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# Ocular Artifact Removal from EEG Using Stationary Wavelet Enhanced ICA

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***Abstract :*** To analyze EEG accurately, it is necessary to remove artifacts from EEG, which gets coupled with signal at the time of recording and can't be eliminated at preprocessing stage. Ocular artifact is most obvious artifact in EEG. In this paper, a new method using Stationary Wavelet Enhanced Independent Component Analysis with a novel thresholding, is proposed for ocular artifact removal from EEG. Proposed method incorporates strengths of Stationary Wavelet and Independent Component Analysis. Limitations of these method are minimized by using proposed novel thresholding technique, which is proved by results. Proposed denoising method with novel thresholding technique is analyzed in terms of correlation coefficient and mutual information. Superiority of proposed method is also proved by measuring frequency domain coherence between raw EEG data and noise free EEG data.

***Keywords :*** EEG, DWT, ICA, Ocular Artifact, Stationary Wavelet.

## 1. INTRODUCTION

Brain's spontaneous electrical activity is recorded in form of EEG [1]. Flow of electrical currents across the membranes is result of information processes by human brain's neurons [2]. EEG has various advantages over other techniques to study the brain functions as it has less hardware cost and due to absence of radiations or injections, it is considered very safe. The correct analysis of EEG and detection of various diseases can sometimes be difficult due to various artifacts that may be added to pure EEG signals during EEG recording. The main artifacts can be divided into classes of patient-related (physiological) artifacts and system artifacts [2]. The patient-related or internal artifacts are body movement-related like Electro-Myogram (EMG), ECG (and pulsation), Electro-Oculogram (EOG) or Ocular artifact, ballistocardiogram and sweating. The system artifacts are 50/60 Hz power supply interference, impedance fluctuation, cable defects, electrical noise from the electronic components and unbalanced impedances of the electrodes. The main cause of EOG artifacts is eye movement and eye blinks during EEG recording. A significant potential difference occurs between the cornea and the retina due to eye blinking which affects the EEG recording [2]. Extensive research work is carried out with the aim of artifacts removal from EEG and at the same time to maintain originality of EEG to preserve important information in the original signal and to cause minimum distortion [3].

In this paper, a new method using Stationary Wavelet Enhanced Independent Component Analysis, is proposed for ocular artifact removal from EEG. The main contributions of the paper are as follows:

- Proposed method overcomes the shortcomings of wavelet enhanced ICA and hard thresholding, used for ocular artifact removal from EEG.
- Proposed method effectively deals with shortcomings of stationary wavelet transform (SWT) and adaptive thresholding also.
- Proposed novel thresholding technique makes denoising more efficient.

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This paper is divided into five sections, Section-II covers literature survey. Section-III explains proposed method. Section-IV shows the results obtained and Section-V, follow by reference, is a summary of conclusions.

## 2. LITERATURE SURVEY

Estreda et al [6] has proposed method for denoising of EEG signal using DWT thresholding technique. Since ocular artifacts have significant components in 0-16 Hz, thresholding is done only to those sub-bands lying in the frequency region of 0-16 Hz. In this method, 4 level decomposition of DWT is done with raw EEG signal to obtain DWT coefficients and then thresholding is applied on these DWT coefficients. In case of ocular noise, hard thresholding is preferred over soft thresholding because ocular artifact occurs for short time duration and soft thresholding modifies entire signal. Efficiency of proposed method is restricted due to shift variance and aliasing issues of DWT [5]. Shift variance is perturbation in wavelet pattern oscillation around a singularity because of small shift in signal. Due to discrete time decimation at each stage with non-ideal filters aliasing comes into role and inverse DWT overcomes this issue only when there is no modification in wavelet coefficients, but wavelet coefficients get modulated whenever thresholding is applied. Shift variance problem can be avoided by using un-decimated DWT, *i.e.* stationary wavelet transform [14].

Krishnaveni et al [7] has proposed a method to remove ocular artifacts using stationary wavelet transform (SWT) and adaptive thresholding. SWT is applied to expanded contaminated signal and optimal threshold is selected for 3$^{rd}$ to 6$^{th}$ level of decomposition on minimum risk value. Since soft thresholding functions have discontinuous derivatives, they cannot be used for adaptive thresholding as continuous derivatives are required for minimum condition criteria calculation. Hence a modified version of soft thresholding, known as soft-like thresholding, is applied for optimal noise removal. SWT is used because of its time invariance property. Since there is no down sampling so no time information is lost and it produces smoother results in low frequency bands. SWT produce smoother results in low frequency bands by ocular artifact suppression but it also suppresses EEG signal, which result in information loss [4].

In Castellanos et al [8], the method suggested for ocular artifact removal, is blind source separation using independent component analysis and then zeroing the artifactual components. In proposed method, independent components and mixing matrix using ICA are estimated then artifactual sources are identified using IC marker. Column corresponding to artifactual independent components are made zero in estimated mixing matrix and in last step estimated sources are mixed by multiplying them with modified estimated mixing matrix. To apply ICA on EEG signals some assumptions are made like cerebral signal and artifact signal are linearly combined and are statistically independent, number of recording channel must be greater or equal to number of independent sources and finally delay because of propagation through mixing medium is insignificant. Efficiency of proposed method depends upon these assumptions and it is very difficult to meet these assumptions for real EEG [15].

