

Research Article

Performance Evaluation of Different Threshold Estimation Rules in Denoising EEG Singal with Hamming Window-Based Shrinkage Technique

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Abstract

Signal denoising is an integral part of contaminated signal processing to obtain the signal of interest. In this research, a developed system for reliable removal of powerline interference from Electroencephalographic (EEG) signal based on discrete wavelet transform technique is designed which includes soft thresholding –based shrinkage function called hamming window (Ham-WSST). A practical EEG signal was acquired by measurement from Federal Medical Centre, Owerri and contaminated with powerline noise of 50Hz. This was sampled at a frequency of 1000Hz. Due to the new shrinkage function, decomposition level of 7 and daubechies 7 (db7) mother wavelet, the denoising of the powerline noise was extensively performed in combination with Sqtwolog, Rigrsure, Heursure and Minimaxi rule. The outcome results for the four threshold rules of the system were evaluated and compared using power spectral density (PSD), signal to noise (SNR), mean square error (MSE) and maximum absolute error (MAE) estimation functions. The power spectral density result established on the optimum decomposition level of 7 at 0.1 radian normalised frequency was 35.89 dB for Sqtwolog rule, 37.68dB for Rigrsure, 37.68dB for Heursure and for Minimaxi value is 36.52dB. For signal to noise ratio (SNR) the value for Sqtwolog is 42.26 dB, Rigrsure is 38.68dB, Heursure is 38.68dB and Minimaxi is 40.55dB. The estimation values for mean square error (MSE) and maximum absolute error (MAE) for Sqtwolog rule, Rigrsure rule, Heursure rule and Minimaxi rule in this order is giving as 0.00147, 0.0046, 0.00492, and 0.00206; 0.1147, 0.1245, 0.1245 and 0.1158. Less PSD value means more noise attenuation at the considered frequency instant, higher value for SNR indicate more signal of interest than noise while lower values of MSE and MAE indicate less error. The research further shows that the window thresholding shrinkage function based on the Hamming window with the Sqtwolog estimation rule is more effective at denoising contaminated EEG signals with powerline noise..

Keywords

EEG, Mother Wavelet, Powerline Noise, Spectral Density, Sqtwolog Threshold

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1. Introduction

Noise removal is an integral part of signal processing that involves analysis, identification, modification, and synthesis of signals, with the primary objective of extracting useful information while eliminating noise. The only way to remove noise from the mixture of noisy signal is through filtration. Filtration is an essential part in Digital Signal Processing (DSP). Over a long period of time, it has been discovered that conventional filters have low efficiency; therefore, engineers and scientists have resorted to other means of denoising noisy information to achieve better efficiency. The above realization gave birth to other methods like the Fourier series method, Frequency sampling method or Window method, where the FIR filter can be obtained [1]. For instance, implementation of FIR filters using Fourier series method has shown to result in abrupt truncation at the edges of stop band and pass band of the Fourier series results. These oscillations are due to slow convergence of the Fourier series, particularly near the points of discontinuity. These problems can be solved by using an appropriate window function which in recent times, has resulted to being one of the widely used technique in noise removal. This technique involves a function called window function or apodization function which states that if some interval is chosen, it returns with finite non-zero value inside that interval and zero value outside that interval.

Over time, as more effective means of improving the ratio of actual signal extracted to noise during processing are considered, the combination of methods was introduced. One of such methods is window thresholding method. The importance of thresholding as a method these days is emphasized by its applications in telecommunications, biomedical engineering, and audio processing field, where certain specific threshold level (cutoff point) to distinguish between meaningful signals and background noise is put in place. The wavelet thresholding first proposed by Ref [2], is a signal estimation technique that exploits the capabilities of WT for signal denoising. It removes noise by killing coefficients that are insignificant relative to some threshold, and turns out to be simple and effective, depends heavily on the choice of this threshold determines to a great extent the efficiency of denoising [3], this is known as hard thresholding. Wavelet shrinkage is main process responsible for denoising which depends on threshold selection and thresholding method [4]. In the more recent times, discrete wavelet transforms based thresholding is used to resolve the limitations on efficient noise removal from EEG signals using window filtering methods [5]. Therefore, when a discrete wavelet transform window filter is combined with a soft threshold rule method in denoising a signal in signal processing, it is known as Window Shrinkage Discrete Wavelet Transform method.

