Efficient Noise removal from ECG signals using EKRLS algorithm

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Abstract: The main goal of this project is that the implementation of Recursive Least Squares Adaptive Filtering Algorithm for the filtering of five different noises that occur in ECG signals during data acquisition. Electrocardiogram (ECG) is a diagnostic procedure that measures and records the electrical activity of heart in detail. By reviewing an ECG report, one’s condition of heart can be evaluated. But ECG signals are often affected and altered by the presence of various noises that degrade the accuracy of an ECG signal and thus misrepresents the recorded data. Adaptive filters adapt their filter coefficients with the continuous change of signal using adaptive algorithms, providing the optimum noise removal features for non-stationary signals like ECG. In this study, the adaptive filter algorithm, RLS has been used in cancellation of various noises in ECG signals. We have also performed noise removal using LMS adaptive filter algorithm to compare the performance of RLS algorithm.

Keywords: Electrocardiogram (ECG), Adaptive Filter Algorithm, LMS Adaptive Filter Algorithm, RLS Algorithm.

I. INTRODUCTION

The electrocardiogram (ECG) is a graphical representation of the cardiac activity and it is widely used for the diagnosis of heart diseases. Several noises contaminate the ECG signal while recording, the predominant artefacts present in the ECG signal are Power - line Interference (PLI), Baseline Wander (BW), Muscle Artefacts(MA) and Motion Artefacts (EM). In this paper Power - line Interference is considered for SNR simulations. The goal for ECG signal enhancement is to separate the valid signal components from the undesired artifact, so as to present an ECG that facilitates easy and accurate interpretation. As adaptive filters do not have fixed filter coefficients, these filters can change their filter coefficients to reduce the noise present in the signal through adaptation. Even the most basic adaptive filter algorithms, like the least mean squares (LMS), have shown promising performance in noise removal from nonstationary signals. However, in this study we have performed noise removal with the help of recursive least squares (RLS) adaptive filter algorithm. It is a more complex algorithm than the LMS. To understand how well the RLS algorithm performs in removing various noises from ECG signals, we have corrupted ECG signals with specific noises and removed those noises with both LMS and RLS algorithm based adaptive filters. Afterwards, we have compared the filtered signals in terms of Signal to Noise Ratio (SNR) Improvement, Mean Square Error (MSE), Percentage Root-Mean-Square Difference (PRD), plots of convergence, plots of Power Spectral Density (PSD) and Spectrograms. Depending on these performance criteria it has been observed that the RLS algorithm has removed all types of noises more effectively than the LMS algorithm.

II. LITERATURE SURVEY

The theoretical results form the basis of a computer model of the electrocardiogram that relates skin potentials to the spatial and temporal distribution of action potentials in the heart. Hence the ECG signals are required to be very accurate. Even slight distortions in the ECG waveforms can impair the understanding of the patient’s heart conditions. But due to some inherent measurement and instrumentation faults, some noises get induced to the ECG signals, thus distorting the information carried by the signals. These noises typically are: white noise, various harmonics of power line interference, baseline wander noises, electrode movement noise and muscle artifacts. To filter out these noises, conventional digital filters like Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) have been employed. Diverse digital methods have been advanced previously to remove power line (AC) interference in the ECG. Representative notch filters, adaptive filters and a globally derived filter are surveyed in this study; their performances are compared on artificial signals as well as actual ECGs. The ECGs, recorded at four European medical centers, are from the Common Standards in Electrocardiography (CSE) ECG tape library. AC interference in these ECGs is shown to exhibit two qualities especially relevant to filter design: considerable deviations from a nominal 50 Hz frequency and substantial noise at higher harmonics. Some criteria and useful quantitative measures are suggested to evaluate AC digital filters. Traditionally, analog circuits have been used for signal conditioning of electrocardiograms.

