GEVD Based on Multichannel Wiener Filter for Removal of EEG Artifacts

K. Srinivas, J. Tarun Kumar, Shyamsunder Merugu

Abstract: The electroencephalography (EEG) signals are contaminated by ocular artifacts usually called as ElectroOculoGraphy(EOG) artifacts. This occurs due to an eye movement and repeatedly blinking eyes, it is a major barrier to overcome when analyzing ElectroEncephaloGram (EEG) data. In this paper, Generalized Eigen Value Decomposition (GEVD) algorithm based on Multichannel Wiener filter (MWF) was proposed. In the GEVD algorithm, the covariance matrix of the artifact is identified and substituted by low rank approximation. For both real and hybrid EEG data is demonstrated using this algorithm and also compared with other existing methods for removal of artifacts. This paper determines generic, robust and fast algorithm for artifact removal of various types of EEG signals. Signal to Error Ratio (SER) and Artifact to Residue Ratio (ARR) both are expressed in dBs. The better performance of artifact removal is expressed with high SER which measures clean EEG distortion and ARR measures the artifact estimation.
Index Terms: EEG, EOG, Multichannel Wiener filter, Generalized Eigen Value Decomposition, Signal to Error Ratio (SER) and Artifact to Residue Ratio (ARR).

I. INTRODUCTION

The electroencephalogram (EEG) is non-invasive technique to measure electrical potentials of brain by using electrodes on the scalp[1]. EEG is the most ideal method due to its non-invasive and low cost; it is most preferred in clinical studies, diagnosis, monitoring patient's health, lab experiments, and many other applications[2]. There are two types of artifacts which occur while measuring the EEG are biological and technical artifacts. Primarily, biological artifacts are most common can be caused by blinking and moving the eyes, motion artifacts caused by head movements, muscle contractions occurred when speaking, movement of jaws or swallowing[3]. Measuring EEG while the patient's eyes are closed but it may change the dynamics of EEG and it is not a desirable process. Technical artifacts are occurred from the machines at the point when there is obstruction in electrical cables, electrical devices, or impedance changes in the recording electrodes[4]. Many algorithms are proposed for removal of artifacts in that the most popular and common method is Independent Component Analysis(ICA)[5].It is used to remove movements of eye and blinking artifacts[5].The other popular method which has the capability to remove muscle artifacts is Canonical Correlation Analysis (CCA)[6].

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The method targets both muscle and ocular artifacts is Blind Source Separation (BSS)[7].It is a semi-automatic process, the artifacts components are to be selected for removal after source separation[8][9]. In this paper, MWF based GEVD algorithm is proposed to removal of EEG artifacts[10]. In order to estimate a clean signal from noisy measurements, MWF is preferred due to its linear filtering nature. It is widely used in audio and speech related problems now it also applicable for biomedical data processing[11][12]. Different types of artifacts are removed from the EEG signal simultaneously by MWF based GEVD algorithm[13]. This process is partially automatic and for every time a user has to select the artifact segments from the displayed EEG signal because it is semi supervised.EEGLAB software toolbox allows processing of collections of single EEG data spectral analysis as well as data averaging techniques[14]. Using this toolbox, MWF based on GEVD approach advantages are demonstrated. Section 2 describes about the data model for MWF andthe GEVD based on MWF algorithm. In Section 3, the performance and simulation results are included. The section IV, deals with the conclusion and future scope of the proposed algorithm.

II. METHODOLOGY

2.1 Data Model for Multi-Channel Wiener Filter

The Multi-channel of EEG signal $x[t] \epsilon\ R^M$ at a sampling time of t is as follows

$$\boldsymbol{x}[\boldsymbol{t}] = \boldsymbol{s}[\boldsymbol{t}] + \boldsymbol{v}[\boldsymbol{t}] \quad (1)$$

where $s[t]$, $v[t]$represents the true neural signals and various types of artifacts of neural signals respectively. Note that $v[t]$ may considered as any type of artifact, e.g., it may be due to blinking or movement of eyes and due to the movement of muscles, jaws etc. For preprocessing mean is subtracted the output signal (x), true (s) and various types of artifacts (v) of neural signals are assumed with zero mean and it is often satisfied EEG signals. The signal covariance matrices $\mathcal{R}_{xx}, \mathcal{R}_{ss}, \mathcal{R}_{vv}$are defined as $\boldsymbol{E}\{xx^T\}$, $\boldsymbol{E}\{ss^T\}$, and $\boldsymbol{E}\{vv^T\}$respectively, where$\boldsymbol{E}$ stands for expectation. Assumes s and v are not correlated, then

$$\mathcal{R}_{xx} = \mathcal{R}_{ss} + \mathcal{R}_{vv} \quad (2)$$

The Multi-channel Weiner Filter generates an estimation of the M-channel artifact signal $v$with $\hat{v}$by linear combination of $x$channelsi.e. $\hat{v} = W^T x$.
Minimum Mean Square

