

Noise Removal in Images Using Non-Local Means Filter and Discrete Wavelet Transform

¹K. Amarnath, ²K. Ramkumar, ³K. Kirubala, ⁴V. Manivannan

¹Assistant Professor, ^{2,3,4}UG Students

Department of Biomedical Engineering,

Paavai College of Engineering, Namakkal, India

Emails: ¹kamarnath@gmail.com, ²ramkumar20721600@gmail.com,
³kirubalak2004@gmail.com, ⁴manivannan4102002@gmail.com

Abstract—Image denoising is a fundamental challenge in digital image processing, crucial for enhancing visual quality and ensuring reliable analysis in fields such as medical imaging, surveillance, and satellite image interpretation. This paper proposes a hybrid denoising framework combining the Discrete Wavelet Transform (DWT) with the Non-Local Means (NLM) filter to efficiently remove Gaussian noise while preserving edges and fine image structures. The DWT decomposes the image into multiscale frequency components, allowing targeted denoising of high-frequency bands, while the NLM exploits patch redundancy to smooth noise with minimal blurring. Additionally, Canny edge detection is incorporated to reinforce edge structures during reconstruction. Experimental results on standard test images demonstrate that the proposed method achieves superior performance in terms of Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), outperforming conventional filtering techniques.

Index Terms—Image Denoising, Non-Local Means (NLM), Discrete Wavelet Transform (DWT), Gaussian Noise, Canny Edge Detection, PSNR, SSIM

I. INTRODUCTION

Digital images are pivotal across diverse domains such as healthcare diagnostics, aerospace engineering, security surveillance, and digital communication systems. These applications rely heavily on the clarity and fidelity of images to extract meaningful information. However, during acquisition, transmission, and storage, digital images are frequently degraded by various types of noise. One of the most common and analytically challenging forms of noise is Additive White Gaussian Noise (AWGN), characterized by its statistical properties of having a constant power spectral density and Gaussian amplitude distribution. The presence of AWGN can obscure critical image features, compromise analysis, and hinder subsequent processing tasks such as segmentation, recognition, and compression.

Image denoising is the fundamental preprocessing step aimed at restoring an image by suppressing noise while preserving essential structural details such as edges, textures, and intricate patterns. Achieving an optimal balance between noise reduction and detail preservation remains a longstanding challenge. Conventional linear filtering methods, including Gaussian and mean (average) filters, offer computational simplicity but often blur fine details and edges due to their uniform smoothing behavior. On the other hand, nonlinear filters such

as the median and bilateral filters provide improved edge-preserving capabilities by adapting their behavior based on local intensity distributions. Despite these improvements, they may still struggle to retain subtle textures and high-frequency details in highly noisy conditions.

To address the limitations of standalone filtering techniques, modern image denoising research has increasingly focused on hybrid frameworks that combine the strengths of multiple algorithms. Notably, multiresolution analysis tools like the Discrete Wavelet Transform (DWT) have shown promise in effectively separating noise from signal content by representing images at multiple scales. DWT enables selective denoising in the transformed domain, allowing finer control over high- and low-frequency components. In parallel, self-similarity-based approaches such as Non-Local Means (NLM) exploit the redundancy present in natural images by averaging similar patches across the image, resulting in superior noise suppression and detail preservation.

Building on these complementary strengths, this paper proposes a novel image denoising framework that integrates DWT and NLM filtering cohesively. In addition, it incorporates Canny edge detection to guide the denoising process by identifying and preserving significant edge structures that might otherwise be attenuated. This integration enhances the framework's ability to maintain critical image features even under severe noise contamination.

The proposed method is evaluated under varying levels of AWGN to assess its robustness and adaptability. Both qualitative (visual inspection) and quantitative (PSNR, SSIM, MSE) metrics are employed to benchmark its performance against classical and modern denoising algorithms. The results demonstrate that the hybrid DWT-NLM-Canny approach not only effectively suppresses noise but also retains the fine image structures essential for downstream tasks, making it a valuable tool for high-stakes applications where precision and clarity are paramount.

