

Removing Jaw Clench, Teeth Squeeze and Forehead Movement EMG Artifacts from EEG Signal using Dynamic Size Segmentation and Multilevel Decomposed Wavelet with Adaptive Thresholding

K. P. Paradeshi^{1*} and U. D. Kolekar²

¹PVPIT, Budhgaon, Sangli – 416304, Maharashtra, India; kiranparadeshi@rediffmail.com

²APSIT, Thane west, Thane – 400615, Maharashtra, India; uttamkolekar@gmail.com

Abstract

Background: Jaw clench, teeth squeeze and forehead movement EMG artifacts affected the Electroencephalogram and suppress clinically important information regarding brain neural activity. EMG artifact contaminates the EEG signal and creates an obstruction in proper diagnosis of patients suffering from brain related diseases. EEG recording takes place almost from 30 to 40 minutes and it is often that EMG artifacts get embedded in important brain neural activity. Hence it is required to suppress the EMG artifacts. **Materials and Methods:** 16 channel EEG signals are acquired with EMG artifacts. The subject is instructed to do jaw clenching, forehead movement, teeth squeezing at different instances during the time of recording. Sampling rate chosen is 1024 Hz. The present work tried to remove these artifacts using dynamic size segmentation of EEG signal and multilevel decomposed wavelet enhanced independent components. This new method not only removes the artifact but also estimates data present in the time span of artifact region. In this present work, three methods of artifact removal are discussed and compared. The first method is wavelet Enhanced Independent Component analysis with static segmentation; the second method is wavelet Enhanced independent components with dynamic size segmentation of EEG signal and the third method is multilevel decomposed wavelet with adaptive thresholding with the time-frequency domain approach. The statistical parameters like PSNR, PSD, RMSE, standard deviation are used for performance measurements. **Results:** Proposed method in study, namely automatic dynamic segmentation with adaptive thresholding shows superior performance than other two methods discussed. It suppresses EMG artifacts significantly. **Conclusion:** Extensive lab results showed that dynamic size segmentation is a better tool to remove out EEG artifact over static size segmentation, but the third method is most suitable for estimation of data present in the time span of artifacts.

Keywords: Adaptive Threshold, Automatic Partition, Automatic Segmentation, EMG Artifacts, Independent Components Analysis, PSD, PSNR, RMSE

1. Introduction

Electroencephalogram (EEG) is an essential tool in the clinical diagnosis and analysis purpose. The Brain neuron action potential is responsible for Scalp potentials and these potentials are recorded using electrodes. EEG is a rhythmic nonstationary signal lies in the frequency band of 4-30 Hz and having an amplitude less than 100 μ V. EEG signal is the time vector sum of potential

at each scalp electrode those are contaminated due to event-related potential generated by the movement of body organs such as eye, forehead, facial muscles, tooth squeeze, jaw clenches etc. When these artifacts are present in EEG signal the amplitude of EEG signal becomes greater than few 100 μ V and affects all channels at that particular time span in multichannel EEG signal. Various methods have been reported in the literature to remove EEG artifacts out of these two well-known methods are

*Author for correspondence

Principal Component Analysis (PCA)^{1,2} and Independent Component Analysis (ICA)^{3,4}. ICA method relies on segmentation of EEG signal and quality of EEG processing alters with thresholding. A further improvement in ICA is suggested in applying semi-automatic segmentation⁵. Wavelet based decomposition and removal of OA suggested in^{6,7}. Independent Component (IC) analyzed using wavelet packets and this method removes OA and other artifacts. Wavelet based IC analysis shows poor correlation in case of original and processed EEG signal due to non-stationary property of segments and threshold value. Inappropriate threshold value results into uncorrelated EEG signal. Hard and soft threshold techniques suggested in the articles^{8,9}. Researchers have been trying to remove EMG artifacts reported in¹⁰⁻¹².

