International Transactions on Electrical Engineering and Computer Science
Koteswara Rao et.al., Vol: 4, No: 1, pp: 32-37, March 2025

Denoising of Images using Wavelet Transform

M. Koteswara Rao[1], G. Chandra Reddy[1], K. V. Rama Rao[1]

Abstract: Denoising images corrupted by noise is a critical task in image processing, where wavelet shrinkage methods have proven to be highly effective. Traditional approaches, such as the SCAD and Soft thresholding functions, are commonly used for noise suppression. This paper proposes a novel shrinkage function designed to improve the accuracy of image denoising. The proposed function is evaluated under various methods, including the Top method, Universal method, and Translation Invariant method, to handle images contaminated by additive white Gaussian noise. Performance is benchmarked against SCAD, Soft thresholding, and Wiener filter methods using Root Mean Square Error (RMSE) and Peak Signal-to-Noise Ratio (PSNR) metrics. Experimental results demonstrate that the novel shrinkage function consistently achieves superior noise reduction and image quality restoration compared to existing methods, making it a robust solution for denoising applications.

Keywords: Wavelet transform, Wavelet shrinkage denoising, Novel shrinkage function, Top method, Wiener filter and translation invariant method.

1. Introduction

Images play a critical role in various domains, including satellite communication and medical diagnostics. However, during transmission, images are often corrupted by noise, which degrades their quality and affects their usability. Effective denoising techniques are essential to restore image clarity and ensure accurate analysis at the receiver [1]. The wavelet transform has emerged as a powerful tool in signal and image processing due to its superior localization capabilities.

History
Received: 16-11-2024; Revised: 18-02-2025;
Accepted: 03-03-2025

M. Koteswara Rao
raodecs@gmail.com

[1]Department of Electronics and Communication Engineering, Chalapathi Institute of Engineering and Technology, Guntur – 522034, India

It is widely used for tasks such as noise reduction and image compression. Among wavelet-based denoising methods, thresholding techniques are particularly popular for their balance of simplicity and effectiveness. These methods aim to suppress noise while preserving the essential details and characteristics of the image [2]. This study introduces a thresholding-based wavelet denoising method designed to tackle noise contamination in images. The approach involves decomposing noisy images into wavelet coefficients using wavelet transform, applying a thresholding rule to determine the optimal threshold, and modifying the coefficients accordingly [3]. The denoised image is then reconstructed using the inverse wavelet transform. To evaluate its performance, the proposed method is applied to images with varying noise levels, types, and wavelets. Results are compared against existing techniques, highlighting the method's ability to achieve significant noise reduction while maintaining image quality [4-10].

The remaining paper is organized as follows. Section 2 presents the wavelet shrinking diagnosing, and Section 3 presents the conclusions.