In Mahajan et al [10], method for automatic noise removal of ocular artifact using wavelet enhanced ICA (wICA), is proposed. In proposed method, independent components and mixing matrix are estimated using extended infomax ICA. Sample entropy and kurtosis are calculated for each independent component and then threshold for sample entropy and kurtosis is calculated to identify artifactual source. DWT with thresholding is applied on artifactual source and then mixed signal are estimated by multiplying independent components with estimated mixing matrix. EEG signal is very random in nature and eye-blinks occur for very small duration hence the entropy value of ocular signal is very less compared to EEG signal. The entropy can be used as IC marker to identify the artifactual independent component. In Bose et al [11] it is revealed that multi-scale entropy (mMSE) gives better information regarding EEG than other existing entropy. In proposed method modified multi-scale entropy (mMSE) is used and it is calculated by initially coarse graining of each independent component for multiple scales and then sample entropy of each scale is calculated [12]. Kurtosis is a fourth-order statistical parameter and used for study of the peaked distribution of any random variables [13]. The signals with peak distribution have higher values of kurtosis; hence ocular signals also have higher values of kurtosis than EEG signals. With support of these arguments kurtosis is also used as IC marker in proposed method. Threshold value for mMSE (lower limit) and kurtosis (upper limit) is calculated as discussed in Mahajan et al [10]. Independent components having mMSE values less than lower limit or kurtosis value above upper limit are considered as artifactual components. Proposed wavelet enhanced ICA method does not affect non artifactual region as it uses hard thresholding for DWT denoising but results are not optimal due to shift variance issue of DWT and again hard thresholding make zero to all undesired part of signal, which introduces some discontinuities.

## 3. PROPOSED METHOD

**Block diagram of proposed method is shown in Fig.1.**

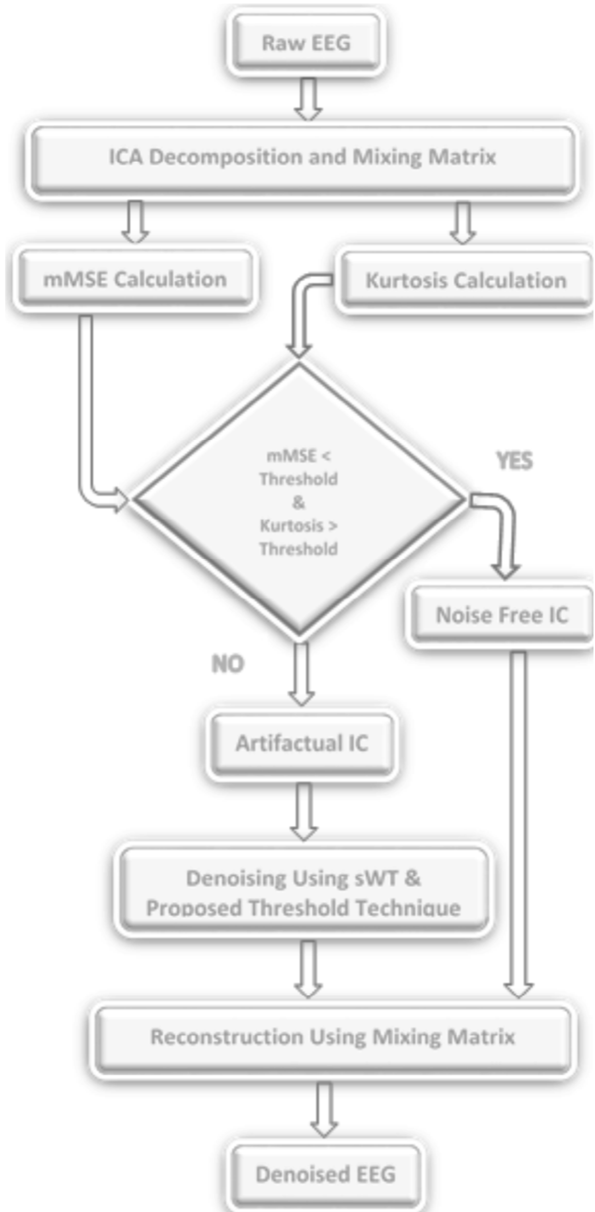


**Fig. 1. Proposed Methodology.**

**Proposed method has following steps:**

1. ICA decomposition of ocular artifact corrupted EEG with mixing matrix.
2. Calculation of modified multi scale entropy (mMSE) and kurtosis.
3. Separation of artifactual independent components (IC) from noise free ICs by comparing calculated values of mMSE and kurtosis with their threshold values (Lower limit of mMSE and upper limit of kurtosis).
4. Denoising of artifactual ICs using sWT and proposed novel thresholding technique.

5. Reconstruction of signal using mixing matrix, noise free ICs and denoised artifactual ICs.
6. Comparison of proposed method with other latest proposed methods in terms of correlation coefficient, mutual information and coherence.

