and discriminate are the measure statistical property of time lag provides information regarding signal. These parameters are vital in the determination of segments and artifacts present in the signal. Skewness is a measure of symmetry or, more precisely, the lack of symmetry of the distribution. A distribution, or data set, is symmetric if it looks the same to the left and right of the centre point. The skewness is defined for a real signal as,

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

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

Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution; i.e. data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case. The kurtosis for a real signal x(n) is defined as,

$$\text{kurt} = \frac{m_4[x(n)]}{m_2^2[x(n)]}$$

$$m_i\left[x(n)\right] = E\left[(x(n)-\mu)^j\right] \tag{2}$$

A second level discriminate d2(m) is then defined as (m=segment),

$$d_2(m) = \text{kurt}_x(m) - \text{kurt}_x(m-1) \tag{3}$$

Automatic segmentation with dynamic size is based on the stationary property of segments that is quantified using equation 1, 2 and 3. Algorithm for automatic segmentation is as follows,

I: Take channel as counter. Initially select first channel.

II: obtain number of Rows(R) and column (C) of channel.

III: Initialize a variable to store RowStart of each segment.

IV: Take maximum row as counter

V: calculate skewness and Kurtosis and calculate difference of current and old values of skewness and Kurtosis.

VI: if difference is greater than 0.5 then mark the current row as end of segment and (row +1) as start of new segment. Store the values of skewness and kurtosis as old segment values.

VII: repeat V to VI to last row.

VIII: store the RowStart to the memory

IX: repeat II to VIII to last channel.

ADAPTIVE THRESHOLD CALCULATION

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

$$\gamma 1 = \frac{N}{\mu+\sigma} \tag{4}$$

$$\gamma 2 = mad * 1.5 \tag{5}$$

N=100, mad=median absolute deviation of signal

$$\gamma = \max(\gamma 1, \gamma 2) \tag{6}$$

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

a. zero replacement threshold
   x[n] = x[n] x[n] <= γ
   = 0
   n=1, 2, 3,.......K (K=maximum row)

b. mean replacement threshold
   x[n]= x[n] x[n] <= γ
   = μ
   n=1, 2, 3,.......K

c. maximum level threshold
   x[n]= x[n] x[n] <= γ
   = γ
   n=1, 2, 3,.......K

d. co-ordinate to co-ordinate / spatial replacement threshold
   x[n]= x[n] x[n] <= γ
   = a[n]
   n=1,2,3,.......K
   a[n]= IDWT of decomposed wavelets of x[n] after threshold.

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

MULTILEVEL DECOMPOSITION

OA and EEG data both are present in the same bandwidth and it is difficult to identify (separate) the useful information available in the region of artifact. Removing of OA is only possible by sacrificing useful data or valuable information. Wavelet multilevel decomposition is versatile that can remove the OA with estimation of information present in that particular region. EEG signal is automatically segmented into number of IC and each IC is analysed and processed independently. First GTV of current IC is calculated and then decomposed into four wavelets. This is first level decomposition n=1 and M=4. LTV of four wavelets are

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calculated. Four wavelets are treated as IC and decomposed into 16 wavelets n=2 and M=16. LTV of 16 wavelets are calculated. Previously calculated LTV of four wavelets is GTV at n=2. This process repeats to maximum value of decomposition, here n=5. Maximum threshold is carried out at n=5 and then IDWT is taken (a[n]). Spatial threshold is employed at n=4 and IDWT is taken (a[n] is replaced with new data). This process repeats for n=3 to 1 in descending order. Final segment is obtained by IDWT of n=1 decomposed level. This process repeats for all IC and finally obtained clean EEG signal with estimated data.

RESULTS AND DISCUSSION

The methodology is implemented using MATLAB. Computation using MATLAB is short time process suitable for real time. First computation did for selection of suitable and better wavelet family for the purpose of EEG artifact removing. EEG decomposition seems to be better 'HAAR' wavelet family, due to improved SNR and better higher cross correlation (Xcorr) as compared to other wavelets (Table 1).However, SNR is non-positive value indicating lost of useful information. WICA method gives non-positive values of SNR.

