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An Effective Approach for Motion Artifacts Suppression from EEG Signal

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Abstract

Electroencephalographic(EEG) is a vital signal to analysis the neurological diseases in human being. This EEG signal captured even in highly hospitalic and standard environment may currpted by some non-physiological signals which are termed as artifact in medical term. These artifacts may disturb the quality of signal. Thus, mitigation of these artifacts from EEG signal is an important step. In this work an improved filtering mechanism is proposed forsingle channel EEG signal motion artifacts eradication. The input single channel EEG signal isdecomposed into multi-channel signal. Moreover, this multichannel signal is applied to an cascaded approach of Blind Source Separation (BSS) and wavelet transform in order to eleiminate the artifacts as well as randomness available in the signal due to this artifats. The results are tested with the existing work in the EEG artifact removal which shows outperformance of the proposed method.

Keywords

EEG, EEMD-ICA, CCA, DWT, EEMD-DWICA

INTRODUCTION

The superlative health assessment is a dynamic research area in medical sciences, which needs accuracy with low computing cost in signal recording and imaging. The simplicity of a measuring instrument is also essential, because these instruments are mostly applied for acquiring signals from patients which prerequisite easy and error-free handling of the system. The non-physiological signal introduced in the EEG signal may disturb the quality of signal. Thus artifact mitigation is an important research field [1]. For this artifact suppression many algorithm such as BSS and wavelet transform and adaptive filters are applied [2]

Many artifacts such as electrooculogram (EOG), Electromyography (EMG), Elctrocardiography (ECG) and motion artifact [4-8] influence the regular behavior of the EEG signal. However, amongst them motion artifact rigorously disturb the quality of signal because this artifact get superimposed on the signal. Moreover affect the signal in broad sectrum [17]. Therefore, in the next section the methodology is proposed and discussed in detail to mitigate the motion artifact from EEG signal.

PROPOSED SYSTEM MODEL

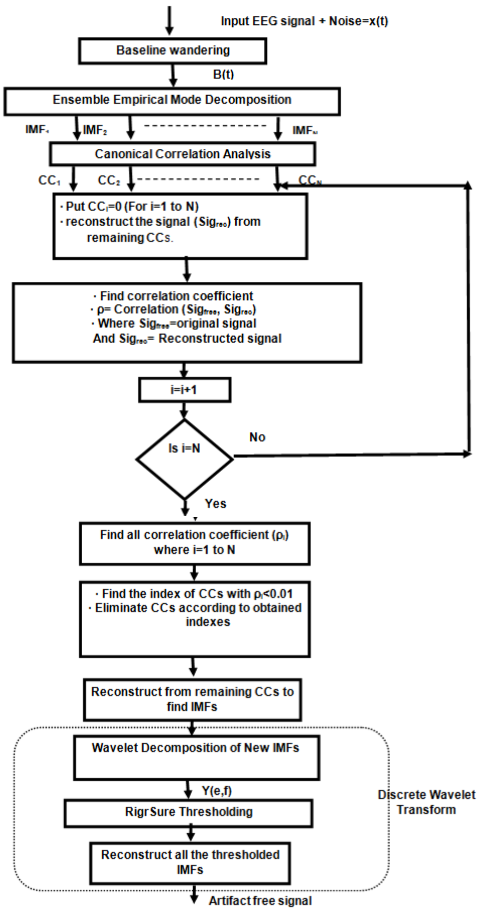

Figure 1: Proposed Architecture for EEG artifacts removal in single channel EEG signal.

PROPOSED ALGORITHM

Step 1: Consider the EEG signal available on[18] as the ground truth signal, and then prepared the synthesized data by creating a different artifact templates and simulating these templates with different amplitude, different duration (stretching from 15 µS to 1S) and at added at different locations and finally superimposed these templates onto the ground truth signalto impressionist the motion artifacts behavior.

Step 2: This created signal is preprocessed (baseline wandering) by suppressing the noise with two pass band frequencies of 0.5 Hz to 99 Hz.

