Kufa Journal of Engineering
Vol. 16, No. 3, July 2025, P.P. 312-330
Article history: Received 29 August 2024, last revised 23 November 2024, accepted 23 November 2024

IMAGE DENOISE BASED ON UNDECIMATED WAVELET TRANSFORM: A COMPARATIVE ANALYSIS

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https://doi.org/10.30572/2018/KJE/160317

ABSTRACT

Image denoising is a key challenge in the field of image processing, focusing on eliminating undesirable noise while maintaining essential features like edges and textures. This research comparatively analyzed various methods of the Undecimated Wavelet Transform (UWT) for achieving image denoising. The initial section examined the performance of Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) utilizing MATLAB, indicating that biorthogonal wavelets provide optimal noise reduction with minimal degradation of detail.

The subsequent section investigated various thresholding techniques, specifically SURE, Hybrid, and Universal by calculating their processing times evaluated over four levels of decomposition in LabVIEW. Results demonstrated that SURE exhibits the longest computational duration, particularly at elevated levels of decomposition, whereas the Hybrid approach offered a favorable balance between performance and processing time. Conversely, the Universal thresholding method is identified as the most expedient, proving to be the most efficient at greater levels of wavelet decomposition.

KEYWORDS

Image denoising, undecimated wavelet transforms, thresholding techniques, LabVIEW.

1. INTRODUCTION

The Undecimated Wavelet Transform (UWT) is an effective tool in the field of signal processing and plays a main role in providing advanced capabilities for feature extraction and data analysis. The Undecimated Wavelet Transform (UWT) offers advantages over traditional Discrete Wavelet Transform (DWT) by preserving all original signal samples since it avoids decimation. However, the UWT is prone to aliasing due to its down-sampling step. Despite this, the UWT effectively retains temporal and spatial correlations in data, making it a suitable choice for audio analysis and image processing (Jebur *et al.*, 2024). While UWT does experience aliasing, the resulting artifacts are generally less problematic for denoising tasks compared to those encountered in typical image reconstruction or compression processes. To counteract the effects of aliasing and improve noise removal, techniques such as wavelet thresholding and cycle spinning are frequently used in conjunction with UWT. Moreover, the translation invariance characteristic of UWT aids in reducing noise without producing the artifacts often seen with DWT-based methods (Bnou, Raghay and Hakim, 2020). Another important attribute of UWT is its inherent shift-invariance, which enhances robustness during the image denoising process. This quality is particularly crucial for security applications and processing multi-language data. Researchers have effectively utilized UWT as a feature extraction tool to bolster security measures by detecting anomalies and differentiating between legitimate and harmful content (Engineering, 2019). Incorporating the UWT into sophisticated frameworks like the Word Embedded Semantic Marginal Auto encoder enhances semantic understanding during image denoising and improves image quality. The versatility and effectiveness of the UWT make it a valuable tool for developing security systems and ensuring high-level data integrity that necessitate various languages and contexts. (Abdulazeez, Zeebaree and Abdulqader, 2020). To successfully minimize noise within a signal, it is crucial to begin a decomposition process by utilizing wavelet transform. The UWT allows for the division of a signal into a set of coefficients that relate to different frequency ranges. Upon successful completion of this initial phase, relevant information pertaining to the signal's characteristics can be extracted. A comprehensive understanding of the signal's behavior across different frequency segments will enable the selection of the most appropriate threshold during the subsequent phase. The following step involves identifying and applying optimal threshold techniques to the derived coefficients, thereby enabling the removal of extraneous data (Patil and Pawar, 2012).

2. IMAGE DENOISING USING UNDECIMATED WAVELET

Nowadays, enhancing image content is important to understand and learn the structured features of images, as well as initiate end-to-end large data training in image analysis (Mohammed *et al*, 2022). This enhancing process of image quality can be achieved usefully by using the Undecimated Wavelet Transform (UWT), which has become one of the most common, important and effective in many applications, especially medical imaging to obtain a maximum image resolution (Larbi, Naimi and Bourennane, 2023). Unlike the discrete wavelet transform (DWT), which down samples the approximation coefficients and detail coefficients at each decomposition level, the undecimated wavelet transform (UWT) does not incorporate the down sampling operations (Li *et al.*, 2023). Thus, the approximation coefficients and detail coefficients at each level are the same length as the original signal. The UWT up samples the coefficients of the lowpass and high pass filters at each level. The up-sampling operation is equivalent to dilating wavelets. The resolution of the UWT coefficients decreases with increasing levels of decomposition (Rodriguez-Hernandez and Emeterio, 2016).

UWT waves facilitate reliable interpretation of visual information across a variety of application domains, enabling analytical innovations that manage and control the distortions of noisy data. This has led to a significant transformational step in the accuracy of interpreting data transmitted in the digital scene, facilitating researchers' use of these waves in their imaging techniques (Gupta *et al.*, no date).

