Wireless Personal Communications (2019) 108:1311–1327
https://doi.org/10.1007/s11277-019-06470-3

Designing Efficient Blind Source Separation Methods for EEG Motion Artifact Removal Based on Statistical Evaluation

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Published online: 6 May 2019

Abstract

As the electroencephalography (EEG) biomedical signals are affected under the presence of the muscular motion artifacts. Presence of these artifacts leads to error in visual analysis of EEG signal, thus results in wrong diagnosis of human diseases. The variants of blind source separation (BSS) methods are available. This paper aims to design the efficient BSS based method for effectively eradicating the EEG motion artifacts. This is accomplished by evaluating the six different methods, which are combination of independent component analysis (ICA) and canonical correlation analysis (CCA) along with the discrete wavelet transform and stationary wavelet transform methods. Each of above combination methods are applied on the ensemble empirical mode decomposed, Intrinsic Mode Functions for EEG motion artifact suppression. This research paper tests the performance over pure EEG signal and also on the simulated EEG sinusoids to mimic the effect of motion artifacts. The performance of six BSS artifact removal algorithms are evaluated using efficiency matrices such as del signal to noise ratio, lambda (λ), spectral distortion (P_{dis}) and root mean square error. The execution time is also calculated to evaluate the computation efficiency of the algorithms. The results suggest that CCA algorithm outperforms over ICA in the case of the high noisy condition of EEG signal.

Keywords EEG · BSS · ICA · CCA · Motion artifacts · DWT · SWT · EEMD

1 Introduction

The EEG signal is a good mean to explore brain activity and preferred over other physiological signals, because these signal are sensitive to detect changes within a millisecond span. EEG analysis is preferred over other similar methods since it potentially takes

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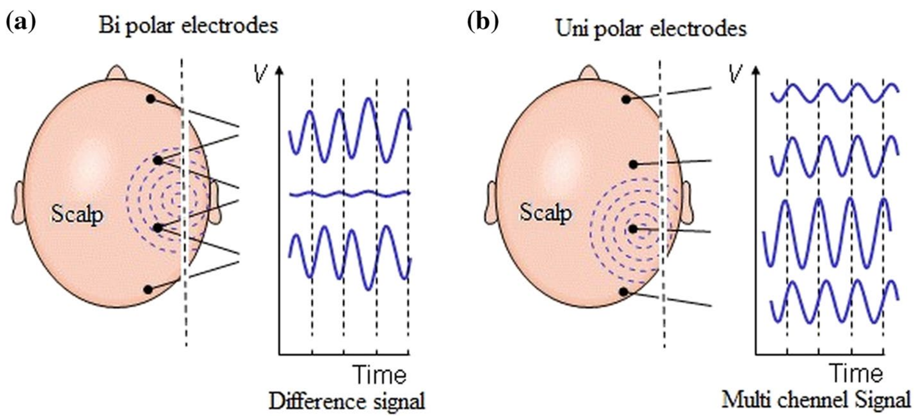

Fig. 1 EEG signal acquisition model for multichannel output with each channel having different features due to its location on scalp

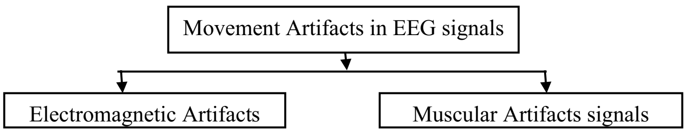

Fig. 2 Classifications of artifacts

0.5–130 ms approximately to propagate across a single neuron or electrode. However, other methods likewise functional magnetic resonance imaging (fMRI) by P M Matthews and positron emission tomography (PET) [1] are less efficient as they have time resolution in terms of seconds and minutes. Methods such as fMRI record changes in blood flow and PET record changes in metabolic activities which are indirect markers of electrical movement belonging to the brain. However, EEG directly measures the electrical movement of the brain using electrodes. EEG signals are captured using Bipolar or Unipolar electrodes as shown in the Fig. 1. In Bi-polar method potential difference between a pair of electrodes is measured. Whereas, in Unipolar method the potential of each electrode is compared either to a neutral electrode or to the average of all electrodes.

The measurement of the EEG signal is a critical stage before human neural diseases diagnosis. It can be observed that the each EEG channel is sensitive to any kind of muscular motions. Thus, different muscular motions may affect different EEG channel data due to their location on scalp. The EEG signal measurements not in the standard clinical environment causes disturbance due to artifacts such as an electrocardiogram (ECG), electrooculogram (EOG) and electromyogram (EMG). There are various type of artifacts associated to the EEG signal capturing. Major EEG artifacts are classified in Fig. 2.

1.1 Motion Artifacts

Movement artifacts are always being the part of the acquired EEG signal data. They are existing due to the pressure imposing on the chemical gel layer kept between the body and electrode. Any kind of muscular motion of human body parts causes the pressure on this layer thus provides artifacts signals. The artifacts are broadly classified as electromagnetic (EM) noise and/motion artifacts. The EM noise artifact is interference present due to other EM devices in the vicinity of EEG electrodes. Whereas, motion artifact is the noise induced due to motion of the human body parts or muscular movement. It may include the artifacts like eye blinks, muscular motions or any kind of head nodding.

