Adaptive filtering based artifact removal from electroencephalogram (EEG) signals

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***Abstract*—The electro-encephalogram (EEG) is useful for clinical diagnosis and in biomedical research. EEG signals, however, especially those recorded from frontal channels, often contain strong artifacts produced by eye movements. Existing regression–based methods for removing artifacts require various procedures for pre-processing and calibration that are inconvenient and time consuming. The paper describes a method for removing artifacts based on adaptive filtering. The method uses separately recorded original EEG and clean EEG as two reference inputs. Each reference input is first processed by a finite impulse response filter of length M (M=3 in this application) and then subtracted from the original EEG. The method is implemented by a least mean square algorithm that includes a forgetting factor (λ=0.9999 in this application) to track the non-stationary portion of the EEG signals. Results from experimental data demonstrate that the method is easy to implement and converges fast.**

***Index Terms*— Adaptive filtering, EEG, eye movements, eye blinks, artifacts removal, LMS algorithm**

I. INTRODUCTION

THE EYE forms an electric dipole, where the cornea is positive and the retina is negative. When the eye moves (saccade, blink or other movements), the electric field around the eye changes, Producing an electrical signal .it appears in the recorded electro-encephalogram (EEG) as noise or artifacts that present serious problems in EEG interpretation and analysis. To correct or remove artifacts from EEG, many regression-based techniques have been proposed, including simple time-domain regression (VERLEGER et al. 1982; GRATTON et al., 1983), multiple-leg time-domain regression (KENEMANS et al., 1991) and regression in the frequency domain (WHITTON et al., 1978; WOESTENBURG et al., 1983). Since different artifact removal algorithms are required for each application, it is essential to choose the most appropriate one depending on the problem. For instance, in real time applications of EEG signals such as BCI systems, Epileptic seizure detection etc., fast online denoising techniques are required. On the contrary, in off-line analysis of EEG signals, algorithms with better performance are often preferred regardless of how computationally complex and time-consuming they are. Therefore, comparing the efficiency and speed of the various proposed methods for artefact removal of the EEG signal could be of great interest.

So far, research studies based on adaptive filtering, wavelet transform, principal component analysis (PCA), independent component analysis (ICA), time and frequency domain regression methods etc. have been conducted in this regard [1-13]. In this paper, we describe a noise cancellation method based on adaptive filtering (WIDROW et al., 1975; HAYKIN, 1996) to remove ocular artifacts from EEG. This method is particularly suitable to our applications because it does not require calibration trials, and the EEG artifacts can be removed online. Previous studies (CROFT and BARRY, 2000) have shown that there are at least two kinds of EOG artifact to be removed: those produced by the vertical eye movement and those produced by the horizontal eye movement. Consequently, a noise canceller with two reference inputs is used in this application.

II. DATA ACQUISITION

We have used BIOPAC MP 36 system that integrates hardware and software for data acquisition process. The specifications used in this study are as follows: bandwidth-0.05 Hz to 35 Hz, sampling frequency- 500 Hz, recording duration-300 seconds. The EEG signals of five subjects aged between 22 to 25 years have been recorded.

Fig.1. Biopac MP 36 Data Acquisition Unit

The following eye movement activities were performed while recording the EEG signals in this experiment:

1) Horizontal eye movements,

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2) Vertical eye movements,

3) Eye blinks

III. Adaptive Filter Structure

The block diagram of adaptive filter system used to derive strong artifacts signal from EEG signal is shown below:

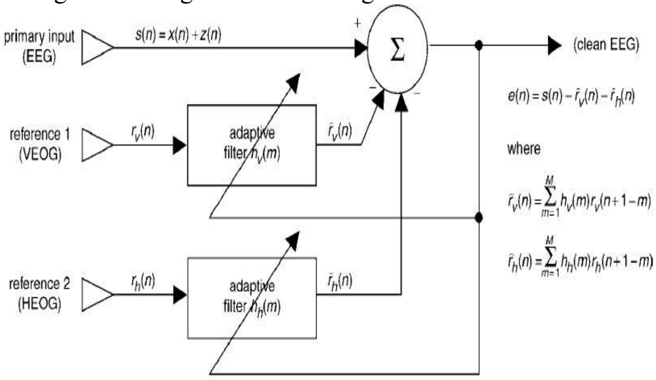

Fig 2. Block diagram of EEG noise canceller using adaptive filtering with two reference inputs [1]