Step 3: The single channel signal $B(t)$is decomposed into multi-channel signal through EEMD algorithm[9][11] results into Intrinsic Mode Functions(IMFs) [10]. These IMFs are mono-componets and zeromean oscillatory functions.

$$B(t) = \sum_{i=1}^{n} C_i(t) + r_n(t) \qquad (1)$$

Where, $C_i(t)$are IMFs components,$r_n(t)$is residual of the data and *n* is the number of iteration.

Step 4: These IMFs are processed through Blind Source Separation approach (CCA). The CCA algorithm [17] provides components which are statistically uncorrelated (CCs), each having distinguished properties, so one or more CCs can represent sources of motion artifacts. Hence, blind source separation of IMFs has been done by CCA as:

$$Y_i(t) = \mathrm{CCA}\,[C_i(t)] \quad \text{Where, i=1, 2,...n} \qquad (2)$$

CCA algorithm generates correlated source components$Y_i(t)$from IMFs $C_i(t)$.

$$\text{Where,} C_i(t) = P * Q \qquad (3)$$

Where, P is source signal, Q is mixing matrix and both are unknown.

Step 5: The steps required for identifying motion artifact CCs after CCA algorithm areas follows:

a. Let Y_i is CC components matrix. Consider first sourceCC of Y_i(i.e. Y_1) by putting zero value to all components except first column. Further, restCCs are mixed with mixing matrix to recreate the new IMFs.

$$\mathrm{imf} = w * \widetilde{Y_1} \qquad (4)$$

Where, ^{w} is the mixing matrix and $\widetilde{Y_i}$ is reconstructed CC.

b. Reconstruct the signal by adding all IMFs.

$$\mathrm{rec}(k) = \sum_{k=1}^{t} \mathrm{imf} \qquad (5)$$

Measure Pearson's correlation coefficients between an original signal X(t)and reconstructed signalrec(k).

$$\mathrm{corr}(k) = \frac{\sum_n (X(k)-\overline{X})(\mathrm{rec}(k)-\overline{\mathrm{rec}})}{\sqrt{\sum_n (X(k)-\overline{X})^2}\sqrt{\sum_n (\mathrm{rec}(k)-\overline{\mathrm{rec}})^2}} \qquad (6)$$

Where, X(k) is the k^{th} value of the X(t);
$\overline{X}$is the mean of X(t);
rec(k)isthe k^{th} value of the reconstructed signal;
$\overline{\mathrm{rec}}$is the mean value of the reconstructed signal;
and total reconstructed signal components k=1 to t.

c. Repeat this step (from a to c) for i=1 to n

$$Y(i,:) = 0$$

Where, i^{th} row become zero.

d. Put all CCs zero having Pearson's correlation coefficient below a given threshold $corr(k) < 0.01$.

e. Now mix all rest CCs with mixing matrix and reconstruct the new IMF $z(k)$ as follows:

$$z(k) = \mathrm{imf} = w' * \widetilde{y_1} \qquad (7)$$

Where, w′ is transpose of the mixing matrix.

Step 6: Motion artifacts CCs identification and removal is followed by Discrete Wavelet Transform over each IMFs Z(k) to have artifact free CCs.

Step 7: Wavelet decomposition is trailed by Rigrsure Thresholding.

Step 8:Reconstruct the Signal B by summing all IMFs.

$$\widehat{B(t)} = \sum_{k=1}^{h} \mathrm{imf}(k) \qquad (8)$$

Where, k=1 to h(Rest number of CCs)

This signal(B(t)) ĭ snow artifact-freeEEG signal.

In order to evaluate the effectiveness of proposed algorithm, a synthetically artifactual EEG signal is generated and compared with ground truth (original) EEG signal is shown in Figure 2.The synthetic motion artifactual EEG signal is presented in red color while original EEG signal is in blue color. It is observed from Figure 2 that even after synthetically artifact generation, the information has been preserved while maintaining high peaks as shown in highlighted black boxes in the figure below.