1.2 Scope of Paper

This research paper focuses on removal of EEG motion artifacts. These artifacts are generated due to movement in patient's body part and also due to electrode movement during EEG signal capturing. Thus, the elimination of these artifacts from the original EEG signal is a challenging process. The methodology proposed in this paper provides descriptive quantitative and qualitative results for EEG signal after artifact removal. The filtered EEG signal helps in accurate diagnosis of human neurological diseases. It is required to design an algorithm so that it does not degrade the features of EEG signal and also improves the signal to noise ratio. The research paper organization is as follows: In the Sect. 2 ensemble empirical mode decomposition method (EEMD) is explained. Section 3 is followed by overview of the blind source separation concept. In Sect. 4 synthetically artifactual EEG data generation through simulation is deliberated. The quantitative and qualitative result analysis of different combinations of these techniques was implemented and is detailed in Sect. 5. Further, outcomes of the evaluation process are concluded and future scope are discussed in Sect. 6.

2 Ensemble Empirical Mode Decomposition (EEMD)

Let data vector is denoted by $x(t)$, the EEMD method can decompose data vector into series of frequencies i.e. intrinsic mode functions (IMFs), abbreviated as $IMF_i(i = 1, 2 \ldots N)$, where N is the number of IMFs [2]. The data vector $x(t)$ can be expressed as;

$$\boldsymbol{x}(\boldsymbol{t}) = \sum_{i=1}^{N} IMF_i((t) + R_n(t) \tag{1}$$

where R_n the residual signal is obtained after extraction of the N number of IMF's form data signals. The EEMD method identifies the true IMF components of the data. As this method evaluates the mean of an ensemble of estimates, each estimate consist of original signal plus white noise of finite amplitude. Each estimate has different amount of noise, and it is cancelled out in the ensemble mean after enough tests. The value of added white noise is of finite amplitude and can force the ensemble to exhaust all the possible solutions in separating process and collate the portion of the source signal of comparable scale in called one IMF [3]. By adding the finite noises, the EEMD eliminates mode mixing in all cases automatically.

3 Blind Source Separation

The blind source separation (BSS) is an un-substantiated learning algorithm used for separating the signal and artifacts sources using decomposition process. The source separation is performed using the recorded sensor signals with some assumptions on the underlying signals. Once the estimations of the original sources are known, then the sources representing the artifact signals are removed. The choice of the best BSS algorithm to employ depends on a priori knowledge of the signal and how critical is the application area. The most common BSS algorithms are defined sequentially in the following sub-sections.

These BSS algorithms [4] are used in various fields in addition to EEG signal artifact removal. The BSS–ICA algorithm decomposes the EEG signal into statistically self-determining components also known as independent components (ICs) based on higher-order statistics. To attain clean EEG data, artifacts related ICs are removed and remaining ICs are reconstructed. However, muscular artifacts critically affect the most ICs part, results in noticeable crosstalk between brain and muscle movements [5, 6]. The BSS–ICA algorithm was proposed for EMG artifacts mitigation from EEG signal [7]. The EMG artifacts have wide frequency band and sequential white noise results in lower autocorrelation with EEG signal. The BSS approaches based EEG muscle artifact suppression was proposed and concluded that, CCA method presented better EMG cancelation than ICA on simulated data [8].

In practical EEG measurement methods based on a single channel is preferred over many existing multiple channel measurement methods to reduce operational and maintenance cost [2]. A cascaded approach of ensemble empirical mode decomposition and canonical correlation analysis (EEMD–CCA) technique was introduced by [9] for artifact removal in single channel EEG signal. The single channel EEG signal is transformed into the multi-channel by EEMD algorithm. Then CCA technique (second order statistics) is applied to segregate the artifact components from the input multi-channel signal and remaining components are added to get artifact free EEG signal. The techniques single-channel ICA (SCICA), Wavelet-ICA (WICA) and EEMD–ICA are applied for single channel EEG signal EMG artifact removal. It is concluded that EEMD–ICA cascaded algorithm outperforms than the SCICA and WICA algorithm in terms of root mean square error (RMSE) parameter [10]. Commonly used BSS methods are discussed below.

3.1 Independent Component Analysis (ICA)

$$S = A_{N\times M}C + n \tag{2}$$

It is assumed that during ICA the added noise is non-orthogonal or non-Gaussian. The Fast ICA algorithm is based on a mathematical and computational approach to distinct the signal combination into their independent components (ICs). The ICA algorithm [11, 12] is applied on signal combination $C = \left[c_1, c_2, c_j \dots c_N\right]$ as input. The independent sources $S = \left[s_1, s_2, s_j \dots s_N\right]$ generated by Fast ICA algorithm are presented as:

$$X = A * S \tag{3}$$

where n is the noise and A is the $N \times M$ mixing matrix. To find linear transformation W of X, the independent outputs are determined as:

$$\mathrm{I = W\ X = W\ A\ s} \tag{4}$$

where I is the estimated ICs. It is highly required that components must be statistically independent instead of a mixture. The BSS–ICA algorithm attains spectral improvement, but does not consider the temporal profile. However, the real-time EEG signal has both the spatial and temporal structure. The BSS–CCA algorithm considers the correlation between both temporal and spatial structures of the signal is discussed in next section.

3.2 Canonical Correlation Analysis

The BSS–CCA algorithm is used to measure the correlation among two multi-dimensional random variables. In this algorithm the primary multi-dimensional random variables considered as first basis vector and the secondary multi-dimensional random variable is considered as temporally delayed version of the first basis vector [13].

