Noise Cancellation of Ocular and Muscular Artifacts from EEG Signals Based on Adaptive Filtering

G. Geetha and S. N. Geethalakshmi

***Abstract*—The Electroencephalogram (EEG) is a useful tool for clinical diagnosis. Artifacts in EEG records are caused by various factors like line interference, Electro-oculogram (EOG), Electro-Cardiogram ECG, Electromyogram EMG. These noise sources increase the difficulty in analyzing the EEG and for obtaining proper clinical information. Regression based methods for removing various artifacts require various procedures for preprocessing and calibration that are inconvenient and time consuming. Independent Component Analysis (ICA) [1] method requires off-line processing of data collected from a sufficiently larger number of channels and its success depends on correct identification of noise components. When application requires real-time removal of artifacts or when calibration trials cannot be conducted owing to various constraints, this method becomes unsuitable. This paper describes a method of removing EOG and EMG artifacts from EEG based on adaptive filtering using RLS algorithm.**

***Index Terms*—Adaptive filtering, Artifacts, EEG, EOG, EMG.**

I. Introduction

Eye Movement, Muscle noise, heart signals, and Line interference produce large and distracting artifacts in electroencephalographic (EEG) recordings. Fixing the target may reduce voluntary eye movement (EOG) [3] and facial muscle movement (EMG) in case of cooperative subjects during brief EEG recording sessions, but fixation does not eliminate involuntary eye movements .Due to the presence of artifacts, it is difficult to analyze the EEG, for they introduce the spikes which should be attenuated from EEG to ensure a correct analysis and diagnosis. In this work, adaptive filters are proposed to remove EOG and EMG artifacts.

II. Methodology

A. Adaptive Filtering

Conventional filtering cannot be applied to eliminate those types of artifacts because EEG signal and artifacts have overlapping spectra. Herein, we propose the use of adaptive filters, which are based on the optimization theory. Adaptive filters have the capability of modifying their properties according to selected features of the signals being analyzed. Fig. 1 illustrates the structure of an adaptive filter. Adaptive filters learn by themselves. As a signal into the filter continues, the adaptive filter coefficients adjust themselves to achieve the desired results coefficients of the linear filter, and hence its frequency response, to generate a signal similar to the noise present in the signal to be filtered. The adaptive process involves minimization of a cost function, which is used to determine the filter coefficients. The adaptive filter adjusts its coefficients to minimize the squared error between its output and a primary signal. In an adaptive filter, there are basically two processes:

A filtering process, in which an output signal is the response of a digital filter. Usually, FIR filters are used in this process because they are simple and stable.

An adaptive process, in which the transfer function *H(z)* is adjusted according to an optimizing algorithm. The adaptation is directed by the error signal between the primary signal and the filter output. The optimizing criterion adopted in this paper is Recursive Least squares (RLS) algorithm. The benefit of the RLS algorithm is that, the computational power can be saved. Another advantage is that it converges to the Kalman filter.

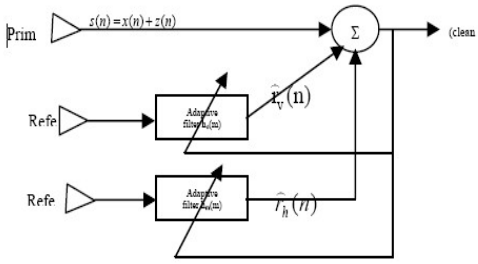

Fig. 1. Structure of an adaptive filter using RLS

The primary input to the system is the EEG signal s(n), picked up by a particular electrode (e.g. F7). This signal is modeled as a mixture of a true EEG x(n) and a noise component z(n),. r_o(n) and r_m(n) are the two reference inputs, EOG and EMG, respectively. r_o(n) and r_m(n) are correlated, in some unknown way, with the noise component z(n) in the primary input. h_o(n) and h_m(n) represent two finite impulse response (FIR) filters of length M (the two filters can have different lengths). The desired output from the noise canceller e(n) is the corrected EEG.