### A. Independent Component Analysis (ICA)

ICA is a statistical tool to separate mixed recordings from several channels into independent sources. Suppose that an array of channels to provide N observed signal

$$x(k) = [x_1(k), x_2(k) \ldots , x_N(k)]^T \quad (1)$$

And the actual sources are

$$s(k) = [s_1(k), s_2(k) \ldots , s_N(k)]^T \quad (2)$$

Here the assumptions are that the sources have non Gaussian distribution and they are mutually statistically independent. The main purpose of ICA is to estimate a demixing matrix W such that

$$s = W \times x \quad (3)$$

Where, W defines that the transformed occurred in such a way that the mutual information is minimized among all independent sources. Mutual information measures the information dependency between two random variables. Many algorithms are designed to perform ICA. In proposed method, infomax ICA is selected since for sources having super-Gaussian distribution, this technique is most efficient and approximate model for raw EEG with ocular artefact is most close to super-Gaussian distribution. It is an unsupervised technique which uses information maximization in a single layer neural network (feed forward) and gives nonlinear outputs [9].

### B. Stationary Wavelet Transform (sWT)

sWT is calculated same as DWT but down-sampling and up-sampling blocks are not present. SWT decomposition filter bank is shown in Fig.2.

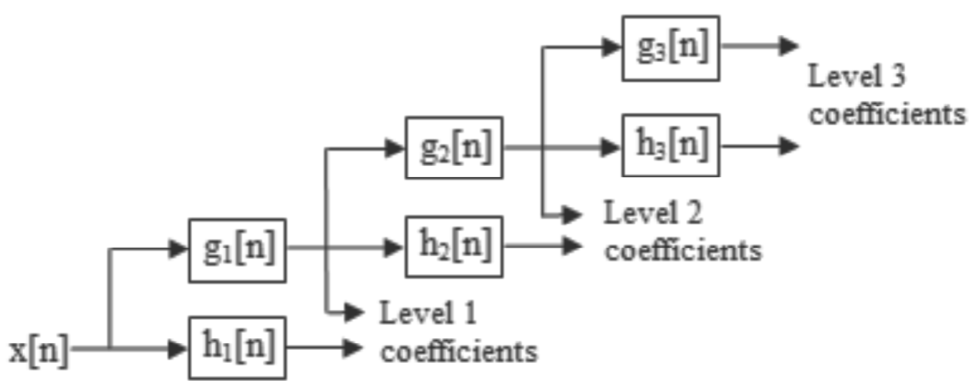


**Fig. 2. Stationary wavelet transform decomposition tree.**

Stationary wavelet transform is also called un-decimated DWT, *i.e.* the decimators after filters are not applied. Since there is no down-sampling, it does not lose any time information and have shift invariance property. Because of oversampling, it has very good time resolution at low frequencies and hence it produces smoother results in low frequency bands. It also does not suffer with aliasing because no down-sampling is done at any stage [14]. In proposed method, SWT with bior-4.4 mother wavelet is used. Decomposition is done up to 6$^{th}$ level and threshold is applied from 3$^{rd}$ to 6$^{th}$ level of decomposition.

### C. Proposed Thresholding Technique

This technique is inspired from hard thresholding and it does not affect the coefficients in the desired range but modulates the coefficients in undesired range (above a threshold value).Hard thresholding in such cases produces undesired discontinuities. Steps of proposed thresholding technique are :

1. Calculate the threshold using any standard risk rule.
2. Keep coefficients unfazed below threshold value.

3. Calculate the maxima for the intervals having values above threshold.
4. Calculate scaling factor for each interval, it can be calculated as follows:

$$\mathrm{SF}(j) = \frac{d(\mathrm{ind}(j)-1)}{\max_j} \tag{4}$$

Where $j$ denotes $j^{th}$ interval, ind($j$) denotes starting index of interval and denotes the maxima in interval.

5. Multiply all values of $j^{th}$ interval by $SF(j)$.

## 4. RESULTS

14 channels (10s) of 32 channel pre-processed EEG signal, taken from www.physionet.org, are used in this method and are plotted in Fig 3. X-axis shows time in seconds and Y-axis shows channel numbers.

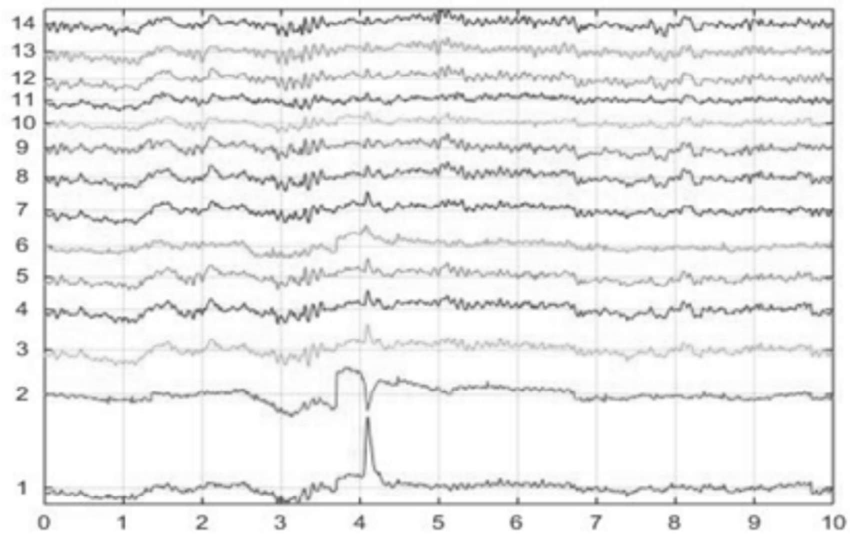


**Fig. 3. Raw (Contaminated) EEG.**

From Fig.3, it is clearly visible that channel 1 is severely affected by ocular artifact around time instant 4*s*. After decomposition of raw signal using Infomax ICA, 14 independent components are obtained as shown in Fig.4.