As an alternative, algorithms implemented as programs on microprocessors can do similar filtering tasks. Also, digital filter algorithms can perform processes that are difficult or impossible using analog techniques. Presented here are a set of real-time digital filters each implemented as a subroutine.
By calling these subroutines in an appropriate sequence, a user can cascade filters together to implement a desired filtering task on a single microprocessor. Included are an adaptive 60-Hz interference filter, two low-pass filters, a high-pass filter for eliminating dc offset in an ECG, an ECG data reduction algorithm, band-pass filters for use in QRS detection, and a derivative-based QRS detection algorithm. These filters achieve real-time speeds by requiring only integer arithmetic. They can be implemented on a diversity of available microprocessors. But as these filters have fixed number of filter coefficients, they have been of little avail in removing the noises successfully. To achieve better noise removal from non-stationary signals like ECG, various adaptive filter algorithms have been employed. This topic describes the concept of adaptive noise cancelling, an alternative method of estimating signals corrupted by additive noise or interference. The method makes use of a "primary" input containing the corrupted signal and a "reference" input containing noise correlated in some unknown way with the primary noise. The reference input is adaptively filtered and subtracted from the primary input to obtain the signal estimate. Adaptive filtering before subtraction allows the treatment of inputs that are deterministic or stochastic, stationary or time variable. Wiener solutions are developed to describe asymptotic adaptive performance and output signal-to-noise ratio for stationary stochastic inputs, including single and multiple reference inputs.

III. PROPOSED METHODOLOGY

The adaptive noise canceller is the circuit configuration that has been used in this experiment to remove the various noises from ECG and improve the signal quality. This act of noise cancelling depends upon subtraction of noise from a received signal which is controlled in an adaptive manner. The adaptive noise canceller depicted here is basically a dual input closed loop feedback system. The primary sensor receives the corrupted ECG signal d(n), which contains the clean ECG signal s(n) and additive noise v1(n). The signals s(n) and v1(n) are uncorrelated. We write d(n) as,

\[ d(n) = v_1(n) + s(n) \]  

(1)

The reference sensor receives a noise v2(n) which is uncorrelated with s(n) but is correlated with v1(n). The reference signal is processed by the adaptive filter to produce an output y(n), which is the estimate of noise. This y(n) is given as,

\[ y(n) = \sum_{k=0}^{M-1} w_k v_2(n-k) \]  

(2)

Here, wk are the adjustable tap weights or filter coefficients. The filter output y(n) gets subtracted from the primary signal d(n) and produces the error signal e(n). The error signal e(n) is defined as,

\[ e(n) = d(n) - y(n) \]  

(3)

\[ e(n) = s(n) + v_1(n) - y(n) \]  

(4)

This error signal is used to update the filter coefficients of the adaptive filter. Also this error signal comprises the overall system output. From Eq. (4) we see that the noise component present in the system output is v1(n) – y(n). The adaptive filter attempts to minimize the average power of the error signal e(n) which leaves the clean ECG signal largely unaffected. As the clean ECG signal remains unaffected, minimizing the average power of the output error signal e(n) is equivalent to minimizing the average power of the noise v1(n) – y(n) that was present on the signal. In this way the noises present in the ECG signal gets removed.

A. Noise Cancellation

The combined signal and noise from the "primary input" to the canceller. A second sensor receives a noise n1, which is uncorrelated with the signal but correlated in some unknown way with the noise n0. This sensor provides the "reference input" to the canceller. The noise n1 is filtered to produce an output “y” that is a close replica of n0. This output is subtracted from the primary input “s+n0” to produce the system output, s+n0-y. If one knew the characteristics of the channels over which the noise was transmitted to the primary and reference sensors, one could, in general, design a fixed filter capable of changing n1 into y= n0. The filter output could then be subtracted from the primary input, and the system output would be the signal alone. Since, however, the characteristics of the transmission paths are assumed to be unknown or known only approximately and not of a fixed nature, the use of a fixed filter is not feasible. Moreover, even if a fixed filter was feasible, its characteristics would have to be adjusted with a precision difficult to attain, and the slightest error could result in increased output noise power. In the system shown in figure 3, the reference input is processed by an adaptive filter that automatically adjusts its own impulse response through a least-squares algorithm such as RLS that responds to an error signal dependent, among other things, on the filter's output. In noise canceling systems the practical objective is to produce a system output, s+n0-y that are a best fit in the least-squares sense to the signal s. This objective is accomplished by feeding the system output back to the adaptive filter and adjusting the filter through an adaptive algorithm to minimize the total system output power. In an adaptive noise-canceling system, in other words, the system output serves as the error signal for the adaptive process.

