DIGITAL IMAGE RESTORATION TECHNIQUES

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***Abstract*—Image Restoration is a critical aspect of digital image processing, aimed at restoring images degraded by noise and other distortions. This paper introduces an advanced restoration approach that combines impulse noise suppression with an Enhanced Recursive Median Filter (ERMF) incorporating noise detection and uncertainty modeling. The proposed method begins with detecting impulse noise and quantifying uncertainty.Corrupted pixels are selectively processed using a modified recursive median filter, effectively handling high noise densities while maintaining computational efficiency.To address motion blur, a color image of a car is converted to grayscale, followed by the application of motion blur based on a degradation model governed by adjustable parameters a and b. Random noise is then introduced to simulate real-world conditions. Restoration is performed using inverse filtering and Wiener filtering techniques, applied to both motion-blurred and noisy motion-blurred images. Comparative analyses highlight the performance differences between these methods, emphasizing the effectiveness of the proposed technique in terms of restoration quality and processing time.**

Keywords— Color image, grayscale image, motion blurring, random noise, inverse filtering, Wiener filtering, restoration of an image.Morphological Operations, Recursive Median Filter, Salt-Pepper Noise, Image Restoration.

I. INTRODUCTION

Image processing often faces challenges from various types of noise that degrade the quality and clarity of visual data, with salt-and-pepper noise and motion blur noise being two significant examples. Salt-and-pepper noise, also known as impulse noise, manifests as random black and white pixels scattered across an image, typically caused by errors in data transmission, sensor malfunctions, or storage issues. Its unpredictable nature can hinder accurate image analysis. Motion blur noise, on the other hand, occurs when there is relative motion between the camera and the scene during exposure. This leads to elongated streaks or smears in the direction of motion, resulting in a loss of sharpness and obscured details, commonly due to camera shake, fast-moving objects, or extended exposure times. Addressing these types of noise is crucial for enhancing image quality and ensuring reliable performance in fields like computer vision, medical imaging, and surveillance systems.

Image restoration plays a vital role in retrieving an uncorrupted image from blurred and noisy versions affected by motion blur, noise, and other distortions. Common reasons for image blur include motion blur from slow camera shutter speeds relative to the object's motion, while Gaussian noise often arises from electronic components or broadcast transmission effects. Digital image restoration has a wide range of applications, including astronomical imaging, medical diagnostics, media production, security footage enhancement, forensic science, and video coding. Filtering techniques are central to image restoration, with inverse filtering and Wiener filtering being the most commonly used approaches. Inverse filtering is particularly effective in noise-free conditions, as it reverses the effects of the degradation function, such as motion blur. However, its performance degrades significantly in the presence of noise, as it cannot effectively suppress high-frequency noise components. Wiener filtering, by contrast, incorporates both high-pass and low-pass filtering to handle noise and blur simultaneously. It performs deconvolution to address motion blur while compressing noise, making it more effective in noisy environments.

For salt-and-pepper noise, detection involves identifying pixels with intensity values of 0 (black) or 255 (white), which are then processed using filtering methods. Morphological opening, which applies erosion followed by dilation, effectively removes isolated noise pixels while preserving the overall structure of the image. Recursive median filtering uses a local window to calculate the median intensity, replacing noisy pixels without affecting edges. Enhanced recursive median filters improve upon this by adapting processing based on local statistics such as entropy or variance, enabling better handling of varying noise densities. Hybrid filtering pipelines combine methods like morphological opening for initial noise reduction with adaptive filters for refinement, ensuring both isolated and clustered noise are effectively managed. Uncertainty-based noise handling further enhances this process by selectively applying filtering only to regions of high noise uncertainty, preserving fine details and edges.

II. LITERATURE REVIEW:

The literature on image restoration techniques within the domain of digital image processing emphasizes their critical role in addressing noise and blur-related challenges like motion blur encountered in diverse applications such as remote sensing, satellite imaging. Image processing comprises essential steps like image enhancement, segmentation, and restoration, with a particular focus on restoration for removing distortions caused by environmental factors and equipment limitations.