B. Principles of Removing EOG and EMG Artifacts by Adaptive Filtering

This signal is modeled as a mixture of a true EEG x(n) and a noise component z(n). r_o(n) and r_m(n) are the two reference inputs, EOG and EMG, respectively. r_o(n) and r_m(n) are correlated, in some unknown way, with the noise component z(n) in the primary input. h_o(m) and h_m(m) represent two finite impulse response (FIR) filters [7] of length M (the two

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filters can have different lengths). The desired output from the noise canceller e(n) is the corrected, or clean, EEG

$$e(n) = s(n) - \hat{r}_o(n) - \hat{r}_m(n) = x(n) + [z(n) - \hat{r}_o(n) - \hat{r}_m(n)] \tag{1}$$

where

$$\hat{r}_o(n) = \sum_{m=1}^{M} h_o(m) r_o(n+1-m)$$

And are the filtered reference signals Under the assumption that x is a zero-mean stationary random signal that is uncorrelated with z, r_o and r_m the expected value of e^2 can be calculated

$$\hat{r}_m(n) = \sum_{m=1}^{M} h_m(m) r_m(n+1-m) \tag{2}$$

$$\begin{aligned} E(e^2) &= E[(x + z - \hat{r}_o - \hat{r}_m)^2] \\ &= E[x^2] + E[(z - \hat{r}_o - \hat{r}_m)^2] \end{aligned} \tag{3}$$

The goal of the noise canceller is to produce an output signal e(n) that is as close to x(n) as possible, by adjusting the filter coefficients h_o(m) and h_m(m). Statistically, this requires a minimization of $E[z - \hat{r}_o - \hat{r}_m)^2]$. As E[$x^2$] is not affected by the adjustment of the filter coefficients, minimizing $E[z - \hat{r}_o - \hat{r}_m)^2]$ is equivalent to minimizing E [e^2].

$$\begin{aligned} \varepsilon(n) &= \sum_{i=M}^{n} \lambda^{n-1} e^2(i) \\ &= e^2(n) + \lambda e^2(n-1) + \ldots + \lambda^{n-M} e^2(M) \end{aligned} \tag{4}$$

Among the various algorithms of adaptive filtering, we chose the recursive least-squares (RLS) algorithm [5] for our application, because of its superior stability and fast convergence Assuming at time t_n we have obtained the following samples:s(i), r_o(i), r_m(i) and e(i), for I=1, 2, . . . ,n, we form the following target function e(n) to minimise:
where $0 < \lambda \leq 1$ is called the forgetting factor, and

$$\begin{aligned} e(i) = s(i) &- \sum_{m=1}^{M} h_o(m) r_o(i+1-m) \\ &- \sum_{m=1}^{M} h_m(m) r_m(i+1-m) \end{aligned} \tag{5}$$

By minimizing e(n) instead of E[e^2], we simply use the sample mean to approximate the expected value. In addition, by introducing the forgetting factor l, the algorithm can also be applied to a random process that is not strictly stationary. The filter parameters h_o(m), h_m(m), m=1, 2, . . . ,M, that minimize e(n) can be obtained by solving the following two sets of equations (a total of 2*M equations):

$$\begin{aligned} \frac{\partial \varepsilon(n)}{\partial \varepsilon(m)} &= 2\sum_{i=M}^{n} \lambda^{n-i} e(i) \frac{\partial e(i)}{\partial h_o(m)} \\ &= -2\sum_{i=M}^{n} \lambda^{n-i} e(i) r_o(i+1-m) = 0 \end{aligned} \tag{6}$$

$$\begin{aligned} \frac{\partial \varepsilon(n)}{\partial h_h(m)} &= 2\sum_{i=M}^{n} \lambda^{n-i} e(i) \frac{\partial e(i)}{\partial h_m(m)} \\ &= -2\sum_{i=M}^{n} \lambda^{n-i} e(i) r_m(i+1-m) = 0 \end{aligned} \tag{7}$$

The above two sets of equations can be represented by the following matrix forms:

$$\mathrm{R_{oo}(n).\underline{H}_o + R_{om}(n).\underline{H}_m = \underline{P}_o(n)} \tag{8}$$

$$\mathrm{R_{mo}(n).\underline{H}_o + R_{mm}(n).\underline{H}_m = \underline{P}_m(n)} \tag{9}$$

where R_{oo}, R_{om}, R_{mo} and R_{mm} are each an (MxM) square matrix, and H_o, H_m, P_o and P_m are each a column vector having a dimension of M

$$R_{oo}(n)(j,k) = \sum_{i=M}^{n} \lambda^{n-i} r_o(i+1-j) r_o(i+1-k) \tag{10}$$

$$R_{om}(n)(j,k) = \sum_{i=M}^{n} \lambda^{n-i} r_o(i+1-j) r_m(i+1-k) \tag{11}$$

$$R_{mv}(n)(j,k) = \sum_{i=M}^{n} \lambda^{n-i} r_m(i+1-j) r_o(i+1-k) \tag{12}$$

$$\begin{aligned} R_{mm}(n)(j,k) &= \sum_{i=M}^{n} \lambda^{n-i} r_m(i+1-j) r_m(i+1-k) \\ &\quad for\ j,k = 1,2,\ldots,M \end{aligned} \tag{13}$$