C. RLS Algorithm

The objective here is to choose the coefficients of the adaptive filter such that the output signal y(k), during the period of observation, will match the desired signal as closely as possible in the least-squares sense. The minimization process requires the information of the input signal available so far. Also, the objective function we seek to minimize is deterministic. The generic FIR adaptive filter realized in the direct form is shown in Fig. 3. The input signal information vector at a given instant k is given by

\[ x(k) = [x(k) x(k-1) \ldots x(k-N)]^T \]  

(5)

the inverse of the deterministic correlation matrix can then be calculated in the following form
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\[
S(k) = R(k)^{-1} - \frac{1}{\lambda}[S(k-1) - \frac{S(k-1)x(k)x'(k)S(k-1)}{\lambda + x'(k)S(k-1)x(k)}]
\]

D. Kernel Adaptive Filtering Algorithm

A Matlab benchmarking toolbox for kernel adaptive filtering. Kernel adaptive filters are online machine learning algorithms based on kernel methods. Typical applications include time-series prediction, nonlinear adaptive filtering, tracking and online learning for nonlinear regression. This toolbox includes algorithms, demos, and tools to compare their performance.

Fig.1. Nonlinear system identification using kernel adaptive filtering.

IV. SIMULATION RESULTS

Simulation was done on MATLAB R2013a, the results was shown that the previous and proposed results. To show that RLS algorithm is really effective in clinical situations, the method has been validated using several ECG recordings with a wide variety of wave morphologies from MIT-BIH arrhythmia database. We used the self generated ECG signal contaminated with noises of various varying frequencies for our work which were digitized at 200 samples per second per channel with 20mV range. However, a real noise can be obtained from MIT-BIH Normal Sinus Rhythm Database (NSTDB). For all the figures number of samples is taken on x-axis and amplitude on y-axis, unless stated.

Fig.2. GUI for ECG signal denoising using RLS algorithm.

We are designing an ECG signal denoising GUI. In all the sections are covered

- Select the Noise Type under the “Noise Config” Block
- Select the type of Filter Algorithm
- Select the Dataset under the “Data” Block
- Click “Save Figure” for all the plots to be saved in the folder names “Plot Images”
- Click “Run Algorithm” Button.
- Note: Always select the algorithm(s) before clicking the Run button.
- Click the “Research Paper” Button to view the IEEE Research Paper
- Click the “Read Me” Button to view this read me file
- Once the program has finished its execution, the status and the run time will be displayed on the bottom left. Refer Fig.1

Fig.3. Pure ECG signal and white noise effected signal and RLS filtered ECG signals.

The datasets were downloaded from Physionet ECG Database. Info files (.info) have been provided for all the various datasets downloaded from the given website for additional information regarding the datasets.

Fig.4. Pure ECG signal and PLI noise effected signal and RLS filtered ECG signals.
Fig. 5. Pure ECG signal and BW noise effected signal and RLS filtered ECG signals.

Fig. 6. Pure ECG signal and EM noise effected signal and RLS filtered ECG signals.

Fig. 7. Pure ECG signal and MA noise effected signal and RLS filtered ECG signals.

Fig. 8. Periodogram of power line interference noise ECG signal and its RLS filtered signal.

Fig. 9. Periodogram of power line interference noise ECG signal and its LMS filtered signal.

Fig. 10. Periodogram of power line interference noise ECG signal and its EKRLS filtered signal.
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V. CONCLUSION
In this paper the process of noise removal from ECG signal using RLS based adaptive filter is presented. For this, the input and the desired response signals are properly chosen in such a way that the filter output is the best least squared estimate of the original ECG signal. The proposed treatment exploits the modifications in the weight update formula and thus pushes up the speed over the respective LMS based realizations. Our simulations, however, confirm that the SNR of the proposed algorithm gives better result. Also, the convergence rate is faster than LMS and computational complexity is less in the proposed implementation than its time domain.

VI. REFERENCES

Author’s Profile:
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