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A Blackman Window-Based Shrinkage Soft Thresholding Technique for Improving Voice Signal Transmission in Telecommunication Systems

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Abstract
Human speech is the principal medium of communication in modern telecommunication systems, enabling efficient human-to-human and human-to-machine interactions. However, speech signals transmitted through communication channels are often degraded by additive white Gaussian noise (AWGN), leading to reduced speech quality and intelligibility. This study presents a novel Blackman Window-Based Shrinkage Soft Thresholding (Bman-WSST) technique for enhancing speech signals contaminated by AWGN. The proposed method integrates a newly developed Blackman window-based shrinkage function with the Discrete Wavelet Transform (DWT) to improve noise suppression while preserving essential speech characteristics. A speech signal comprising 73,113 samples, sampled at 44.1 kHz, was corrupted with 10.5 dB AWGN to evaluate the performance of the proposed algorithm. Speech denoising was performed using the Symlet 4 (Sym4) mother wavelet at decomposition levels 1–4 and assessed using four threshold selection rules: Sqtwolog, Rigrsure, Heursure, and Minimax. The results identified the Sqtwolog threshold selection rule and Level 2 decomposition as the optimum configuration. Performance evaluation based on the power spectral density (PSD), signal-to-noise ratio (SNR), mean square error (MSE), and maximum absolute error (MAE) yielded values of −68.23 dB, 25.553 dB, 0.0108, and 0.07870, respectively. These findings demonstrate that the proposed Bman-WSST technique effectively suppresses AWGN while preserving speech fidelity, providing a robust and efficient alternative to conventional wavelet coefficient shrinkage methods for speech enhancement in telecommunication systems.

Keywords: Blackman window-based shrinkage, discrete wavelet transform, speech signal denoising, signal-to-noise ratio, voice signal processing.

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1.0 Introduction

Telecommunication plays a major role in security configuration, human interaction, and socio-economic development, as it enhances infrastructural development, quality education, business operations, public safety, and emergency response (Agboola et al., 2023). Human voice or speech is a natural and basic means for humans to convey message and thoughts to other humans or interact with machine objects (Brahim, 2021). Notably, the human voice enhances organic and effective connections between people, as it is a versatile and essential instrument for interpersonal communication (Fagherazzi et al., 2021). Human voice and speech modes are vital in human-to-human and human-to-machine communications, as these parameters primarily transmit voice and speech data through telecommunication routes. Typically, these pathways are frequently prone to noise interference and bandwidth limitations (Muddaloor et al., 2025). These limiting parameters tend to degrade the integrity of the communication signals, thereby compromising the transmission standard, particularly in conditions that require long-distance communication networks. Telephone speech signals can be contaminated by noises from the transmission medium and the surroundings. If these noise components are not removed, they will degrade the quality and intelligibility of the speech signals. Regarding these scholars Kumar et al. (2015), different wavelet algorithms relying on wavelet transform (WT) and wavelet packet transform (WPT) were configured and implemented.

Recently, there have been numerous methods used to enhance signals in telecommunication, including signal amplification, thresholding techniques, error detection and correction codes, modulation techniques, multiple-input multiple-output (MIMO), and digital signal processing (Yang et al., 2024). Basically, these approaches help to improve and stabilize the communication route, data rates, and interconnectivity. Jiaet al (2024) stated that thresholding techniques are a powerful approach with the potential to denoise the communication pathway and restore the transmission signals. In particular, window shrinkage thresholding has drawn a lot of interest because it can selectively reduce noise while maintaining crucial speech characteristics. By dividing the speech signal into overlapping windows and using adaptive thresholding functions, the window shrinkage thresholding technique can reduce the noise-related coefficients while keeping the ones that are pertinent to the speech content. The time-frequency domain is frequently used to execute such shrinkage techniques, either with wavelet or short-time.

There are numerous benefits associated with the utilization of window shrinkage thresholding in communication channels (Geng et al., 2023). This approach works perfectly in low signal-to-noise ratio (SNR) situations, and it is adaptive to signals fluctuations. Furthermore, it has been verified that it causes lower speech distortion, when compared to the conventional filtering techniques. These characteristics make it appropriate for real-time applications including digital broadcasting systems, VoIP, and cellular networks. Despite its potential to provide optimal enhancement performance, adjustments must still be made to the window size, threshold selection strategies, and shrinkage function parameters for different channel conditions (Leu, et al., 2014; Suman and Qu, 2025). In Singh et al. (2011) research, a model for denoising speech signals corrupted by noise using discrete wavelet transform and mother wavelets of Haar and biorthogonal wavelet families was proposed. The thresholding functions used include both hard and soft thresholding functions. The experiment was conducted in a MATLAB environment, and SNR was used to evaluate the performance of the various algorithms resulting from different wavelets. This study explores the implementation and optimization of window shrinkage thresholding techniques for the improvement of voice signal transmission over telecommunication channels. The aim of this research is to model a

voice signal denoising system that enhances speech signal processing in telecommunication channel signal transmissions.

2.0 Materials and Methods

2.1 Data Acquisition

The proposed voice signal denoising system was developed and implemented using the MATLAB software environment. A speech utterance spoken by the researcher**,** "Education is key to the sustainable development of any nation," was recorded using the built-in microphone of a laptop computer. The recorded speech signal was digitized, stored in the computer memory, and imported into the MATLAB workspace for subsequent signal processing and analysis.

The acquired speech signal consisted of 73,116 samples and was sampled at a frequency of 44.1 kHz, which is sufficient to preserve the frequency content required for speech processing. To simulate a realistic noisy communication environment, additive white Gaussian noise (AWGN) with a noise level of 10.5 dB was artificially generated and superimpo on the clean speech signal, thereby producing a contaminated speech signal for denoising.