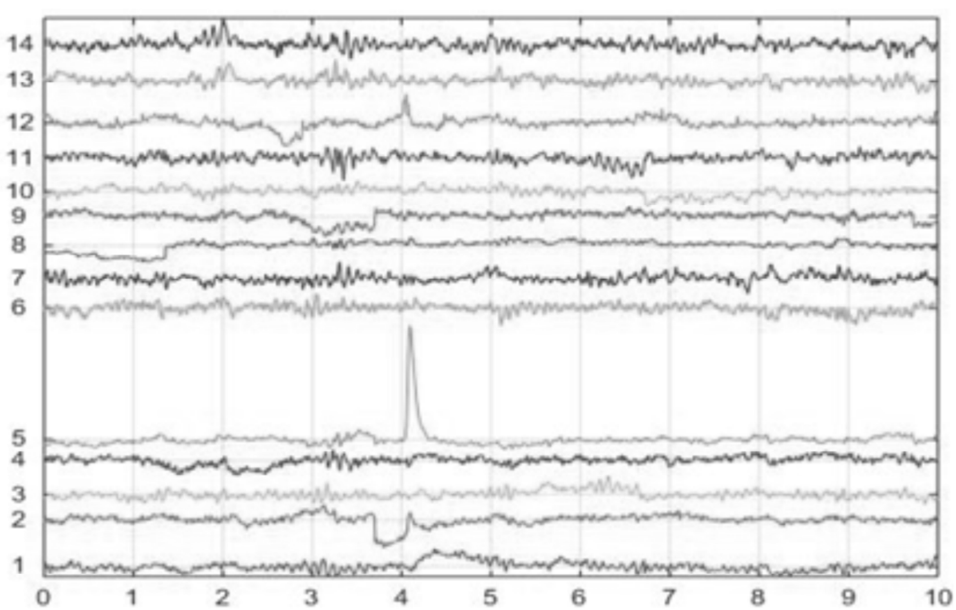


**Fig. 4. Independent components of raw EEG**

In first stage, using modified multi scale entropy (mMSE) and kurtosis, the ocular artifact related independent components are identified and then stationary wavelet transform and novel thresholding technique are applied on artifactual components to suppress noise. The mMSE is calculated by initially coarse graining of each independent component (IC) for multiple scale, then sample entropy of each scale is calculated. The coarse graining of IC can be mathematically given as

$$y_j^{(\mathrm{T})} = \frac{1}{\tau}\sum_{i=(j-1)\tau+1}^{j\tau} u_i ; 1 \leq \mathrm{N}/\tau \tag{5}$$

Where, $y$ is coarse grained sequence at scale factor $\tau$. '$u$' is the IC time sequence and N is length of each IC.

The mMSE for each grained independent component can be calculated as [12]

$$m\mathrm{MSE}(m, r) = \log\left(\frac{\mathrm{B}_r^m}{\mathrm{A}_r^m}\right) \tag{6}$$

Where $m = 2$ and $r = 0.2*$

Standard deviation of data sequence.

The mMSE plot for each channel is shown in Fig.5. Y-axis shows sample entropy for each channel and X-axis shows channel number.

