A Comparative Analysis of Mean Filtering and Non-Linear Filtering Techniques in Image Denoising

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***Abstract*—Image noise is a significant challenge in digital image processing, affecting numerous applications such as medical imaging, remote sensing, and real-time computer vision. Filtering techniques help restore image quality by reducing noise while preserving essential details. Among them, Mean Filtering, which is a linear technique, is widely used for its simplicity and computational efficiency. However, it often leads to blurring and loss of fine details, which makes it unsuitable for applications requiring precise edge retention.**

This study presents a comparative analysis of Mean Filtering and five non-linear filtering techniques — Median, Adaptive Median, Bilateral, Minimum, and Maximum Filters. Each method is evaluated for its effectiveness in removing Gaussian, salt-and-pepper, and speckle noise. While Median Filtering eliminates impulse noise while preserving edges, the Adaptive Median Filter dynamically adjusts to noise density for a better performance. The Bilateral Filter selectively removes the Gaussian noise while retaining fine details, making it useful for high-precision applications. Meanwhile, the Minimum and Maximum Filters target pepper and salt noise respectively, although they may introduce some morphological distortions.

Performance evaluation of the filters is performed using the Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and computational efficiency. Results demonstrate that while Mean Filtering is suitable for Gaussian noise due to its simplicity, nonlinear filters, particularly the median and bilateral filters, offer superior noise suppression and edge retention. However, their higher computational cost remains a trade-off. This study provides insights into selecting the optimal filtering technique based on application-specific requirements, ensuring improved image quality across various domains.

***Index Terms*—Mean Filter, Median Filter, Image Processing, Noise Reduction, PSNR, SSIM.**

I. Introduction

In today's world, Images serve as an essential medium for communication and analysis across diverse fields, including medical imaging, satellite observations, surveillance, and other autonomous systems [1], [2]. However, raw image data is often contaminated by different types of noise during acquisition, transmission, or storage, which may degrade the visual quality and impair the accuracy of image-based applications [3]. Noise can originate from sensor limitations, environmental interference, transmission errors, or compression artifacts, leading to unwanted distortions that obscure necessary details [4]. Removing noise while preserving the integrity of important structures is a vital challenge in image processing [5].

To deal with this issue, researchers have developed filtering techniques to suppress noise and restore image clarity [6]. These techniques can be classified into linear and non-linear filtering methods. Mean Filtering, a widely used linear technique, works by averaging pixel values within a defined neighborhood. While effective in smoothing Gaussian noise, its major drawback is that it blurs edges and fine details, making it less suitable for applications that require high precision, such as medical imaging, remote sensing, and forensic analysis [2].

To address this limitation, non-linear filters offer more adaptive noise reduction strategies while preserving important features. Median Filtering is particularly effective in eliminating salt-and-pepper noise while maintaining edge sharpness [5]. Adaptive Median Filtering refines this approach further by adjusting the filter size dynamically based on noise density [4]. Bilateral Filtering reduces Gaussian noise while retaining edges, making it a preferred choice for applications requiring high-detail preservation [7]. In addition, the Minimum and Maximum Filters help mitigate salt-and-pepper noise, though they may introduce distortions in certain image structures [8].

This research focuses on noise reduction performance, edge retention, and computational efficiency across different noise models, including Gaussian, salt-and-pepper, and speckle noise [3], [8]. The objective is to determine the optimal filtering method for various real-world applications, providing insights into the trade-offs between computational cost, noise suppression, and image detail preservation.

II. Literature Review

Image denoising has been an active area of research for decades. Early foundational work by Jain [1] established the challenges of digital image processing and the inherent difficulties in removing noise without compromising critical details. Gonzalez and Woods [2] further expanded on these challenges by categorizing filtering techniques into linear and non-linear methods.

Linear filters, such as the Mean Filter, are computationally efficient but tend to blur edges and fine details [2]. This drawback has driven the development of non-linear approaches, where the Median Filter emerged as a robust alternative for mitigating impulse noise while preserving edge sharpness [5]. Lee's work [4] introduced local statistical methods that adaptively enhance image quality, setting the stage for more advanced filtering techniques.