Error (MMSE) of the linear combination is

$$\min_{W} E\{\llbracket v - W^T x \rrbracket^2\} \quad (3)$$

The $\boldsymbol{i^{th}}$column of $\boldsymbol{W}$ is the linear combiner used to estimate the $\boldsymbol{i^{th}}$ channel of$\boldsymbol{v}$. The solution to this minimization problem is

$$W = \mathcal{R}_{xx}^{-1}\mathcal{R}_{xv} \quad (4)$$

where $\mathcal{R}_{xv} = E\{xv^T\}$. Using (1) and the assumed non-correlativeness between $v$and s, R_{xv} is shown approximately equal toR_{vv},

$$\mathcal{R}_{xv} = \mathcal{R}_{(s+v)v} = \mathcal{R}_{sv} + \mathcal{R}_{vv} = \mathcal{R}_{vv} \quad (5)$$

so, from (4)the filter solution can be written as

$$W = \mathcal{R}_{xx}^{-1}\mathcal{R}_{vv} \quad (6)$$

The two mutually exclusive sets Y_a and Y_c containing T_a and $T_c$samples with and without artifacts respectively are segmented from T observations of observation matrix$Y$ by using an artifact detection method. This segmentation allows R_{xx} to be estimated as

$$\hat{\mathcal{R}}_{xx} = \frac{1}{T_a} Y_a Y_a^T \quad (7)$$

where, the estimation is denoted with hat symbol. Likewise, to estimateR_{ss} from M x Tobservations theY_c observation matrix contains samples which does not include artifacts, as

$$\hat{\mathcal{R}}_{ss} = \frac{1}{T_c} Y_c Y_c^T \quad (8)$$

from (2), estimation ofR_{nn} can be written as

$$\hat{\mathcal{R}}_{vv} = \hat{\mathcal{R}}_{xx} - \hat{\mathcal{R}}_{ss} \quad (9)$$

so from eq(6)the Wiener filter solution W is estimated using covariance matrix of the data as

$$\widehat{W} = \hat{\mathcal{R}}_{xx}^{-1}\hat{\mathcal{R}}_{vv} \quad (10)$$

Finally we get the true responses using eq (1) by subtracting artifacts which are estimated is

$$\hat{s} = x - \widehat{W}^T x \quad (11)$$

true neural responses are calculated.

2.2 GEVD-based on MWF

The rank of the covariance matrix R_{vv} is typically low because the number of artifact sources is less than the number of M channels.

However, from noisy observations covariance matrices are estimated, the estimated matrix rankR_{vv}isnot equal to Q instead it is equal to M. Moreover, the subtraction of$\hat{\mathcal{R}}_{xx} - \hat{\mathcal{R}}_{ss}$givesoptimistic semi-exactness of$\hat{\mathcal{R}}_{vv}$ which is not definite. Using GEVD method the subtraction is performed it forces$\hat{\mathcal{R}}_{vv}$ to be real value semi-exact and not with high rank, so it improves the performance of the Multi channel Weiner Filter. Since R_{xx} and R_{vv} are both are exactly similar and positive, an invertible matrix V can be found such that

$$V^T\mathcal{R}_{xx}V = \mathrm{diag}(\sigma_{x1}, \dots, \sigma_{xM}) = \Sigma_x ,$$
$$V^T\mathcal{R}_{ss}V = \mathrm{diag}(\sigma_{s1}, \dots, \sigma_{sM}) = \Sigma_s \quad (12)$$

