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Denoising of EEG Signal based on Matlab Wavelet Toolbox and Estimation of Signal to Noise Ratio (SNR), Root Mean Square Error (RMSE) and Power Spectral Density (PSD)

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***Abstract*— Most signals in the real world contain noise. Any undesired signal that distorts the desired signal is considered noise in this context. Noise must be removed to obtain valuable information from the signal. Electroencephalography (EEG) is the primary signal of interest for the analysis of brain activity. EEG uses electrodes attached to the scalp to capture the electrical activity of the brain. From the diagnosis of neurological diseases to controlling external devices using brain-computer interface (BCI), EEG signal processing is of utmost importance. Nevertheless, artifacts created while recording the EEG signal in a real-world setting can significantly reduce the signal's effectiveness. The recorded signals are typically so severely noise-corrupted that they are useless and limit the use of the EEG signal. The wavelet transform (WT) is the most widely used and effective method for signal denoising with non-stationary signals, including electroencephalogram (EEG) and electrocardiogram (ECG). In this paper, a wavelet signal denoiser application is used, which is available in the wavelet toolbox of MATLAB. Signal denoising is implemented using different sets of combinations of parameters, such as mother wavelets, methods of thresholding, and rules of thresholding. The effectiveness of signal denoising is dependent on setting its control parameters in the best possible way, which is frequently done through experimentation. Fortunately, measuring parameters like the mean squared error (MSE), signal-to-noise ratio (SNR), and power spectral density (PSD) may be used to assess how well these factors work together. Later, we will compare the results of different combinations of control parameters and determine the best one using the values of the measuring parameters. The real-time dataset is taken from the Mind wave Mobile 2 headset, which is an effective and portable EEG device. It uses Bluetooth connectivity to transfer the EEG signal from the device into a CSV file on our mobile phone. This noisy EEG signal is decomposed into up to four levels. This EEG signal decomposition results in approximate and detailed coefficients, which can be further used for the process of feature extraction from the EEG signal.**

***Index Terms*— Wavelet transform,EEG signal processing, Mindwave Mobile 2, Wavelet toolbox.**

I. INTRODUCTION

Electro-encephalogram (EEG) signals are termed as the voltages that are observed and generated by the electrical

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activity of the live nerve cells. Formation of local current flows holds true when stimulation of brain cells occurs. The recordings that are obtained graphically to demonstrate the electrical activities of the brain depict the voltage variation induced by ionic current flows enclosed within the brain's neurons. The recorded local currents generated by the brain are a function of time.

EEG signals are recorded using invasive or non-invasive procedures, and they can lay out most of the information essential as far as brain activities are concerned. Invasive techniques are claimed during Surgical procedures and brain damage monitoring. Whereas in non-invasive procedures EEG signals from the scalp are surveilled and recorded. One more rectifying difference is, EEG recordings made invasively are carried out using electrodes that are encased inside the cranium and non-invasively by electrodes affixed to the scalp surface.

Nowadays, monitoring and analyzing chemical processes in the brain is made possible by a cheap and accessible technology called Brain Computer Interface (BCI). This apparatus records electrical activity at an electrode. The gadget records brain-controlled actions, such as those associated with learning. Electroencephalogram (EEG) is the most frequent brain signal that may be detected by inserting measuring electrodes on the scalp, even with low-cost systems. After that, it can communicate with a computer by cable, Bluetooth, or Wi-Fi, among other options. For this study, we employ NeuroSky Inc.'s NeuroSky Mindwave mobile 2 to record electrical brain activity.

The amplitude of EEG waves is low. When computed peak to peak, their amplitude typically falls between 1 to 2 mV when measured on the surface of the brain. EEG can be divided into four primary frequency bands based on the frequency level: Theta (4–8 Hz), Alpha (8–13 Hz), Delta (0.4–4 Hz), Beta (13–30 Hz), Gamma (30-100 Hz). The information of interest in an EEG signal is located between 0.4 Hz and 30 Hz, while the frequency domain runs from 0.1 Hz to 100 Hz. EEG recordings are frequently prone to artifacts from various sources. The sources of the most typical artifacts include environmental, physiological, experimental, baseline movement, EMG (muscular activity) disturbance, electrode noise and ECG disruptions. Artifacts can be termed as unwanted signals that can alter recordings and have an impact on the desired signal. It can be also defined as change of the original signal by the addition of activity from other elements that are not of interest to the observer. The most frequently observed physiological artifacts include ocular artifacts caused by eye blinks and eye movement, muscle artifacts brought on by the natural flexion and relaxation of the muscles on the forehead and scalp, and cardiac artifacts introduced by electrode placement on or near a blood vessel. The EEG signals, which are of the magnitude of micro volts, are contaminated by artifacts associated with ocular activity in the milli-volt range. In comparison to the EEG signal, which has a frequency range of 0 to 64 Hz, ocular artifacts (OA) have a frequency range of 0 to 16 Hz. Due to the overlapping spectrum, a significant amount of EEG activity is lost.