In this research work, powerline noise of 50Hz frequency is removed from a contaminated electroencephalographic (EEG) signal using Hamming Window Discrete Wavelet Transform Technique in conjunction with four separate soft threshold

shrinkage estimate rules; Sqtwolog, Heursure, Rigrsure and Minmax, and their outcome compared using Power Spectral Density (PSD), Signal to Noise Ratio (SNR), Mean Square Error (MSE) and Maximum Absolute Error (MAE). The EEG signal was acquired from a patient in Federal Medical Centre, Owerri, Nigeria contaminated by powerline noise, put into a Matlab environment decomposed to level 7 using mother wavelet of Daubechies 7 (db7) and thresholding was performed on it with the developed hamming window-based shrinkage soft thresholding (Ham-WSST) function based on four different types of threshold estimation rules, namely sqtwolog, rigrsure, heursure and minimaxi threshold rules in sequence. The whole idea is to determine the better method of denoising the EEG signal contaminated with powerline noise of 50Hz.

Ref [5] in ECG Signal Denoising Using Wavelet Thresholding Techniques in Human Stress Assessment, worked on denoising electrocardiological signals from ten female patients aged approximately 20-25 years. They used Discrete Wavelet Transform with *coif5*, *db4*, and *sym7*, and incorporated fixed, Rigrsure, Heursure, and minimax soft threshold rules. The results were compared and the outcome showed that the “*coif5*” wavelet and rigrsure threshold rule gave the best result for ECG signal denoising. A research was carried out to identify Prolong Fatigue (PF) in sportmen [6], high quality surface electromyogram (SEMG) was employed, pre-processed using Stationary Wavelet Transform (SWT) ‘*db*’ 45 with different soft thresholding estimation rule of de-noising such as RigrSURE, HuerSURE, minimax, universal threshold. For effective data collection, SEMG data was collected from twenty healthy participants who were made to performed five consecutive days of rigorous training that was based on Bruce Protocol treadmill test to induce in them PF symptoms. The result of the performance at the end of the research, showed that denoised signal was extracted based on. The de-noised signals extracted based on time, frequency, time-frequency features. Classification results by Naïve Bayes have the highest accuracy (98%), compared to RigrSURE (85%), HuerSURE (68%), Universal Threshold (74%) and minimax (76%) in PF identification. In research work, Enhancing Long Term Evolution (LTE) Rss for a Robust Path Loss Analysis with Noise Removal, effort was made by the researchers to select the best possible means of removal of noise to enhanced LTE signal by limiting noise. To achieve this, data was acquired through a drive test (DT) measurement campaigns in Lokoja, Nigeria where commercial LTE system network transmitting at a carrier frequency of 2600MHz and the signals needed were extracted through a laptop pre-installed with Test Mobile System (TEMS) software, Mobile phone, and a Global Positioning System (GPS) module. Result showed that results that Rigrsure thresholding with the Daubechies family outperforms others when engaged in practical signal processing [7].

2. Methodology

Discrete Wavelet Decomposition

Wavelet decomposition is the process of breaking down a mother wave into components in time- frequency domain with their various coefficients of which carries different information and vanishes as time progresses towards infinity (Lohbare, 2022). The complex information structure (information with various frequency ranges and amplitudes) of the original signal can now be separated such that the hidden information in a particular time- frequency plane can be studied [8]. The analyzing wavelet in wavelet transform can be discretised by using discrete values of the dilation parameter “a” and translation parameter “b” to produce a discretised analyzing wavelet as shown in Equation (1).

$$\Psi_{m,n}(t) = \frac{1}{\sqrt{a_0^m}} \Psi\left(\frac{t - na_0^m b_0}{a_0^m}\right) \quad (1)$$

The wavelet transform of the signal $x(t)$ using the discretised analyzing wavelet of (2.0) is called discrete wavelet transform (DWT) of the signal $x(t)$ as presented in Equations (2) to (3).

$$X_{m,n} = \frac{1}{\sqrt{a_0^m}} \int_{-\infty}^{\infty} x(t) \Psi^*\left(\frac{t - na_0^m b_0}{a_0^m}\right) dt \quad (2)$$

$$= \langle x(t), \Psi_{m,n}(t) \rangle \quad (3)$$

Equation (3) is the inner product of the functions $x(t)$ and $\Psi_{m,n}(t)$.

