Noise Removal of EEG Signal Using Wavelet Transform

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Abstract: Electroencephalography (EEG) is a method to record an electrogram of the spontaneous electrical activity of the brain. As the electrical activity monitored by EEG originates in neurons (brain tissue), the recordings made by the electrodes on the surface of the scalp vary in accordance with their orientation and distance to the source of the activity. Furthermore, to remove the noises(artifacts) from the EEG signal the denoising techniques must be taken in application. In this paper, the discrete wavelet transform (DWT) noise removal technique is presented for denoising of noisy EEG signal which is further used to extract significant features from synthesized signal. Numerical Simulation of Statistical parameters have been performed to validate the accuracy of proposed method

Keywords: Electroencephalography, Wavelet Transform, Standard Deviation, Mean Square Error, Alpha-Beta-Gamma-Theta-Delta EEG waves.

I.INTRODUCTION

An electroencephalogram (EEG) is a test used to evaluate the electrical activity in your brain. It can help detect potential problems with brain cell communication. Small flat metal discs called electrodes are attached to your scalp with wires. The electrodes analyze the electrical impulses in your brain and send signals to a computer that records the results. These signals are generally categorized as delta, theta, alpha, beta and gamma based on signal frequency ranges from 0.1Hz to more than 100Hz [1]. A typical EEG signal, measured from the scalp, will have an amplitude of about 10μV to 100μV and a frequency in the range of 1Hz to about 100Hz.There are various events, namely: sleep, epilepsy, reflexology, drugs/anesthesia, diabetes, meditation, music and artifacts, influence the EEG signal.

Table.1: Different type of EEG waves (all the waves represent different mental states) are categorized by the frequency known as EEG bands are as follows:

Bands	Frequency(Hz)	Description
Delta	<4	Too much: Brain injuries, learning problems, inability to think Too little: inability to rejuvenate body, inability to revitalize the brain, poor sleep Optimal: Immune system, natural healing, restorative / deep sleep
Theta	4-7	Too much: depression, hyperactivity, impulsivity, inattentiveness Too little: Anxiety, poor emotional awareness, stress Optimal: Creativity, emotional connection, intuition, relaxation
Alpha	8-12	Too much: Daydreaming, inability to focus, too relaxed Too little: Anxiety, high stress, OCD Optimal: Relaxation
Beta	13-30	Too much: Adrenaline, anxiety, high arousal, inability to relax, stress Too little: Daydreaming, depression, poor cognition Optimal: conscious focus, memory, problem solving
Gamma	>32	Too much: Anxiety, high arousal, stress Too little: Depression, learning disabilities Optimal: Binding senses, cognition, information processing, learning, perception

A general EEG waveform is shown in Fig.1 consists of 1000 EEG sample points in the particular interval of time having the amplitude taken in microvolts. The particular EEG signal defines the neural activity performed by the healthy person during the normal state.

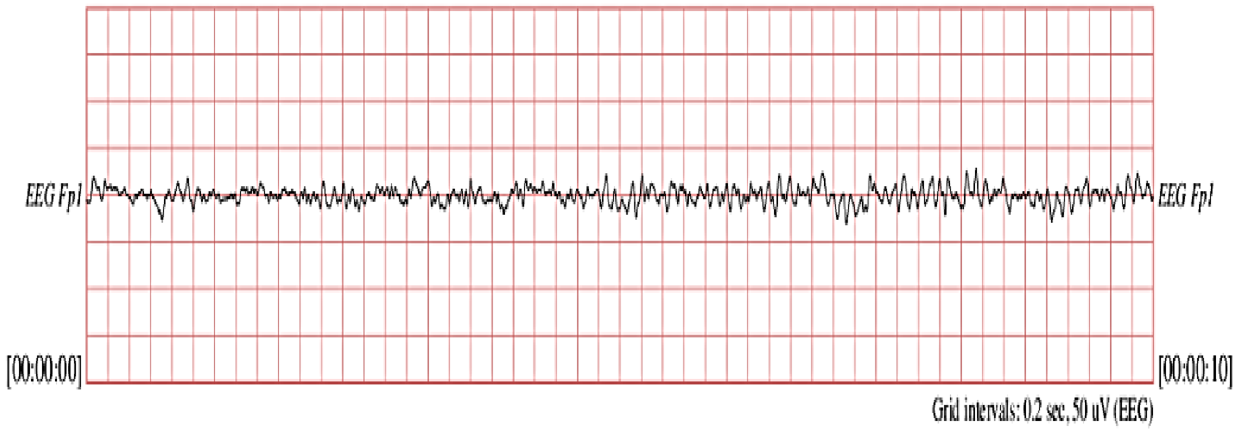

Fig.1: Graphical representation of basic EEG signal for healthy person.