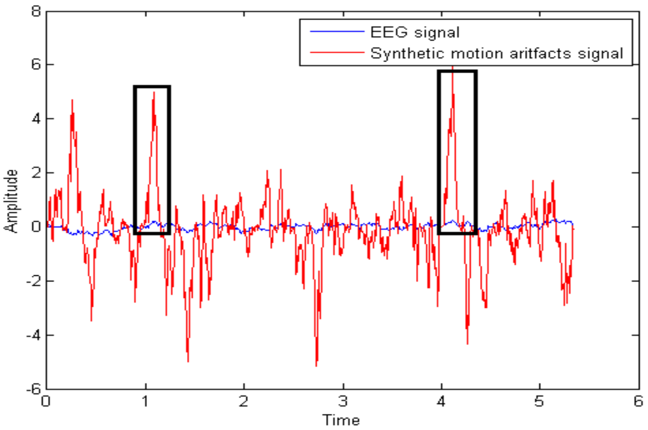

Figure 2: Properties of Synthetic Artifact Signal.

Therefore, it can be stated that synthetical motion artifacts corrupt the EEG signal neural information. The performance of EEG artifact removal methods discussed in this research paper are evaluated by some evaluation matrices. These evaluation parameters are discussed in the next section.

Performance Evaluation Parameters

To perform quantitative evaluation, the statistical performance of the proposed EEG artifact removal method are calculated by following parameters.

3.1 ΔSNR: TheΔSNR is calculated by:

$$\Delta SNR = 10\log_{10}\left(\frac{\sigma_x^2}{\sigma_{after}^2}\right) - 10\log_{10}\left(\frac{\sigma_x^2}{\sigma_{before}^2}\right) \quad (9)$$

Where,$\sigma_x^2$is the variance of the ground truth signal and σ_{before}^2 is the variance of error signal before applying artifact removal technique and σ_{after}^2 is the variance of error signal after applying artifact removal technique. Error signal is calculated by the difference between motion artifact contaminated signal and ground truth signal [5].

3.2 Lambda: This is a difference in correlation between signals which shows the percentage reduction in artifacts denoted by λ.

$$\lambda = 100\left(1 - \frac{R_{clean} - R_{after}}{R_{clean} - R_{before}}\right) \quad (10)$$

Here R_{before} is a correlation between ground truth and artifact contaminated signal andR_{after} is a correlation of signal after denoising process and R_{clean} is the correlation between epochsof known clean data.highλ value shows effective artifact removal performance[5].

3.3 Power Spectral Density (PSD): An arbitrary signal has finite average power can be characterized by PSD. This PSD can be defined as distribution of average signal power over frequency. The PSD can be presented as:

$$\emptyset(\omega) = \lim_{N\to\infty} E\left\{\frac{1}{N}\left|\sum_{t=1}^{N} y(t)e^{-j\omega t}\right|^2\right\} \quad (11)$$

Where, $y(t)$is a zero meanrandomsignal, N is length of the signal $y(t)$ and E function is used to calculate the mean value of function.

Pearson's correlation coefficient is also calculated to evaluate the measure of similarity between two input signals if they are shifted from one another.

3.4 PSD Improvement: PSD Improvement is calculated by finding the change between PSD of the synthetic EEG signal to PSD of the ground truth EEG signal.

$$psd\_improvement = (sum(p2)/sum(p2(1{:}891))) - (sum(p1)/sum(p1(1{:}891))) \quad (12)$$

Where,$p1$ is the PSD of artifact signal and $p2$ is the PSD of artifact removed signal. The length of the EEG signal is considered till 891 units.

3.5 Correlation Improvement: The correlation difference between noisy and ground truth signal is used as the performance measure. The percentage correlation improvement $\mu$is defined as:

$$\mu = 100 * (1 - corr((GT - AFT)/(GT - BEF)) \quad (13)$$

The term in the denominator defines the improvement in the correlation, therefore, the higher value of μgives better artifact removal capacity.Where, *GT* denoted the ground truth (original) value, *AFT* denotes the signal after artifact removal and *BEF* denotes the signal before artifact removal.

3.6 RMSE: The root mean square error between the ground truth data, signal with artifacts and signal after artifact removal is calculated and defined as;

$$RMSE_{free} = sqrt\left(mean\left((GT - AFT).^2\right)\right) \quad (14)$$

$$RMSE_{art} = sqrt(mean((GT - BEF).^2)) \quad (15)$$

The$RMSE_{free}$ is an error between the original signal and signal after artifact removal and $RMSE_{art}$is an error between the original signal and signal before artifact removal.The method which minimizes the value of $RMSE_{free}$ in comparison to $RMSE_{art}$ is suggested as an optimal method for artifact removal.The minimum value of RMSE justifies improved artifact separation.