$$\underline{P}_o(n)(j) = \sum_{i=M}^{n} \lambda^{n-i} s(i) r_o(i+1-j) \tag{14}$$

$$\underline{P}_m(n)(j) = \sum_{i=M}^{n} \lambda^{n-i} s(i) r_m(i+1-j) \tag{15}$$

$$\underline{H}_o = [h_o(i) h_o(2) \ldots h_o(M)]^T \tag{16}$$

(T stands for vector transposition)

$$\underline{H}_m = [h_m(i) h_m(2) \ldots h_m(M)]^T \tag{17}$$

$$\mathrm{R(n).\underline{H} = \underline{P}(n)} \tag{18}$$

Equations (8) and (9) can further be reduced to one matrix equation
where

$$R(n) = \begin{bmatrix} R_{oo} & R_{om} \\ R_{mo} & R_{mm} \end{bmatrix} \underline{H} = \begin{bmatrix} \underline{H}_o \\ \underline{H}_m \end{bmatrix} \underline{P} = \begin{bmatrix} \underline{P}_o \\ \underline{P}_m \end{bmatrix} \tag{19}$$

From (18), the filter coefficients that minimize e (n) can be solved

$$\underline{H} = [R(n)]^{-1} . \underline{P}(n) \tag{20}$$

Calculating the filter coefficients by directly solving (20) involves matrix inversion, which is computationally expensive. The computation load can be greatly reduced by using a recursive least-squares (RLS) algorithm that calculates the filter coefficients by implementing (20) recursively in n. From (10)–(19), we can show that

$$R(n)=\lambda R(n-1)+\underline{r}(n)\underline{r}(n)^T \quad (21)$$

$$\underline{P}(n)=\lambda \underline{P}(n-1)+s(n)\underline{r}(n)^T \quad (22)$$

$$\underline{r}(n)=\begin{bmatrix}\underline{r}_o(n)\\ \underline{r}_m(n)\end{bmatrix}$$

$$\underline{r}_o(n)=[r_o(n)\,r_o(n-1),\ldots,r_o(n+1-M)]^T \quad (23)$$

$$\underline{r}_m(n)=[r_m(n)\,r_m(n-1)\ldots r_m(n+1-M)]^T$$

Now, using the matrix inversion lemma [4], we can obtain the following recursive relationship:

$$[R(n)]^{-1}=\lambda^{-1}[R(n-1)]^{-1}-\lambda^{-1}\underline{K}(n)\underline{r}(n)^T[R(n-1)]^{-1} \quad (24)$$

where

$$\underline{K}(n)=\frac{[R(n-1)]^{-1}\underline{r}(n)}{\lambda+\underline{r}(n)^T[R(n-1)]^{-1}\underline{r}(n)} \quad (25)$$

Finally, by substituting (24) and (22) into (20) and using (25), we can obtain the following formula for updating filter coefficients:

$$\underline{H}(n)=\underline{H}(n-1)+\underline{K}(n)e\left(\frac{n}{n-1}\right) \quad (26)$$

where $\underline{H}(n) = R(n)]^{-1}$. $\underline{P}(n)$ are the filter coefficients at sample n; $\underline{\boldsymbol{H}}(n-1) = [\boldsymbol{R}(n-1)]^{-1}.\underline{\boldsymbol{P}}(n-1)$ are the filter coefficients at sample (n - 1); and

$$e\left(\frac{n}{n-1}\right)=s(n)-\underline{r}(n)T\,\underline{H}(n-1) \quad (27)$$

The RLS algorithm is implemented in the following steps:

Set initial values:

$\underline{\boldsymbol{H}}(n-1) = 0$ (i.e. $h_v(m) = h_h(m) = 0$
For m = 1, 2, …, M) (28)
$[R(n-1)]^{-1} = \boldsymbol{I}/\sigma$

where I is the (2Mx2M) identity matrix, and = 0.01;

Starting from n=M, steps for every set of new samples s(n),

Rv(n) and rh(n), perform the following,
Form $\underline{\boldsymbol{r}}(n)$ based on (23);
Calculate $\underline{\boldsymbol{K}}(n)$ using (25);
Calculate e(n/n-1) using (27);
Calculate $\underline{\boldsymbol{H}}(n)$ using (26);
Update $[\boldsymbol{R}(n)]^{-1}$ using (24);
Calculate $e(n) = s(n) = \underline{\boldsymbol{r}}(n)^T\,\underline{\boldsymbol{H}}(n)$;
n = n + 1, go back to (b). (29)

III. Results

EEG records were filtered using the proposed adaptive filters. Initially, the recordings of EEG with artifacts is depicted in Fig. 2.This figure has interference which needs to be cancelled .Now the signals in Fig. 2 is fed as an input to the adaptive filter, wherein the RLS algorithm is used. This leads to results shown in Fig. 3, which has EOG, removed. When the reference input for EMG is considered and fed via the filter, the noises due to EMG artifacts are removed as shown in Fig. 4.

