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Adaptive Noise Cancellers using LMF Algorithm for Enhancing the EEG Signal

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***Abstract*— An adaptive filter is a system with a linear filter that has a transfer function controlled by variable parameters and a means to adjust those parameters according to an optimization algorithm. This adaptive filter is also used for enhancing the signals, because the adaptive filter does not need the filter characteristics, in this paper we present the adaptive noise cancellers using the LMF algorithm for enhancing the EEG signal. This LMF algorithm was proposed by walach and widrow in 1984. The LMF algorithm can be used in several applications such as channel equalization with co-channel interference, removing the noise components from the signals and it can also be used in sensor signals. The convergence speed of the LMF algorithm is based on the step size. This algorithm improves the stability of the mean fourth cost function and achieves a faster convergence for signals with additive white Gaussian noise (AWGN). This LMF algorithm is not a mean square stable when the input regress or is Gaussian-distributed. The LMF algorithm exhibits lower steady state error than the conventional least mean square (LMS) algorithm. These are various types of mean fourth based algorithms are implemented. These are normalized (NLMF) and error normalized LMF(ELNMF) and their block based versions are BBNLMF and BBENLMF. In this paper the LMF algorithm is applied on real EEG signals obtained from the MIT-BIH data base.**

Keywords*— *Adaptive noise cancelation, artifacts, EEG signals, LMS, LMF

I. INTRODUCTION

Electroencephalography (EEG) is the recording of electrical activity along the scalp. This EEG measures the voltage fluctuations resulting from the ionic current flows with in the neurons of the brain. In clinical contexts, EEG measure the recoding of the brains spontaneous electrical activity over a short period of time, usually 20 to 40 minutes, as recorded from multiple electrodes placed on the scalp. This EEG signal is an important tool used for diagnosis of brain abnormalities such as coma, encephalopathy, brain death, studies of sleep and sleep disorders, stroke and other focal brain disorders. In clinical environment during acquisition, the EEG signal affected by various types of artifacts. The predominant artifacts present in the EEG includes power line interference, baseline wander. These artifacts strongly degrades the signal quality, frequency resolution and produces a large amplitude signals in the EEG. So, that the cancelation of these artifacts in EEG signals is an important task for better diagnosis to separate a valid signal components from the undesired artifacts by using adaptive noise cancellers. These adaptive noise cancellers can be designed by using adaptive systems and its algorithms. These adaptive systems are a automatic systems whose structure is changeable or adjustable in such a way that its behavior or performance improves through contact with its environment. The word adaptive in the name itself represents a self adjustment. The simple example of this automatic adaptive system is the automatic gain controller which is used in radio and television receivers. The function of this circuit is to adjust the sensitivity of the receivers inversely as the average incoming signal strength. Characteristics of the adaptive systems are it can be automatically adapt in the face of changing environments and changing system requirements. The adaptive system does not require the signal statistical characteristics because they tend to be a self-designing. The essential and principal property of the adaptive system is a time varying and self adjusting performance. The general structure of the closed loop adaptive system is as shown below:

