Removal of ocular artifacts from EEG signals in Brain Computer Interface

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ABSTRACT

For removal of EOG artifacts from EEG, a non-linear model based on regression, is presented. The method is developed for multi channel EEG and the performance of the method is tested up to third order. The results of this method are compared with standard linear regression models and cross covariance models. It was found that quadratic non-linear model performs better than all the linear and cubic regression models studied.

1. INTRODUCTION

A brain-computer interface (BCI) is a system which translates a subject's intentions into a control signal for a device, e.g., a computer application, a wheelchair or a neuroprosthesis [1]. When measuring non-invasively, brain activity is acquired by scalp-recorded electroencephalogram (EEG) from a subject that tries to convey its intentions by behaving according to well-defined paradigms, e.g., motor imagery, specific mental tasks, or feedback control. 'Features' (or feature vectors) are extracted from the digitized EEG-signals by signal processing methods. These features are then translated into a control signal.

One of the major noise contaminations in EEG recordings is due to the electrooculographic (EOG) artifacts. The EOG signal is generated by electrical eye activity such as eye blink or eye moment which propagates all over the body through volume conduction and can be recorded at the body surface. The EOG potentials originate from the electric dipole between the cornea and retina and depend on its orientation with respect to the eyelid. Since eye moments are difficult to suppress over the period of EEG recording, almost all the EEG recordings get contaminated with EOG artifacts.

The amplitude of the EOG signal is attenuated approximately as square of the distance and as a result, EOG contamination prominent in the frontal EEG channels. Due to the volume conduction effect, EEG and EOG activities are propagated to the surface of the scalp where the superposition of both is recorded. The goal of ocular artifact removal methods is to remove EOG artifacts from scalp recorded EEG's, leaving underlying background signals due to brain activity intact.

Artifacts in EEG are commonly handled by discarding the affected segments of EEG. The recognition of the eye blinks and eye moment artifacts are generally affected by detecting a voltage increase in the EOG channel above a threshold, generally 100 μV. Discarding segments of EEG data with artifacts can greatly decrease the amount of data available for analysis.

There are several different methods available for both reducing and removal of EOG artifacts. Most common methods are application of spatial filters [2], blind source separation [3], and linear regression models [4] in both time domain and frequency domain. The blind source separation method is the most popular method used in removing artifacts. This method is based on multivariate statistical analysis techniques such as principal component analysis (PCA) [5], Signal fractional analysis (SFA) and independent component analysis (ICA) [6]. However, for a small number of EEG channels, it is very likely that regression methods perform better than principal component analysis and independent component analysis. On the other hand, some recent work [4, 7] suggests that the regression methods are appropriate for EOG reduction.

In this paper we report results of two non-linear regression methods that have been implemented for removing EOG artifacts for the BCI system, which is currently, being developed in our laboratory. For comparison we compare our results with a recent linear model developed by Schlogl et al [8].

2. METHOD

The model present in this paper is based on the following assumptions

(1) EOG signals are not contaminated by EEG activities

(2) The EEG signals are contaminated by EOG instantaneously. That is, there is no time lag between EOG activity and the EEG contamination.

Our non-linear model is constructed as

$$Y = S + \sum_{k=0}^{d} U^k \bullet a^{(k)} \tag{1}$$

Where the matrix Y has dimensions $T \times M$ and any element $Y_{t,ch}$ is the recorded EEG value of channel *ch* at time *t*, the matrix *S* has dimensions $T \times M$ and any element $S_{t,ch}$ is the EEG value of channel *ch* at time *t* without artifact contamination, the matrix *U* has dimensions $T \times N$ and any element $U_{t,n}$ is the noise source of the n^{th} EOG signal at time *t*. U^k is the k^{th} point power of the matrix U. That is $\left(U^k\right)_{t,n} = \left(U_{t,n}\right)^k$ for all *k*.

$a^{(k)}$ is the k^{th} weight coefficient matrix having dimensions $N \times M$ associated with U^k, $0 \le k \le d$ and d is the degree of non-linearity.

$\bullet$ is the matrix multiplication. And

(1) T =Total time steps

(2) M =Number of EEG channels

(3) N = Number of EOG channels

Note that matrices $a^{(k)}$ contain the strength of contamination of EEG signals due to EOG artifacts and they are constants in time. The matrices $a^{(k)}$ depend on surface conduction properties of the scalp and the volume conduction properties of the brain. It is also assumed that Signal S (i.e. EEG) and the noise U are statistically independent.

