International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.9, No.5 (2016), pp.321-338
http://dx.doi.org/10.14257/ijsip.2016.9.5.29

# Enhanced Empirical Mode DecompositionApproach toEliminateMotion Artifacts in EEG using ICA and DWT

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***Abstract***

*To ease the concept of diagnosing human health a strong and viable biomedical signal is of importance. Biomedical signal measurement and processing of signal cause the probability of artifacts which can obstruct the features of interest and quality of information available in the signal. So elimination of artifacts from physiological signals is an essential step. The single channel measurement is important when instrumentation complexity is needed to be minimized, in spite of many multichannel signals recording methods available.In this paper, an enhanced empirical approach to remove the artifacts of single channel signal is described followed by filtering mechanism using ICA and DWT. The input EEG is a single channel and is converted into multichannel for ICA operations. The multi-channel EEG signal is filtered with fast ICA algorithmand DWT is employed to reject any traces of artifacts left in the signal. This technique is tested against currently available wavelet de-noising and EMD-ICA technique using functional near infrared spectroscopy (EEG) signal. Artifact removal technique has been evaluated by DSNR, Lambda (λ), Autocorrelation and PSD. The results pronounce the eligibility of proposed algorithm to stand on top of currently deployed algorithms with 12% improvement in DSNR and alsoa significant improvement in different parameters too.*

***Keywords****: EEG,EEMD-ICA, ICA, DWT,EEMD-DWICA*

## 1. Introduction

The design of a physiological signal is a long followed approach that illustrates the present condition of health of an individual. The dynamic research in medical sciences towards superlative health assessment calls for paramount accuracy with low computing cost in signal recordings and imaging. The life of an instrument to function with minimal operational and maintenance cost is one of the primary factors that defines the probability of its selection as the practically acceptable technology. Also, the simplicity of an instrument is directly measured by its capability to function in a standard environment without failure in operation. Further, the complexity of an instrument holds a direct relationship with cost ensemble in it.

It is evident that measurement of physiological signals in the even surgical environment is accustomed to some noise also referred as artifacts in medical terms. These artifacts are unwanted signals generated due to unregulated sources besides the source under consideration. The artifacts in neural signals have two prominent sources other than the machine and environment noise. The muscular and ocular activities of an individual generate electric pulses of low amplitude and frequency that falls in filter range of sensors and recording equipment. Artifacts rejection hence is a fundamental subject of research and is well researched [1]. This paper considers the artifacts caused due to motion. Till this point, numerous applications of ICA, wavelets, and adaptive filters are proposed in the same context of research [2].

ISSN: 2005-4254 IJSIP

Normally, a common approach is to reject all EEG epochs containing the signal amplitude larger than some selected value. These schemes are inflexible and do not allow for any adaption which causes in loss of a portion of meaning full data.A component based automated separator of artifacts is required to overcome this issue based on the linear decomposition of signals into source components. The components give individual nature of information, where artifacts information combines into separate sources and reconstruction of signals without this source are claimed as artifact free information. Hyvärinen[[6]-[14]] on a 30s window size applied Fast-ICA Algorithm using EEGLAB platform. They developed an automated system for artifact removal based on ICA and Bayesian Classification. Author [[5]] introduce ensembleempiricalmode decomposition with a canonical correlation analysis (EEMD-CCA) technique for single channel artifact removal.Single channel signal is converted intoa multi-dimensionalsignalby EEMD technique.ThenCCAtechniqueissecond order statisticsapplied to segregate the artifact components from the input signal.Authors of [[7]] analyzedEEG waves by DWT for frequency domain analysis. Authors of [4] presented a statistical method based on wavelet transform to mimic ocular artifacts in EEG. Haslaile Abdullah[[8]] proposed wavelet-based image processing technique at various window sizes. 1-D double density and 1-D double density complex were tested at a window size of 10s, 30s, 60s and 300s for EEG signals.Mijovic et al [[9]]studiedtwo techniques Single-Channel ICA (SCICA)and Wavelet-ICA (WICA) and applied EEMD-ICA algorithmon single channel EEG signal for artifact removal. TheEEMD-ICA algorithmwas tested on simulated data andthen appliedto real EEG and EMG data for comparison. The conclusion fromresultsisthat the SCICA algorithm has the worst performancewith root mean square error (RRMSE) as consideration. The WICA algorithm has weaker performance in thesimulationsand although is comparable to the EEMDICAtechnique.

Authors [[5]] have shown better artifacts removal results with EEMD-CCA technique. But following issues has to be taken care:

Ground truth signals are not available in practical cases, which causes difficulties in de-noising result evaluation.

(a) Blind source separation technique which the author has employed in paper [[5]].
Problem with Blind Source Separation using Canonical Correlation Analysis:

A blind source separation problem is always solved using two major assumptions:

1. Source signals must be independent and highly uncorrelated to each other.
2. Each source signal value must have non-Gaussian distributions.

IMFs generated from EMD or EEMD can be mixed output of different sources. Hence separated components by ICA or CCA should be independent of each other. ICA is an efficient BSS algorithm because it satisfiesabove-mentioned condition properly while Canonical correlation analysis (CCA) is another technique which can also be used for separating a number of mixed or contaminated signalsusing BSS method. The CCA and ICA both the technique have a conditionthatrecorded signals must be greater than or equal to anumber of principal sources. CCA uses a differentapproachforseparating the sources than ICA. CCA uses second order statistics (SOS)to create components which are based on uncorrelated nature rather than their independence**.** Additionally, if a random vector having multivariate normal distribution then any two or more of its components can be uncorrelated and can also be independent.Thus,in this case, ICA and CCA will produce the same result. Otherwise, CCA will return components which are uncorrelated but not independent. Therefore, artifact separation through ICA produces better results than CCA [[21]].

limitation of above mentioned CCA is that separated sources with CCA are uncorrelated to each other but not independent which causes a frequency sharing between CCA components, so when we eliminating a component to remove motion artifacts, it also removes the part of the signal which is not motion artifact, results degraded EEG signal with lower SNR.

The organization of the paper is as follows: In this paper, the limitation of ICA of operations only on multichannel signals is overcome using EEMD approach. The EEMD decomposes a single channel EEG to a multi-channel function and sourced to fast ICA algorithm for filtering. The results of ICA are improved using DWT algorithm as the output of ICA contains the traces of artifacts. The decomposition through DWT is performed on the frequency domain of signal obtained via frequency transformation (Fast-Fourier) and applied Pearson's correlation coefficient for artifact removal. The results brace the splendid performance of proposed architecture and paper ends with a conclusion.

