Removing Ocular Artifacts from EEG Signals using Adaptive Filtering and ARMAX Modeling

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Abstract—EEG signal is one of the oldest measures of brain activity that has been used vastly for clinical diagnoses and biomedical researches. However, EEG signals are highly contaminated with various artifacts, both from the subject and from equipment interferences. Among these various kinds of artifacts, ocular noise is the most important one. Since many applications such as BCI require online and real-time processing of EEG signal, it is ideal if the removal of artifacts is performed in an online fashion. Recently, some methods for online ocular artifact removing have been proposed. One of these methods is ARMAX modeling of EEG signal. This method assumes that the recorded EEG signal is a combination of EOG artifacts and the background EEG. Then the background EEG is estimated via estimation of ARMAX parameters. The other recently proposed method is based on adaptive filtering. This method uses EOG signal as the reference input and subtracts EOG artifacts from recorded EEG signals. In this paper we investigate the efficiency of each method for removing of EOG artifacts. A comparison is made between these two methods. Our undertaken conclusion from this comparison is that adaptive filtering method has better results compared with the results achieved by ARMAX modeling.

Keywords— Ocular Artifacts, EEG, Adaptive Filtering, ARMAX

I. INTRODUCTION

THE surface electroencephalogram (EEG) is the electrical activity of the brain obtained by scalp electrodes. When eyes move, the electrical field around them changes and produces an electrical signal known as EOG. As this signal propagates over the scalp, it appears on the recorded EEG as noise or artifacts that should be removed in order to cancel its interpretation with background EEG. Because the magnitude of the EOG artifact is usually about the order of the amplitude of EEG signal, removing this artifact is one of the most important problems in studying the brain activities.

Several regression-based techniques have been proposed to remove ocular artifacts (OAR) from EEG Signals. These methods include simple time-domain regression [8], multiple-leg time-domain [9] and regression in the frequency domain [10]. In regression methods EEG and EOG must be uncorrelated, which is not the case in practice. On the other hand, in all these regression-based methods, calibration trials should be conducted at first to determine the transfer functions between each EOG and EEG channel.

Independent Component Analysis (ICA) is the more recently proposed method which assumes that the potential on the scalp is a weighted sum of potentials in the source, so EOG and EEG signals can be separated by finding the independent sources of them in the brain [7]. However, this method cannot be applied online and it requires storing the data and off-line processing.

Haas et al [2] suggested a general subtraction method, ARMAX, which is based on the assumption that the measured EEG is described as a linear combination of a background EEG and corrupting ocular artifacts that background EEG can be estimated by ARMAX method.

He et al [1] suggested real-time removal of Ocular Artifacts using adaptive filtering. In this method, the primary input is the measured EEG and the reference input is the EOG signal.

In this paper, we compare two newly proposed methods for ocular artifact removing, ARMAX modeling and adaptive filtering method. In next section we explain theoretical aspects of these two methods. Our experimental results are presented in section III and compared in section IV. Our finding is that adaptive filtering method has better results compared with those achieved by ARMAX.

II. METHODS

A. ARMAX Modeling Method

Linear subtraction methods are based on the assumption that the measured EEG is described as a linear combination of underlying cortical activities and corrupting ocular artifacts. Equation (1) shows a typical variation of these kinds of models that relates the measured EEG, background EEG and ocular artifacts together:

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$$y(n)=\sum_{i=1}^{n} b_i u_i(n)+w(n) \quad (1)$$

Where $y(n)$ is the measured EEG, $u_i(n)$ denotes the (n – i)th sample of the recorded EOG and $w(n)$ is the true background EEG. This model assumes that the background EEG is an uncorrelated white noise with zero mean and all frequencies of EOG channels have the same propagation characteristics. So, in order to relax these assumptions which are not completely true in general, the measured EEG is modeled as an ARMAX process described as:

$$y(n)=\sum_{k=1}^{p} A_k y(n-k)+\sum_{k=0}^{q} B_k u(n-k) + \sum_{k=1}^{r} C_k w(n-k)+w(n) \quad (2)$$

Where (p,q,r) is the model order. The Recursive Extended Least Squares estimator can be used to determine the coefficients of this model. Then the background EEG is estimated by using the previous and the present values of y and u. Since the background EEG is assumed as a zero mean white noise, the criterion which is used to select the model order (p,q,r) is to minimize the variance of the estimated background EEG, $\hat{w}(n)$.

$$\sigma_n(p,q,r)=\sum_{k=n_0}^{n} \|\hat{w}(n)\| \quad (3)$$

However in order to prevent choosing unnecessary high orders, we add a cost function term to the above equation and try to minimize combined information criterion (CIC) [6]:

$$CIC(p,q,r)=\sigma_n(p,q,r)+(p+q+r)\log(n-n_0)\,\gamma \quad (4)$$

where n_0 is a delay or starting time and γ is a scaling factor.