To apply this model to real EEG data, matrices $a^{(k)}$ must be determined. In order to determine $a^{(k)}$'s, the EEG signals are collected while the subject is not doing any specific mental tasks. This is corresponding to base line EEG and therefore, average values of S and cross covariance of S with U are zero. Then $a^{(k)}$ s can be determined by non-linear regression methods with the equation

$$Y = U^0 \bullet a^{(0)} + U \bullet a^{(1)} + U^2 \bullet a^{(2)} + U^3 \bullet a^{(3)} + \ldots \quad + U^d \bullet a^{(d)} \tag{2}$$

In this study we investigated this model up to $d = 3$. Corrected general EEG signals corresponding to any metal task are given by

$$S = Y - \sum_{k=0}^{d} U^k \bullet a^{(k)} \tag{3}$$

Results of this model are presented in the next section. For comparison purposes we implemented the method developed by Schlogl et al [8]. Their model is a linear model and equation (1) becomes

$$Y = S + U \bullet a \tag{4}$$

and a is given by the equation

$$a = \langle U^T U \rangle^{-1} + \langle U^T Y \rangle, \tag{5}$$

where $\langle U^T U \rangle$ is the auto-covariance matrix of the EOG channels and $\langle U^T Y \rangle$ is the cross covariance between the EOG and EEG channels. In this model corrected EEG is given by

$$S = Y - U \bullet a \tag{6}$$

These models were investigated with the EEG and EOG data sets available from Artificial Intelligence Group, Department of Computer Science, University of Colorado. Ten data sets which consist of six channels of EEG and single channel of EOG that correspond to baseline and four mental tasks (multiplication, rotation, letter composing and counting) were used. Each data set contains 2500 samples of EEG data per channel for specific mental task and there are six such EEG channels in a data set along with one EOG channel. Samples have been taken at 250 Hz for 10 seconds, for 2500 samples. EOG was recorded between the forehead above the left browline and another on the left cheekbone. Recording has been performed with a bank of Grass 7P511 amplifiers whose bandpass analog filters were set at 0.1 to 100 Hz.

3. RESULTS AND DISCUSSION

The above described Schlogl et al's linear model, standard linear regression model, and quadratic and cubic non-linear regression models were implemented using MATHLAB 7.0. Data sets corresponding to ten trials were investigated using these models. In this investigation it was found that for most of the data sets all the methods performed reasonably well. However, quadratic non-linear regression method performed very well for all the data sets. To illustrate this, two cases are presented here in this paper. For the first data set all the methods removed EOG artifacts reasonably well and it is shown in Figure 1. For this data, there are four well defined peaks in the EOG signal indicating possible eyeblinks occurred in four instances. It can also be observed in the EEG signal that there are four large peaks at the same instances showing artifacts contamination. All the contamination peaks were successfully removed by all four methods.

In the second case, a data set with a negative peak in the EOG signal was used. This case is illustrated in Figure 2. For the negative peak in the EOG signal, it seems like there is no significant artifacts contamination in the EEG signal. (see Figure 2a). However, when we apply four methods described for removing artifacts in this paper, outcome from linear methods are found to be different from the non-linear methods. Linear methods introduced a large positive peak in the corrected EEG signal which is not acceptable (Figures 2c and 2d). On the other hand cubic non-linear method introduced a large negative peak in the corrected EEG signal. (see Figure 2f). However, the quadratic non-linear method produced a reasonably good result for all the data sets we have studied so far. In this study, it was found that quadratic method is suitable for removing EOG artifacts for both usual EOG contamination and unusual EOG contaminations as in Figure 2.