Therefore, CCA algorithm determines the linear association between two set of source variables with the help of the variance and co-variance matrix of the data. There is a set of linear combinations named A and B which are considered as:

$$\mathrm{B_Q} = [\mathrm{b_{11}}, \mathrm{b_{12}}, \ldots \mathrm{b_{1n}}]^{\mathrm{T}} \tag{5}$$

$$\mathrm{A_P} = [\mathrm{a_{11}}, \mathrm{a_{12}}, \ldots ..\mathrm{a_{1m}}]^{\mathrm{T}} \tag{6}$$

Let $\mathrm{C_{pp}}$ be the variance of $\mathrm{A_p}$, $\mathrm{C_{qq}}$ be the variance of $\mathrm{B_Q}$ and $\mathrm{C_{pq}}$ be the covariance between A_P and B_Q. Then the correlation between A_P and B_Q can be written as

$$\mathrm{P}^* = \frac{\mathrm{A_p^T C_{pp} B_Q}}{\sqrt{\mathrm{A_p^T} \mathrm{C_{pp}} \mathrm{A_p}} \sqrt{\mathrm{B_q^T} \mathrm{C_{qq}} \mathrm{B_q}}} \tag{7}$$

This P^* should be maximum to achieve the best self-correlation. Thus, this optimization can be solved by

$$C_{pp}^{-1} C_{pq} C_{qq}^{-1} C_{qp} A_P = \rho A_P \tag{8}$$

$$C_{qq}^{-1} C_{qp} C_{pp}^{-1} C_{pq} B_Q = \rho B_Q \tag{9}$$

This ρ represents the Eigen value whose square is equal to P^*.

$$\rho = \sqrt{P^*} \tag{10}$$

These canonical pairs are calculated and separated by obtaining self-correlation and mutual decorrelation between input sources [9, 14]. These BSS based approaches are applied on the artifactual EEG signal for motion artifacts removal. The synthetic artifactual process of EEG signal generation is discussed in the next section.

4 Data Synthesis and Simulation

The motion artifact is a common source of EEG data contamination. Therefore, a reliable motion artifact removal algorithm is required to attain pure EEG signal. The main objective of this research paper is to design an effective method for EEG motion artifacts

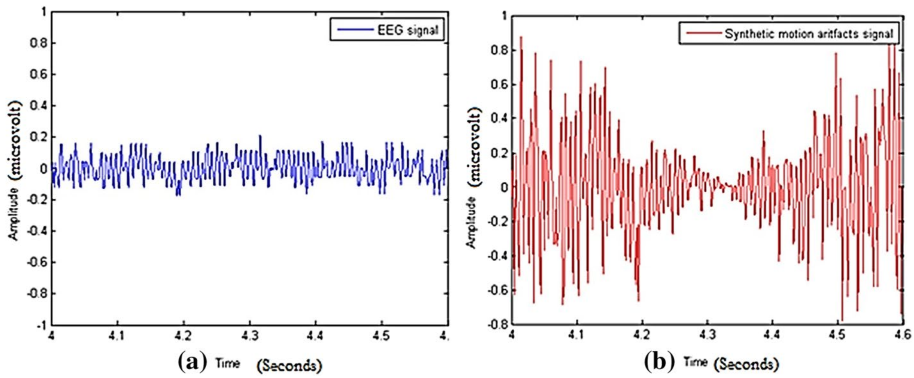

Fig. 3 **a** Input EEG signal. **b** Synthetic motion artifact EEG Signal

removal while preserving the neural information of EEG data. Therefore, the filtered EEG data can be provided or acquired for the accurate diagnosis and analysis of the human neurological diseases.

The data for this form of experimentation is contributed by the Kevin T Sweeney at the National University of Ireland at Maynooth. The data is available on an online open source interface [15] and description of recording is acquired from the same source only. These online open source interface provides artifact-free data which is considered as a ground truth (original) signal. The motion artifacts are generated due to the movement of the head and electrodes, sudden impulse response variations which can be considered as amplitude modulated signals. Therefore, with this assumption, synthetic artifactual EEG signal is generated by simulating amplitude modulated sinusoids to the original EEG signal.

These artifacts are clearly observe or are visible and mimic the behavior of the motion artifacts in the EEG signal. The ground truth and artifactual EEG signal are shown in Fig. 3. The Fig. 3a presents the original ground truth signal and Fig. 3b presents the EEG signal with simulated synthetic motion artifactual EEG signal. It is concluded from state of the art studies that cascaded algorithms are more effective for EEG artifacts suppression than single algorithms [9]. Thus, the synthesized data is applied to BSS (ICA or CCA) [16] based two and three stages cascaded algorithms for EEG motion artifact filtering.

BSS algorithms (ICA and CCA) are applied in two and three stages artifact removal methods along with wavelet (DWT and SWT) filtering to compare the performance of ICA and CCA algorithms. Six combinations of such BSS (ICA and CCA) based two-stage and three-stage algorithms are discussed in the subsequent sub-section.

4.1 EEMD–ICA

The EEMD–ICA algorithm was first documented by [10]. The EEMD algorithm is employed to convert single channel EEG signal into multi-channel signal. Further, these generated IMFs are applied as an input to the second stage ICA approach for source separation. This ICA approach separates the input components into the underlying source signals which are generated due to their independent nature. The source signal identified as artifacts are removed and remaining components are reconstructed to acquire artifact-free signal.

4.2 EEMD–CCA

EEMD–CCA algorithm was showcased by [9]. In this motion artifact removal approach EEMD outputs (IMFs) are applied to CCA [17] algorithm for source separation based on self-correlation and mutual un-correlation. The identified artifact sources are removed and remaining components are reconstructed to acquire artifact-free EEG signal.

