*International Journal of Computational Research and Development (IJCRD)*
*Impact Factor: 4.775, ISSN (Online): 2456 - 3137*
*(www.dvpublication.com) Volume 1, Issue 2, 2016*

# EXTRACTION OF EOG ARTIFACT FROM MULTICHANNEL EEG SIGNAL USING MULTICHANNEL SINGULAR SPECTRUM ANALYSIS AND RLS ADAPTIVE NOISE CANCELER

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**Cite This Article:** R. Rengalakshmi & Dr. C. Kumar Charlie Paul, "Extraction of EOG Artifact from Multichannel EEG Signal Using Multichannel Singular Spectrum Analysis and RLS Adaptive Noise Canceler", International Journal of Computational Research and Development, Volume 1, Issue 2, Page Number 36-40, 2016.

**Abstract:**

Electroencephalogram (EEG) are the neurological signals which help in the study of various se are diseases. These are contaminated with various artifacts like electrooculogram (EOG). It is difficult to study and analysis of brain signals in the existence of artifact. Usually adaptive filter has been used to remove artifact in biomedical signals. An effective approach is proposed in this paper to remove ocular artifacts from the raw EEG recording. In proposed technique, carried out by multichannel singular spectrum analysis (MSSA) and recursive least square (RLS) adaptive filter. To validate the proposed algorithm some noisy simulated signals are used. The performance of the technique is also examined using synthetic EEG signals. In terms of mean absolute error (MAE) and relative root mean square error (RRMSE).

**Index Terms**: Electroencephalogram (EEG), Electrooculogram (EOG) & Multichannel Singular Spectrum Analysis (MSSA)

## 1. Introduction:

EEG signals are recorded from the scalp surface around the head with electrodes, which, however, may be contaminated by interferences. Eye movements and blinks constitute a major source of artifacts in EEG recordings, and such artifacts are commonly referred to as ocular artifacts (OA) or electrooculography (EOG) artifacts. One possible solution in reducing EOGartifact in EEG signals is instructing the subject to make no eye blink or movement [1]. The electrical signals of the brain provide a suitable representation of the control signals used in BCI systems. The technology needed for recording the brain's electrical signalscan be relatively cheap, especially when these signals are recorded from the scalp [2]. Adaptive noise cancelers (ANCs) [3] are widely used to remove artifacts from the biomedical signals [4].How-ever, these techniques assumes that the reference signal for ANC is available. In [5], ANC has been used along with the independent component analysis (ICA) to identify the independent components representing the EOG artifact. The reference signals for ANC is obtained by employing the ICA on the EEG signals recorded at electrodes closet to the eye. In order to remove the EOG artifact from single channel EEG signal using local singular spectrum analysis (SSA) [6], has been proposed. In this technique, the feature vectors of the embedded matrix, obtained by arranging delayed version of original signal, are clustered by *k*-means [7] algorithm. The eigenvalues and eigenvectors of the covariance matrix of each cluster are computed using singular value decomposition (SVD). In order to estimate EOG artifact, the minimum description length (MDL) [8] criteria is used, which gives the information regarding the dimension of signal subspace or the number of eigenvectors needed to estimate the EOG signal. The MSSA has been proposed to separate electrocardiogram (ECG) from the electromyogram (EMG) signals by exploiting the periodicity of ECG signal. Unlike ANC, where two separate inputs are needed to filter out the artifact, here, by exploiting the periodicity of the artifact present in the contaminated signal and its delayed version, the ALE removes the artifact signal. In general, this delay is set based on the periodicity of the artifact present in the contaminated signal. However, as the EEG and EOG signals are non-stationary signals, such technique exhibits poor performance in removing the EOG artifact from the EEG signal [9]. More recently, a combined use of discrete wavelet transform (DWT) and ANC, namely DWT-ANC, has been proposed in [10] to remove EOG artifact from EEG signals. In this technique, firstly, the DWT is used to construct the reference signal, *i.e.* EOG, from the contaminated EEG signal and is applied to reference input of the ANC. Finally, the ANC removes the EOG artifact from the contaminated EEG signal by changing the filter coefficients based on the adaptive algorithm.SSA is a powerful technique for time series analysis and signal processing incorporating the elements of classical time series analysis, linear algebra, multivariate statistics, multivariate geometry, dynamical systems and signal processing [11]. This approach circumvents many limitations such as nonlinearity of the signals. Moreover, contrary to the traditional methods of time series analysis and signal processing, the SSA method is non-parametric and does not require any prior assumption about the data. Furthermore, SSA decomposes a series into its component parts, while excluding the random (noise) component which is very important for the EEG extraction. It is worth mentioning that most of the current algorithms do not consider any potential information hidden in the signal Structure [12]. The SSA technique has also been used as a filtering method for longitudinal measurements. It has been shown that noise reduction is important for curve fitting in growth curve models, and that SSA can be employed as a powerful tool for noise reduction for longitudinal measurements.