(a)

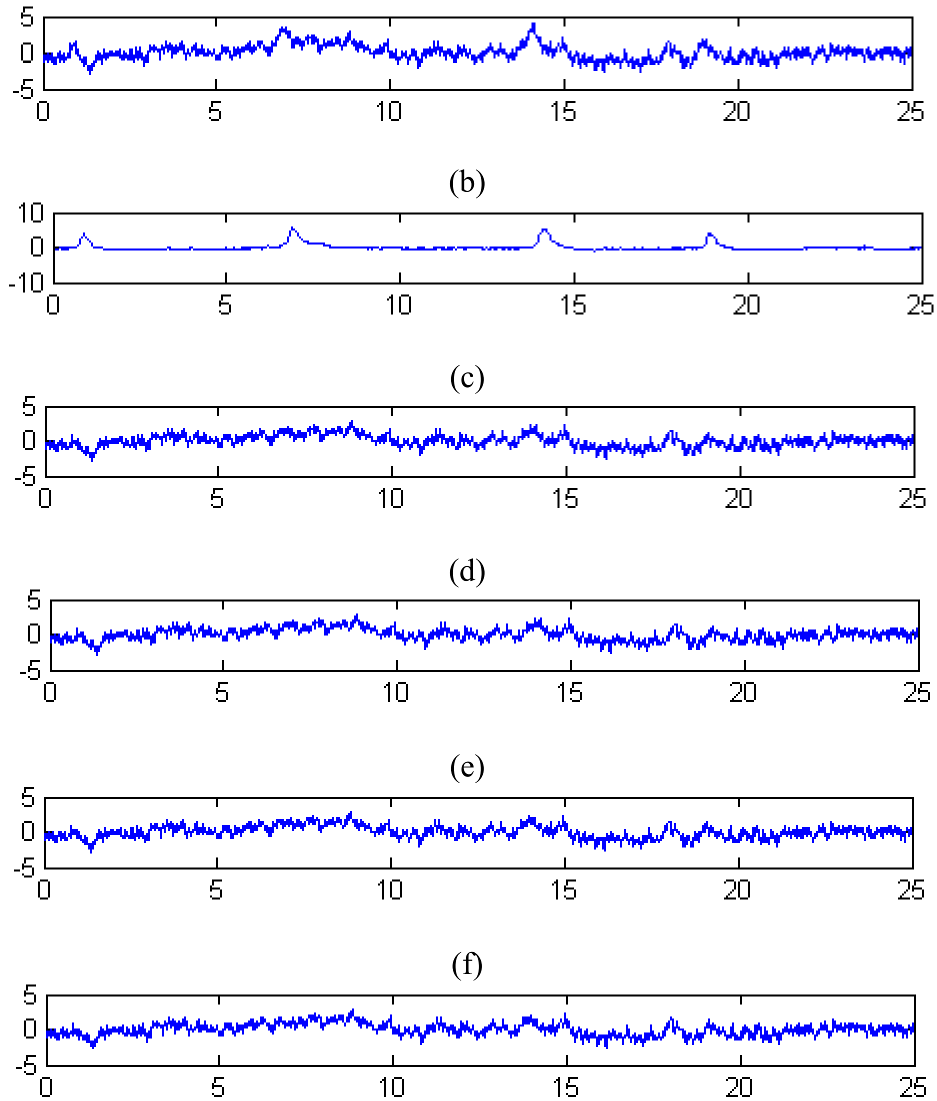

Figure 1: A typical EEG signal before and after removal of artifacts with various methods. For this EEG data, all the methods perform in a similar manner. (a) Reordered EEG signal before removing artifacts. (b) EOG signal showing artifacts. (c) EEG signal after removing artifacts with Schlogl et al's linear model (d) EEG signal after removing artifacts with standard linear regression model. (e) EEG signal after removing artifacts with Quadratic regression model. (f) EEG signal after removing artifacts with Cubic regression model.

Note that *x* axis in the above plots are in milliseconds.

(a)

