DE - NOISING ECG SIGNALS USING ADAPTIVE FILTERING ALGORITHMS

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Abstract: The electrocardiogram is the recording of the electrical potential of heart versus time. The analysis of ECG signal has great importance in the detection of cardiac abnormalities. The electrocardiographic signals are often contaminated by noise from diverse sources. These noises can be classified according to their frequency content. It is essential to reduce these disturbances in ECG signal to improve accuracy and reliability. Different types of adaptive and non-adaptive digital filters have been proposed to remove these noises. In this paper, LMS, NLMS, and RLS algorithm are used for de-noising the ECG signals, Results of simulations in MATLAB are presented. Also, the Performances of the filters are compared based on the SNR values, complexity and mean square error.

Keywords: **ECG Signal, Adaptive Filter, SNR.**

I. INTRODUCTION

The ECG signal is extremely important for the diagnosis of the cardiac patients. Studies show that ECG signals are probably deterministic chaotic process [1, 2, 3]. It is also a non-invasive test that records the electrical activity of the heart over time and it is very useful in determining whether a person has heart disease, for example a cardiac arrhythmia[4,5].. However, when the ECG signal is recorded, it may be corrupted by various kinds of noises, such as, power line interference, base line wandering, electrode contact noise, motion artifacts, muscle contraction, instrumentation noise generated by electronic devices and electrosurgical noise, etc [6]. During the diagnosis of arrhythmia or myocardial infarction, the 50 Hz power line noise can affect the ECG signal. The frequency range of ECG signal is generally 0.05 Hz to 100 Hz, and, that of the power line interference is 50 Hz which lies in the ECG signal band. So, it has become very crucial to remove the power line interference from the ECG signal. [1] Different types of digital filters (FIR and IIR) have been used to solve the problem. However, it is difficult to apply filters with fixed filter coefficients to reduce the instrumentation noise, because the time varying behavior of this noise is not exactly known. Adaptive filter technique is required to overcome this problem, as the filter coefficients can be varied to track the dynamic variations of the signals. In this study, we have used Adaptive filtering techniques such as LMS, NLMS and RLS to remove the artifacts of an ECG signal.

II. ECG SIGNAL ADAPTIVE FILTERING METHOD

Adaptive filter is an algorithm that attempts to model the relationship between two signals in an iterative manner. An adaptive filter is defined by four aspects: the signals being processed, the structure that defines the input /output relation, the parameter, which can be iteratively varied to alter the filter's input /output relationship, and the adaptive algorithm, which describes how the parameters are adjusted [7,8]. Here, signals are the pair of input and reference signals, and structure is used for implementing digital filter (finite or infinite impulse response FIR or IIR filter). While parameters regulate input to output mapping or computational relationship according to requirement of the designer, and adaptive algorithms act as a set of rules defined to update the filter coefficients in successive iterations, and have closed relation with the parameters [7,8].
Adaptive filtering involves the change of filter coefficients over time. It adapts to the change in signal characteristics in order to minimize the error [9] Fig. 1 shows the general structure of an adaptive filter.

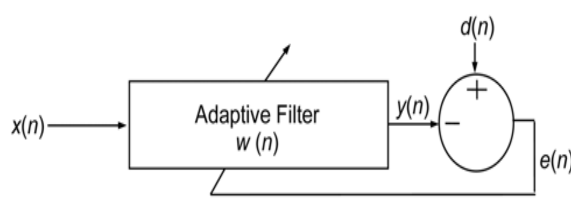


Fig. 1. Adaptive filter structure

Here, x (n) is the input signal, and d (n) is the reference signal or the desired output signal (some noise component are present in it). While y (n) is the output signal, and the error signal is computed by

$$e(n) = d(n) - y(n) \quad (1)$$

Adaptive algorithm exploits the error signal produced at every instant to update the adaptive filter coefficient vector w (n) in each successive iteration with the help of performance criterion. Commonly, the adaptation process tries to minimize the cost function of the error signal, and aspires to approximate the output signal as reference signal in a statistical sense.

This basic structure is modified according to several practical applications such as system identification, noise cancellation, channel equalization, and signal prediction .In this work, a noise cancelling structure is used with to filter ECG[9]. The concept that modifies the adaptive filter as adaptive noise canceller is shown in Fig. In Fig. 2, s (n) is a signal of interest, which is corrupted by a noise component q (n), and pure version of s (n) is desired signal, but cannot be obtained directly in practice. Then, the noisy signal s(n) + q(n) is employed as a reference signal for the adaptive filter whose input must be correlated version of q(n), is represented as q'(n). Adaptive algorithm adjusts the filter weights w(n) such that the filter input signal q'(n) is translated as output signal y(n), which is close estimation of q(n), if y(n) is equivalent to q(n). Then, the error signal e (n) is equivalent to s (n) in the form of s' (n) [9].