2.1. The Noise in digital images

Noise in image processing occurred due to the random variation where caused a different intensity value of pixels in the recontacted image instead of true pixel values of the original image. The noise will lead to loss the essential information that is hidden inside images and then the image quality will decrease due to variation of image brightness or color. In general, the noise is added to the digital image during the image acquisition or transmission (Deswal, Gupta and Bhushan, 2015). The quality of image sensors is altered by various parameters like atmospheric conditions at the time of image acquisitions as well as the quality of sensor itself. The image degradation during its acquisition and transmission is occurred due to the electromagnetic interference in the channel (Gupta, Mishra and Singh, 2021).

2.1.1. Sources of noise

Digital images are frequently impacted by noise, which can diminish their quality. Common sources of noise include inadequate lighting conditions, environmental effects on image sensors, and transmission errors over networks. It is crucial to comprehend these sources in order to choose effective denoising techniques.(Nayak, S and Student, 2021)-(Jebur *et al.*, 2024).

2.1.2. Noise Types:

Digital images can be affected by various types of noise, which can degrade their quality. A brief overview of the most common types of noise that might affect on the reconstructed image:

1. Gaussian Noise: The Gaussian noise has a bell-curve distribution, where pixel values are altered by a random value drawn from a Gaussian distribution (Jebur *et al.*, 2024).
2. Salt-and-Pepper Noise: This noise adds random white and black pixels to an image, resembling salt-and-pepper sprinkled over it (Jebur *et al.*, 2024).
3. Poisson Noise: This noise, also known as shot noise, results from the discrete nature of light photons. It is prevalent in low-light conditions (Tun, Sugiura and Shimamura, 2024).
4. Speckle Noise: Common in radar and medical imaging, speckle noise causes granular interference due to random variations in the reflected signals (Qun *et al.*, 2023).
5. Quantization Noise: Arises when continuous signal values are mapped to discrete levels, commonly seen in the analog-to-digital conversion process (Ilesanmi and Ilesanmi, 2021).
6. Color Noise: Description: This affects the color channels of an image, introducing random variations in color values (Ilesanmi and Ilesanmi, 2021).

2.1.3. The Gaussian White Noise Technique

Gaussian white noise is one of the most important techniques used in signal processing fields, as it is characterized by its statistical properties due to the distribution of values in a symmetrical form around the mean, which in turn helps to hide signals in some applications, reducing the possibility of making an accurate interpretation of these signals. Therefore, the use of the Undivided Wavelet Transform (UWT) technique was resorted to in order to preserve critical temporal and spatial correlations within the data, which leads to the possibility of processing and interpreting signals correctly (Rodriguez-Hernandez and Emeterio, 2016). Additionally, advanced frameworks integrating UWT can polish semantic understanding while effectively reducing noise levels, which leads to improve the quality of data and facilitate the security measures through anomaly detection. Thereby, the incorporation of Gaussian white noise filters into these methodologies will deskill the researchers' work in developing more practical and flexible systems with high-level data integrity across different contexts and applications (Aziz, 2024). Analyzing the effects of Gaussian white noise with studying effective methods to mitigate it will help to achieve great progress in scientific fields such as telecommunications and artificial intelligence applications (Rajini, 2016).

2.2. The Orthogonal and Bi-Orthogonal Undecimated Wavelets

Orthogonal and bi-orthogonal waves are the two main types of UWT wavelets. In orthogonal waves, the wave functions are orthogonal to each other, meaning that their inner product is zero, which helps in accurately and clearly reconstructing the original image based on the wave coefficients without repetition. Due to the orthogonality of these waves, the image decomposition and reconstruction process is efficient, accurate, and successful. Some common types of these wavelets are Haar, Dubuisches waves, and Symlets wavelets (Wang, Liu and Zhou, 2024). The Bi-orthogonal wavelets have two sets of waves: one for image decomposition and the other for image reconstruction. The most special feature of bi-orthogonal wavelets is that the wavelets and scaling functions used in image analysis are completely different from those that are used in image synthesis. This type of wavelet is also flexible and can be used in specific applications (C. and Chui, 1993).

2.3. Different Thresholding Techniques

There are various thresholding techniques that used with Undecimated Wavelet Transform (UWT) in the image denoising process. These thresholding techniques are played a very important and effective role in preserving the resolution and details of the transferred image and complex thresholding, basing on the shift-invariant property of UWT which enables it to adapt to different noise characteristics and image features (Ismael and Baykara, 2022).

2.3.1. SURE-Based Thresholding (SureShrink) Technique

SURE (Stein's Unbiased Risk Estimate) thresholds are adapted to UWT wavelets by calculating the number of thresholds that minimize the unbiased estimate of risk, designed according to the piecewise coefficients. The SURE value for a given threshold λ is calculated as in Eq.1:

$$SURE(\lambda) = \frac{1}{N}\sum_{i=1}^{N}\left(W_i - \widehat{W}_i\right)^2 + 2\lambda^2 - \frac{\sigma^2}{\lambda^2} \quad (1)$$

Where:

- Wi represents the original wavelet coefficient at index i.
- $\widehat{Wi}$ represents the thresholded wavelet coefficient.
- σ^2 represents the estimated noise variance, and
- N represents the number of wavelet coefficients (Ismael and Baykara, 2022).