Fig 2 shows the block diagram of the noise canceller used in this application. The primary input to the system is the EEG signal s(n), picked up by a particular electrode (e.g. F7). This signal is modelled as a mixture of a true EEG x(n) and a noise component z(n). r_v(n) and $r_h(n)$ are the two reference inputs, VEOG and HEOG, respectively. r_v(n) and $r_h(n)$ are correlated, in some unknown way, with the noise component z(n) inthe primary input. h_v(m) and $h_h(n)$ 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, or clean, EEG

$$e(n) = s(n) - \hat{r}_v(n) - \hat{r}_h(n) \qquad (1)$$

Where,

$$\hat{r}_v(n) = \sum_{m=1}^{M} h_v(m) r_v(n+1-m) \qquad (2)$$

$$\hat{r}_h(n) = \sum_{m=1}^{M} h_h(m) r_h(n+1-m) \qquad (3)$$

are the filtered reference signals. Under the assumption that x is a zero-mean stationary random signal that is uncorrelated with z, $r_v$and r_h the expected value (denoted by [ ]) of e^2 can be calculated

$$E[e^2] = E[(x + z - \hat{r}_v - \hat{r}_h)] \qquad (4)$$

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_v(m) and $h_h(n)$. Statistically, this requires a minimisation $E[e^2]$.

Among the various algorithms of adaptive filtering, we chose the least mean squares (LMS) algorithm for our application, because of its superior stability and fast convergence. Parallel to the derivation given by Vaseghi (1996) for the case of one reference input, we present here the algorithm development for the case of two reference inputs.

By minimising 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_v(m) and $h_h(m)$ m=1, 2, . . . , M, that minimise e(n) can be obtained by solving the following two sets of equations (a total of 2*M equations):

$$\frac{\partial \varepsilon(n)}{\partial h_v(m)} = 2\sum_{i=M}^{n} \lambda^{n-i} e(i) \frac{\partial e(i)}{\partial h_v(m)} \qquad (5)$$

$$\frac{\partial \varepsilon(n)}{\partial h_h(m)} = 2\sum_{i=M}^{n} \lambda^{n-i} e(i) \frac{\partial e(i)}{\partial h_h(m)} \qquad (6)$$

The above two set of equations can be represented by the following matrix form:

$$R_{vv}(n).\underline{H_v} + R_{vh}(n).\underline{H_h} = \underline{P_v}(n) \qquad (7)$$

$$R_h(n).\underline{H_v} + R_{hh}(n).\underline{H_h} = \underline{P_h}(n) \qquad (8)$$

Equation (7) and (8) can be further reduced by one matrix form:

$$R(n).\underline{H} = \underline{P}(n) \qquad (9)$$

Where,

$$R(n) = \begin{bmatrix} R_{vv} & R_{vh} \\ R_{hv} & R_{hh} \end{bmatrix} \underline{H} = \begin{bmatrix} \underline{H_v} \\ \underline{H_h} \end{bmatrix} \underline{P} = \begin{bmatrix} \underline{P_v} \\ \underline{P_h} \end{bmatrix} \qquad (10)$$

From (9), filter coefficients that minimise $\varepsilon(n)$ can be solved

$$\underline{H} = [R(n)]^{-1}.\underline{P}(n) \qquad (11)$$

The LMS algorithm can be developed by the following steps:

1)$\underline{H}(n-1) = 0$ (i. e . h_v(m) =$h_h(m)$ =0 for m=0,1,2.....M)

$$[R(n-1)]^{-1} = I/\sigma \qquad (12)$$

Where R is (2M×2M) identity matrix and $\sigma = 0.01$.

