Transaction on Biomedical Engineering Applications and Healthcare
Vol-1 Issue-1, June 2020, PP.1-11

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 certain noise which are termed as artifact in therapeutic term. These noise may disturb the quality of signal. Thus, mitigation of these EEG artifacts is an significant step. In this work an developedfiltering mechanism is projected formotion artifacts eradicationfrom single channel EEG signal. The input sole channel EEG signal isdecomposed into many different channel signal. Moreover, this multichannel signal is applied to an cascaded Blind Source Separation (BSS) and wavelet transform approachs 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, CCA, DWT, EEMD-ICA, EEMD-DWICA.**

I. Introduction

Superlative health evaluations are a complex field of study for medical science, where precise signals and imaging are subject to low computational costs. The simplicity of a measuring device is also important because they are used primarily to acquire signal from patients which make handling of the system simple and error-free.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 for example 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.

2. Proposed System Model:

The proposed architecture (Figure 1) presents the prototype of efficientexplanation. In this algorithm, primary the signal is preprocessed and futher applied to EEMD algorithm to convert single channel EEG signal into multi-channel signal. Further, ths multichannel EEG signal is sourced to a CCA algorithm for filtering and Pearson's correlation coefficient is applied for detection of artifacts. These processed results are passed through the DWT algorithm to filter the left traces of artifacts from EEG signal.