Most recently, in most image denoising applications, SURE is combined with other statistical methods or within certain hybrid models by considering the frequency domain and spatial information.

2.3.2. Universal Thresholding Technique

Universal thresholding, also known as VisuShrink, is a well-known method for removing noise from images that preserves fine image details by applying a thresholding technique to the waveforms. This threshold technique is calculated basing on the noise level of the image and is defined as in Eq. 2:

$$\lambda = \sigma\sqrt{2\log(N)} \quad (2)$$

Where:

σ represents the estimated noise standard deviation, and

N represents the number of pixels in the image.

The threshold value λ is applied uniformly to all wave coefficients. When the threshold is determined, all these coefficients are reduced to zero if their absolute value is less than the threshold value λ, otherwise they are reduced by λ (Zach *et al.*, 2024).

2.3.3. Hybrid Thresholding Technique

Hybrid thresholding is achieved by combining multiple thresholding strategies, taking advantage of the features and strengths of each threshold. Hybrid thresholding typically combines hard and soft thresholding, Bayesian techniques, adaptive thresholding, and machine learning.

As an example, Hybrid thresholding, the of combining of VisuShrink (universal thresholding) with adaptive thresholding, which can be represented in the following Eq. 3:

$$T_{hybrid}(i) = \min(\max(T_{universal}, T_{adaptive}(i)), T_{max}) \quad (3)$$

Where:

$T_{hybrid}(i)$ represents the hybrid threshold for coefficient iii.

$T_{universal}$ represents the universal threshold (Ismael and Baykara , 2022).

3. RELATED WORKS

Over the past decades, researchers have done a lot of research on the topic of transmitted images de-noising, and in this section, many of these research articles are presented in this section.

Zhou, X., & Yang, Z.2024 (Li *et al.*, 2024), Investigated the UWT for denoising hyperspectral images and addressing the unique challenges posed by this imaging modality. W. Rahmann, 2024 (Rahmann, 2024) encompassed common types of noise such as Gaussian noise, salt and pepper noise, and speckle noise, and evaluates the performance of filtering techniques including mean filtering, median filtering, and Gaussian filtering. M. Elad, B. Kawar 2023 (Elad, Kawar and Vaksman, 2023) , provided a broad view of the history of the field of image denoising and closely related topics in image processing to give a better context to recent discoveries, and to the influence of the AI revolution in the domain.R. Gondal & et al, 2021 (Gondal *et al.*, 2021), in his research reviewed the types of noise generated in mammography images and reviewed the most important methods used to remove them. A. N. Amiri Golilarz, H. Gao.(Amiri Golilarz *et al.*, 2020) 2020, Focused on adaptive thresholding techniques within the UWT framework, aiming to improve denoising performance by dynamically adjusting thresholds based on local image characteristics. Nayak & A. Verma, 2018 (Nayak and Verma, 2018) presented detailed research on the topic of images denoise, by presenting the different used techniques, with their performance, and comparing these methods and their efficiency. S. Sumanth & A. Suresh, 2017 (Sumanth and Suresh, 2017) reviewed many mechanisms for image denoise for some types of digital images during transmission. They also presented different types of image filtering methods to choose the appropriate filter in terms of efficiency and speed based on noise behavior. J. Nader & et al, 2017 (Nader, A. and Zahran, 2017) presented research on the type of salt and pepper with Gaussian noise effects and using many methods to reduce this type of noise. S. Tania & R. Rowaida, 2016 (Tania and Rowaida, 2016), presented research including an experimental study with comparative work on several models to improve corrupted and blurred images by checking the performance of all the applied models. The researchers G. Kaur & et al, 2016 (Boyat and Joshi, 2015), They reviewed different methods of removing noise from images with their masks to accurately transfer images while preserving their edges. The results showed the efficiency of some filters in removing noise from images, while showing some inefficient types that increased the deterioration of image quality and removed edges. P. Athira & et al, 2016 (P., K. and Krishnan, 2016), The researchers reviewed the field of biomedical research and focused on the types of methods used in image denoise from mammography images. M.Pious & et al, 2015 (Saha and Mandal, 2015) in their research presented many noise cases that have different impact on image quality and reviewed many effective image denoise methods that can attack the image collectively, sometimes the transmitted images are attacked by more than one type of noise, they showed in their research some methods to reduce this noise.

S. Kaur, 2015 (Kaur, 2015), reviewed several axes in her research and focused on the form of noise and how it affects the quality of transmitted images, with a presentation of some algorithms used to purify these images and a presentation of some types of filters and their performance. A. Vijayalakshmi & et al, 2014 (Vijayalakshmi and Beaulah, 2014) presented a detailed and extensive work to describe and compare denoise models to demonstrate their efficiency in purifying images. The researchers M. Farooque & J. Rohankar, 2013 (Farooque, 2013), divided their article into two stages: the first stage reviewed the types of noise, and the second stage discussed the use of each type in denoising process by using wavelets to prove its efficiency in improving transmitted images. Mallat 2013, ('A Wavelet Tour of Signal Processing', 1999) presented an introduction to UWT-Based Denoising with a seminal reference providing comprehensive coverage of wavelet transforms, including UWT, and their applications in signal and image processing.