The motivation for this is that by using additional information such as the temporal dynamics and linear and nonlinear interdependency among signals (which we use in SSA, particularly in MSSA), we can improve the performance of existing signal processing methods. The method is based on SSA. The proposed algorithm consists of several complementary stages. First, the EEG signal is extracted from a noisy composite signal using multichannel SSA. This paper is organized as follows: Section II provides a detailed instruction about the existing techniques. The proposed MSSA-ANC technique and the key steps are explained in Section III. The discussion of simulation resultsand conclusion are outlined in section IV and V, respectively.

**2. Techniques:**

**A. Adaptive Noise Canceler:** The adaptive noise canceler as shown in Fig. 1, basically consists of filtering and weight updating blocks. The weights of the adaptive filter can be updated using either least mean square (LMS) or recursive least square (RLS) algorithms [3]. In this paper, we have employed RLS because of the fact that the filter coefficients using this algorithm are tuned to optimum values in a less number of iterations, *i.e.* fast convergence.There are four major types of adaptive filtering configurations; adaptive system identification, adaptive noise cancellation, adaptive linear prediction, and adaptive inverse system. All of the above systems are similar in theimplementation of the algorithm, but different in system configuration.

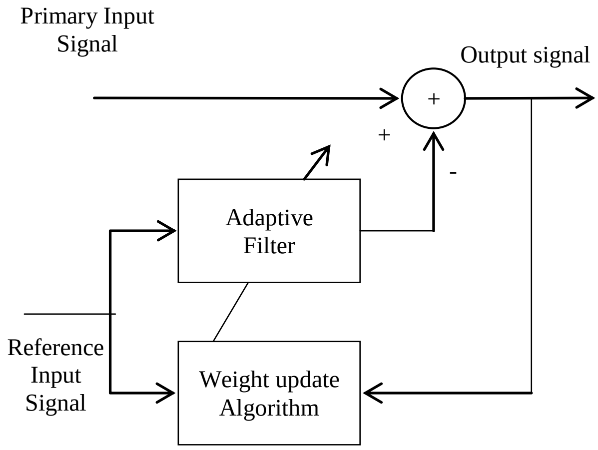


Figure 1: Block Diagram of Adaptive Noise Canceler

**B. SSA- ANC for Single Channel EEG:** In single channel SSA-ANC [1], to construct reference signal *i.e.* EOG signal, needed for ANC. Firstly decomposition is employed on the contaminated EEG signal and obtained approximate and detailed coefficients. Later, constructed EOG signal is used as reference signal and at the output of the ANC, corrected EEG signal is obtained by subtracting the adaptive filter output from the contaminated EEG signal in single channel. Here only one channel is consider, the performance analysis is based on relative root mean square error (RRMSE) and mean absolute error (MAE). Based on this single channel EEG error removal technique the multichannel EEG signal artifact removal technique is developed.

**3. Proposed MSSA-ANC Methodology:**

Consider a proposed MSSA-ANC based EOG artifact removal system as shown in Fig. 2, it receives the contaminated EEG signal. The MSSA technique can be operated a block of data, first the incoming data sequence y(n) is stored into buffer of length N, results a signal vector Y = [y(1),y(2), . . . , y (n)]. After that MSSA is applied on the signal vector 'y' to extract reference signal for the ANC. The following subsections present the key steps in SSA and construction of reference signal for ANC.

**A. Multichannel Singular Spectrum Analysis:** Singular Spectrum Analysis (SSA) can be extended to Multi-channel Singular Spectrum Analysis (MSSA) for a multivariate time series of vectors at concurrent moments at a same location or at different locations. MSSA is used to approach to systems of ordinary or partial differential equations. The major areas of MSSA are multivariate statistics, multivariate geometry and dynamical systems and signal procession.