The contaminated speech signal was decomposed using the Discrete Wavelet Transform (DWT) based on the Symlet 4 (Sym4) mother wavelet. The decomposition process was performed up to Level 4**,** resulting in one approximation coefficient sequence and four detail coefficient sequences corresponding to different frequency bands of the speech signal. During decomposition, the noisy speech signal was passed through a pair of quadrature mirror filters consisting of a low-pass analysis filter and a high-pass analysis filter. The approximation coefficients represent the low-frequency components of the signal, while the detail coefficients contain the high-frequency components where the majority of the noise energy is concentrated.

Following decomposition, each coefficient sequence was downsampled by a factor of two in accordance with the Mallat wavelet decomposition algorithm. Downsampling reduces computational complexity and memory requirements while preserving the essential frequency characteristics of the signal.

The detail coefficients were subsequently processed using the proposed Blackman Window-Based Shrinkage Soft Thresholding (Bman-WSST) technique. This technique applies the Blackman window function to modify the wavelet coefficients before soft thresholding, thereby improving noise suppression while preserving the important temporal and spectral characteristics of the speech signal. Since the approximation coefficients predominantly contain useful speech information with relatively little noise, thresholding was applied only to the detail coefficients.

After thresholding, the modified approximation and detail coefficients were reconstructed using the Inverse Discrete Wavelet Transform (IDWT). Signal reconstruction was achieved by first upsampling the wavelet coefficients by a factor of two and then passing them through the corresponding synthesis filters. This reconstruction process restores the speech signal to its original sampling resolution while substantially reducing the influence of additive white Gaussian noise. The overall processing procedure adopted in this study comprises speech acquisition, noise generation, wavelet decomposition, coefficient thresholding using the proposed Bman-WSST technique, and signal reconstruction through the inverse discrete

wavelet transform. The complete architecture of the proposed voice signal denoising system is illustrated in Figure 1.

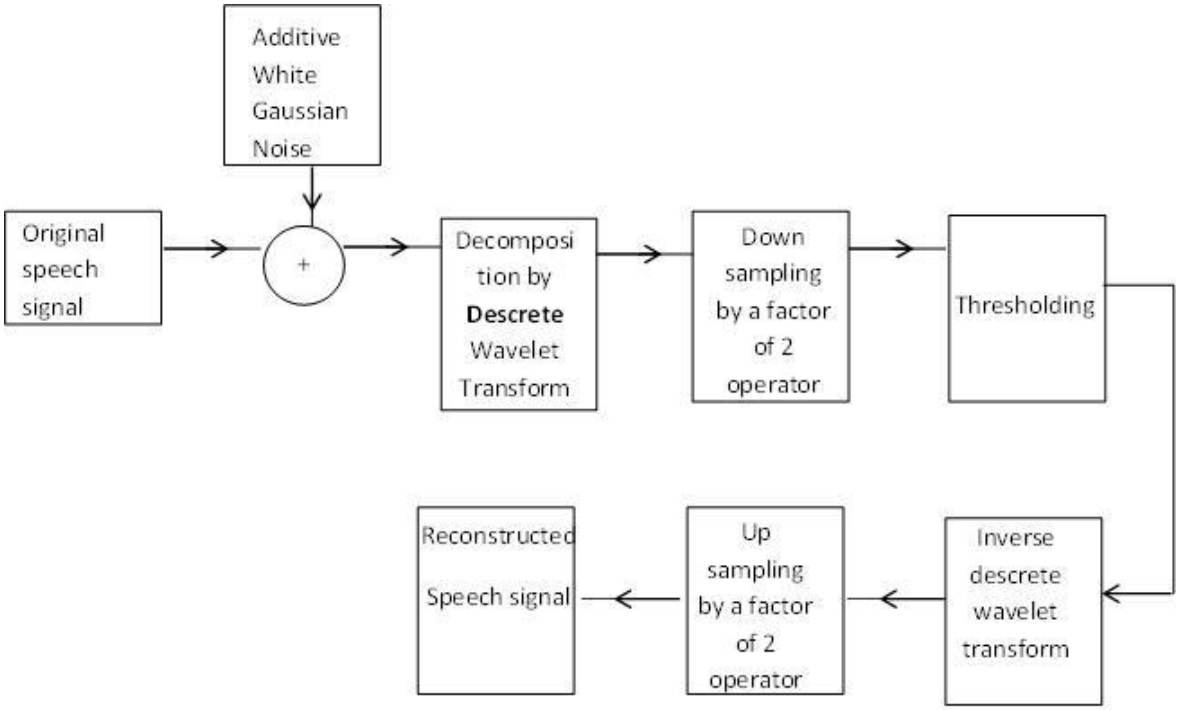


Figure 1: Block diagram of voice signal denoising system

2.2 Mathematical Modelling of the Wavelet Decomposition Function

The mathematical model of the wavelet decomposition process consists of two fundamental components. The first component comprises the decomposition filters, namely the low-pass filter, g(n), and the high-pass filter, h(n), which are responsible for separating the input signal into its low-frequency and high-frequency components, respectively. The second component consists of the resulting wavelet coefficients, namely the approximation coefficients and the detail coefficients. The approximation coefficients represent the low-frequency characteristics of the signal, whereas the detail coefficients contain the high-frequency information, including the noise components.

The theoretical relationship between the scaling function, $\emptyset(t)$, and the wavelet function, $\Psi(t)$forms the foundation of the discrete wavelet transform (DWT). This relationship is expressed by Equations 1 to 15 as presented by Kumar and Patel (2012).

$$\emptyset(t) = \sum_n g(n)\emptyset_{1,n}(t) = \sqrt{2}\sum_n g(n)\emptyset(2t-n) \quad 1$$

$$\Psi(t) = \sum_n h(n)\emptyset_{1,n}(t) = \sqrt{2}\sum_n h(n)\emptyset(2t-n) \quad 2$$