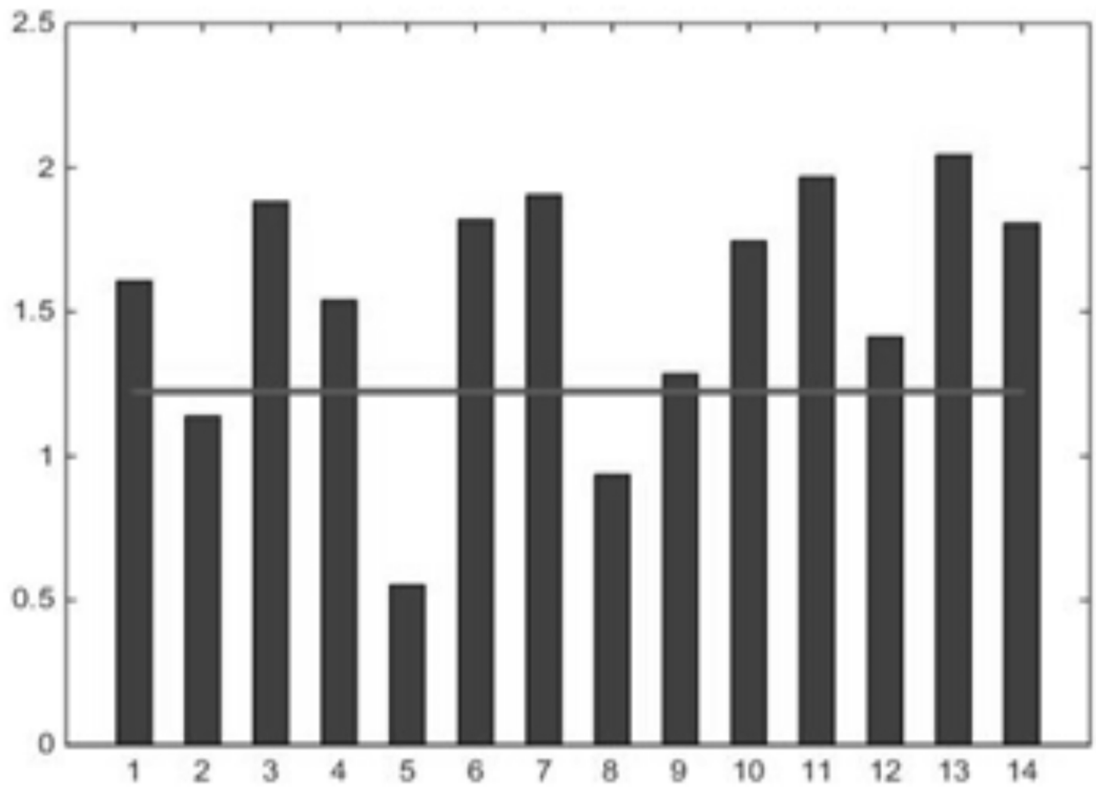


**Fig. 5. Plot of mMSE.**

The ocular signal will have lower values of mMSE than EEG signals. Kurtosis is a fourth-order statistical parameter to study the peaked distribution of any random variables, it can be mathematically calculated as

$$k = m_4 - 3m_2^2 \tag{7}$$

And

$$m_n = \mathrm{E}\{(x - m_1)^n\} \tag{8}$$

Where, $m_n$, $m_1$ and E are nth order moments of the random variable, mean and expectation function respectively.

The signals with peak distribution will have higher values of kurtosis, hence ocular signals will have higher values of kurtosis than EEG signals. The kurtosis is calculated and plotted as shown in Fig.6.

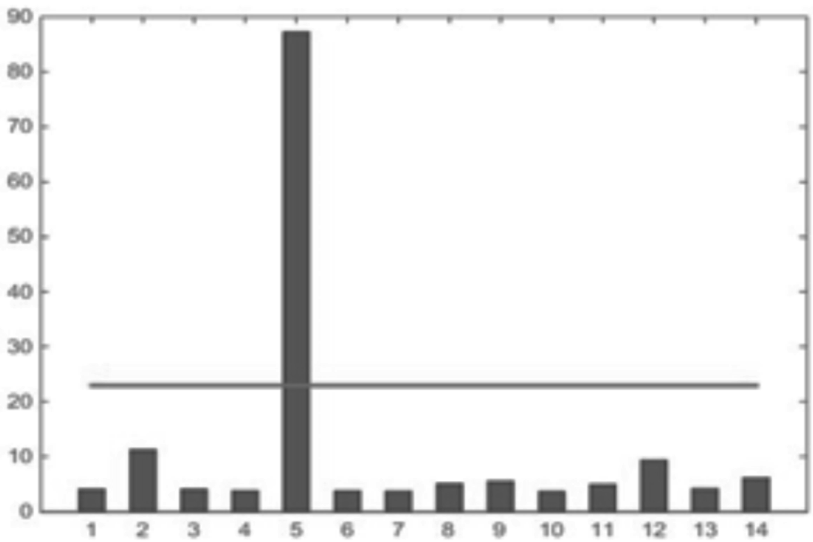


**Fig. 6. Plot of kurtosis**

Threshold value for mMSE is given as [12],

$$\text{Lower limit} = \bar{x} - \frac{s}{\sqrt{N}} \times t_{N-1} \tag{9}$$

Threshold value for kurtosis is calculated by [13],

$$\text{Upper limit} = \bar{x} - \frac{s}{\sqrt{N}} \times t_{N-1} \tag{10}$$

Where, $\tilde{x}$ is sample mean, $s$ is sample standard deviation, N no. of ICs and $t_{N-1} = 2.201$.

Threshold value (Lower limit) of mMSE is calculated equal to 1.26 and threshold value (Upper limit) of kurtosis is calculated equal to 22.7. ICs having mMSE values less than lower limit or kurtosis value above upper limit are considered as artifactual components. It can be notice from Fig.5 and Fig.6 that channel 2, 5 and 8 are the components affected by ocular artifact. Stationary wavelet transform and novel thresholding technique are applied on artifactual components to suppress noise. The final reconstructed noise free signal is shown in Fig.7.