4.3 EEMD–ICA–DWT and EEMD–CCA–DWT

A deep study of the existing artifact removal approaches suggest that after BSS decomposition some artifact residues are still present in the EEG signal [3]. Furthermore, occasionally some EEG components are also eliminated in addition to artifacts components which results in an underdetermined problem. Therefore, it is recommended to apply discrete wavelet transform (DWT) to the BSS processed signal for effective artifact removal. The EEG artifact removal efficiency is evaluated by applying the EEMD and BSS (ICA and CCA) processed signal to the DWT algorithm [18]. Further, the reconstructed signal after DWT thresholding provides the clean EEG signal. The DWT based methods are better than the conventional BSS based methods. In this paper the performance of EEMD–ICA–DWT and EEMD–CCA–DWT are compared.

4.4 EEMD–ICA–SWT and EEMD–CCA–SWT

Additionally the BSS algorithms (ICA and CCA) performance is also evaluated with stationary wavelet transform (SWT). This SWT algorithm is preferred for EEG artifact removal because it provides effective artifacts suppression along with preserved EEG neural information [19]. These discussed EEG artifact removal techniques are implemented on synthetically generated artifactual EEG signal. The simulations and implementations have been done using MATLAB (MathWorks), Microsoft Windows 8.1×64 OS on the computer with Intel(R) core(TM) i-5-4200U, 2.30 GHz CPU and 8.00 GB RAM. The simulation results are discussed in the next section.

5 Results and Discussion

The EEG motion artifact removal algorithms are implemeted on artifactual EEG signal. The efficiacy of artifact removal algorithms are evaluated based on some evaluation parameters. Thereafter, the results of qualitative and quantitative analysis is discussed in the preceding sub-sections of the paper.

5.1 Quantative Analysis and Discussion

The BSS based artifact removal approaches are quantatively evaluated based on some assessment parameters as difference in signal to noise ratio (Del SNR), lambda (% artifact reduction), root mean square error (RMSE) and spectral distortion. These parameters are introduced in [9] to evaluate the performance.

DSNR The ΔSNR is defined by the difference of SNR between signal before and after artifact removed. Differential SNR defined as ΔSNR is calculated by the following formula.

$$\Delta\mathrm{SNR} = 10\log_{10}\left(\frac{\sigma_{\mathrm{x}}^2}{\sigma_{\mathrm{after}}^2}\right) - 10\log_{10}\left(\frac{\sigma_{\mathrm{x}}^2}{\sigma_{\mathrm{before}}^2}\right) \tag{11}$$

The parametric evaluation results and their comparisons are encapsulated in Table 1. The first column of Table 1 presents the performance evaluation for cascaded two-stage approach of EEMD and ICA algorithm [10] for EEG motion artifact removal. Correspondingly, second column represents results analysis for EEMD–CCA [9] algorithm. The comparison of the first and second column in Table 1 shows that EEMD–CCA outperforms than EEMD–ICA with significant improvement in DSNR values. High DSNR value shows the improved signal quality after artifact removal. The EEMD–CCA algorithm implementation results in the corresponding reduction in RMSE values and improvement in Lambda parameter with respect to different artifact SNR values. Improved Lambda value reflects the better reduction of artifact in percentage. The CCA algorithm is based on correlation of source components, thus, EEMD–CCA results in improved correlation based separation with respect to EEMD–ICA.

Similarly, the DWT based three-stage filtering approach EEMD–CCA–DWT performs better than EEMD–ICA–DWT. This is observed from third and fourth column of Table 1 with better DSNR and Lambda values. Moreover, the improved DSNR, Lambda, PSD, Correlation and reduced RMSE suggest the success of EEMD–CCA–SWT than EEMD–ICA–SWT for artifact removal as can be observed from fifth and sixth column of Table 1.

Thus, the overall conclusion from Table 1 is that CCA based filtering method outperforms than ICA based artifact removal methods. The CCA algorithm provides reduced computation time for source separation because the CCA is based on second order statistics whereas, ICA algorithm is based on higher order statistics. Moreover, the CCA algorithm offers improved computationally efficiency than other artifact removal methods [14]. The ICA algorithm separates the sources based on Gaussian distribution which is not practically promising method. To attain more comprehensive comparative analysis, the evaluation parameters (DSNR, Lambda and RMSE) are plotted to compare the ICA and CCA based methods performance as shown in Figs. 4, 5 and 6.

The CCA based artifact removal methods attain improved DSNR than the ICA based artifact removal methods particularly with low artifact SNR as shown in Fig. 4. However, the performance of both ICA and CCA based algorithms in the high SNR conditions is almost comparable. The improved DSNR indicates that CCA filtered EEG signal quality is more improved than ICA filtered EEG signal.

Figure 5 shows the performance comparison of two and three-stage artifact removal methods with Lambda as evaluation parameter. It is vibrant from Fig. 5 that the artifact removal with CCA based algorithms provide improved artifact removal in comparison of ICA based algorithms.