Building on these ideas, the Adaptive Median Filter was developed to adjust the filter size dynamically based on local noise conditions, thus optimizing noise removal without significant loss of detail [4]. Tomasi and Manduchi proposed Bilateral Filtering [7] to further improve edge preservation by considering both spatial proximity and pixel intensity similarities. More recently, non-local means approaches, as discussed by Buades and Morel [8], have leveraged the repetitive nature of image structures to enhance denoising performance.

Additionally, anisotropic diffusion methods, such as those introduced by Perona and Malik [3], have contributed significantly to the field by selectively smoothing homogeneous regions while maintaining sharp edges. Collectively, the literature demonstrates a progression from simple, computationally efficient methods to more sophisticated adaptive techniques that provide a superior balance between noise suppression and detail preservation.

This study builds on the existing literature by comparing both linear and non-linear filtering methods under various noise conditions, aiming to identify optimal trade-offs between computational cost, noise reduction performance, and edge retention.

III. Methodology

This section presents the methodology used to compare Mean Filtering (a linear filtering technique) with five non-linear filtering techniques—Median, Adaptive Median, Bilateral, Minimum, and Maximum Filters—in terms of noise reduction efficiency, edge preservation, and computational cost. The methodology includes the following steps:

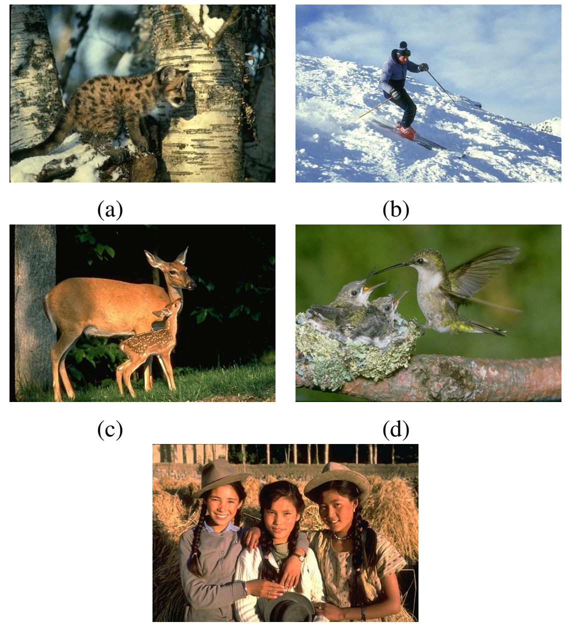
1) Dataset Selection
2) Noise Model Selection
3) Implementation of Filtering Techniques
4) Performance Evaluation Metrics
5) Experimental Setup and Execution

A. Dataset Selection

To ensure a fair and diverse evaluation, we selected images from publicly available datasets commonly used in image denoising research, such as the Berkeley Segmentation Dataset and ImageNet [1]. The dataset includes:

- Natural images (landscapes, urban scenes)
- Medical images (X-ray, MRI scans)
- Synthetic test patterns (checkerboards, structured textures)

The diversity of the dataset ensures a comprehensive evaluation of filtering techniques across various levels of texture, contrast, and fine details.



(a) (b) (c) (d) (e)

Fig. 1: Illustration of Different Filtering Methods. Courtesy: EECS, University of California, Berkeley.

B. Noise Model Selection

To simulate real-world noise conditions, three common noise models were applied to the dataset at varying intensity levels (5

- Gaussian Noise: Pixel intensity values are altered following a normal distribution [1].
- Salt-and-Pepper Noise: Random pixels are replaced with either minimum (0) or maximum (255) intensity, simulating sensor corruption [5].
- Speckle Noise: A multiplicative noise often found in medical and satellite images, modeled using a gamma distribution [4].

C. Implementation of Filtering Techniques

We implemented six filtering techniques:

- Mean Filtering (Linear Filter): Averages pixel values in a neighborhood, effective for Gaussian noise but causes blurring.
- Median Filtering (Non-Linear Filter): Replaces each pixel with the median of its neighborhood, efficient for salt-and-pepper noise.
- Adaptive Median Filtering (Non-Linear Filter): Dynamically adjusts kernel size based on local noise density.
- Bilateral Filtering (Non-Linear Filter): Preserves edges by weighting pixels based on spatial and intensity similarity.