EEG has been used to analyze sleep patterns of people and comprehend learning or attention difficulties. EEG is captured using differential amplifiers, which require two electrical inputs to show the output as the deviation between them. Hence in the field of biological signal processing, denoising EEG has attracted a lot of attention. Electromyographic (EMG) and electro oculographic (EOG) signals are two of the most typical causes of noise in the EEG. EMG derives from contractions of the surrounding muscles, whereas EOG arises from eye movements like blinking and rolling. EOG and EEG signals are reciprocal. The nature of EEG impulses makes them non-stationary. The wavelet transform is one of the most used methods for analyzing non-stationary signals. Its effectiveness in converting a time-domain signal into a time-frequency-domain signal gives significant benefits in the extraction of numerous signal components. The EEG signal's integrity is preserved while the artifacts are removed using a wavelet-based technique.

II. Related Work

The electroencephalogram (EEG) data is gathered from the brain and transmitted to a computer for subsequent visualization and analysis via a Brain Computer Interface (BCI). As will be seen below, the approach makes use of cognitive processes, signal theories, and signal processing models.

A. The brain function

The human brain is one of the major organs with intricate parts. [19] The cerebral cortex is a component of the cerebrum, which is the front of the brain. Many functions of the brain are carried out by this area, including: moving and regulating, thinking, feeling, resolving problems, and learning. Personality is governed by the cerebral cortex. A person's close companions might observe changes in their demeanors, psychological state, and feelings if they have a cerebrum injury, particularly to the frontal lobe. The cerebral cortex, which has several folds, covers the cerebrum. Because of its huge size, the cerebral cortex makes up 50% of the weight of the entire brain.

Four lobes make up the cerebral cortex:

1. *Frontal lobe:* This region controls language, movement, personality, memory, and other cognitive processes.

2. *Temporal lobe*: The Wernicke area, a region in charge of interpreting language, is in the temporal lobe. Additionally, it manages emotions and thoughts and is crucial for auditory and visual perception.
3. *Parietal lobe*: It is responsible for processing visual and aural information. It interprets additional sensory data as well.
4. *Occipital lobe:* The visual cortex is in the occipital lobe, which also interprets visual data.

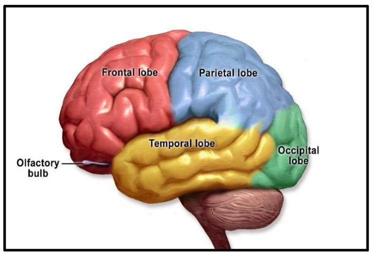


Figure 1: Brain parts

B. Brain wave Signal

Electrical voltages that oscillate within the brain and measure only a few millionths of a volt are called brain waves. Brain waves are propagated along the perineural system. [A2] The brain's neurotransmitter activity produces brain wave signals. Neurotransmitters are chemical messengers that produce brain signals and transfer them from one neuron to another or from one neuron to peripheral destinations that neuroscientists call as synapse. Electrical potential is then produced. Many kinds of technology, including electroencephalography (EEG), electrocorticography (ECoG), and magnetoencephalography (MEG), can pick up on this electrical signal [A3]. There are five primary frequencies of human EEG waves that have come to be identified as brain waves [A4, A5]. Delta waves have a frequency between 0.1 and 3 hertz (Hz), theta waves between 4 and 7 hertz (Hz), alpha waves between 8 and 12 hertz (Hz), beta waves between 12 and 30 hertz (Hz), and gamma waves between 30 and 100 hertz (Hz) [A5]. As can be seen in Table 1, distinct tasks are associated with each wave [A6].