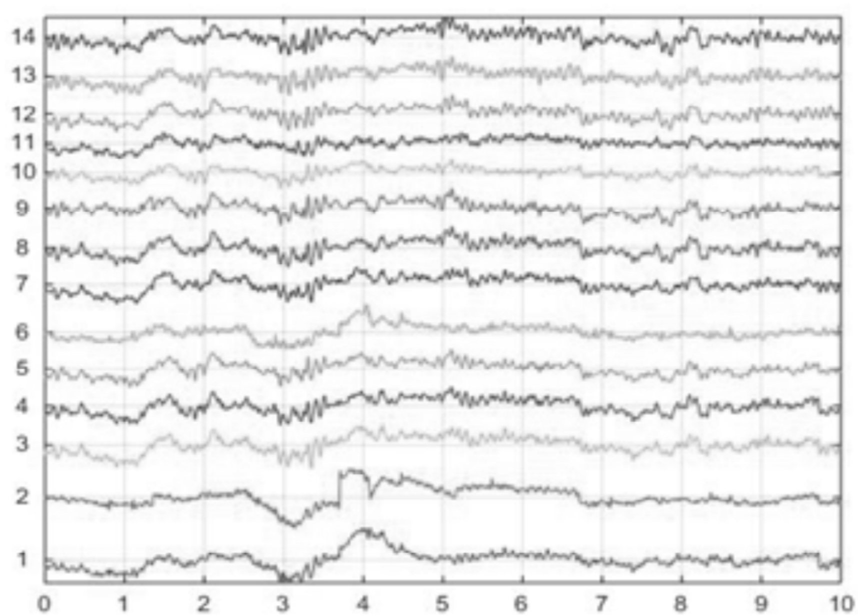


**Fig. 7. Reconstructed noise free signal**

It can be observed from Fig.7 that ocular artifact has been efficiently removed from channel 1 while keeping the rest signal unfazed. Result of proposed novel thresholding technique is compared with result of hard thresholding. In both cases DWT with bior-4.4 mother wavelet is used. Corresponding results are shown in Fig.8. In this plot X-axis shows number of samples in signal.

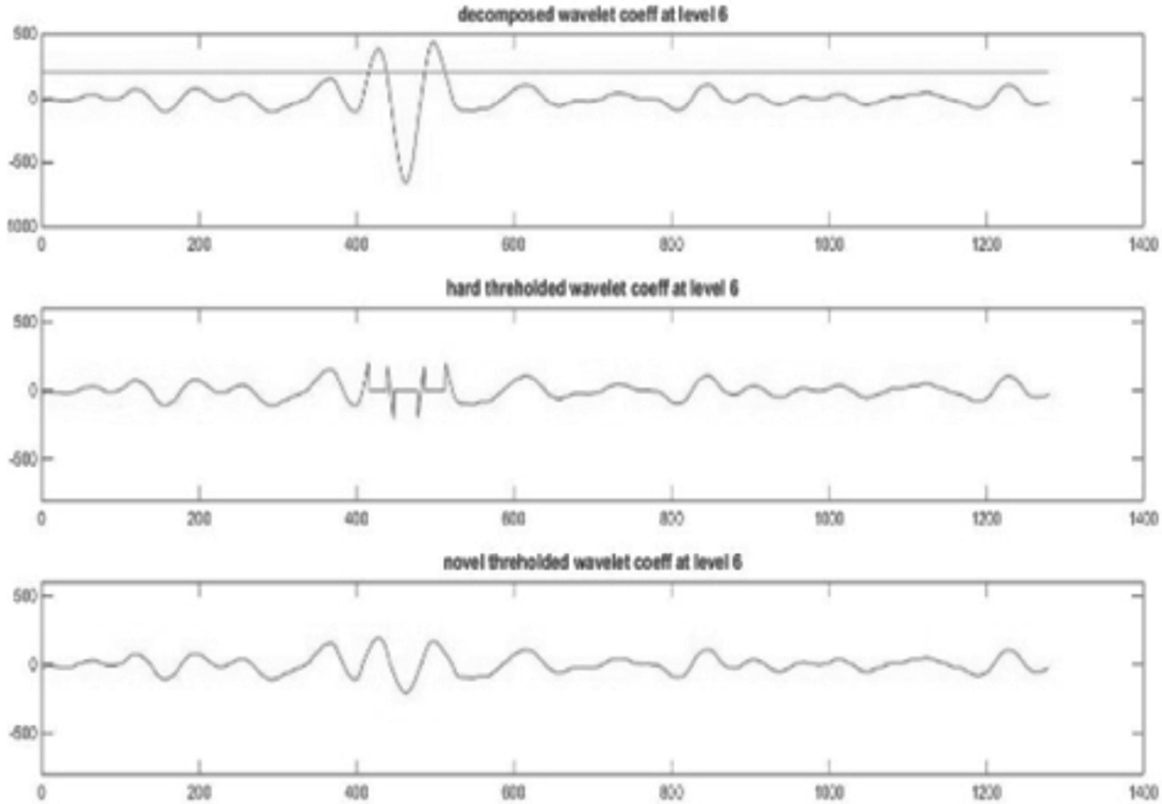


**Fig. 8. Comparison of proposed novel thresholding technique**

It can be seen that hard thresholding introduce undesired discontinuities, while proposed novel thresholding technique is not only suppressing the noise part but also maintaining smoothness of the signal. To measure the performance of proposed method, the results are compared with most recent techniques, proposed by Mahajan et al [10] using wavelet enhanced ICA (wICA) and zeroing ICA technique, in terms of correlation coefficient, mutual information and coherence. Correlation is used to measure the linear relationship between two random variables and it is defined as

$$\gamma_{xs} = \frac{\operatorname{cov}(x, x)}{\sigma_x \sigma_s} \tag{11}$$

Where, $x$ is the raw EEG signal, $s$ is the noise free EEG signal, $\sigma$ is the standard deviation and cov is the covariance of two random variable x and s. Maximum value of correlation coefficient between two signal can be '1'.