Several studies have addressed the challenges posed by Gaussian noise, impulse noise, and blurring (e.g., motion blur, atmospheric blur). Various methods, including the Median filter, Wiener filter, and Inverse filter, have been explored, each with unique strengths and limitations. However, Wiener and Inverse filtering are often identified as robust and effective techniques due to their simplicity and reliability in noise and blur reduction.

Recent advancements in the field have introduced innovative approaches. For instance, Convolution Neural Network (CNN)-based methods have demonstrated success in non-local color denoising, while iterative techniques address linear inverse problems. Other adaptive algorithms, such as the k-Th nearest neighbor strategy, provide enhanced restoration capabilities. Despite the effectiveness of some traditional methods, limitations persist; for example, Median filters suffer from computational complexity, and Arithmetic mean filters fail to preserve edge sharpness. In contrast, Wiener and Inverse filters excel in minimizing mean square error and restoring noisy, blurred images effectively.

Impulse noise, particularly salt-and-pepper noise [3], significantly degrades image quality during acquisition or transmission, requiring robust restoration techniques. Early approaches used pixel intensity thresholding, identifying noise by marking extreme values (0 or 255) as noisy pixels. While computationally efficient, this method was limited in handling high-density scenarios. To address these issues, local statistics-based techniques were introduced, where deviations from the local mean or median helped detect noise. These adaptive methods enhanced detection accuracy but at the cost of increased computational complexity. Morphological opening [1], a process involving erosion followed by dilation, was also explored to clean isolated noise spots effectively. This method preserved edges well but struggled with clustered noise in high-density regions. Similarly, median filtering became a popular technique for noise removal due to its edge-preserving properties. However, it often failed to retain fine image details under severe noise conditions.

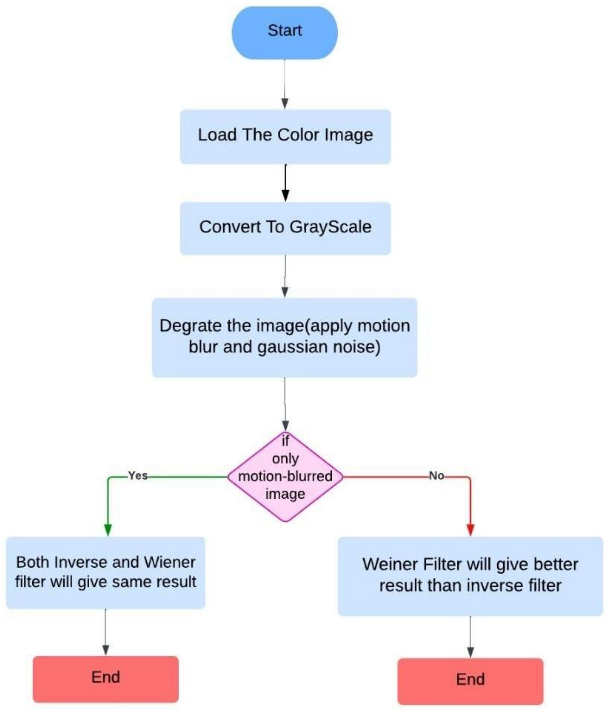
Advanced techniques, such as the Enhanced Recursive Median Filter (ERMF) [2], overcame these limitations by incorporating entropy-based uncertainty thresholds. ERMF adaptively selected between standard or recursive median filtering based on the noise characteristics, providing better suppression in high-uncertainty regions. Further advancements combined morphological opening with the Modified Enhanced Recursive Median Filter (MERMF) [4] to form a hybrid pipeline. This cascade approach effectively reduced noise while maintaining structural integrity, demonstrating superior performance for both low- and high-density noise scenarios. Using metrics like PSNR and MSE, the hybrid pipeline consistently outperformed simpler methods in terms of noise suppression and detail retention. However, its higher computational cost emphasizes the need for further optimization to enhance efficiency and scalability for diverse noise conditions.