2) Form $\underline{r}(n)$ based on

$$\underline{r}(n) = \begin{bmatrix} r_h(n) \\ r_v(n) \end{bmatrix} \qquad (13)$$

Calculate$\underline{K}(n)$, $e(\frac{n}{n-1})$,$\underline{H}(n)$, using below equation

$$\underline{K}(n) = \frac{[R(n-1)]^{-1}\underline{r}(n)}{\lambda + \underline{r(n)}^T [R(n-1)]^{-1}\underline{r}(n)} \qquad (14)$$

$$e\left(\frac{n}{n-1}\right) = s(n) - \underline{r}(n)^T \underline{H}(n-1) \qquad (15)$$

$$\underline{H}(n) = \underline{H}(n-1) + \underline{K}(n) e\left(\frac{n}{n-1}\right) \qquad (16)$$

Updating$\underline{[R(n)]^{-1}}$,

Calculate $e(n) = s(n) - \underline{r}(n)^T \underline{H}(n) \qquad (17)$

n=n+1 go back to step 2

IV. Experimental Results

The EEG signals were recorded in a single lead configuration- a pair of electrodes were placed above (negative terminal) and below (positive terminal) the behind scalp and ground position at the back left side of neck. All signals were band pass filtered at 0.48–30 Hz and sampled at 256 Hz. The data were recorded while the subject was performing the eye blinks/ movements. Although the algorithm for noise cancelling described above is suitable for real-time applications, in the present study, we first recorded all the data and then applied the algorithm off-line. Real-time filtering was simulated by sequential feeding of the sample data to the program. The representative results of noise cancelling using LMS algorithm are presented in fig 3.the particular parameters used by algorithm are M=3and lambda=0.9999 figure shows segments of simultaneously eye blinks, horizontal movements, vertical movements and clean EEG.

Fig. 3 to 5 show the results of adaptive filtering based artifact removal for the EEG signals with eye blinks, horizontal and vertical eye movements, respectively. Each figure contains the reference EEG, recorded EEG, error or artifact and clean EEG. Table I and II show the MSE, SNR (before and after removal of artifacts) and normalized correlation coefficient (NCC) values for subject 1 and 2, respectively.

TABLE I
PARAMETERS FOR ARTIFACT REMOVAL FROM EEG SIGNALS- SUBJECT 1

Movement	MSE	SNRb	SNRa	NCC
Eye Blinks	0.0019	27.3170	27.5744	0.9652
Horizontal	0.0032	24.9771	25.7156	0.9396
Vertical	0.0047	23.2805	24.6672	0.9094

TABLE II
PARAMETERS FOR ARTIFACT REMOVAL FROM EEG SIGNALS- SUBJECT 2

Movement	MSE	SNRb	SNRa	NCC
Eye Blinks	0.0022	26.6746	27.0654	0.9803
Horizontal	0.0039	24.0938	25.8165	0.9640
Vertical	0.0032	24.8944	24.9658	0.9702

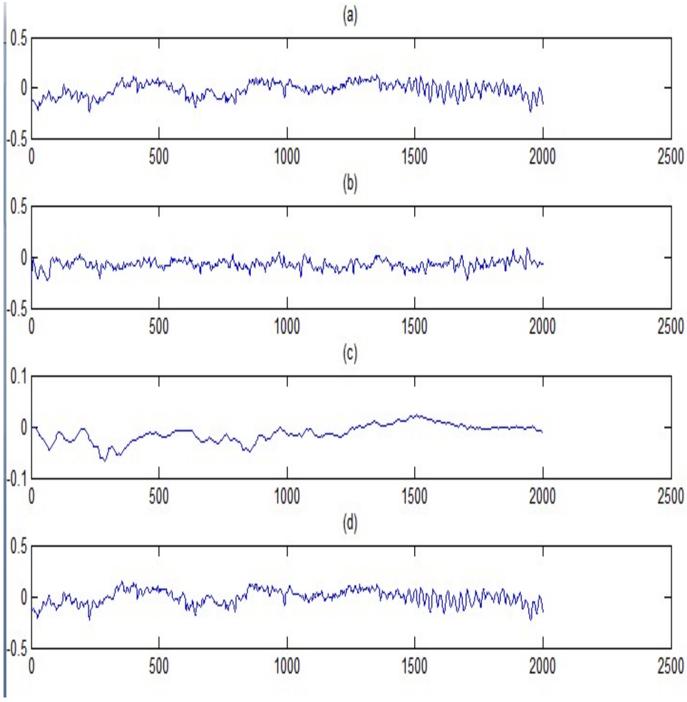

Fig. 3: (a) Reference EEG signal (b) EEG signal with eye blinks (c) error (d) clean EEG for subject 1