3.7 Spectral Distortion (P_{dis}): The Spectral Distortion $P_{dis}$is calculated asfollows:

$$P_{dis} = \frac{\sum PSD_{recon}(f)^2}{\sum PSD_{ref}(w)^2} \quad (16)$$

Where,

$PSD_{ref}(w)$= PSD of the reference signal;

$PSD_{recon}(f)$= PSD ofthe reconstructed signal.

The spectral distortion P_{dis}isgiven by PSD ratio of the reconstructed signal to the reference EEG signal [18].

RESULTS AND DISCUSSION

The EEG signal database is assimilated from the Physionet database [18]. The synthetic motion artifactual EEG signal is simulated. The statistical evaluation of the proposed work is performed using above synthetic datasets. Table I presents the comparison of the proposed EEG motion artifact removal methods with existing methods based on various evaluation parameters. The artifact removal methods are implemented on artifactual EEG signal with different amount of noises as (5, 10, 15, 20 and 25).

Table I: Comparison of the proposed method with existing methods.

SNR	EEMD[10]	EEMD-ICA[19]	EEMD-CCA[5]	EEMD-CCA-DWT[Proposed]
DSNR(Difference in Signal to Noise ratio) in dB				
5	12.980	1.174	24.6843	31.7012
10	13.896	10.1385	16.7186	24.016
15	13.851	15.215	41.945	49.108
20	13.894	1.996	20.131	27.4324
25	13.993	13.051	23.943	31.2015

Lambda(Ideal Value= 100)				
5	52.247	11.5139	70.526	81.9765
10	56.851	62.969	59.63	77.7068
15	56.3122	75.373	83.884	88.0863
20	56.5040	18.599	65.193	80.089
25	56.40	70.669	70.313	82.209
PSD Improvement				
5	-0.9032	-0.1965	-0.8987	1.3523
10	-0.9904	1.6767	-1.037	1.2353
15	-0.9366	0.388	-0.7271	1.3846
20	-0.998	-0.5352	-0.9644	1.7338
25	-0.9425	2.117	-0.9544	1.5165
Correlation Improvement (μ)				
5	0.0072	0.0044	0.0056	0.0111
10	0.0079	0.0076	0.0056	0.01
15	0.0121	0.0161	0.012	0.0209
20	0.0073	0.0073	0.0038	0.0064
25	0.0066	0.0275	0.0052	0.0093
Improvement in Spectral Distortion (P_{dis})				
5	0.8556	0.6487	0.7099	0.7374
10	0.8965	0.880	0.8625	0.8288
15	0.8963	0.884	0.8285	0.8341
20	0.9021	0.660	0.8309	0.8802
25	0.9008	0.9107	0.9115	0.9237
RMSE(Root Mean Square Error)				
5	0.1594	0.2782	0.1099	0.0971
10	0.1519	0.1776	0.1367	0.1111
15	0.1520	0.1446	0.089	0.0881
20	0.1510	0.2607	0.1223	0.1035
25	0.1509	0.1575	0.111	0.0977

Table I summarizes the detail information based on artifact removal and signal distortion. The proposed artifact removal method is compared with an existing artifact removal algorithms like EEMD-CCA[5], EEMD-ICA [19] and EEMD [10] with evaluation parameter as DSNR, Lambda, Spectral Distortion, PSD, Correlation improvement and RMSE. It is observed from Table I that the parameter DSNR has been improved significantly using the proposed method as compared to existing artifact removal method [5] by 28%.This results in EEG signal quality improvement after motion artifact removal.

Parameter Lambda (λ) signifies the percentage of artifact removal. The proposed method shows improved artifact removal in comparison to existing artifact removal method [5] by 17%, due to wavelet filtering. The DWT algorithm mitigates the random effect of motion artifacts from EEG signal effectively. The Pearson's correlation coefficient results in a better correlation of signal according to the sources, resulting in improved separation of artifacts from EEG signal. Therefore, the correlation coefficient has been improved by the proposed method as can be observed from Table I. One important issue which must be discussed here is that, due to the simulation of artifacts at different locations and added at different time durations, the performance of proposed algorithm do not follow any specific trend and sometimes results behave randomly.