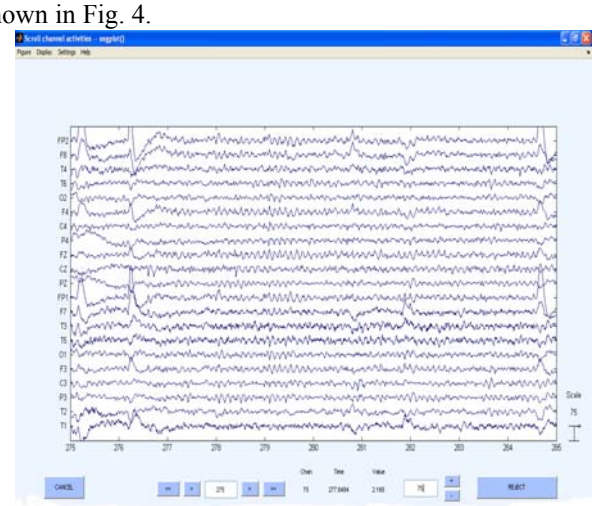

Fig. 2. Represents the original EEG with artifacts

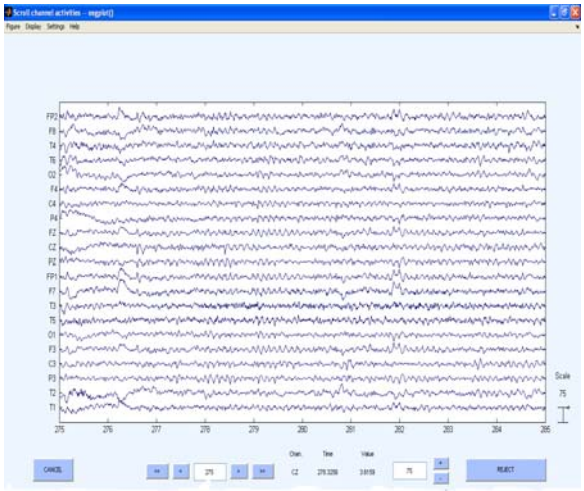

Fig. 3. Represents the EEG signal with EOG artifact removed

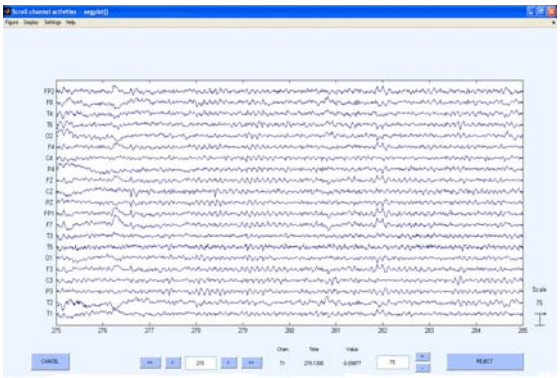

Fig. 4. Represents the corrected EEG signal with EOG and EMG artifacts removed

IV. Discussion and Conclusion

Adaptive filters [2] based on RLS algorithm, were described in order to cancel common artifacts EOG and EMG present in EEG records. The advantage of using filters, instead of going in for Artifact removal using Regression and ICA is that any type of regression needs Calibration trials. ICA[6] though can handle large amount of data needs off-line

analysis and processing of data. Owing to such constraints the above methods become unsuitable and hence Noise Cancellation method based on Adaptive Filtering is highly suitable.

1) The coefficient's adaptation is simpler and faster comparatively.
2) At each stage output, the error signals *ei(n)*, EEG with one of the three attenuated artifacts are present; such separation (by artifact) may be useful in some applications where such output might

Advantages of adaptive filters over conventional ones include preservation of components intrinsic to the EEG record. Besides, they can adapt their coefficients to variations in muscle movements, abrupt modifications due to eye movements.

The parameters that are very important and used in this algorithm are M and λ; where M is the filter order and is chosen to be equal to 3 in our work. The value of M has an impact over removal equal of artifacts and computation time. Larger the value of M; it tends to remove useful information from EEG.

λ ,the forgetting factor represents how fast the RLS algorithm forgets the past samples. In our proposed work, it is chosen to be .9999. If the value is equal to 1, then all the past values are considered. Results show that the proposed filter attenuates EOG and EMG artifacts leaving the necessary EEG information intact.

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