A novel technique (Automatic Wavelet Independent Component Analysis, AWICA) for automatic EEG artifact removal is presented. AWICA is based on the joint use of the Wavelet Transform and of ICA. It consists of a two-step procedure relying on the concepts of kurtosis and Renyi's entropy. Both synthesized and real EEG data are processed by AWICA and the results achieved were compared to the ones obtained by applying to the same data the "wavelet enhanced" ICA method recently proposed by other authors. Simulations illustrate that AWICA compares favorably to the other technique. The method here proposed is shown to yield improved success in terms of suppression of artifact components while reducing the loss of residual informative data, since the components related to relevant EEG activity are mostly preserved¹³.

A new method for muscle artifact removal in EEG is presented, based on canonical correlation analysis (CCA) as a blind source separation (BSS) technique. This method is demonstrated on a synthetic data set. The method outperformed a low-pass filter with different cutoff frequencies and an independent component analysis (ICA) based technique for muscle artifact removal. In addition, the method applies to a real ictal EEG recording contaminated with muscle artifacts. The proposed method removed successfully the muscle artifact without altering the recorded underlying ictal activity¹⁴.

In this paper, the method of automatic segmentations, and independent components of EEG signal is discussed to remove the artifacts like Jaw clench, teeth squeeze and forehead movement. EEG signal information is estimated in the time band of artifact using novel multilevel decomposed wavelets. The threshold value is calculated and

categorized as global and local threshold value using two different statistical formulas.

2. Methodology

16 channel EEG signals are acquired with Jaw clench, teeth, squeeze and forehead movement artifacts instructing the subject during the time of recording. The captured EEG data is taken in MATLAB with sampling rate of 1024 Hz. Unprocessed EEG data with Jaw clench, teeth squeeze and forehead movement artifacts are shown in the Figure 1, Figure 2 and Figure 3 respectively. Dynamic size segmentation is carried out to divide the EEG signal and further these segments are processed using independent component analysis. Segments are stationary in nature as compared with non-stationary EEG signal. Global threshold value (GT) of independent components is calculated using the property of mean, median and standard deviation. Out of these threshold values the numerical highest selected as GT.

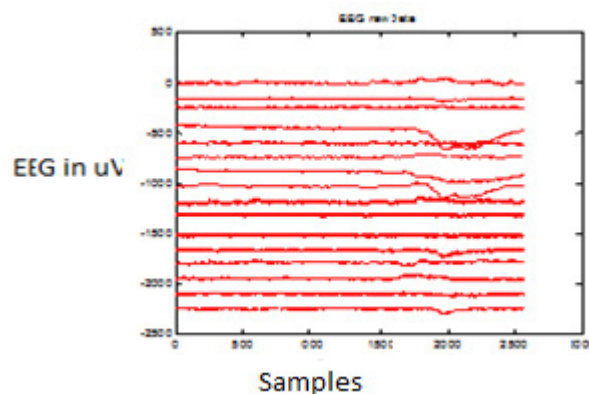


Figure 1. EEG with Jaw clench artefact.

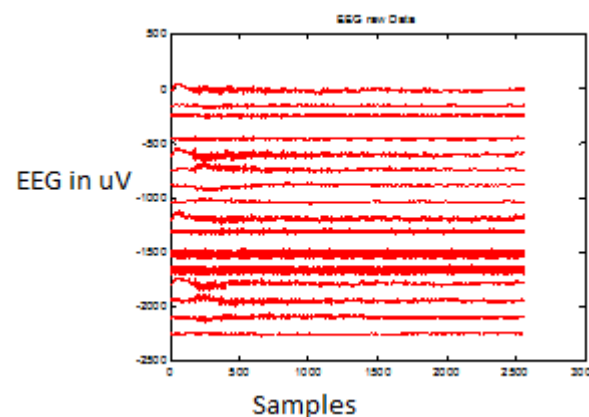


Figure 2. EEG with teeth squeeze artefact.