Mutual information (MI) is a measure of amount of information, noise free EEG contains, about raw EEG signal. If two random variables are closely related they will have large number of mutual information. According to Shannon information theory MI can be calculated by Kullback-Leibler distance between product of the marginal pdfs of random variable $x$ and $y$ and their joint pdf, which can be given as

$$\mathrm{I}(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \log\left(\frac{f(x, y)}{f(x) f(y)}\right) dxdy \tag{12}$$

Comparison among three methods in terms of correlation coefficient and mutual information, are given in Table 1 and Table 2 respectively.

**Table 1**

| *Channel No* | *Correlation Coefficient* | | |
|---|---|---|---|
| | ***Zeroing ICA*** | ***wICA*** | ***Proposed Method*** |
| 1. | 0.4443 | 0.5835 | 0.8606 |
| 2. | 0.7034 | 0.7936 | 0.9751 |
| 3. | 0.7809 | 0.8315 | 0.9753 |
| 4. | 0.8690 | 0.8957 | 0.9866 |
| 5. | 0.8243 | 0.8653 | 0.9870 |
| 6. | 0.7419 | 0.8150 | 0.9768 |
| 7. | 0.7889 | 0.8422 | 0.9790 |
| 8. | 0.9382 | 0.9520 | 0.9906 |
| 9 | 0.8338 | 0.8565 | 0.9971 |
| 10. | 0.7931 | 0.8487 | 0.9841 |
| 11. | 0.8682 | 0.8857 | 0.9852 |
| 12. | 0.8766 | 0.9015 | 0.9925 |
| 13. | 0.8798 | 0.9106 | 0.9960 |
| 14. | 0.9217 | 0.9371 | 0.9915 |

**Table 2**

| *Channel No* | *Mutual Information* | | |
|---|---|---|---|
| | ***Zeroing ICA*** | ***wICA*** | ***Proposed Method*** |
| 1. | 0.3043 | 0.4213 | 0.6093 |
| 2. | 0.4967 | 0.6191 | 0.8159 |
| 3. | 0.4991 | 0.6241 | 0.9568 |
| 4. | 0.6915 | 0.7022 | 0.9784 |
| 5. | 0.6407 | 0.7315 | 1.0551 |
| 6. | 0.5815 | 0.6057 | 1.1179 |
| 7. | 0.6008 | 0.7123 | 0.9953 |
| 8. | 0.9769 | 1.1989 | 1.6181 |
| 9. | 0.6134 | 0.9528 | 1.5221 |
| 10. | 0.5712 | 0.7498 | 1.0797 |
| 11. | 0.7344 | 0.8187 | 1.7097 |
| 12. | 0.7245 | 0.9009 | 1.6661 |
| 13. | 0.8090 | 0.9772 | 1.6155 |
| 14. | 0.9765 | 1.2705 | 1.5738 |

To analyse the performance in frequency domain coherence is measured between raw EEG data and noise free EEG data. It is calculated in magnitude square term. For all three method coherence is plotted in Fig. 9 to Fig.11.