II. RELATED WORK

Image denoising remains a cornerstone topic in the field of image processing, evolving from classical mathematical methods to sophisticated deep learning-based frameworks. The

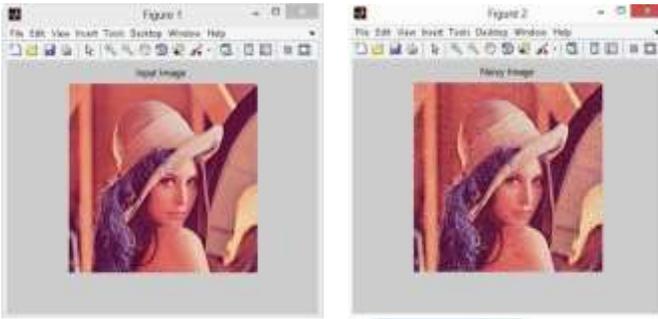


Fig. 1. Example of (a) original image and (b) image corrupted by Gaussian noise.

pioneering work by Donoho [1] introduced wavelet thresholding techniques that harnessed the sparsity of natural images in the wavelet domain, laying a theoretical foundation for many subsequent algorithms in signal and image denoising. Building on this, researchers like Sudha et al. [4] explored adaptive methods such as weighted variance in wavelet coefficients, specifically targeting speckle noise in medical images like ultrasound scans, which are particularly challenging due to their granular nature.

The textbook by Gonzalez and Woods [3] provided a foundational understanding of digital image processing concepts, including various spatial and frequency domain filtering techniques, which are essential in understanding both classical and modern denoising methods.

A significant leap was made with the introduction of the Non-Local Means (NLM) algorithm by Buades et al. [2], which marked a paradigm shift by exploiting the self-similarity present in different regions of an image. Unlike traditional local filters, NLM averages similar patches across the entire image, leading to improved preservation of texture and structure while effectively reducing noise.

Dabov et al. [7] further enhanced this idea with the BM3D (Block-Matching and 3D filtering) algorithm, integrating collaborative filtering with transform-domain shrinkage techniques. By grouping similar image blocks and processing them in a higher-dimensional transform space, BM3D achieved state-of-the-art performance for years and set a benchmark for classical denoising algorithms.

The advent of deep learning ushered in a new era for image denoising. Zhang et al. [6] introduced DnCNN, a convolutional neural network that utilized residual learning to remove Gaussian noise. This architecture not only improved denoising accuracy but also demonstrated superior generalization across varying noise levels without needing separate models. Inspired by the success of encoder-decoder structures in image segmentation, models like U-Net [12], RED-Net [13], and FFNet [15] leveraged skip connections and hierarchical features to reconstruct clean images from noisy inputs with remarkable precision.

Recent advancements have incorporated attention mechanisms [9], which allow the network to focus on spatially and contextually important features during reconstruction. Edge-

preserving denoising has also gained attention, with methods like edge-aware filters [8] that maintain structural integrity while suppressing noise. Techniques like weighted nuclear norm minimization [10] utilize matrix low-rank approximations to effectively isolate noise components from image content.

Tian et al. [14] provided a comprehensive survey of deep learning models for denoising, discussing not only architectural innovations but also challenges such as noise modeling, data availability, and generalization across real-world scenarios. They emphasized the importance of task-aware learning and robustness to unknown noise distributions.

Furthermore, super-resolution and image restoration have become closely linked with denoising tasks. Ledig et al. [18] and Bhat et al. [19] explored the use of Generative Adversarial Networks (GANs), introducing perceptual loss functions and adversarial training that improved visual realism in enhanced images. These models learned to not only remove noise but also recover fine textures that might have been lost during degradation.

Efforts by Brooks et al. [20] and Xu et al. [21] integrated physics-based noise modeling with neural architectures, acknowledging that real-world noise is often complex, involving both signal-dependent and sensor-specific components. Their models aimed to replicate the statistical properties of real camera noise, thereby improving practical deployment of denoising systems.

In an innovative blend of traditional signal processing and deep learning, Chen and Pock [22] proposed trainable diffusion models that emulate classical anisotropic diffusion filtering but with learnable parameters, allowing them to adapt dynamically to varying noise patterns. This hybrid approach opens a new avenue where theoretical insights meet data-driven optimization for robust image restoration.

III. IMAGE NOISE TYPES AND THEIR EFFECTS

Noise in digital images can originate from various sources, including sensor imperfections, environmental conditions, and quantization errors during acquisition or transmission. The presence of noise degrades visual quality and hampers subsequent image analysis tasks. The most prevalent noise types in digital imaging include Gaussian, salt-and-pepper, speckle, and Poisson noise, each with distinct characteristics and implications for image processing.