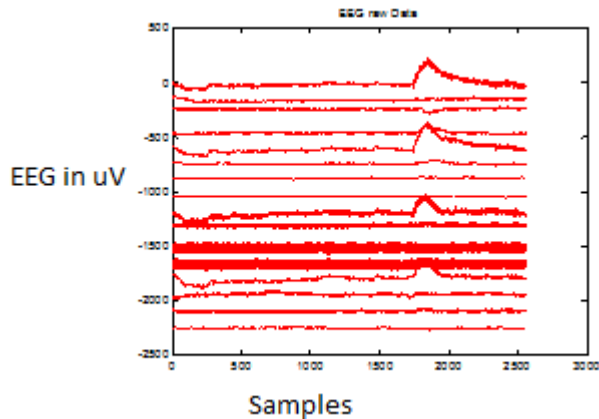


Figure 3. EEG with forehead movement artefact.

Two dimensional Discrete Wavelet Transform (DWT) of every ICA is taken using 'HAAR' wavelet family. One IC is first decomposed into four wavelets. succeeding DWT is taken of the decomposed wavelets. Thus, the wavelets are spread as 4 wavelets for first decomposition, 16 wavelets for second decomposition, 64 wavelets for third decomposition, 256 wavelets for fourth decomposition, and 1024 wavelets for fifth decomposition and so on.

3. Fully Automatic Dynamic Segmentation method

EEG is non-stationary signal which does not possess certain properties of statistics. A stationary signal is significant in the signal processing due to its predefined statistical property. As EEG is non-stationary, it is divided into a number of segments in which within that segment signal possess stationary property. These segments are treated as independent components of EEG signals. Analysis and processing of EEG segments give noise filtering, artifacts removing and many additional applications. A segment is valid, if it satisfy the law of statistics for stationary signal. Analysis of non-stationary segments results into uncorrelated data and loss of precious certain information within that segment. Identical size segments do not hold property of a stationary signal¹⁰. Identical size static segmentation method is not suitable for EEG signal processing. Hence, unequal size or dynamic segmentation is desirable.

A data set, is symmetric if it looks the same to the left and right of the center point. The skewness is defined for a real signal as,

$$\text{Skewness} = \frac{E[(x(n) - \mu)^3]}{\sigma^3} \quad (1)$$

For a symmetric distribution such as Gaussian, the skewness is zero. μ =mean, σ =standard deviation.

Automatic segmentation with dynamic size is based on the stationary property of segments that is quantified using equation 1. Algorithm for automatic segmentation is as follows,

- 1: Take channel as a counter. Initially select foremost or first channel.
- 2: Obtain the number of Rows and column of the channel.
- 3: Initialize a variable to store up RowBegin of each segment.
- 4: Assign highest row as a counter.calculate skewness. calculate difference of current and previous values of skewness.
- 5: If the difference is greater than 0.5 then locate the current row as end of segment and (row +1) as the begin of a new segment.Store the values of skewness as old segment values.
- 6: Repeat step 5 to last row. Store the RowBegin to the memory
- 7: Repeat 2 to 6 to last channel.

4. Adaptive Threshold Calculation

Wavelet threshold process is used to remove EMG artifacts present in the EEG signal. Threshold means replacing current data which is greater than the threshold value with the new value. The threshold value is calculated as,

$$\gamma 1 = \frac{N}{\mu + \sigma} \quad (2)$$

$$\gamma 2 = \text{mad} * 1.5 \quad (3)$$

$N=100$, mad =median absolute deviation of signal

$$\gamma = \max(\gamma 1, \gamma 2) \quad (4)$$

The threshold value is the numerical maximum of $\gamma 1, \gamma 2$.

Co-ordinate to co-ordinate / spatial replacement threshold method is used in this research work

$$\begin{aligned} X[n] &= x[n] \quad x[n] <= \gamma \\ &= a[n] \\ n &= 1, 2, 3, \dots, K \end{aligned}$$

$a[n]$ = IDWT of decomposed wavelets of $x[n]$ after threshold.

The spatial replacement threshold method is used in this research work except at the highest decomposition level (highest level $n=5$). The maximum level threshold is employed only once at the highest level of decomposition.