B. Adaptive Filtering Method

Figure1 illustrates the typical block diagram of an EOG noise canceller using adaptive filtering. The primary input to the system $s(n)$ is modeled as a combination of background EEG $x(n)$ and the effect of EOG artifacts $z(n)$ on the EEG signal. Reference input to the system $r(n)$ is the EOG signal picked up by an electrode.

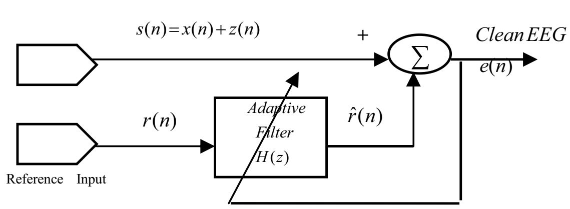

Fig. 1 EOG noise canceller system using adaptive filtering

Reference input and the noise component of primary input are correlated in some unknown way. $h(m)$ represents a finite impulse response (FIR) filter of length M. Adjusting the coefficients of the filter, the noise canceller produces an output signal $e(n)$ which is an estimation of background EEG $x(n)$.

$$e(n)=s(n)-\hat{r}(n) \quad (5)$$

where

$$\hat{r}(n)=\sum_{m=1}^{M} h(m)r(n+1-m) \quad (6)$$

Here, we used Recursive Least-squared (RLS) algorithm to compute filter coefficients. It is mainly because of the stability and fast convergence of this method. In this approach, we have to minimize the following target function $\varepsilon(n)$:

$$\varepsilon(n)=e^2(n)+\lambda e^2(n-1)+\cdots+\lambda^{n-M}e^2(M) \quad (7)$$

where $0<\lambda\le 1$ is the forgetting factor.

Using equations (5)-(7) and setting zero the partial differentiation of $\varepsilon(n)$, results can be represented as the following matrix form:

$$R(n)\,\underline{H}=\underline{P}(n) \quad (8)$$

$$R(n)(j,k)=\sum_{i=M}^{n}\lambda^{n-i}r(i+1-j)\,r(i+1-k) \quad (9)$$

$$\underline{P}(n)(j)=\sum_{i=M}^{n}\lambda^{n-i}s(i)r(i+1-j) \quad (10)$$

$$\underline{H}=[h(1)\ h(2)\ \cdots\ h(M)]^T \quad (11)$$

From equations (9)-(11) we can show that:

$$R(n)=\lambda R(n-1)+\underline{r}(n)^T \quad (12)$$

$$\underline{P}(n)=\lambda\underline{P}(n-1)+s(n)\underline{r}(n) \quad (13)$$

Using the matrix inversion lemma [5], the following recursive formula can be obtained:

$$\underline{H}(n)=\underline{H}(n-1)+\underline{K}(n)\,e(\frac{n}{n-1}) \quad (14)$$

where

$$\underline{K}(n)=\frac{[R(n-1)]^{-1}\underline{r}(n)}{\lambda+\underline{r}(n)^T R(n-1)]^{-1}\underline{r}(n)} \quad (15)$$

$$e(\frac{n}{n-1})=s(n)-\underline{r}(n)^T\,\underline{H}(n-1) \quad (16)$$

This formula is used to update filter coefficients.

III. Experiments

A. Applying ARMAX Modeling

All of our EEG and EOG data were obtained from online database provided in http://www.cs.colostate.edu/~anderson. EEG was recorded from six different sites on scalp: C3, C4, P3, P4, O1, and O2. Recording was performed with a bank of Grass 7P511 amplifiers whose band-pass analog filters were set at 0.1 to 100 Hz. EEG and EOG signals are recorded in a period of 10 seconds with a sampling frequency of 250 Hz.

The ARMAX model was applied to each of these EEG channels. Figure 2 shows the results of applying ARMAX with order (1, 1, 1) and (10, 10, 10) to channel P4.

