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Denoising of EEG Signals using Wavelets and Various Thresholding Techniques

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Abstract: The Electroencephalogram (EEG) is the standard technique for investigating the brains electrical activity in different psychological and pathological states. Analysis of Electroencephalogram (EEG) signal is a challenging task due to the presence of different artifacts such as Ocular Artifacts (OA) and Electromyogram. Normally EEG signals falls in the frequency range of DC to 60 Hz and amplitude of 1-5 µv. Ocular artifacts do have the similar statistical properties of EEG signals, often interfere with EEG signal, thereby making the analysis of EEG signals more complex. In this research paper, different thresholding techniques were employed by using different wavelet functions, in the removal of ocular artifacts (OA) present in the EEG signal. Later performance of these thresholding techniques were compared in the removal of OA's with the help of various parameters. In this paper the collected EEG signal is normalized and later linearly mixed with the normalized EOG signal resulting in a noisy EEG signal. This noisy EEG signal is decomposed to 4 levels using different wavelets. This decomposition of EEG signals yields approximate and detail coefficients. Later different thresholding techniques were applied to detail coefficients and estimated the statistical parameters of it. To arrive at the best thresholding technique and wavelet to be considered for removal of ocular artifacts, the algorithm is applied to two different data sets, which were taken from Physionet data base. The results show that the sym8 wavelet is the best choice in removing noise from the EEG signal.

Keywords: WT, DWT, Ocular Artifacts.

I INTRODUCTION

Electroencephalogram (EEG) has been long utilized to diagnose different disorders of the nervous system such as epilepsy, classifying stages of sleep in patients, seizures and brain damage. EEG is the electrical activity recorded from the scalp surface, which is picked up by conductive media and electrodes [1-2]. EEG has been performing a vital role to investigate brain activities in clinical application and scientific research for several years [3-5]. The EEG signals can be contaminated by various artifacts, of which the major noise source is ocular artifact. Eye-movement and eye-blink artifacts are the major sources of ocular artifacts [6]. However, artifacts are the major enemies of high-class EEG signals.

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The mixing up of these ocular artifacts with the EEG signal at the time of recording causes the problems in the precise estimation of EEG signal. These artifacts will plunge into either of the 2 categories namely, technical and physiological artifacts. Power line noise 50/60Hz falls into technical artifact category while the artifacts that crop up because of ocular(EOG), heart(ECG) and muscular activity(EMG) falls into physiological artifacts category respectively [7].

Regression in the time domain and frequency domain [8-10] methods were proposed in removing eye blinks artifacts. These methods require a reliable reference channel. This channel can be contaminated by EEG. So, EEG has to be removed from the reference channel by regression techniques. Hence, the regression methods are not the finest to remove EOG artifacts.

In this research paper, noisy EEG signal is decomposed to four levels using different wavelets. This decomposition gives low frequency and high frequency components of noisy Electroencephalogram signal. The high frequency components contain more noise information than low frequency components, hence are processed with various thresholding techniques.

II METHODOLOGY

EEG signal that is collected from Physionet data base is normalized by using the following formula:

$$\text{Normalized EEG signal} = \frac{\text{collected EEG Signal} - \text{Mean(Collected EEG Signal)}}{\text{Std (Collected EEG Signal)}}$$

The collected and normalized EEG signals are shown in Figure 1.

