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# Histogram-Based Hybrid Wavelet-Curvelet Denoising for Medical Images

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**ABSTRACT**

Medical images often contain noise that degrades image quality and obscures important diagnostic details. This paper proposes a histogram-based hybrid denoising method that integrates Wavelet Transform and Curvelet Transform to enhance medical image clarity. The wavelet transform is utilized for efficient noise suppression in high-frequency components, while the curvelet transform effectively preserves edge information and directional features. A histogram-based adaptive fusion strategy is employed to combine the outputs of both transforms by analyzing intensity distribution and local image characteristics. The proposed method is implemented using MATLAB and evaluated on various medical images. Performance is assessed using quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Experimental results demonstrate that the proposed hybrid approach outperforms conventional denoising techniques by achieving higher PSNR and SSIM values, along with improved visual quality. The enhanced images retain critical structural details, making the method suitable for reliable pre-diagnostic analysis and medical image interpretation.

**Key Words**

***Medical Image Processing, Image Denoising, Wavelet Transform, Curvelet Transform, Histogram Analysis, Hybrid Image Enhancement, PSNR, SSIM.***

## I.INTRODUCTION

Medical imaging has become an essential component of modern healthcare systems, playing a vital role in disease diagnosis, treatment planning, and clinical analysis. Imaging modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and X-ray provide detailed insights into internal body structures. However, the quality of medical images is often degraded by noise during image acquisition, transmission, and storage processes. The presence of noise reduces image clarity and obscures critical details, which may lead to inaccurate diagnosis and affect clinical decision-making. Therefore, effective image denoising is a crucial step in medical image processing.

Traditional image denoising methods primarily rely on spatial filtering techniques such as mean filtering, median filtering, and Gaussian filtering. Although these methods are simple and computationally efficient, they often result in loss of important image features such as edges, textures, and fine structural details. This limitation makes them less suitable for medical applications where preservation of anatomical structures is highly important. These challenges highlight the need for advanced denoising techniques that can effectively remove noise while preserving essential image information.

Recent advancements in transform-domain techniques have significantly improved the performance of image denoising methods. Among these, Wavelet Transform has been widely used due to its ability to decompose images into multiple resolution levels and separate noise components from useful signal information. However, wavelet-based methods have limitations in capturing directional and curved features present in medical images. To overcome this issue, Curvelet Transform has been introduced, which provides an efficient representation of edges and curved structures, making it more suitable for preserving important image features.

In this context, this paper presents a histogram-based hybrid denoising approach that combines the advantages of Wavelet Transform and Curvelet Transform. The proposed method utilizes histogram analysis to evaluate the intensity distribution of the image and guide an adaptive fusion mechanism. The outputs obtained from wavelet and curvelet processing are combined using adaptive weights to achieve optimal noise reduction and feature preservation. The entire algorithm is implemented using MATLAB, enabling efficient processing and visualization of results.

The proposed system is designed to enhance medical image quality while maintaining important structural details required for accurate analysis. It provides improved performance in terms of noise suppression, contrast enhancement, and edge preservation. The method can be applied in various medical imaging applications, including diagnostic imaging, clinical research, and computer-aided diagnosis systems. By improving image quality and interpretation accuracy, the proposed approach contributes to more reliable and effective healthcare solutions.

## II. LITERATURE REVIEW

Medical image denoising has gained significant attention due to its critical role in improving image quality and supporting accurate diagnosis. Traditional denoising methods based on spatial filtering techniques such as mean, median, and Gaussian filters are simple and widely used; however, they are often unable to preserve important image features and tend to blur edges and fine details. These limitations have led researchers to explore transform-domain approaches for more effective noise reduction.

Previous studies have shown that Wavelet Transform is a powerful tool for image denoising, as it decomposes the image into multiple frequency components and effectively separates noise from useful signal information. Wavelet-based thresholding techniques have been widely adopted due to their ability to reduce noise while maintaining overall image structure. However, wavelets have limitations in capturing directional features and curved edges, which are commonly present in medical images.

To address this limitation, Curvelet Transform has been introduced as an advanced multi-scale and multi-directional technique that provides better representation of edges and curved structures. It has been successfully applied in medical image processing to enhance structural details and improve visual quality. By capturing geometric features more efficiently, curvelet transform complements the shortcomings of wavelet-based methods.