4. METHODOLOGY

1. First Comparative Analysis

The first Comparative Analysis was achieved using MATLAB environments program to calculate the values of Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) quantitative metrics which are essential to evaluate the effectiveness of denoising algorithms.

2. Second Comparative Analysis.

For Evaluating Execution Time, a proposed LabVIEW 2023 simulation system is designed as shown in Fig. 1 and Fig. 2.:

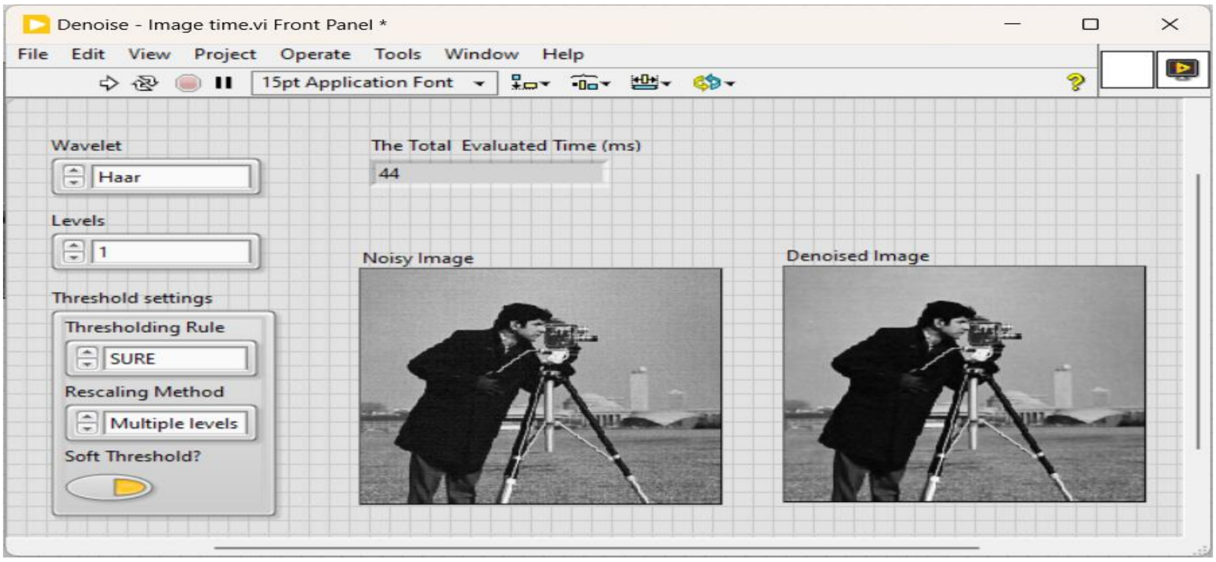


Fig.1. The front panel of LabVIEW 2023 simulation design for image denoising

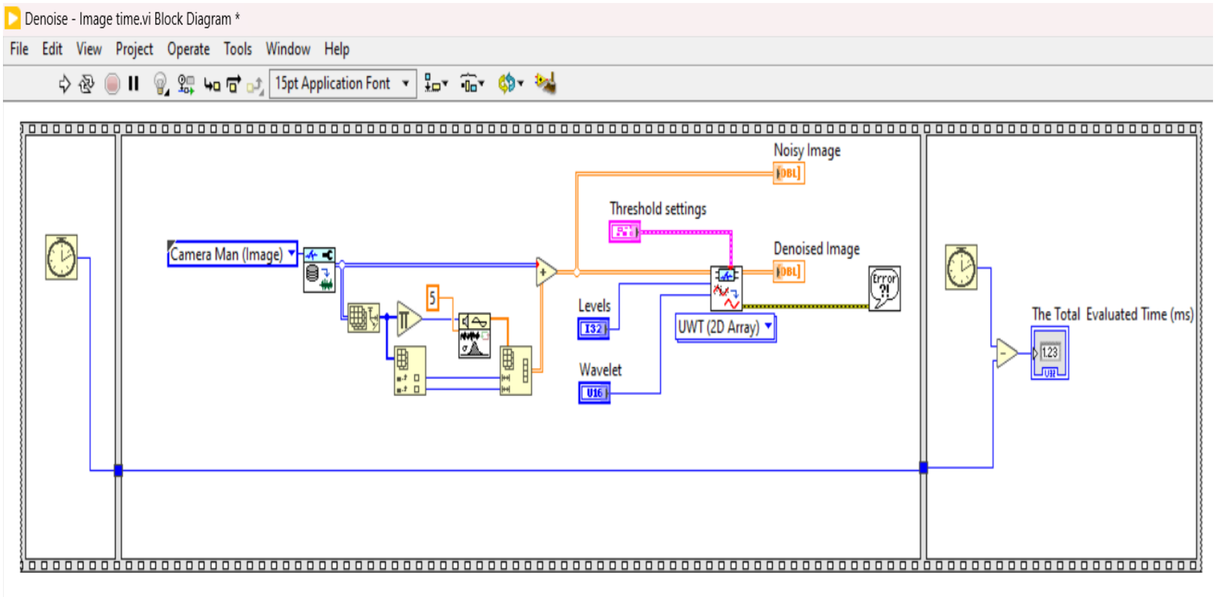


Fig.2 The block diagram of LabVIEW 2023 simulation design for image denoising

The LabVIEW2023 proposed system outlines a methodical approach. It uses the camera man as the test image which is contaminated by Gaussian white noise. The comparison is based on calculating the evaluated time values by using different Undecimated Wavelet Transforms (UWT), the orthogonal wavelets (e.g., Haar, Daubechies (db5, bd10 and db14), symlets (sym2 and sym8), coiflets (coif2 and coif5) and biorthogonal wavelets (e.g., Bior2_4, Bior4_4 and Bior6_8) with different thresholding techniques (Universal, SURE, and Hybrid techniques. These choices will provide a range of wavelet transforms to be evaluated within four decomposition levels (1, 5, 10 and 15) in LabVIEW2023.