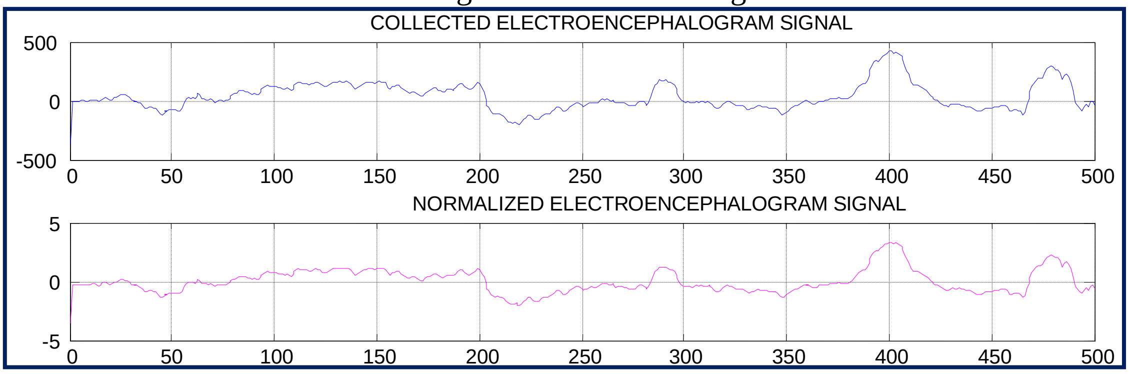

Fig 1: Collected EEG Signal and the Normalized EEG Signal

The EOG signal that is collected from Physionet data base is normalized by using the following formula:

$$\text{Normalized EOG signal} = \frac{\text{collected EOG Signal} - \text{Mean(Collected EOG Signal)}}{\text{Std (Collected EOG Signal)}}$$

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The collected and normalized EOG signals are shown in Figure 2.

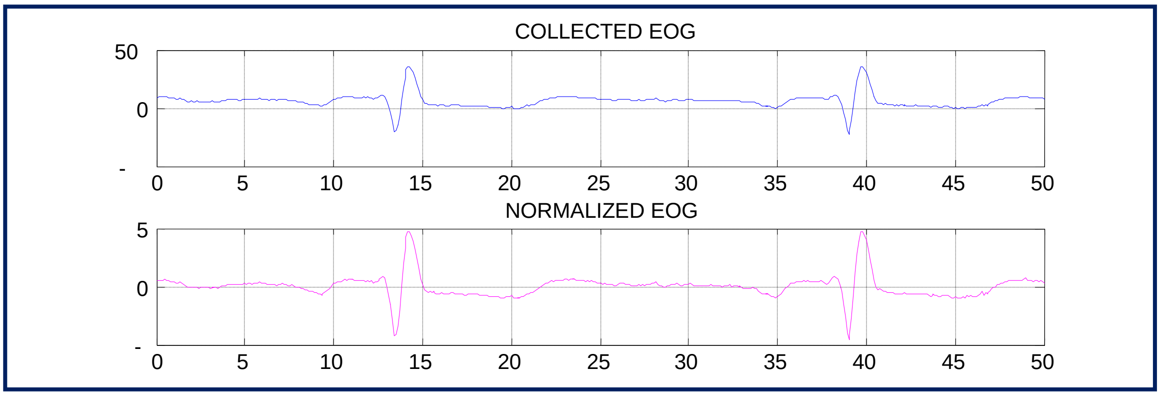

Fig 2: Collected ElectroOculoGram Signal and Normalised EOG signal

The corrupted EEG (observed) signal can be modeled in the following manner:

$$y(n) = x(n) + \sigma e(n) \quad \ldots\ldots\ldots\ldots(1.3)$$

Where, x(n) is the original Electroencephalogram signal ,e(n) is the ElectroOculoGram signal, σ is the noise variance and y(n) is the Noisy EEG signal

To achieve the noisy EEG signal, the normalised Electroencephalogram signal is mixed with the ElectroOculoGram signal with noise variance of 0.4, and is shown in the Figure 3.