The original signal $x(t)$ can be obtained from its discrete wavelet transform $X_{m,n}$ by the expression called inverse discrete wavelet transform (IDWT) as in Equation (4) [9, 10].

$$x(t) = A \sum_{m=0}^{\infty} \sum_{n=0}^{\infty} X_{m,n} \Psi_{m,n}(t) \quad (4)$$

Where “A” is a constant value for normalization.

The major reason for decomposing the mother wave signal is to eliminate the noise aspect from the actual EEG signal, obtaining in essence the approximation coefficient A_k and detail coefficients D_k where k varies from 1 to the decomposition level. (Lohbare, 2022) The level of decomposition is determined from Equation (5) [11], which computes the maximum decomposition level denoted by MDL.

$$MDL = \log_2(N) \quad (5)$$

Where N is the signal length.

The sampling frequency for this research work is 500Hz and that means that 11060 samples of the signal are captured per second. In this work the capturing is done for 60 seconds and that corresponds to 5,530,000 samples of the signal. Therefore, the maximum decomposition level is

$$MDL = \log_2(5,530,000) = 7.04376 \approx 7$$

Let's choose a decomposition level of 7.

Window Shrinkage Thresholding Function

Thresholding is a technique employed by which certain level of the decomposed signal coefficients that constitute noise in a noisy signal are removed or reduced drastically [12]. Thresholding is of two major kinds; hard thresholding and soft thresholding. For this work soft thresholding is used.

Soft thresholding is a type of thresholding with better performance characteristics and mathematical properties when compared to hard thresholding. In performing its thresholding job, first it sets the elements of coefficient with absolute values below that of the threshold value to zero, then shrinks the non zero coefficient values. In soft thresholding type, the coefficients are linearly reduced in value. Mathematically soft threshold is defined as [13].

$$y = \begin{cases} \text{Sign}(x) (|x| - T), & |x| > T \\ 0, & |x| < T \end{cases}$$

Where T is the threshold and x , wavelet coefficients.

For the enhancement of quality and efficient signal features, Window shrinkage thresholding function is used in signal processing, to denoise and separate the noisy signal coefficient from the actual signal coefficient. Window shrinkage thresholding as a technique is efficient in signal processing as it adapts so well for localised signal characteristics, allowing for effective noise reduction and feature preservation within the window boundaries. For effective application, first, a threshold value is obtained by using an appropriate thresholding rule. Threshold rule is a method of determining the threshold value to be applied in the processing. There are various thresholding rules in existence such as universal, minimax, rigsure and heursure thresholding rules. SURE standards for Stein's unbiased risk estimate. In this research, the Sqwalog (Universal), minimax, rigsure and heursure thresholding rules are each used in combination with the hamming window function and their outcome performances are measured compared.

Sqtwolog Rule

The threshold value for universal thresholding or sqtwolog rule is given as in Equation (6) [14].

$$T = \sqrt{2 \log(N)} \quad (6)$$

If the data is not normalized with respect to noise standard deviation, then the threshold value is given as in Equation (7) [3, 14].

$$T = \sigma_n \sqrt{2 \log(N)} \quad (7)$$

where T is the threshold value, N , the number of data samples and σ_n is the standard deviation of the noise component. The standard deviation of the noise σ is given by Equation (8).

$$\sigma_n = \frac{MAD}{0.6745} \quad (8)$$

Where MAD represents the median absolute deviation of the coefficients of noise components.

Minimax Rule

Minimax rule finds threshold by the usage of Minimax principle with fixed threshold to yield Minimax performance for mean square error against normal ideal procedure and its used in statistics to design estimators. Since the de-noised signal can be assimilated to the estimator of the unknown regression function, the Minimax estimator is the option that realizes the minimum, over a given set of functions of the maximum Mean Square Error (MSE). This procedure finds optimal thresholds [15].