5. Results and Discussion

The methodology is implemented using MATLAB. Table 1 shows an EEG signal with Jaw Clench artifacts for three different subjects. The raw EEG signal is processed using three methods 1. Wavelet Enhanced Independent Component Analysis (wICA) with static size segmentation of EEG signals 2. Wavelet Enhanced Independent Component Analysis (wICA) with dynamic size segmentation of EEG signals 3. The proposed method is implemented using multilevel wavelet decomposition with time, frequency method and dynamic size segmentation of EEG signals. wICA method has greater value of RMSE and least value of mean power density indicating loss of valuable information. Improvements over wICA are observed in other two methods especially proposed method which estimates brain neural information in the time span where artifacts lies. Dynamic size segmentation is better than static segmentation. The similar type of trend in result is observed in other two artifacts teeth squeeze and forehead movement Table 2 and Table 3. Figure 4 and 5 shows results with wICA and proposed method for jaw clench artifacts. Figure 6 and 7 shows results with the wICA and proposed method for teeth squeeze artifacts. Figure 8 and 9 shows results with the wICA and proposed method for forehead movement artifacts.

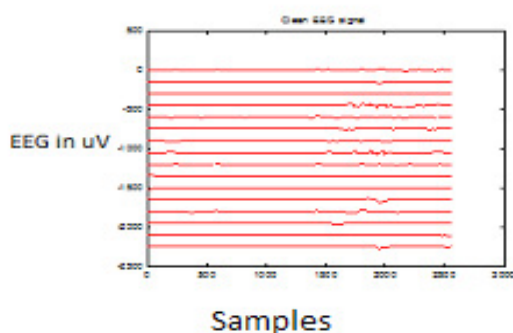


Figure 4. Clean EEG with wICA.

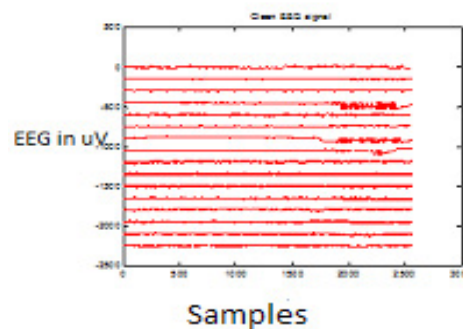


Figure 5. Clean EEG with Proposed method.
Figure 4 and 5. Results for Jaw clench artefact.

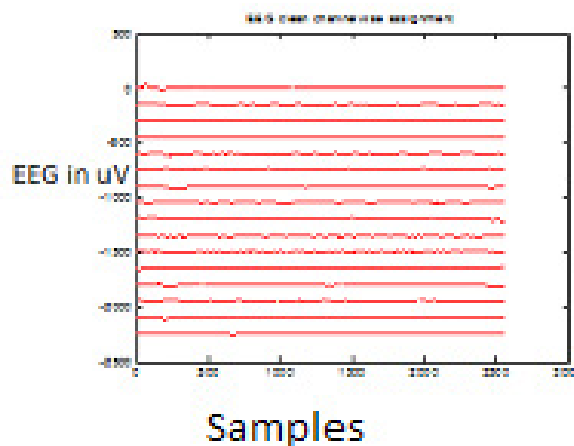


Figure 6. Clean EEG with wICA.

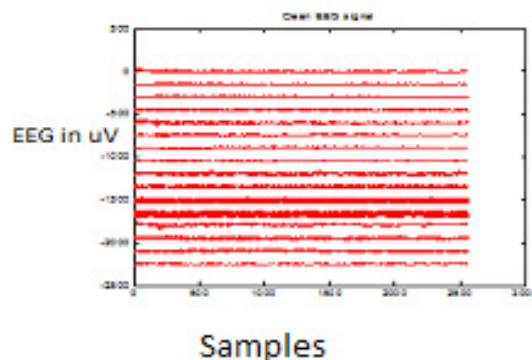


Figure 7. Clean EEG with Proposed method.
Figure 6 and 7. Results for Teeth squeeze artefact.

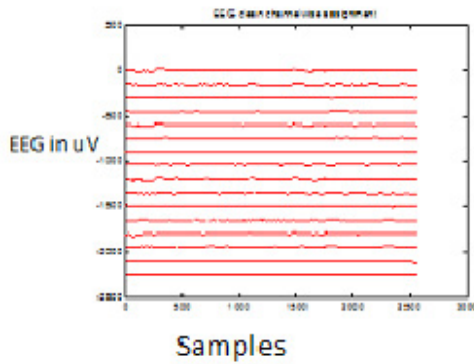


Figure 8. Clean EEG with wICA.