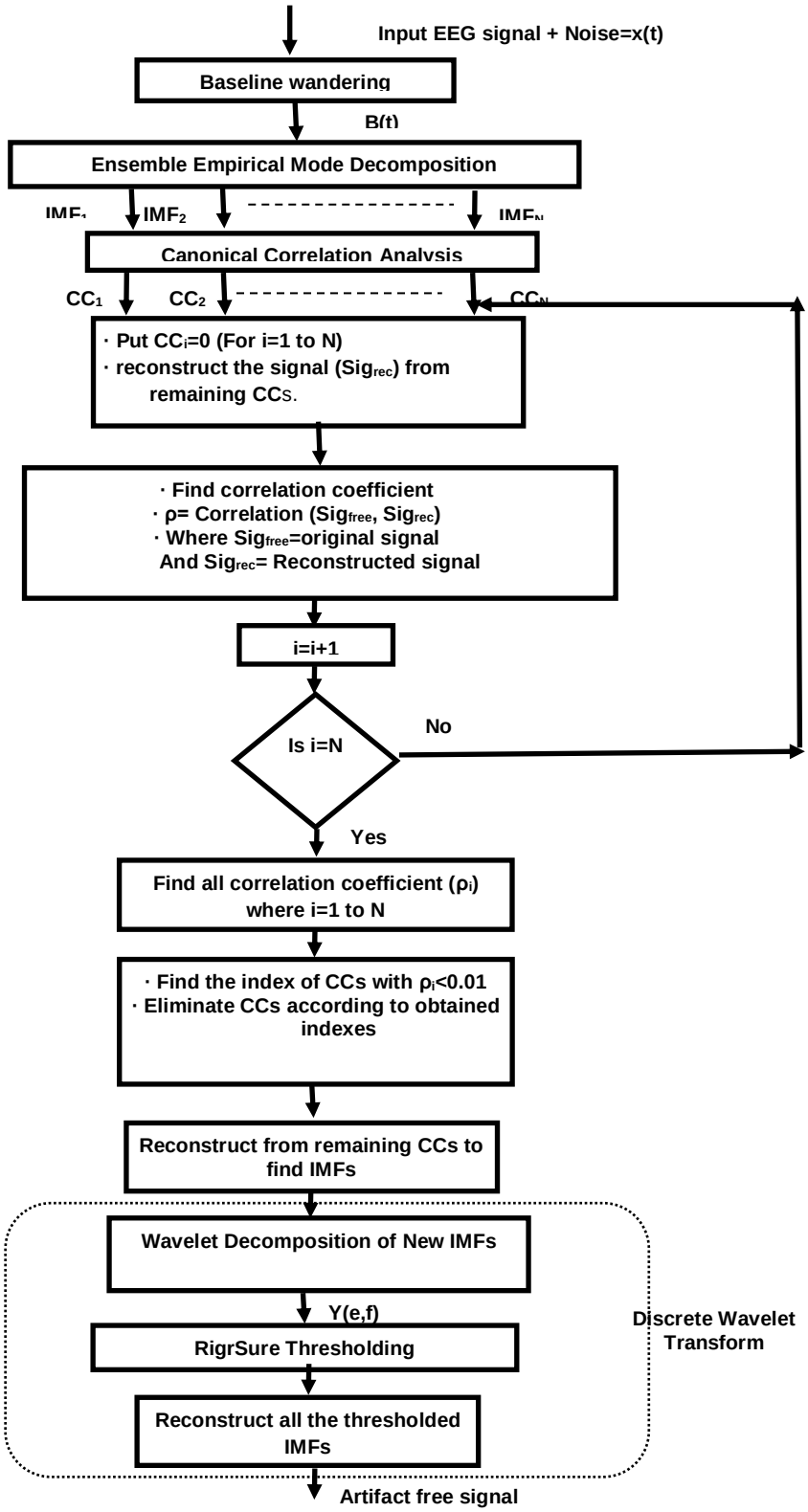

Figure 1: Proposed Architecture for EEG artifacts removal in single channel EEG signal.

3. 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 15μS to 1S)andat added at different locations and finally superimposed these templates onto the ground truth signalto impressionist the motion artifacts behavior.

Step 2: This createdsignal is preprocessed (baseline wandering) by suppressing thenoise 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.

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

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 Separationapproach (CCA). The CCA algorithm[17] provides components which are statistically uncorrelated (CCs), each having distinguished properties, so some CCs can represent motion artifactssources. Hence, blind source separation of IMFs has been done by CCA as:

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

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

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

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

Step 5: The steps required foridentifying motion artifact CCs after CCA algorithmareas 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.

$$imf = w * \tilde{Y}_l \quad (4)$$

Where, w is the mixing matrixand $\tilde{Y}_l$ is reconstructed CC.

b. Reconstruct the signal by adding all IMFs.

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

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

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

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

d. Repeat this step (from a to c) fori=1 to n

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

Where,i^{th} row become zero.

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

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

$$z(k) = imf = w' * \tilde{y}_i \quad (7)$$

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 RigrsureThresholding.

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

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

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

This signal$\widehat{B(t)}$isnow artifact-freeEEG signal.

In order to estimate the efficacy 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 ispresented 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.