Where: $g(n) = \langle \emptyset,\ \emptyset_{1,n} \rangle$

$$h(n) = \langle \Psi,\ \emptyset_{1,n} \rangle$$

A fact to note is that the dual-scale relationship exists only between two successive scales$j\ and\ j-1$, meaning that

$$\emptyset_{j,0}(t) = \sum_n g(n)\emptyset_{j\ 1,n}(t) \quad 3$$

$$\Psi_{j,\theta}(t) = \sum_n h(n)\emptyset_{j\ 1,n}(t) \quad 4$$

Again, the coefficients g(n) and h(n) will not change with the scale j. The proof of this claim is as follows:

$$\langle \emptyset_{j,0}(t), \emptyset_{j\ 1,n}(t) \rangle = \int_R \left[2^{j\frac{1}{2}}\emptyset(2^j t)\right]\left[2^{j\frac{1}{2}}\emptyset^*(2^{j+1}t - n)\right]dt \quad 5$$

$$= \sqrt{2}\int \emptyset(t^1)\,\emptyset^*(2t^1 - n)dt^1 \quad 6$$

Let $t^1 = 2^j t$

Equation 5 becomes

$$= \langle \emptyset(t), \emptyset_{1,n}(t) \rangle = g(n) \quad 7$$

Similarly, it can be proved that

$$= \langle \Psi_{j,\theta}(t)\emptyset_{j\ \ 1,n}(t) \rangle = h(n) \quad 8$$

This result indicates that the filter coefficients g(n) and h(n) are determined solely by the scaling function $\emptyset(t)$ and the wavelet function $\Psi(t)$, respectively and are independent of the choice of the decomposition scale j. To further establish the properties of these filter coefficients, both sides of Equation (4) are integrated, yielding the following expression:

$$\int_R \emptyset_j, o(t) = \sum_n g(n) \int_R \phi_{j\ 1,n}(t)\,dt \quad 9$$

and

$$\int_R \emptyset_{j\ 1,n}(t)dt = 2^{\frac{j+1}{2}} \int_R \emptyset\left(2^{j+1}t - n\right)dt \quad 10$$

With $t^1 = 2t$, Equation 9 becomes

$$= \sqrt{2}\int_R 2^{\frac{j}{2}}\emptyset\left(2^j t^1 - n\right)\frac{1}{2}dt^1 \quad 11$$

$$= \frac{1}{\sqrt{2}}\int_R \emptyset_{j,n}(t)\,dt$$

$$= \frac{1}{\sqrt{2}}\int_R \emptyset_{j,0}(t)\,dt \quad 12$$

Subsisting (12) in (9) gives

$$\sum_n g(n) = \sqrt{2} \quad 13$$

Similarly, integral operations can be performed on both sides of equation 4 as:

$$\int_R \Psi_{j,0}(t)\,dt = \sum_n h(n) \int_R \emptyset_{j\ \ 1,n}(t)dt \quad 14$$

Given that $\int_R \Psi(t)\,dt = 0$, equation 14 can be simplified as:

$$\sum_n \mathrm{h(n)} = 0 \quad 15$$

The coefficients g(n)in Equation (7) and h(n)in Equation (8) constitute a pair of low-pass and high-pass wavelet filters, respectively. These filters form the fundamental building blocks of the Discrete Wavelet Transform (DWT) and are employed to implement the wavelet decomposition and reconstruction processes based on the Mallat algorithm.

2.3 Thresholding Functions

Thresholding is a fundamental signal denoising technique used to suppress or eliminate noise components from a contaminated signal after wavelet decomposition. During the decomposition process, the noise is primarily concentrated in the detail coefficients, while the approximation coefficients retain most of the useful signal information. Consequently, thresholding is applied to the detail coefficients to attenuate the noise while preserving the significant features of the original speech signal.

Wavelet-based denoising generally employs two conventional thresholding methods, namely hard thresholding and soft thresholding. Hard thresholding completely removes wavelet coefficients whose magnitudes are below a specified threshold, whereas soft thresholding not only suppresses these coefficients but also shrinks the remaining coefficients towards zero. Owing to its ability to produce smoother signal reconstruction and reduce discontinuities, **soft** thresholding was adopted in this study. According to Selesnick (2018), conventional thresholding functions can be formulated mathematically by assuming that the original signal of interest, x, is contaminated by additive noise, n. Consequently, the observed noisy signal, d, can be expressed as

$$d = x + n \quad 16$$

Where x represents the original (noise-free) speech signal, n denotes zero-mean additive white Gaussian noise (AWGN), and d is the observed noisy speech signal.

The objective is to estimate the original noise-free signal, x, from the observed noisy signal, d, with the highest possible accuracy. In the transform domain, such as the Discrete Wavelet Transform (DWT) or the Short-Time Fourier Transform (STFT), this denoising problem can be represented by Equation (17):

$$y = w + n \quad 17$$

where:

- Y represents the observed noisy wavelet coefficient;
- w denotes the true (noise-free) wavelet coefficient; and
- n represents the zero-mean additive white Gaussian noise (AWGN) component.

The primary objective is to estimate the true wavelet coefficient, w, from the observed noisy coefficient, y. Let the estimate of w be denoted by $\hat{w}$. Since the estimate is a function of the observed coefficient y, it can be expressed as $\hat{w}(y)$.

In this study, the estimation of the noise-free coefficient is performed using the Maximum A Posteriori (MAP) estimator. The MAP estimator is based on Bayesian estimation theory and determines the value of the unknown coefficient that maximizes the posterior probability density function (PDF) of the coefficient, given the observed noisy coefficient. In other words, for an observed coefficient y, the MAP estimator identifies the value of w that has the highest posterior probability of occurrence.

Accordingly, the MAP estimator is defined by Equation (18):

$$e(y) = argmax_w P_{w/y}(\frac{w}{y}) \quad 18$$

where 'argmax' is the value of the argument where the function has its maximum. The Pdf of w/y given as $P_{w/y}$ $(^{w}/_{y})$ is the distribution of w given a specific value of y.

3.0 Results and Discussions

Results of Denoising the Contaminated Voice Signal with the Developed Bman-WSST

The simulation parameters for the signal generations are shown in Table 1.