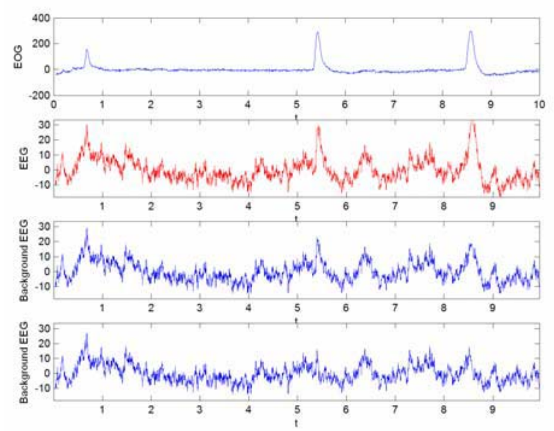

Fig. 2 (A) Measured EOG. (B) Measured EEG at siteP4. (C) Background EEG obtained by using ARMAXwith order (1, 1, 1). (D) Background EEG obtained by using ARMAX with order (10,10,10).

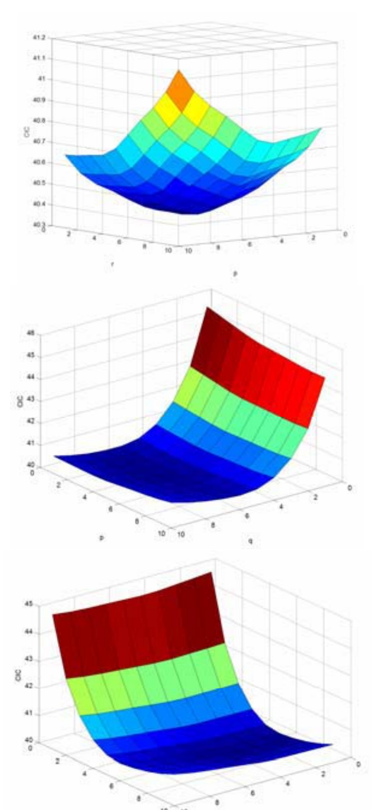

Fig. 3 The effect of model order on the noise variance. (A) Effect of p, r for q = 10. (B) Effect of p, q for r = 10. (C) Effect of q, r for p = 10.

As it is depicted, the ARMAX with higher order has better results but increasing the model order does not enhance the performance after a certain model order. In lower order ARMAX method, we can see a negative spike on the background EEG just at the moment of EOG spike, but this spike is nearly disappeared when increasing the model order.

In order to investigate on the effects that an ARMAX model order has on the performance of noise cancellation, we have plotted CIC value versus different p, q and r parameters in figure 3. In each plot, one parameter of model order is assumed to be constant, and the CIC value versus two other parameters is depicted.

Lower noise correlation and variance are two signs of better system modeling, which are corresponded to lower CIC. As it is depicted in figure 3, increasing the model order will cause a rapid reduction in CIC information at lower model orders. However, after a certain model order, CIC information will be increased when the model order increases. This is due to the second term in equation (4) which is responsible for preventing the criteria from selecting unnecessary higher orders.

It should be noted that regardless the parameter order, ARMAX method can not detect and correct the effects of early artifacts (under 350 samples or about 1.5 s).

B. Applying Adaptive Filtering

We have applied the same data as previous section to an adaptive filtering system. The results are shown in figure 4. The values of parameters λ and M are chosen 1 and 6 respectively.

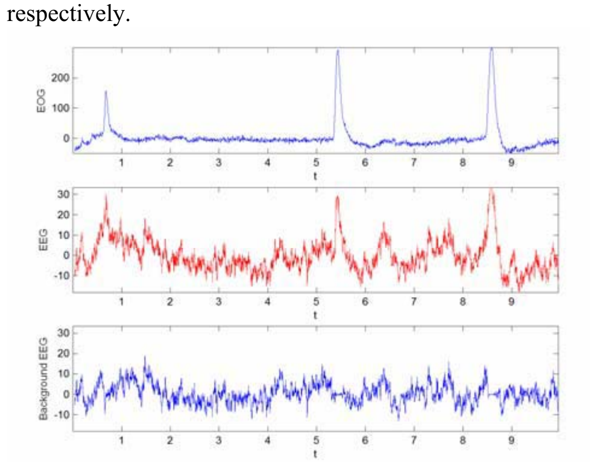

Fig. 4 (A) Measured EOG. (B) Measured EEG at site P4. (C) Background EEG obtained by using adaptive filtering with M = 6.