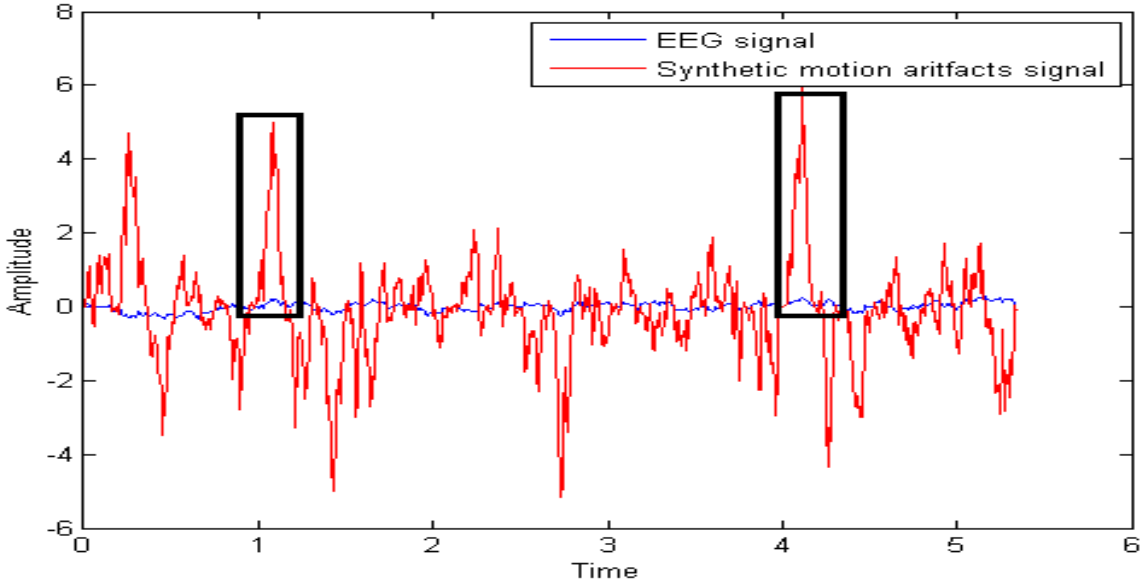

Figure 2: Properties of Synthetic Artifact Signal.

Therefore, it can be stated that synthetical motion artifacts corrupt the EEG signal neural information. The deliberated EEG artifact removal methods enactmentsare assessed by certain evaluation matrices. These evaluation parameters are discussed in the next section.

4. Performance Evaluation Parameters

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

a. **ΔSNR:** TheΔSNR is calculated by:

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

Where,$\sigma_x^2$is the pure EEG signal variance and σ_{before}^2 is the artifactual EEG signal variance and σ_{after}^2 is the cleaned EEG signal variance. Error signal is calculated by the difference between motion artifactual EEG signal and pure EEG signal [5].

b. **Lambda:**This is a difference in correlation between signalswhich shows the percentage reduction in artifacts denoted by λ.

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

Here R_{before} is a correlation between pure and artifactual EEG signal and R_{after} is a correlation of signal after artifacts mitigation process and R_{clean} is the correlation between epochsof known clean data. high λ value shows effective artifactremovalperformance [5].

c. Power Spectral Density (PSD): Anarbitrary signal hasfinite 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.

d. **PSD Improvement:**PSD Improvement is calculated by finding the change between PSD of the syntheticEEG signal to PSD of the ground truthEEG signal.

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

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.

e. **Correlation Improvement:**The correlation difference between artifactual and pure EEG signal is used as the performance measure. The percentage correlation improvement $\mu$is defined as:

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

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.

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

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

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

The$RMSE_{free}$ is an error between the pure EEG signal and cleaned EEG signal and $RMSE_{art}$is an error between the original signal and artifactual EEG signal.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.

g. **Spectral Distortion (P_{dis}):** The Spectral Distortion $P_{dis}$is calculated asfollows:

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

Where,

$\text{PSD}_{\text{ref}}(w)$= PSD of the reference signal;
$\text{PSD}_{\text{recon}}(f)$= PSD ofthe reconstructed signal.

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

5. Results and discussion:

The EEG signal databaseisassimilated from the Physionet database [18]. Themotion artifactual EEG signal issynthetically simulated. The proposed work numericalassessmentis performed using above synthetic generated EEG datasets. Table I presents the comparison of the projected EEG motion artifact eliminationapproaches with present methods based on various evaluation parameters. The artifact removal methods are applied on artifactual EEG signal withvariousnoises amount as (5, 10, 15, 20 and 25).

Table I: Comparison ofthe 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 withan existing artifact removal algorithmslike EEMD-CCA[5], EEMD-ICA [19] and EEMD [10] with evaluation parameter as DSNR, Lambda, Spectral Distortion, PSD,Correlation improvement and RMSE. It isobserved from Table I that the parameter DSNR has been improvedsignificantly usingthe proposed method as compared to existing artifact removal method [5] by 28%.This results inEEG 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 thePSD of the reference signal.This signifies an improvement in spectral distortion by the proposed method. In addition, the proposed method also demonstrates reduction in RMSEparameter 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.

a. **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.