TABLE I: EEG FREQUENCY BANDS AND BRAIN STATES [A5, A6, A7]

Brainwave Type:	**Frequency Range**	**Mental states and conditions**
Delta	0.1Hz to 3Hz	Deep, dreamless sleep, non-REM sleep, unconscious
Theta	4Hz to 7Hz	Intuitive, creative, recall, fantasy, imaginary, dream
Alpha	8Hz to 12Hz	Relaxed (but not drowsy) tranquil, conscious
Low Beta	12Hz to 15Hz	Formerly SMR, relaxed yet focused, integrated
Midrange Beta	16Hz to 20HZ	Thinking, aware of self and surrounding.
High Beta	21Hz to 30Hz	Alertness, agitation
Gamma	31Hz and above	associated with attention, perception, and cognition

In this research we have used Electroencephalography (EEG) to collect the brain wave signals with the help of an electrode attached to the scalp. These signals are further denoised and analyzed based on parameters like signal to noise ratio (SNR), root mean square error (RMSE) and power spectral density (PSD).

C. NeuroSky MindWave Mobile 2 Device

This research's goal is to gather EEG brain signals, denoise and analyze them using wavelet techniques using inexpensive equipment. NeuroSky Mindwave Mobile 2 is one such instrument that is appropriate for the purpose of evaluation. The MindWave Mobile 2 accurately measures and safely produces 12 bit Raw-Brainwaves (3 - 100Hz) at a Sampling rate of 512Hz, as well as EEG power spectra (Alpha, Beta, etc.), and NeuroSky's unique eSense meters like Attention and Meditation. The gadget has three parts: a headset, an ear clip, & a sensor arm. The ear clip serves as a reference and ground electrode for the headset, while the EEG electrode is attached to the sensor arm and placed on the forehead, just above the eye (FP1) location. It operates on a single AAA battery that lasts for eight hours. [A8] The device is shown in figure 2

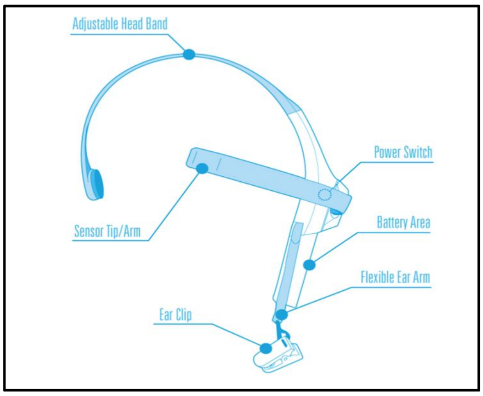


Figure 2: Mindwave Mobile 2

D. EEG Signal Processing

Biomedical signal processing includes mainly five processes starting from data collection, data pre- processing, feature extraction, classification, and interfacing methods. In this research, we collected a real time EEG database using Mindwave Mobile 2 portable EEG kit. However, the real time dataset contains noise artifacts. Hence, in data processing, it is essential to denoise the signal in such a way that the features are retained and the noise is eliminated. Wavelet transform is used to do the same. The fundamental tenet of wavelet thresholding, also known as wavelet denoising, is that for many real-life signals and images, the wavelet transform results in a sparse representation. Raw EEG signal is displayed in figure 3.

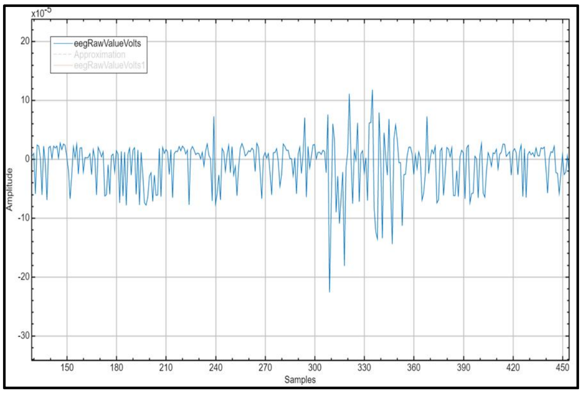


Figure 4: Raw EEG signal with 512 HZ sampling frequency.