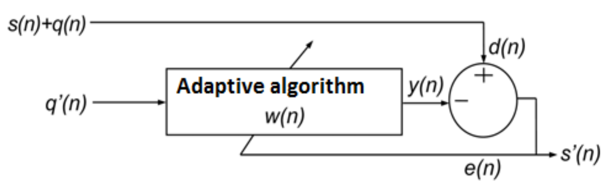


Fig. 2. Structure of Adaptive Noise Caneller

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 the use of **MATLAB** functions designed to remove the contaminating signal.

a. LMS algorithm

It is a stochastic gradient descent method in which the filter weights are only adapted based on the error at the current time [10]. According to this LMS algorithm the updated weight is given by

$$W(n+1) = W(n) + 2.\mu\, x(n).e(n) \qquad (2)$$

where μ is the step size or the convergence factor.[10]

a. NLMS algorithm

The NLMS algorithm is a modified form of the standard LMS algorithm. The NLMS algorithm [10] updates the coefficients of an adaptive filter by using the following equation

$$W(n+1) = W(n) + 2.\mu \frac{x(n)}{\|x(n)\|^2}.e(n) \qquad (3)$$

Equation (3) can be written as

$$W(n+1) = W(n) + 2.\mu(n).x(n).e(n) \qquad (4)$$

where,

$$\mu(n) = \frac{\mu}{\|x(n)\|^2}$$

The NLMS algorithm has a time-varying step size $\mu(n)$. This step size improves the convergence speed of the adaptive filter.

b. RLS Algorithm

The Recursive Least Squares (RLS) algorithm is an adaptive solution to the method of least square. Moreover, this algorithm converges in the mean to the optimal solution. The main difference between the RLS algorithm and the LMS and is that the step- size parameter in LMS is replaced with the inverse of the correlation matrix of the input vector u (n) [11]. This modification has an excellent impact on the convergence behavior of the RLS algorithm. The RLS algorithm can be written as

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mathbf{g}(n)e(n), \qquad (5)$$

where the updating gain vector is defined as

$$\mathbf{g}(n) = \frac{\mathbf{r}(n)}{1 + \mathbf{u}^T(n)\mathbf{r}(n)}$$

and

$$\mathbf{r}(n) = \lambda^{-1}\mathbf{P}(n-1)\mathbf{u}(n) \qquad (6)$$

III. RESULTS AND DISCUSSIONS

The LMS filtered output is shown in fig. 4, the mean square error generated as per adaption of filter is shown in fig., the step size μ controls the performance of the algorithm. If the μ is too small, the convergence speed

is too fast bur filtering is not proper, if μ is too small the filter gives slow response.
Hence the selection of proper step size is very essential for good response of the algorithm.

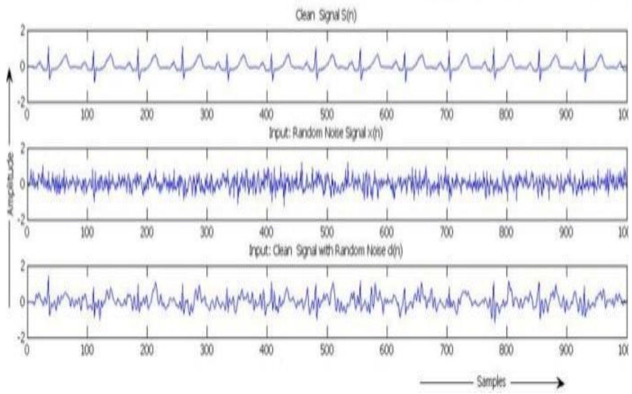


Fig. 3. Input clean signal (a), random noisy signal (b) input and noisy signal (c)