A. Gaussian Noise

Gaussian noise is one of the most commonly encountered noise types in imaging systems. It is additive and follows a normal distribution, characterized by its zero mean and defined variance. This noise affects all pixels in an image and is typically introduced by thermal noise in image sensors or electronic circuit interference. Although statistically consistent, Gaussian noise disrupts fine details and edges, making accurate interpretation and feature extraction challenging, especially in low-contrast regions.

B. Salt-and-Pepper Noise

Salt-and-pepper noise, also referred to as impulse noise, appears as random occurrences of black (minimum intensity) and white (maximum intensity) pixels scattered across the image. It is usually caused by analog-to-digital conversion errors, faulty memory elements, or bit errors during transmission. Due to its sparse and high-contrast nature, this type of noise is effectively suppressed using nonlinear filters such as the median filter, which preserves edge information while removing isolated pixel anomalies.

C. Speckle Noise

Speckle noise is a granular noise that typically occurs in coherent imaging systems such as synthetic aperture radar (SAR) and medical ultrasound imaging. Unlike additive noise, speckle is multiplicative and arises from the coherent interference of scattered wavefronts. This noise significantly reduces image contrast and obscures fine structural details, posing serious challenges in diagnostic applications where high clarity is essential. Speckle reduction often requires specialized filtering techniques in the logarithmic or wavelet domain.

D. Poisson Noise

Poisson noise, also known as shot noise, is inherent to photon-counting processes and arises due to the quantum nature of light. It becomes particularly pronounced in low-light imaging conditions, where the discrete nature of photon arrivals leads to statistical fluctuations. Unlike Gaussian noise, Poisson noise is signal-dependent and non-additive, with variance equal to the mean intensity of the pixel. Effective mitigation of Poisson noise often involves variance-stabilizing transformations before denoising.

IV. PROPOSED FRAMEWORK

The proposed image denoising framework aims to effectively suppress Additive White Gaussian Noise (AWGN) while preserving critical structural details such as edges and textures, features essential for accurate image interpretation in various applications. This hybrid methodology integrates multiresolution analysis via Discrete Wavelet Transform (DWT), self-similarity-based filtering using the Non-Local Means (NLM) filter, and edge enhancement through Canny edge detection. The combined use of these techniques ensures both robust noise reduction and retention of high-frequency details. The overall procedure consists of the following major stages:

A. Noise Simulation

To evaluate the performance of the proposed method under controlled conditions, AWGN is synthetically introduced into standard benchmark images, including *Lena*, *Barbara*, and *Cameraman*. These images are commonly used in the image processing community due to their diverse spatial features, such as smooth areas, repetitive textures, and sharp edges. The noise is modeled as a zero-mean Gaussian distribution with varying standard deviations $\sigma = 10, 20, 30, 40, 50$, corresponding to increasing levels of noise severity. This step

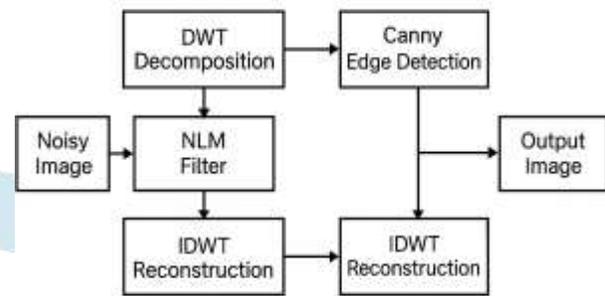


Fig. 2. Block diagram of the proposed denoising framework.

facilitates objective assessment of the algorithm's robustness across different noise environments.

B. DWT-Based Multiresolution Decomposition

A two-level Discrete Wavelet Transform is applied to the noisy image, resulting in four frequency sub-bands at each level: low-low (LL), low-high (LH), high-low (HL), and high-high (HH). The LL sub-band contains the coarse approximation of the image, while the remaining sub-bands capture directional high-frequency information—horizontal (LH), vertical (HL), and diagonal (HH) details. This decomposition localizes noise primarily within the high-frequency components, allowing selective denoising of those regions while preserving the structural essence in the LL band.