E. Wavelet Transform Denoising

1. Wavelet Transform

The Wavelet Transform is a development of the Fourier Transform, it operates on multiple scales rather than just one (time or frequency) and solves the problems associated with non-stationary signals, signal denoising, feature selection, signal compression. [1]. This method describes the signal by correlating the translation and dilation of a mother wavelet function. Dilations are transformations that result in an enlargement or a decrease. Compatible transformations called translations are movements of an object without altering its size or shape. Wavelet transforms are classified as two different fo0rms: discrete wavelet transform (DWT) and continuous wavelet transform (CWT). [2]. DWT is regarded as a unique and dynamic wavelet transform used to generate wavelet representation of a signal. In DWT, the signal is filtered over a half-band high-pass and low-pass filter, yielding detail coefficients and approximation coefficients, respectively. [3]

2. Wavelet Denoising with Thresholding

Wavelet coefficient thresholding is the foundation for effective wavelet denoising technique. There are three crucial steps in this process: (i) wavelet decomposition: wavelet coefficients are generated from the input signals. (ii) thresholding: modifies the wavelet coefficients in accordance with a threshold. iii) reconstruction: To recover the noise-free signal, updated coefficients are employed in the inverse transform. [3]

3. Denoising Parameters

a) Wavelets

Wavelets are defined as a character vector or string scalar. The wavelet needs to be either biorthogonal or orthogonal. Symlet (sym), Daubechies (db), Biorthogonal spline wavelet (bior) and coiflets(coif) are part of wavelet family.**Symlet (sym):** Symlet Wavelet specifies a collection of orthogonal wavelets and is also referred to as "least asymmetric" wavelet. It is a family of wavelets with enhanced symmetry in a modified form of the Daubechies wavelet. Symlet Wavelet symbolizes the order 4 Symlet wavelet. The Daubechies wavelets are a family of orthogonal wavelets that define a discrete wavelet transform. They are distinguished by the maximum number of vanishing moments (number of wavelets). Biorthogonal wavelet is referred to as a related wavelet transform that is invertible but not necessarily orthogonal. There are more degrees of flexibility available when designing biorthogonal wavelets than orthogonal wavelets. Coiflets (coif) wavelets are Nearly symmetric, biorthogonal, and possess orthogonal properties. Signals can be effectively denoised using an orthogonal wavelet, which can be Daubechies or Symlet wavelet. Energy is retained through an orthogonal transformation. In applications like image processing biorthogonal wavelets are comparatively a good choice.

b) Number (vanishing moment)

The wavelet's name is followed by a number that indicates how many vanishing moments are present. (An exact mathematical definition of the quantity of wavelet coefficients). Numerous vanishing moments may occur in the wavelets utilized for analysis. Less statistically significant wavelet coefficients are obtained when a wavelet with a large number of vanishing moments is used. This also improves the compression of a wavelet. The wavelet's oscillation and the quantity of vanishing moments are loosely related. The wavelet oscillates more when the vanishing moments are more prevalent.

c) Denoising methods [mathworks]

Empirical Bayes method applies a threshold criterion by assuming that measurements have distinct prior distributions provided by a mixture model. The approach often performs better with more samples as measurements are utilized to determine the weight in the mixture model. The posterior median rule is the standard method for calculating risk. The foundation of BlockJS (Block James-Stein) approach is choosing an "optimal block size and threshold." FDR — False Discovery Rate approach makes use of a threshold rule that regulates the predicted percentage of false positive observations to all positive observations. With sparse data, the FDR approach functions well. In Minimax — Minimax Estimation method a predetermined threshold is selected to produce the best mean square error performance when compared to the ideal process. SURE (Stein's Unbiased Risk Estimate) method employs a threshold selection procedure based on the quadratic loss function of Stein's Unbiased Estimate of Risk. It gives insight as to how accurate a particular estimator is. Universal Threshold technique produces minimax performance multiplied by a modest factor proportional to log(length(X)). When minute details of the signal are close to the noise range, SURE and Minimax denoising methods are considered to be more practical. The outputs from these two functions are more accurate, which improves signal denoising.

d) Level

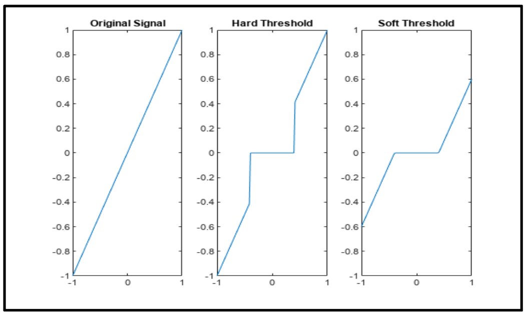
It is defined as the level of wavelet decomposition. Every decomposition level represents a certain frequency band. Therefore, each band will be narrowed as the number of decomposition levels is increased, improving frequency resolution. If you already know the sampling frequency within your original signal, you can quickly determine the precise frequency range of a given level. More processing power and memory is needed for higher number of levels for wavelet decomposition.