RMSE The RMSE is given as root mean square error between the original data signal with artifacts and that of signal after artifact removal and is mathematically defined as;

$$\mathrm{RMSE}_{\mathrm{free}} = \mathrm{sqrt}\left(\mathrm{mean}\left((\mathrm{GT} - \mathrm{AFT}).^{2}\right)\right) \tag{12}$$

$$\mathrm{RMSE}_{\mathrm{art}} = \mathrm{sqrt}(\mathrm{mean}((\mathrm{GT} - \mathrm{BEF}).^{2})) \tag{13}$$

Table 1 Tabular comparison of the BSS methods for two and three stages artifact removal algorithms

1	2	3	4	5	6	7
SNR	EEMD_ICA [10]	EEMD_CCA [9]	EEMD_ICA_DWT	EEMD_CCA_DWT	EEMD_ICA_SWT	EEMD_CCA_SWT
DSNR (difference in signal to noise ratio) in dB						
5	3.1741	6.5871	22.0730	32.3860	22.510	35.8634
10	2.4793	8.611	19.199	25.9530	23.1084	37.2775
15	2.959	10.0850	25.3340	35.3610	25.432	38.4963
20	2.9969	12.7920	20.4560	29.0530	21.104	32.8229
25	4.2413	15.4018	21.9620	32.6640	20.226	31.3270
Lambda (ideal value = 100)						
5	11.514	21.5139	87.710	83.2980	87.928	92.5767
10	14.1620	33.009	85.724	79.2630	79.5024	90.6307
15	26.0305	34.8310	82.3234	84.2110	89.739	89.838
20	18.5990	47.5610	78.576	81.0150	82.201	95.746
25	25.0800	51.9953	80.125	82.9220	83.433	87.2213
PSD improvement						
5	−0.1965	−0.1965	1.477	0.1872	0.1298	1.6905
10	−0.4633	−0.9983	2.6831	0.2368	1.7308	1.7467
15	−0.237	−0.9660	1.1125	0.1689	−0.4936	1.9926
20	−0.5350	−0.9995	0.087	0.2034	−0.3589	2.0352
25	−0.1659	−0.9843	0.7046	0.1848	0.0539	2.128
Correlation improvement						
5	0.004	0.004	0.0141	0.0096	0.0197	0.023
10	0.007	0.0047	0.0151	0.0082	0.0059	0.0161
15	0.019	0.0059	0.0140	0.0105	0.0226	0.0222
20	0.007	0.0060	0.0083	0.0110	0.0216	0.0258
25	0.017	0.0054	0.0100	0.0100	0.008	0.0140
Spectral distribution (P_{dis})						
5	0.6487	0.6492	0.7323	0.8120	0.8312	0.8543

Table 1 (continued)

1	2	3	4	5	6	7
SNR	EEMD_ICA [10]	EEMD_CCA [9]	EEMD_ICA_DWT	EEMD_CCA_DWT	EEMD_ICA_SWT	EEMD_CCA_SWT
10	0.656	0.7974	0.7992	0.8383	0.8438	0.8680
15	0.6773	0.801	0.8102	0.8524	0.8782	0.9012
20	0.660	0.7342	0.7568	0.8210	0.8610	0.9235
25	0.775	0.8285	0.8316	0.8921	0.9012	0.9543
RMSE (root mean square error)						
5	0.278	0.2480	0.118	0.0968	0.0962	0.0941
10	0.270	0.2285	0.1268	0.1066	0.098	0.093
15	0.2499	0.2022	0.1438	0.0936	0.0959	0.094
20	0.261	0.2166	0.1591	0.1008	0.099	0.096
25	0.2327	0.2072	0.1839	0.0960	0.0969	0.0954

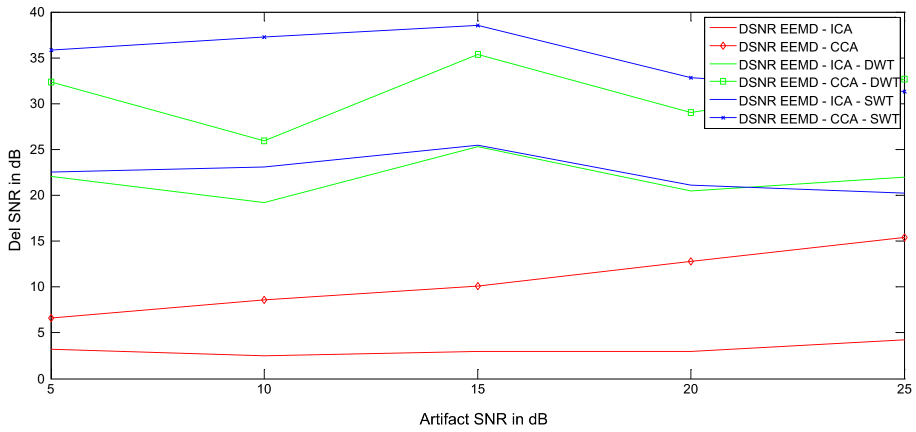

Fig. 4 Comparison of ICA and CCA based motion artifact removal methods based on DSNR

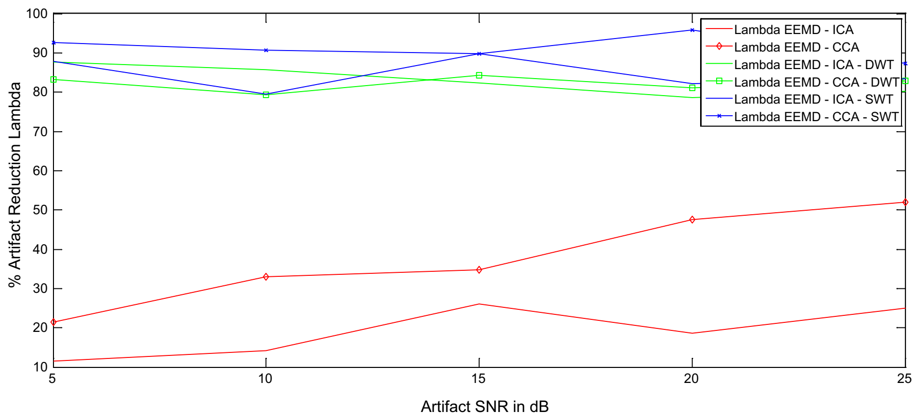

Fig. 5 Comparison of ICA and CCA based motion artifact removal methods based on Lambda