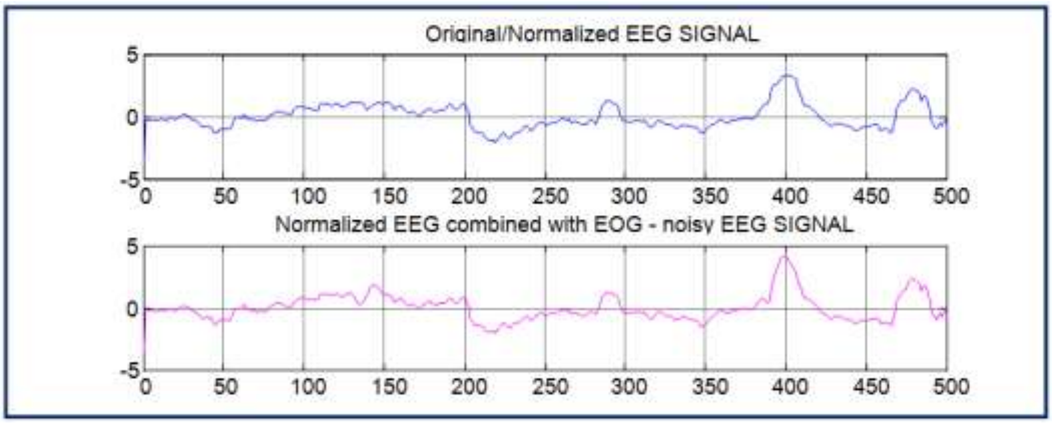

Fig 3: Normalized EEG combined with EOG- noisy EEG

The decomposition of noisy EEG signal is done to four levels by different wavelet functions. This decomposition gives low frequency and high frequency components of noisy Electroencephalogram signal. The high frequency components contain more noise information than low frequency components, hence are processed with various thresholding techniques.

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Various thresholding techniques such as Heursure, Rigrsure, minimaxi, and sqtwolog [12] along with soft and hard thresholding techniques were employed in the removal of OAs in the EEG signal [13], as shown in Figure 4.

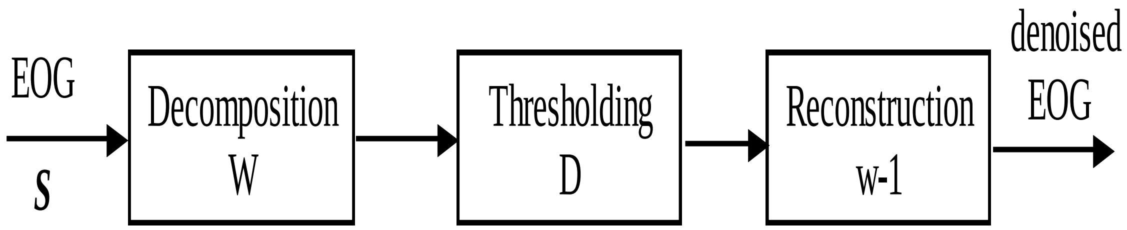

Fig 4: Wavelet Denoising

III RESULTS

The results obtained using various thresholding techniques namely Heursure, Rigrsure, minimaxi and sqtwolog thresholding with different wavelet functions such as dB8, Sym8 and Haar wavelets and the results are tabulated in the table1.1 and table 1.2 respectively. One of the waveforms of data set-1 using using Heursure-soft thresholding using dB-8 wavelet is shown in Figure 5. One of the waveforms of data set-2 using using Heursure-soft thresholding using dB-8 wavelet is shown in Figure 6.