The PSD of reconstructed signal after motion artifact removal is close to the PSD of the reference signal. This signifies an improvement in spectral distortion by the proposed method. In addition, the proposed method also demonstrates reduction in RMSE parameter by 12% in comparison to existing algorithms [5].In the proposed algorithm, the application of DWT after EEMD-CCA cascaded approach supresses the motion artifacts randomness and preserves the EEG signal information discussed in the next subsection.

Meaningfulness of Data after artifact removal: In this section the prominence of the proposed method is elaborated for maintaining the EEG neural information after motion artifact removal.

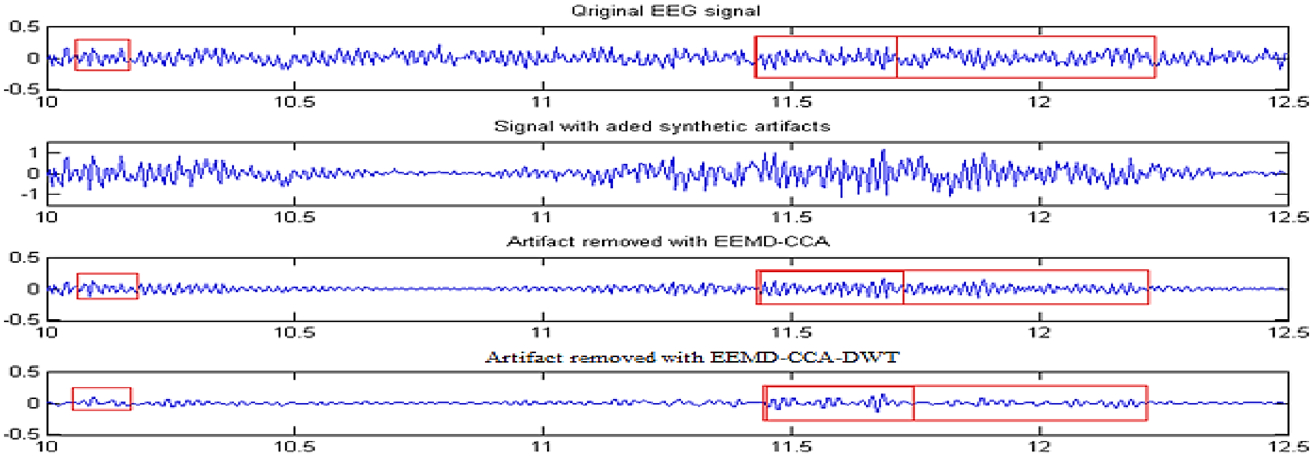

Figure 3: Comparison of synthetic Artifact signal and with artifact removal.

Figure 3suggests that the proposed method removes the motion artifacts from the synthetically generated artifactual EEG data and also preserve the peak amplitude variations. The EEG signal contains required information and important features which is maintained even after artifact elimination. The EEG signal doesn't lose the meaningful data as can be seen under the red color boxes. It can be observed from the first red box that initially there is a peak impulse which remains there after the artifact is suppressed.

Validation of the proposed method with real-time data: In order to check the feasibility of the proposed method, the proposed algorithm is also tested on real-time original EEG data without any additional synthetic artifact generation. The real-time EEG data has been taken from an online open source interface [18]. It is observed from Figure 4 that the proposed algorithm preserves meaningful information from the EEG data even when applied on real time captured EEG. Many real-time ambulatory services such as seizure detection of epilepsy patients need additional motion sensors such as an accelerometer to track the motion artifacts. However, with the proposed method, there is no need for such additional attachment, because EEMD-CCA-DWT approach removes the EEG motion artifact automatically and successfully. This artifacts removal facilitates the accurate prediction of neural diseases.