The threshold is given by:

$$T = \begin{cases} (0.3936 + 0.1829 \log_2 N) & N > 32 \\ 0 & N < 32 \end{cases} \quad (9)$$

Where $\sigma = \text{median} \frac{|w|}{0.6745}$, and w is the wavelet coefficient vector at unit scale and N is the length of signal vector.

Rigrsure Rule

Rigrsure rule is a soft threshold evaluator of unbiased risk. Suppose $W = [w_1, w_2, \dots, w_N]$, is a vector consists of the square of wavelet coefficients from small to large. Select the minimum value r_b ($b^{th}r$) from risk vector, which is given as in Equation (10) as the risk value

$$R = \{r_i\}_{i=1,2,\dots,N} = \frac{N-2i+(N-i)w_i + \sum_{k=1}^k w_k}{N} \quad (10)$$

The selected threshold is where, is the $T = \sigma \sqrt{w_b}$ squared wavelet coefficient (coefficient at minimum risk) chosen from the vector and σ is the standard deviation of the noisy signal [16].

Heursure Rule

Heursure rule is a threshold selected based on the combination of Sqrtwolog and Rigrsure methods. If the ratio of signal to noise is small, then the SURE estimation is poor. In such case, fixed form threshold of Sqrtwolog method gives better threshold estimation [15]. Let obtained threshold from Sqrtwolog method is T_1 and that obtained from Rigrsure is T_2 then Heuristic SURE gives the threshold given by Equation (11).

$$T = \begin{cases} T_1 & A > B \\ \min(T_1, T_2) & A \geq B \end{cases} \quad (11)$$

Where $A = \frac{S-N}{N}$, and $B = \log(\log_2 N)^{3/2\sqrt{N}}$. N is length of wavelet coefficient vector where S is the sum of squared wavelet coefficients given as $S = \sum_{i=1}^N w_i^2$. Threshold determination is an important problem. A small threshold may yield a result which may be noisy and large threshold can cut significant part of signal thus losing the important details of

the signal [16].

Developed Shrinkage Function

The researcher's input is the developed shrinkage function for the detail coefficients shrinkage. The window considered here is Hamming window function. The Hamming window function is as shown in equation (12) [17].

$$w(n) = 0.54 - 0.46 \cos \frac{2\pi n}{M-1}, 0 \leq n \leq M-1 \quad (12)$$

Where $M=N+1$, the number of samples.

Decomposition detail coefficients are denoted by D_k , while the window coefficients are given by $w(k)$.

where k and n vary from 0 to N , the number of samples. The new developed shrinkage function is as stated in Equation (13).

$$D(w) = \begin{cases} \text{sgn}(D_k \cdot w(k))(|D_k \cdot w(k) - T|) & |D_k \cdot w(k)| > T \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

where $D(w)$ is the denoised signal coefficient sequence, T , the threshold value, $D_k \cdot w(k)$, the unshrunk product of detail coefficient and window coefficient sequence. Equation (13) is called hamming window-based shrinkage soft thresholding (Ham-WSST) function. A block diagram depicting the position of the shrinkage function in the denoising scheme of ECG below the threshold value and retain all coefficients equal or above the threshold value. But in soft thresholding the retained detail coefficients after thresholding are further modified by shrinking them to further remove noise component coefficients.

3. Result and Discussion

The parameters used for simulation for this research work were acquired from a matlab 2018b environment when a physical EEG signal measurement of a patient contaminated by powerline noise from the Federal Medical Centre, Owerri, Nigeria was loaded into matlab environment. In the matlab environment, a discrete wavelet decomposition was performed on the contaminated EEG signal to level 7 using mother wavelet of Daubechies 7 (db7) and thresholding was further carried out on it with the developed hamming window-based shrinkage soft thresholding (Ham-WSST) function based on four different types of threshold estimation rules, namely sqrtwolog, rigrsure, heursure and minimax threshold rules in sequence. The summaries of parameters obtained are given below:

Decomposition Level = 7

Mother Wavelet = Daubechies 7 (db7)

Shrinkage Window = Hamming Window

Noise Type = Powerline

Iteration Number = 11060

Threshold Rule = Sqtwolog, rigrsure, heursure and minimax

Signal = EEG

The researchers developed scheme in this thresholding technique is aimed at using the inverted hamming window function coefficient sequence gotten to shrink the decomposed detail coefficients amplitudes D_k of the contaminated EEG signal within the powerline noise region after which thresholding is carried out to further attenuate the contaminated signal more effectively.