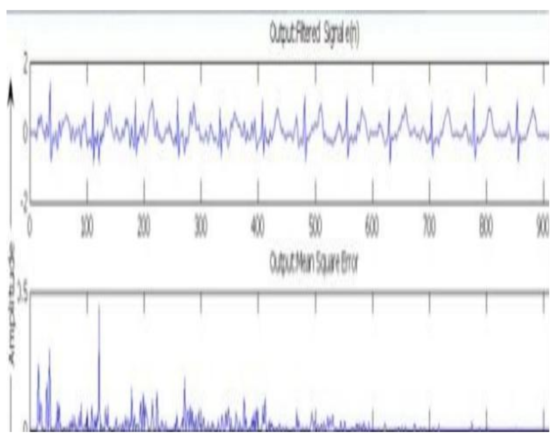


Fig. 4. Matlab simulation for LMS, N=19, step size=0.009

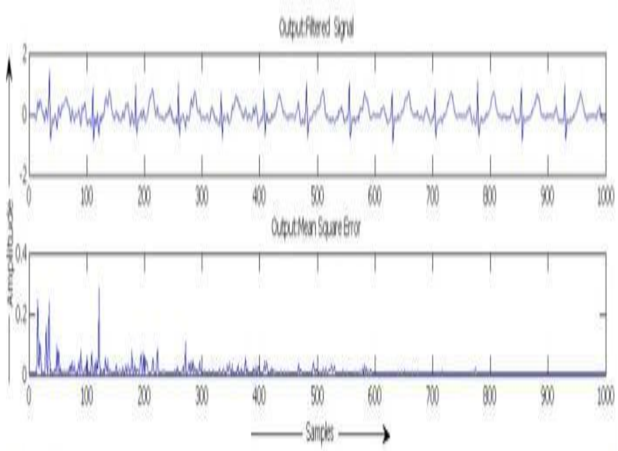


Figure 5 Matlab simulation for NLMS, N=19, c =0.001,alpha=0.07

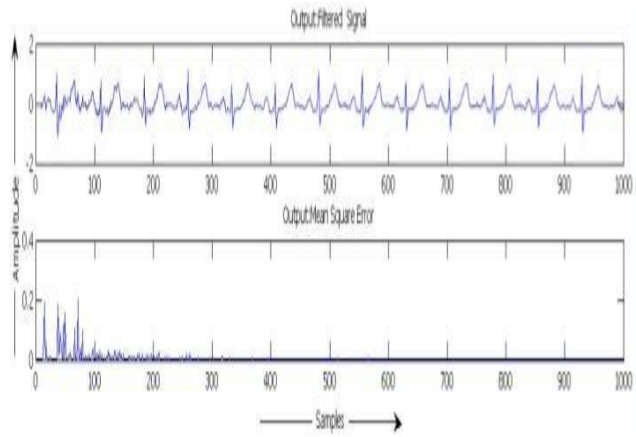


Fig. 6. Matlab simulation for RLS,N=19.

Fig.5 and fig.6 shows the simulation results of NLMS and RLS respectively. If we investigate the filtered output of all the three algorithms, LMS adopt the approximate correct output in 740 samples, NLMS adopt in 620 samples, and RLS adopt in 255 samples. This shows that RLS has the fastest learning rate.

Table 1, shows the performance of all the three algorithms used in terms of SNR, in which RLS have better results than the other two. However RLS gives the results at the cost of computational complexity and it is also less stable than the other too. Table 2 shows the comparison in terms of complexity, MSE and stability.

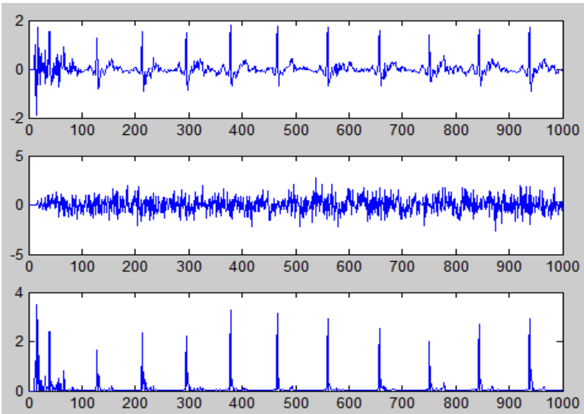
S.No	Algorithm	SNR Pre	SNR Post	SNR Improved
1	LMS	0.89	6.97	6.08
2	NLMS	0.89	9.09	8.2
3	RLS	0.89	10.21	9.32

Table 1- SNR comparison of various Adaptive Filters (N=19)

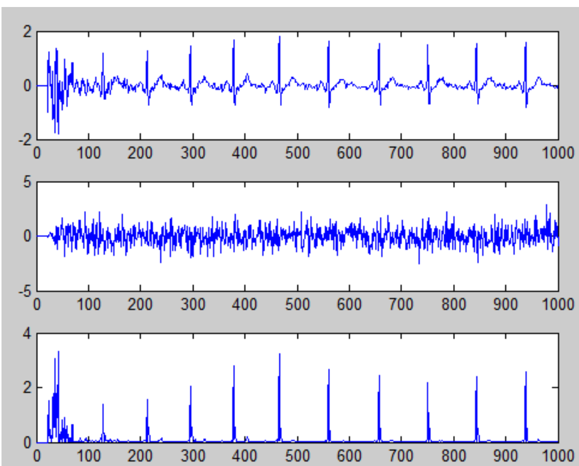
S.No	Algorithm	MSE	Complexity	Stability
1	LMS	1.5×10^{-2}	2N+1	Highly stable
2	NLMS	9.0×10^{-3}	3N+1	Stable
3	RLS	6.2×10^{-3}	$4N^2$	Less Stable