Recent research has focused on hybrid approaches that combine multiple transforms to achieve improved denoising performance. In addition, histogram-based techniques have been used to analyze intensity distribution and enhance contrast in medical images. Adaptive fusion strategies have also been explored to combine the outputs of different denoising methods based on local image characteristics, thereby improving overall image quality.

Although existing methods demonstrate effective noise reduction, many approaches either fail to preserve fine structural details or involve complex processing techniques. The proposed method addresses these limitations by integrating wavelet and curvelet transforms with histogram-based adaptive fusion. This combination enables efficient noise suppression, enhanced edge preservation, and improved contrast, resulting in superior denoising performance suitable for medical image analysis.

### III. PROPOSED SYSTEM

The proposed system is a medical image denoising framework designed to enhance image quality by effectively removing noise while preserving important structural details. As illustrated in the block diagram, the system integrates histogram analysis with hybrid transform-based techniques to achieve improved denoising performance. The entire processing pipeline is implemented using MATLAB, which serves as the primary platform for image processing, analysis, and visualization. The input to the system consists of medical images such as MRI or CT scans, which are often degraded by noise during acquisition or transmission.

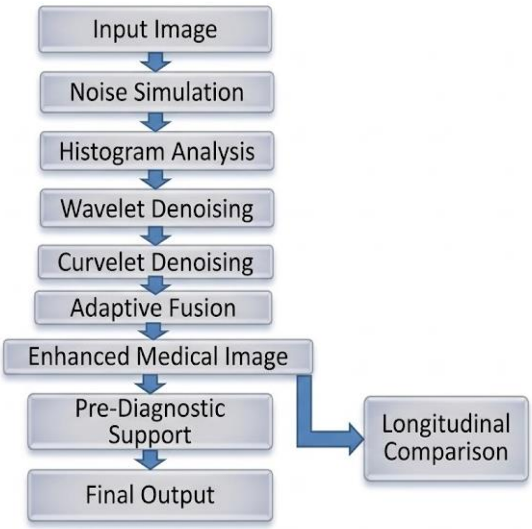


**Fig. 1** – Block Diagram

Initially, the input image undergoes pre processing, where it is converted into gray scale (if required) and filtered using suitable techniques to remove basic noise components. This step ensures that the image is prepared for further analysis and transformation. Following pre processing, histogram analysis is performed to examine the intensity distribution of the image. The histogram provides valuable information about contrast levels and pixel distribution, which is further utilized in guiding the adaptive fusion process. The histogram output can be visualized as a graph, as shown in Fig.1, representing the frequency distribution of pixel intensities. This analysis helps in identifying suitable enhancement strategies and improves the overall effectiveness of the denoising process.

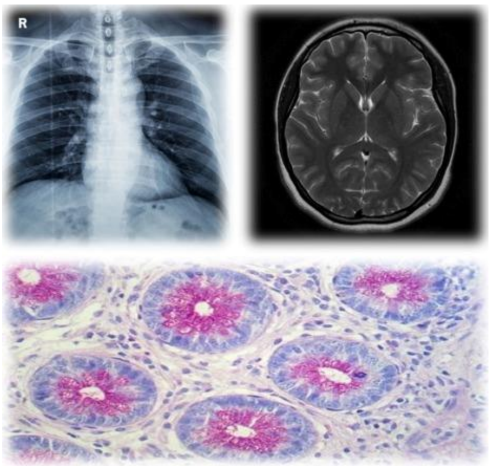

**Fig. 2** – Input Medical Image

After histogram analysis, the image is processed using Wavelet Transform, which decomposes the image into multiple frequency sub-bands. This decomposition enables efficient separation of noise from useful signal components, particularly in high-frequency regions. The wavelet-based denoised image retains the overall structure while significantly reducing noise levels. The corresponding output of the wavelet transform can be included as Fig.2 to illustrate the intermediate result.