In order to compensate loss of useful information present new method is implemented. EEG signal is decomposed and then using adaptive threshold artifact is removed. Table 2 shows performance of artifact removing from raw EEG signal with various decomposition levels. If decomposition level is greater than 3 then the values of SNR, PSNR and Xcorr are satisfactory and non-negative. SNR is 1.5402, PSNR is 19.3292 and EEG signal is best correlated with normalised correlation of 0.799.

Table 3 indicating normalized cross correlation values for 16 channels with 1 to 6 decomposition levels. Cross correlation is the best statistical parameter for evaluation and comparison of various methods in signal processing. There is progressive improvement of cross correlation values as proceed from level 1 to level 6 (min=0.7072, max=0.9823).It can be interpreted that suitable data is estimated in artifacts zone using suggested method in this paper.

Table 1: Comparison of performance of wavelet families

	Haar	Daubechies	Symlets	Coiflets	Biorthogonal	Reverse biorthogonal
SNR	-1.2434	-1.6444	-1.7816	-2.0477	-1.9508	-1.8845
PSNR	12.9711	14.2909	13.6431	14.6212	14.0078	14.0099
Xcorr	0.7689	0.7629	0.7479	0.7620	0.7608	0.7455

Table 2: Comparison of effect of decomposition level

	WICA	n=1	n=2	n=3	n=4	n=5	n=6
SNR	-1.2434	-1.2434	-1.103	-0.4349	0.1493	0.9172	1.5402
PSNR	12.9711	12.9711	14.0147	14.8431	16.0018	17.7282	19.3292
Xcorr	0.7689	0.7689	0.7718	0.7643	0.7662	0.7738	0.799