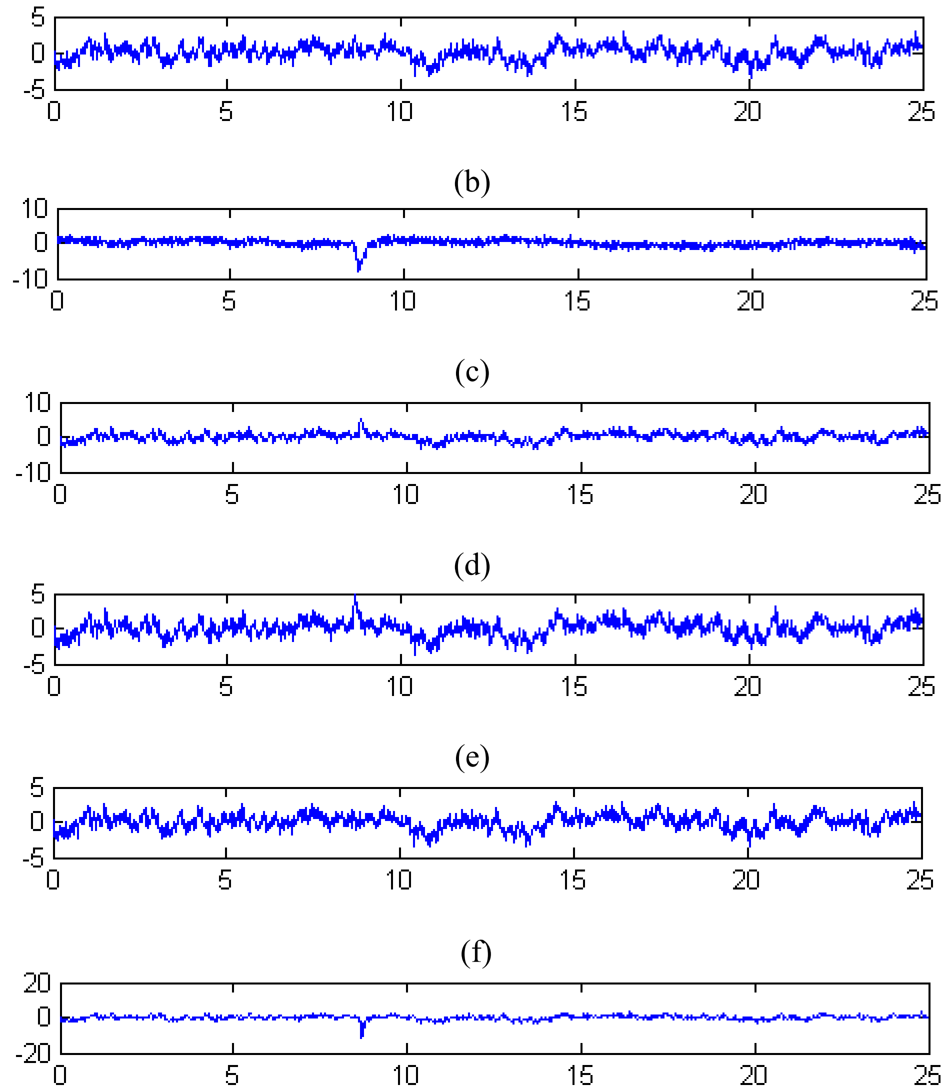

Figure 2: Another EEG signal before and after removal of artifacts with all four methods is shown. For this EEG data, nonlinear models perform very differently from the linear models. (See text for details.) (a) Reordered EEG signal before removing artifacts. (b) EOG signal showing artifacts. (c) EEG signal after removing artifacts with Schlogl et al's linear model (d) EEG signal after removing artifacts with standard linear regression model. (e) EEG signal after removing artifacts with Quadratic regression model. (f) EEG signal after removing artifacts with cubic non-linear regression model.

Note that *x* axis in the above plots are in milliseconds

REFERENCES

1. Kennedy, P. R., Adams, K., Bakay, R. A. E., Goldthwaite, J., Montgomery, G., & Moore, M., IEEE *Transactions on Rehabilitation Engineering*, 8, (2000)198; J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, 113 (2002) 767.
2. Lagerlund T. D., Sharbourgh F. W., and Busacker N. E, *J*. Clin. Neurophysiol 14 (1997) 73.
3. Joyce C. A, Forodnitsky I. F., Kutas M, *J. Clin. Neurophysiol* 47 (2003) 199
4. Moretti D. V., Babiloni F, Carducci F, Cincotti F, Remondini E., RossiniP. M., Salinari S, Babiloni C. *Int. J. Psychophysiol* 47 (2003) 199.
5. Moulines E, Cardoso J. F, and Gassiat E, *Proc. ICAASSP97 IEEE Int. Conf*. (1997) 3617
6. Xu L., Cheung C. C, Yang H. H, and Amari S, *IEEE Trans. Neural Networks* 5 (1997) 1821
7. Wallstorm G. L, Kass R. E, Miller A, Cohn J. F, Fox N. A, *Int. J. Psychophysiol* 53 (2004) 105
8. Schlogl A., Keinrath C, Zimmermann D, Scherer R, Leeb R, Pfurtscheller G, *J. Clin. Neurophysiol* 118 (2007) 98