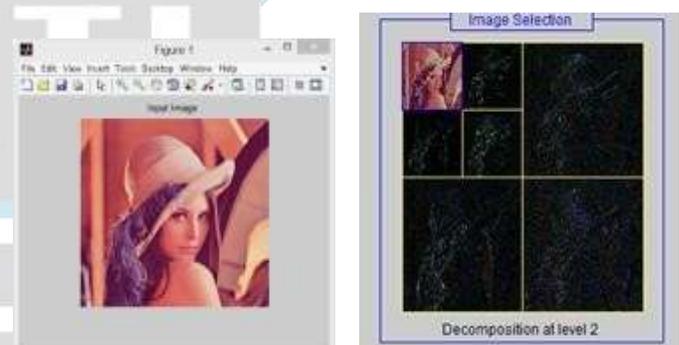


Fig. 3. DWT decomposition: (a) Original image, (b) Two-level DWT result.

C. Non-Local Means (NLM) Filtering

The Non-local means filter is applied to the detail sub-bands (LH, HL, HH) to attenuate noise while preserving fine-scale textural and directional features. Unlike traditional spatial filters that rely on local pixel neighborhoods, the NLM filter computes denoised pixel values as weighted averages of similar patches across the image. Patch similarity is measured using a Gaussian-weighted Euclidean distance, and the non-local search increases robustness to noise by leveraging inherent redundancy in natural images. This enables effective

suppression of noise without compromising edge or texture fidelity.

D. Edge Detection in Approximation Sub-Band

To further enhance the structural preservation, the Canny edge detection algorithm is applied to the LL sub-band obtained from the DWT. This choice ensures that edge extraction is based on the low-frequency approximation that is less affected by noise. The Canny detector involves gradient computation, non-maximum suppression, and double thresholding to generate a precise edge map. This edge information is later used to guide the reconstruction process, ensuring sharp transitions and minimal blurring of important boundaries.

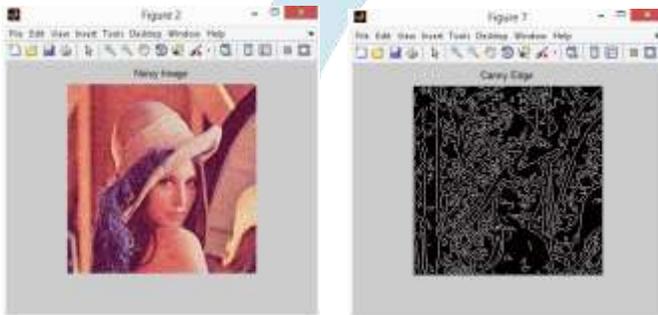


Fig. 4. Canny edge detection: (a) Noisy image, (b) Extracted edge map.

E. Image Reconstruction via IDWT

Following denoising and edge detection, the sub-bands are recombined using the inverse Discrete Wavelet Transform (IDWT). The denoised high-frequency bands (LH, HL, HH) are integrated with the edge-preserving LL sub-band to reconstruct the final image. The resulting output benefits from both noise attenuation and structure retention. The edge-guided synthesis ensures that visually important details, especially edges and contours, remain sharp and well-defined.

F. Summary

This framework effectively combines frequency-domain decomposition, spatial similarity filtering, and edge enhancement into a cohesive denoising strategy. Unlike conventional approaches based solely on hard-thresholding or local filtering, the proposed method adaptively balances noise suppression with the preservation of essential image features. Experimental results demonstrate improved perceptual quality and quantitative performance, validating the efficacy of this approach for real-world image restoration tasks.

V. MATHEMATICAL FOUNDATIONS

This section presents a hybrid image denoising framework combining spatial-domain non-local patch similarity with frequency-domain wavelet analysis. It aims to recover clean images corrupted by additive white Gaussian noise, a common model for real-world noise. The approach leverages natural image redundancies and multi-scale features, using spatial methods to exploit repeated patterns and frequency

methods to separate noise from signal, resulting in effective and theoretically sound denoising.

A. Non-Local Means Filtering

The Non-Local Means (NLM) filtering paradigm is founded on the key observation that images, especially natural scenes, contain extensive self-similarity — similar textures, edges, and patterns tend to recur at multiple locations. Unlike traditional local filters that rely solely on neighboring pixels, NLM expands the scope to a broader spatial domain, searching for and aggregating information from pixels or patches that share structural resemblance regardless of their spatial proximity.