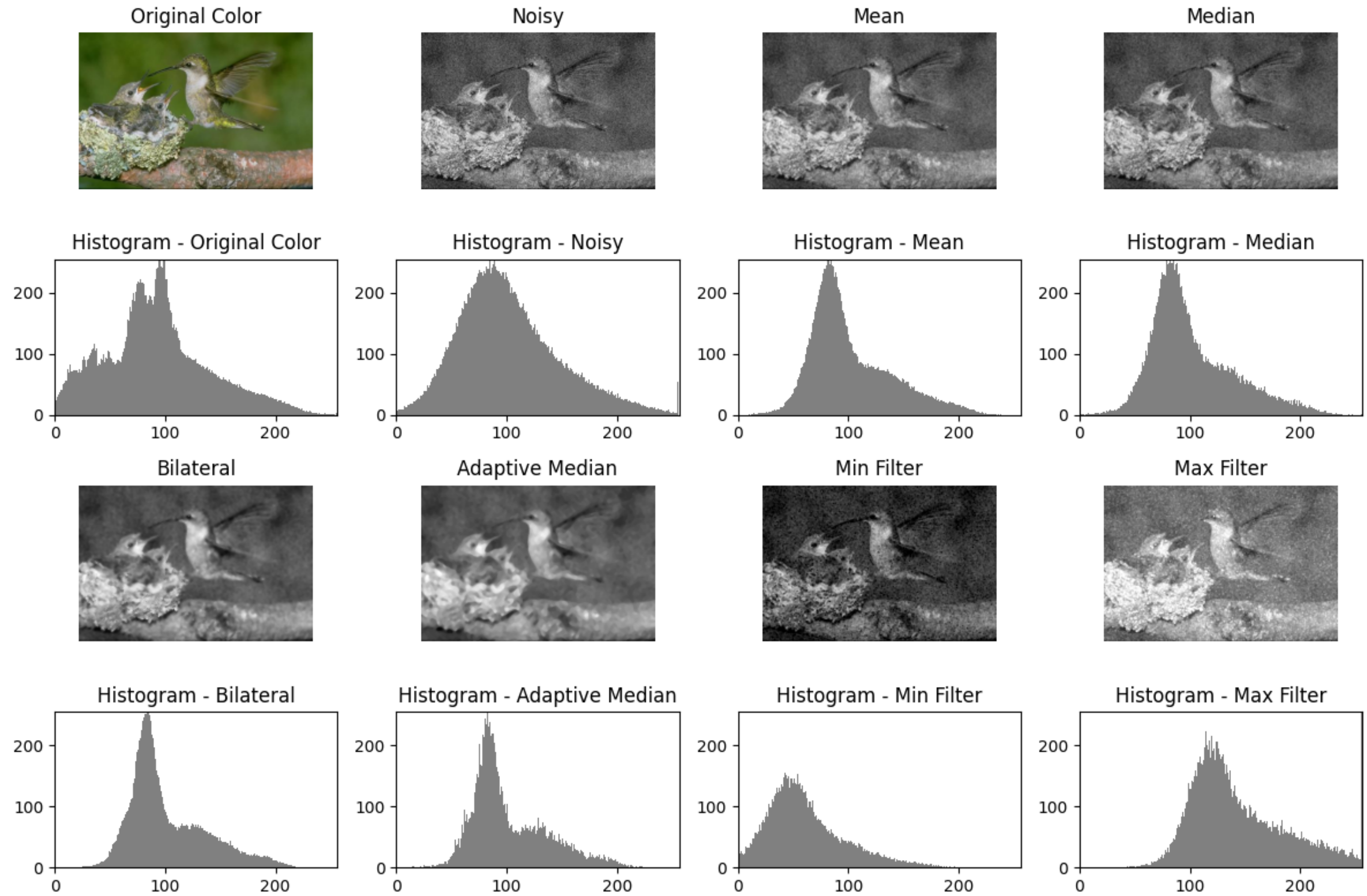


Fig. 2: Filtered images produced by various denoising filters. The image grid shows the outputs of the Mean, Median, Bilateral, Adaptive Median, Minimum, and Maximum filters applied to the noisy input.