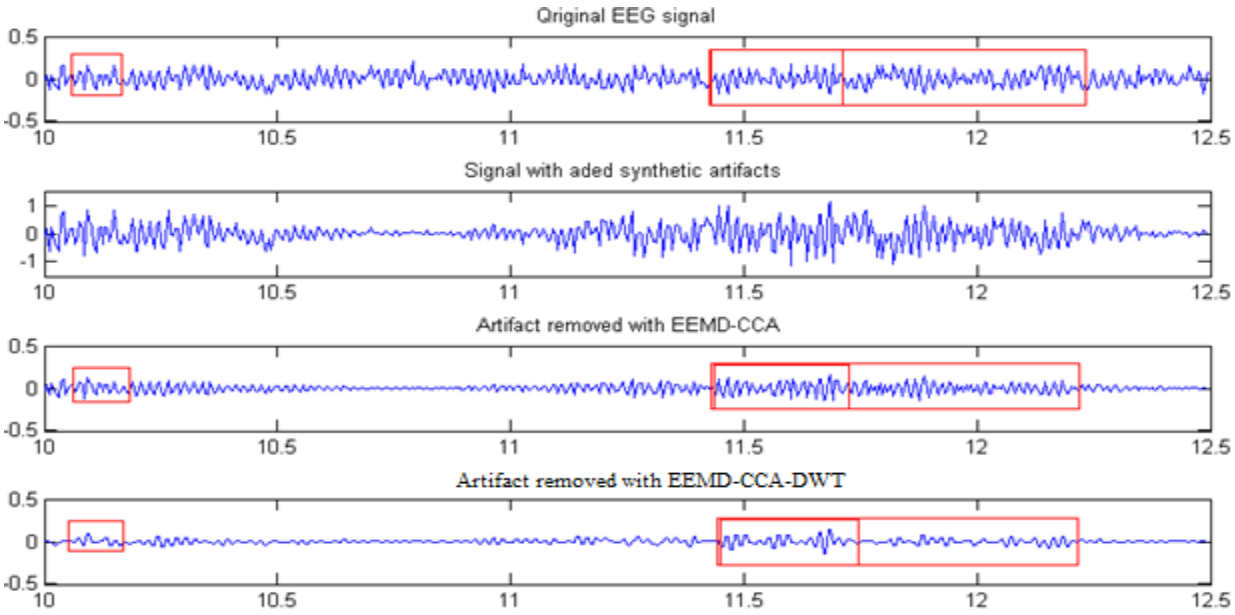

Figure 3: Comparison of synthetic Artifact signal and with artifact removal.

Figure 3suggests that the proposed method removes the motion artifacts from the synthetically generated artifactualEEG 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 remainsthere after the artifact is suppressed.

b. **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 artifactautomatically and successfully. This artifacts removalfacilitatesthe accurate prediction of neural diseases.