e) Thresholding

The wavelet coefficients are reduced using a threshold rule that is provided as a character array. All denoising techniques comply with the "ThresholdRule". [mathworks]

Hard Thresholding: The procedure of hard thresholding involves limiting coefficients to zero with absolute values below the threshold. The function of a hard threshold is discontinuous. Compared to soft thresholding, hard thresholding offers effective edge preservation. [4]

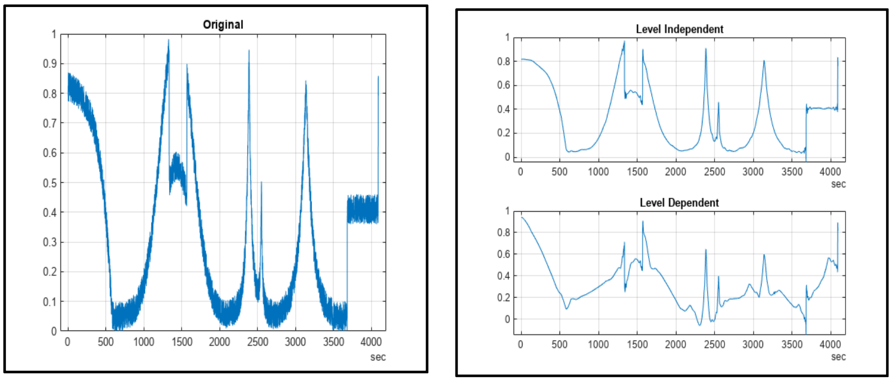
Soft Thresholding: Soft thresholding is considered as an expansion to hard thresholding. It works by first setting all coefficients with absolute values below the threshold to zero and then reducing the absolute values of the nonzero coefficients until they are zero. Smoother outcomes are produced by soft thresholding. Continuous deviations are resulted using a soft threshold function. [4]



*f. Noise estimate***:** used for estimating variance of noise in the data

Level-Independent: Using the high-resolution (finest-scale) wavelet coefficients, it calculates the noise variance. In level-independent denoising, a single threshold is applied to all wavelet coefficients regardless of their decomposition level.

Level-Dependent: Using the wavelet coefficients for each resolution level, it calculates the noise variance. In level-dependent denoising, different thresholds are applied to the wavelet coefficients at each decomposition level.



Signal to Noise Ratio (SNR)

An essential aspect that influences data analysis is the SNR of EEG signals. The SNR is the ratio of the ERP's (event-related potential) magnitude to that of the background EEG's noise. SNR is calculated by taking the ratio of the amplitude of the signal to the amplitude of the noise. [13]

With a greater SNR, the signal is stronger in comparison to the noise, which facilitates signal detection and analysis. As a result, it is more challenging to detect and analyze the signal when the SNR is lower because the signal is weaker in comparison to the noise. Separating the "clean" signal from all the noise sources is necessary to determine the accurate SNR for EEG recordings. SNR maps are an effective tool for displaying EEG sensitivity.[14]

$$SNR = Pnoise/Psignal$$

P signal stands for the signal's power or population mean where

P noise stands for either the power of noise or the data's standard deviation.

SNR is most frequently expressed in dB, a logarithmic scale that makes comparing big and small numbers simpler. Different formulas can be used to compute SNR depending on how the signal and noise are measured and characterized.

SNR in decibels is calculated as follows:

$$SNR\ (dB) = 10 \log10\ (Psignal/Pnoise).[15]$$

When calculating the SNR of an EEG signal, the power of both the signal and the noise must be measured in the same frequency band and during the same time period.