Once the selection is made, the next step involves setting up the LabVIEW environment to facilitate UWT implementation. This includes utilizing LabVIEW's Wavelet Toolkit or creating custom Virtual Instrument (VI) blocks to perform the wavelet transforms on prepared test images or signals that are standardized for consistent analysis. The computation of UWT is carried out for each selected wavelet family and decomposition level.

The thresholding techniques, Universal, SURE, and Hybrid techniques are integrated into the LabVIEW program. These techniques are applied to the transformed coefficients at each UWT level within the same VI.

To gauge performance, execution times for each combination of UWT and thresholding techniques across different decomposition levels are measured using a built-in timing function. A comparison of average execution times is then made to identify the most efficient combinations and understand the differences in performance.

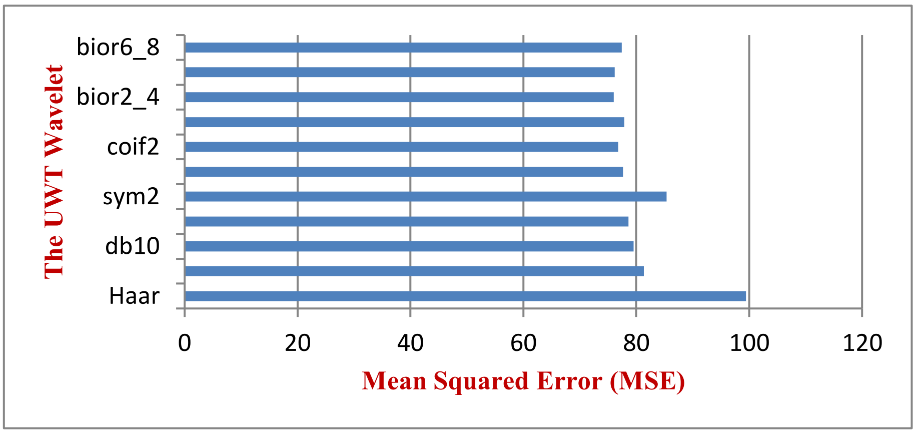
5. RESULTS AND DISCUSSION

5.1. First Comparative Analysis Results

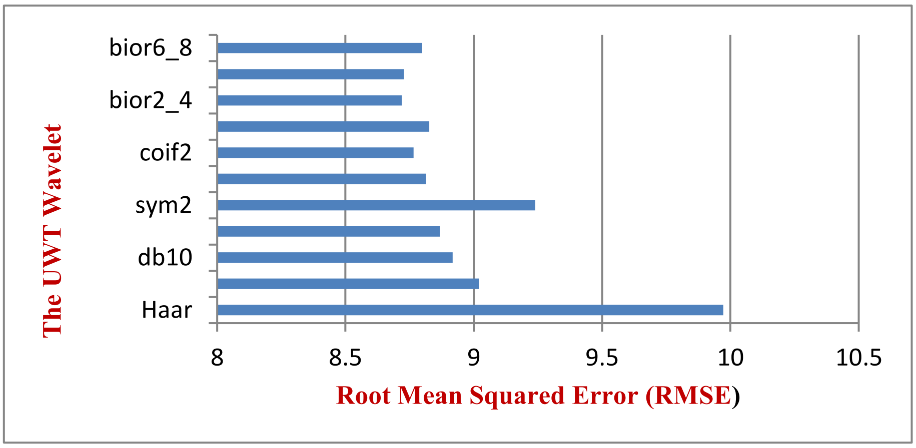
The MATLAB Environment program was used to calculate the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) quantitative metrics values. The programs were initiated based on Gaussian White Noise filters and SURE-Based Thresholding (SureShrink) functions. The MSE results are shown in Fig.3.