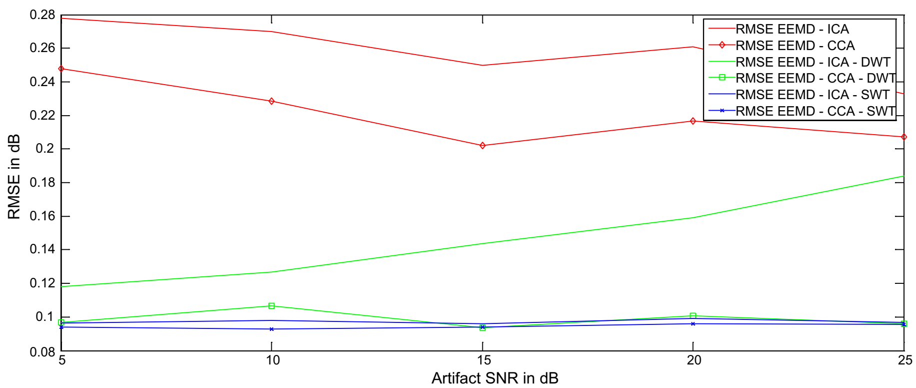

Fig. 6 Comparison of ICA and CCA based motion artifact removal methods based on RMSE

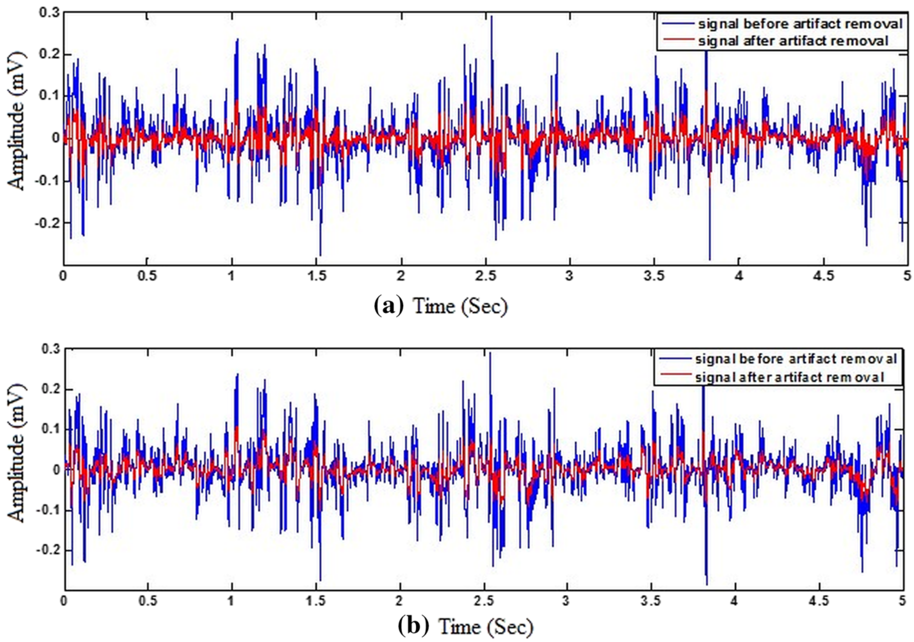

Fig. 7 **a** EEG signal comparison after EEMD-ICA artifact removal algorithm. **b** EEG signal comparison after EEMD–CCA artifact removal algorithm

Figure 6 demonstrates the paramount results for the CCA based artifact removal methods in comparison to ICA based methods with the RMSE as evaluation parameter. The results show that errors introduced due to artifacts have been reduced to a great extent with CCA based methods. Additionally the analysis is extended based on signal behavior discussed in next sub-section.

5.2 Qualitative Analysis and Discussion

The two-stage motion artifact removal methods (EEMD–ICA and EEMD–CCA) are evaluated qualitatively as shown in Fig. 7. In Fig. 7, the blue color represents the signal before artifact removal whereas, red color represents the signal after filtering approach. The broad spectrum peaks introduced in EEG signal due to motion artifacts are greatly suppressed in Fig. 7b as compared a. The CCA based algorithms separate the sources effectively result in improved suppression of artifact sources than ICA based algorithms.

The three-stage filtering approaches along with discrete wavelet transform algorithm outperform over other two-stage artifact removal methods, because Wavelet Transform smoothens the motion artifacts randomness which is partially present even after two stage filtering.

The more effective three-stage cascaded algorithms are also evaluated to compare BSS algorithms. The DWT algorithm is applied after BSS approaches (ICA and CCA) to remove the randomness available in EEG signal even after BSS algorithms filtering. The evaluation comparison of ICA and CCA with DWT is shown in Fig. 8.