Most EEG signal analysis methods falls into four categories: time domain, frequency domain, time-frequency domain, and nonlinear methods. The most conventional method for EEG analysis is Frequency domain analysis also known as spectral analysis. It gives insight into information contained in the frequency domain of EEG waveform by applying statistical and Fourier Transform methods [2]

EEG signals are having very small amplitudes and because of that they can be easily contaminated by noise. The noises in the EEG signals are called the artifacts and these artifacts are needed to be removed from the original signal for the proper analysis of the EEG signal. The various types of noises that can occur in the signals during recordings are the power source, environment, eye blinks, heart rate and muscle movements, electrode noise, baseline movement (frequency range 0.5 Hz) [3].

Various filtering methods and approaches are in practice to remove these noise components. From a review wavelet transform is found to be the most popular tool used to effectively remove several noises from an ECG signal while preserving desirable signal features [4,5]. Wavelet transform has been widely used in representing signals in the time-frequency domain [6]. In the context of wavelets, "denoising" means reducing the noise as much as possible without distorting the signal. Denoising makes use of the time-frequency-amplitude matrix created by the wavelet transform. It's based on the assumption that the undesired noise will be separated from the desired signal by their frequency ranges.

II. LITERATURE SURVEY

Several works about the noise removal of EEG signals for the proper analysis are available in literature. The most efficient and widely used wavelet denoising is based on thresholding wavelet coefficients. This process follows three important steps: (i) wavelet decomposition: the input EEG signal are decomposed into wavelet coefficients; (ii) thresholding: the threshold set of rules modifies the value of the wavelet coefficients; and (iii) reconstruction: modified coefficients are used in inverse transform to obtain the noise-free signal. Several researchers have used thresholding wavelet denoising techniques [7,8]. The author [9] proposes the wavelet denoising techniques for EEG signals using the discrete wavelet transform (DWT). It offered the noise removal to the respected eye blink corrupted EEG signal. Dora et al. [10] developed a flexible technique to remove EEG noise (artifacts) in the context with minimal supervision. A new wavelet-based method has been proposed that allows to remove artifacts from single-channel EEG based on a data-driven renormalization of the wavelet coefficients. Their method has a capability of attenuating artifacts of a different nature.

Zikov et al. [11] performed thresholding on lower-frequency bands as OAs (ocular artifacts) have very low-frequency characteristics. They estimated the threshold by simple statistical analysis of baseline EEG. Phadikar et al. [12] proposed an automatic eye blink artifact correction technique using wavelet transform and metaheuristic algorithms. In their method, the wavelet coefficients are thresholder in a backward manner to modify only the lower frequency bands of the observed EEG signals. Further, to make the system fully automatic, the optimal thresholds are selected through the grey wolf optimizer.

Choudhry et.al [13] the work implies the application of 5 different wavelet transform (WT) techniques in basic and various complex forms along with 5 different thresholding techniques to investigate and evaluate their performance for the removal of EMG noise from the EEG signal. This provides the results for both the Real-Time EEG data as well as for the Simulated EEG data which shows the concrete proof that the observed results are genuine for the EMG noise. For both the Real-Time EEG data and the Simulated EEG data the best result is corresponding to decomposition using DDDT-DWT with Soft Thresholding. In this case percentage denoising for Real-Time EEG data and simulated EEG are 96.9573% and 99.0017 %. Estrada et.al [14], the author explored the application of wavelet denoising method to EEG signals acquired during different sleep stages classified according to the RK rules, with the objective to identify suitable thresholding rules and threshold values. Preliminary results showed that the combination of soft thresholding rule applied to the Detailed wavelet coefficients with the Universal threshold value produced better performance measures such as a smaller Minimum Squared Error (MSE) and a larger signal-to-Noise Ratio (SNR).

III. EXPERIMENTATION

To perform the feature extraction, the following steps have to be followed shown as below:

1. To acquire and analyze EEG signal from dataset taken by physionet [15].
2. To apply pre-processing for making the EEG signal free from noise using wavelet transform technique.
3. To perform feature extraction method using wavelet coefficient selection technique for particular frequency level information