From the above chart, it appears that the Biorthogonal (bior2_4, bior4_4) wavelets are more effective for image denoising using the undecimated wavelet transform based on their lower MSE values. Conversely, the Haar and and Symlet (sym2) wavelets show poorer performance in this specific denoising task. The RMSE results are shown in Fig.4.

Similar to the MSE chart, the Biorthogonal (bior2_4, bior4_4) wavelets are the most effective for denoising as they have the lowest RMSE values. The Haar wavelet performs the worst, followed by the and Symlet (sym2). Lower RMSE values reflect better denoising performance, and this comparison confirms the preference for certain wavelets like the biorthogonal family for this particular task.



Fig, 3. The Mean Squared Error (MSE) values for different The UWT Wavelets



Fig, 4. The Root Mean Squared Error (MSE) values for different The UWT Wavelets

5.2. Second Comparative Analysis Results

By using The LabVIEW2023 proposed system, the four decomposition levels (1, 5, 10 and 15) are examined to produce a systematic comparison of the evaluated execution times for different UWT and thresholding techniques, providing actionable insights for optimizing image processing tasks in LabVIEW.

The results for these four image denoise decomposition levels are shown below:

5.2.1. Image Denoise Decomposition Level 1 Results and Discussion

The results of image denoise decomposition level 1 are shown in Fig. 5. Sure Thresholding (blue line) shows variable evaluation times across wavelet families, with lower times for Haar and db5, while db10 and db14 exhibit significant increases, peaking at db14. Universal Thresholding (red line) generally has lower evaluation times, particularly for Haar and db5, but shows a similar trend to Sure Thresholding with a peak at db14. Hybrid Thresholding (green line) consistently takes more time than the other methods, especially at db14, and is most computationally intensive with complex wavelets like Biorthogonal and coif2.

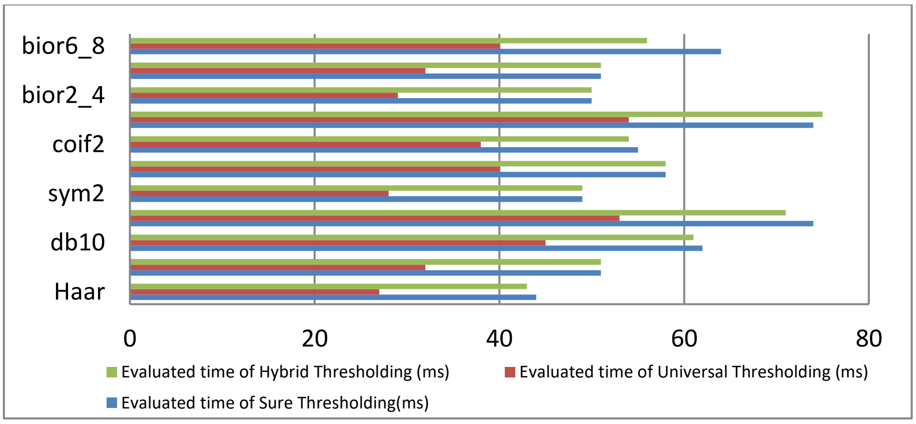


Fig. 5: The Evaluated time of different UWT and thresholding techniques for image denoise decomposition Level 1

5.2.2. Image Denoise Decomposition Level 5 Results and Discussion

The results of image denoise decomposition level 5 is shown in Fig. 6.

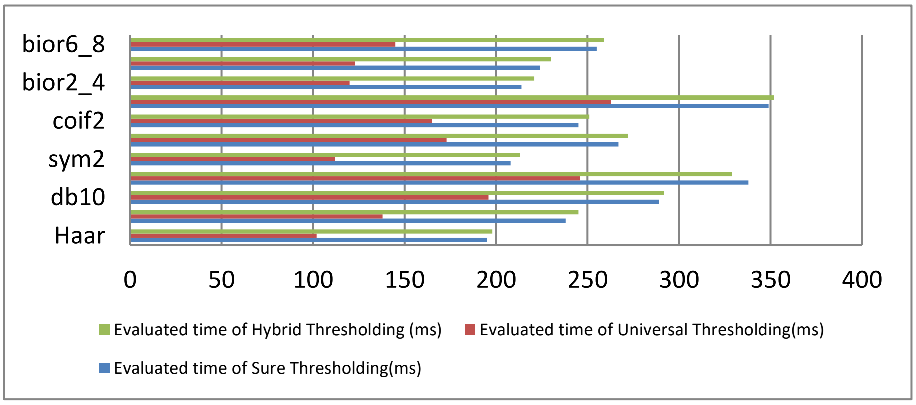


Fig. 6: The Evaluated time of different UWT and thresholding techniques for image denoise decomposition Level 5

Sure Thresholding (blue line) shows an increasing trend in evaluated time with complex wavelets, peaking at db14 before slightly decreasing. Haar has the lowest time, while Coif5 also indicates high complexity. Universal Thresholding (red line) consistently features the lowest evaluated times, with notable peaks for db14, while the times for other wavelets vary after db14. Hybrid Thresholding (green line) mirrors Sure Thresholding's pattern but generally has higher times, with significant peaks at db14 and Coif5, similar to Sure. Biorthogonal Wavelets maintain stable but elevated times.