Table 1: Simulation Parameter

Parameter	Specification
Decomposition Level	2
Mother Wavelet	Symlet 4 (sym4)
Noise Frequency	All frequencies Depending on Source
Noise Type	Additive White Gaussian Noise
Iteration Number	73116
Threshold Rule	Sqtwolog, rigrsure, heursure and minimaxi
Signal	Voice/Speech

A speech signal was acquired by recording the researcher speaking the statement, “education is key to a sustainable development of any nation” using the built-in microphone of a laptop computer. The microphone converted the acoustic speech signal into an electrical signal, which was subsequently digitized, stored as an audio file, and imported into the MATLAB environment for signal processing and analysis.

To simulate a noisy telecommunication channel, 10.5 dB additive white Gaussian noise (AWGN) was artificially generated and superimposed on the original speech signal, thereby producing a contaminated speech signal. The noisy speech signal was decomposed to Level 2 using the Symlet 4 (Sym4) mother wavelet, after which denoising was performed using the proposed Blackman Window-Based Shrinkage Soft Thresholding (Bman-WSST) technique. The performance of the proposed method was evaluated using four threshold selection rules, namely Sqtwolog**,** Rigrsure**,** Heursure**,** and Minimax**.**

Figure 2 illustrates the original (noise-free) speech signal, Figure 3 presents the generated additive white Gaussian noise, and Figure 4 shows the speech signal after contamination with AWGN.