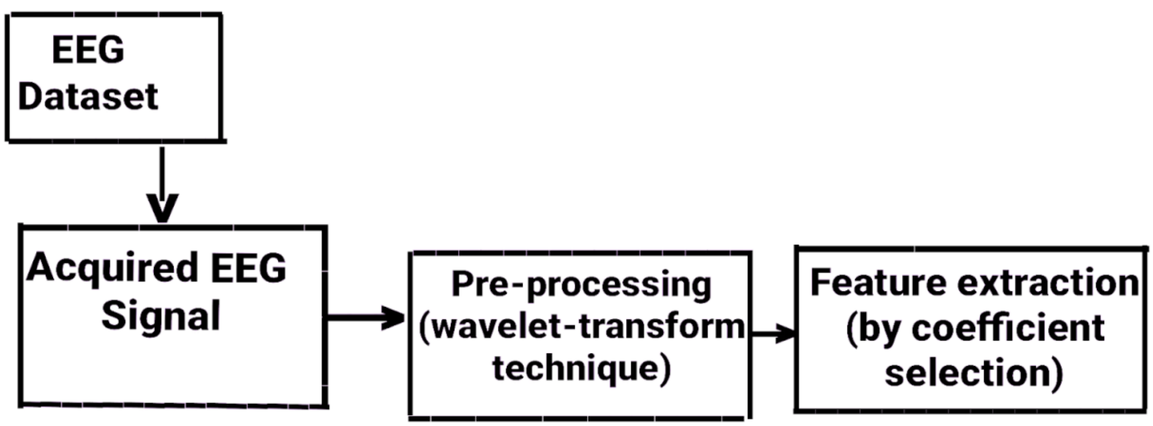

Fig. 2:-The final framework for EEG signal feature extraction processing stages is as shown in the following block level diagram.

For the recorded EEG signal, the dataset (subjects1 / arithmetic task performed by human) has been imported in the Matlab file to study various categories shown by the EEG signal [15].

Step1: Acquisition of EEG signal from Physionet to MATLAB workspace

Table2: Algorithm to Import EEG signal on MATLAB

Algorithm:

load('filename.mat');
EEGsignal=(val - 0) / gain;
fs=Hz;
t=(0: length (EEGsignal) - 1) / fs;

plot(t,EEGsignal);
where; filename=downloaded dataset from physionet.atm[15] fs= sampling frequency(Hz) the

The simulates EEG signal in MATLAB is shown in Fig.3:

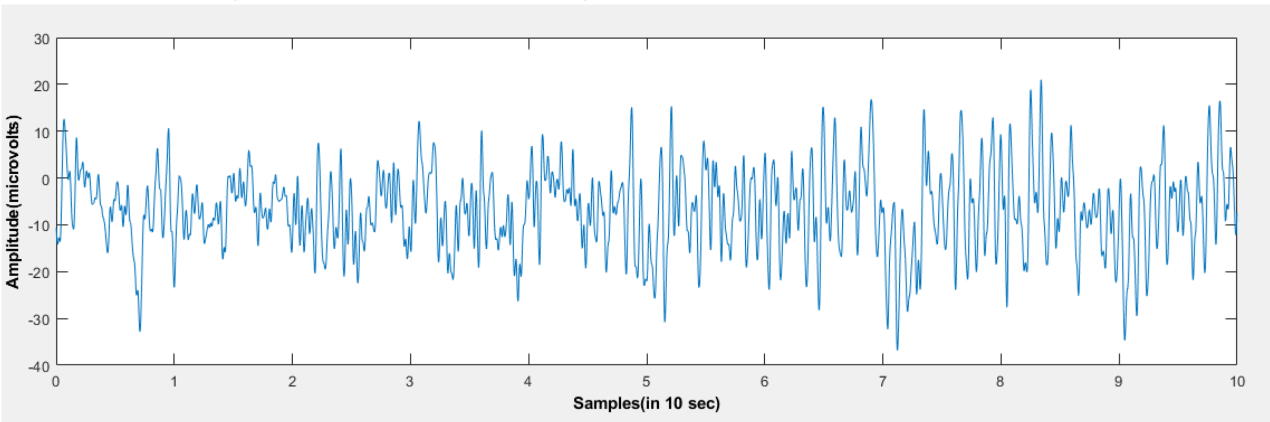

Fig. 3: EEG signal with samples (Subject1 of 5000 samples in 10 sec) and amplitudes (microvolts)

Step2: Applying Discrete Wavelet Transform (DWT)

Discrete wavelet transform (DWT) transforms a discrete time signal to a discrete wavelet representation. It is a mathematical tool used to represent signal in time as well as in frequency domain. After the pre-processing of the dataset for subject1 the different decomposition levels will get differentiated.

For the taken EEG signal the sampling frequency (fs)=500 Hz, the approximation and detail coefficients contains the frequency terms corresponding to [0-fs / 2^j] and [(fs / 2^{j+1}) , (fs / 2^j)], respectively, here j is the level of decomposition.