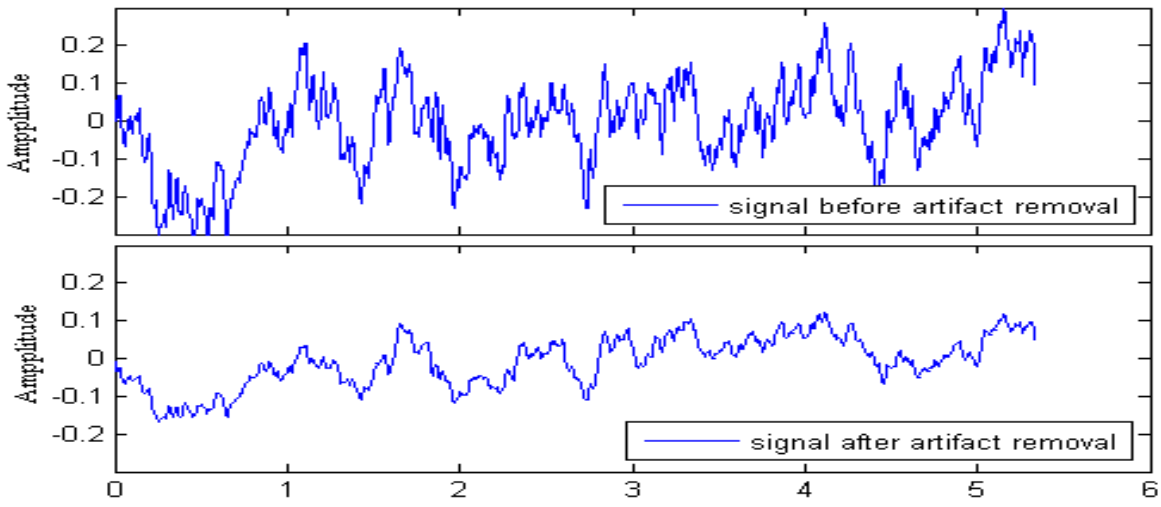

Figure 4: Comparison of Original and Smoothen EEG Signal with EEMD-CCA-DWT.

Moreover, the proposed method quantitative evaluationis performedby plotting different parameters with respect to artifact SNR as shown in Figure5, 6, 7 and 8.

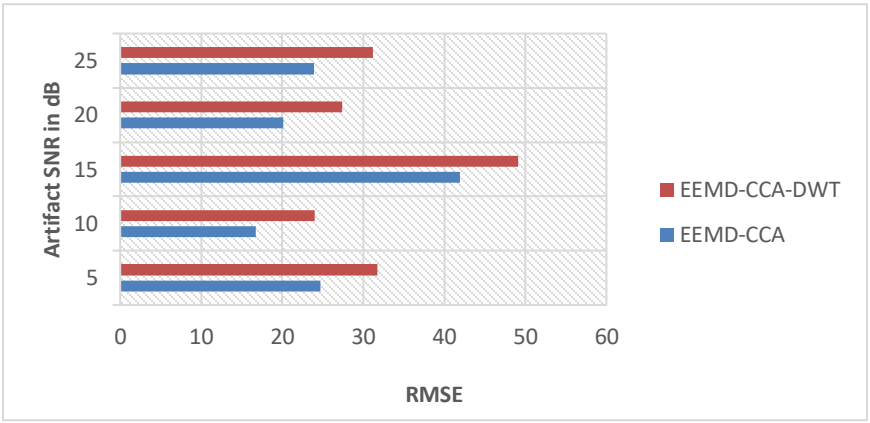

Figure 5: Signal Distortion Measurement in terms of RMSE for Different Artifact SNR.

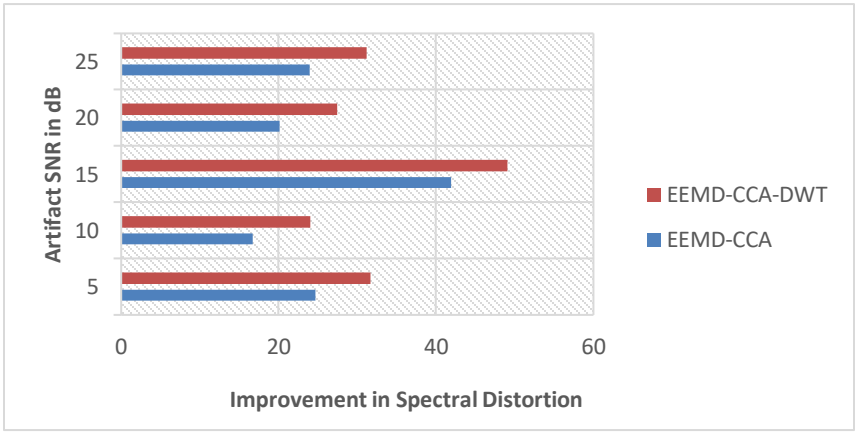

Figure 6: Signal Distortion Measurement in terms of Spectral Distortion Improvement for Different Artifact SNR.