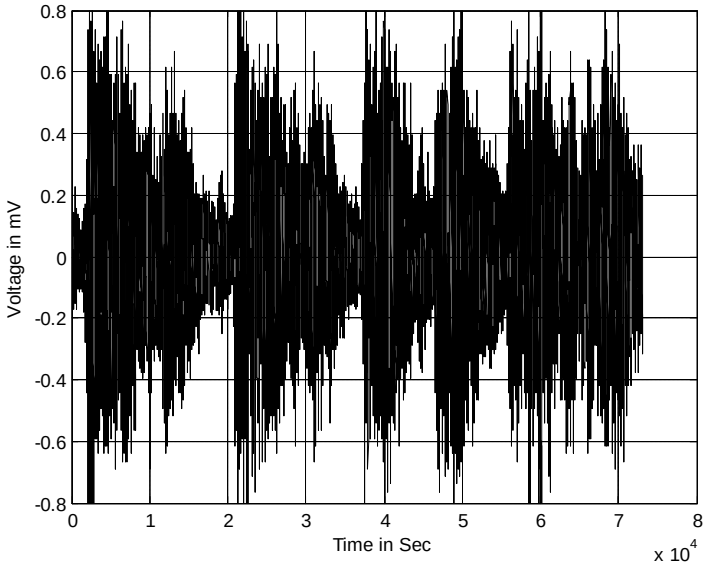


Figure 2: Original Voice Signal

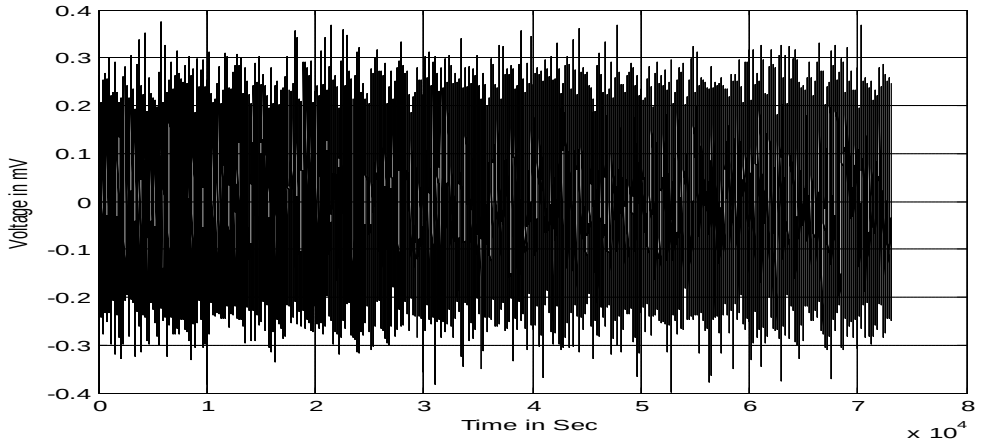


Figure 3: Additive White Gaussian Noise

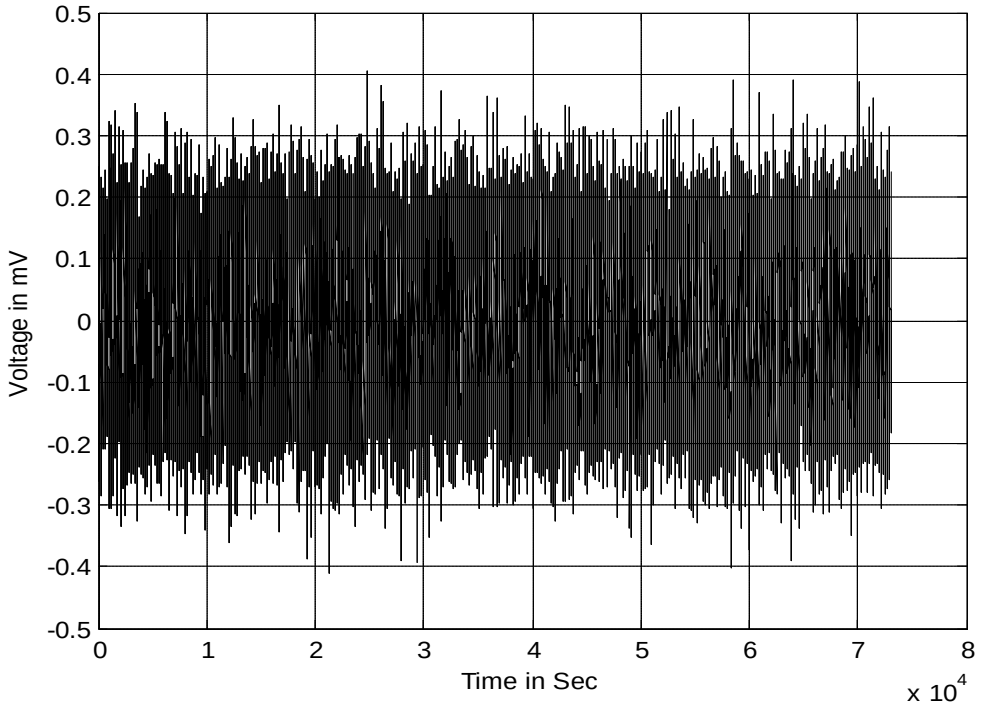


Figure 4: Contaminated Voice Signal

The Level 2 approximation coefficients and the Level 1 and Level 2 detail coefficient sequences are presented in Figures 5–7, respectively. These results demonstrate the successful implementation of the proposed wavelet decomposition process and confirm the practical applicability of the developed denoising technique. As shown in Figure 5, the approximation coefficients predominantly contain the low-frequency components of the speech signal, with most of the additive noise effectively suppressed during decomposition. Consequently, no thresholding operation is applied to the approximation coefficients in order to preserve the essential speech information.

In contrast, the Level 1 and Level 2 detail coefficients, shown in Figures 6 and 7, contain a significant proportion of the high-frequency components, where the additive white Gaussian noise (AWGN) is primarily concentrated. Therefore, thresholding is applied exclusively to the detail coefficients to attenuate the noise while retaining the significant speech-related components. This selective thresholding strategy improves the quality of the reconstructed

speech signal by achieving effective noise suppression with minimal distortion of the original speech information.