The rank depends on the autocorrelation of every source. It also satisfying below equation

$$\mathcal{R}_{xx}\mathrm{V} = \mathcal{R}_{vv}\mathrm{V}\,\Lambda \quad (13)$$

where $\Lambda = \mathrm{diag}(\lambda_1, \dots, \lambda_M)$ and $\lambda_i = \sigma_{xi}/\sigma_{vi}$
equation (13) is gives the data of the GEVD algorithm for $i = 1, \dots, M$.The Generalized Eigen Vectors are represented by columns of matrix $V$and Generalized Eigen values are with diagonal elements of Λ. All the eigen values are arranged in descending order i.e. $\lambda_1 > \cdots > \lambda_M$ and was assumed without any loss of generality.
$\mathcal{R}_{vv}$ can be written from the diagonalization of eq(12) as

$$\begin{aligned}\mathcal{R}_{vv} &= \mathcal{R}_{xx} - \mathcal{R}_{ss}\\ &= V^{-T}\Sigma_{\mathrm{x}}\mathrm{V}^{-1} - \mathrm{V}^{-\mathrm{T}}\Sigma_{\mathrm{v}}\mathrm{V}^{-1}\\ &= V^{-T}(\Sigma_x - \Sigma_s)V^{-1}\\ &= V^{-T}\Sigma_v V^{-1} \quad (14)\end{aligned}$$

Where$\Sigma_v = \mathrm{diag}(\sigma_{v1}, \dots, \sigma_{vM})and\sigma_{vi} = \sigma_{xi} - \sigma_{si}$. Since$\mathcal{R}_{vv}$ has rank$\mathbf{Q}$, only the first $\mathbf{Q}$ diagonal elements of $\hat{\Sigma}_v$will be non-zero. However, as $\hat{\mathcal{R}}_{vv}$ generally doesn't have rank$\mathbf{Q}$, the GEVD can be used to compute a rank-Q approximation of R_{vv}.

III. RESULTS

3.1 Selecting Artifacts in GUI

The implementation of MWF in a graphical user interface (GUI), all channels of EEG are envisioned in a user friendly software called EEGLAB [8], it allows to evaluate the characteristic features such as spatial and temporal of EEG signal by user. Once the segments with undesired amplitudes are selected, and then click on save results it exports the selection part to MATLAB, it is compiled by the MWF algorithm. Selection of artifacts in GUI window is shown in Figure 1.