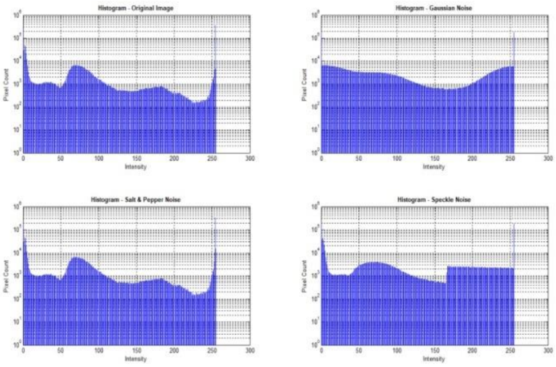


**Fig. 3** – Histogram Output

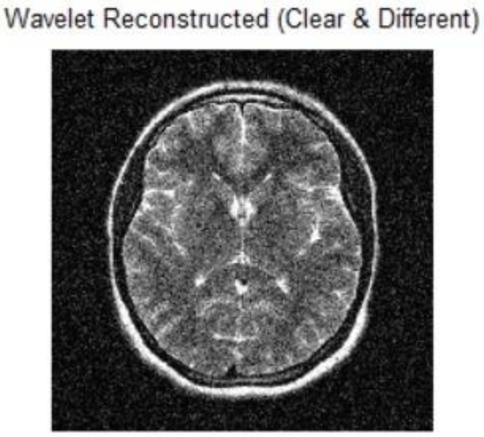


**Fig. 4** – Wavelet Output

Subsequently, Curvelet Transform is applied to further enhance the image by preserving edges and directional features. Unlike wavelets, curvelets are highly effective in representing curved structures and fine details present in medical images. This step improves edge continuity and enhances structural information, which is crucial for accurate medical interpretation. The curvelet-processed image can be presented as Fig.3, highlighting improved edge representation.

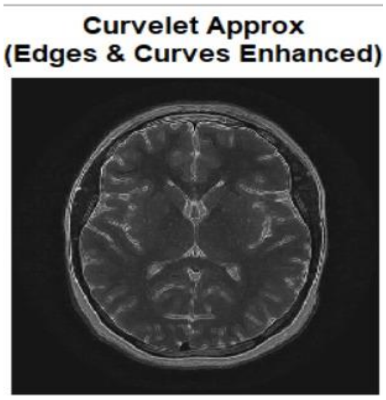


**Fig. 4** – Curvelet Output

The outputs obtained from wavelet and curvelet processing are then combined using a histogram-based adaptive fusion mechanism. In this stage, adaptive weights are assigned based on intensity distribution and local image characteristics, ensuring that both noise suppression and feature preservation are optimally balanced. The fusion process generates a final denoised image with enhanced clarity, contrast, and structural integrity. The final output image can be included as Fig.4, demonstrating the effectiveness of the proposed method.

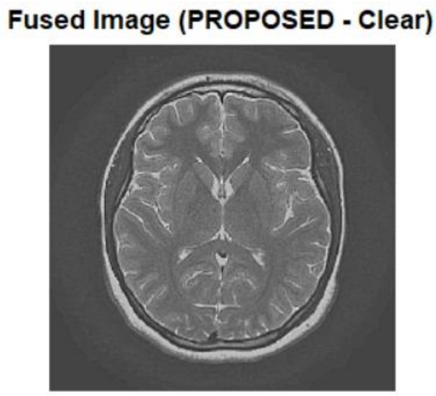


**Fig. 6** – Final Denoised Image

The proposed system is designed to provide improved denoising performance compared to conventional methods by integrating multi-stage processing and adaptive techniques. It supports accurate visualization of medical images and assists in better pre-diagnostic analysis. The modular structure of the system allows easy implementation and extension for advanced image processing applications. By combining preprocessing, histogram analysis, transform-based denoising, and adaptive fusion, the system achieves a reliable and efficient solution for medical image enhancement.

Additionally, the enhanced output generated by the proposed system supports effective pre-diagnostic analysis by providing clearer visualization of anatomical structures, enabling better identification of abnormalities such as tumors, lesions, and tissue variations. The improved image quality assists

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medical professionals in making more accurate and reliable preliminary assessments before detailed clinical diagnosis, as illustrated in Fig. 7**.**

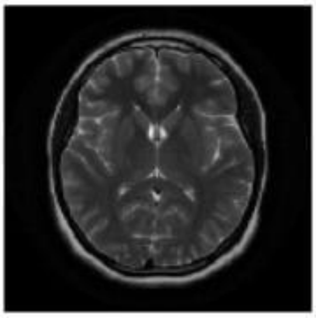

**Fig. 7** – Pre-Diagnostic Enhanced Image

Further analysis can be performed by focusing on specific regions of interest (ROI) within the medical image, where critical features are more prominent. This allows detailed examination of localized structures and improves the accuracy of interpretation, as shown in Fig. 8**.**