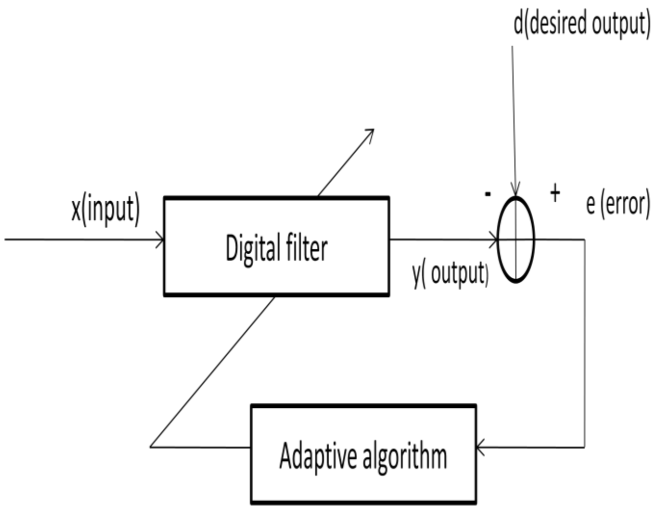

Fig. 1 General Adaptive Filter Structure

In the above figure 'X' is called the input signal and 'd' is called the desired response signal, which is assumed to represent the desired output of the adaptive system. The signal'd' is, for our purpose here, the error signal, 'e' is the difference between the desired output signal and the actual output signal, 'y' of the adaptive system, using this error signal, an adaptive algorithm adjusts the structure of the adaptive system, thus changing its response characteristics in order to minimizing some measure of the error, there by closing the performance loop. Here the adaptive algorithm is used for adjusting the structures of the adaptive system. There are various types of adaptive algorithms are implemented for this adaptive systems. Some of the algorithms had been developed for these adaptive systems such as Newton's method, steepest descent algorithm and LMS algorithm.

II. EXISTING ALGORITHMS

A. Newton's Method

It is a method of gradient search that causes all components of the weight vector to be changed at each step in the search procedure for each iteration cycle. The changes are always in the direction of the minimum of the performance surface, provided that the surface is quadratic. In this method, the process converges in one step with quadratic function 'ε' is called Newton's method. Newton's method is primarily a method for finding the zeros of a function i.e..,

$$f(w)=0$$

The discrete form of Newton's method may be expressed as

$$w_{k+1}=w_k-\frac{f(w_k)(w_k-w_{k-1})}{f(w_k)-f(w_{k-1})}.$$

This method starts with initial guess and it almost goes to the optimum at W*=0.448, after only four iterations.

B. Steepest descent Algorithm

The steepest descent algorithm proceeds always in the direction of the gradient of the performance. The general form of the algorithm was given as

$$w_{k+1}=w_k+\mu(-\nabla_k)$$

Where 'μ' is a constant that regulates the step size and has dimensions of reciprocal signal power. The alternative (or) solved version of the steepest algorithm is given as

$$w_k=w*+(I-2\mu R)^k(w_\circ-w^*)$$

This algorithm was seen to be stable if the condition

$0<\mu<\dfrac{1}{\lambda_{\max}}$ is met.

This algorithm is generally too fast and not really desirable. This algorithm convergence in one step is a source of satisfaction to a numerical analyst who would like to minimize the number of iterations necessary to accomplish a surface search.

C. LMS Algoithm

The above two algorithms is used for quadratic performance surface curve. Suppose, if the performance surface curve is not quadratic the above two algorithms are not applicable. To overcome this disadvantage we go for the LMS algorithm. The LMS algorithm is more restricted in its use than the Newton's method algorithm & the steepest descent method algorithm. This LMS algorithm uses a special estimate of the gradient that is valid for the adaptive linear combiner. On the other hand, the LMS algorithm is important because of its simplicity and ease of computation and it does not require the repetitions of data. If the adaptive system is an adaptive linear combiner and if the input vector x_k and the desired response d_k are available at each iteration the updated weighted vector of the LMS algorithm is as shown below

$$\begin{aligned} w_{k+1} &= w_k-\mu\hat{\nabla}_k \\ &= w_k+2\mu\varepsilon_k x_k \end{aligned}$$

Where 'μ' is the gain constant that regulates the speed and stability of adaptation. These weights can be changed at each iteration are based on imperfect gradient estimates. This LMS algorithm is generally good choice for many different applications of adaptive signal processing. It adjusts the filter coefficients to minimize the cost function. This algorithm cannot produce the sufficient steady state error for the signals

III. PROPOSED LMF ALGORITHM

The proposed algorithm presented in this paper is LMF algorithm. The least mean fourth algorithm was proposed by walach and widow almost 20 years ago. This algorithm is alternative to the least mean square(LMS) algorithm.
Consider a time-invariant adaptive system identification structure is as shown below

