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CONTROL AND ESTIMATION OF BIOLOGICAL SIGNALS (ECG) USING ADAPTIVE SYSTEM

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Abstract: In this paper, we present a simple and efficient adaptive noise removal technique for de-noising the (ECG) signal. There are different techniques earlier used for de-noising the ECG signal ,adaptive filtration like least mean square (LMS), NLMS, BLMS , etc. In this paper we used recursive least square technique for adaptive filtration. The power line noises have been implemented according to their basic properties. After that, these noises have been mixed with ECG signal and nullify these noises using the LMS,NLMS and the RLS algorithms. Finally a performance study has been done between these algorithms based on their parameters and also discussed the effect of filter length and the corresponding signal to noise ratio. Results indicate that the noises cannot be handled by the LMS filtering whereas the RLS can handle these types of noises. Furthermore, most of the cases the RLS has achieved best effective noise cancellation performance although its computation time is slightly high. We are using the RLS Algorithm by matlab for simulation

Keywords: *Adaptive filtering, artifact , ECG signal, power line noise, LMS, NLMS and RLS algorithm, MATLAB etc.*

1. INTRODUCTION

The electrocardiogram (ECG) is the most commonly used for diagnosis of heart diseases. However, in real situations, ECG signals are corrupted by artifacts[1]. So the noise removal is a classical problem in ECG records, that generally produces artifactual data when measuring the ECG parameters. When the doctors are examining the patient on-line and want to review the ECG of the patient in real-time, there is a good chance that the ECG signal has been contaminated by baseline wander (BW), power line interference (PLI), muscle artifacts (MA) and electrode motion artifacts (EM) etc., mainly caused by patient breathing, movement, power line noise, bad electrodes and improper electrode site preparation. All these noises mask the tiny features of the ECG signal and leads to false diagnosis[1,3] . To allow doctors to view the best signal that can be obtained, we need to develop an adaptive filter to remove the artifacts in order to better obtain and interpret the ECG data. we discuss here about the power line interface. whether a person has heart disease, for example a cardiac arrhythmia[3]. In recording a heart beat (an ECG), which is being corrupted by a PLI (50Hz/60Hz) noise (the frequency coming from the power supply(50Hz) in many countries) [4]. We remove the noise is to filter the signal with a notch filter at 50 Hz. However, due to slight variations in the power supply to the hospital, the exact frequency of the power supply might (hypothetically) wander between 47 Hz and 53 Hz. A static filter would need to remove all the frequencies between 47 and 53 Hz, which could excessively degrade the quality of the ECG since the heart beat would also likely have frequency components in the rejected range. To circumvent this potential loss of information, an adaptive noise cancellation filter[2] has been used. The adaptive filter would take input both from the patient and from the power supply directly and would thus be able to track the actual frequency of the noise as it fluctuates. Such an adaptive technique generally allows for a filter with a smaller rejection range, which means, in our case, that the quality of the output signal is more accurate for medical diagnoses. The most commonly used structure in the implementation of adaptive filters is the transversal structure. In this case, the adaptive filter has a single input, x(n) and an output y(n) sequence d(n) is the desired signal. The output y(n) is generated as a linear combination of the delayed samples of the input sequence x(n), according to (1),

$$y(n) = \sum_{i=0}^{N} w_i(n)\, x(n-i) \qquad (1)$$

where N is the filter length, $w_i(n)$ are the filter tap weights (coefficients) that vary in time and are controlled by the adaptation algorithm, $x(n_i)$ for i=0,1,….,N-1 are the input samples being referred to as filter tap inputs.The Least Mean Squares (LMS) algorithm and the Recursive Least Squares (RLS) algorithm are used in adaptive filters to find the filter coefficients that relate to producing the least mean squares of the error signal (difference between the desired and the actual signal).The LMS and the RLS adaptive filter written with use of MATLAB functions designed to remove the contaminating signal, as shown in Fig. 1. The ECG signal, S_1 is the original uncontaminated input signal of program. The desired output is the contaminated ECG signal $d=(s_1+n_1)$. The Adaptive Filter will do its best to reproduce this contaminated signal but it only knows about the original 50 Hz noise source, n_1. Thus, it can only reproduce the part of d that is linearly correlated with n_1 , so that the output of the filter y will be close to the contaminating noise . In this way the error *e* will be close to the original uncontaminated ECG signal s_1. We call (s_1+n_1) the primary input and *y* is be the reference signal. Since the Adaptive Filter output is *y* and the error is *e*, then the mean square error (MSE) is (3). Fig. 1 shows an adaptive filter with a primary input that is an ECG signal s_1 with additive noise n_1. While the reference input is noise n_2, possibly recorded from another generator of noise n_2 that is correlated in some way with n_1. If the filter output is y and the filter error