III. TECHNIQUES AND APPROACHES:

The Median filter is primarily used to remove impulse noise, such as salt-and-pepper noise, by replacing each pixel's intensity with the median value of the intensity levels in its neighborhood. This approach is effective at preserving edges while eliminating outlier noise. However, the method is computationally intensive due to the sorting operations required to calculate the median, especially for larger images.The Arithmetic Mean filter reduces noise by computing the average intensity in a pixel's neighborhood and replacing the pixel's intensity with this arithmetic mean. While it effectively smooths random noise variations, it also tends to blur edges and fine details in the image, as it does not differentiate between noise and useful image features. Additionally, it is ineffective for handling impulse noise or noise with large intensity differences.

The Wiener filter is designed to minimize mean square error (MSE), making it particularly effective at reducing Gaussian noise and blur. It excels at preserving image details and edges compared to basic filters like the Median or Arithmetic Mean filters. By offering a good balance between noise suppression and detail preservation, the Wiener filter is well-suited for environments with both noise and slight blur.The Inverse filter restores images degraded by known blur functions, such as motion blur or lens distortions, by assuming a linear degradation model. It operates in the frequency domain to invert the blur operation and recover the original image. Simple and computationally efficient, the Inverse filter is effective for well-characterized blur kernels. However, its performance diminishes when noise levels are high or the degradation function is not well-defined.

Among these methods, the Wiener and Inverse filters stand out for their balanced performance in handling noise and blur. The Wiener filter excels in environments with both noise and slight blur, offering a good compromise between noise suppression and detail preservation. On the other hand, the Inverse filter's simplicity and speed make it suitable for deblurring tasks where noise levels are low or well-managed, providing an efficient solution when the degradation function, such as a motion blur kernel, is well understood.



Degrade the Image (Apply Motion Blur and Gaussian Noise)

1. To simulate degradation, apply motion blur and Gaussian noise.

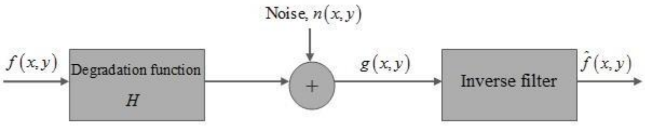
Equation for Motion Blur:

$$H(u,v)=\frac{\sin(\pi(ua+vb)T)}{\pi(ua+vb)}e^{-j\pi(ua+vb)T}$$

2. Add gaussian Noise Ngauss(x,y) with mean μ=0 and variance σ^2 to the Motion Blur Image.

Check if the degradation only includes motion blur (without additional Gaussian noise). If only motion blur is present, apply either the Inverse or Wiener filter to restore the image.

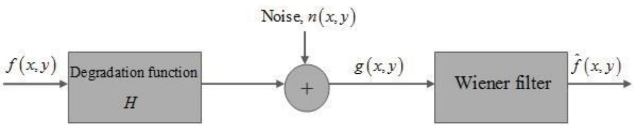
Image Restoration model (Inverse Filtering):



Formula to Restore the image without Noise using inverse Filter:

$$\hat{F}(u,v)=\frac{G(u,v)}{H(u,v)}$$

Image Restoration model (Wiener Filtering):



Wiener filter is represented as L(u,v) :

$$L(u,v)=\frac{H^*(u,v)S_f(u,v)}{|H(u,v)|^2\,S_f(u,v)+S_n(u,v)}$$

$$=\frac{H^*(u,v)}{|H(u,v)|^2+\dfrac{S_n(u,v)}{S_f(u,v)}}$$

$$=\frac{1}{H(u,v)}\frac{|H(u,v)|^2}{|H(u,v)|^2+K}$$

Where,

$$K=\frac{S_n(u,v)}{S_f(u,v)}$$

$S_f(u,v)$ = Power spectrum of the original image

$S_n(u,v)$ = Noise power spectrum

If the noise power is zero, which means no noise, then the Wiener can restore the exact image which was corrupted by motion blur effect. Here, the restored image is almost exactly similar to the image before motion blur.