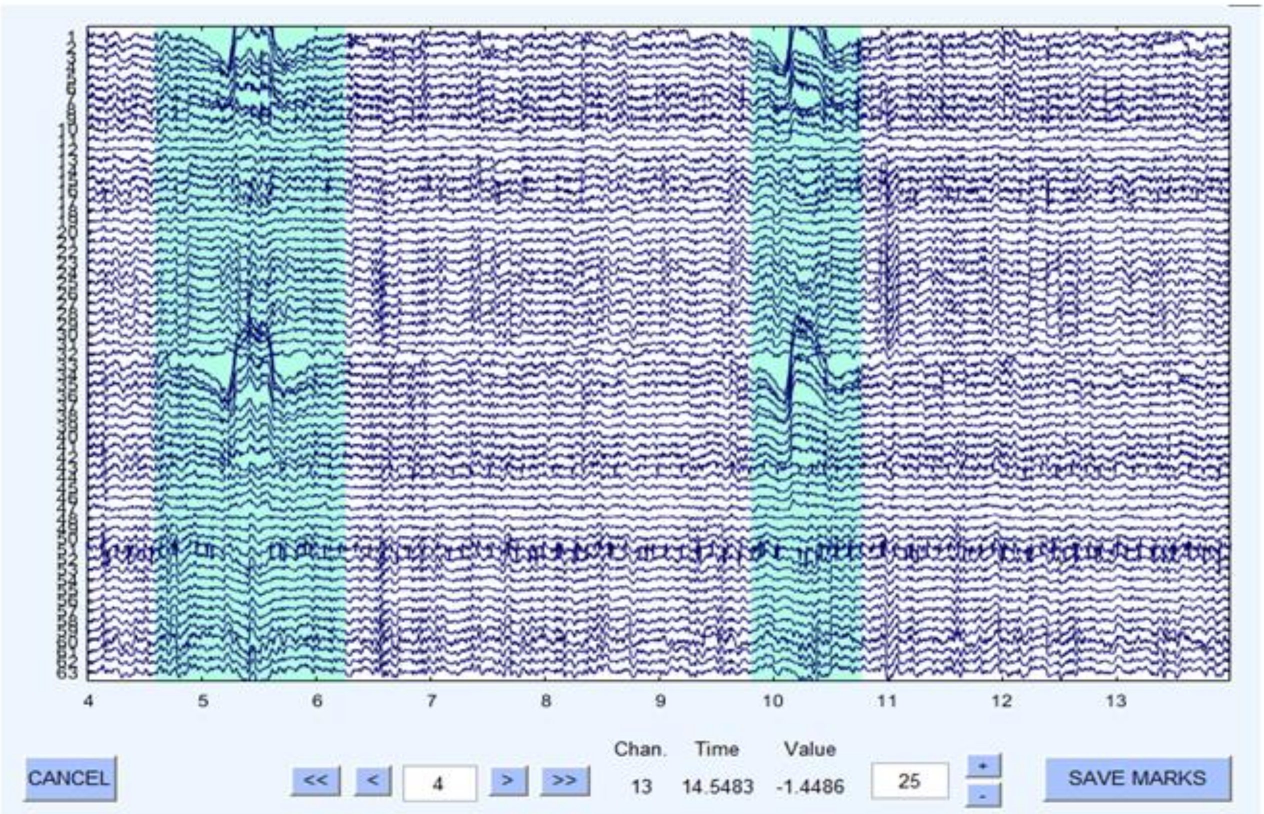

Figure 1:Artifact Marking in Graphical User Interface

The signal with high amplitudes are considered as artifacts, while selecting artifacts the marking position should not start or end in the middle of an artifact segments. If there is any failure in capture, the entire marked part leads to errors in true segments of EEG, it fluctuates the calculation of $\hat{\mathcal{R}}_{vv}$ in eq.(8).

3.2 Performance measures

The artifact removal quality is evaluated by two complementary measures. The first measure is Signal-to-Error Ratio (SER) it measures the noise in the clean EEG signal which is free from artifact segments, and the second measure is computed from the degree of artifact segments removal ratio as Artifact-to-Residue Ratio (ARR). The estimated artifact signals in the artifact-free segments of channel i, given by $\hat{v}_i$, should be as close to zero as possible. To calculate this, the use of Signal-to-Error Ratio (SER) in a single channel i, computed as

$$SER_i = 10\log_{10}\frac{E\{(x_i)^2\}}{E\{(\hat{v}_i)^2\}}\bigg|_{clean\ segments} \qquad (15)$$

To obtain a single measure, the SERs of individual channels are combined by weighted averaging over channels as

$$SER = \sum_{i=1}^{M} p_i . SER_i \qquad (16)$$

where pi represents the stabilized weights in every channel which are proportional to the power of the artifact, it can be achieved by calculating the difference between power of clean segments and artifact segments.

$$p_i = \frac{E\{(x_i)^2\}|_{artifacts} - E\{(x_i)^2\}|_{clean}}{\sum_{i=1}^{M}\left(E\{(x_i)^2\}|_{artifacts} - E\{(x_i)^2\}|_{clean}\right)} \qquad (17)$$

The estimation of artifact is represented with $\hat{v}_i$ it is similar to the real artifact signal, and the residue $n_i - \hat{n}_i$ possibly very small. In a single channel i Artifact-to-Residue Ratio (ARR), is calculated as

$$\mathrm{ARR_i} = 10\log_{10}\frac{E\{(v_i)^2\}}{E\{(v_i-\hat{v}_i)^2\}}\bigg|_{artifact\ segments} \qquad (18)$$

3.3 Simulation results

This valid artifact segments are approximated

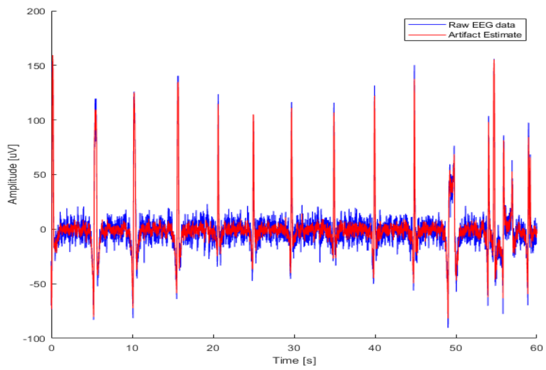

Figure 2: Mixed signal with EEG and Artifacts

with high amplitudes. The raw EEG data $s(t)$ is represented with blue color where as artifacts estimated $v(t)$ are drawn in red color.

