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Simulation of Noise Cancellation in ECG Signals using Adaptive Filters

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Abstract - *Several adaptive filter structures are proposed for noise cancellation and arrhythmia detection. The adaptive filter essentially minimizes the mean-squared error between a primary input, which is the noisy electrocardiogram (ECG), and a reference input, which is 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. Different filter structures are presented to eliminate the diverse forms of noise: baseline wander, 60 Hz power line interference, muscle noise, and motion artifact. An adaptive recurrent filter structure is proposed for acquiring the impulse response of the normal QRS complex. The primary input of the filter is the ECG signal to be analyzed, while the reference input is an impulse train coincident with the QRS complexes. This method is applied to several arrhythmia detection problems: detection of P-waves, premature ventricular complexes, and recognition of conduction block, atrial fibrillation, and paced rhythm.*

Keywords- *Simulation, Noise, ECG Signals, Adaptive filters*

1 Introduction

Digital Signal processing has become one of the very important fields in the areas of Communications, Speech Processing, Instrumentation and control systems, Image processing, Industrial automation, Robotics, computer vision etc. In today's digital communication and mobile multimedia world, adaptive signal processing is one of the most important areas of real time DSP implementation.

The ability of adaptive filter to operate satisfactorily in an unknown environment and track time variations of input statistics makes the adaptive filter a powerful device for real time signal processing and control applications.

In this project, several simple and efficient sign and error nonlinearity-based adaptive filters, which are computationally superior having multiplier free weight update loops are used for cancellation of noise in electrocardiographic (ECG) signals.

The proposed implementation is suitable for applications such as biotelemetry, where the large signal-to-noise ratios with less computational complexity are required. These schemes mostly employ simple addition, shift operations and achieve considerable speed up over the other least mean square (LMS)-based realizations.

Simulation studies shows that the proposed realization gives better performance compared to existing realizations in terms of signal-to-noise ratio and computational complexity.

2 Literature Survey

Researchers came out with variety of algorithms, each one has their own advantages and disadvantages in terms of convergence time, number of operation, computation complexity, memory requirements artifacts etc. A considerable amount of research in the field of Digital Signal processing is still going on, especially for improving the performance of adaptive filters in terms of convergence time, robustness and computational complexity which started decades back. Some of that work is mentioned here as starting point for the present thesis work.

Research work on performance improvement of Adaptive filters

The Least-Mean-Square algorithm is one of the most widely used algorithms for adaptive signal processing because of its simplicity and robustness. But, its performance in terms of convergence rate and tracking capability depends on the Eigenvalue spread of the input signal correlation matrix. To overcome the above-mentioned problem, F. Beaifays, proposed Transform domain LMS

algorithms, like the discrete cosine transform (DCT) and the discrete Fourier transform (DFT). In general, it consists of using an orthogonal transform together with power normalization for speeding up the convergence of the LMS algorithm [5]. Very interesting, efficient, and different approaches have also been proposed in the literature [6]. Another alternative to overcome the aforementioned drawbacks of nonrecursive adaptive systems is the split processing technique. The fundamental principles were introduced when Delsarte and Genin proposed a split Levinson algorithm for real Toeplitz matrices in [7].

Subsequently, the same authors extended the technique to classical algorithms in linear prediction theory, such as the Schur, the lattice, and the normalized lattice algorithms [8]. K. C. Ho and P. C. Ching, proposed split LMS adaptive filter for autoregressive (AR) modeling(Linear prediction) [9] And then P.C. Ching and K.F. Wan generalized it to a so- called unified approach [10], [11] by the introduction of the continuous splitting and the corresponding application to a general transversal filtering problem.

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Electrocardiogram

This means of studying the activity of the heart from electrical signals detectable from the body surface stemmed directly, early in the twentieth century, from the invention of the *string galvanometer* by the Dutch physiologist, Einthoven. Electrocardiography was demonstrated to the Royal Society in London in 1909.

The „ECG" (or sometimes still „EKG" in the US, from the German spelling) has become an icon representing the heart's activity. The waveform is the most familiar „high tech" sign of the electrical behavior of the heart. In various versions, its characteristic shape (see figure) reporting a healthy rhythm, or the flat line suggesting the patient's demise, is familiar to any viewer of television medical soap operas. A clever variation on the theme forms the distinctive logo for the British Heart Foundation, the largest UK charity dedicated to funding cardiovascular research.The electrocardiogram (as a paper trace or a TV monitor display) shows the changes in the voltage, detectable during the time course of the heart beat, between pairs of electrodes placed at certain points on the skin.