https://doi.org/10.62760/iteecs.4.1.2025.125

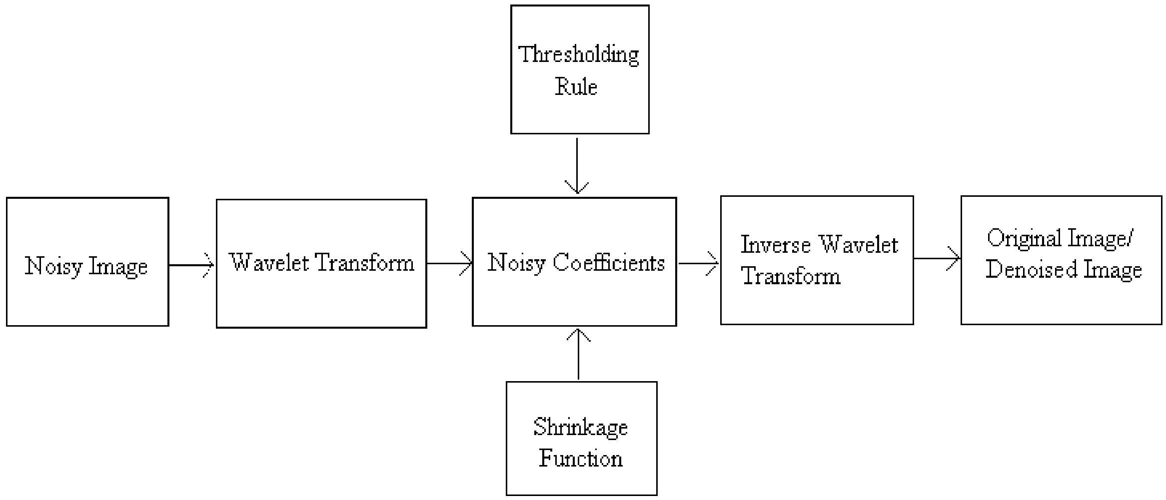

Fig. 1: Block Diagram

2. Wavelet shrinking denoising

The denoising process begins by applying the Wavelet Transform to the noisy image. This mathematical transformation decomposes the image into a set of coefficients, representing the image's low-frequency components (approximation coefficients) and high-frequency components (detail coefficients). While the approximation coefficients capture the primary structure of the image, the detail coefficients often contain noise and fine details such as edges and textures, the block diagram of the proposed method is shown in Fig. 1.

To minimize noise, a thresholding rule is employed to determine a suitable threshold value. This threshold acts as a boundary to distinguish between coefficients dominated by noise and those containing meaningful information. The detail coefficients are then modified using a thresholding filter, which selectively suppresses or eliminates coefficients below the threshold value while retaining significant data.

After modifying the detail coefficients, the Inverse Wavelet Transform (IWT) is applied. This step reconstructs the denoised image by combining the unchanged approximation coefficients and the filtered detail coefficients. The result is an image with reduced noise and preserved structural and textural details. In this study, three advanced techniques—Top Method, Universal Method, and Translation Invariant Method—are implemented to optimize the denoising process. These methods ensure robustness and adaptability across various noise levels and image types. The Symlet Wavelet is used for both the forward and inverse wavelet transforms, as its symmetry properties help minimize distortion during reconstruction and improve overall denoising performance.

To assess the quality of the denoising process, two well-known metrics are utilized: Peak Signal-to-Noise Ratio (PSNR) and Root Mean Squared Error (RMSE). PSNR indicates the clarity of the reconstructed image, while RMSE is calculated as the square root of the average squared differences between the original and reconstructed images, offering an insight into reconstruction accuracy and overall denoising quality as presented in equations (1) and (2), as below.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X(i) - \hat{X}(i)\right)^2} \quad (1)$$

$$\text{PSNR}=20\ \log_{10}\left(255/\sqrt{MSE}\right) \quad (2)$$

In this study, the denoising process is evaluated using $X(i)$the original image is $\hat{X}(i)$ is the de-noised image, with n representing the number of samples. The simulation is repeated 100 times, and the average results are considered to ensure reliability.

Table. 1: Denoising performance of coifman image using top method

Parameter	σ =10		σ =20		σ =30	
	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Noisy Image	9.9897	28.1397	19.9701	22.1232	29.8222	18.64
SCAD function	5.9938	32.5768	10.105	28.04	17.348	23.3458
Soft function	4.9952	34.1597	8.3028	29.7464	10.8504	27.4219
Novel shrinkage function	4.9935	34.1628	8.4846	29.5582	13.6977	25.3978

Table. 2: Denoising results of coifman image using universal method

Parameter	σ =10		σ =20		σ =30	
	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Noisy Image	10.0083	28.1236	19.9903	22.1144	30.0162	18.5837
SCAD function	4.4647	35.1349	7.2833	30.8842	10.0462	28.0908
Soft function	7.5863	30.5302	11.3976	26.9946	14.2223	25.0714
Novel shrinkage function	5.692	33.0255	8.5333	29.5085	11.3042	27.066

The experiments are conducted on various images, and the outcomes remain consistent across the different datasets. The implementation and simulation are carried out in a MATLAB environment. The original image is presented in Fig. 2, Fig. 3 presents the noisy image, Fig. 4 presents the estimated image using SCAD function, Fig. 5 presents the estimated image using soft function and the Fig. 6 presents the image using novel shrinkage function respectively. The denoising results are analysed for noise levels of σ=10, 20 and 30 using the Soft, SCAD, and the proposed Novel shrinkage function. These functions are evaluated under different methods, including the Top method, Universal method, Translation Invariant method, and the Wiener filter method. The comparisons highlight the performance of the novel shrinkage function across varying noise intensities and denoising techniques.