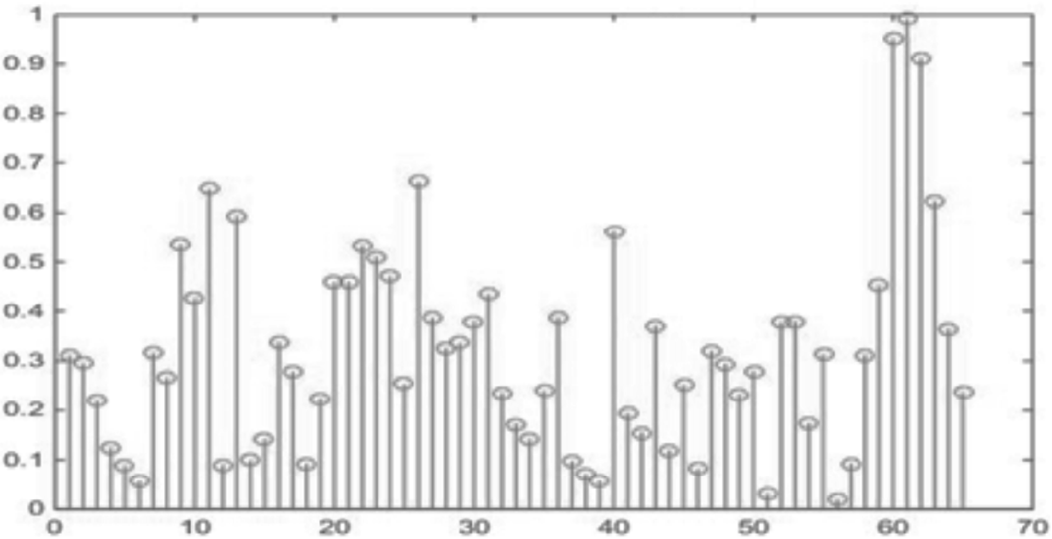


**Fig. 9. Coherence of zeroing ICA**

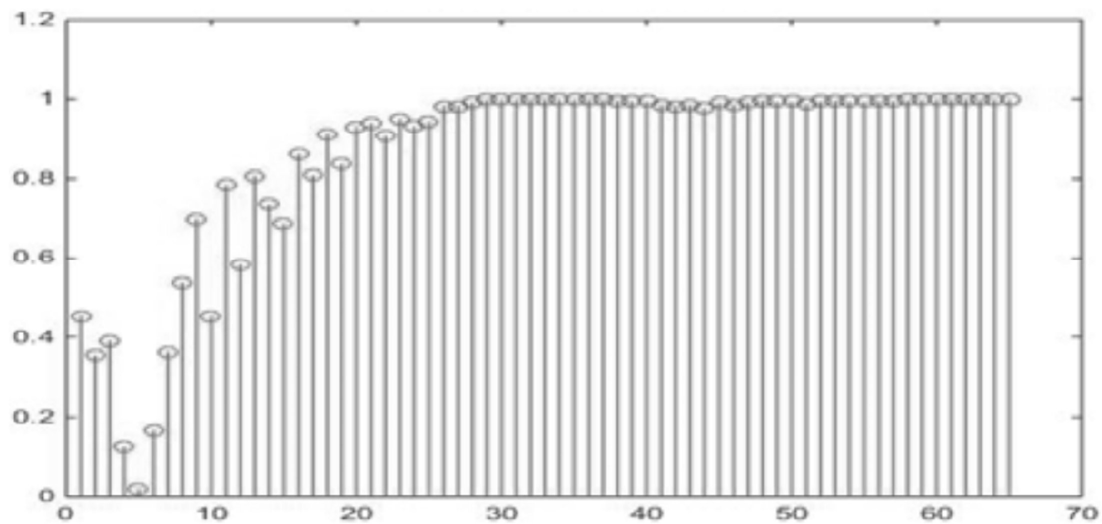


**Fig. 10. Coherence of wICA**

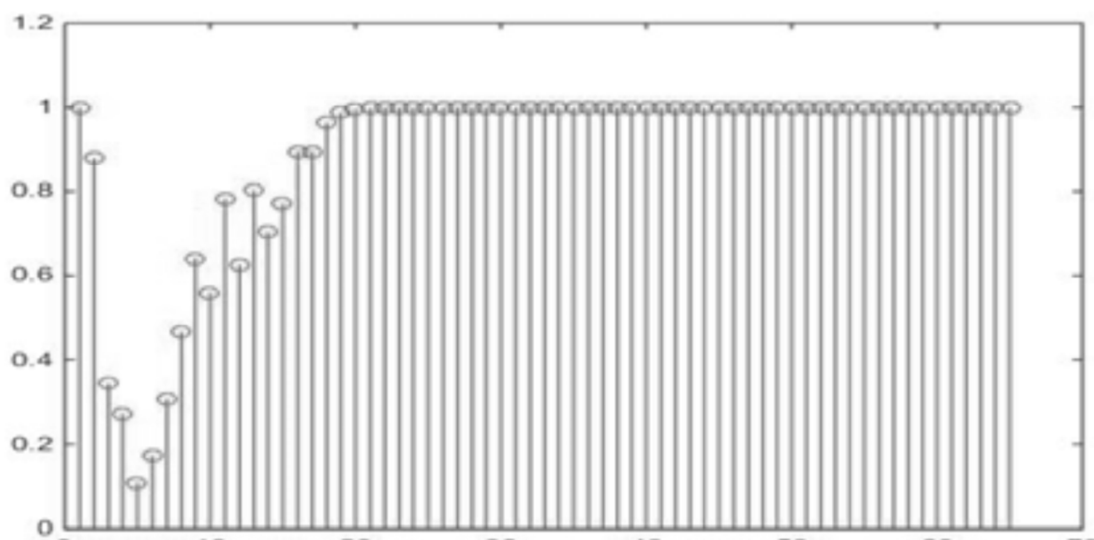


**Fig. 11. Coherence of proposed method**

## 5. CONCLUSION

In this work, a new approach towards wavelet enhanced ICA is presented by using stationary wavelet transform in place of DWT and a new method for thresholding has suggested, which does not introduce any discontinuity like other thresholding methods. Stationary wavelet transform is preferred to DWT because of its time invariance property. Results of proposed method are compared with two other ICA based methods, zeroing ICA and wICA, in terms of correlation, mutual information and coherence. Results of proposed method are far superior to them in all three terms. In terms of correlation, proposed method not only gives better results for unaffected recording channel but it improves the result from 0.58 to 0.86 for most affected recording channel, it means that proposed method suppresses the ocular artifact without introducing additional noise. When the results are compared in terms of mutual information, it improves from 0.42 to 0.60 for most affected recording channel. The coherence graphs show that the wICA method is affecting those frequencies too, which are not present in ocular artifacts frequency range but proposed method has only affected the frequency range 0-16 Hz, which is ocular artifact frequency band.

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