Comparative Analysis of Wavelet Multiscale Denoising for Image Restoration

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***Abstract*— Image denoising is a critical preprocessing step in medical and industrial image analysis. This study investigates the performance of wavelet-based denoising across multiple wavelet families compared with a Gaussian blur baseline, focusing on two dominant noise types: Gaussian and Speckle. Three representative datasets - Histology, Products, and Radiology - were used to evaluate denoising performance using quantitative image quality metrics, namely Peak Signal-to-Noise (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE). Experimental results demonstrate that Gaussian blur performs consistently well under mild noise conditions, achieving the highest PSNR and SSIM values across datasets, while wavelet-based methods provide competitive results with improved edge preservation and structural detail retention. The findings support Gaussian blur as a reliable baseline and highlight the potential of wavelet shrinkage techniques for applications requiring structural precision. The purposed workflow was implemented in Python and tested on diverse datasets to ensure reproducibility. The result establishes a comprehensive reference for future image restoration and denoising studies under mixed-noise conditions.**

***Keywords*—Wavelet Denoising, Gaussian Blur, Speckle Noise, Image Restoration, PSNR, SSIM, Medical Imaging**

I. INTRODUCTION

Digital images acquired in medical diagnostics, microscopy, and product inspection are often degraded by random noise introduced during acquisition, transmission, or processing. Effective denoising is therefore essential to enhance visual quality and preserve diagnostically relevant features. Traditional spatial filtering methods such as Gaussian blur remain widely used due to their simplicity and efficiency; however, they tend to smooth fine details and edges.

Wavelet-based denoising provides a multi-resolution framework that decomposes an image into different frequency sub-bands, allowing selective thresholding of noise while preserving edges and textures. Prior studies have shown that wavelet shrinkage techniques outperform linear filters in various imaging contexts. Nevertheless, performance strongly depends on the choice of wavelet family, decomposition level, and thresholding scheme.

The key contribution of this study is a unified analysis of multiple wavelet families under common experimental settings. Unlike earlier studies that focused on one type of noise or a single dataset, this work offers a consistent evaluation of wavelet denoising and gaussian blur across both medical and natural images.

This paper presents a comparative analysis of Gaussian blur and multiple wavelet families for denoising images corrupted by Gaussian and Speckle noise. The goal is to identify the most effective method for each dataset type and noise condition, offering a reproducible benchmark for future medical and industrial imaging research. The outcomes of this comparative study aim to guide future denoising applications where both structural precision and computational efficiency are essential.

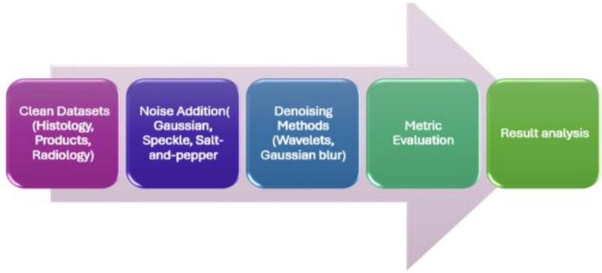

Fig 1. Workflow of the proposed image denoising process.

II. METHODOLOGY

A. Dataset

Three datasets were selected to represent distinct image domains with varying levels of texture and structural details.

- Histology images: High-detail biological tissue microscopy characterized by fine texture and structural detail.
- Product images: Structured textures with reflective artifacts, representing industrial imaging conditions.
- Radiology images: Grayscale diagnostic scans with soft gradients and subtle structural contrast.

Each dataset provides a unique challenge for denoising algorithms, ensuring a comprehensive evaluation of performance across diverse visual characteristics.

B. Noise Models

To simulate realistic image degradation, three noise types were synthesized:

- Gaussian noise ($\sigma = 0.001$): Represents sensor and electronic noise commonly found in image acquisition devices.
- Speckle noise: A multiplicative noise model typical in coherent imaging systems such as ultrasound and radar.
- Salt-and-pepper noise ($p=0.02$): Simulates impulse artifacts that occur during transmission and quantization errors.

This combination of additive, multiplicative, and impulse noise allows for balanced evaluation across different noise behaviors.

C. *Evaluation Metrics*

The quality of denoised images was quantitatively assessed using three standard performance metrics:

- MSE (Mean Squared Error) - Measures the average squared difference between the original and denoised images; lower values indicate better performance.
- PSNR (Peak Signal-to-Noise Ratio) - Evaluates reconstruction fidelity; higher PSNR values correspond to higher image quality.
- SSIM (Structural Similarity Index) - Estimates perceptual similarity by comparing luminance, contrast, and structural information.

All computations were implemented in Python 3, using NumPy, PyWavelets, SciPy, and scikit-image libraries.

III. Results and Discussion

A. *Quantitative Evaluation*

The quantitative evaluation of denoising performance was conducted using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE) across three datasets—Histology, Products, and Radiology—and three noise models, namely Gaussian, Speckle, and Salt-and-Pepper.