**Embedding:** In order to explain MSSA, we need to include vector or location variablesm = 1, . . . ,M, except window length L between 2 and T/2. M can be either multi-variables for one location or multi-channels for various locations. MSSA uses two parameters in describing each data as $\{X_{l,\, n:} l = 1, \ldots, L; m=1, \ldots, M\}$. we assume that M is equally spaced or timely intervals, window length L, and multi-channel M. There are special cases in MSSA. If M = 1, MSSA becomes SSA because there is no other vectors or channels. If L = 1, MSSA becomes PCA like multivariate statistics. When we decompose the grand covariance matrix $C_x$, we previously require two more steps: the each-channel's trajectory matrix $X_m$and the full augmented trajectory matrix called the multi-channel trajectory matrix also $X_m$ We form the each-channel's trajectory matrix $X_m$ with $\{X_{l,\, n:} l = 1, \ldots, L; m=1, \ldots, M\}$ and then the full augmented trajectory matrix X. The last step of decomposition in MSSA calculates the grand covariance matrix $C_{x.}$

**SVD:** The SVD step,makes the singular value decomposition of the trajectory matrix and represents it as a sum of rank-one bi-orthogonal elementary matrices. Denote by λ1, . . . , λL the eigenvalues of $XX_T$in decreasing order of magnitude (λ1 ≥ . . . ≥ λL ≥ 0) and by $U_1$, . . . , $U_L$the orthonormal system of the eigenvectors of the matrix $XX_T$corresponding to these eigenvalues. The SVD is used to decompose any trajectory matrix X into two or several orthogonal components.

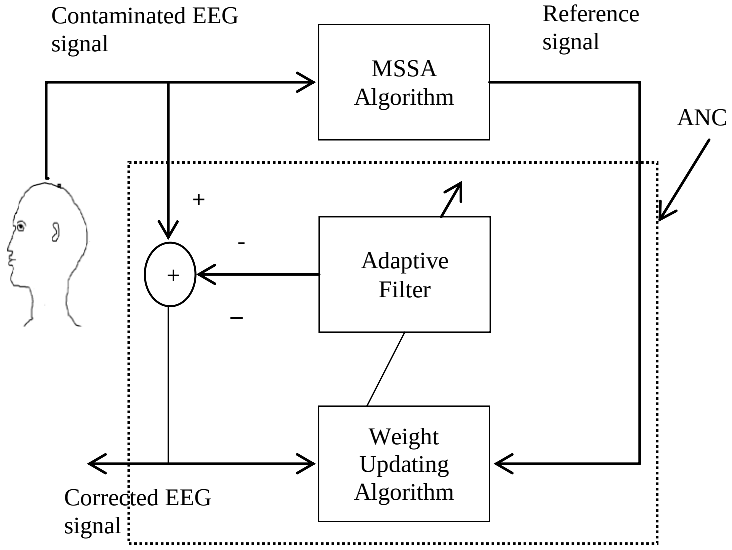


Figure 2: Block Diagram of MSSA-ANC

**c. Reconstruction:**

**1st Step: Grouping:** The grouping step corresponds to splitting the elementary matrices into several groups and summing the matrices within each group. Let I = {i1. . . ip} be a group of indices i1, . . . , ip. Then matrix $X_I$corresponding to the group I is defined as $X_I$= $X_{i1}$+ . . . +$X_{ip}$.The procedure of choosing the sets $I_1$. . . $I_m$is called theEigentriple grouping.

**2nd Step: Diagonal Averaging:** The purpose of diagonal averaging is to transform a matrix to the form of a Henkel matrix which can be subsequently converted to a time series. If $Z_{ij}$stands for an element of a matrix Z, then the K-th term of the resulting series is obtained by averaging $Z_{ij}$over all i, j such that i + j = k + 1. This procedure is called diagonal averaging.

**B. MSSA-ANC:**

In the proposed MSSA-ANC, contaminated EEG signal vector y and the extracted EOG signal and applied to primary and reference inputs of the ANC. Adaptive filter takes the samples one by one and estimates the signal by updating the filter coefficients using RLS algorithm. The estimated signal is subtracted from the contaminated EEG signal at every time instant *n*, results a corrected EEG signal. This process will be repeated for each block of data separately. The time taken to obtain the corrected EEG signal of each block is equal to the sum of the computation times of the serial to parallel convertor and the MSSA, parallel to serial convertor and the ANC. Since the computation time to obtain the corrected EEG signal is less than the sampling interval of the EEG signal, the proposed method is practically feasible.

**4. Simulation Results:**

To validate the performance of proposed MSSA-ANC, simulation were performed on synthetic EEG signal. To qualify the performance of technique relative root mean square error (RRMSE) is used as performance measure and is defined as

$$RRMSE = \frac{RMS(s-\hat{s})}{RMS(s)}$$

Where RMS(s) and RMS (ŝ) represents the root mean square of true and corrected EEG signal respectively. In general as the EOG signal is a slowly time varying signal, the numerator quantity is small.