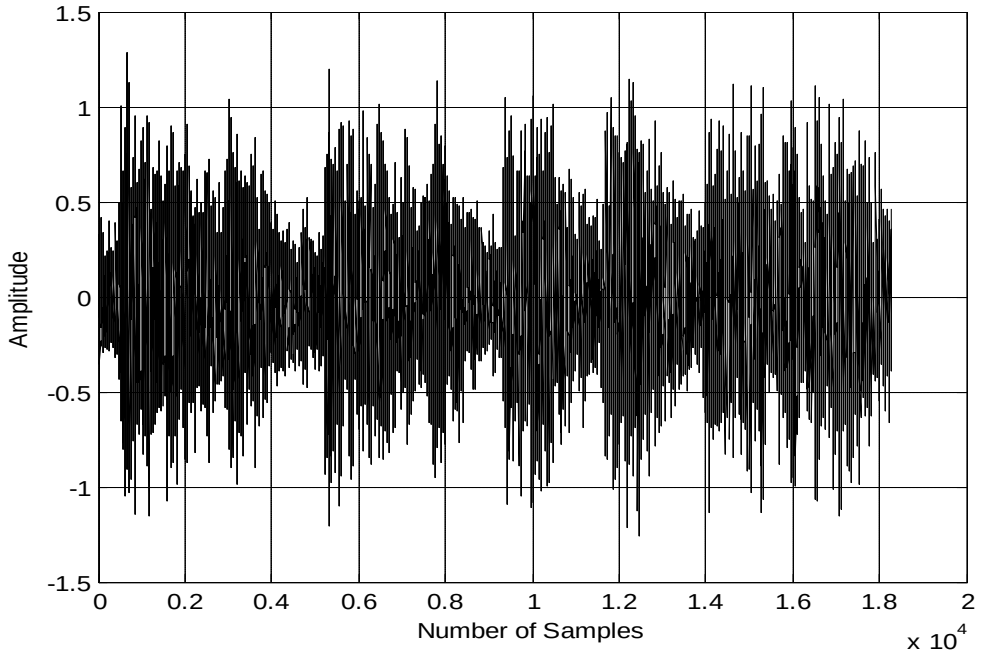


Figure 5: Level 2 Approximation Coefficients

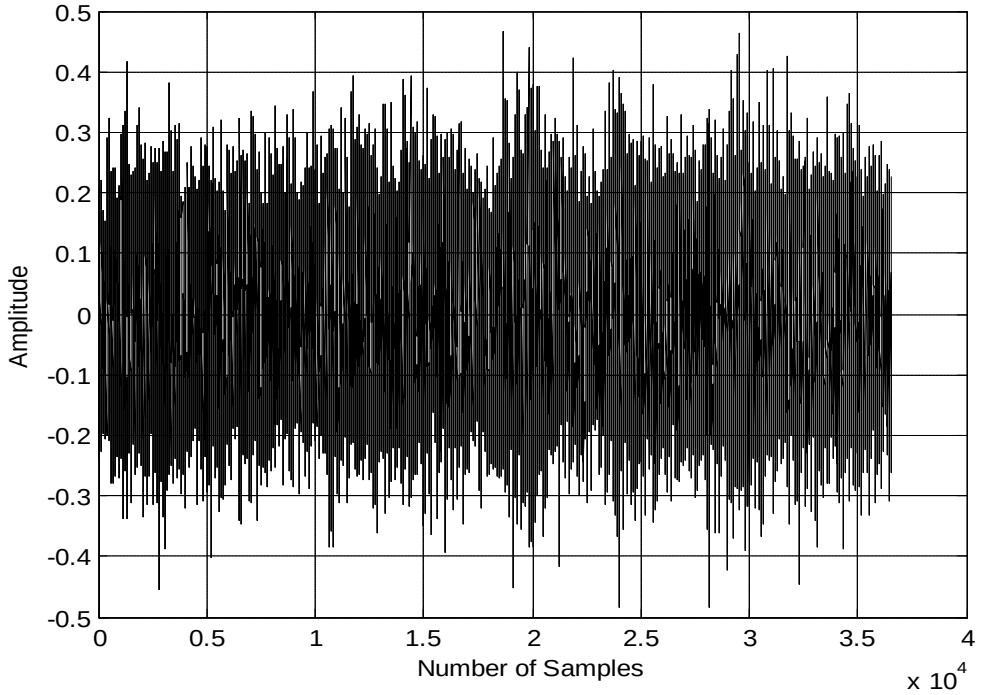


Figure 6: Level 1 Detail Coefficients

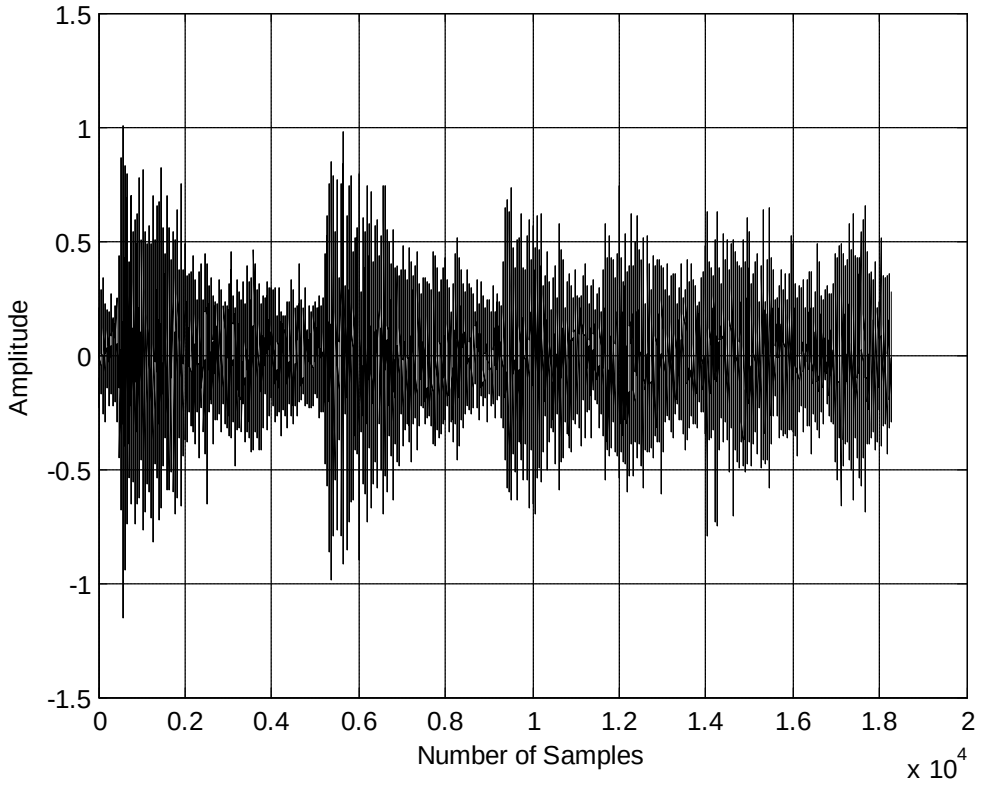


Figure 7: Level 2 Detail Coefficients

The thresholding technique is based on applying the inverted Blackman window coefficient sequence to the detail coefficients, D_k, of the contaminated speech signal prior to the conventional soft-thresholding operation. This preliminary shrinkage stage selectively attenuates the amplitudes of the wavelet coefficients within the frequency region predominantly occupied by additive white Gaussian noise (AWGN)**.** By reducing the noise components before the final thresholding process, the proposed method enhances noise suppression while minimizing distortion of the desired speech signal.

The inverted Blackman window serves as a weighting function that adaptively scales the detail coefficients according to their frequency distribution. As a result, coefficients associated with the dominant noise region are more strongly attenuated, whereas coefficients containing significant speech information are preserved. This two-stage shrinkage strategy improves the effectiveness of the denoising process by achieving greater noise reduction without compromising the integrity of the reconstructed speech signal.

The coefficient distribution of the inverted Blackman window used in the proposed shrinkage technique is illustrated in Figure 8**.**

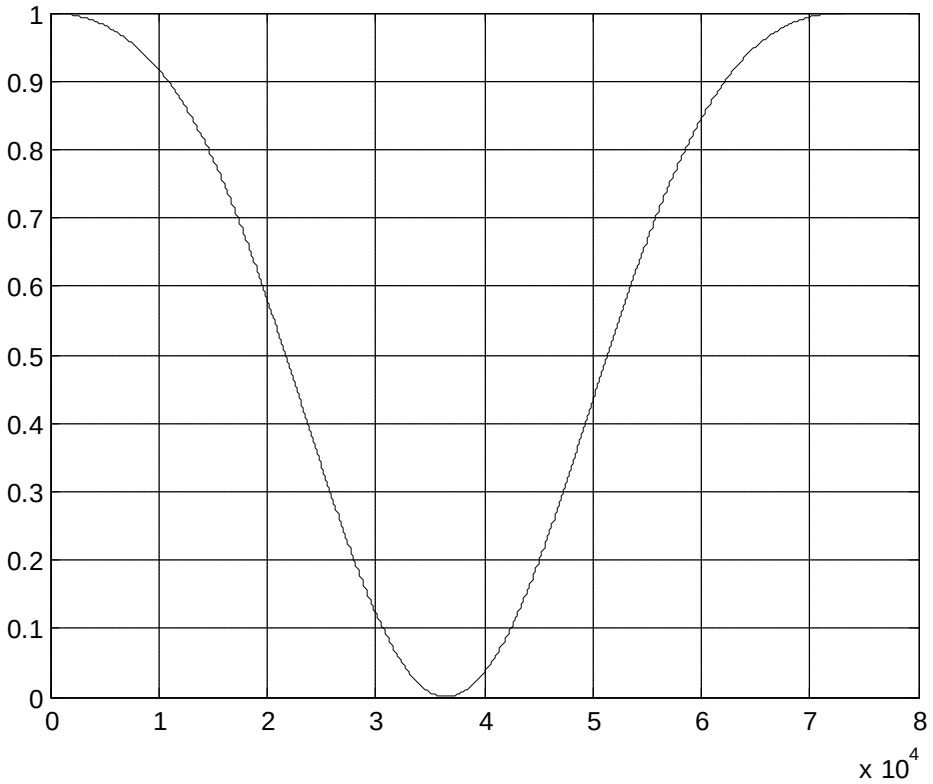


Figure 8: Inverted Blackman Window Function for First Stage Shrinkage

The effective bandwidth of conventional telephone speech signals typically ranges from 300 Hz to 3400 Hz**.** In the proposed denoising technique, the target noise component is additive white Gaussian noise (AWGN) superimposed on the speech signal. The inverted Blackman window was designed to selectively attenuate wavelet coefficients within the frequency regions where the noise energy is most pronounced. At the central region of the inverted Blackman window, the window coefficient approaches zero, thereby significantly reducing the amplitudes of the corresponding noisy detail coefficients before the application of the soft-thresholding operation. This preliminary shrinkage stage enhances the effectiveness of the thresholding process by suppressing noise while preserving the essential characteristics of the speech signal.