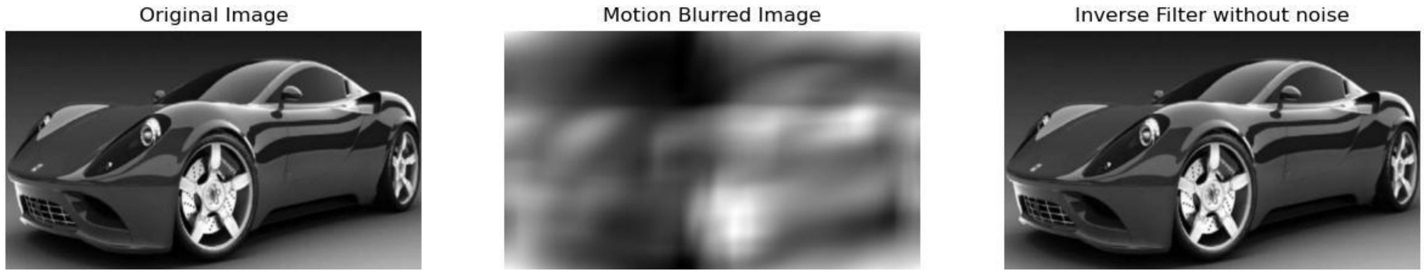
However, if we change the K to 0.01, then there would be 1% noise added after the motion blur effect.

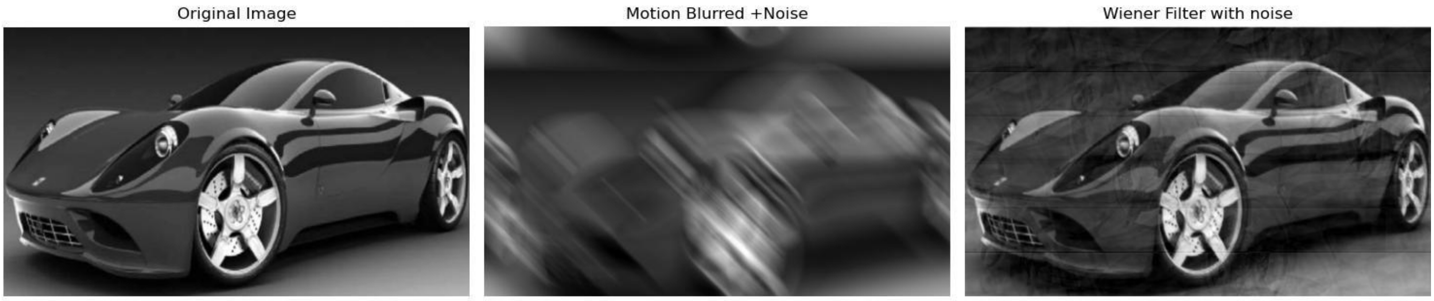
A. The Results of Inverse Filtering

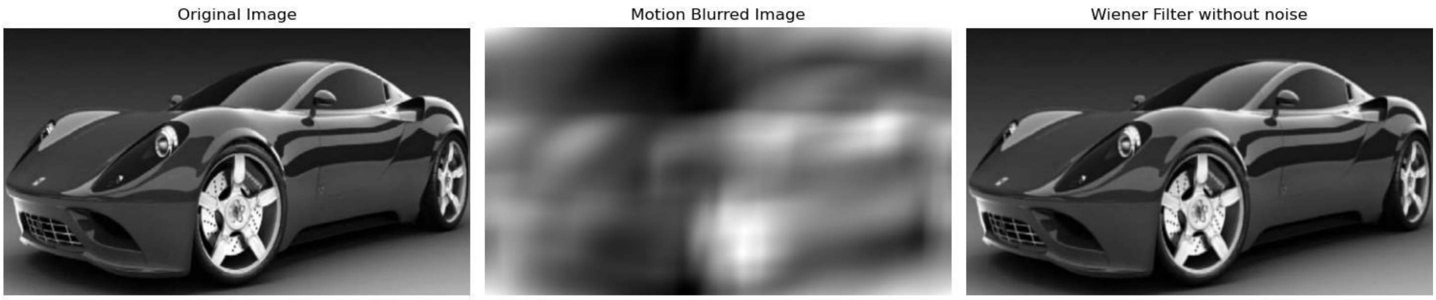
For inverse filtering, if we do not add any noise after the motion blur, then we can restore the same image before motion blur. The figure below shows the effectiveness of inverse filtering without any noise. Now, if we add some random noise to the image, then the filter performance degrades to some extent. The consequence of noise on the performance of inverse filtering is made known in figure below.