The contaminated EEG signal frequency range is from about 0.5Hz to about 100Hz. The powerline noise to be removed is 50Hz. At this 50Hz region, the inverted hamming window amplitude is zero; thus, this will completely decimate the amplitude of the noise before second stage shrinkage. Figure 1 shows the contaminated EEG signal; Figure 2 illustrates the powerline noise suspected of contaminating the EEG, while Figure 3 depicts the inverted hamming window function for first stage shrinkage.

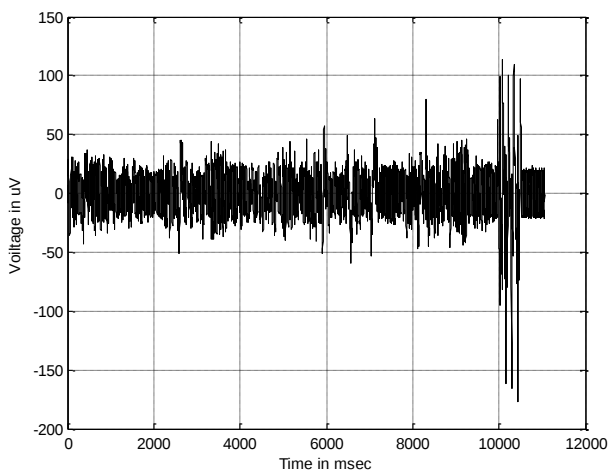


Figure 1. Contaminated EEG Signal.

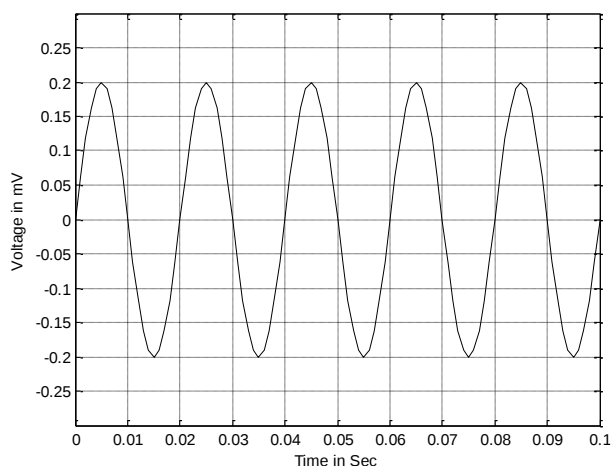


Figure 2. Powerline Noise.

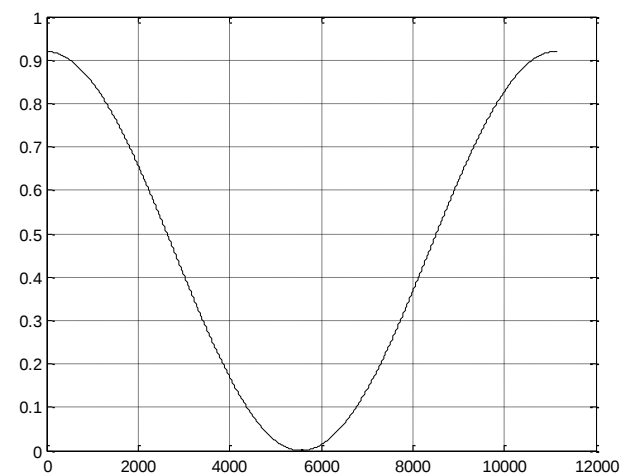
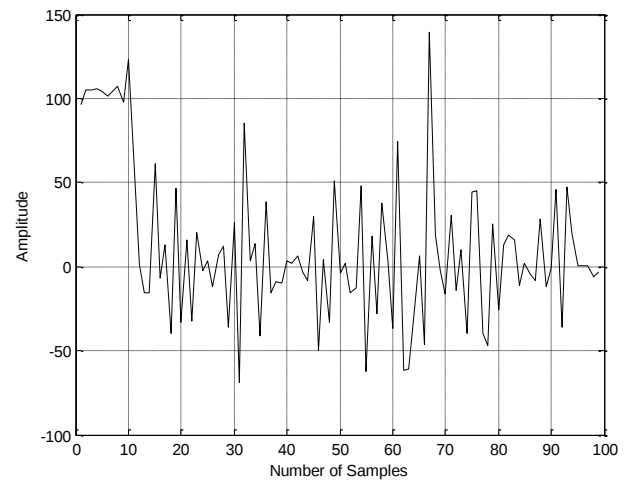