The rank guess and quantity of time lags of the MWF based GEVD are very essential parameters to reflect on. By expanding the quantity of time lags, lot of degrees opportunities are accessible in the MWF structure.

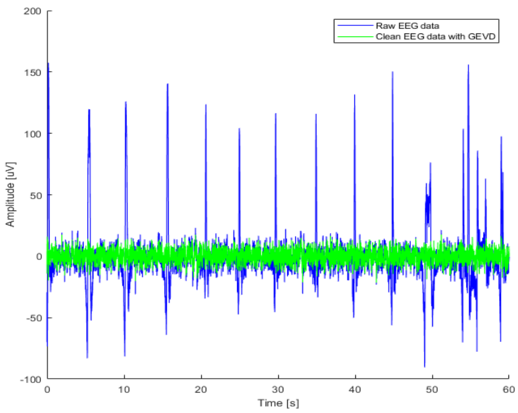

Figure 3: Clean signal achieved after applying MWF based GEVD algorithm

The better performance of the MWF based GEVD artifact removal algorithm is specified by high SER and ARR which are expressed in dBs. The performance of these two measures reflects complementary phase of artifact removal and always assessed simultaneously.

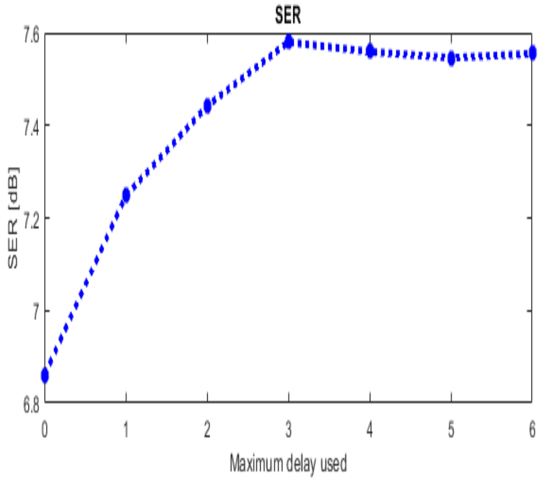

Figure 4: Signal to Error Ratio [dB]

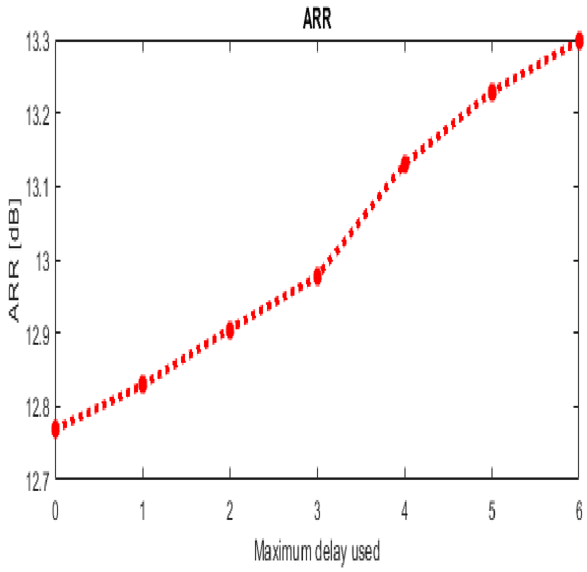

Figure 5 Artifact Rejection Ratio [dB]

The results for eye blink demonstrate the most elevated SER and ARR for the GEVD-based MWF. By and large for ICA and CCA, the muscle artifact segments were extremely not well isolated from the clean EEG parts, almost 50% of the segments are being available. The dismissal of numerous not well isolated parts unavoidably prompts bigger EEG distortion, which gives the low SERs for ICA and CCA.

IV. CONCLUSION

In this study, MWF based GEVD algorithm was effectively implemented and approved as a technique for semi-automatic artifact removal from EEG. It is found the best performance in terms of SER and ARR.

The algorithm automatically chosen the

artifact approximation covariance matrix and the rank is calculated the estimation of artifacts contributes only positive generalized eigen values. The practical assessment demonstrated the viability of utilizing the preceding evaluation of the parameters and execution of artifact reduction was progressed and evaluated with the technique without an earlier. The MWF subtracts a reduced-rank artifact estimate from the EEG, which for the most part does not diminish the rank of the prepared EEG. It is noticed that the MWF-based technique can be stretched out towards a completely programmed and unsupervised one by identifying proper artifacts in the EEG data utilizing different detection techniques.

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