Figure 9 illustrates the speech signal denoised using the proposed Blackman Window-Based Shrinkage Soft Thresholding (Bman-WSST) technique with the Sqtwolog threshold selection rule. Similarly, Figures 10 and 11 present the denoised speech signals obtained using the Rigrsure and Heursure threshold selection rules, respectively. (If the Minimax threshold result is also presented elsewhere, it should be included as an additional figure or discussed separately). The results demonstrate that the proposed Bman-WSST technique effectively suppresses additive white Gaussian noise while preserving the important temporal and spectral characteristics of the speech signal. Among the threshold selection rules investigated, the Sqtwolog rule produced the best denoising performance, yielding superior speech quality and reduced residual noise. These findings are consistent with previous studies that reported the effectiveness of Discrete Wavelet Transform (DWT)-based denoising techniques for speech enhancement in the presence of additive white Gaussian noise (Chavan & Mastorakis, 2010; Singh et al., 2011; Kumar et al., 2015; Thu et al., 2019; Srikar& Prasad, 2017).

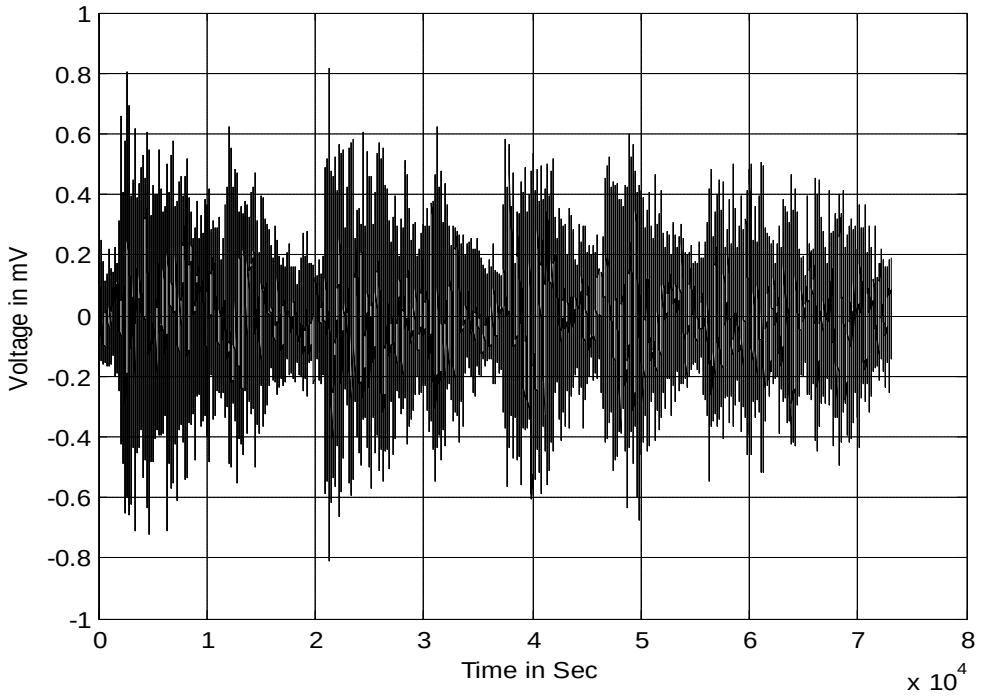


Figure 9: Voice Signa lDenoised with Bman-WSST and Sqtwolog Threshold Rule at level 2

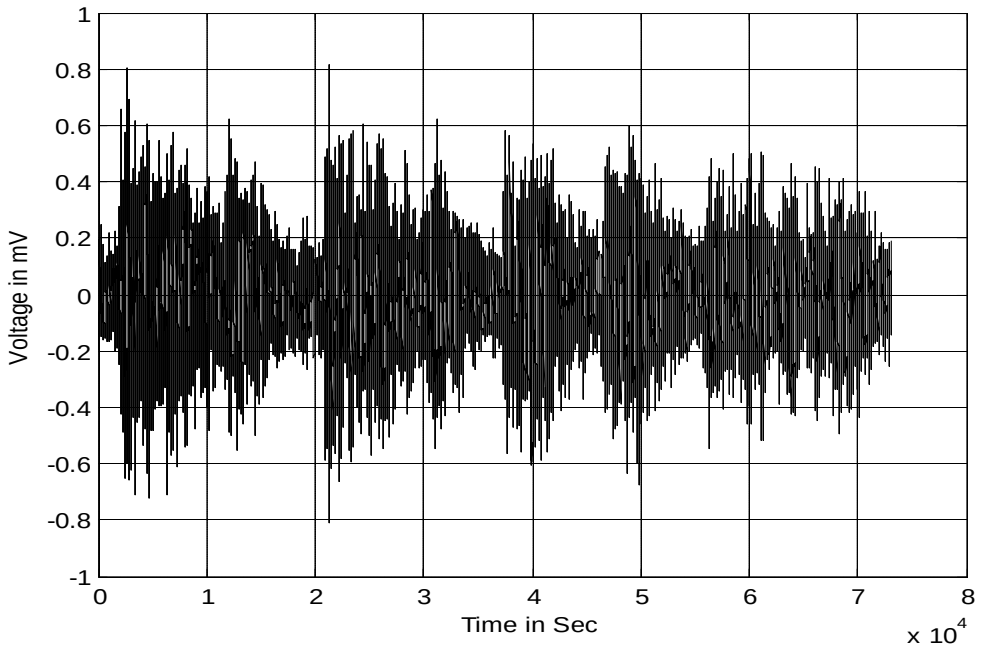


Figure 10: Voice Signal Denoised with Bman-WSST and Rigrsure Threshold Rule at Level 2