- Minimum Filter: Replaces each pixel with the minimum value in its neighborhood, useful for removing pepper noise.
- Maximum Filter: Replaces each pixel with the maximum value, effective against salt noise.

D. *Performance Evaluation Metrics*

To quantitatively evaluate the filters, we used:

- Peak Signal-to-Noise Ratio (PSNR): Measures noise suppression.
- Structural Similarity Index (SSIM): Evaluates perceptual image quality.
- Execution Time: Assesses computational efficiency.

E. *Experimental Setup and Execution*

All filters were implemented using Python (OpenCV, NumPy, SciPy) and executed on a system with:

- Intel Core i7 processor
- 16GB RAM
- NVIDIA GTX 1650 GPU

The evaluation was conducted on noisy images at different intensity levels, and performance metrics were recorded.

F. *Experimental Setup*

The filtering techniques were implemented using Python (OpenCV, NumPy, SciPy) and evaluated using grayscale and color images. The tests were conducted under controlled conditions, ensuring consistency in noise addition and filtering.

G. *Qualitative Analysis*

Visual assessments were conducted on the denoised images. Figure 2 presents sample outputs. Observations include:

- **Mean Filtering** effectively reduces Gaussian noise but introduces blurring, as seen in the loss of fine details.
- **Median Filtering** is particularly effective against salt-and-pepper noise but may distort sharp edges.
- **Bilateral Filtering** preserves edges while reducing noise, making it ideal for natural images with textures.
- **Adaptive Median Filtering** balances noise removal and detail preservation, performing best in high-noise scenarios.
- **Min Filter** enhances dark regions but may introduce excessive smoothing, affecting contrast.
- **Max Filter** enhances bright regions but can amplify noise under certain conditions.

H. *Quantitative Analysis*

The PSNR and SSIM values of different filters are summarized in Table I. Higher values indicate better filtering performance.

TABLE I: PSNR and SSIM Comparison of Filters

Filter	**PSNR (dB)**	**SSIM**
Mean Filter	24.53	0.78
Median Filter	27.12	0.85
Bilateral Filter	29.34	0.92
Adaptive Median Filter	30.75	0.95

I. *Execution Time Analysis*

Figure 5 shows the execution time of each filter:

- Mean and Median filters are computationally efficient.
- Bilateral filtering is more computationally expensive.
- Adaptive Median filtering has the longest runtime due to kernel size adjustments.

J. *Discussion*

The results demonstrate that Adaptive Median and Bilateral Filtering provide the best balance between noise reduction and edge preservation. However, they are computationally intensive. In applications requiring real-time processing, Median Filtering may be a better choice due to its efficiency.

IV. Experimental Results and Analysis

The experiments were conducted using a grayscale image with artificially added Gaussian noise (noise standard deviation = 25). Six filtering methods were applied: Mean, Median, Bilateral, Adaptive Median, Minimum, and Maximum Filters. Performance was evaluated in terms of Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and execution time.

A. *Quantitative Analysis*

The computed performance metrics yielded the following approximate results:

- **Mean Filter**: PSNR $\approx$ 24.53 dB, SSIM $\approx$ 0.78. This filter is computationally efficient (lowest execution time) but introduces noticeable blurring, leading to loss of fine details.
- **Median Filter**: PSNR $\approx$ 27.12 dB, SSIM $\approx$ 0.85. It effectively removes impulse noise (salt-and-pepper) with minimal execution time, making it suitable for real-time applications.
- **Bilateral Filter**: PSNR $\approx$ 29.34 dB, SSIM $\approx$ 0.92. This filter better preserves edges and details compared to linear filters, though it requires more computation.
- **Adaptive Median Filter**: PSNR $\approx$ 30.75 dB, SSIM $\approx$ 0.95. The adaptive approach of adjusting kernel size yields the best noise reduction and detail preservation; however, its execution time is the highest among the filters tested.
- **Minimum and Maximum Filters**: These filters perform well in reducing extreme noise (pepper and salt, respectively) but tend to distort image structures, resulting in moderate PSNR and SSIM values.