Table. 1 illustrates the denoising performance of different thresholding functions for a noisy image with σ=10\sigma = 10σ=10. The SCAD function achieves an RMSE of 5.9938 and a PSNR of 32.5768, while the soft thresholding function shows improved results with an RMSE of 4.9952 and a PSNR of 34.1597. The proposed Novel shrinkage function outperforms both, with an RMSE of 4.9935 and a PSNR of 34.1628. These results clearly demonstrate the superior performance of the novel shrinkage function in terms of both RMSE and PSNR. This trend is consistent across higher noise levels (σ=20\sigma = 20σ=20 and σ=30\sigma = 30σ=30), confirming the robustness and effectiveness of the proposed method in denoising tasks.

Table. 2, highlights the denoising performance for a noisy image at σ=10\sigma = 10σ=10 using different thresholding functions. The SCAD function achieves an RMSE of 4.4647 and a PSNR of 35.1349, while the soft thresholding function shows a higher RMSE (7.5863) and lower PSNR (30.5302), indicating reduced effectiveness. In contrast, the Novel shrinkage function achieves an RMSE of 5.6920 and a PSNR of 33.0255, outperforming the soft thresholding function. These results demonstrate that the Novel shrinkage function provides better denoising performance than soft thresholding. A similar pattern of improved performance is observed for higher noise levels (σ=20\sigma = 20σ=20 and σ=30\sigma = 30σ=30), further validating the robustness of the proposed method.

Table. 3: Denoising results of coifman image using translation variant method

Parameter	σ =10		σ =20		σ =30	
	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Noisy Image	10.0361	28.0995	19.9761	22.1206	30.0756	18.5665
SCAD function	6.1247	32.3891	9.0033	29.0428	10.3005	27.8736
Soft function	7.2772	30.8915	9.9589	28.1666	12.1021	26.4736
Novel shrinkage function	4.335	35.391	7.4676	30.6672	9.9818	28.1466

Table. 4: Denoising results of coifman image, using wiener filter method

Parameter	σ =10		σ =20		σ =30	
	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Noisy Image	10.0038	28.1275	20.0108	22.1055	30.1656	18.5406
Weiner filter	3.7892	36.5599	5.5404	33.26	6.8255	31.4481

Table. 3 show cases the denoising performance for a noisy image at σ=10\sigma = 10σ=10 using different thresholding functions.

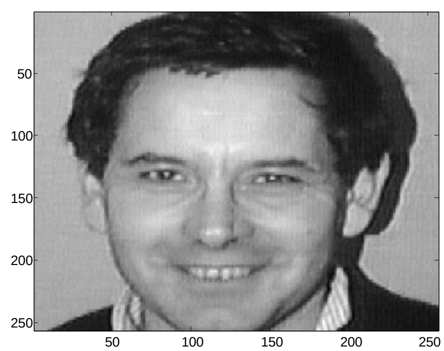

Fig. 2: Original image

Fig. 3: Noisy image (σ=30)

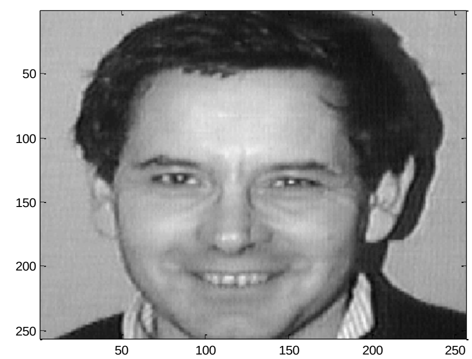

Fig. 4: Estimated image using SCAD function

Fig. 5: Estimated image using soft function

The SCAD function achieves an RMSE of 6.1247 and a PSNR of 32.3891, while the soft thresholding function results in an RMSE of 7.2772 and a PSNR of

30.8915, indicating less effective denoising. In contrast, the Novel shrinkage function achieves superior results with an RMSE of 4.3350 and a PSNR of 35.3910, outperforming both the SCAD and Soft thresholding functions. This trend of improved performance with the Novel shrinkage function is consistently observed for higher noise levels (σ=20\sigma = 20σ=20 and σ=30\sigma = 30σ=30), further affirming its effectiveness and robustness in image denoising tasks. Table. 4, presents the results for wiener filter method.