5.2.3. Image Denoise Decomposition Level 10 Results and Discussion

The results of Image Denoise decomposition level 10 are shown in Fig. 7. SURE Thresholding (blue line) is the most computationally intensive with the longest evaluation times, especially for complex wavelets like coif5 and sym8. Hybrid Thresholding (green line) offers a balance, taking more time than Universal (red line) but less than SURE. Universal Thresholding is the least demanding and consistently shows the lowest evaluation times due to its simpler approach. As wavelet complexity increases, notably in Daubechies and Symlets, evaluation times rise for all techniques, with SURE showing the most significant increases. Biorthogonal wavelets generally have lower evaluation times, except bior4.4, which peaks in SURE times. Overall, Universal thresholding remains the quickest, while SURE's efficiency declines as wavelet complexity grows, suggesting scalability issues.

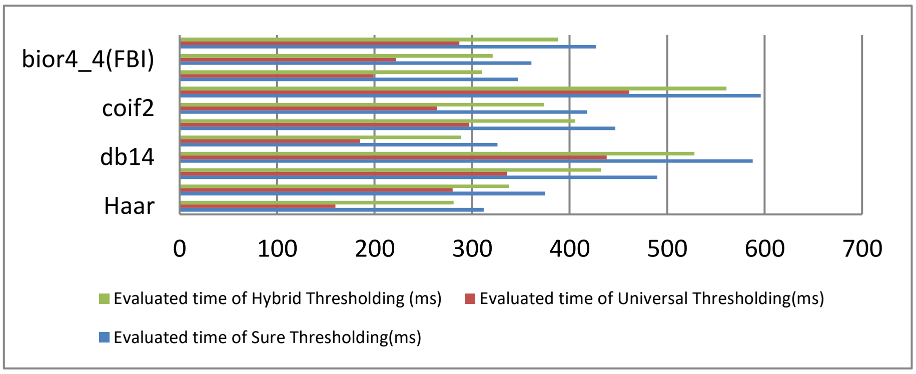


Fig. 7: The Evaluated time of different UWT and thresholding techniques for image denoise decomposition Level 10

5.2.4. Image Denoise Decomposition Level 15 Results and Discussion

The results of image denoise decomposition level 15 are shown in Fig. 8.

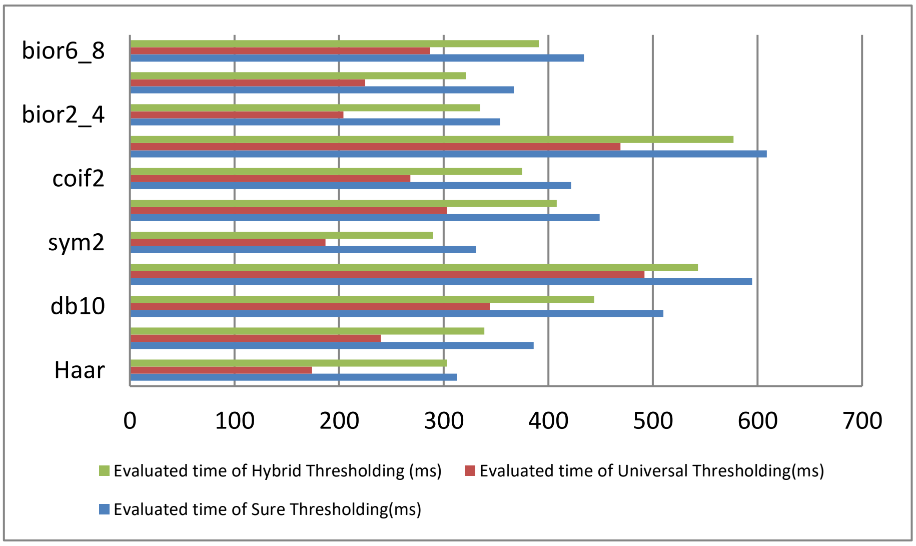


Fig. 8. The Evaluated time of different UWT and thresholding techniques for image denoise decomposition Level 15

At Level 15 of wavelet decomposition, evaluation times are generally higher due to increased complexity compared to Level 10. SURE thresholding (blue line) consistently incurs the longest processing times, particularly noticeable at deeper levels, while Hybrid thresholding (green line) shows moderate times and is more intensive than Universal thresholding (red line), which remains the most efficient method with the lowest evaluation times. The Haar wavelet has the least complexity, while Daubechies wavelets, especially db14, show significantly higher evaluation times. Symlets, particularly sym8, and Coiflets, particularly coif5, also exhibit increased computational demands. Biorthogonal wavelets tend to have lower times overall but still reflect substantial increases with SURE. Higher decomposition levels amplify the differences in processing times among techniques, with Universal thresholding proving more scalable and efficient, making it advantageous for computation-intensive applications.