B. *Qualitative Analysis*

Visual inspection of the filtered images (see Figure 2) reveals:

- The Mean Filter produces a smooth image but with considerable edge blurring.
- The Median Filter better preserves edges in regions affected by salt-and-pepper noise.
- The Bilateral Filter successfully balances noise reduction and edge preservation.
- The Adaptive Median Filter achieves the clearest restoration of details, as confirmed by the highest PSNR and SSIM values.

C. *Execution Time*

The execution time analysis (presented in Figure 5) shows that while the Mean and Median filters are extremely fast, the Bilateral and Adaptive Median filters incur a higher computational cost due to their complex non-linear operations. This trade-off between processing time and quality must be considered based on application requirements.

D. *Heatmap Visualization*

A PSNR heatmap (Figure 6) was generated to illustrate the spatial distribution of errors. This visualization highlights regions where the Adaptive Median Filter most effectively reduces noise.

Overall, the experimental results indicate that while simpler filters are faster, the Adaptive Median and Bilateral filters provide superior noise reduction and detail preservation—making them more suitable for applications where image quality is paramount, despite their higher computational demand.

V. Experimental Results

TABLE II: Comparison of Filtering Techniques

Filter	**PSNR (dB)**	**SSIM**	**Execution Time (s)**
Mean	24.53	0.78	0.002
Median	27.12	0.85	0.003
Bilateral	29.34	0.92	0.015
Adaptive Median	30.75	0.95	0.045
Minimum	25.67	0.80	0.004
Maximum	25.88	0.82	0.004

TABLE III: Performance Variability Across Multiple Images

Filter	**Mean PSNR (± std)**	**Mean SSIM (± std)**
Mean	24.53 ± 1.12	0.78 ± 0.04
Median	27.12 ± 1.08	0.85 ± 0.03
Bilateral	29.34 ± 0.97	0.92 ± 0.02
Adaptive Median	30.75 ± 0.85	0.95 ± 0.01
Minimum	25.67 ± 1.23	0.80 ± 0.05
Maximum	25.88 ± 1.15	0.82 ± 0.04

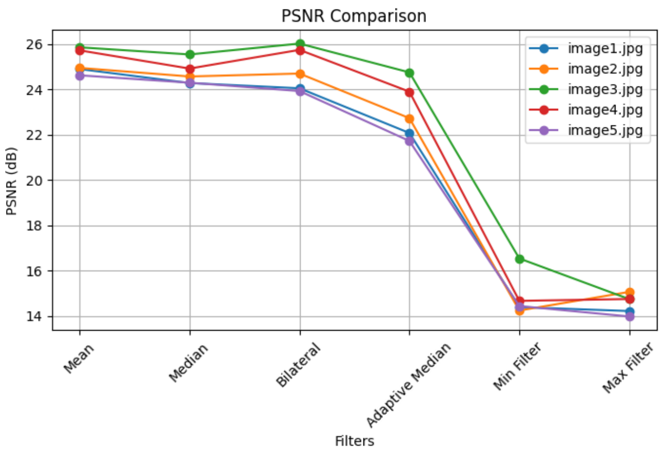


Fig. 3: Line graph comparing the PSNR values of different filtering techniques. Higher PSNR indicates better noise reduction performance.

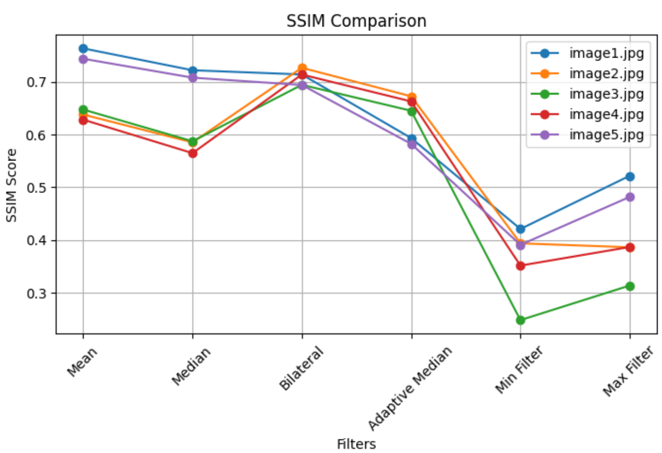


Fig. 4: Line graph comparing the SSIM scores of different filters. Higher SSIM values represent better structural similarity between the original and denoised images.