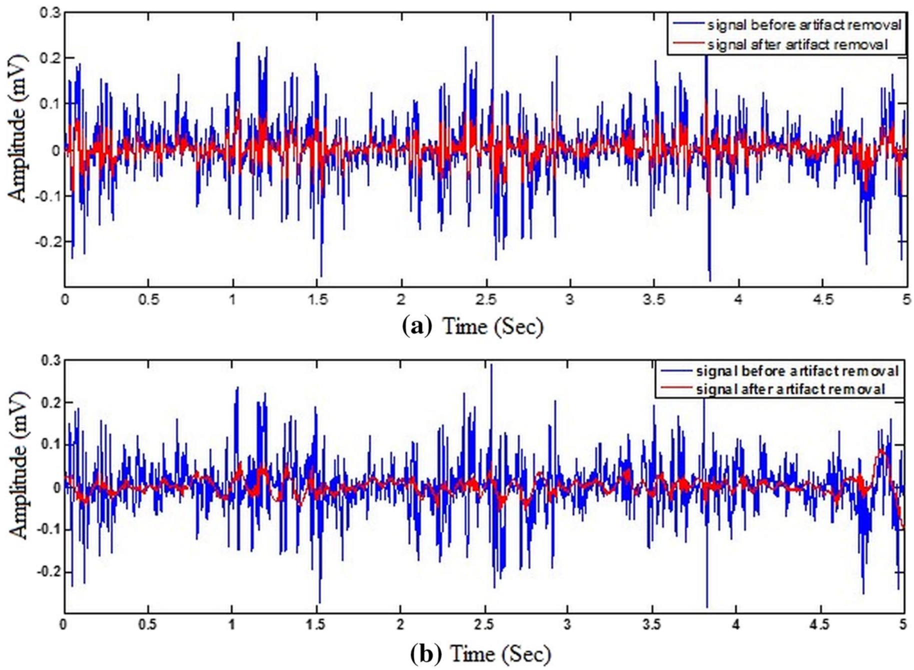

Fig. 8 **a** EEG signal comparison after EEMD-ICA-DWT artifact removal algorithm. **b** EEG signal comparison after EEMD–CCA-DWT artifact removal algorithm

It is clearly visible from Fig. 8a, b that CCA algorithm performs well for artifact suppression than ICA algorithm (color convention applied is same as in Fig. 8. The artifact filtering is improved with cascaded BSS and DWT algorithms.

In the case of EEG signal with motion artifact, SWT algorithm outperforms than DWT, because SWT algorithm is translation invariant and no down sampling of the data is involved. The SWT algorithm is also preferred to remove unpredictable behavior of motion artifact which is left after two stage filtering of EEG signal [19]. Thus, EEG signal gets smoothened over the length while containing all their fundamental properties. Thus, SWT filter removes the randomness as well as preserves the EEG neural information. Therefore, the BSS algorithm performance is evaluated with SWT filtering is shown in Fig. 9.

The vigilant observation of Fig. 9 suggests that BSS–CCA algorithm performs well for EEG motion artifact removal with SWT filter. This approach removes the broad spectrum randomness of motion artifact as well as conserves the neural information of EEG signal which is mandotary for neural analysis. Therefore, red color filtered EEG signal has only neural movements and artifact effect is suppresssed to a great extent.

It can be observed from comparison of power spectral density in the Fig. 10 that the methods like EEMD–CCA–DWT and EEMD–CCA–SWT performs equaly well for all SNR values and SWT based methods perfrom superior then the DWT in terms of PSD.

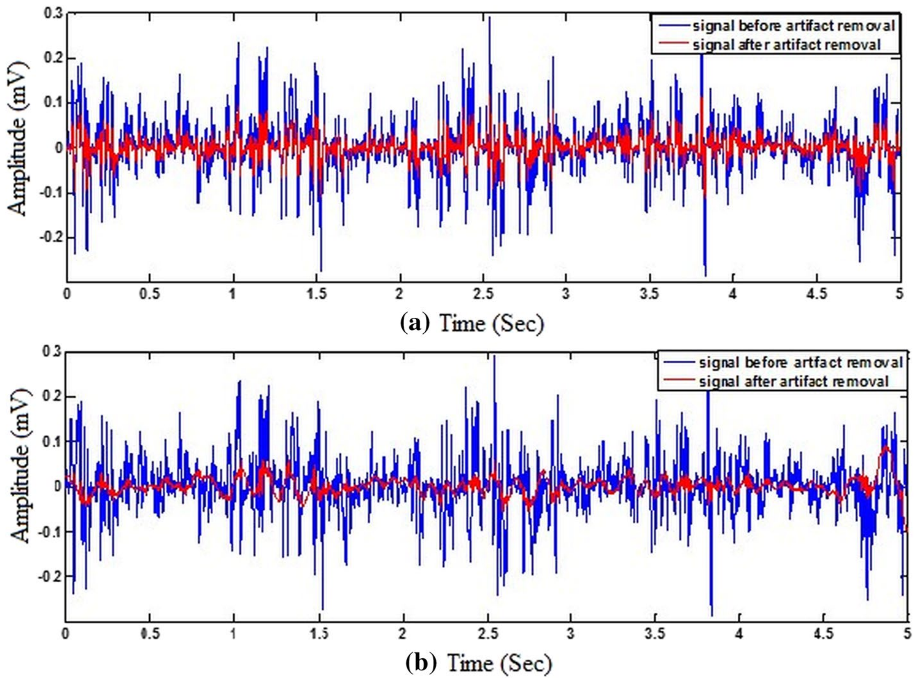

Fig. 9 **a** EEG signal comparison after EEMD-ICA-SWT artifact removal algorithm. **b** EEG signal comparison after EEMD–CCA–SWT artifact removal algorithm