Figure 5 presents the RMSE evaluation parameter for EEG motion artefact removal (EEMD-CCA-DWT) and EEMD- CCA with RMSE as evaluation parameter for different SNR artifacts. It is found that RMSE values were reduced considerably in order to suggest that artifacts were greatly removed for the proposed process filtered signal. Figure 6 shows that a spectral distortion improved by the EEMD-CCA-DWT filtered signal for the particularly low and high Artifact SNR values is obtained in comparison with the EEMD-CCA .. Current methods[5] work well however from SNR artefact 7.5 to 15dB due to the enhanced segregation of artifacts.

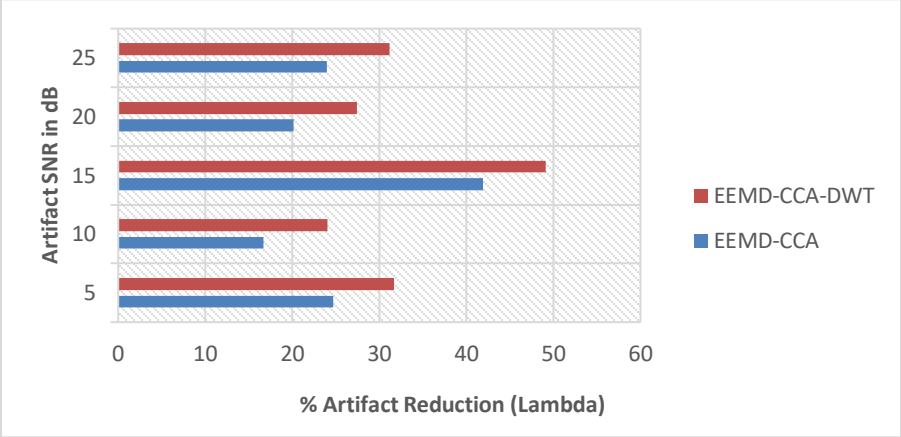

Figure 7: Artifact removal measurement in terms of Lambda for different artifact SNR.

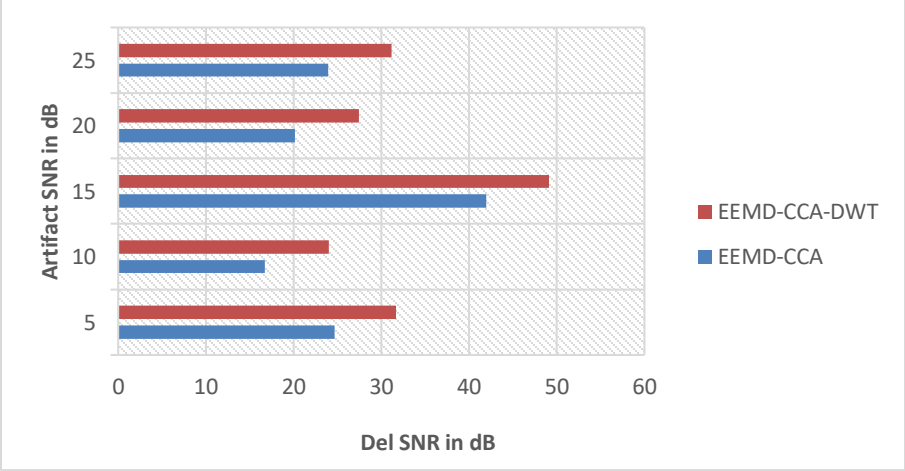

Figure 8: Artifact removal measurement in terms of DSNR for different artifact SNR.