The basis of the ECG is that the heart, like other muscles, is triggered to contract by electrical activity. The heart is a relatively large piece of tissue, so the flow of electrical current associated with (and immediately preceding) contraction produces detectable voltages (typically a few mill volts) on the surface of the body.Electrode pairs can be placed at various versions, its characteristic shape (see figure) reporting a healthy rhythm, or the flat line suggesting the patient's demise, is familiar to any viewer of television medical soap operas. A clever variation on the theme forms the distinctive logo for the British Heart Foundation, the largest UK charity dedicated to funding cardiovascular research.

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Electrode pairs can be placed at various positions on the body to yield information about the status of the heart. The classic „limb leads" are attached to one leg and two arms; other pairings are placed at defined positions on the chest itself. Even more detail can be obtained with leads inserted in the *esophagus* (the gullet) or even from within the heart itself (with the electrode introduced via a vein). Abnormal enlargement (*hypertrophy*) of the heart's various chambers produces characteristic distortions of the „ideal" ECG form which are readily interpreted by experienced users

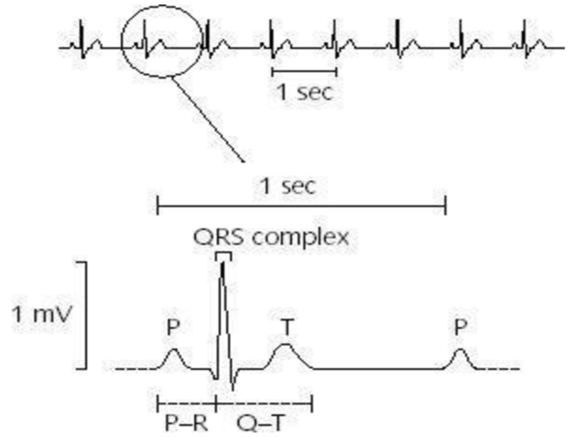

Figure .1 :Characteristic ECG pattern of a healthy heart beating at 60/minute

The spread of the electrical wave across the heart varies in speed (see heart). Simple physics dictates that where a change in potential of a large fraction of the heart occurs in a relatively brief time, the resulting ECG wave is large too. When most of the heart is at a similar potential, no voltage *difference* will appear at the surface. Thus, prominent waves in the waves in the ECG indicate the synchronized start (or finish) of activity in significant fractions of the heart.

These potentials amount to one or two *mille*-volts. The impulse of electrical activity causing the heart to contract in a co-ordinates manner progresses through the heart in a complex three-dimensional pattern. The appearance of the electrocardiogram, therefore, varies from person to person as heart shape and position can be significantly different even in entirely normal individuals. Any person's pattern further alters with the location of the recording electrodes. Nevertheless, there are significant, consistently observed deflections and intervals in a typical electrocardiogram; the main „peaks" are labeled as P, QRS, and T(see figure).

The most basic feature of the ECG is that the time from any one such „peak" to the same one in the next cycle indicates precisely how long the heart cycle is taking. At slow rates, the timing of the waves can be easily correlated to the heart sounds heard with the stethoscope. But far more precise information can be gleaned once the

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relationship of the waves to the phases of the cycle is understood.

Noise Cancellation in ECG Signal

Noise Cancellation in Ambulatory ECG:

Noise Generator: The reference signal shown in Fig. 1 is taken from noise generator. A synthetic PLI with 1 mv amplitude is simulated for PLI cancellation, no harmonics are synthesized. In order to test the filtering capability in a non-stationary environment, we have considered real BW, MA, and EM noises. These are taken from the MIT-BIH Normal Sinus Rhythm Database (NSTDB). This database was recorded at a sampling rate of 128 Hz from 18 subjects with no significant arrhythmias. A Gaussian noise with variance of 0.001 is added to resemble the channel noise, while transmitting through free space.

The input SNR for the above non stationary noise is taken as 1.25 dB . In the considered simplified algorithms because of the sign present in the recursion some tiny noise remains along the ST segment of the ECG signal. In order to extract the residual noise, a tiny PLI is added to the noise reference signal. This improves the performance of the filter.

Noise in ambulatory recordings is contributed both by biologic and environmental sources. Examples of environmental noise are 60 (or 50) Hz and its harmonics generated by power lines, radio-frequency and electrosurgibiologic interference are: baseline drift and wander, electro myo gram (EMG), and motion artifact. The first aim of this paper is to present a step- by-step approach to cancellation of these diverse noise contributions to ambulatory ECG.