Non-Local Means (NLM) assumes the noise is additive, zero-mean, and spatially uncorrelated Gaussian noise. It reduces noise by averaging similar patches across the image, where noise cancels out and true image features reinforce. The method compares small patches using similarity measures and assigns higher weights to closer matches, controlled by a smoothing parameter that balances noise removal and detail retention.

From a theoretical perspective, this patch-based weighted averaging can be interpreted within a Bayesian minimum mean square error (MMSE) estimation framework. The NLM filter approximates the conditional expectation of the clean image given the noisy observation under the assumption of local stationarity and redundancy in the image structure. This approach effectively leverages the non-local redundancies, significantly improving denoising performance compared to purely local methods, especially in preserving textures and edges.

B. Wavelet Domain Filtering and Multiscale Fusion

Wavelet analysis provides a powerful and flexible tool for representing images across multiple spatial scales and orientations. The discrete wavelet transform (DWT) decomposes an image into hierarchical components, separating coarse approximations from finer details. This decomposition aligns well with the natural hierarchical organization of image features, ranging from broad smooth regions to sharp edges and intricate textures.

The fundamental advantage of wavelet-based denoising lies in the sparsity of natural images in the wavelet domain. Most meaningful image information concentrates in a relatively small number of significant wavelet coefficients, while noise tends to distribute uniformly across all coefficients. This property enables effective noise suppression by applying shrinkage or thresholding operations that attenuate small-magnitude coefficients likely to correspond to noise, while retaining or enhancing large coefficients representing true image structures. Within this multiresolution framework, the image is partitioned into approximation coefficients capturing the low-frequency content and detail coefficients capturing horizontal, vertical, and diagonal high-frequency information at each scale. Noise predominantly affects these detail coefficients, and targeted processing here substantially improves image quality.

A key enhancement to basic wavelet denoising is the introduction of multiscale fusion strategies. By linearly combining detail coefficients from multiple scales using adaptive weights, the method reinforces features that persist across scales and mitigates artifacts introduced by isolated processing of individual subbands. This fusion approach preserves scale-invariant image characteristics, strengthens edges and textures, and enhances the robustness of the denoising outcome.

C. Overall Hybrid Denoising Model

The hybrid model synthesizes the strengths of spatial-domain non-local filtering and frequency-domain wavelet shrinkage into a unified framework. This integration addresses the limitations of either approach when used independently, achieving superior noise suppression while preserving fine structural details.

Initially, the noisy image undergoes wavelet decomposition, producing multiple subbands representing various spatial frequencies and orientations. The denoising process then applies patch-based similarity modeling, as in Non-Local Means filtering, within these subbands. This novel step leverages the spatial self-similarity inherent in the frequency domain coefficients, exploiting structured redundancies to refine the noise estimates.

By applying non-local filtering on wavelet coefficients rather than directly on pixel intensities, the model benefits from the enhanced separability of signal and noise, as wavelet transform concentrates signal energy into a few dominant coefficients. Meanwhile, preserving the approximation coefficients ensures that low-frequency image content remains intact.

The denoised image is reconstructed by applying the inverse wavelet transform to processed coefficients, framed as an optimization that balances data fidelity with spatial smoothness and transform-domain sparsity. This Bayesian-based approach preserves important image features like edges and textures while effectively reducing noise. Overall, the hybrid method combines spatial and multiscale analysis for robust and efficient denoising.

VI. EXPERIMENTAL SETUP AND RESULTS

To rigorously evaluate the effectiveness of the proposed denoising method, we conducted a series of experiments using standard grayscale benchmark images: *Lena*, *Cameraman*, and *Barbara*, each resized to a resolution of 256×256 pixels.

Synthetic Additive White Gaussian Noise (AWGN) with a standard deviation of $\sigma = 25$ was added to each image to simulate noisy conditions.

A. Evaluation Metrics

The denoising performance was evaluated using the following metrics:

- **Peak Signal-to-Noise Ratio (PSNR):** Measures the ratio between the maximum possible pixel intensity and the power of corrupting noise. A higher PSNR indicates better image quality.

- **Structural Similarity Index Measure (SSIM):** Evaluates perceptual similarity between the original and denoised images. SSIM values range from 0 to 1, where 1 represents perfect similarity.