Figures 7 and 8 show the level of deletion by plotting and analysing the Lambda and DSNR parameters for various SNR artefacts, respectively. There is an increase in both the evaluation parameters, suggesting that artifacts have been substantially eliminated from the artifactual EEG signal. The proposed filtering

method has therefore improved signal quality. This contrast shows the excellent efficiency of the system proposed.

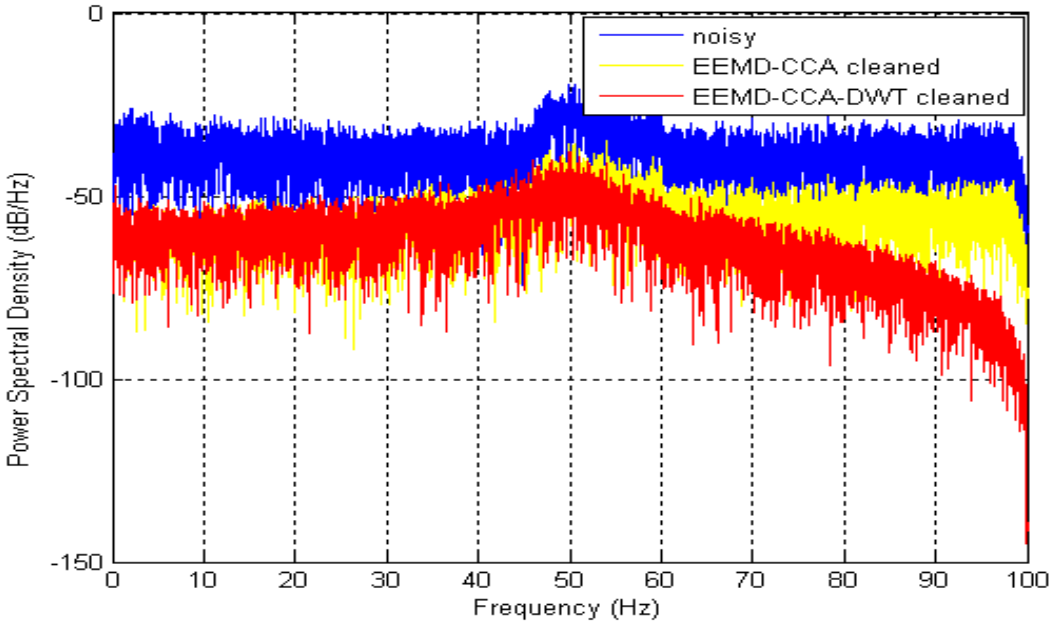

Figure 9: PSD plot comparison for EEG signal and artifact removal algorithms.

The PSD is used to measure signal strength relative to the frequency. PSD (Power Spectral Density). The PSD is determined from the FFT signal spectrum, and thus provides an efficient way to discern the frequency difference in amplitude. Figure 9 shows the compare PSD plot for blue-colored random EEG data, filtered in a yellow colour by EEMD-CCA process, filtered in a red colour using the suggested method.

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,betterEEG 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 removalit is clear from the red color PSD plot.

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

Conclusion

Enhanced technique is proposed for eliminating EEG motion artefacts. The artifactual EEG signal is pre-processed by EEMD to break down single-channel EEG signal to multi-channel signal. Each IMF displays a different little set of frequencies. Nevertheless, if the signality is disrupted as objects, these low-amplitude IMFs in the high-frequency region would be available. The use of the CCA algorithm

isolates certain high-frequency components. As a separate signal source, the signal and the objects source are considered. After removing the artefact portion all the IMFs will be reconstructed. On these re-engineered IMFs the DWT algorithm is used to smooth the randomness of the motion system that is possible even with the EEMD-CCA approach. The performance of the work proposed increases with a 28% increase in DSNR, a 17% improvement for the Lambda and a 12% decrease in RMSE compared toexisting artifact eliminationtechnique [5]. The statistical results of the study showed that the proposed algorithm exceeds the artifact removal approach and retains useful EEG signals.

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