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DENOISING ECG SIGNALS USING ADAPTIVE FILTER ALGORITHM

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ABSTRACT - *One of the main problem in biomedical data processing like electrocardiography is the separation of the wanted signal from noises caused by power line interference, external electromagnetic fields, random body movements and respiration. Different types of digital filters are used to remove signal components from unwanted frequency ranges. It is difficult to apply filters with fixed coefficients to reduce Biomedical Signal noises, because human behavior is not exact known depending on the time. Adaptive filter technique is required to overcome this problem. In this paper type of adaptive filters are considered to reduce the ECG signal noises like PLI and Base Line Interference. Results of simulations in MATLAB are presented. In this we have used Recursive Least Squares (RLS). RLS algorithm is proposed for removing artifacts preserving the low frequency components and tiny features of the ECG. Least-squares algorithms aim at the minimization of the sum of the squares of the difference between the desired signal and the model filter output .When new samples of the incoming signals are received at every iteration, the solution for the least-squares problem can be computed in recursive form resulting in the recursive least-squares (RLS) algorithms. The RLS algorithms are known to pursue fast convergence even when the Eigen value spread of the input signal correlation matrix is large. These algorithms have excellent performance when working in time-varying environments. All these advantages come with the cost of an increased computational complexity and some stability problems, which are not as critical in LMS-based algorithms*

Keywords*: ECG Signal, Dirichlet's Condition, Adaptive Filter*

1. INTRODUCTION

The extraction of high-resolution ECG signals from recordings contaminated with background noise is an important issue to investigate. The goal for ECG signal enhancement is to separate the valid signal components from the undesired artifacts, so as to present an ECG that facilitates easy and accurate interpretation. Many approaches have been reported in the literature to address ECG enhancement using adaptive filters [1]-[3], which permit to detect time varying potentials and to track the dynamic variations of the signals. In [4]-[6] proposed an LMS based adaptive recurrent filter to acquire the impulse response of normal QRS complexes, and then applied it for arrhythmia detection in ambulatory ECG recordings. The reference inputs to the LMS algorithm are deterministic functions and are defined by a periodically extended, truncated set of orthonormal basis functions. In these papers, the LMS algorithm operates on an instantaneous basis such that the weight vector is updated every new sample within the occurrence, based on an instantaneous gradient estimate. There are certain clinical applications of ECG signal processing that require adaptive filters with large number of taps. In such applications the conventional LMS algorithm is computationally expensive to implement The LMS algorithm and NLMS (normalized LMS) algorithm require few computations, and are, therefore, widely applied for acoustic echo cancellers. However, there is a strong need to improve the convergence speed of the LMS and NLMS algorithms. The RLS (recursive least-squares) algorithm, whose convergence does not depend on the input signal, is the fastest of all conventional adaptive algorithms. The major drawback of the RLS algorithm is its large computational cost. However, fast (small computational cost) RLS algorithms have been studied recently.In this paper we aim to obtain a faster algorithm by incorporating knowledge of the room impulse response into the RLS algorithm. Unlike the NLMS and projection algorithms, the RLS algorithm does not have a scalar step size. Therefore, the variation characteristics of a ECG signal cannot be reflected directly in the RLS algorithm. Here, we study the RLS algorithm from the viewpoint of the adaptive filter because (a) the RLS algorithm can be regarded as a special version of the adaptive filter and (b) each parameter of the adaptive filter has a physical meaning.Computer simulations demonstrate that this algorithm converges twice as fast as the conventional algorithm.These characteristics may plays a vital role in biotelemetry, where extraction of noise free ECG signal for efficient diagnosis and fast computations, high data transfer rate are needed to avoid overlapping of pulses and to resolve ambiguities. To the best of our knowledge, transform domain has not been considered previously within the context of filtering artifacts in ECG signals. In this paper we present a RLS algorithm to remove the artifacts from ECG. This algorithm enjoys less computational complexity and good filtering capability. To study the performance of the proposed algorithm to effectively remove the noise from the ECG signal, we carried out simulations on MIT-BIH database for different artifacts.

2. PRINCIPLE : FOURIER SERIES

Any periodic functions which satisfy Dirichlet's Condition can be expressed as a series of scaled magnitudes of sin and cos terms of frequencies which occur as a multiple of fundamental frequency.

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$$f(x)=(a_0/2)+\sum_{n=1}^{\infty} a n cos\left(\frac{n\pi x}{l}\right)+\sum_{n=1}^{\infty} b n sin\left(\frac{n\pi x}{l}\right)$$

$$a_0=(1/l)\int_T f(x)dx \quad , T=2l \quad \rightarrow (1)$$

$$a_n=(1/l)\int_T f(x)cos\left(\frac{n\pi x}{l}\right)dx \quad , n=1,2,3 \quad \rightarrow (2)$$

$$b_n=(1/l)\int_T f(x)sin\left(\frac{n\pi x}{l}\right)dx \quad , n=1,2,3 \quad \rightarrow (3)$$

ECG signal is periodic with fundamental frequency determined by the heart beat. It also satisfies the Dirichlet's Condition.