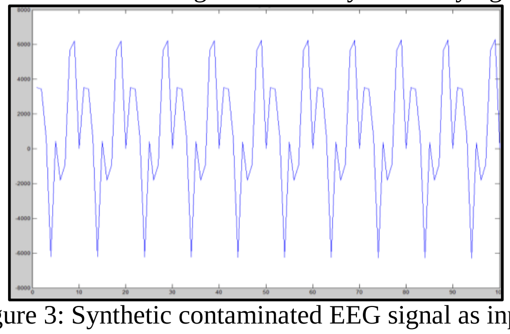

Figure 3: Synthetic contaminated EEG signal as input

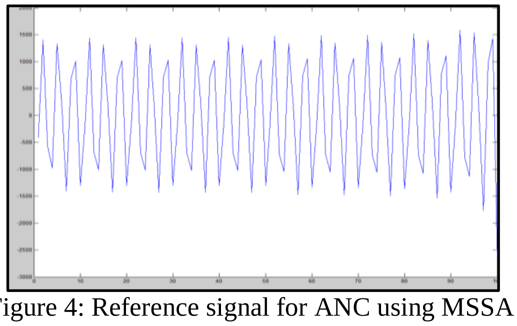

Figure 4: Reference signal for ANC using MSSA

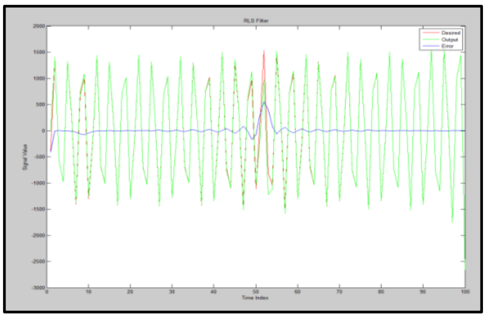

Figure 5: RLS adaptive filter output

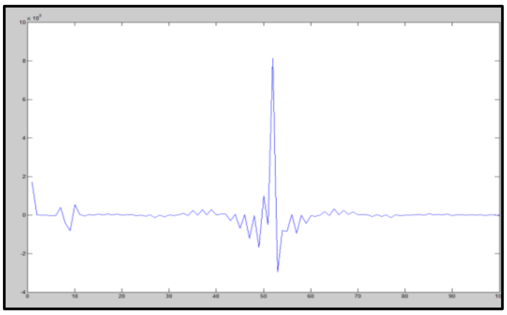

Figure 6: Corrected EEG signal

With the above parameter settings, proposed MSSA with ANC techniques are applied on synthetically contaminated EEG signal. The Fig. 3 shows the synthetic contaminated EEG signal as input given to the MSSA block. After that the reference signal is produced by the MSSA block which is shown in the Fig. 4. as given to the ANC. The ANC uses the RLS filter output shown in Fig.5 and finally the corrected EEG signal is created by the weight updating algorithm shown in Fig. 6. In conventional methods, the extracted EOG signal is simply subtracted from the contaminated EEG to obtained artifact free EEG signal. However, this technique fails to track the signal changes due to the eye blink. Hence use of ANC enhance in the process of estimating EOG artifact. In order to show that the proposed MSSA-ANC technique is preserves the EEG component, we define a parameter called, mean absolute error (MAE) and is given by

$$\text{MAE} = \frac{\sum_{k=j}^{l} |Pe(k) - Py(k)|}{l - j}$$

Where Pe and Py are the PSD of the corrected and contaminated EEG signals respectively j and l are the specific bands. Depending on RRMSE and MAE value, the efficiency of MSSA-ANC method is reliable. The table 1 shows the RRMSE and MAE value of proposed MSSA- ANC technique. This technique is not alter the EEG component.

Table 1: RRMSE and MAE value of MSSA-ANC technique

| Segment | RRMSE (%) | MAE(dB) |
|---|---|---|
| EEG signal 1 | 0.3326 | 0.027 |
| EEG signal 2 | 0.2753 | 0.022 |
| EEG signal 3 | 0.4212 | 0.036 |
| EEG signal 4 | 0.3123 | 0.021 |

**5. Conclusion:**

In this paper, combined MSSA-ANC technique is presented to remove the EOG artifacts from the multichannel EEG signals. The method is based on SSA.The proposed algorithm consists of severalcomplementary stages. First, the EEG signal is extracted from a noisycomposite signal using multichannel SSA. The results clearly confirmed that the SSA technique could be used for extraction the EEG signal and separating noise component. The computational aspect of the proposed algorithm can be considered as another advantage since only a few first largest singular values are used. The proposed algorithm is applicable for extraction of the desired components in any composite signal, where the original signal can be formed in the trajectory matrix X. Simplicity and capability of MSSA for separation can be considered as other advantages of MSSA such that it can be easily adapted to a broad class of biomedical signals.

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