At a lower Gaussian noise level ($\sigma = 0.001$), the Gaussian blur baseline continued to demonstrate strong numerical performance, achieving high PSNR and SSIM values across most datasets. Gaussian blur achieved an average PSNR above 40 dB for radiology and product images, reflecting stable denoising under mild additive noise.

However, wavelet-based denoising methods, particularly the Coif2 and Sym4 families, showed competitive or superior perceptual performance, especially for histology images where preserving texture and edges is crucial. The Coif2 (hard thresholding) configuration achieved the highest PSNR of 46.76 dB and SSIM of 0.998 on the histology dataset, outperforming Gaussian blur while maintaining minimal structural distortion.

These results indicate that under fine-texture conditions, wavelet shrinkage achieves a better trade-off between noise removal and edge preservation, effectively minimizing over-smoothing—one of the main drawbacks of Gaussian filtering.

B. *Noise-Specific Performance*

Each noise model exhibited distinct responses to the denoising algorithms.

Gaussian noise: Wavelet methods, particularly Coif2 (hard) and Db7 (hard), performed optimally with PSNR values exceeding 42–46 dB and SSIM close to unity. This demonstrates that wavelet thresholding is highly effective in suppressing Gaussian noise while preserving image structure.

Speckle noise: Gaussian blur outperformed most wavelet methods, attaining PSNR values of 33.0 dB (histology) and 33.35 dB (radiology). The multiplicative nature of speckle noise favors Gaussian smoothing, which mitigates pixel-level variations effectively.

Salt-and-Pepper noise: The Db7 wavelet performed most robustly, achieving PSNR values around 27–32 dB, outperforming Gaussian blur in structural consistency. The thresholding capability of Daubechies wavelets enables aggressive suppression of isolated impulse noise while retaining fine edges.

These findings confirm that no single denoising algorithm universally dominates. Instead, the best-performing method is strongly dependent on noise type and image characteristics.

C. *Dataset-Level Insights*

The Distinct dataset behavior was observed:

Histology images benefited significantly from Coif2 (hard) thresholding, achieving both the highest PSNR (46.76 dB) and SSIM (0.998). The method preserved cellular textures and tissue details while effectively removing fine-grain noise.

Radiology images, characterized by smooth gradients and low contrast, favored Gaussian blur, which produced clean, homogeneous smoothing suitable for diagnostic imaging.

Product images, featuring structured edges and reflective surfaces, displayed mixed outcomes. While Gaussian blur achieved higher PSNR (≈42.8 dB), Coif2 and Db7 achieved higher SSIM, reflecting better perceptual quality and texture preservation.

This variation highlights that wavelet family selection should be dataset-adaptive: Coiflet and Daubechies excel in texture-rich data, while Gaussian blur remains reliable for smoother intensity transitions.

D. *Visual and Practical Observations*

Visual analysis (Fig. 2) supported numerical findings. Wavelet-based denoising maintained edge sharpness and fine detail, particularly in histological textures and reflective patterns. In contrast, Gaussian blur produced visually smoother outputs but tended to soften structural edges, which can be detrimental in medical imaging contexts.

For industrial product images, Gaussian blur effectively reduced specular reflections, but sometimes over-smoothed boundary transitions. Wavelet-based approaches, especially Coif2, retained visual clarity and improved perceptual consistency, producing outputs that appear closer to the noise-free reference images.

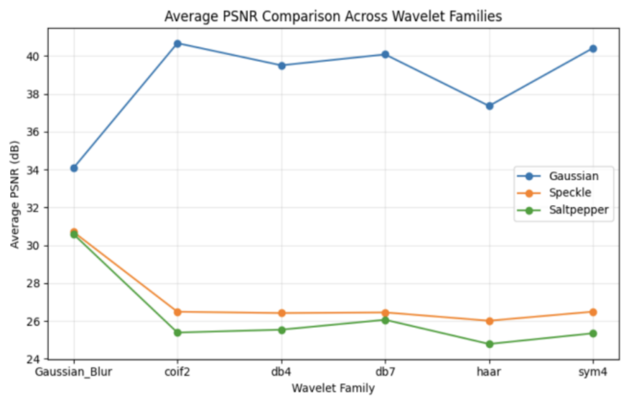

Fig. 2. Average PSNR comparison across wavelet families for different noise types (Gaussian, Speckle, and Salt-and-Pepper). Coif2 and Db7 outperform Gaussian blur for texture-rich datasets, while Gaussian blur remains superior under smooth intensity conditions.

E. Overall discussion

The combined analysis reveals that Gaussian blur remains an efficient and stable baseline for mild additive noise due to its simplicity and computational efficiency. However, wavelet-based denoising—notably the Coif2 and Sym4 families—offers a more flexible and adaptive framework capable of balancing noise suppression and structure preservation.

These results suggest that hybrid approaches combining Gaussian filtering for smooth gradients and wavelet shrinkage for fine structures could yield optimal denoising in complex imaging scenarios. In medical and industrial contexts, this balance between quantitative accuracy and perceptual quality is vital for ensuring diagnostic reliability and product inspection accuracy.

