Journal of Advanced Research in Image Processing and Applications
Volume 9, Print Issue 1 - 2026, Pg. No. 25-30
Peer Reviewed Journal

Review Article

Noise Removal and Image Restoration Using Hybrid Filtering and CNN-Based Approaches

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How to cite this article:
Mishra N K. Noise Removal and Image Restoration Using Hybrid Filtering and CNN-Based Approaches. *J Adv Res Image Proc Appl* 2026; 9(1): 25-30.

Date of Submission: 2026-02-20
Date of Acceptance: 2026-03-29

A B S T R A C T

Image denoising and restoration are fundamental and long-standing problems in the field of digital image processing, with the primary objective of recovering high-quality, clean images from degraded or corrupted observations. These degradations may arise due to various factors such as sensor noise, transmission errors, low illumination, compression artifacts, or environmental disturbances during image acquisition. Traditional image restoration techniques, including median filtering, Gaussian filtering, Wiener filtering, and adaptive filtering methods, have been widely used due to their simplicity, low computational complexity, and ease of implementation. However, these classical approaches are often limited in their ability to handle complex, non-linear noise distributions and frequently lead to loss of fine structural details, edge blurring, and reduced perceptual quality.

In recent years, deep learning-based approaches, particularly Convolutional Neural Networks (CNNs), have significantly transformed the field of image restoration by enabling data-driven feature learning. CNN-based models are capable of automatically learning hierarchical representations of images, allowing them to effectively model complex noise patterns and reconstruct high-fidelity images with improved structural preservation. These models have demonstrated superior performance over traditional filtering techniques in terms of both quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), as well as subjective visual quality.

Furthermore, hybrid approaches that integrate classical filtering techniques with deep learning models have gained increasing attention in recent research. These methods aim to combine the strengths of both paradigms—leveraging the noise suppression capability and computational efficiency of traditional filters along with the powerful feature learning ability of CNNs. Such hybrid architectures have shown promising results in enhancing denoising performance, improving edge preservation, and reducing computational overhead in certain scenarios.

Keywords: Image denoising, CNN, hybrid filtering, image restoration, deep learning, noise reduction, medical imaging

Introduction

Digital images play a central role in modern communication systems, medical diagnostics, remote sensing, surveillance, and multimedia applications. However, during image acquisition, transmission, and compression, images are often degraded by unwanted distortions commonly referred to as noise. This noise can arise from various sources such as sensor imperfections, low-light imaging conditions, atmospheric disturbances, electronic transmission errors, and compression artifacts. As a result, the quality of the observed image is significantly reduced, which can adversely affect subsequent image processing tasks such as segmentation, feature extraction, recognition, and interpretation.

Common types of noise encountered in digital images include Gaussian noise, which follows a normal distribution and is typically associated with electronic sensor noise; salt-and-pepper noise, characterized by random occurrences of black and white pixels due to bit errors or faulty sensor elements; and speckle noise, which is multiplicative in nature and is commonly observed in coherent imaging systems such as ultrasound, radar, and medical imaging modalities. Each type of noise exhibits distinct statistical properties, making the development of a universal denoising approach a challenging task.

The primary objective of image denoising is to remove or reduce noise while preserving essential image structures such as edges, textures, and fine details. Traditional denoising techniques, including mean filtering, median filtering, and adaptive filtering methods, have been widely used due to their simplicity, low computational complexity, and ease of implementation. Mean and Gaussian filters perform smoothing by averaging pixel intensities, which is effective in reducing random noise but often results in blurring of sharp edges. Median filtering is particularly effective for impulse noise removal, especially salt-and-pepper noise, but its performance degrades when dealing with Gaussian or complex mixed noise distributions. Adaptive filtering techniques attempt to improve performance by adjusting filter behavior based on local image statistics; however, they still struggle to generalize across diverse noise conditions and often fail to preserve fine structural details in highly corrupted images.

In contrast to classical approaches, recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have significantly transformed the field of image denoising and restoration. CNN-based models are capable of automatically learning hierarchical feature representations directly from data without the need for handcrafted filters or manually designed features. These models effectively capture spatial dependencies and complex nonlinear relationships between noisy and clean images, enabling superior restoration performance. CNN-based denoising systems have demonstrated strong robustness across different noise types and imaging conditions, outperforming traditional methods in both quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM), as well as in perceptual visual quality.