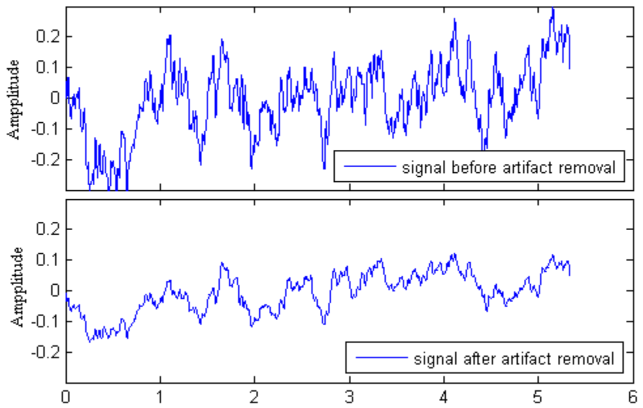

Figure 4: Comparison of Original and Smoothen EEG Signal with EEMD-CCA-DWT.

Moreover, the proposed method quantitative evaluation is performed by plotting different parameters with respect to artifact SNR as shown in Figure5, 6, 7 and 8.

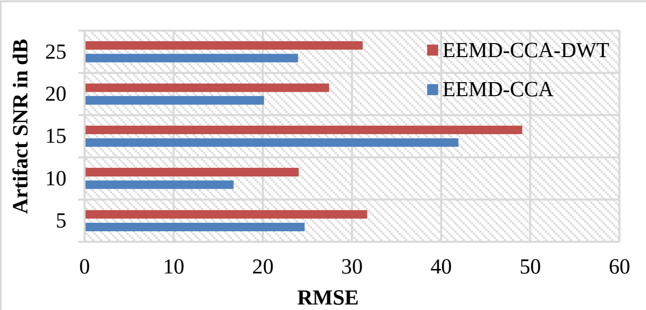

Figure 5: Signal Distortion Measurement in terms of RMSE for Different Artifact SNR.

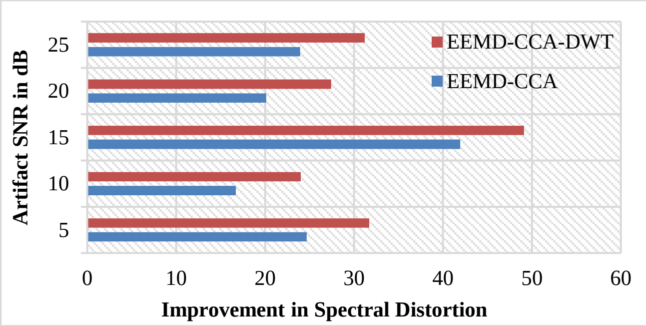

Figure 6: Signal Distortion Measurement in terms of Spectral Distortion Improvement for Different Artifact SNR.

Figure 5 shows the comparison of proposed method (EEMD-CCA-DWT) and EEMD-CCA for EEG motion artifact removal with RMSE as evaluation parameter at different artifact SNR. It is observed that RMSE values for proposed method filtered signal has been reduced to a great extent which indicates that artifacts have been removed significantly. Figure 6demonstrates that EEMD-CCA-DWT filtered signal has improvement in spectral distortion than the EEMD-CCA filtered signal for specifically low and high artifact SNR values. However, from 7.5 to 15dB artifact SNR, existing methods [5] perform well due to better artifact separation.

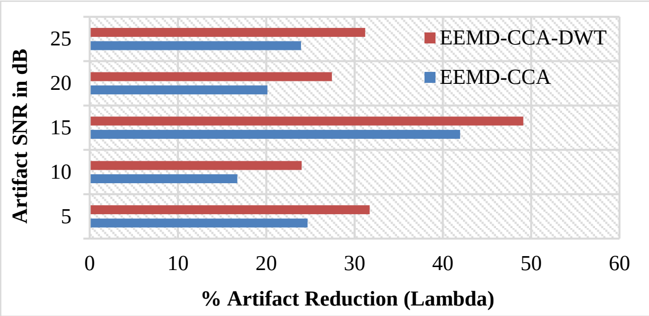

Figure 7: Artifact removal measurement in terms of Lambda for different artifact SNR.