$e = (s_1 + n_1) - y$, then $e^2 = (s_1+ n_1)^2 - 2y(s_1 + n_1) + y^2$

$= (n_1 - y)^2 + s_1^2 + 2s_1 n_1 - 2ys_1$ -------------- (2)

Since the signal and noise are uncorrelated, the mean-squared error (MSE) is

$E[e^2] = E[(n_1 - y)^2] + E[s_1^2]$ ------------------(3)

Minimizing the MSE results in a filter error output that is the best least-squares estimate of the signal s_1. The adaptive filter extracts the signal, or eliminates the noise, by iteratively minimizing the MSE between the primary and the reference inputs.

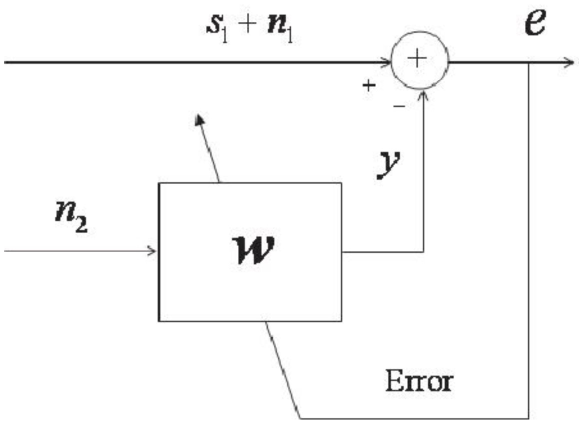

Figure: 1 Adaptive filter structure (the reference input is noise n_2 correlated with noise n_1 , the desired signal appears at e.)

block diagram of adaptive noise canceller is shown in figure 2 . error, $e_k = d_k - y_k$ (4)

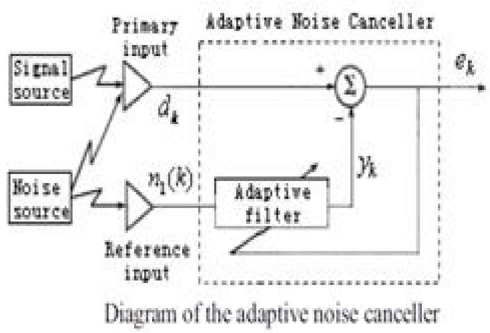

Figure 2 adaptive noise canceller

2. ADAPTIVE FILTERING ALGORITHMS

2.1 LMS Algorithm

The **Least Mean Square** (LMS) algorithm, introduced by Widrow and Hoff in 1959 [3] is an adaptive algorithm, which uses a gradient-based method of steepest decent [2]. LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. Compared to other algorithms LMS algorithm is relatively simple; it does not require correlation function calculation nor does it require matrix inversions. With each iteration of the LMS algorithm, the filter tap weights of the adaptive filter are updated according to the following formula. .

$W(n+1)=w(n)+2\mu e(n)x(n)$……. (5)

Here x(n) is the input vector of time delayed input values, x(n) = [x(n) x(n-1) x(n-2) .. x(n-N+1)]T. The vector w(n) = [w0(n) w1(n) w2(n) .. wN-1(n)]T represents the coefficients of the adaptive FIR filter tap weight vector at time.

2.2 NLMS Algorithm

One of the primary disadvantages of the LMS algorithm is having a fixed step size parameter for every iteration. This requires an understanding of the statistics of the input signal prior to commencing the adaptive filtering operation. In practice this is rarely achievable. Even if we assume the only signal to be input to the adaptive noise cancellation system is speech, there are still many factors such as signal input power and amplitude which will affect its performance. The normalised least mean square algorithm (NLMS) is an extension of the LMS algorithm which bypasses this issue by calculating maximum step size value. Step size value is calculated by using the following formula. Step size=1/dot product (input vector, input vector) (6) This step size is proportional to the inverse of the total expected energy of the instantaneous values of the coefficients of the input vector x(n). This sum of the expected energies of the input samples is also equivalent to the dot product of the input vector with itself, and the trace of input vectors auto-correlation matrix.

tr(R)= = …(7)

The recursion formula for the NLMS algorithm is stated in equation .