Recent research in this domain has further explored hybrid denoising approaches, which integrate classical filtering techniques with deep learning architectures. The motivation behind these hybrid methods is to combine the computational efficiency and initial noise suppression capability of traditional filters with the powerful learning and generalization ability of CNNs. Such integrated frameworks have shown improved performance in preserving edges, reducing artifacts, and enhancing fine structural details while maintaining reasonable computational complexity. Additionally, hybrid models are particularly useful in scenarios where noise levels are extremely high or when computational resources are limited.

Image Noise Models

Noise in digital images refers to unwanted random variations in pixel intensity values that degrade image quality and obscure important structural information. These distortions typically arise during image acquisition, transmission, or compression stages, and their statistical properties vary depending on the source and imaging modality. Understanding the nature and behavior of noise is a fundamental step in designing effective denoising and restoration algorithms.

Image noise can broadly be categorized into several types:

- **Gaussian Noise:** Gaussian noise is one of the most commonly encountered noise types in digital imaging systems. It is additive in nature and follows a normal (Gaussian) distribution. This type of noise is primarily introduced due to electronic circuit fluctuations, sensor thermal noise, and low-light conditions. It affects all pixels in the image uniformly and is mathematically modeled using mean and variance parameters.
- **Salt-and-Pepper Noise:** Also known as impulse noise, salt-and-pepper noise appears as random black and white pixels scattered throughout the image. It is typically caused by bit errors in transmission, faulty memory locations, or sensor malfunctions. This type of noise significantly degrades image quality but affects only a subset of pixels, making it suitable for specialized filtering techniques.
- **Speckle Noise:** Speckle noise is a multiplicative noise commonly observed in coherent imaging systems such as ultrasound, radar, sonar, and synthetic aperture radar (SAR) images. Unlike additive noise, speckle noise depends on the underlying pixel intensity, making it more complex to model and remove effectively.

In addition to these, real-world images may also contain mixed noise distributions, where multiple noise types coexist, further complicating the denoising process. Therefore, accurate modeling and understanding of noise characteristics are essential for developing robust image restoration systems. A comprehensive study of image degradation models and noise behavior can be found in prior research literature.[1]

Traditional Filtering Techniques

Traditional image denoising techniques are based on classical signal processing methods that rely on spatial domain operations. These methods are widely used due to their simplicity, interpretability, and low computational cost. However, they often struggle to handle complex noise patterns and preserve fine image details.

Mean and Gaussian Filters

Mean filtering, also known as average filtering, works by replacing each pixel value with the average of its neighboring pixels. Gaussian filtering improves upon this by assigning higher weights to pixels closer to the center of the kernel, resulting in smoother and more natural denoising.

While these filters are effective in reducing random noise, they tend to blur edges and remove fine textures, which are critical for tasks such as medical diagnosis and object recognition. This limitation arises because these filters do not distinguish between noise and important structural information.

Median Filter

The median filter is a nonlinear filtering technique that replaces each pixel value with the median of its neighboring pixels. It is particularly effective in removing impulse noise, such as salt-and-pepper noise, while preserving edges better than linear filters.

However, median filtering performs poorly when dealing with Gaussian noise or complex mixed noise environments. Additionally, its performance degrades in preserving fine textures and subtle structural details in high-resolution images.

Adaptive Filters

Adaptive filtering techniques dynamically adjust their filtering behavior based on local image statistics such as mean, variance, or gradient information. This adaptability allows them to better preserve edges while reducing noise.

Despite their improved performance compared to fixed filters, adaptive methods still face limitations in handling highly non-linear and spatially varying noise distributions. They also struggle in scenarios involving complex textures and high-density noise levels.

Overall, although traditional filtering methods are computationally efficient and easy to implement, their inability to adapt to diverse noise conditions and preserve intricate image details limits their effectiveness in modern image processing applications.

CNN-Based Image Denoising

Convolutional Neural Networks (CNNs) have fundamentally transformed the field of image denoising by enabling data-driven learning of complex mappings between noisy and clean images. Unlike traditional filters, CNNs do not rely on manually designed operations; instead, they learn optimal feature representations directly from large datasets.

CNN-based denoising models typically operate by taking a noisy image as input and producing a restored image as output through multiple layers of convolution, non-linear activation, and feature aggregation.

Key Characteristics of CNN-Based Denoising Systems:

- **Hierarchical Feature Learning:** CNNs learn multiple levels of feature representations, starting from low-level edges and textures to high-level structural information.
- **Spatial Dependency Modeling:** These networks effectively capture spatial correlations between neighboring pixels, enabling more accurate noise separation.
- **Noise Adaptability:** CNN models can be trained to handle multiple types of noise distributions, including Gaussian, impulse, and real-world mixed noise.