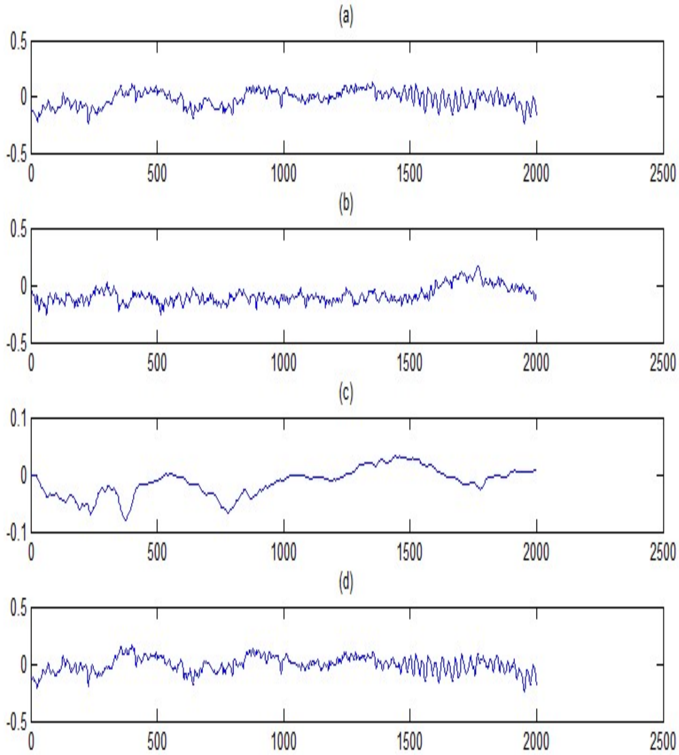

Fig. 4: (a) Reference EEG signal (b) EEG signal with horizontal eye movements (c) error (d) clean EEG for subject 1

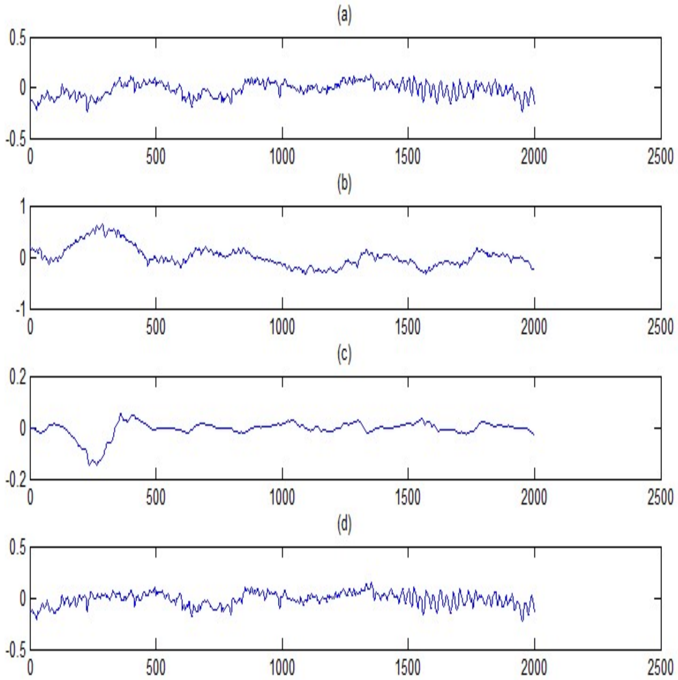

Fig. 5: (a) Reference EEG signal (b) EEG signal with vertical movements (c) error (d) clean EEG for subject 1

V. Discussion and Conclusion

An EEG noise canceller based on adaptive filtering has been described. The most appealing feature of this noise canceller is its ability to remove EEG artifacts without any pre- processing and calibration. By implementing a least mean square algorithm, the method described in this paper is fast enough for real-time processing. Although the noise canceller developed in this paper contains two FIR filters having the same length, it can easily be shown that the algorithm development will be exactly the same when the two filters have different lengths. The performance of the adaptive filtering based artifact removal algorithm from EEG signal has been measured by parameters like MSE, PSNR and NCC. The reduction of MSE values for clean EEG signals as compared to noisy (recorded) EEG signals and enhancement in SNR and NCC values indicate the effectiveness of the algorithm.

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