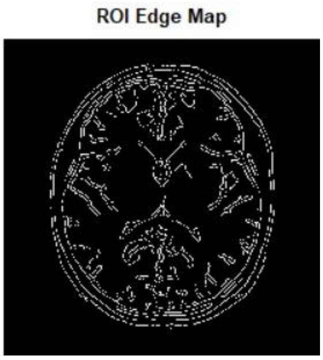


**Fig. 8** – Region of Interest (ROI) Analysis

The proposed system also facilitates longitudinal comparison by enabling analysis of medical images captured at different time intervals. By comparing these images, it becomes easier to observe structural changes, disease progression, or treatment response over time, as depicted in Fig. 9**.**

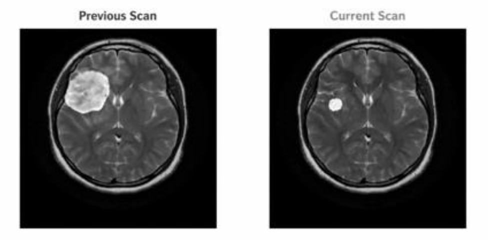


**Fig. 9** – Longitudinal Comparison (Time-Series Images)

To highlight the effectiveness of the denoising and enhancement process, a difference image can be generated by comparing the original and processed images. This helps visualize the extent of noise removal and feature enhancement, as presented in Fig. 10**.**

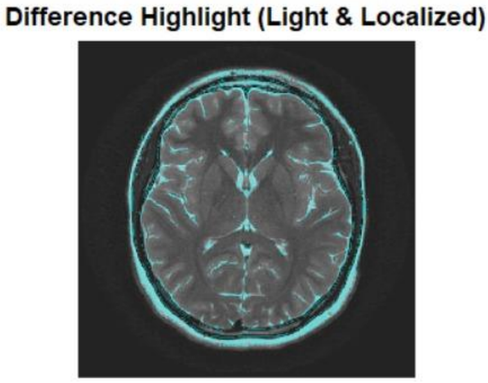


**Fig. 10** – Difference Image

Edge preservation is a critical factor in medical image processing, as it directly affects the visibility of important structures. The proposed method maintains edge continuity and sharpness, which can be analyzed and verified through edge detection results, as shown in Fig. 11

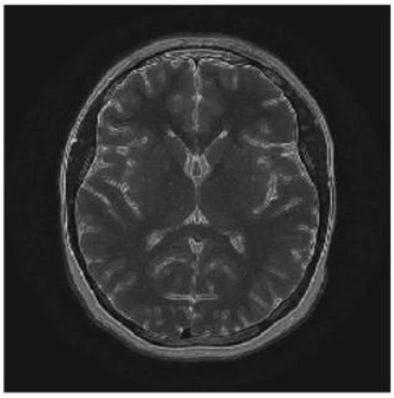

**Fig. 11** – Edge Preservation Analysis

Finally, a comprehensive comparison of different denoising methods, including the proposed hybrid approach, can be visualized to demonstrate performance improvements in terms of clarity, contrast, and detail preservation, as illustrated in **Fig. 12**

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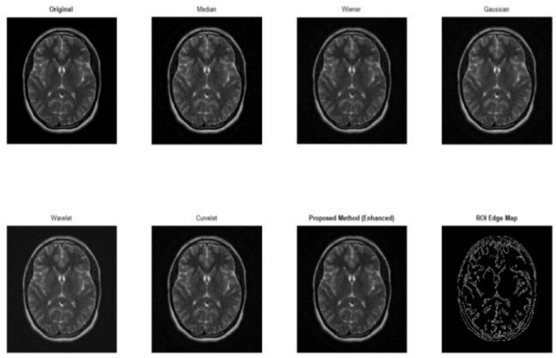


**Fig. 12** – Final Comparative Visualization of Methods

## VI. RESULTS

The proposed histogram-based hybrid wavelet–curvelet denoising system was successfully implemented and evaluated for enhancing medical image quality. The system effectively processed input medical images and produced denoised outputs with improved clarity and structural preservation. Significant reduction in noise levels was observed after applying wavelet and curvelet transforms, while important features such as edges and fine details were well maintained. Histogram analysis further contributed to improved contrast and intensity distribution, enabling better visualization of anatomical structures.