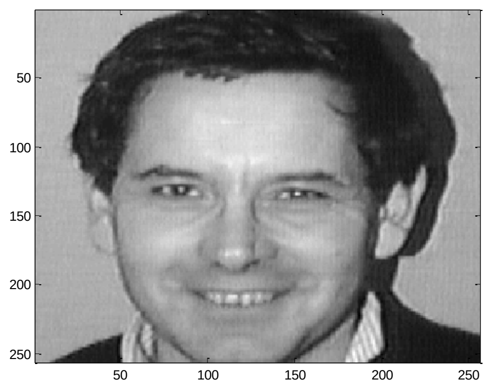

Fig. 6: Estimated image using novel shrinkage function

3. Conclusion

This paper introduces a new shrinkage function designed for wavelet-based image denoising. The proposed method is tested using the Coifman image, and its performance is benchmarked against established techniques, including the SCAD function, the soft thresholding approach, and the Wiener filter. The analysis reveals that the proposed shrinkage function demonstrates superior performance compared to the SCAD and Soft thresholding methods, particularly when combined with the Translation Invariant and Top strategies. It also shows superior performance compared to the soft function in the Universal method and outperforms the Wiener filter method. The proposed novel shrinkage function is initially applied to denoising black and white images. In the future, this method has the potential to be extended to color images and videos, offering broader applicability for image and video denoising tasks.

Conflict of interest

The authors declared 'No conflict of interest'.

References

[1] B. Mantosh, and H. Om "A new soft-thresholding image denoising method", *Procedia Technology*, Vol. 6, pp. 10-15, 2012. https://doi.org/10.1016/j.protcy.2012.10.002

[2] H. H. Cho, S. H. Kim, T. K. Cho and M. R. Choi, "Efficient image enhancement technique by decimation method", *IEEE Transactions on Consumer Electronics*, Vol. 51, No. 2, pp. 654-659, 2005. https://doi.org/10.1109/TCE.2005.1468015

[3] K. Mallaparapu, B. A. Krishna, S. Masthan and D. Susmitha "Analysis of denoising on different signals using new thresholding function", *2018 Conference on Signal Processing And Communication Engineering Systems (SPACES)*, Vijayawada, India, pp. 154-162, 2018. https://doi.org/10.1109/SPACES.2018.8316336

[4] M. Koteswararao, VVKDV Prasad "Decimated and Undecimated Wavelet Transforms Based Estimation of Images", *International Journal of Innovative Research in Science, Engineering and Technology*, Vol. 3, No. 10, pp. 16981-16988, 2014. https://doi.org/10.15680/IJIRSET.2014.0310080

[5] K. Kumar, L. Varshney, A. Ambikapathy, K. Malik, K. Vanshika and A. Vats "Image Denoising by Wavelet Based Thresholding Method", *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, Greater Noida, India, pp. 63-73, 2022. https://doi.org/10.1109/ICACITE53722.2022.9823415

[6] A. E. Rodrigo, H. Dore, and E. R. Morales "An experimental method for bio-signal denoising using unconventional sensors", *Sensors*, Vol. 23, No. 7, art. no. 3527, 2023. https://doi.org/10.3390/s23073527

[7] M. AlMahamdy and H. B. Riley "Performance study of different denoising methods for ECG signals", *Procedia Computer Science*, Vol. 37, pp. 325-332, 2014. https://doi.org/10.1016/j.procs.2014.08.048

[8] A. Sharma and A. Khunteta "Satellite Image Enhancement using Discrete Wavelet Transform, Singular Value Decomposition and its Noise Performance Analysis", *2016 International Conference on Micro-Electronics and*

Telecommunication Engineering (ICMETE), Ghaziabad, India, pp. 594-599, 2016. https://doi.org/10.1109/ICMETE.2016.32

[9] M. E. Alexander, R. Baumgartner, A. R. Summers, C. Windischberger, M. Klarhoefer, E. Moser, and R. L. Somorjai "A wavelet-based method for improving signal-to-noise ratio and contrast in MR images", *Magnetic Resonance Imaging*, Vol. 18, No. 2, pp. 169-180, 2000. https://doi.org/10.1016/S0730-725X(99)00128-9

[10] X. H. Wang, R. S. H. Istepanian and Yong Hua Song "Microarray image enhancement by denoising using stationary wavelet transform", in *IEEE Transactions on NanoBioscience*, Vol. 2, No. 4, pp. 184-189, 2003. https://doi.org/10.1109/TNB.2003.816225

***