Adaptive Power-Line Interference Canceller :

This experiment demonstrates power-line interference (PLI) cancellation. The input to the filter is ECG signal corrupted with a synthetic PLI of frequency 60 Hz and sampled at 200 Hz, which is generated in the noise generator. The reference signal is synthesized PLI, the output of the filter is recovered signal

Baseline Wander Reduction :

Van Alste and Schilder describe an efficient finite impulse response (FIR) notch filter that is rather effective at removing baseline wander and power line interference. The adaptive filter to remove baseline wander is a special case of notch filtering, with the notch at zero frequency (or dc). Only one weight is needed, and the reference input is a constant with a value of 1. This filter has a "zero" at dc and consequently creates a notch with a bandwidth of (p/n) * *fs* where *fs* is the sampling rate. Frequencies in the range of 0-0.5 Hz should be removed to reduce baseline drift. If the sampling rate is 500 sample **/s,** the convergence parameter p should be smaller than 0.003. $p$may be dynamically adjusted to obtain the desired low-frequency response. Note that this filter will produce some distortion of the ST-segment since low-frequency components of ECG are attenuated. Since the selected value of p is small, this filter converges slowly and therefore cannot track abrupt transients produce by motion artifacts.

Least mean squares (LMS) algorithms are a class of adaptive filter used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean square of the error signal (difference between the desired and the actual signal). It is a stochastic gradient descent method in that the filter is only adapted based on the error at the current time. It was invented in 1960 by Stanford University professor Bernard Widrow and his first Ph.D. student, Ted Hoff.

In its search for the least square error filter coefficients, the steepest-descent method employs the gradient of the *averaged* squared error. A computationally simpler version of the gradient search method is the LMS filter, in which the gradient of the *mean* square error is substituted with the gradient of the *instantaneous* squared error function. The LMS adaptation method is defined as

$$w(m+1) = w(m) + \mu - \partial' E[e^2\ m\ ]$$

where the error signal *e(m)* is the difference between the adaptive filter output and the target(desired) signal *x(m),* given by

$$e \quad = x \quad - w^T\ m \quad (m)$$

The instantaneous gradient of the squared error can be re-expressed as

$$\frac{\partial e^2(m)}{\partial w\,(m)} = \frac{[x\ m - \ (m)(m)]^2}{\partial w\,(m)}$$

$$= -2y\ m\ [x\ m - w^T\ m \quad]\ (4.3)$$

$$= -2 \quad (m)$$

Substituting Equation (4.20) into the recursion filter update Equation (4.18) yields the LMS adaptation equation:

$$w(m+1) = w(m) + \mu[y(m)e(m)] \qquad (4.4)$$

It can be seen that the filter update equation is very simple. The LMS filter is widely used in adaptive filter applications such as adaptive equalization, echo cancellation, radar, etc.

The main advantage of the LMS algorithm is its simplicity both in terms of the memory requirement and the computational complexity, which is *O(P)*, where *P* is the filter length

Implementation Of The NLMS Algorithm

The NLMS algorithm has been implemented in MATLAB As the step size parameter is chosen based on the current input values, the NLMS algorithm shows far greater stability with unknown signals. This combined with good convergence speed and relative computational simplicity makes the NLMS algorithm ideal for the real-time adaptive echo cancellation system [16].

As the NLMS is an extension of the standard LMS algorithm, the NLMS algorithm's practical implementation is very similar to that of the LMS algorithm. Each iteration of the NLMS algorithm requires these steps in the following order.

1. The output of the adaptive filter is calculated.

$$y(n) = \sum_{i=0}^{N-1} w(n)x(n-i) = \mathbf{w}^T(n)\mathbf{x}(n)$$

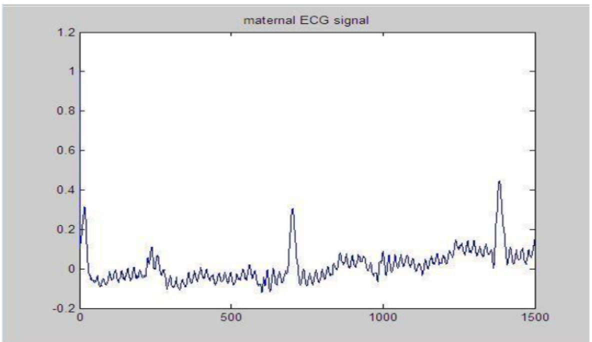
2. An error signal is calculated as the difference
3. between the desired signal and the filter output.
4. The step size value for the input vector is calculated.

$$\mu(n) = \frac{1}{\mathbf{x}^T(n)\mathbf{x}(n)}$$

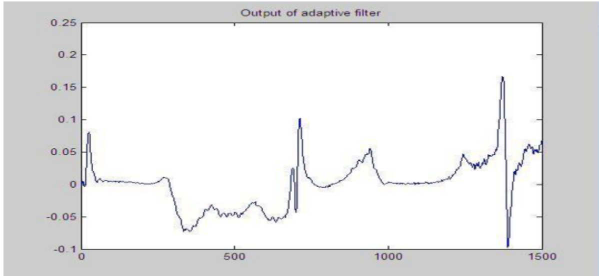
5. The filter tap weights are updated in preparation for the next iteration.