Extensive research has demonstrated that CNN-based methods significantly outperform traditional denoising techniques in both synthetic and real-world noise removal scenarios, achieving higher PSNR and SSIM scores.[2]

Popular CNN Architectures for Denoising

- **DnCNN (Denoising Convolutional Neural Network):** One of the earliest and most influential CNN-based denoising models, DnCNN uses residual learning to predict noise instead of clean images, improving convergence and performance.
- **U-Net-Based Denoisers:** U-Net architectures utilize encoder-decoder structures with skip connections, enabling precise reconstruction of spatial details while effectively removing noise.
- **Residual Learning Networks:** These models incorporate skip connections to improve gradient flow and allow deeper network architectures, enhancing denoising performance.

Recent Advances

Recent developments in CNN-based image denoising include:

Frequency-domain CNNs: These models operate in the frequency domain to better separate noise from signal components.

Hybrid Deep Architectures: These combine CNNs with traditional filtering or optimization techniques to improve robustness.

Attention-based Networks: These models focus on important image regions, enhancing edge and texture preservation.

Such advancements have further improved the performance of deep learning-based denoising systems, making them highly effective for real-world applications such as medical imaging, satellite imaging, and surveillance systems.[14]

Table1.Comparison Table: Image Denoising Methods

Category	Method Type	Advantages	Limitations	Typical Applications
Classical Filtering	Mean / Gaussian Filter	Simple, fast, low cost	Blurs edges, poor detail preservation	Basic image smoothing
Classical Filtering	Median Filter	Good for impulse noise	Not effective for Gaussian noise	Salt-and-pepper noise removal
Transform-Based	Wavelet Transform	Better edge preservation	Complex tuning required	Compression + denoising
Sparse Representation	Dictionary Learning	High-quality restoration	Computationally expensive	Medical + remote sensing
CNN-Based	DnCNN, FFDNet	High accuracy, learns noise patterns	Requires large dataset	General image restoration
CNN-Based	U-Net / Encoder-Decoder	Strong structural recovery	High computation cost	Medical imaging
Self-Supervised CNN	Noise2Noise, Noise2Void	No clean dataset needed	Lower accuracy than supervised CNN	Real-world noisy images
GAN-Based	Generative Adversarial Networks	Sharp, realistic outputs	Training instability	Image enhancement
Hybrid Methods	Filter + CNN	Balanced performance	Design complexity	Real-time systems, medical imaging

Hybrid Filtering and CNN Approaches

Hybrid image denoising methods represent a promising direction in modern image restoration research by integrating traditional filtering techniques with deep learning-based models. The primary objective of hybrid approaches is to leverage the complementary strengths of classical signal processing methods and data-driven neural networks, thereby overcoming the limitations inherent in each individual approach.

Traditional filters are effective in removing simple and well-defined noise patterns with low computational complexity, whereas Convolutional Neural Networks (CNNs) excel in learning complex, non-linear mappings and preserving fine structural details. By combining these two paradigms, hybrid models achieve improved denoising performance, enhanced edge preservation, and better generalization across diverse noise conditions.

Motivation for Hybrid Models

The development of hybrid denoising frameworks is motivated by several key factors:

- **Effectiveness of Classical Filters:** Classical filtering methods such as median and Gaussian filters are highly efficient in reducing simple noise types, particularly impulse and low-level Gaussian noise.
- **Superior Representation Learning of CNNs:** CNN-based models are capable of capturing intricate spatial patterns and textures, allowing them to preserve fine details and structural information.
- **Complementary Strengths:** The integration of traditional filters with CNNs enables the system to first suppress noise at a coarse level and then refine the output using deep feature learning, resulting in improved stability and robustness.
- **Improved Performance under High Noise Conditions:** Hybrid models are particularly effective in scenarios involving high-density noise or mixed noise distributions, where standalone methods often fail.

Common Hybrid Strategies

Several hybrid strategies have been proposed in the literature, each differing in how classical and deep learning components are integrated:

Pre-filtering Followed by CNN Refinement

In this approach, traditional filters such as median, Gaussian, or adaptive filters are applied as a preprocessing step to reduce noise levels before feeding the image into a CNN model. This reduces the burden on the neural network and improves convergence during training. The CNN then performs fine restoration and detail enhancement.

CNN Followed by Post-Filtering

In this strategy, the CNN is first used to remove noise and reconstruct the image. Subsequently, classical filters are applied to refine the output by smoothing artifacts, improving edge consistency, or enhancing visual quality.