Table. 3: Decomposition levels for the particular sampling frequency(fs)

Decomposition Level (J)	Approximation Coefficients[a_j]	Detailed Coefficients[d_j]
Level 1	[a_1]0-250	[d_1]125-250
Level 2	[a_2]0-125	[d_2] 62.5-125
Level 3	[a_3] 0-62.5	[d_3] 31.25-62.5
Level 4	[a_4] 0-31.25	[d_4] 15.625-31.25
Level 5	[a_5] 0-15.625	[d_5] 7.8125-15.625
Level 6	[a_6] 0-7.8125	[d_6] 3.90625-7.8125
Level 7	[a_7] 0-3.90625	[d_7] 1.953125- 3.90625
Level 8	[a_8] 0-1.953125	[d_8] 0.09765625- 1.953125
Level 9	[a_9] 0-0.9765625	[d_9] 0.48828125- 0.09765625
Level 10	[a_{10}] 0-0.48828125	[d_{10}] 0.244140625- 0.244140625

According to the above table, wavelet frequency bands after decomposition is shown in figure 4, using Daubechies (Db) wavelet function and level of decomposition is 10. EEG signal is corrupted by baseline wander noise, in the frequency range of 0.5 Hz, and represented by wavelet detail coefficient d1.

To make de-noised signal, wavelet coefficient correspond to noise is eliminated using threshold rule.