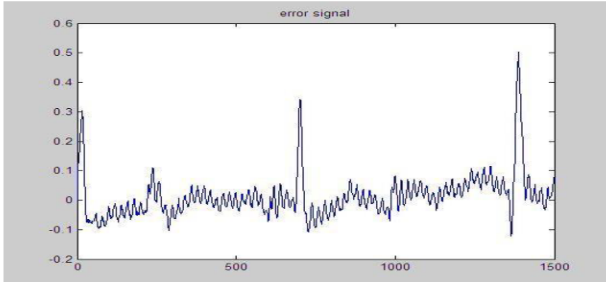
Each iteration of the NLMS algorithm requires 3N+1 multiplications, this only N more than the standard LMS algorithm. This is an acceptable increase considering the gains in stability and echo attenuation achieved.

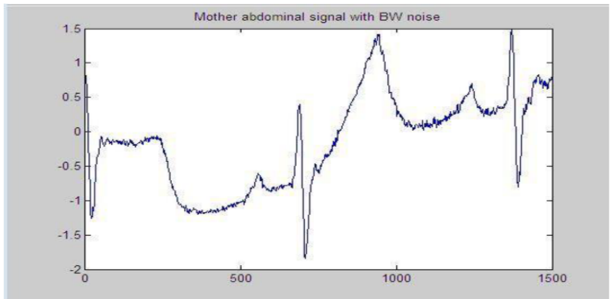
3 RESULTS ANALYSIS

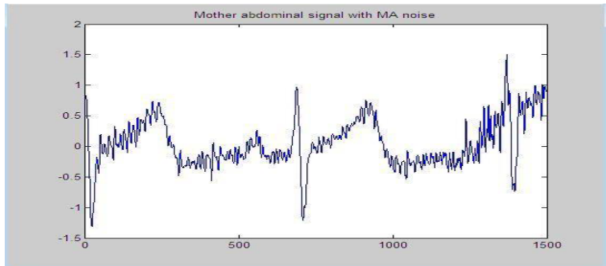


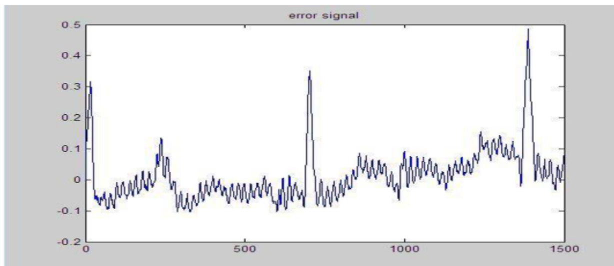
LMS SIMULATIONS FOR BASELINE WANDER :