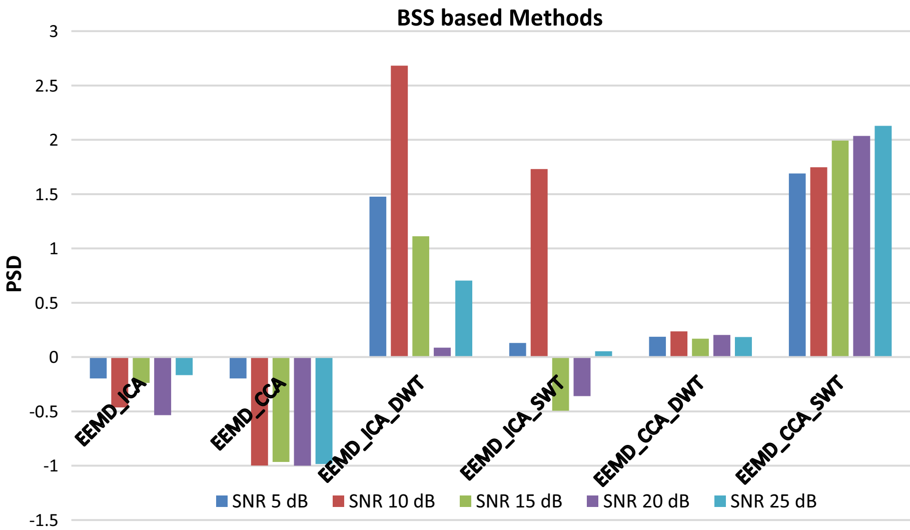

Fig. 10 Comparison of the power spectral density for different BSS based methods

Table 2 Comparison of the elapsed time (or execution time)

Methods	EEMD	EEMD-SWT	EEMD-DWT
With ICA	21.920304	24.789552	22.7842
With CCA	20.967756	24.418560	**22.4401**

The bold elapsed time value shows the success of the method. As the proposed method have minimum elapsed time in comparison to other state of the art artifact removal methods

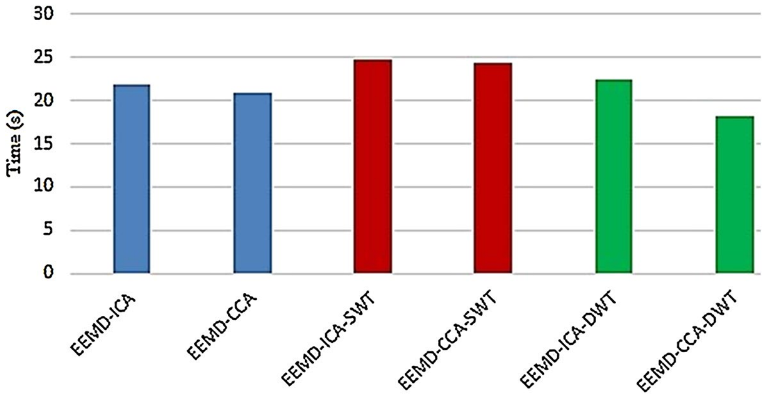

Fig. 11 Comparison plot for ICA and CCA based method based on execution time

5.3 Execution Time

The execution time is the complete computational time taken by any algorithm to perform the artifact removal progression. In order to test the speed of the algorithms the execution time of various BSS based artifacts removal methods are encapsulated in Table 2.

It is observed from Table 2 that CCA based methods perform faster than ICA based algorithms. The average computational time of CCA based method is 21.02 s whereas, ICA-based method is 34.577 s. Table 2 suggests that, EEMD–CCA–DWT algorithm provides faster artifact removal performance than other methods. However, SWT based methods provides good artifacts suppression with preserved EEG neural information [19].

It is clear from Fig. 11 that computational time of CCA based methods is less than ICA-based artifact removal methods. Thus, CCA algorithm is found to be fast and effective source separation method. It can be stated that artifact removal approaches are effective, if it is cascaded with BSS–CCA approach.

6 Conclusion

The research paper have proposed different design methods for the EEG motion artifact removal and based on the quantitative and qualitative analysis the efficient method is designed. A comparative analysis of blind source separation methods for single channel EEG signal motion artifacts removal is performed. Single channel EEG signal is decomposed into IMFs through EEMD and converted into multiple channel signals with different frequencies. Each IMF has a small frequency range, but if the signal is containing artifacts, then IMFs will be low amplitude high-frequency components. To separate these high-frequency components, the CCA and ICA filtering process is performed and compared over these IMFs.

To get the best performance of motion artifact removal, a single level SWT and DWT is applied to both EEMD–CCA and EEMD–ICA processed signal. The two and three stages artifact removal methods with ICA and CCA are evaluated and compared based on different evaluation parameters like DSNR, PSD, Correlation Improvement, Lambda and RMSE. It is concluded that the SWT based method with combination to CCA outperforms over other methods in terms of PSD and error. It is found that the CCA based methods are faster than the ICA based methods. Moreover, the performance of these algorithms is also compared based on execution time. All these evaluation results suggest that CCA based artifact removal algorithms are comparatively faster and performed better for motion artifact suppression than ICA based artifact removal methods. Over all it is found that the performance of the ICA based methods is not consistent for the fluctuating EEG channels, while CCA based methods are more consistent.

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