W(n+1)=w(n)+——— ……………(8)

algorithm alone, or in combination with a least squares type of method. This allows our fuzzy systems to learn from the data they are modeling.

2.3 RLS Algorithm

There are two main classes of adaptive filtering algorithms LMS and RLS algorithms [5] the RLS algorithms aims at minimizing the weights least error

$$J_{LS} = \sum_{i=0}^{k} \lambda^{k-i} \left|e(k)\right|^2 = \sum_{i=0}^{k} \lambda^{k-i} \left|d_k - \underline{w}_k^T \underline{x}_k\right|^2$$

where $0<\lambda\leq 1$is the exponential forgetting factor. the RLS algorithm operates in three steps at each recursion[5]

$$\pi_k = \frac{P_{k-1}\underline{x}_k}{\lambda + \underline{x}_k^T P_{k-1}\underline{x}_k}$$

$$\underline{w}_k = \underline{w}_{k-1} + \pi_k(d_k - \underline{w}_{k-1}^T \underline{x}_k)$$

$$P_k = \lambda^{-1}P_{k-1} - \lambda^{-1}\pi_k x_k^T P_{k-1}$$

with $P_0=\rho^{-1}I$, where ρ is a small positive constant.

3. NOISE CANCELLATION

Noise in ECG recordings is contributed both by biologic and environmental sources. Examples one of the environmental noise are 60Hz or 50Hz(in our country) and its harmonics generated by power lines, radio-frequency and electrosurgical noise, and instrumentation noise [7]. Examples of biologic interference are: baseline drift and wander,and motion artifact [8]. The aim of this paper is to remove the power line noise from the ECG.

3.1 Power-line Interference(50/60 Hz) Removal

Power-line interference is a most common source of noise during ECG recording. Adaptive filtering can track the statistical nature of the noise by updating filter coefficients and finally eliminates the noise. To demonstrate power line interference cancelation we have chosen ECG data of 1072 samples from data base . The input to the filter is original ECG signal and is corrupted with synthetic PLI of amplitude of frequency 50Hz, of 1072 samples. The synthesized PLI is given as reference. These results are shown in Fig.3.

4. EXPERIMENTAL WORK

We generate noise signals due to power line interface of 50Hz for 1072 samples of data has been taken the signal having strength 3.0257db.

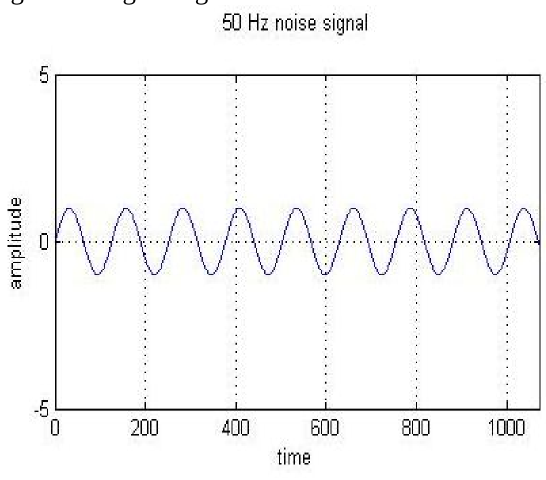

Figure3: 50 Hz noise signal

The ECG signal taken from MITBIH data base[9] of 1072 samples taken with strength of signal is 8.0519 db shown in figure 4.