Table 2-Results analysis in terms of MSE, complexity and stability

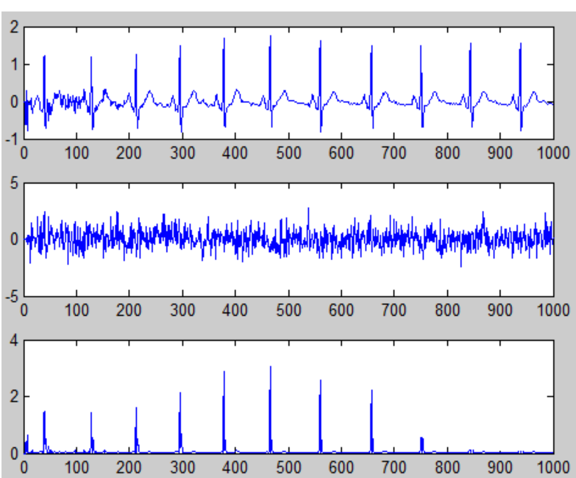
However, the comparison shown above is for the filter order 19. Performance of the algorithms may be improved for higher or lower order of the filter Fig.7



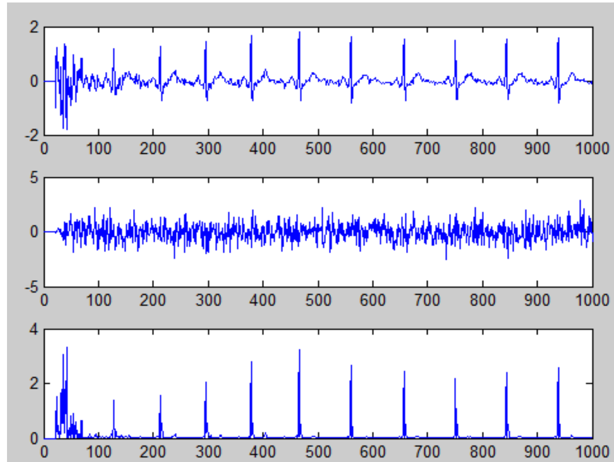
LMS, N=11, snr=7.832



NLMS, N=11, alpha=0.07, snr=8.698

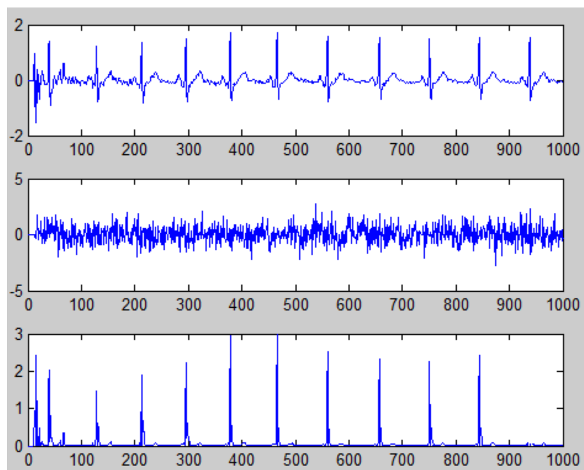


RLS, N=11, snr=9.89

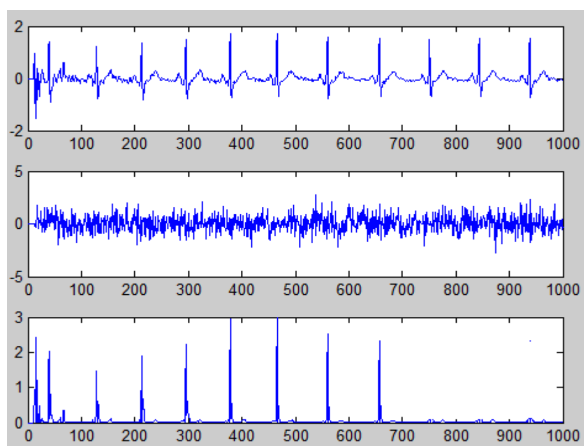


LMS, N=22, snr=8.845

Fig.7 Variation in SNRs: output filtered ECG signal, estimated error signal, and the learning rate



NLMS, N=22, alpha=0.07, snr=7.218



RLS, N=22, snr=6.445

Shows the variations in the output filtered signal for the filter order 11 and 22

IV. CONCLUSION

In NLMS based adaptive filter, the step size is greater than LMS algorithm and hence the convergence is faster. NLMS based adaptive filter offers better performance than the LMS counterpart. The computational complexity of NLMS is slightly higher. In all the sign LMS algorithms, the computation is faster because these algorithms does not involve multiplication when error *e(n)* or input *x(n)* or both are zero. But the major drawback is that the weight update mechanism is degraded compared to LMS algorithm. Increase in steady state error and decrease in the convergence rate are other minor drawbacks. So, NLMS algorithm is preferred when better performance is required.

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