Mean Square Error (MSE)

Mean Square Error (MSE) measures how closely a set of values resembles the true mean value. MSE is a characteristic for classification and prediction tasks in the context of EEG signals. The MSE can be used to evaluate the accuracy of the wavelet transform in reconstructing or denoising the original EEG signal.[16]

Here is a mathematical formula to represent the MSE calculation:

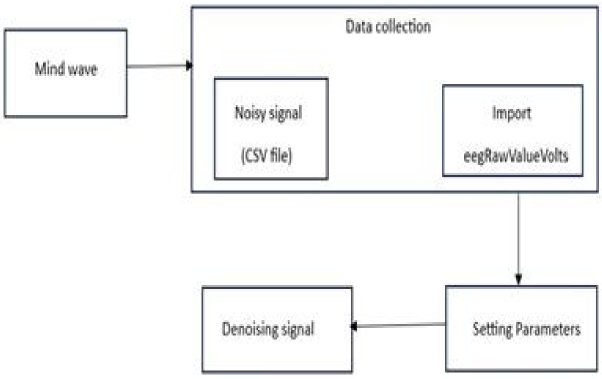
$$MSE = (1/N) * \Sigma[(x[n] - y[n])^2]$$

where:
MSE is the Mean Square Error.
N is the total number of samples in the EEG signal.
x[n] represents the original EEG signal at sample n.
y[n] represents the reconstructed EEG signal at sample n.
It's important to note that the choice of wavelet function, decomposition level, and other parameters can affect the MSE values.[17]

III. METHODOLOGY

1. Experiment Workflow

Firstly, add your files to be denoised in the current folder of Matlab. After that import the column of ‘eegRawValueVolts’ into the workspace, selecting the Output type ‘Column Vectors’ or ‘Numeric Matrix’. Further open the Wavelet Signal Denoiser app and import the updated files there. By selecting the appropriate parameters according to the type of signal it will be denoised giving the coefficient in accordance to the number (vanishing moments) preferred.



Denoising EEG signals using the Wavelet Signal Denoiser app in MATLAB.
For this first step will be to add EEG signal files you want to denoise are present in the current folder of MATLAB. Secondly, import the 'eegRawValueVolts' column from your EEG signal file(s) into the MATLAB workspace in CSV format and select the appropriate output type. Then start the Wavelet Signal Denoiser application. By entering waveletSignalDenoiser in the MATLAB command window, the Wavelet Signal Denoiser application can be started. After importing the Updated Files into the App in the Wavelet Signal Denoiser app, we need to import the updated EEG signal file(s) containing the 'eegRawValueVolts' column. Depending on the EEG signal's characteristics and denoising requirements, adjust the app's denoising parameters. We can view the denoised signal in the app to evaluate the denoising effect. Once we are satisfied with the denoising parameters and the denoised signal, we can export the denoised EEG data from the app.

2. Data Collection

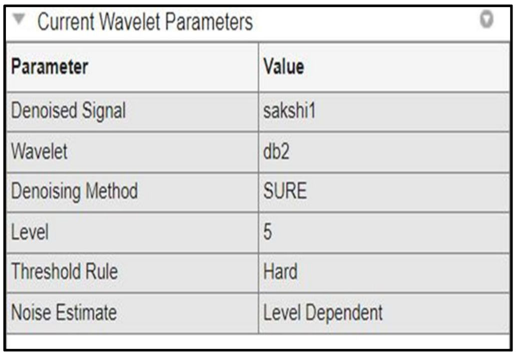
The data is collected by using the “NeuroSky MindWave Mobile 2 Device” and “MindWave Mobile” android application which are connected with each other with Bluetooth connectivity. We had collected the data for the duration of 60 seconds for each activity of the person. The activities involved are Meditation, Normal and Horror. We collected the raw eeg signal data.

3. Parameters

Different wavelets from the wavelet family have specific significance according to the signal. Daubechies wavelet is suitable for capturing transient events in EEG signals. Sym wavelet is effective for denoising EEG signals with smoother variations. Coif is used for denoising EEG signals with abrupt changes or discontinuities. The most effective method for identifying distinct variations in EEG signals is the Daubechies wavelet of order 2 (db2).
Selecting the appropriate number gives us significant wavelet coefficients Fewer significant wavelet coefficients are produced when a wavelet with a large number of vanishing moments is used. Hence Compression is enhanced.