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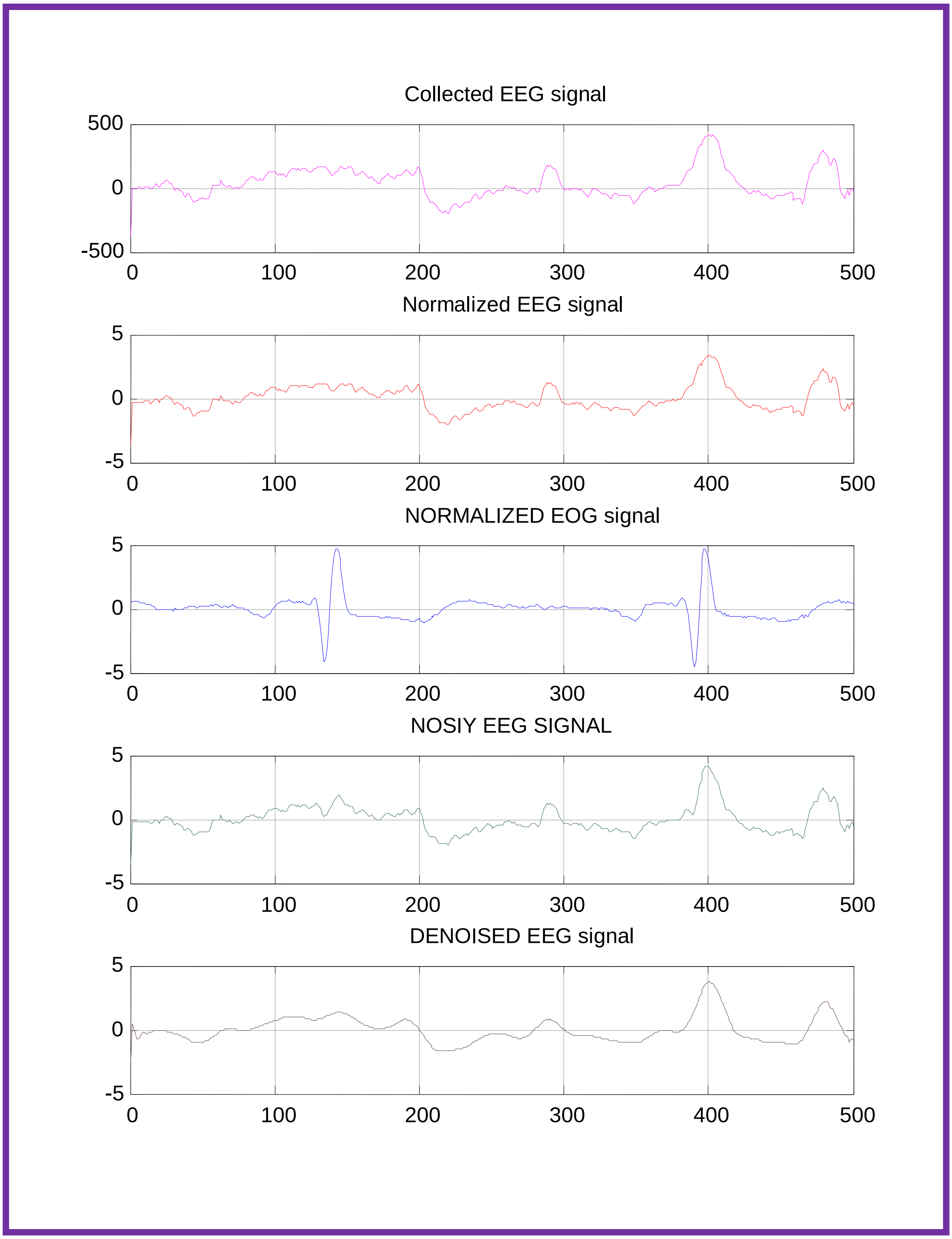

Fig 5: COLLECTED, NOISY and DENOISED EEG Signal Using Heursure-Soft Thresholding Using Db-8 Wavelet