## 2. Ensemble Empirical Mode Decomposition

In 1998 Empirical mode decomposition (EMD) is first defined [[11]], for nonlinear signal processing and iswellappropriate for non-stationary data.A time series signaldecomposes into multiple "intrinsic mode functions"(IMFs) by EMD. IMFsmust have following property:
(1) Mono-component means all the IMFs should have only one frequency component at a time known as instantaneous frequency.
(2) zero-mean oscillatory functions define that signals have the same number of local maxima and minima, having always positive maxima and negative minima.
(3)Orthogonal means different IMF's should not have the samefrequency.

The EMD technique uses a different approach for decomposition rather than Wavelet analysis. Decomposition of thesignalin EMD is a data-driven process whereas wavelet analysis decomposition is based on the selectionof the appropriate wavelet. Since EMD technique is data-driven, hence this approach is more flexibleinnature.

The IMFs are functions that must fulfill two conditions:(1) number of maximaand the number of zero crossings must be the same or differat most by one over the full length of data (2) the meanvalue of the envelope defined by the maxima and the envelopedefined by the minima must be zero at any point over the data[[12]].

To calculate IMF of a time series,steps are as follows: Time series is $y \in P^L$ where L is the number of samples.EMD is based on using a sifting process that uses onlylocal extreme.
Step 1: All the local maximaand minima will find over the full length of the time series. Then, anupper envelope is created by connecting all the maxima using a cubic spline, andthe same process is repeated for alllocalminima. Step 2: average of thetwo envelopes nare calculated and this average is subtracted from the datasignal, which produces a new signal$c = p_0 - n$, where$p_0 = y$.
Step 3: Now signal c is considered as a new data signal and above mention steps are repeated till cfulfills all the above-detailedproperties ofIMFs. Finally, when c have all the properties of IMF, it is termed as first IMF ($f_1$).
Step 4: Then all the above mention steps arerepeatedon the residual signal$p_1 = p_0 - f_1$. When the residual signal $p_n$ becomes a monotonic function this sifting process will stop .Once all the IMFs $f_j$ are calculated, the original data y (or $p_0$) can berestored by adding them together as

$$y = \sum_{j=1}^{l} f_j + p_l \quad (1)$$

Where, IMF components areextracted and $p_l$ is the residual of data[[13]].

The method of detecting IMFs is sensitive to the amalgam of undesired signal components present in surrounding. These noises affect the EMD process and mode mixing is used to overcome the disparate scale oscillations with amplitude in near range of the IMFs peaks and available randomly in thewhole dataset [[13]]. Also, the momentary spectral components are sometimes misinterpreted as artifact components. The original EMD algorithm has the drawback of high sensitivity to noise. Consequently, a more robust and noise-assisted version of the EMD algorithm was introduced named as EEMD(Ensemble Empirical Mode Decomposition) [[13]], which solves this mode mixing quandary. Ensemble-EMD (EEMD) employsthe average value of EMDensemblesthat filters out the IMFs from given signal and also this method depends on the amplitude of noise added to theinput signal and a number of trials.

The IMFs from the EEMD process are filtered to discard the artifacts present in them through Independent component analysis. Then filtered IMFs are further processed for second stage filtering through wavelet transform for better outputs of evaluation parameters and signal quality.

## 3. Independent Component Analysis

Fast ICA employs statistical and computationaltechniques for separating the mixture of signals intoindependent components. The IMF(s) generated by EMD are further sampled to ICA as input in terms of $C = [c_1, c_2, c_j \dots c_n]$ are generated by independent sources $S = [s_1, s_2, s_j \dots s_n]$ where A is the $n \times m$ mixing matrix.

$$S = AC \tag{2}$$

With this filtering technique spectral enhancement can be achieved but at the same time, it is very difficult to estimate the variances of Independent components [[14]]. To make more precise analysis in time and frequency further wavelet technique is adopted[[7]].

## 4. Discrete Wavelet Transform

The wavelet technique is used to de-noise the corrupted signal more preciselyand came into existence to avoid the resolution limitations of spectral analysis of Fourier Transform. The first step is to choose mother wavelet and corresponds to the shape selection this mother wavelet according to the type of source we are interested in.In this paper,we have implemented Haar wavelet as mother wavelet.Then the signal is decomposed into a number of time-shifted and scaled version of mother wavelet. The details and approximations coefficient of the wavelet transform has been calculated at each level.Then artifact components are identified and removed then finally remaining components are added to reconstruct the cleaned artifact-freesignal.

## 5. Proposed System Model

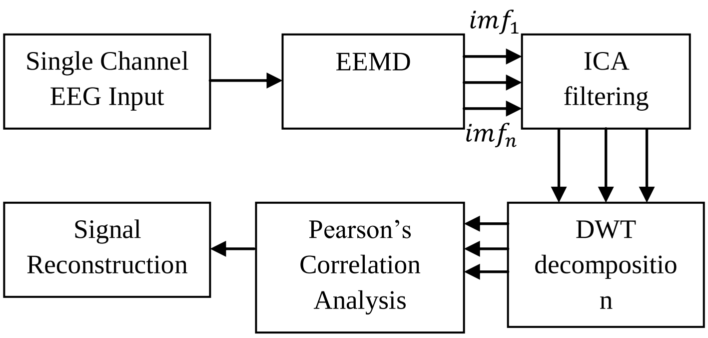


**Figure1. Proposed Architecture for EEG Artifacts Removal in Single Channel Signal**

The proposed architecture (Figure 1) shows the functional description of theprototype. Sweeeny *et al* [[5]] first proposed the EEMD and CCA in combined form for removal of artifacts from single channel signal. The author used the system to eradicate motion artifacts from EEG signals in more efficient way. The signal is reconstructed ($S'$) again as their respective IMF(s) with minimum artifacts.

## 6. Proposed Algorithm:

- Divide the signal into two segments of 50 seconds each, signal A – consisting no Motion artifacts and signal B – Consisting Motion artifacts. Signal A would be a reference (Ground truth for method).
- Weare assuming that EEG signal and artifact signal are coming from different sources and interfering with each other, so if we can separate this sources, we will get the original EEG signal.
- Decompose signal B into IMFs using EEMD. Which will convert the single channel signal into multiple channel components.
- IMFs are spectrally independent mode so these IMFs are applied for Blind Source separation. ICA will provide components which are statistically independent (ICs), each having distinguished properties, so one or more ICs can representa source of motion artifacts.
- Before Identifying this ICs of motion artifacts, we perform wavelet de-noising over each ICs with Discrete wavelet transform to have a completely noise free ICs.
- Now the process of Identifying ICs having motion artifacts source take places as:
    a. Take IC no. 1 and put all its value zero.
    b. Mix rest all ICs with mixing matrix and reconstruct the new IMFs.
    c. Reconstruct the Signal B' by summing all IMFs.
    d. Measure Pearson's correlation coefficients between signal A and signal B'.
    e. Repeat the procedure a to d for all ICs and note all Correlation Coefficient.
- Put all ICs zero havingPearson's correlation coefficient below a given threshold.
- Mix all ICs now with mixing matrix and reconstruct the new IMFs.
- Reconstruct the Signal B by summing all IMFs. This signal is now artifact free.