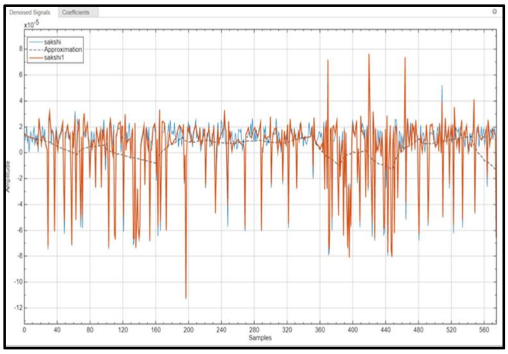
The Minimax and SURE denoising techniques have been found to be more effective. These two functions' outputs are more precise, which enhances signal denoising.Levels are selected according to the requirement of decomposition levels of a signal. As the number of decomposition levels are increased, frequency bands are narrowed.
For denoising EEG signals, both soft and hard thresholding can be used. The approach of thresholding that is used depends on the application as well as how well it works with the specific signal being studied.
Level dependent is significant where the noise is concentrated at specific decomposition levels.

4. Denoised Signal



Current Wavelet Parameters

Parameter	Value
Denoised Signal	sakshi1
Wavelet	db2
Denoising Method	SURE
Level	5
Threshold Rule	Hard
Noise Estimate	Level Dependent



IV. RESULT

data set	Noisy Data				Denoised Data				
	mean	SNR	SD	RMS	mean	SNR	SD	RMS	Name
Person 1	-7.53E-06	9.6566	4.03E-05	4.10E-05	-7.59E-06	17.165	3.80E-05	3.87E-05	aarti
Person 2	-2.45E-06	4.6114	3.28E-05	3.29E-05	-2.43E-06	12.453	2.7595	2.65E-05	anand
Person 3	-1.65E-05	3.1097	4.09E-05	4.41E-05	-1.66E-05	11.1845	2.69E-05	3.15E-05	sameer
Person 4	5.17E-07	8.9542	3.04E-05	3.04E-05	4.23E-07	18.3661	2.84E-05	2.84E-05	pd
Person 5	3.08E-07	13.3834	5.84E-05	5.84E-05	2.44E-07	19.1785	5.70E-05	5.70E-05	sakshi

As a result of denoising procedure, the mean of a denoised EEG signal is lower than the mean of the noisy EEG signal. The EEG signal contains high-frequency components contributing to the mean of the signal, which are intended to be removed during the denoising process. Hence, the denoised signal is shown to have a lower mean value than the noisy signal after the removal of these components.
Denoising procedure also causes the denoised EEG signal's signal-to-noise ratio (SNR) to be higher than the noisy EEG signal. Denoising attempts to reduce noise from the EEG signal and improves the signal's SNR. The SNR is a measurement of the desired EEG signal's strength compared to the signal's amount of noise or artefact. The SNR of the EEG signal is therefore increased by reducing noise, giving the denoised signal a higher SNR value than the noisy signal.
Further, due to the elimination of noise components throughout the denoising process, it is observed that RMS (root mean square) values of a denoised EEG signal are lower compared to that of the noisy EEG signal. The square root of the average of a signal's squared values is represented by the RMS value. It is a measurement of the signal's "effective" amplitude. When noise exists in the original signal, it affects the squared values needed to calculate the RMS, which raises the RMS value. The denoising procedure successfully lowers the noise's contribution to the squared values utilized in the RMS computation by lowering the noise content. As a result, the squared value average drops, which lowers the RMS value of the denoised signal relative to the noisy signal. Mathematically, the relationship between a signal's amplitude (A) and its RMS value (RMS) is given as

$$RMS = A / \sqrt{2}$$

The standard deviation quantifies the variability or dispersion of a set of values relative to their mean. In the instance of EEG signals, it offers an estimate as to the degree of variability or fluctuations in the signal. Since noise introduces random fluctuations to the initial EEG signal, it raises the standard deviation of the signal. These noise components are targeted for elimination by denoising techniques, which therefore lowers the denoised signal's standard deviation.

V. Conclusion

The denoising of EEG data was successfully performed by taking the raw data and applying appropriate parameters to the denoising algorithm. This process effectively removed unwanted noise and artifacts from the EEG signals, resulting in reliable data for further analysis and application. By carefully selecting the parameters for the denoising algorithm, such as the filter settings and threshold values, we were able to enhance the signal quality while preserving the relevant information contained within the EEG data. This denoised data will serve as a valuable resource for further research and applications in the field of EEG analysis, contributing to our understanding of the brain's dynamics and advancing the development of neuroscientific, clinical applications and portable biomedical device

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