The above results are summarized in Fig. 9.

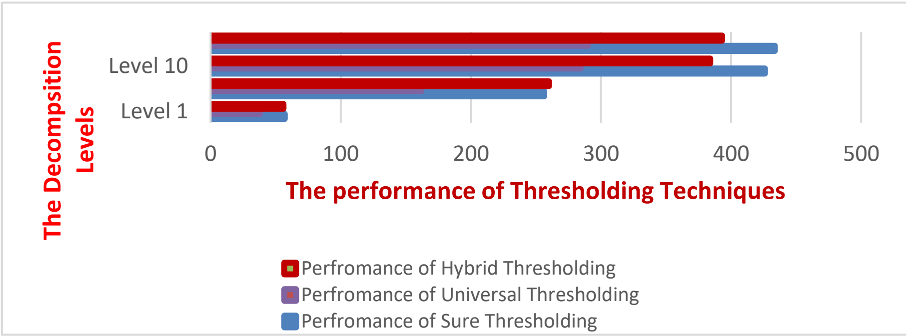


Fig. 9. The total performance of thresholding Techniques over the four decomposition Levels

Fig. 10. shows the output results of the LabVIEW proposed system design of image denoising using Undecimated Haar wavelet transform (least evaluated time) for the selected decomposition levels (Level 1, Level 5, Level 10, and Level 15) using three different thresholding techniques: SURE, Universal, and Hybrid.

Fig. 11 shows the output results of the LabVIEW proposed system design of image denoising using Undecimated Coif5 wavelet transform (higher evaluated time) for the selected decomposition levels (Level 1, Level 5, Level 10, and Level 15) using three different thresholding techniques: SURE, Universal, and Hybrid.

From Figs 10 and 11, we notice that as the decomposition level increases, the thresholding techniques perform better, but certainly at the expense of some detail of the original image, especially at decomposition level 15. The SURE thresholding is the most effective of the other techniques, especially at the highest decomposition level of 15, despite some noise. Universal thresholding has a balanced performance across the four decomposition levels, as the resulting image after denoising is a detail-preserving image despite the effective removal of noise. Finally, hybrid thresholding showed strong performance, especially at level 10, where this technique can become a compromise in the process of denoising the image, as it supports the balance between reducing noise for the image while preserving its detail.

Image Denoise Decomposition Levels	**Noisy Image**	**Denoise Image based on SURE Thresholding Technique**	**Denoise Image based on Universal Thresholding Technique**	**Denoise Image based on Hybrid Thresholding Technique**
Level 1				
Level 5				
Level10				
Level15				

Fig. 10. The output results of the LabVIEW proposed system design for Haar wavelet

Image Denoise Decomposition Levels	**Noisy Image**	**Denoise Image based on SURE Thresholding Technique**	**Denoise Image based on Universal Thresholding Technique**	**Denoise Image based on Hybrid Thresholding Technique**
Level 1				
Level 5				
Level10				
Level15				

Fig. 11. The output results of the LabVIEW proposed system design for Coif5 wavelet

6. CONCLUSION

This study emphasizes the benefits of employing the Undecimated Wavelet Transform (UWT) for the purpose of image denoising. Key advantages include substantial noise reduction, preservation of edge details, and improved texture representation, all of which collectively enhance the overall quality of the image. The utilization of MATLAB for the computation of Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) facilitates precise performance assessment, streamlines the evaluation process, and supports the optimization and visualization of denoising outcomes. The analysis indicates that specific wavelets, namely bior2_4, bior4_4, and coif5, yield optimal MSE results for this task, while wavelets such as Haar and sym2 should be avoided when high accuracy and minimized error are paramount. This investigation underscores the criticality of selecting the appropriate wavelet contingent upon the application demands, as well as the inherent trade-off between computational complexity and reconstruction accuracy.

Moreover, the integration of UWT with LabVIEW enhances the implementation process, enabling real-time processing and facilitating flexible adjustments of parameters. It is noteworthy that different UWT variants and thresholding methods exhibit considerable disparities in computational efficiency for image denoising. Of these, SURE thresholding is identified as the most computationally intensive, particularly at elevated decomposition levels, rendering it less suitable for applications requiring rapid processing. Conversely, hybrid thresholds provide a compromise between efficiency and effectiveness, while Universal thresholds are characterized by their speed and resource efficiency. The selection of an appropriate wavelet and thresholding technique is contingent upon the specific objectives of the task, necessitating a careful balance between processing duration and the quality of noise elimination.

In Summary, the tools reviewed in this study significantly enhance the quality of real-time image denoising, rendering them both effective and user-friendly. The resultant denoised images exemplify the efficacy of the UWT-based denoising approach, particularly when utilizing SURE thresholding, demonstrating a pronounced improvement in noise reduction while preserving critical details and edges. This substantiates the practical applicability of this methodology in high-quality image processing endeavors.

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