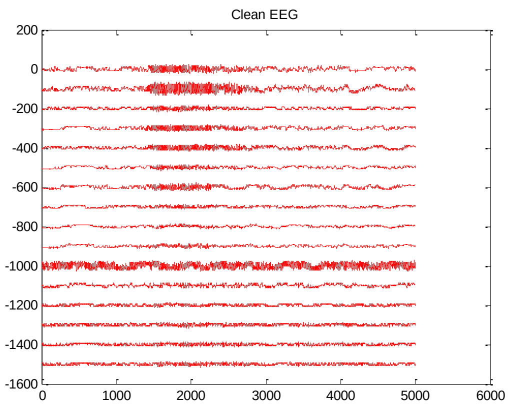

Figure 3: n=1 clean EEG

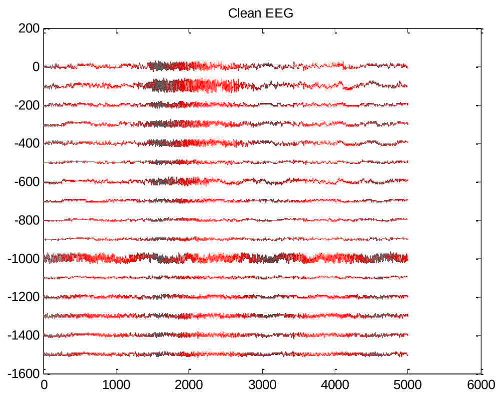

Figure 4: n=2 clean EEG

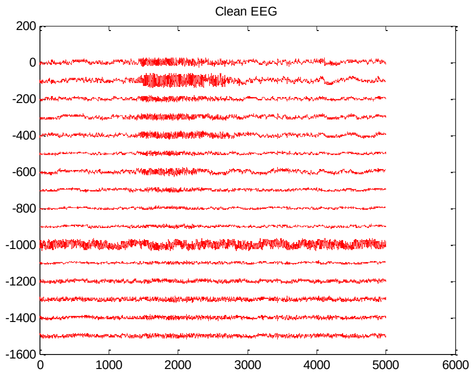

Figure 5: n=3 clean EEG

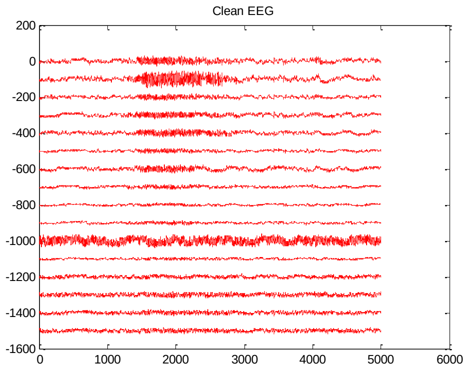

Figure 6: n=4 clean EEG

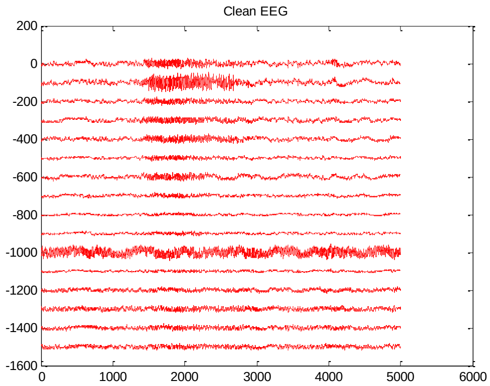

Figure 7: n=5 clean EEG

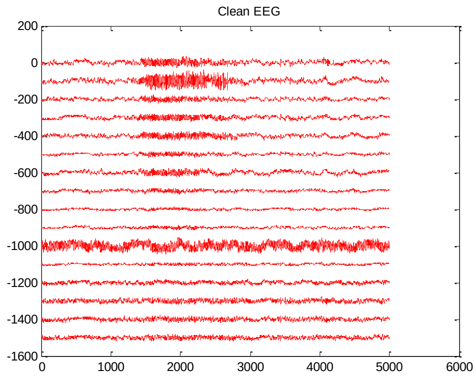

Figure 8: n=6 clean EEG

Table 3: Normalized Cross correlation

Channel	n=1	n=2	n=3	n=4	n=5	n=6
1	0.7689	0.7718	0.7643	0.7662	0.7738	0.799
2	0.7072	0.7577	0.7643	0.7694	0.7774	0.791
3	0.8563	0.8479	0.8611	0.8723	0.8873	0.897
4	0.8527	0.842	0.8257	0.8199	0.8282	0.838
5	0.815	0.8551	0.8469	0.8562	0.8734	0.878
6	0.962	0.8549	0.8688	0.8836	0.9045	0.919
7	0.8806	0.8673	0.8759	0.8844	0.9037	0.911
8	0.9176	0.854	0.8551	0.8611	0.8701	0.89
9	0.9823	0.8775	0.8837	0.8847	0.8935	0.904
10	0.977	0.8638	0.8769	0.892	0.9105	0.928
11	0.8895	0.9022	0.914	0.9281	0.9442	0.958
12	0.965	0.8812	0.9024	0.92	0.9367	0.947
13	0.9191	0.8797	0.894	0.9071	0.9266	0.943
14	0.8654	0.8591	0.8825	0.9055	0.9242	0.937
15	0.8772	0.8543	0.8746	0.8988	0.9212	0.932
16	0.8929	0.8705	0.8931	0.9136	0.9401	0.949

CONCLUSION

Results obtained using present methods are more satisfactory as compare to earlier method. The HAAR wavelet family is suitable for EEG signal decomposition. As decomposition levels are increased the results become most accurate and precise. Ocular artifacts are completely removed and successfully estimated original data in OA time band. Automatic and dynamic segmentation is the key feature of this method. A particular segment can be analysed and processed independent of other segments. Present adaptive threshold method is best suitable for estimation of data within OA time band.

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