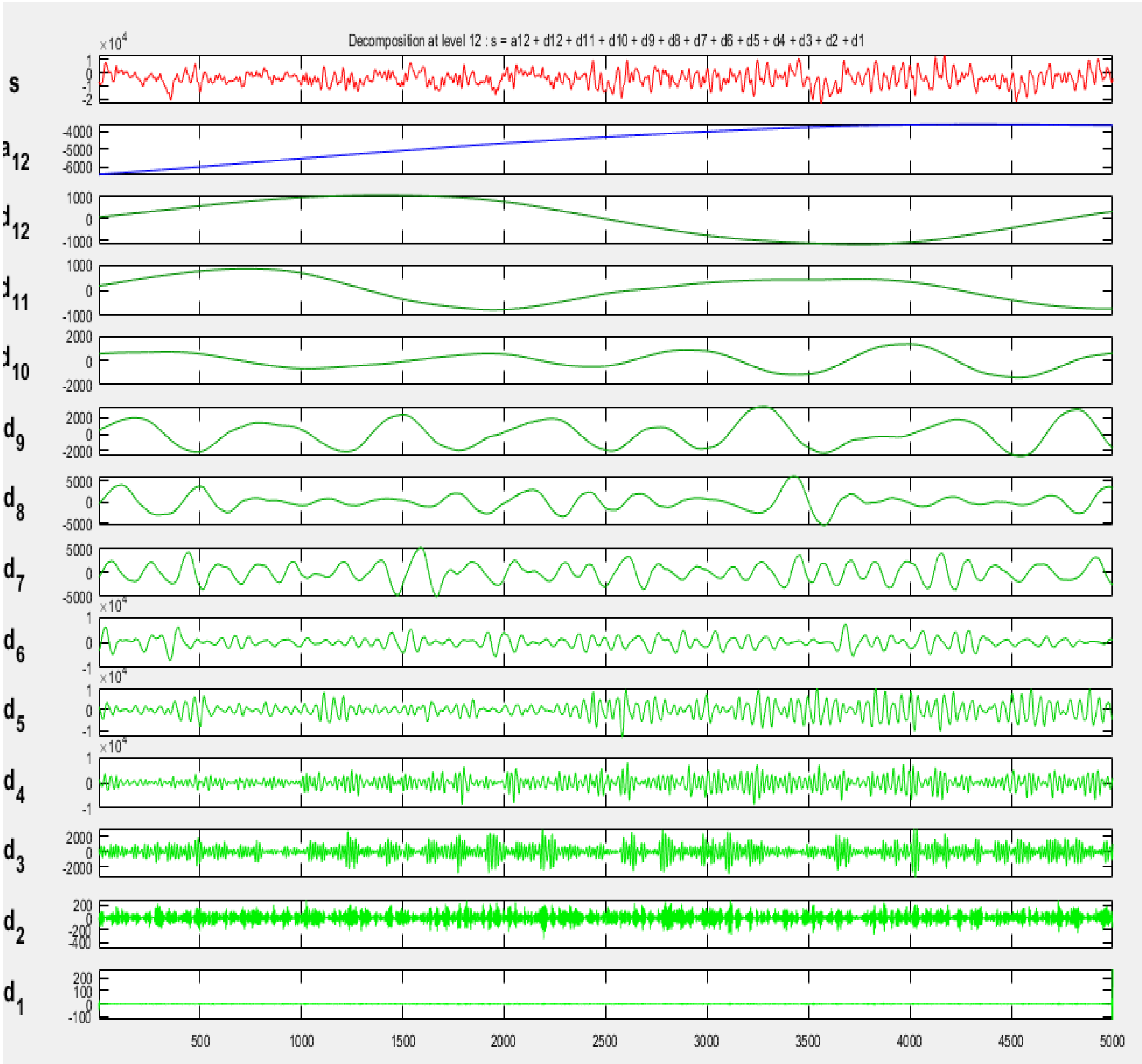

Fig 4: Decomposition levels after applying wavelet transform on the subject1.

It is shown in above figure that, on the application of wavelet transform signal is decomposed at various level. The information of each level can be extracted, for further stages. Similar method is followed for two another subjects of EEG, downloaded from Physionet import on MATLAB.

Table.4: Numerical Simulation of Statistical Parameters for de-noised EEG signal

EEG records	Standard Deviation		Mean Square Error (MSE)	Energy (%)
	Original	After De-noised		
Subject 1	8.626	3.12	1.805	98.52
Subject 2	7.543	2.591	1.818	98.23
Subject 3	10.85	3.446	2.632	98.32
Subject 4	6.737	2.723	1.76	98.25

It is shown in table 3, that wavelet transform based de-noising method is able to remove noise at satisfactory level. The de-noised EEG signal waveform for Subject 1 is shown in fig. 5

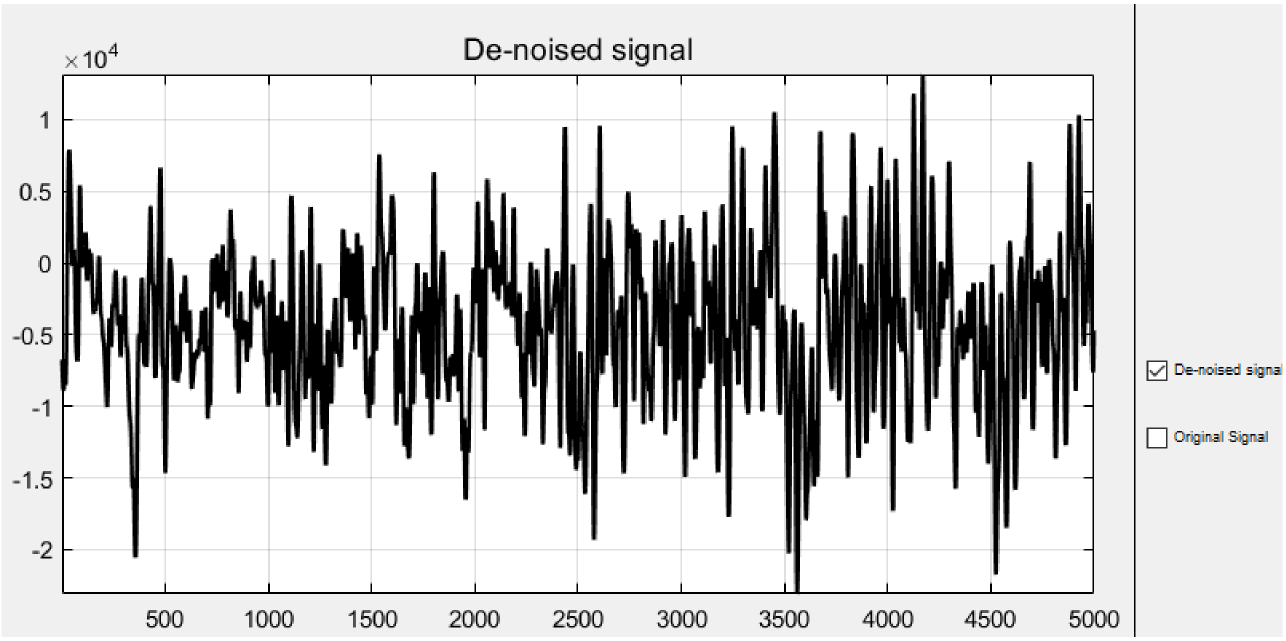

Fig. 5: De-noised signal

IV. CONCLUSION

This paper presents wavelet based denoising technique for getting the desired original EEG signal for further study. It is employing discrete wavelet transform technique having the approximation and the detail coefficient for the decomposition levels based on the required thresholding rules. The proposed technique has been implemented on the Mathlab Mathswork and the respected simulated output of the database of the task performed during the mental arithmetic task has been attached previously.

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