## 7. Data Acquisition

The data for experimentation is contributed by Kevin T Sweeney at the National University of Ireland at Maynooth. The data is available on an online open source interface [[20]] and description of recordings is acquired from the same source only. The recorded samples are Electroencephalographic(EEG) samples (Figure 2) contaminated by motion artifacts. Every recording is a single pair of similar psychological signals recorded in close proximity via transducers. Keeping the single transducer stationary, the second transducer is manipulated to create artifacts related to motion and of variable duration within each 2-minute interval of recording. TheEEGsignals and the accompanying trigger signal were digitized at 2048 Hz. Comparison of the artifact-freeEEG having high correlation during motion-free intervals and lower correlation during artifact-contaminated intervals defines the efficiency of proposed work.

## 8. Performance Evaluation Parameters

When we employing any artifact removal technique our motive is to identify which component of decomposed signals are artifact and thus should be removed. Thus, the goal of any artifact removal technique is to bring artifact contaminated signal into its true state. SNR, power spectral density, and correlation are parameters to evaluate the performance of de-noising method.

### 8.1. ΔSNR

This SNR is a difference of SNR before and after artifact removal. That's why denoted by ΔSNR. ΔSNR is calculated by the followingformula.

$$\Delta SNR = 10\, log_{10}\left(\frac{\sigma_x^2}{\sigma_{after}^2}\right) - 10\, log_{10}\left(\frac{\sigma_x^2}{\sigma_{before}^2}\right) \quad (3)$$

Where $\sigma_x^2$ is the variance of ground truth signal and $\sigma_{before}^2$ is a variance of error signal before applying artifact removal technique and $\sigma_{after}^2$ is variance of error signal after applying artifact removal technique. Assumption is that motion artifact is additive in nature .We calculate the error signal by difference between motion artifact contaminated signal and ground truth signal [[5]].

### 8.2. Lambda:

This is the difference in correlation between signals, shows the percentage reduction in artifacts, denoted by λ.

$$\lambda = 100\left(1 - \frac{R_{clean} - R_{after}}{R_{clean} - R_{before}}\right) \quad (4)$$

Here $R_{before}$ is correlation between ground truth and artifact contaminated signal, and $R_{after}$is correlation of signal after denoising process and $R_{clean}$ is the correlation between echoes of known clean data. Hence for higher value of λ the denominator should be low and is possible only if better artifact removal has been done. A high λ shows good effective artifact removal technique [[5]]

### 8.3. Power Spectral Density:

The supplemented readings of Electroencephalography signals are sourced by Gaussian noise. The obtained variation in signals in reference to theoretical model leads to restricted access in the accuracy of thepower spectrum of signals.

$$P_{\overline{xx}}(w) = P_{rr}(w) + \Delta P(w) \quad (5)$$

Where,
$P_{rr}$ = Reference Power Spectrum of Artifact free signal
$P_{\overline{xx}}$ = Power Spectrum of ICA modified Signal
$P$ = Distortion Spectrum by side effects of methods (Should be 0 ideally)

$$\Delta P_j(w) = -m_{j1}^2 P_{nn}(w) \quad (6)$$

Here,
$m_{j1}$ Denotes weight from Matrix M
$P_{nn}$ Component of brain signals in ICA

Equation 6 represents the minimization of ICA-EEG based on spectral function ($P_{nn}$) with factors $m_{j1}^2$. As there exists direct relationship among decrease in $j$and $m_{j1}^2$, front end experience high distorted signals of spectrum. DWICA along with reduction of residual EEG signals in artifact components simultaneously minimize $P_{nn}$ on a serious note that leads to improved approximated value of pure EEG power spectrum.

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

 

### 8.4. PSD Improvement:

With the assumption that motion artifact signals are of lower frequency, the difference between PSD of contaminated signal and PSD of lower frequency is called PSD improvement. In our work contaminated signal is of 50 seconds and motion artifacts considered to be of first 10 seconds.

### 8.5. Correlation Improvement:

Correlation Improvement can be calculated by the difference of two correlation values, where first is a correlation between the reference signal and motion artifact contaminated signal and second area correlation between thereference signal and after artifact removal clean signal.

## 9. Results:

EEG signal with motion artifacts are acquired from the physionet [[20]]. Signals having motion artifacts have a low SNR due to the harmonics created by random frequency artifacts as shown in (Figure 2)below:

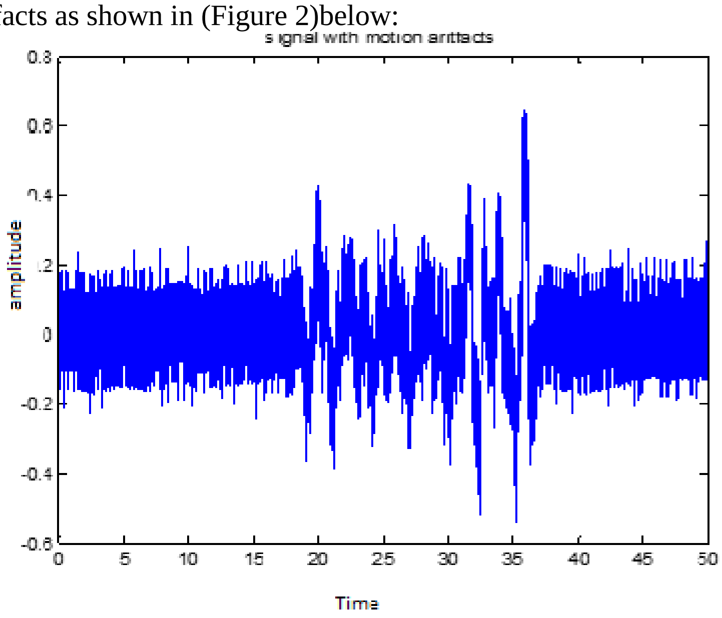


**Figure 2. Input Noisy EEG Channel with Motion Artifacts for Testing Proposed Algorithm**

In Figure2, time information in seconds have been shown by X-axis and amplitude information in microvolts have been shown by Y axis. As we can see from figure motion artifacts has been affecting the signal from 18 to 38 seconds which can be seen clearly through peaks added in the signal, which will distort the information content. Therefore to effectively reduce the artifact from signal following approach has been adapted.

The first signal will pass through EEMD which will decompose to IMFs to find the monotonic component of the signal as a separate source for ICA decomposition as shown in (Figure 3).In the Figure 3,X-axis is the time and y-axis is the amplitude (microvolt).

