mainly caused by the depolarization of the atrium and slow conductance of the associated impulse to the ventricle by the atrioventricular (AV) node. The Q-T interval is defined by the depolarization and repolarization of the ventricle. The S-T interval corresponds to the "average duration of the plateau regions of individual ventricular cells" [9].
The simulated noise signal is produced using sine wave function. The output of the 50/60Hz sine wave is then multiplied by an amplitude scaling factor of 0.25. The ECG plus noise signal is formed simply by adding the above two signals. This sum of signals is sent to the adaptive LMS algorithm component.

4. SIMULATION AND RESULTS
The first test of the implementation is to pass the simulated ECG signal corrupted by noise as well as the simulated reference noise to the LMS algorithm. The algorithm converges to produce a difference of nearly zero between the simulated ECG signal uncorrupted by noise and the filtered ECG signals in a relatively short period of time. Since there are two controls for convergence rate, one for the filter order and one for the step-size parameter. Increasing the filter order above one slows down the convergence rate but makes the results more precise. Decreasing the step-size parameter improves the filtering even further. The recovered signal closely resembles the original simulated signal minus the noise. It can be concluded that the implementation of the algorithm functions correctly and efficiently.

50/60Hz noise is used as the two input signals to the algorithm, as the signal corrupted by noise as well as the reference noise. With this setup, it is observed that the output signal is close to zero. This result is expected since the entire input signal should be attenuated. Again the algorithm approaches convergence quickly. When the step-size is increased, the algorithm reconverges quickly to a value close to zero. The overall system is shown in figure 5.

Step 1: Generation of ECG pattern having amplitude of 3.5mV and pulse repetition rate of 75 per minute. ECG pattern is then smoothed by Savitzkey Golay filter. Figure 4 shows heart beat signal.
Step 2: Generation of a noisy signal having frequency of 50/60Hz and amplitude of 2.5 mV. This noisy signal is shown in Figure 6(b) entitled ‘Noisy time domain signal’.
Step 3: The noisy signal is filtered by using 31st order low pass FIR filter.
Step 4: The ECG signal and filtered noisy signal is summed. Figure 6(c) shows the ECG + noisy signal.

Step 5: Generate the power spectral density of the (ECG + Noise) signal.

Step 6: Set, Filter order, \( M = 3 \), exponential weighting factor =1, initial input covariance estimate =0.1, initial tap weight vector is set to zeros (M, 1), iterations =1000.

Step 7: Noise cancellation by adaptive LMS filter.
   I) Initialize Weight and Noise
   II) Read Noise and (Signal + Noise)
   III) Filter Noise from the (Signal + Noise)
   IV) Compute the error estimate
   V) Update the next Filter Weights
      If error = 0 terminate the subroutine
      Otherwise go to step II.

Step 8: Generate the power spectral density of the filtered signal.
5. CONCLUSIONS
In conclusion, an adaptive LMS algorithm has been implemented in Matlab that effectively removes high frequency noise from an ECG signal. Simulations performed in Matlab. The algorithm converges quickly - even with abrupt changes in filter order or step size, reconvergence takes place rapidly. Relatively little difference was evident between the uncorrupted ECG signal and the filtered ECG signal in simulation. Processing time was slightly longer but convergence was still approached. There was noticeable improvement in the filtered ECG signal as opposed to the unfiltered ECG signal. Experimentally, a combined filter order of five and step size of 0.05 were selected as producing the best results.

6. REFERENCES