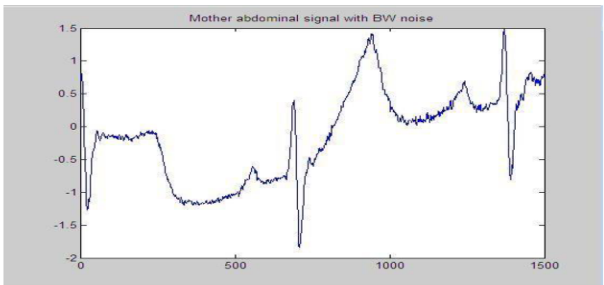




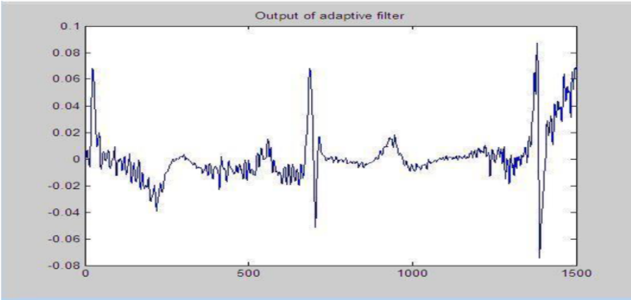


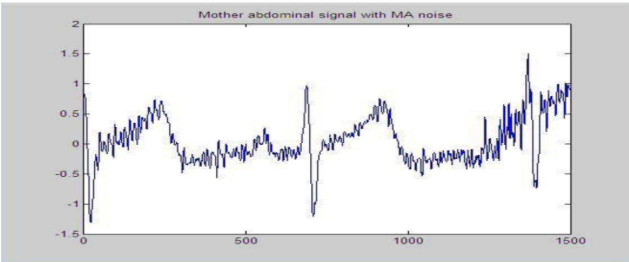


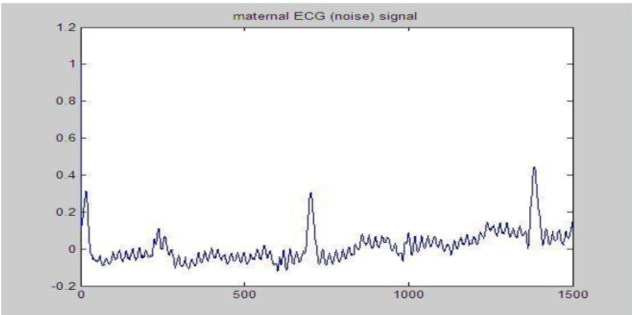


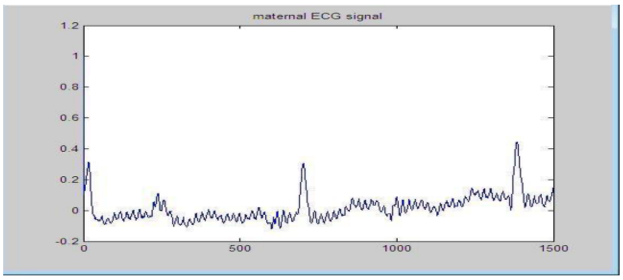


LMS SIMULATION FOR MUSCLE ARTIFACT

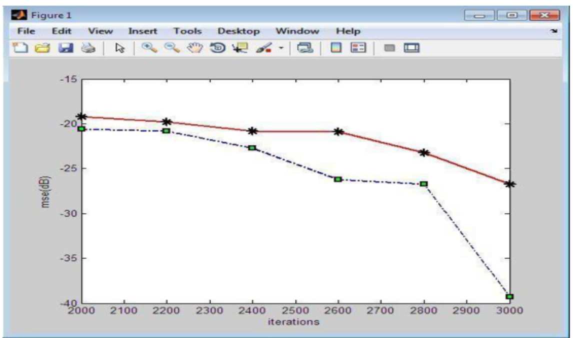


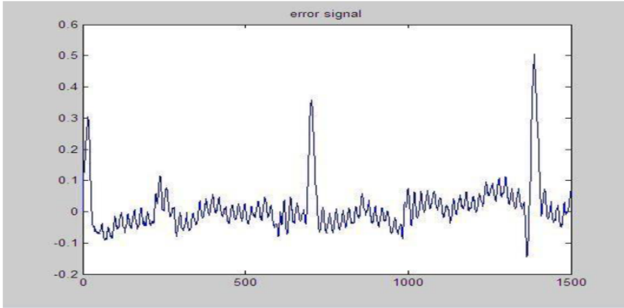


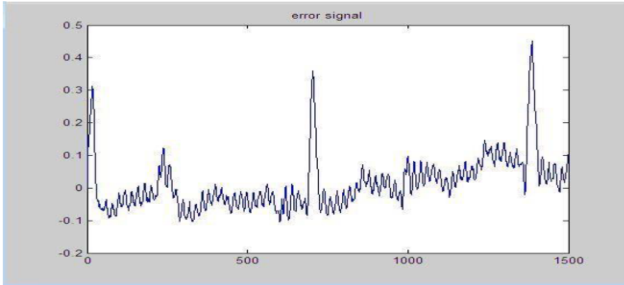




Iteration Plot For LMS And NLMS :







4 CONCLUSION

In this paper, the problem of noise cancellation from ECG signal using error normalization- based adaptive filters, their block-based versions are proposed and tested on real signals with different artifacts. 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. Among the two algorithms, the NLMS performs better than the other. From the simulated results, it is clear that these algorithms remove the artifacts efficiently present in the ECG signal. The proposed treatment provides high SNR with less computational complexity. The computational complexity in terms of MSE and SNR contrast are shown in Tables 1 and 2.

Hence, the proposed LMS, NLMS -based adaptive filters, and their block-based versions are more suitable for Adaptive noise cancellation of ECG signals.

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