Integrated Hybrid Networks

More advanced approaches incorporate traditional filtering operations directly into CNN architectures. These networks may include:

- Learnable filtering layers
- Wavelet transform modules
- Attention mechanisms combined with filtering operations

Such integrated systems allow end-to-end optimization and achieve superior performance by jointly learning filtering and restoration tasks.

Recent studies have demonstrated the effectiveness of hybrid models. For instance, the integration of adaptive median filtering with modified decision-based filters and CNN architectures significantly improves edge preservation and noise suppression, particularly under high-density noise conditions.[3] Another approach combines deep convolutional networks with evolutionary optimization techniques to enhance feature extraction and noise removal performance.[7]

Applications of Hybrid Denoising Systems

Hybrid CNN-based denoising systems have found widespread applications across various domains due to their robustness and high restoration quality:

- **Medical Imaging:** Used in MRI, CT, ultrasound, and X-ray imaging to remove noise while preserving critical anatomical structures. This leads to improved diagnostic accuracy and better clinical decision-making.
- **Satellite and Remote Sensing:** Enhances the quality of satellite images affected by atmospheric disturbances, sensor noise, and transmission errors, enabling more accurate environmental monitoring and geographic analysis.
- **Industrial Quality Inspection:** Applied in automated inspection systems to detect defects in manufactured products by improving image clarity and feature visibility.
- **Biometric Authentication:** Improves the quality of fingerprint, face, and iris images, leading to more reliable identification and authentication systems.
- **Surveillance and Security Systems:** Enhances low-light and noisy video frames for better object detection and recognition.

In particular, hybrid approaches in medical imaging significantly enhance diagnostic performance by effectively removing noise while preserving fine structural details essential for accurate analysis.[9]

Performance Evaluation Metrics

The effectiveness of image denoising algorithms is typically evaluated using both quantitative and qualitative metrics. The most commonly used metrics include:

- **Peak Signal-to-Noise Ratio (PSNR):** Measures the ratio between the maximum possible signal power and the noise power. Higher PSNR values indicate better image quality.
- **Structural Similarity Index (SSIM):** Evaluates perceptual similarity between the original and restored images by considering luminance, contrast, and structural information.
- **Mean Squared Error (MSE):** Measures the average squared difference between the original and reconstructed images. Lower MSE values indicate better performance.
- **Visual Information Fidelity (VIF):** Assesses the amount of visual information preserved in the restored image relative to the original.

Experimental studies show that hybrid CNN-based denoising methods consistently achieve higher PSNR and SSIM values compared to traditional filtering techniques across various benchmark datasets.[2,5]

Challenges

Despite significant advancements, hybrid denoising systems still face several challenges:

- **High Computational Complexity:** Deep learning models require significant computational resources for training and inference, limiting real-time applications.
- **Large Data Requirements:** CNN-based methods depend on large labeled datasets, which are often difficult to obtain in specialized domains such as medical imaging.
- **Generalization Issues:** Models trained on specific datasets may not perform well on unseen real-world noise distributions.
- **Trade-off Between Noise Removal and Detail Preservation:** Excessive denoising can lead to loss of fine details, while insufficient denoising leaves residual noise.

- **Lack of Interpretability:** CNN-based models often act as black boxes, making it difficult to understand their decision-making process.

Future Directions

Future research in hybrid image denoising is expected to focus on the following areas:

- **Lightweight Deep Learning Models:** Development of efficient architectures suitable for real-time and edge-device applications.
- **Self-Supervised and Unsupervised Learning:** Reducing dependence on labeled datasets by learning directly from noisy images.
- **Transformer-Based Image Restoration:** Leveraging attention mechanisms to capture long-range dependencies in images.
- **Frequency-Domain Hybrid Models:** Combining spatial and frequency-domain processing for improved noise separation.
- **Real-Time Applications:** Deployment of hybrid denoising systems in real-time medical imaging, autonomous systems, and video processing.

Conclusion

Hybrid filtering combined with CNN-based approaches represents a powerful and effective solution for image denoising and restoration. Traditional filtering methods provide simplicity, speed, and initial noise suppression, while CNN-based models offer superior adaptability and the ability to learn complex image representations. The integration of these techniques results in enhanced noise reduction, improved preservation of edges and textures, and better overall image quality.

Although challenges such as computational complexity, data dependency, and model interpretability remain, ongoing research in deep learning and hybrid architectures is expected to address these limitations. Future advancements will likely focus on developing efficient, robust, and interpretable models capable of handling real-world noise scenarios. Consequently, hybrid denoising systems are poised to play a crucial role in next-generation image processing applications across diverse fields.

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