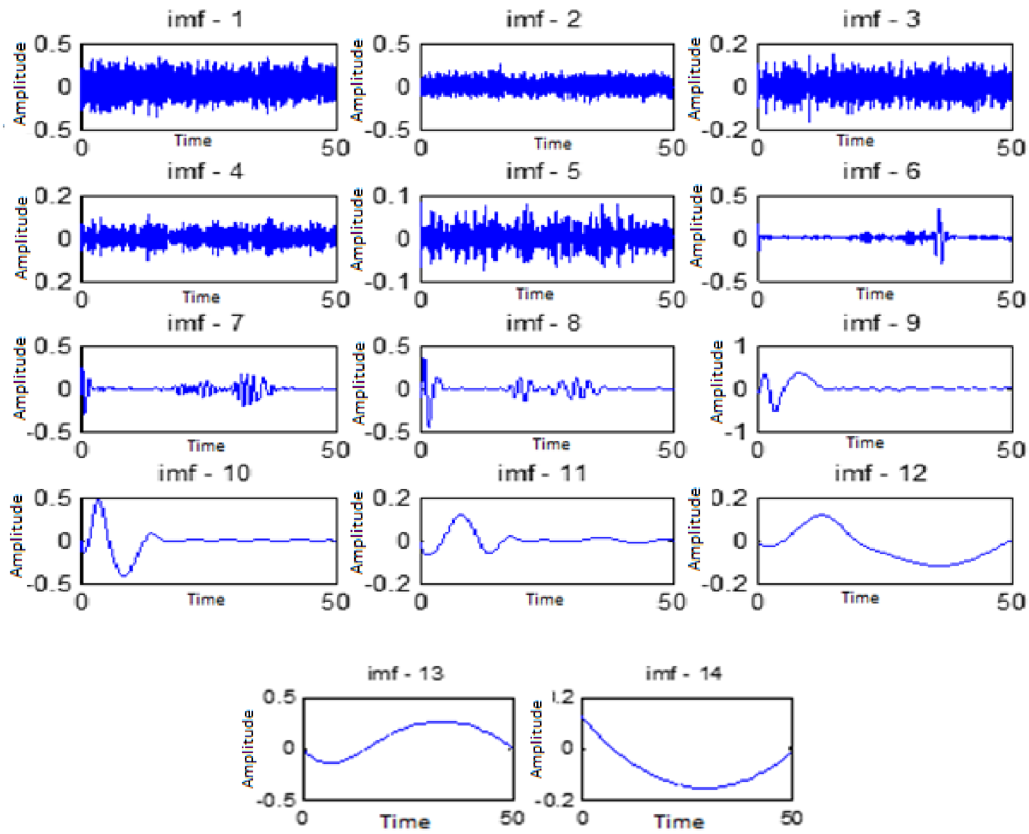


**Figure 3. Output IMFs from EEMD. Total 14 IMFs are Obtained for Single ChannelEEG Signal**

Single channel signal is decomposed by EEMD into spectrally independent modes (IMFs),and these IMFs are allowed to converge till the final mean of signal approaches to zero. Limiting to the number of trails of EEMD will degrade the signal. After EEMD, IMFs generated are spectrally independent but still they are correlated to each other. Hence, a blind source separation with Fast-ICA is performed over these IMFs to obtained statistically independent sources output.Now all the signals following different distribution will be separated as shown below in Figure 4, whose X axis shows time and Y axis shows amplitude.

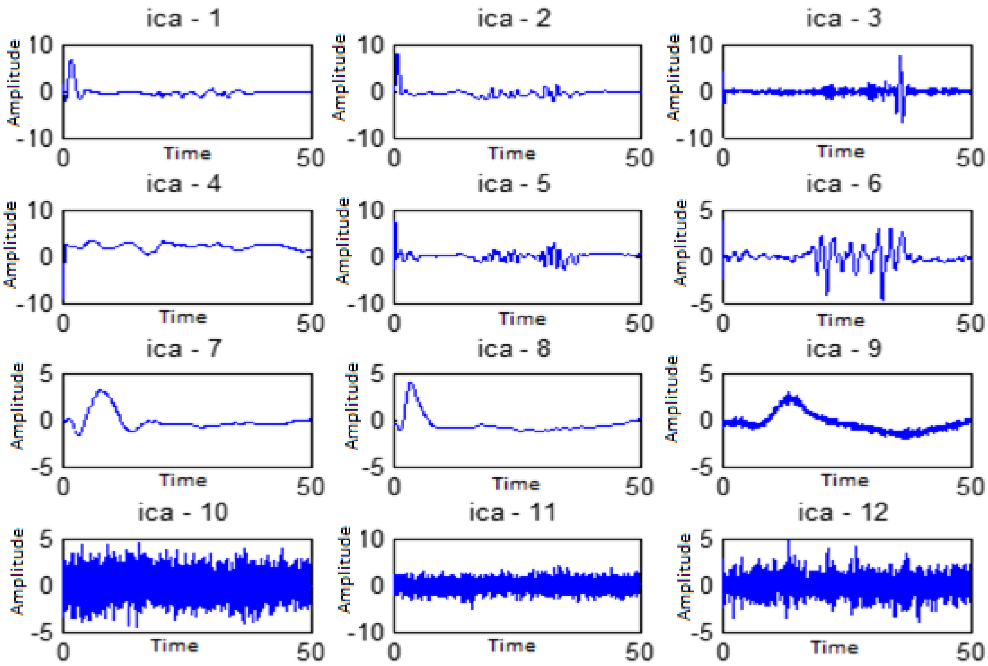


**Figure 4. EEMD-ICA Output Components after Processing**

After EEMD-ICAconclusion is that signals are spectrally separated shown in above figure and standardly theymust be 100% nongaussian and 100% uncorrelated, but practically this is not possible. Still they share some frequency between sources which can be considered as noise for the particular one source. Finally, in practical cases if EEMD – ICA signals are passed through discrete wavelet transform then we get much better artifact removed signal as shown in Figure 5.