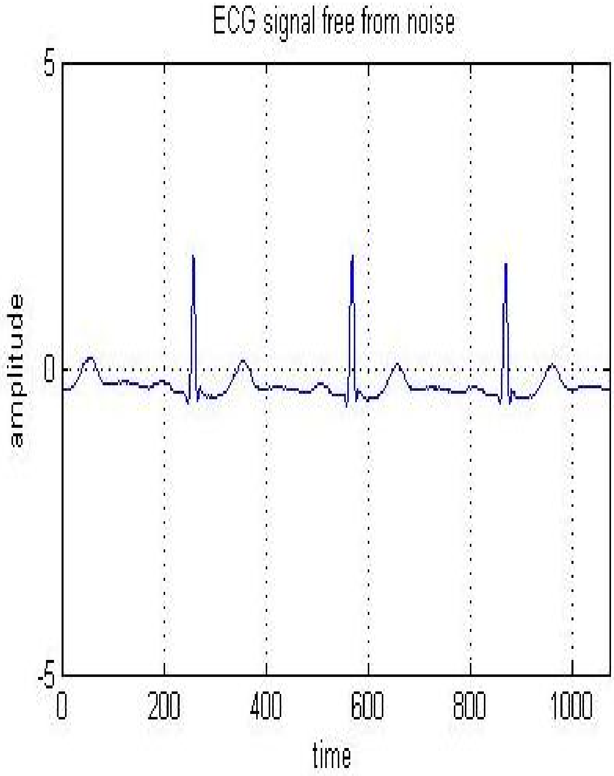

Figure 4 : Original ECG signal

The ECG signal mixed with power line interference (50 Hz) noise (desired signal = ECG signal + noise) is shown in figure 5.

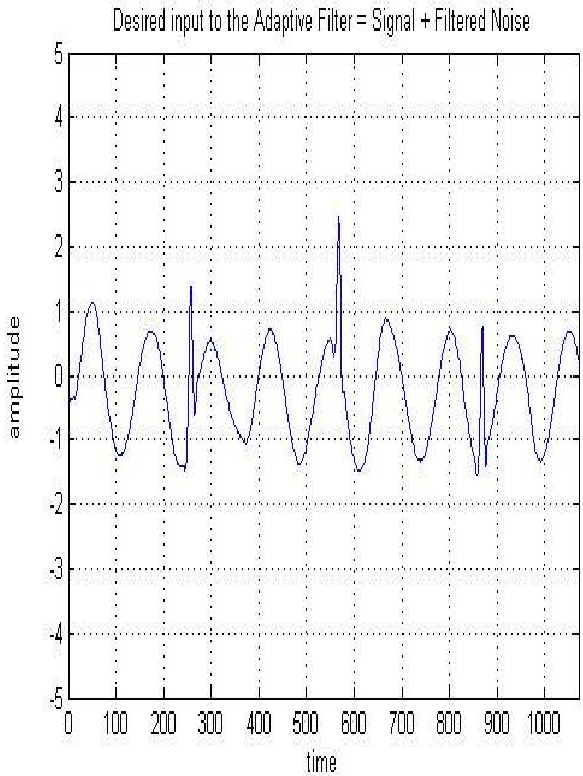

Figure5: ECG signal with 50Hz noise

The output after the filtering by RLS algorithm is shown in figure 6.

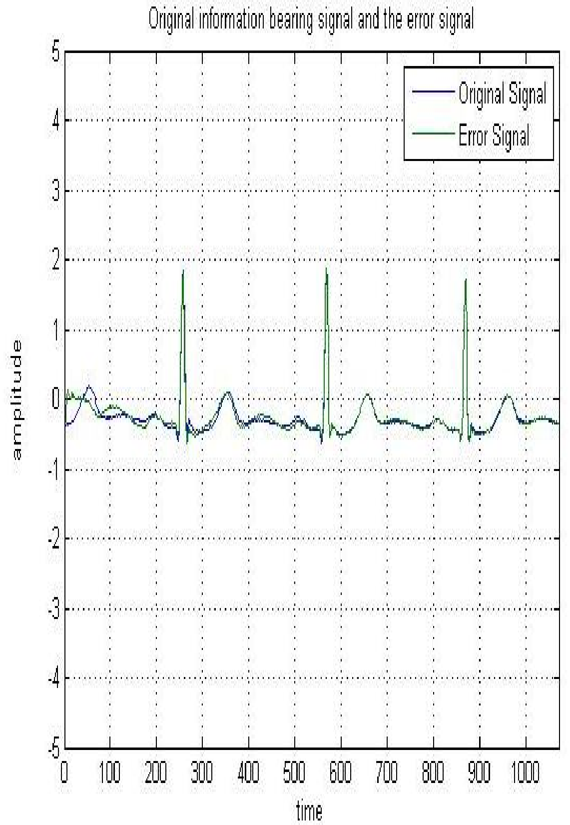

Figure 6:recovered ecg siganl with error .

the recovered ECG signal (actual output) after the RLS filter noise cancellation . shown in figure 7