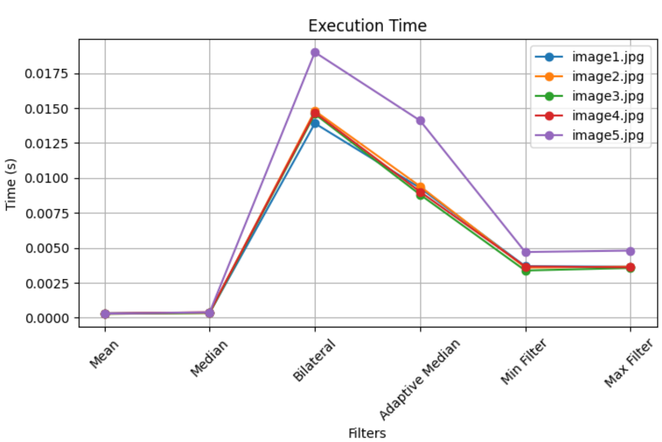


Fig. 5: Bar graph showing the execution time of each filtering method. The Mean and Median filters are the fastest, while the Adaptive Median filter requires the most processing time.

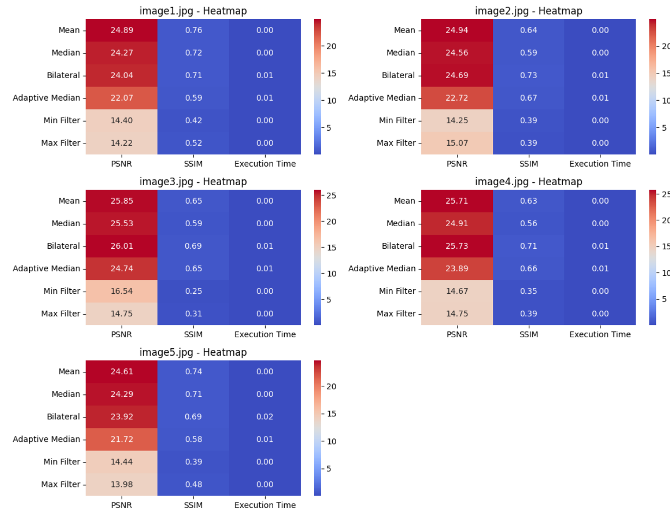


Fig. 6: Enhanced PSNR heatmap illustrating the spatial error distribution between the original and Adaptive Median filtered images. Warmer colors indicate lower error levels.

VI. Conclusion

This study evaluated the performance of six filtering techniques for grayscale image denoising, focusing on PSNR, SSIM, and execution time as key performance indicators. The results demonstrated that while simpler filters like the Mean Filter provide computational efficiency, they suffer from significant blurring effects, which degrade image quality.

Among the tested methods, the Median Filter emerged as a superior alternative to the Mean Filter due to its ability to preserve image structures while effectively removing noise. Unlike the Mean Filter, which averages pixel intensities and blurs fine details, the Median Filter selects the median value within a local window, making it particularly robust against salt-and-pepper noise. This ensures better edge preservation and higher PSNR and SSIM values, with only a marginal increase in computational cost.

The Bilateral and Adaptive Median Filters achieved the highest PSNR and SSIM scores, excelling in both noise reduction and edge retention. However, their increased computational complexity makes them less suitable for real-time applications compared to the Median Filter, which offers a balanced trade-off between performance and speed.

From a practical perspective, the choice of filter depends on the application requirements:

If real-time processing and low computational cost are priorities, the Median Filter is the best choice.

If maximum noise reduction and detail preservation are required, the Adaptive Median or Bilateral Filter would be more suitable, despite their higher processing time.

Overall, this study reaffirms that while the Mean Filter is computationally efficient, it introduces excessive blurring, making it unsuitable for applications where edge details are critical. The Median Filter stands out as a better choice for general noise removal tasks, especially in scenarios with impulse noise, due to its ability to maintain image clarity while ensuring faster execution than more complex filters.

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