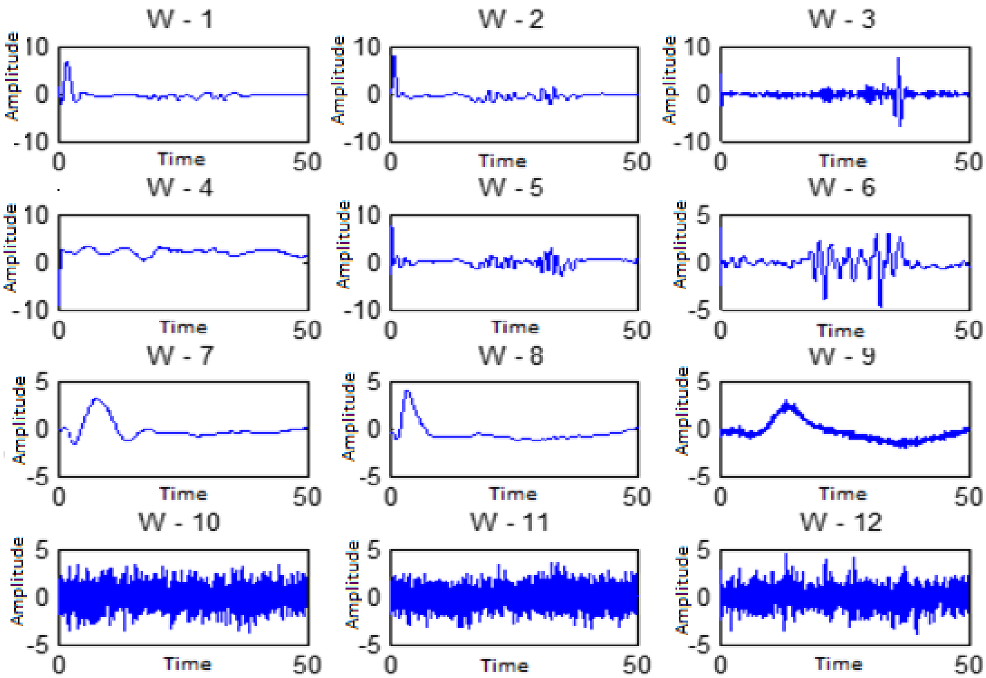


**Figure 5: DWT Decomposition of Single Channel Source Signal Obtained from EMD-ICA**

In Figure 6 we can see that peaks from 18 to 38 seconds has been minimized in a greater way and finally compared with reference signal as shown in Figure 7.Which shows motion artifacts in particular duration have been removed from the signal, and also shows better DSNR and better lambda value to prove our approach as better artifact removal technique.

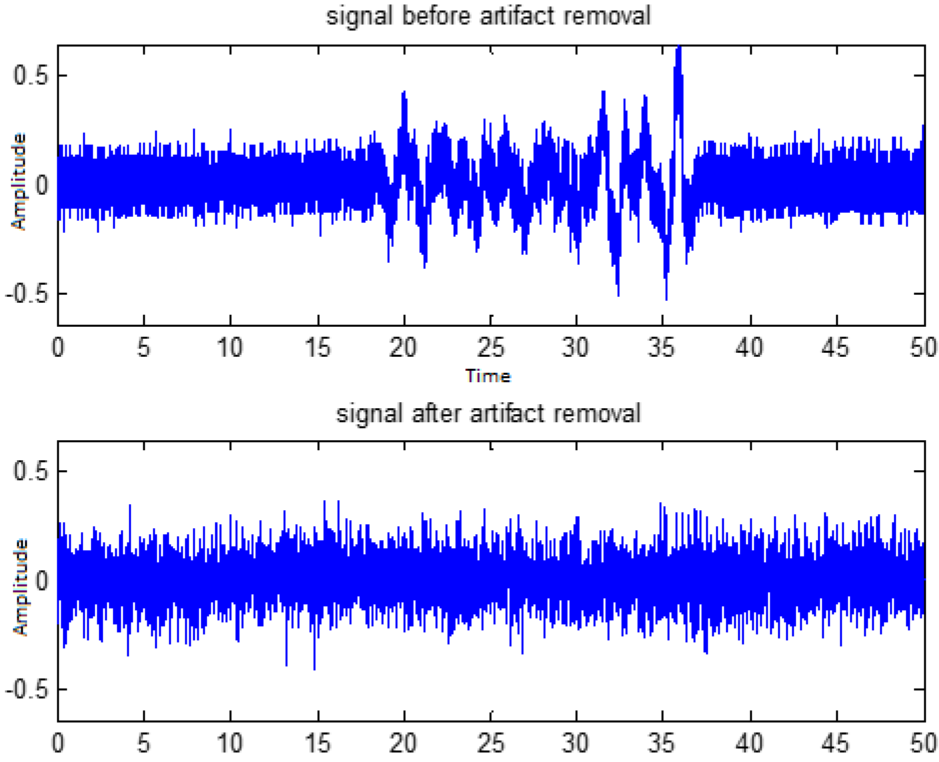


**Figure 6: Artifact-freeEEG Channel Reconstructed after Correlation Analysis and Reconstruction**

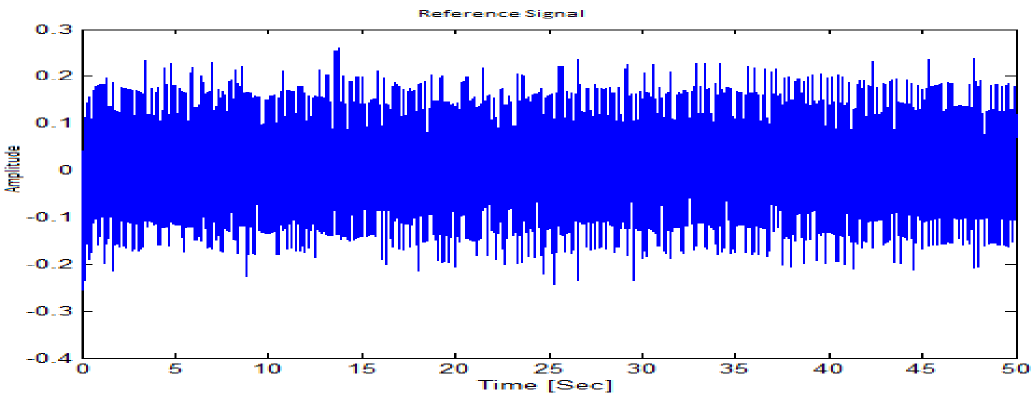


**Figure 7. Reference Signal**

The signal quality can be evaluated with power spectral density as parameter matrixisshown in Figure 8 below:

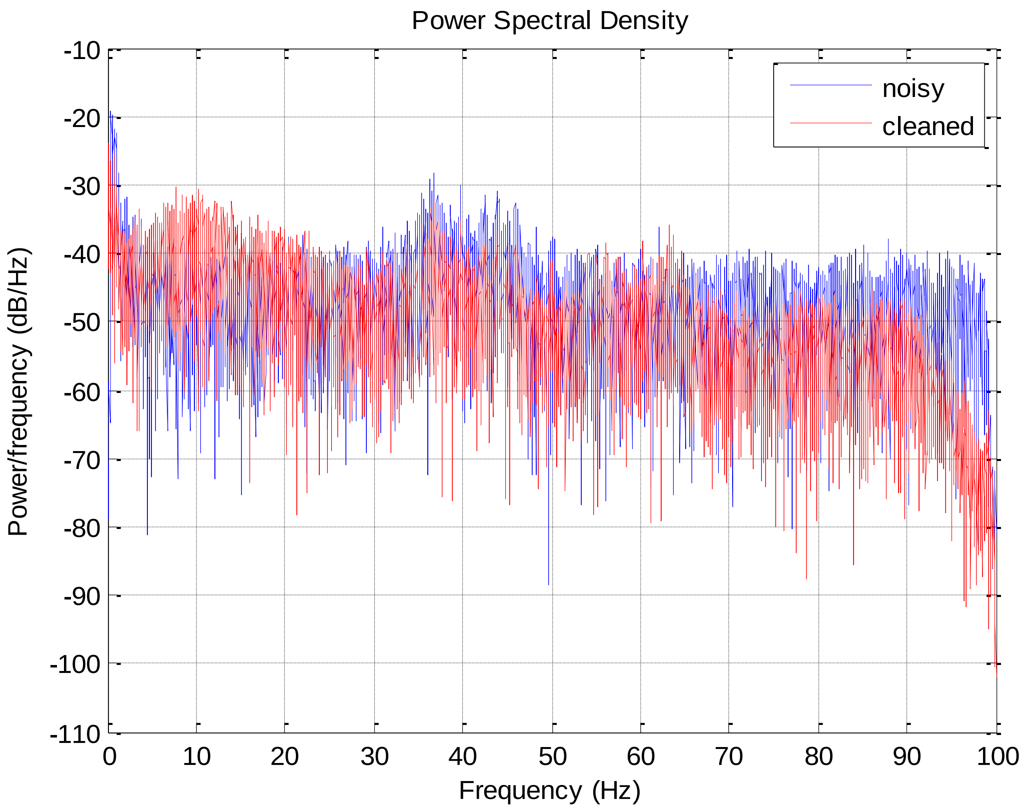


**Figure 8. PSD of EEG Signals with Our Proposed Approach**

The figure above shows the Power Spectral Density for EEG with artifacts (blue) and without artifacts (Red), as observed from Figure, the signal frequency of 20 Hz have high power value and at 80 Hz the power value of the signal is reduced. Athigh-frequencycomponents,power has been lowered which gives PSD improvement of 1.69 DB/Hz as revealed from the figure. Artifact removal will improve PSD of the signal.

**Autocorrelation:** Autocorrelation is a measure of the degree of similarity between a given signal and its lagged version over successive time intervals. Autocorrelation representation of motion artifact contaminated signal and motion artifact clean signal with our approach as following shown in Figure 9.

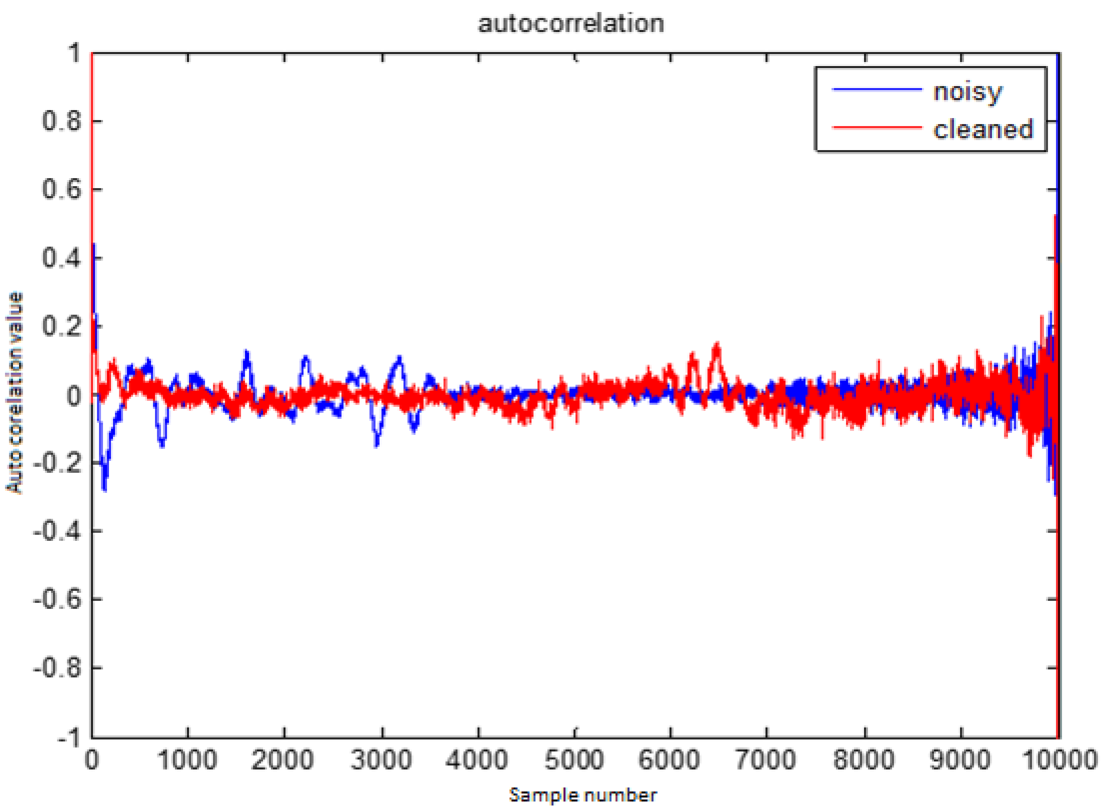


**Figure 9. Autocorrelation Presentation for Clean and Artifact Contaminated Signal**

Autocorrelation is also the best tool to test de-noising methodology. Graphical results show that after de-noising signal quality has been improved at high frequency.

The Table below show that motion artifact de-noising with combined approach of EEMD-ICA-DWTon test signal sequence number 2 of Physionet database for EEG signal which gives optimized and best parameter values as shown in Table 1while considering the practical conditions.

**Table 1. Comparison of Performance of Single Channel Artifact Removal Techniques for EEG signal**

**Comparison Table for Performance of Single Channel Artifact Removal Technique of EEGSignals**

| **Technique →** | EMD | EEMD | EMD-ICA | EEMD-ICA | EEMD-ICA-DWT |
|---|---|---|---|---|---|
| **Parameter ↓** | | | | | |
| DSNR | 2.6293 | 3.133 | 2.7688 | 4.3286 | 4.8503 |
| Λ | 21.9292 | 12.4438 | 41.5087 | 25.6833 | 52.781 |
| PSD Improvement | -0.0303 | -0.5171 | 1.0899 | -0.0193 | 1.69 |
| Correlation Improvement | -0.0026 | 0.0042 | 0.0161 | 0.0073 | 0.0183 |

Table 1 shows that the value of DSNR after EEMD filtering, is 3.133,then after EEMD-ICA it is improved to 4.3286 and after EEMD-ICA-DWT, it is improved to 4.8503, which proves the eligibility of proposed method for motion artifact removal.In the same manner,Λand PSD improvement also has been improved with proposed approach. Good correlation improvement also has been achieved.