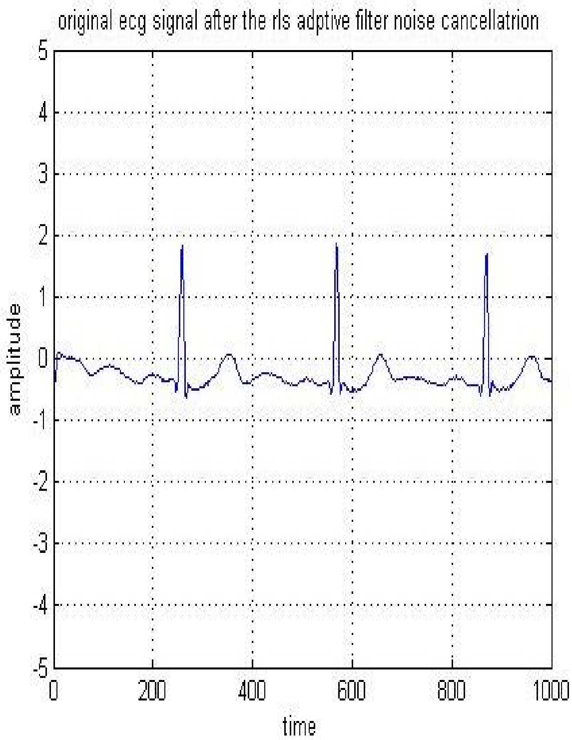

Figure 7: recovered ECG signal

Figure 8, shows the spectra for the original ECG signal of 1000 samples and the filtered ECG processing by the different adaptive filtering approach ,LMS and NLMS of the adaptive noise cancellation for PLI . the parameters are filter length and the step size,

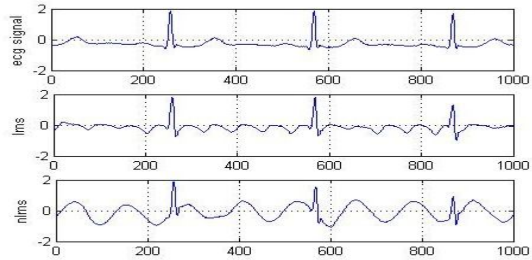

Figure 8. Typical filtering results of PLI Cancelation (a) clean MIT-BIH record 100, (b) recovered signal using LMS algorithm,(c) recovered signal using NLMS algorithm.

For different types of adaptive filter algorithm the minimum square error for LMS, NLMS and RLS system. The mean square error for the processes for the 50 Hz noise shown in table1

Added noise (power line interference)	**LMS (db) Rms error**	**NLMS (db) Rms error**	**RLS (db) Rms error**
50 Hz noise	9.9768	5.5509	8.1084

Table 1

By using the formula for signal to noise ratio we got set of result for the different types of adaptive algorithm for the 50 Hz noise (power line interference) . we observed the input signal to ratio means the original ECG and the noise is 5.0262db and the corresponding output signal to noise ratio after he RLS algorithm is 5.0827db

SNR= —— the improvement in SNR .shown in table 2

Added noise (power line interference)	**LMS (db)**	**NLMS (db)**	**RLS (db)**
50 Hz noise for input SNR	4.9505	4.9505	5.0262
50 Hz noise for output SNR(AFTER FILTERING)	6.9881	2.5622	5.0287

Table 2

the computation time for different filter algorithms where the filter length is varied shown in table 3

5. CONCLUSION AND FUTURE WORK

This study has revealed useful properties of the LMS and the RLS algorithms in case of adaptive noise cancellation. It has been found that the RLS algorithm generally performs better irrespective of the nature of the signal and the noise. The RLS is particularly useful in the case of signals where abrupt changes of amplitude or frequency may occur such as

DC noises. But this better-quality performance comes at a price: The RLS takes more time to compute, especially when the filter length is large. But change in filter length doesn't have too much effect on the convergence behaviour of the RLS. For the LMS, this increase is quite substantial. In the end, it can be stated that the RLS algorithm should be preferred over the LMS for adaptive noise cancellation unless the computation time is a matter of great concern. More tests will be conducted to further investigate its performance in the future.

Filter length	**LMS filter**	**NLMS filter**	**RLS filter**
10	0.0195	0.0256	0.0355
20	0.0192	0.0254	0.0374
30	0.0191	0.0264	0.0423
40	0.0199	0.0265	0.0435
50	0.0197	0.0263	0.0473
60	0.0198	0.0263	0.0536

Table 3. *Comparision table of the computation time of LMS,NLMS, RLS algorithm for(POWER LINE INTERFERENCE) where the filter length is varied.*

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