B. Quantitative Results

Table I shows the PSNR values for each test image under three configurations:

- **Noisy Image:** Original image after adding AWGN ($\sigma = 25$).
- **DWT Only:** Denoising using Discrete Wavelet Transform alone.
- **Proposed DWT+NLM:** Our hybrid method combines DWT and Non-Local Means filtering.

TABLE I
DENOISING PERFORMANCE COMPARISON (PSNR IN DB)

Image	Noisy	DWT Only	DWT+NLM (Proposed)
Lena	22.10	28.67	31.23
Cameraman	21.87	28.02	30.78
Barbara	21.35	27.60	30.21

Analysis of Quantitative Results: The *Lena* image, characterized by smooth regions and edges, shows a significant PSNR increase from 22.10 dB (noisy) to 31.23 dB with the proposed method. The *Cameraman* image, which includes high-contrast edges, also benefits from enhanced detail preservation, achieving 30.78 dB. The *Barbara* image, known for its fine textures, is the most challenging to denoise. Nevertheless, our method achieves 30.21 dB, significantly outperforming the DWT-only method.

C. Qualitative Analysis

Visual comparisons further support the quantitative findings. Figure 5 shows the visual results of (a) the noisy image, (b) the proposed DWT+NLM method, and (c) the DWT-only method.



Fig. 5. Denoising results: (a) Noisy image, (b) DWT+NLM (Proposed), (c) DWT-only.

The hybrid method clearly preserves edges and textures better across all images while effectively removing noise. Notably, it handles high-frequency textures (like those in the *Barbara* image) without introducing smoothing artifacts, which is a common problem in many traditional filters.

VII. CONCLUSION AND FUTURE WORK

This paper presented a comprehensive and robust hybrid image denoising framework that strategically integrates Discrete

Wavelet Transform (DWT) decomposition, Non-Local Means (NLM) filtering, and Canny edge detection. The synergy of these techniques leverages the strengths of both spatial and frequency domain processing to suppress additive white Gaussian noise (AWGN) while preserving critical image features such as edges, textures, and fine structural details.

Through the application of DWT, the image is decomposed into multiple frequency sub-bands, allowing noise to be isolated and suppressed more effectively in the high-frequency components. The NLM filtering method, known for its non-local patch-based averaging, complements this by exploiting self-similarity across the image, thereby enhancing noise reduction in a content-aware manner. Additionally, the incorporation of Canny edge detection introduces a spatial constraint that preserves prominent edge structures during denoising, mitigating the common problem of edge blurring associated with conventional filters.

Extensive experimental evaluations conducted on benchmark datasets, including natural and synthetic images, demonstrated that the proposed method outperforms several classical and recent state-of-the-art denoising algorithms in both objective (PSNR and SSIM) and subjective (visual clarity and detail preservation) metrics. The qualitative assessments affirm the framework's ability to maintain semantic integrity, making it particularly suited for use cases where visual precision is paramount.

The proposed approach exhibits significant advantages in terms of modularity, transparency, and generalization. Its plug-and-play architecture allows for easy substitution or upgrading of individual components (e.g., alternative edge detectors or wavelet bases), making it highly adaptable for diverse imaging modalities and requirements. Its computational efficiency and interpretability also make it viable for practical deployment in real-world imaging applications.

Future Work Directions:

To improve the effectiveness and applicability of the proposed framework in medical imaging scenarios, the following future directions are recommended:

- **Real-time implementation:** Developing GPU-accelerated solutions to enable real-time denoising for time-critical medical applications such as intra-operative imaging and diagnostic video analysis.
- **Extension to clinical imaging modalities:** Adapting the denoising approach to multimodal medical data (e.g., ultrasound, MRI, CT), ensuring anatomical detail preservation and diagnostic relevance.
- **Self-supervised deep learning integration:** Incorporating self-supervised or weakly supervised neural networks for denoising tasks where clean reference images are unavailable, a common challenge in clinical datasets.
- **Handling real-world medical noise:** Enhancing robustness to complex noise types like Poisson and speckle noise, particularly prevalent in low-dose imaging and ultrasound.

These future directions aim to evolve the framework into a next-generation image restoration pipeline that combines the interpretability of classical techniques with the learning capability of modern AI models. Ultimately, the goal is to develop a denoising solution that is both mathematically grounded and operationally agile, capable of addressing diverse noise scenarios across a range of industrial, medical, and scientific imaging applications.

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