Table 1 also shows that EEMD outperforms than EMD. Therefore, In next step authors have applied algorithmotest signalsequence number 8 from physionet database for EEG signal to prove the proposed algorithm qualified as shown in Table 2.

**Table 2. Comparison of Performance of Single Channel Artifact Removal Techniques for EEG Signal**

**Comparison Table for Performance of Single Channel Artifact Removal Technique of Test Signal of EEG Signals**

| **Technique →** | EMD-ICA | EEMD-ICA | EMD-ICA-DWT | EEMD-ICA-DWT |
|---|---|---|---|---|
| **Parameter ↓** | | | | |
| DSNR | 1.7599 | 1.9547 | 4.3187 | 4.4891 |
| Λ | 4.6207 | 2.2948 | 4.3178 | 8.4274 |
| PSD Improvement | 0.0591 | -3.7388 | -0.1524 | 0.5163 |
| Correlation Improvement | 0.364 | 0.0342 | 0.0395 | 0.0557 |

Table 2 conclude that EEMD-ICA-DWT outperforms than two stage approach(EMD-ICA and EEMD-ICA) of denoising and EMD-ICA-DWT algorithm for motion artifact removal. All parameters show good behavior to justify proposed algorithm.

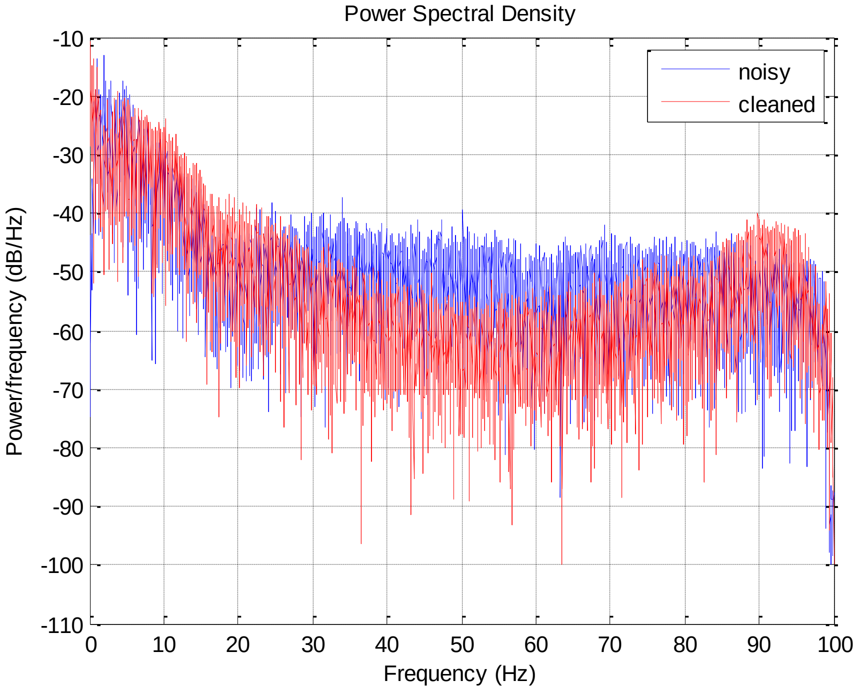


**Figure 10. PSD of EEG Signals with Our Proposed Approach**

The figure above shows the Power Spectral Density for test signal sequence number 8 of physionet database of EEG signal, where blue shows the power of a signal with artifacts and red shows the power of a signal without artifacts. From Figure 10, it can be observed thatpower has been lowered athigh-frequency components which givePSD improvement. Which is desired to attest a better proposed approach.

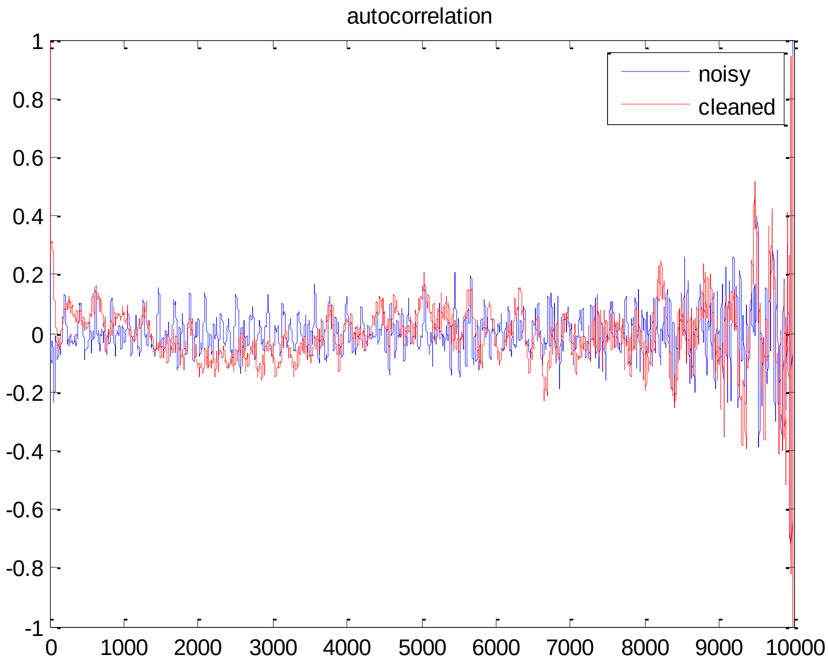


**Figure 11. Autocorrelation Presentation for Clean and Artifact Contaminated Signal**

Graphical results at Figure 11shows that after de-noising signal quality has been improved at high frequency and correlation shows the smoothness of signal.

To prove reliability of proposed algorithm, authors have applied the same approach to test signalsequence number 11 of physionet database for EEG signal too and results produced are as shown in Table 3.

**Table 3. Comparison of Performance of Single Channel Artifact Removal Techniques for EEG Signal**

**Comparison Table for Performance of Single Channel Artifact Removal Technique of EEG Signals**

| **Technique →** | EMD-ICA | EEMD-ICA | EMD-ICA-DWT | EEMD-ICA-DWT |
|---|---|---|---|---|
| **Parameter ↓** | | | | |
| DSNR | 1.7435 | 1.9496 | 4.3165 | 4.4914 |
| Λ | 4.5014 | 2.2846 | 4.3215 | 8.4285 |
| PSD Improvement | 0.0532 | -3.7438 | -0.1457 | 0.5172 |
| Correlation Improvement | 0.367 | 0.0411 | 0.0453 | 0.0585 |

Comparison Table 3 with all parameters also shows proposed algorithm as a better approach to removing motion artifact from EEG signal.