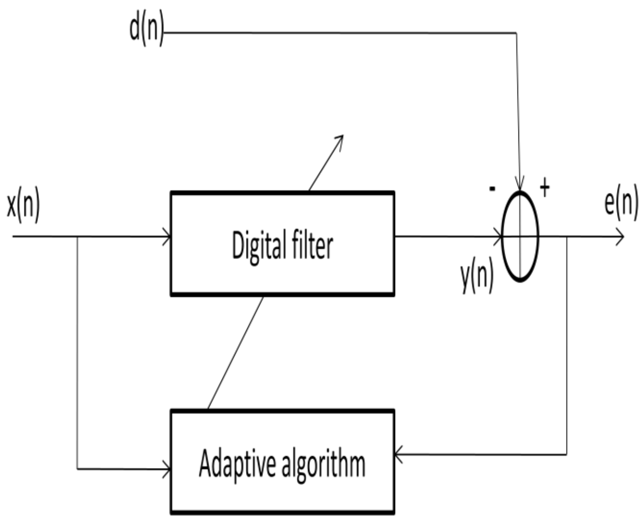

FIG 2. Adaptive Filter using LMF Algorithm

Where $x(n)$ is the input vector,

$$x(n)=[x(n),x(n-1),........x(n-N+1)]^T$$

$d(n)$ is the desired response signal

$$d(n)=x^T(n)w^*(n)+e(n)$$

$w(n)$ is the adaptive filter weight vectors, $w(n)=[w(n),w(n-1),......,w(n-N+1)]^T$,
Where 'T' represents the transpose of a vector and 'N' is the filter order and $w^*(n)$ is the unknown FIR filter weights.
The error signal from Fig.2 can be represented as $e(n)=d(n)-y(n)$
Where

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

To develop the LMF algorithm, first we have to take the derivate of the $[e(n)]^{2k}$ and it can be represented as

$$\nabla_k=-2k[e(n)]^{2k-1}x(n)\text{..........} \qquad (1)$$

Since,

$$\begin{bmatrix} e(n)=d(n)-y(n), \\ e(n)=d(n)-x^T(n)w^*(n) \end{bmatrix}$$

Now, consider the updated tap weight vector from the steepest descent algorithm is

$$w(n+1)=w(n)-\mu(\nabla_k)\text{...........} \quad (2)$$

Substitute equation (1) in to equation (2) we get the equation as follows

Therefore,

$$w(n+1)=w(n)+2\mu k[e(n)]^{2k-1}x(n)\text{......} \qquad (3)$$

For the choice of k=2, the updated tap weight vector of the LMF algorithm becomes as

$$w(n+1)=w(n)+2\mu 2[e(n)]^{2(2)-1}x(n)\text{...} \quad (4)$$

$$w(n+1)=w(n)+4\mu e^3(n)x(n)\text{..........} \qquad (5)$$

Where 'μ' represents the rate of convergence and control-stability.
Therefore, the LMF algorithm produces 3dB less weight noise due to adaptively than the conventional LMS algorithm, the adaptation constant 'μ' for the LMS algorithm is to be chosen as 9×10^{-4} and the adaptation constant 'μ' for the LMF algorithm is to be chosen as 1.5×10^{-6}.
Therefore, the LMF algorithm is expected to outperform the LMS algorithm by almost 6 dB in this case.

IV. SIMULATION RESLUTS

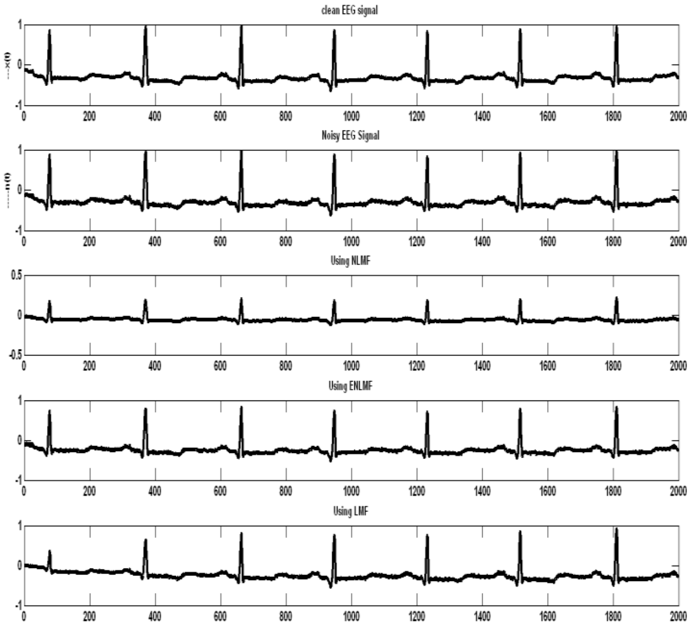

FIG 3. Typical filtering results of noise Cancelation (a) EEG (record 105) with noise, (b) recovered signal using NLMF algorithm, (c) recovered signal using ENLMF algorithm, (d) recovered signal using LMF algorithm.