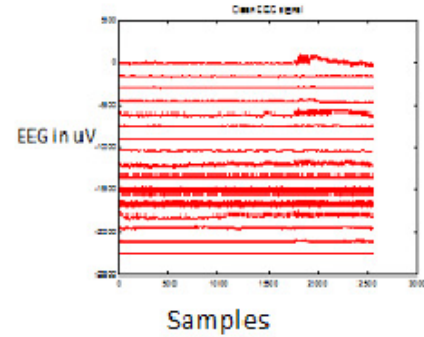


Figure 9. Clean EEG with Proposed method.

Figure 8 and 9. Results for Forehead movements artifact

Table 1. Statistical Parameters of EEG signal with Jaw Clench artifact

Statistical parameter	Subject 1			Subject 2			Subject 3		
	wICA	DwICA	Proposed method	wICA	DwICA	Proposed method	wICA	DwICA	Proposed method
Peak Signal to noise ratio (PSNR)	-4.00	-1.93	3.16	1.89	0.266	3.862	6.8286	0.89661	6.54
Mean power density of Raw EEG (dB)	17.468			22.7844			21.4554		
Mean power density of clean EEG (dB)	-5.66	9.83	13.50	-0.98	10.71	19.45	9.9338	10.1296	16.04
Root mean square error (RMSE)	31.65	30.81	25.71	27.73	26.50	22.77	26.62	25.25	19.75
Standard deviation of Raw EEG	17.3772			9.7918			10.8303		
Standard deviation of clean EEG	0.70185	1.579	6.083	1.27	1.856	3.488	1.932	1.973	5.9

Table 2. Statistical Parameters of EEG signal with teethsquake artifact

Statistical parameter	Subject 1			Subject 2			Subject 3		
	wICA	DwICA	Proposed method	wICA	DwICA	Proposed method	wICA	DwICA	Proposed method
Peak Signal to noise ratio (PSNR)	-0.952	3.74	7.876	9.2517	-0.63	5.691	10.862	1.763	4.22
Mean power density of Raw EEG (dB)	21.3917			22.2516			20.1546		
Mean power density of clean EEG (dB)	-3.159	6.25	14.73	7.6942	9.097	17.41	-0.285	7.904	14.58
Root mean square error (RMSE)	23.19	22.71	16.98	23.65	22.43	17.50	22.64	21.82	17.00

Standard deviation of Raw EEG	6.1659			6.9151			5.8596		
Standard deviation of clean EEG	0.754	1.42	5.837	2.651	2.068	5.44	2.4104	1.5834	4.636

Table 3. Statistical Parameters of EEG signal with forehead movement artifact

Statistical parameter	Subject 1			Subject 2			Subject 3		
	wICA	DwICA	Proposed method	wICA	DwICA	Proposed method	wICA	DwICA	Proposed method
Peak Signal to noise ratio	8.519	-1.851	11.97	8.64	-0.2	11.18	6.4976	-2.6715	11.87
Mean power density of Raw EEG (dB)	29.2146			26.6826			30.2007		
Mean power density of clean EEG (dB)	20.1712	8.494	22.55	12.979	9.929	21.76	-1.46	10.3003	21.85
Root mean square error (RMSE)	33.43	31.90	24.99	30.86	29.38	22.69	32.24	31.28	25.20
Standard deviation of Raw EEG	17.2508			15.1939			16.7868		
Standard deviation of clean EEG	3.2922	1.692	8.48	2.268	1.803	8.025	2.414	1.49	7.994

6. Conclusion

Results obtained using the proposed method are more satisfactory as compare to earlier methods. Artifacts are completely removed and successfully estimated original data in artifact time span. Automatic and dynamic segmentation is the key feature of this method. Particular dynamic size segmentation is better over static size segmentation. MATLAB based real time processing results showed that third method is most suitable for estimation of data present in the time span of artifact. The proposed method removes artifacts significantly as compared with other two methods and preserves brain neural activity.

7. References

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