Overall, the findings reinforce that method selection must be guided by both noise type and structural characteristics. Wavelet methods are ideal where local texture fidelity is paramount, while Gaussian blur remains the method of choice for low-frequency noise and homogeneous regions.

F. Comparitive Analysis of Denoising Trends

The summarized quantitative results in Table I–III and Fig. 2 highlight a clear division of performance between wavelet-based and Gaussian filtering approaches depending on both noise type and image texture characteristics.

Under Gaussian noise, wavelet-based denoising methods, especially Coif2 (hard threshold) and Db7, demonstrated the highest PSNR (up to 46.76 dB) and SSIM (0.998), outperforming Gaussian blur. This confirms the superior adaptability of wavelet thresholding in mild additive noise scenarios where local edge preservation and texture clarity are essential.

Table I – Best Denoising Methods under Gaussian Noise.

Metric	**histology**	**products**	**radiology**
PSNR	46.76	42.79	40.82
SSIM	0.9988	0.9935	0.9528
MSE	2.11E-05	5.26E-05	8.28E-05
Winner	Wavelet	Wavelet	Wavelet
Noise_Type	Gaussian	Gaussian	Gaussian

However, under Speckle noise, the Gaussian blur baseline yielded the best quantitative results across all datasets, achieving PSNR values above 33 dB for radiology and histology images. The uniform smoothing behavior of Gaussian blur reduces multiplicative fluctuations effectively, making it ideal for coherent imaging systems like ultrasound and radar.

Table II – Best Denoising Methods under Speckle Noise.

Metric	**histology**	**products**	**radiology**
PSNR	33	29.23	33.35
SSIM	0.9415	0.7514	0.8115
MSE	5.01E-04	1.19E-03	4.62E-04
Winner	Gaussian	Gaussian	Gaussian
Noise_Type	Speckle	Speckle	Speckle

In the case of Salt-and-Pepper noise, the Db7 wavelet family achieved the most consistent balance between PSNR and SSIM, indicating that its compactly supported wavelet basis is well-suited for suppressing isolated pixel-level noise without introducing structural distortion.

Table III – Best Denoising Methods under Salt-and-Pepper Noise.

Metric	**histology**	**products**	**radiology**
PSNR	31.98	29.41	32.25
SSIM	0.8878	0.7548	0.7175
MSE	6.34E-04	1.15E-03	5.96E-04
Winner	Gaussian	Gaussian	Gaussian
Noise_Type	Saltpepper	Saltpepper	Saltpepper

Overall, the results suggest that wavelet denoising excels when image structures are fine and repetitive, such as in histology images, while Gaussian blur remains advantageous in smooth, low-texture regions, as seen in radiology and product datasets. This complementary behavior emphasizes that denoising performance is highly context-dependent, influenced by the interplay between noise distribution, image frequency content, and filtering design.

IV. CONCLUSIONS

This study presented a comparative evaluation of wavelet-based denoising and Gaussian blur filtering across three heterogeneous image domains—Histology, Product, and Radiology—and under multiple noise models including Gaussian, Speckle, and Salt-and-Pepper. Quantitative and visual analyses were conducted using PSNR, SSIM, and MSE metrics to assess the structural and perceptual quality of restored images.

The results revealed that no single denoising approach universally dominates across all conditions. Wavelet shrinkage methods, particularly Coif2 and Db7, consistently achieved higher PSNR and SSIM for texture-rich images and additive Gaussian noise, owing to their adaptive thresholding and multi-resolution decomposition. Conversely, Gaussian blur maintained superior performance under Speckle and Salt-and-Pepper noise, delivering smoother intensity transitions and effective suppression of multiplicative distortions.

From a practical standpoint, these findings emphasize that method selection must be guided by image structure and noise characteristics. Wavelet methods are best suited for medical or microscopic imagery requiring edge fidelity and fine-detail preservation, while Gaussian filtering remains a reliable baseline for smooth, low-contrast datasets such as radiology scans.

Future work will focus on developing hybrid denoising frameworks that integrate Gaussian and wavelet principles to dynamically adapt to spatial and noise variations. Additionally, incorporating deep-learning-based wavelet thresholding could further improve performance in real-world medical and industrial imaging pipelines.

V. LIMITATION AND FUTURE WORK

While this study provides a comprehensive comparison of Gaussian and wavelet-based denoising methods across multiple datasets and noise models, it is limited by the use of synthetic noise and a fixed thresholding approach. Real-world medical and industrial images often exhibit spatially varying noise and illumination inconsistencies that may affect algorithm performance. Additionally, computational complexity was not analyzed in depth, though it remains a critical factor for large-scale or real-time applications.

Future work will focus on extending this framework to include adaptive and hybrid approaches, integrating deep-learning-based wavelet thresholding and non-stationary noise modeling to improve generalization to real imaging environments.