B. The Results of Wiener Filtering

The Wiener filter has a 'K' component which is inverse to the SNR. Now, if the noise power is zero, which means no noise, then the Wiener can restore the exact image which was corrupted by motion blur effect. In the figure below, we have considered zero noise power here, the restored image is almost exactly similar to the image before motion blur. However, if we change the k to value then noise will be added after the motion blur effect. If then we apply wiener filter, we will get the following result as represented in the below. It is observed that the Wiener filter is reversing the effect of motion blur, but still, there is some noise remaining in the picture.







Noise Detection and Removal Pipeline for Salt and Pepper Noise:

The process begins with the addition of salt-and-pepper noise to a grayscale image, followed by detecting noisy pixels, calculating an uncertainty threshold, and applying adaptive recursive median filtering. Each step is mathematically modeled to ensure robust noise removal while preserving image details.

1. Adding Salt-and-Pepper Noise:

Introduced salt-and-pepper noise to the input image by randomly replacing pixel values with either 0 (black) or 255 (white).

$$p(x,y) = \begin{cases} 0 & \text{with probability } \frac{\text{amount}}{2}, \\ 255 & \text{with probability } \frac{\text{amount}}{2}, \\ \text{original value} & \text{otherwise.} \end{cases}$$

Here, p(x, y) represents the pixel intensity at location (x, y) and amount is the noise density controlling the proportion of noisy pixels.

2. Detecting Impulse Noise:

Creating a binary mask (noise mask) that identifies pixels affected by salt-and-pepper noise. Pixels with intensity values of 0 or 255 are marked as noisy, while all others are considered clean. This can be represented mathematically as:

$$\text{noise\_mask}(x,y) = \begin{cases} \text{True} & \text{if } p(x,y) = 0 \text{ or } 255, \\ \text{False} & \text{otherwise.} \end{cases}$$

This simple threshold-based detection ensures that only corrupted pixels are targeted for filtering, leaving clean regions untouched.

3. Calculating the Uncertainty Threshold:

Compute an uncertainty threshold, based on the variability in noisy regions. For each noisy pixel identified by the noise mask, a 3×3 local window is extracted. The uncertainty of the window is calculated as the ratio of the standard deviation (σ) to the mean (μ) of the pixel intensities:

$$\text{Uncertainty} = \begin{cases} \frac{\sigma}{\mu} & \text{if } \mu > 0, \\ 0 & \text{otherwise.} \end{cases}$$

Here, σ is the standard deviation and μ is the mean of the pixel values in the local window. Once the uncertainties for all noisy pixels are computed, the global uncertainty threshold is determined as their mean:

$$\text{Uncertainty\_Threshold} = \frac{1}{N}\sum_{i=1}^{N} \text{Uncertainty}_i,$$

where N is the number of noisy pixels. This threshold is used to adapt the filtering strategy in the next step.

4. Modified Recursive Median Filter (MRMF)

A recursive median filter with uncertainty-based adaptation. For each noisy pixel, a local window is extracted, and the median of the pixel intensities is calculated. The uncertainty for the local window is recalculated, and a comparison is made with the pre-computed uncertainty threshold. The filtering strategy is then adjusted as follows:

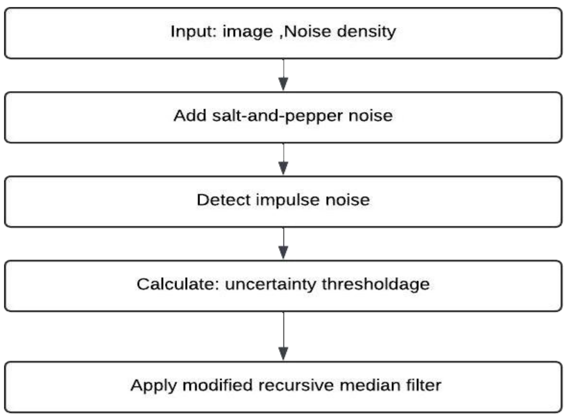
Low Uncertainty (Uncertainty < Threshold):

The pixel value is replaced with the local median.