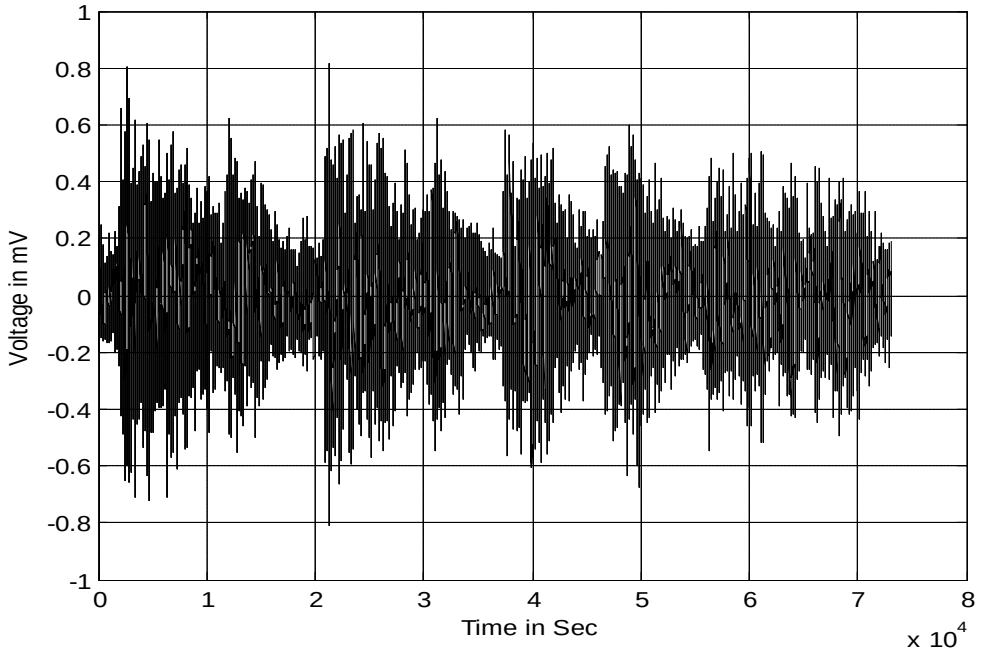


Figure 11: Voice Signal Denoised with Bman-WSST and Heursure Threshold Rule at Level 2

4.0 Conclusion and Recommendations

Conclusion

This study developed a Blackman Window-Based Shrinkage Soft Thresholding (Bman-WSST)technique for the denoising of speech signals contaminated byadditive white Gaussian noise (AWGN) using the Discrete Wavelet Transform (DWT)**.** The proposed technique integrates the Blackman window function with conventional soft thresholding to enhance noise suppression while preserving the essential characteristics of the original speech signal. The performance of the proposed method was evaluated using different threshold selection rules, decomposition levels, and objective performance metrics, including the Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), Maximum Absolute Error (MAE), and Power Spectral Density (PSD)**.**

The major findings of this study are summarized as follows:

1. Threshold selection significantly influences denoising performance. An inappropriate threshold may either fail to remove sufficient noise or excessively attenuate the desired speech signal, thereby degrading speech quality. Among the four threshold selection rules investigated (Sqtwolog, Rigrsure, Heursure, and Minimax), the Sqtwolog rule consistently provided the best denoising performance.
2. The decomposition level plays a critical role in speech signal denoising. Insufficient decomposition produces inadequate wavelet coefficients for effective noise removal, whereas excessive decomposition may introduce signal distortion despite improving noise suppression. Experimental results showed that Level 2 provided the optimum balance between noise reduction and signal preservation.
3. The choice of mother wavelet significantly affects the quality of the reconstructed speech signal. The Symlet 4 (Sym4)mother wavelet demonstrated effective signal decomposition and reconstruction, resulting in improved preservation of speech characteristics following the denoising process.
4. The proposed Bman-WSST technique outperformed the conventional hard and soft thresholding methods. The integration of the inverted Blackman window with soft

thresholding improved the suppression of additive white Gaussian noise while minimizing distortion of the original speech signal. The performance evaluation confirmed that the proposed method achieved superior overall denoising performance based on the selected objective quality metrics.

Overall, the results demonstrate that the proposed Blackman Window-Based Shrinkage Soft Thresholding (Bman-WSST) technique is an effective and reliable approach for speech enhancement in noisy telecommunication environments. The technique provides an improved alternative to conventional wavelet thresholding methods and has significant potential for practical implementation in digital speech communication systems.

Recommendations

The proposed Blackman Window-Based Shrinkage Soft Thresholding (Bman-WSST) technique is recommended for applications involving speech enhancement and signal denoising in telecommunication systems where additive white Gaussian noise may degrade signal quality during transmission. Potential application areas include mobile communication systems, Voice over Internet Protocol (VoIP), wireless communication networks, digital broadcasting, and other speech-based communication platforms.

Beyond telecommunications, the proposed technique may also be applied to biomedical signal processing, particularly in the denoising of physiological signals acquired from medical diagnostic equipment such as electrocardiography (ECG)**,** electroencephalography (EEG)**,** electromyography (EMG)**,** and electrooculography (EOG) systems. In addition, the proposed method could be extended to other engineering applications involving wavelet-based signal denoising, including radar signal processing, sonar systems, seismic signal analysis, image restoration, and industrial monitoring.

Future research should focus on evaluating the performance of the proposed technique under different noise conditions, including babble noise, pink noise, impulse noise, and non-Gaussian noise**,** as well as investigating its implementation in real-time embedded digital signal processing (DSP) systems and machine learning-assisted speech enhancement applications.

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