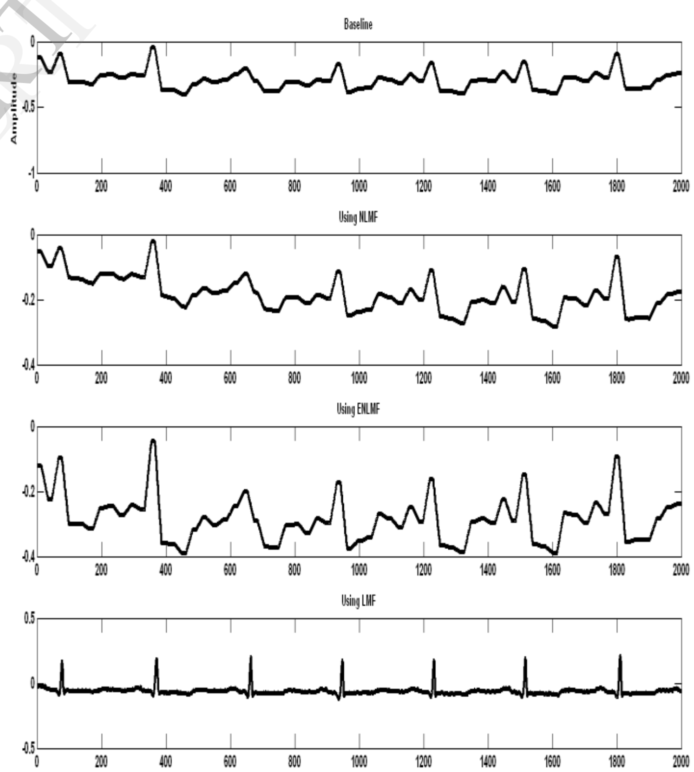

FIG 4. Typical filtering results of BW Cancelation (a) EEG (record 105) with BW noise, (b) recovered signal using NLMF algorithm, (c) recovered signal using ENLMF algorithm, (d) recovered signal using LMF algorithm.

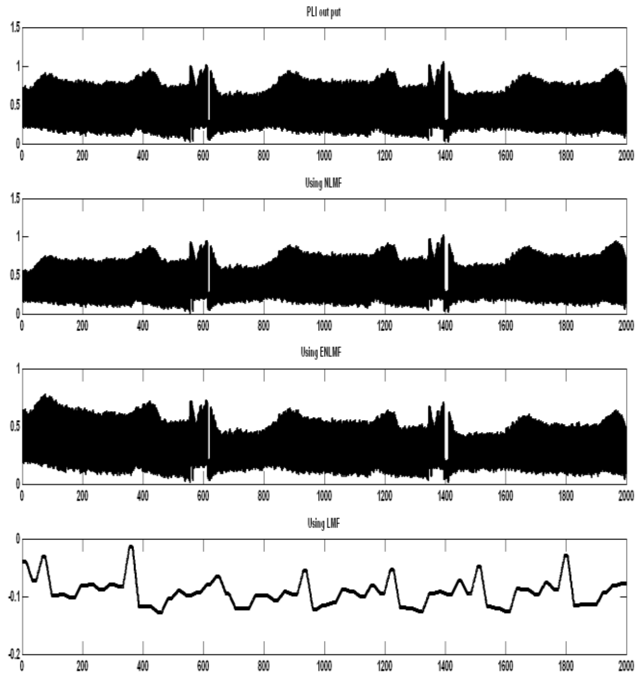

FIG 5. Typical filtering results of PLI Cancelation (a) EEG (record 105) with 60Hz noise, (b) recovered signal using NLMF algorithm, (c) recovered signal using ENLMF algorithm, (d) recovered signal using LMF algorithm

V. CONCLUSION

Therefore, the LMF algorithm produces 3dB less weight noise due to adaptively than the conventional LMS algorithm and the LMF algorithm is expected to outperform the LMS algorithm by almost 6 dB in this case. This algorithm improves the stability of the mean fourth cost function and achieves a faster convergence for signals with additive white Gaussian noise (AWGN). This LMF algorithm is not a mean square stable when the inputs regress or is Gaussian-distributed.

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