High Uncertainty (Uncertainty >= Threshold):

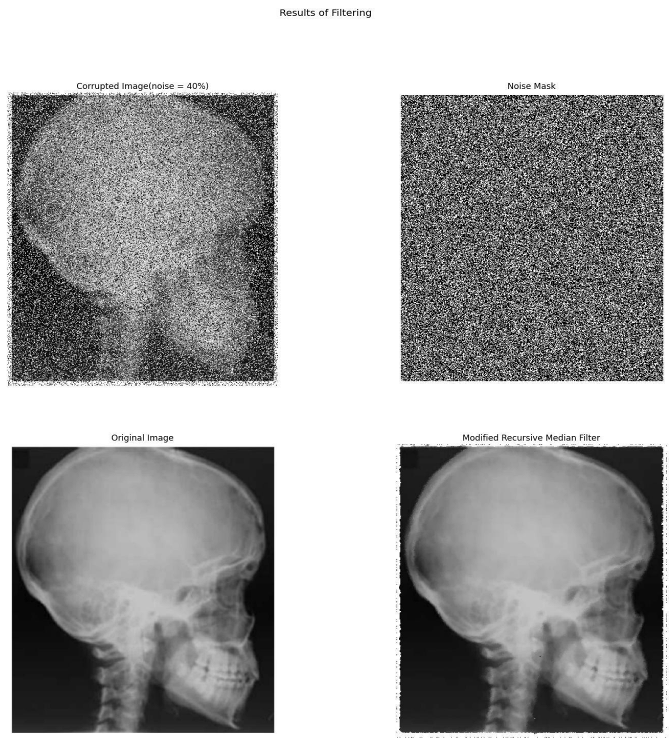
The pixel value is replaced with the median of its 4-nearest neighbours.This adaptive approach ensures that regions with high variability, such as edges and textures, are preserved while effectively suppressing noise.

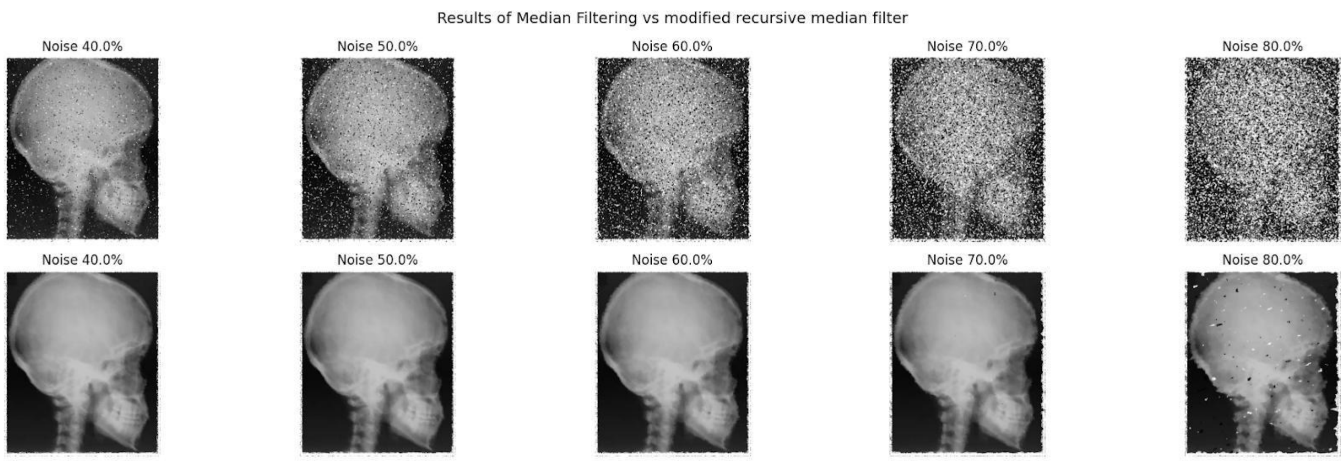
Flowchart:



Results

The results demonstrate the effectiveness of the modified recursive median filter in comparison to the standard median filter for removing salt-and-pepper noise across various noise densities. The first set of results highlights the restoration of a grayscale image with 40% noise. The corrupted image shows extensive pixel degradation, as depicted in the noise mask. In the second set of results, as noise levels increase from 40% to 80%, the standard median filter struggles to preserve structural details, leading to significant blurring and loss of features, whereas the modified recursive median filter successfully removes the noise, producing a clean image that closely resembles the original. In contrast, the modified recursive median filter consistently outperforms the standard approach, effectively restoring the image even at higher noise levels while retaining important details, such as the skull's outline.These results validate the enhanced noise detection and uncertainty modeling capabilities of the modified recursive median filter, which enable it to target corrupted pixels more accurately and maintain visual clarity under challenging noise conditions.





IV. CONCLUSION

This study presented the practical implementation and comparative analysis of inverse and Wiener filtering

Techniques for image restoration across various scenarios. Results indicate that both filters effectively restore degraded images in the absence of noise. However, under the influence of additive noise, the Wiener filter outperforms the inverse filter due to its ability to adaptively balance noise suppression and detail preservation. Similarly, the Modified Recursive Median Filter (MRMF) demonstrates a robust and adaptive approach for impulse noise removal, leveraging uncertainty-based filtering techniques. By dynamically adjusting thresholds based on mean-variance calculations, MRMF efficiently suppresses noise while preserving structural integrity in moderate-density noise conditions.

Experimentation with different window sizes, thresholds, and morphological techniques showed limited success for high-density noise. Despite these challenges, MRMF provides robust noise suppression and structural preservation, making it a reliable solution for moderate-density noise in image restoration. Future work will extend these findings by exploring additional advanced techniques, such as machine learning-based approaches, to address high-density noise scenarios and improve computational scalability.

V. REFERENCES

[1] Khan, Mohammad Mahmudur Rahman, Shadman Sakib, Rezoana Bente Arif, and Md. Abu Siddique. Digital Image Restoration in Matlab: A Case Study on Inverse and Wiener Filtering. 2019. 10.20944/preprints201811.0566.v2.

[2] G. Devarajan, V. K. Aatre, and C. S. Sridhar. "Analysis of Median Filter," ACE '90 Proceedings of [XVI Annual Convention and Exhibition of the IEEE In India], Bangalore, India, 1990, pp. 274-276. doi: 10.1109/ACE.1990.762694.

[3] B. Fu, X. Xiong, and G. Sun. "An Efficient Mean Filter Algorithm," The 2011 IEEE/ICME International Conference on Complex Medical Engineering, Harbin, China, 2011, pp. 466-470. doi: 10.1109/ICCME.2011.5876785.

[4] S. Sivasakthi. A Study on Morphological Image Processing and Its Operations. 2018.

[5] Dehghani Tafti, Abdolreza, and Ehsan Mirsadeghi. "A Novel Adaptive Recursive Median Filter in Image Noise Reduction Based on Using the Entropy," 2012 IEEE International Conference on Control System, Computing and Engineering, 2012. doi: 10.1109/ICCSCE.2012.6487201.

[6] A. K. Boyat and B. K. Joshi. "A Review Paper on Noise Models in Digital Image Processing," Signal & Image Processing: An International Journal (SIPIJ), vol. 6, no. 2, April 2015.

[7] A. E. Saleh, F. J. Zbeda, S. A. Salem, and S. O. Albasheer. "Image Restoration Using Hybrid Technique Based on Noise Detection and Uncertainty," 2021 IEEE 1st International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA), Tripoli, Libya, 2021, pp. 700-704. doi: 10.1109/MI-STA52233.2021.9464503.