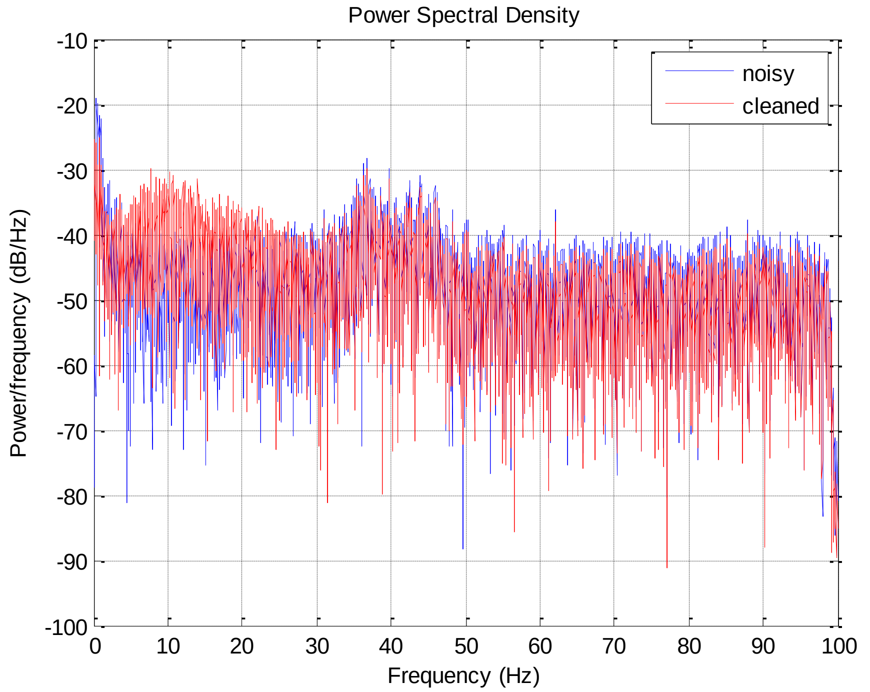


**Figure 12. PSD of EEG Signals with Our Proposed Approach**

Figure 12 shows the Power Spectral Density for test signal sequence number 11 of physionet database of EEG signal, where blue shows the power of a signal with artifacts and red shows the power of asignal without artifacts. From Figure 12, it can be observed thatpower has been lowered athigh-frequency components which give PSD improvement.

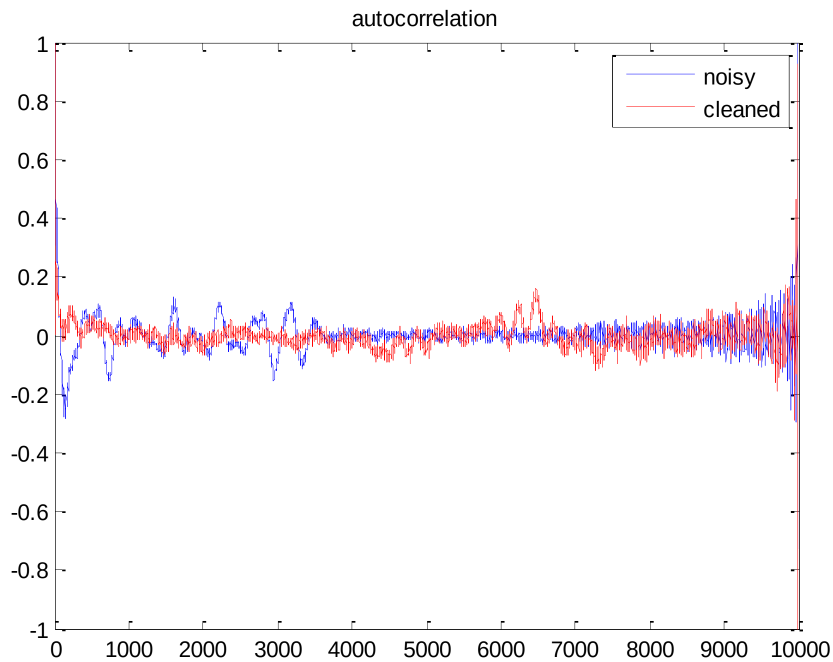


**Figure 13. Autocorrelation Presentation for Clean and Artifact Contaminated Signal**

Graphical results show that after de-noising signal quality has been improved at high frequency as shown in Figure 13.SNR values are plotted for all EEG input signal and the graph shows that proposed methodology is better for EEG Artifact removal.

## 9. Conclusion

New artifacts removaltechniqueforEEG signal has been proposed. The work is a modification of the work proposed in [[5]]. EEG Signals has specified a range of frequency with different amplitude for particular points of EEGacquisition system, but when artifacts are introduced, the range of frequency becomes higher with random high-frequency components shows significant power in the power spectrum. Removing these artifacts directly with filters may lose the necessary information because of amplitude variation, so we decomposed signals to IMFs with EEMD to convert single channel signal to multiple channel signal with different frequencies. Each IMF has a small frequency range, but if the signal has artifacts then IMFs will be having a low amplitude of high-frequency components. To separate thishigh-frequency component we performed ICA over these IMFs to get independent components of the signal so that the component of artifacts will be treated as one IC with arandom distribution, which can easily be eliminated. To get the better performance andbefore artifact removal, we applied signal after EEMD-ICA to single level DWT with soft thresholding, because signals after EEMD-ICA may contain frequency sharing by multiple sources which can be considered as noise for the particular one source. Pearson's correlation coefficient is used on wavelet component to find artifact contaminated signal. Reconstruction of the signal is done by making artifact component zero and finally summed up all the IMF's. Reconstructed signal shows 4.8503 dB of DSNR (improvement of 12%) and lambda value of 52.781dB and PSD improvement by 1.69 and correlation improvement by 0.0183. Our results as compared to results on [[5]] showsbetter-improved performance for artifact removal.The proposed algorithm is applied to two different data sets and the results pronounce the eligibility of proposed algorithm to stand on top of currently deployed algorithms.

## 10. Future Scope

Authors have taken only one level of Haarwavelet in DWT section for artifact removal. A Higher number of levels also have been tried, but performance is degraded with high-level Haarwavelet. Authors can suggest a study for selecting optimal wavelet and an optimal number of levels for the future scope of better motion artifact removal technique.

## Conflict of Interests

The authors declare that there is no conflict of interestsregarding the publication of this paper.

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