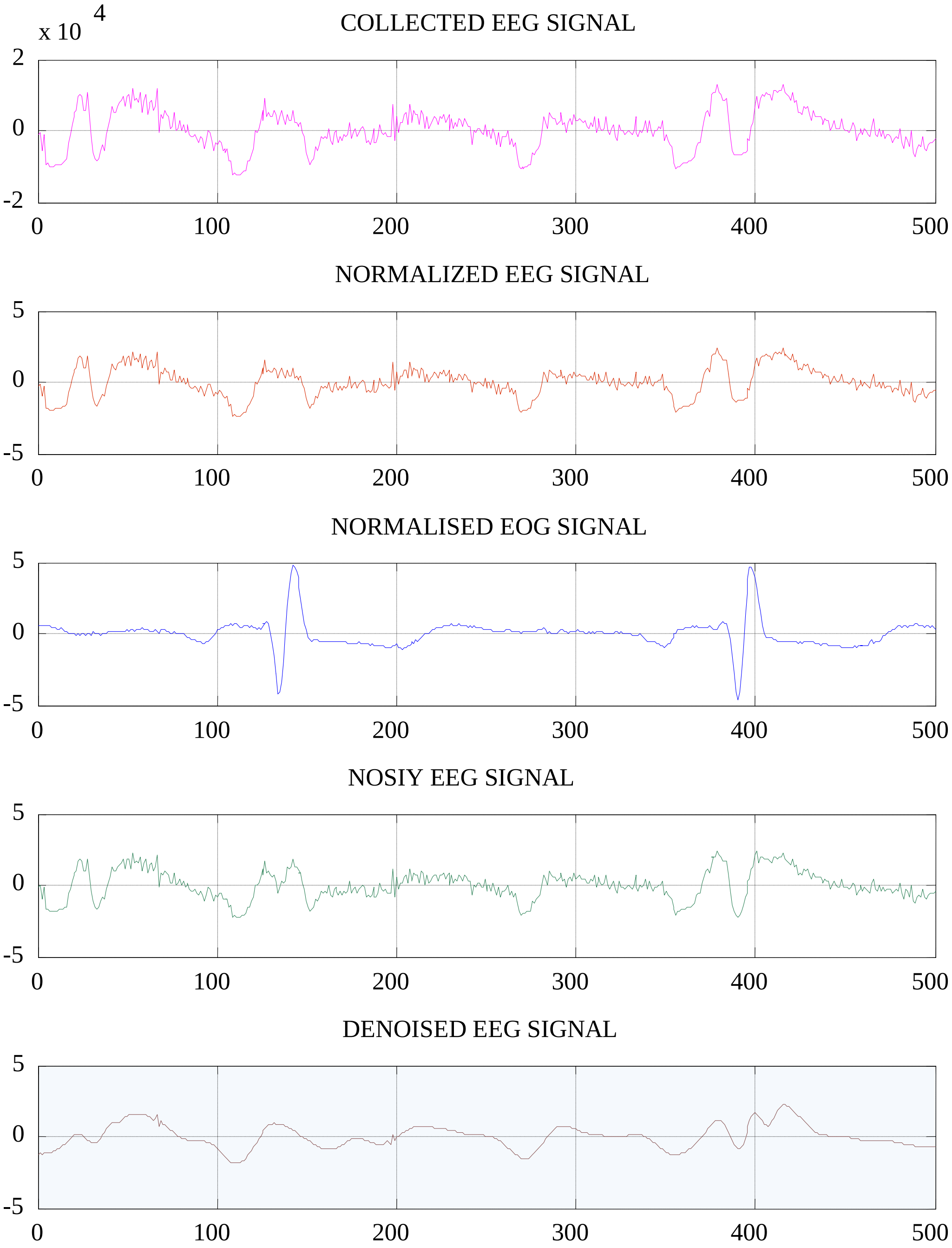

Fig 6: COLLECTED, NOISY and DENOISED EEG signal using Heursure-soft thresholding using dB-8 wavelet

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Table 1: Results of data set-1

wavelet and thresholding	WAVELET db8 for Data set 1							
wavelet and thresholding	WAVELET db8 Data set 2							
Parameters	Heursure (hard)	Heursure (soft)	Rigrsure (hard)	Rigrsure (soft)	Minimaxi (hard)	Minimaxi (soft)	Sqtwolog (hard)	Sqtwolog (soft)
Mean Square Error	0.0697	0.0742	0.0610	**0.0596**	0.0822	0.0722	0.0768	0.0762
Mean Absolute Error	0.2066	0.2103	0.1808	**0.1871**	0.2234	0.2093	0.2147	0.2116
Signal to Noise Ratio (dB)	11.5551	11.2848	12.1373	**12.2357**	10.8385	11.4042	11.1361	11.1716
Peak Signal to Noise Ratio(dB)	22.1157	21.8455	22.6979	**22.7963**	21.3992	21.9649	21.6967	21.7323
Correlation Coefficient	0.9659	0.9634	0.9714	**0.9710**	0.9601	0.9644	0.9622	0.9624

wavelet and thresholding	WAVELET sym8 Data set 1							
Parameters	Heursure (hard)	Heursure (soft)	Rigrsure (hard)	Rigrsure (soft)	Minimaxi (hard)	Minimaxi (soft)	Sqtwolog (hard)	Sqtwolog (soft)
Mean Square Error	0.0790	0.0963	**0.0551**	0.0594	0.0722	0.8418	0.1070	0.1133
Mean Absolute Error	0.2198	0.2391	**0.1705**	0.1942	0.2014	0.2284	0.2419	0.2513
Signal to Noise Ratio (dB)	11.0099	10.1537	**12.5777**	12.2504	11.4048	10.7388	9.6950	9.4479
Peak Signal to Noise Ratio(dB)	21.5705	20.7144	**23.1384**	22.8110	21.9655	21.2994	20.2557	20.0085
Correlation Coefficients	0.9613	0.9509	**0.9744**	0.9703	0.9654	0.9572	0.9464	0.9419