The adaptive fusion mechanism played a key role in combining the advantages of both transforms, resulting in superior denoising performance compared to conventional methods. The final enhanced images demonstrated improved visual quality, making them more suitable for pre-diagnostic analysis and interpretation. Intermediate outputs such as histogram distribution, wavelet-processed images, and curvelet-enhanced images confirmed the effectiveness of each processing stage.

The performance of the proposed method was quantitatively evaluated using metrics such as Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). The results, as presented in **Table 1**, indicate that the proposed hybrid approach achieves higher PSNR and SSIM values along with lower MSE compared to traditional filtering and individual transform methods. These improvements confirm the effectiveness of the proposed system in achieving better noise suppression and feature preservation.

Overall, the system demonstrated reliable performance with consistent results across different medical images. The combination of histogram analysis, transform-based denoising, and adaptive fusion provides an efficient and robust solution for medical image enhancement, making it suitable for clinical and research applications.

| FILTERS | PSNR | SSIM |
|---|---|---|
| Median Filter | 31.07 dB | 0.6577 |
| Wiener Filter | 30.34 dB | 0.6014 |
| Gaussian Filter | 30.55 dB | 0.5693 |
| Wavelet Only | 21.89 dB | 0.4560 |
| Curvelet Only | 28.75 dB | 0.5378 |
| Proposed Method | 31.69 dB | 0.6699 |

## VII. CONCLUSION

This work successfully demonstrates the design and implementation of a histogram-based hybrid wavelet–curvelet denoising system for enhancing medical image quality. By integrating wavelet transform for effective noise suppression, curvelet transform for preserving edge and directional features, and histogram-based adaptive fusion for optimal combination, the proposed method achieves improved image clarity and structural preservation. The system effectively reduces noise while maintaining important anatomical details, making the enhanced images suitable for accurate pre-diagnostic analysis. The implementation using MATLAB ensures efficient processing and visualization of results. The proposed approach provides a reliable and efficient solution for medical image enhancement in clinical and research applications. Furthermore, the modular framework allows easy extension with advanced techniques such as machine learning and deep learning models for further improvement in denoising performance and automated medical image analysis.

**REFERENCES**

[1] R. C. Gonzalez and R. E. Woods, Digital Image Processing, Pearson, 2018.This reference provides fundamental concepts of image processing including filtering, histogram analysis, and enhancement techniques. It supports the basic image processing steps used in this work.

[2] S. Mallat, A Wavelet Tour of Signal Processing, Academic Press, 2009. This book explains wavelet transform theory and its applications in signal and image denoising. It supports the use of wavelet transform for noise reduction.

[3] E. J. Candès and D. L. Donoho, “Curvelets—A surprisingly effective nonadaptive representation for objects with edges,” Stanford University, 2000. This paper introduces the curvelet transform and its effectiveness in representing edges and curved structures. It supports the use of curvelet transform for preserving image features.

[4] A. Le Pogam et al., “Denoising of PET images by combining wavelets and curvelets for improved preservation of resolution and quantitation,” Medical Image Analysis, 2013

[5] M. Unser, “Wavelet theory demystified,” IEEE Transactions on Signal Processing, vol. 44, no. 7, pp. 1840 – 1855, 1996. This work explains the theoretical foundation of wavelet-based processing. It supports the implementation of wavelet-based denoising techniques.

[6] D. L. Donoho, “De-noising by soft-thresholding,” IEEE Transactions on Information Theory, 1995. This paper presents thresholding techniques for noise removal in transform domains. It supports the noise suppression approach used in wavelet processing.

[7] J. Starck, E. Candès, and D. Donoho, “The curvelet transform for image denoising,” IEEE Transactions on Image Processing, 2002. This study demonstrates the application of curvelet transform in image denoising. It supports the hybrid transform approach used in this work.

[8] R. C. Gonzalez, R. E. Woods, and S. L. Eddins, Digital Image Processing Using MATLAB, Pearson, 2004.This reference provides practical implementation details using MATLAB. It supports the development and simulation of the proposed system.

[9] Research articles available in IEEE Xplore. This source provides access to recent research papers related to medical image denoising and hybrid transform techniques. It supports the overall research and comparative analysis.