As depicted in figure 4, adaptive filtering system can detect the artifacts happened in the early samples of the recorded signal (below 350 samples) and it can correct them. This is due to the fast convergence and adaptation of RLS algorithm used in this method.

On the other hand, the implementation of adaptive filtering is simple and fast, and the results can be obtained without requiring complex calculations. However, the drawback of adaptive filtering method is that a negative spike is appeared in the background EEG just at the moment of EOG spike.

IV. Comparision Between Methods

The recorded EEG is a mixture of the background EEG and the EOG artifact, in a complicated unknown way, so there is no standard method which defines the exactly true background EEG and evaluates the performance of different ocular artifact removal methods. The OAR evaluation methods which artificially mix a true noiseless EEG with a proportion of EOG signals and then try to remove the effect of noise from the mixed signal do not seem to be logical, because the real combination of EEG and ocular artifacts is unknown. However, performance evaluation of the OAR methods with visual inspection is often accepted.

The two methods presented in this paper can be applied to remove EOG artifacts on-line, without requiring off-line analysis and data storing. It is ideal for real-time processing of EEG signals. However, the ARMAX modeling requires a priori knowledge about the recorded EEG signal to apply an appropriate model order. Estimation of the model order of ARMAX method using CIC information criterion requires a complicated optimization algorithm which needs extra time and calculations. Adaptive filtering method does not require any calibration trials [1], and its complexity is much less compared with ARMAX method. On the other hand, the convergence of adaptive filter is much faster than ARMAX method. This property is very important when ocular artifacts occur at early samples of the recorded signal. Fast response of adaptive filtering method provides an opportunity to remove early appeared artifacts but with ARMAX modeling it is not possible to do it. Figure 5 illustrates the effect of these two methods on removing early ocular artifacts.

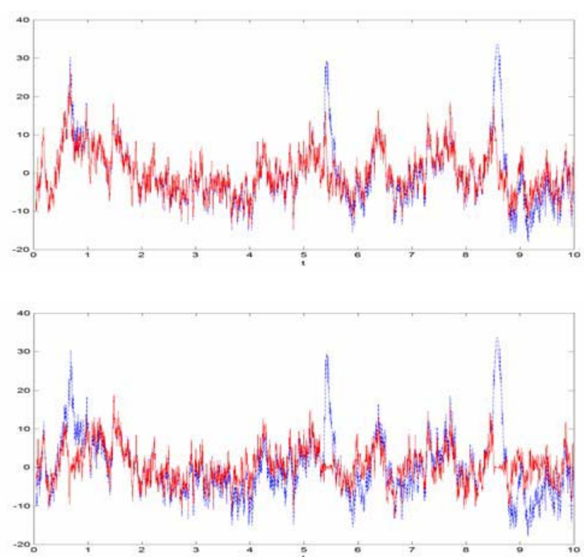

Fig. 5 Effect of noise canceller systems on early ocular artifacts. (A) ARMAX model (10, 10, 10). (B) Adaptive Filter with M = 6.

As mentioned before, a small negative spike appears just at the time of blinking in the output of both adaptive filtering system and ARMAX model with low orders. Although this spike disappears with increasing in model order of ARMAX, higher orders of this method complicate the applied calculations, so for simple implementations of the systems, adaptive filtering method is preferred.

Consequently, the important drawback of ARMAX model as against adaptive filtering method is its higher complexity, and the slower convergence, so for practical on-line experiments, adaptive filtering method has better results for removing ocular artifact .

V. Conclusion

In this paper, we have applied two methods, adaptive filtering and ARMAX modeling, to remove ocular artifacts from EEG signals. Then we have compared the efficiency of these two methods. The results can be summarized as following:

1. Both ARMAX and Adaptive Filtering methods can be applied on real-time data.
2. In both methods, a negative spike appears just at the blinking time. Although this spike disappears in higher orders of ARMAX, it needs more complicated calculations.
3. To have an appropriate performance for ARMAX, model order estimation is necessary that complicates the procedure, but adaptive filtering method does not need any calibration trial and parameter estimation.
4. Adaptive filtering method removes the effect of early ocular artifacts much better than ARMAX because of its fast convergence.

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