- Single valued and finite in the given interval
- Absolutely integrals
- Finite number of maxima and minima between finite intervals
- It has finite number of discontinuities

Hence Fourier series can be used for representing ECG signal.

3. CALCULATION:

If we observe figure1, we may notice that a single period of a ECG signal is a mixture of triangular and sinusoidal wave forms. Each significant feature of ECG signal can be represented by shifted and scaled versions one of these waveforms as shown below.

- QRS, Q and S portions of ECG signal can be represented by triangular waveforms
- P, T and U portions can be represented by triangular waveforms

Once we generate each of these portions, they can be added finally to get the ECG signal.

Let's take QRS waveform as the centre one and all shifting takes place with respect to this part of the signal.

How do we generate periodic QRS portion of ECG signal

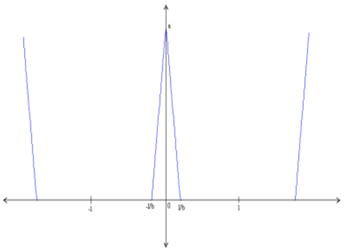


Figure 1. Generating QRS waveform

From equation (1), we have

$$f(x)=(-bax/l)+a \quad 0<x<(1/b)$$
$$=(bax/l)+a \quad (-1/b)<x<0$$
$$a_0=(1/l)\int_T f(x)dx$$
$$=(a/b)*(2-b)$$
$$a_n=(1/l)\int_T f(x)\,cos\left(\frac{n\pi x}{l}\right)dx$$
$$=(2ba/(n2\pi2))*(1-cos(n\pi/b))$$
$$b_n=(1/l)\int_T f(x)\,sin\left(\frac{n\pi x}{l}\right)dx$$
$$=0 \text{ (because the waveform is an even function)}$$
$$f(x)=(a0/2)+\sum_{n=1}^{\infty} a n cos(n\pi x/l)$$

How do we generate periodic p-wave portion of ECG signal

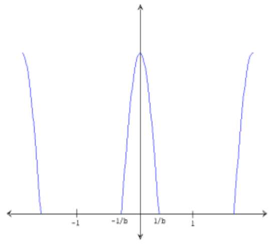


Figure 2. Generation of p-wave

$$f(x) = cos((\pi bx)/(2l)) \quad (-1/b)<x<(1/b)$$

$$a_0 = (1/1)\int_T cos((\pi bx)/(2l))\,dx$$
$$= (a/(2b))(2-b)$$

$$a_n = (1/1)\int_T cos((\pi bx)/(2l))\,cos(n\pi x/l)dx$$
$$= (((2ba)/(i^2\pi^2))(1-cos((n\pi)/b)))\,cos((n\pi x)/l)$$

$$b_n = (1/1)\int_T cos((\pi bx)/(2l))\,sin(n\pi x/l)\,dx$$
$$= 0 \text{ (because the waveform is a even function)}$$

$$f(x) = (a_0/2) + \sum_{n=1}^{\infty} a n\, cos(n\pi x/l)$$

4.NOISE CANCELLATION

The combined signal and noise form 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 out put '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 out put 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 out put 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 another 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 out put serves as the error signal for the adaptive process.

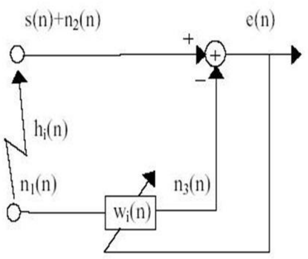


Figure 3: Adaptive Noise Canceller

5. 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

$$\mathbf{x}(k) = [x(k)\; x(k-1) \ldots x(k-N)]^T$$

the inverse of the deterministic correlation matrix can then be calculated in the following form

$$S_D(k) = R_D^{-1}(k) = \frac{1}{\lambda}\left[S_D(k-1) - \frac{S_D(k-1)x(k)x^T(k)S_D(k-1)}{\lambda + x^T(k)S_D(k-1)x(k)}\right]$$

The complete conventional RLS algorithm is described in

Algorithm 5.1

Conventional RLS Algorithm

Initialization

$S_D(-1) = \delta I$

where δ can be the inverse of the input signal power estimate

$p_D(-1) = x(-1) = [0\,0 \ldots 0]^T$

Do for $k \geq 0$:

$S_D(k) = \frac{1}{\lambda}[S_D(k-1) - \frac{S_D(k-1)x(k)x^T(k)S_D(k-1)}{\lambda + x^T(k)S_D(k-1)x(k)}]$

$p_D(k) = \lambda p_D(k-1) + d(k)x(k)$

$w(k) = S_D(k)p_D(k)$

If necessary compute

$y(k) = w^T(k)x(k)$

$\varepsilon(k) = d(k) - y(k)$

Algorithm.