wavelet and thresholding	WAVELET sym8 Data set 1							
Parameters	Heursure (hard)	Heursure (soft)	Rigrsure (hard)	Rigrsure (soft)	Minimaxi (hard)	Minimaxi (soft)	Sqtwolog (hard)	Sqtwolo g (soft)
Mean Square Error	0.0790	0.0963	**0.0551**	0.0594	0.0722	0.8418	0.1070	0.1133
Mean Absolute Error	0.2198	0.2391	**0.1705**	0.1942	0.2014	0.2284	0.2419	0.2513
Signal to Noise Ratio (dB)	11.0099	10.1537	**12.5777**	12.2504	11.4048	10.7388	9.6950	9.4479
Peak Signal to Noise Ratio(dB)	21.5705	20.7144	**23.1384**	22.8110	21.9655	21.2994	20.2557	20.0085
Correlation Coefficients	0.9613	0.9509	**0.9744**	0.9703	0.9654	0.9572	0.9464	0.9419

Table 2: Results of data set-2

Parameters	Heursure (hard)	Heursure (soft)	Rigrsure (hard)	Rigrsure (soft)	Minimaxi (hard)	Minimaxi (soft)	Sqtwolog (hard)	Sqtwolog (soft)
Mean Square Error	0.1986	0.2680	**0.0813**	0.1060	0.1492	0.2087	0.2440	0.3024
Mean Absolute Error	0.3411	0.3911	**0.2101**	0.2498	0.3011	0.3520	0.3610	0.4092
Signal to Noise Ratio (dB)	7.0108	5.7092	**10.8880**	9.7344	8.2521	6.7952	6.1160	5.1845
Peak Signal to Noise Ratio(dB)	14.4081	13.1065	**18.2853**	17.1317	15.6494	14.1925	13.5133	12.5818
Correlation Coefficient	0.8958	0.8565	**0.9592**	0.9454	0.9232	0.8911	0.8696	0.8358

wavelet and thresholding	**WAVELET Haar Data set 2**							
Parameters	**Heursure (hard)**	**Heursure (soft)**	**Rigrsure (hard)**	**Rigrsure (soft)**	**Minimaxi (hard)**	**Minimaxi (soft)**	**Sqtwolog (hard)**	**Sqtwolog (soft)**
Mean Square Error	0.1585	0.1987	**0.0747**	0.0977	0.1201	0.1841	0.1847	0.2861
Mean Absolute Error	0.3101	0.3439	**0.2025**	0.2503	0.2712	0.3303	0.3346	0.4019
Signal to Noise Ratio (dB)	7.9894	7.0084	**11.2572**	10.0891	9.1947	7.3404	7.3266	5.4250
Peak Signal to Noise Ratio(dB)	15.3867	14.4057	**18.6545**	17.4864	16.5920	14.7377	14.7239	12.8223
Correlation Coefficient	0.9176	0.8969	**0.9626**	0.9509	0.9384	0.9052	0.9027	0.8452

wavelet and thresholding	**WAVELET sym8 Data set 2**							
Parameters	**Heursure (hard)**	**Heursure (soft)**	**Rigrsure (hard)**	**Rigrsure (soft)**	**Minimaxi (hard)**	**Minimaxi (soft)**	**Sqtwolog (hard)**	**Sqtwolog (soft)**
Mean Square Error	0.1092	0.1170	**0.0704**	0.0836	0.0918	0.1208	0.1338	0.1827
Mean Absolute Error	0.2466	0.2573	**0.1928**	0.2216	0.2248	0.2729	0.2757	0.3312
Signal to Noise Ratio (dB)	9.6051	9.3072	**11.5095**	10.7619	10.3587	9.1679	8.7247	11.3725
Peak Signal to Noise Ratio(dB)	17.0024	16.7045	**18.9068**	18.1663	17.7516	16.5652	16.1220	14.7698
Correlation Coefficient	0.9445	0.9395	**0.9649**	0.9572	0.9537	0.9379	0.9313	0.9041

IV CONCLUSION

From the tabulated results, it has been observed that the for the elimination of Ocular Artifacts there in the noisy EEG signal, the Sym8 wavelet with the aid of Rigrsure- hard thresholding providing superior results than db8 and Haar wavelets .

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