Figure 3. Inverted Hamming Window Function for First Stage Shrinkage.

Determining the Most Effective Threshold Estimation Rule out of the Four Rules

Sqtwolog, rigrsure, heursure and minimaxi estimation rule have been used in conjunction with hamming window shrinkage soft thresholding scheme developed to denoised the contaminated EEG signals and all four were effective. It is important at this stage to determine the most effective of the estimation rules that work best with the developed scheme for the desired purpose. To achieve this, signal evaluation parameters such as Power Spectral Density (PSD), Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), and Maximum Absolute Error (MAE) were used to measure the outcome of the signal using the four estimation rules.

Examining Table 1 and Table 2, it is clear that sqtwolog threshold rule is the most effective rule that can combine with the developed window shrinkage function to denoised EEG signal of powerline interference because it has a high SNR of 42.26 dB. The sqtwolog threshold rule also exhibited the best MSE and MAE of 0.00147 and 0.1147 respectively.

Table 1. PSDs of EEG Denoised with Ham-WSST at 0.1Rad and Level 7.

Threshold Rule	Contaminated ECG	Denoised (Sqrtwolog)	Denoised (Rigrsure)	Denoised (Heursure)	Denoised (Minimaxi)
PSD in dB	55.07	35.89	37.68	37.68	36.52

From the result as can be seen in Table 2, it implies that the denoising of the signal with the developed shrinkage function and threshold rule, sqrtwolog produced the best attenuation with a PSD of 35.89 dB followed by minimaxi threshold rule with a PSD of 36.52 dB.

Table 2. SNR, MSE and MAE of EEG Denoised with Ham-WSST at Level 7 and Four Threshold Rules.

Threshold Rule	Denoised (Sqrtwolog)	Denoised (Rigrsure)	Denoised (Heursure)	Denoised (Minimaxi)
SNR in dB	42.26	38.68	38.68	40.55
MSE	0.00147	0.00046	0.00492	0.00206
MAE	0.1147	0.1245	0.1245	0.1158

4. Conclusion

This study evaluated the performance of a Hamming window-based threshold shrinkage function applied to various threshold selection rules—Sqrtwolog, Rigrsure, Heursure, and Minimax—for signal denoising. The results demonstrated that integrating the Hamming window into the shrinkage process enhanced noise suppression while preserving important signal characteristics across all threshold rules tested. Notably, the Sqrtwolog and Rigrsure rules showed the most significant improvement in signal-to-noise ratio (SNR) and mean squared error (MSE) metrics, indicating their suitability for applications requiring high fidelity. The Hamming window's smooth tapering effect minimized abrupt coefficient changes, reducing artifacts often introduced by hard or soft thresholding. Comparisons revealed that the proposed method outperformed conventional thresholding approaches in terms of both quantitative performance and visual signal quality. Overall, the findings validate the Hamming window-based shrinkage function as an effective enhancement for diverse threshold rules, offering a reliable and adaptable framework for improving wavelet-based denoising performance.

Abbreviations

EEG	Electroencephalographic
MAE	Maximum Absolute Error
MSE	Mean Square Error
PSD	Power Spectral Density

SNR Signal to Noise

Conflicts of Interest

The authors declare no conflicts of interest.

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