6. SIMULATION 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.

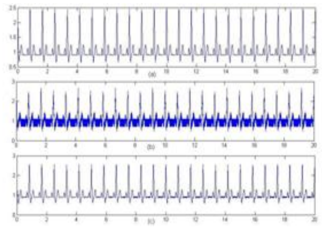
However, a real noise can be obtained from MIT-BIH Normal Sinus Rhythm Database (NSTDB). For all the figures *number of samples* is taken on x-axis and *amplitude* on y-axis, unless stated.

A.Adaptive Power-line Interference Canceller

Power line interference may severely corrupt a biomedical recording. Notch filters and adaptive cancellers have been suggested to suppress this interference. We propose an improved adaptive canceller for the reduction of the fundamental power line interference component and harmonics in electrocardiogram (ECG) recordings. The method tracks the amplitude, phase, and frequency of all the interference components for power line frequency deviations up to about 4 Hz for this purpose a real ECG signal is corrupted by an artificial power line Interference signal. The cleaned signal after applying all methods is compared with the original ECG signal. Our improved adaptive canceller shows a signal-to-power-line-interference ratio for the fundamental component up to 30 dB higher than that produced by the other methods. Moreover, our method is also effective for the suppression of the harmonics of the power line interference. To demonstrate power line interference (PLI) cancelation we have chosen A simulated 50 Hz sine wave. The input to the filter is ECG signal corresponds to the data corrupted.

B. Baseline Wander Reduction

The contaminated ECG signal is applied as primary input to the adaptive filter of Fig.3. The real BW is given as reference signal



.Figure 4. a) Pure ECG signal, b) ECG with PLI noise, c) Filtered output by RLS algorithm

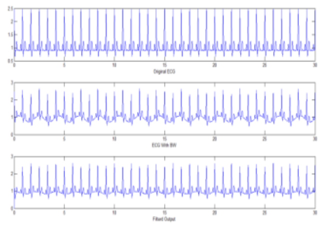


Figure 5. a) Pure ECG signal, b) ECG with BW noise, c) Filtered output by RLS algorithm

C Adaptive Cancelation of Muscle Artifacts

To show the filtering performance in the presence of non-stationary noise, muscle artifact (MA) was taken from the MIT-BIH Noise Stress Test Database.The EEG is frequently contaminated by electrophysiological potentials associated with muscle contraction due to biting, chewing and frowning. These muscle artifacts obscure the EEG and complicate the interpretation of the EEG or even make the interpretation unfeasible .Low-pass filters are commonly used to remove muscle artifact. However, as the frequency spectrum of the muscle artifacts overlap with that of interesting brain signals frequency. Filters not only suppress muscle artifacts but also valuable information.

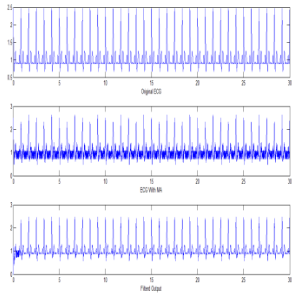


Figure 6. a) Pure ECG signal, b) ECG with MA noise, c) Filtered output by RLS algorithm

D. Adaptive Electrode Motion

To demonstrate this we use a self generated pure ECG signal with electrode motion artifact (EM) added, where EM is generated by taking the frequency greater than 15 Hz. The ECG signal contaminated with EM is given as input to the adaptive filter. The EM noise is given as reference signal. Output of the filter is the required high resolution ECG signal. Fig.7. shows these results.

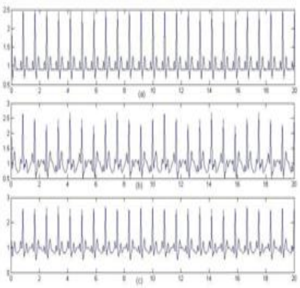


Figure 7. a) Pure ECG signal, b) ECG with EM noise, c) Filtered output by RLS algorithm.

7. 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.

Following table shows the result

Types of Noise	Algorithm	SNR before filtering (in dbs)	SNR after filtering (in dbs)	SNR improvement (in dbs)
PLI	RLS	17.81	26.94	9.13
BW	RLS	18.73	23.70	4.97
MA	RLS	18.73	22.77	4.04
EM	RLS	18.73	20.53	1.8

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