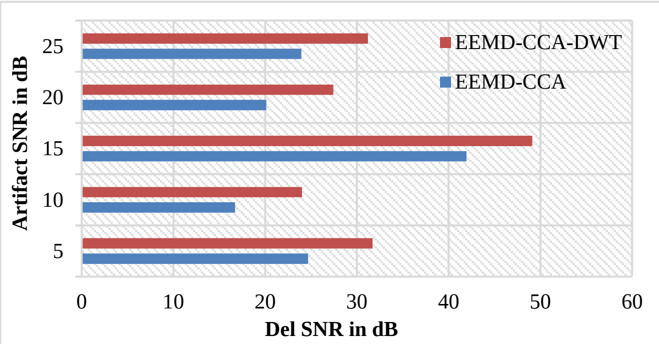

Figure 8: Artifact removal measurement in terms of DSNR for different artifact SNR.

Figure 7 and8present the degree of artifact removal by plotting and analyzing the parameters Lambda and DSNR respectively with respect to different artifact SNR. It is found that both the evaluation parameters have been improved, which in dicates the significant removal of artifacts from artifactual EEG signal. Thus, signal quality has been improved bythe proposed filtering method. This comparison demonstrates the splendid performance of the proposed method.

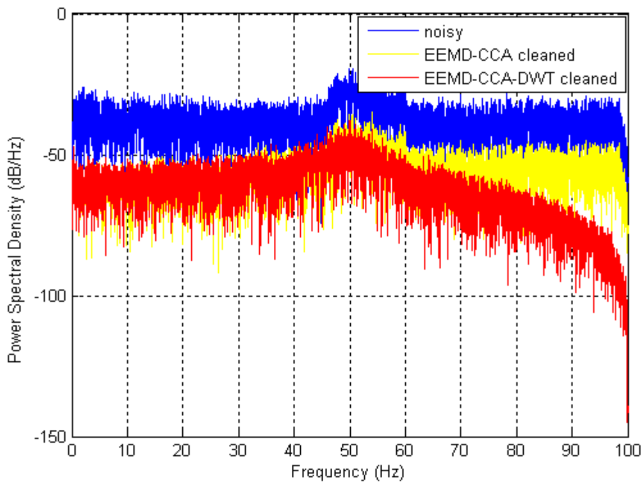

Figure 9: PSD plot comparison for EEG signal and artifact removal algorithms.

Power Spectral Density (PSD) is used to measure the signal power intensity with respect to the frequency. The PSD is computed from the FFT spectrum of the signal, therefore, provides an effective way to characterize the amplitude variation with respect to frequency. Figure 9 shows the PSD plot comparison fornoisy EEG data with the blue color, filtered with EEMD-CCA method by the yellow color and filtered with the proposed method by red color.

It can be seen from Figure 9 that the artifactual EEG signal is better smoothened with EEMD-CCA-DWT approach, specifically in the high-frequency region which is effected due to the motion artifacts. These motion artifacts have broad spectrum behavior with high amplitudes. In the proposed algorithm the application of Pearson's correlation coefficient results in improved correlation, therefore, better EEG artifact separation. Finally, DWT filter is applied to smooth the randomness of the motion artifacts. These motion artifacts have high amplitude and frequencies. Therefore, PSD in the higher frequency region has been reduced after the motion artifact removal it is clear from the red color PSD plot.

Thus, the proposed methodology (EEMD-CCA-DWT) out peforms than the existing artifact removal method by presenting the improved performance in all the evaluation parameters proves the success of method.

CONCLUSION

An improved EEG motion artifact removal technique is proposed. The synthetically simulated artifactual EEG signal is preprocessed through EEMD to decompose single channel EEG signal to multiple channel signal. Each IMF indicates a different small frequency range. Nevertheless, if the signal has some disturbance as artifacts, then these IMFs of low amplitude components will be available in the high-frequency region. These high-frequency components are isolated by applying CCA algorithm. Since, the signal and artifact source are considered as different source of signal. Reconstruction is done by summing all the IMFs after eliminating the artifact component. The DWT algorithm is applied on these reconstructed IMFs to smooth out the randomness of the motion artifact which is available even after EEMD-CCA cascaded approach. The performance of the proposed work is found better with 28% improvement in DSNR, 17% improvement in Lambda and significant 12% reduction in RMSE in comparison to existing artifact removal method [5]. The statistical analysis results showed that the proposed algorithm outperforms than other methods for removing artifacts as well as preserves meaningful information of the EEG signal.

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