1. Introduction

1.1 Background

Image denoising is a fundamental task in the field of image processing, holding significant importance in various applications. In medical imaging, denoising plays a crucial role in enhancing the quality of images for more accurate diagnosis and treatment planning. In the realm of photography, denoising helps in improving the aesthetic and clarity of images captured under suboptimal conditions. Similarly, in astronomy, it aids in the clearer visualization of celestial bodies by reducing noise that often obscures critical details in images captured by telescopes. The overarching goal of image denoising is to remove unwanted noise while preserving essential features of the image, such as edges and textures.

1.2 Objective

The objective of this project is to develop and evaluate an image denoising algorithm. This involves comparing different denoising techniques to identify the most effective approach for reducing noise while retaining the integrity of the original image. The project seeks to apply these techniques to a dataset of images with varying levels of noise, assessing their performance using quantitative metrics and visual analysis.

1.3 Literature Review

The development of the denoising algorithm in this project draws inspiration from several key pieces of literature:

1. Richard Wenzhe Xu's "Techniques and Applications of Image Denoising" [1] discusses various denoising methods, emphasizing the use of Fourier Transform for noise reduction. Xu's work provides a comprehensive overview of denoising techniques, highlighting the effectiveness of Fourier Transform in the frequency domain for isolating and removing noise components.

2. Naveen S. and Aiswarya V. A. (2015) in their paper "Image Denoising by Fourier Block Processing and Wiener Filtering" [2] present an approach that combines block processing with Wiener filtering. This method stands out for its ability to adaptively denoise different parts of an image, thereby maintaining more of the image's original features.

3. Navarro and Molimard's 2019 paper "Directional Denoising Using Fourier Spectrum Cloning" [3] introduces a novel approach that utilizes Fourier Spectrum Cloning for directional denoising. This method is particularly notable for its directional precision in

noise reduction, offering a targeted approach to denoising that is especially useful for images with directional noise patterns.

These studies collectively provide a foundation for the exploration of various image denoising techniques, guiding the methodology of this project. The innovative approaches and findings from these papers significantly contribute to the understanding of effective denoising strategies and their practical applications.

2. Description of Algorithm

2.1 Algorithm Overview

The denoising algorithm developed in this project employs a combination of *Fourier Transform-based Wiener filtering* and traditional spatial domain filters for comparison purpose, specifically mean and median filters, as well as VisuShrink wavelet denoising.

- **Fourier Transform-based Wiener Filter**: This filter operates in the frequency domain. It uses the Fourier Transform to convert the image to the frequency domain, where noise characteristics are distinctively different from the signal. The Wiener filter is then applied to reduce noise while preserving the image's main features.

- **Mean and Median Filters**: These are spatial domain filters. The mean filter replaces each pixel's value with the average of its neighbors, smoothing out variations. The median filter, on the other hand, replaces each pixel's value with the median of its neighboring pixels, which is effective in removing salt-and-pepper noise.

- **VisuShrink Wavelet Denoising**: This method employs wavelet transform for noise reduction. It involves decomposing the image into various frequency subbands and then applying a thresholding technique to remove noise.

2.2 Preprocessing Steps

The preprocessing phase is crucial for preparing the images for effective denoising. It includes the following steps:

- **Image Normalization**: This step adjusts the range of pixel intensity values. The images are converted to a floating-point representation, and their values are scaled to a specified range. This normalization is essential for ensuring consistency across different images and enhancing the effectiveness of subsequent processing steps.

- **Preliminary Noise Reduction (Gaussian Blur)**: A Gaussian blur is applied as an initial noise reduction step. It helps in reducing high-frequency noise components, making the subsequent denoising process more effective.

2.3 Flowchart

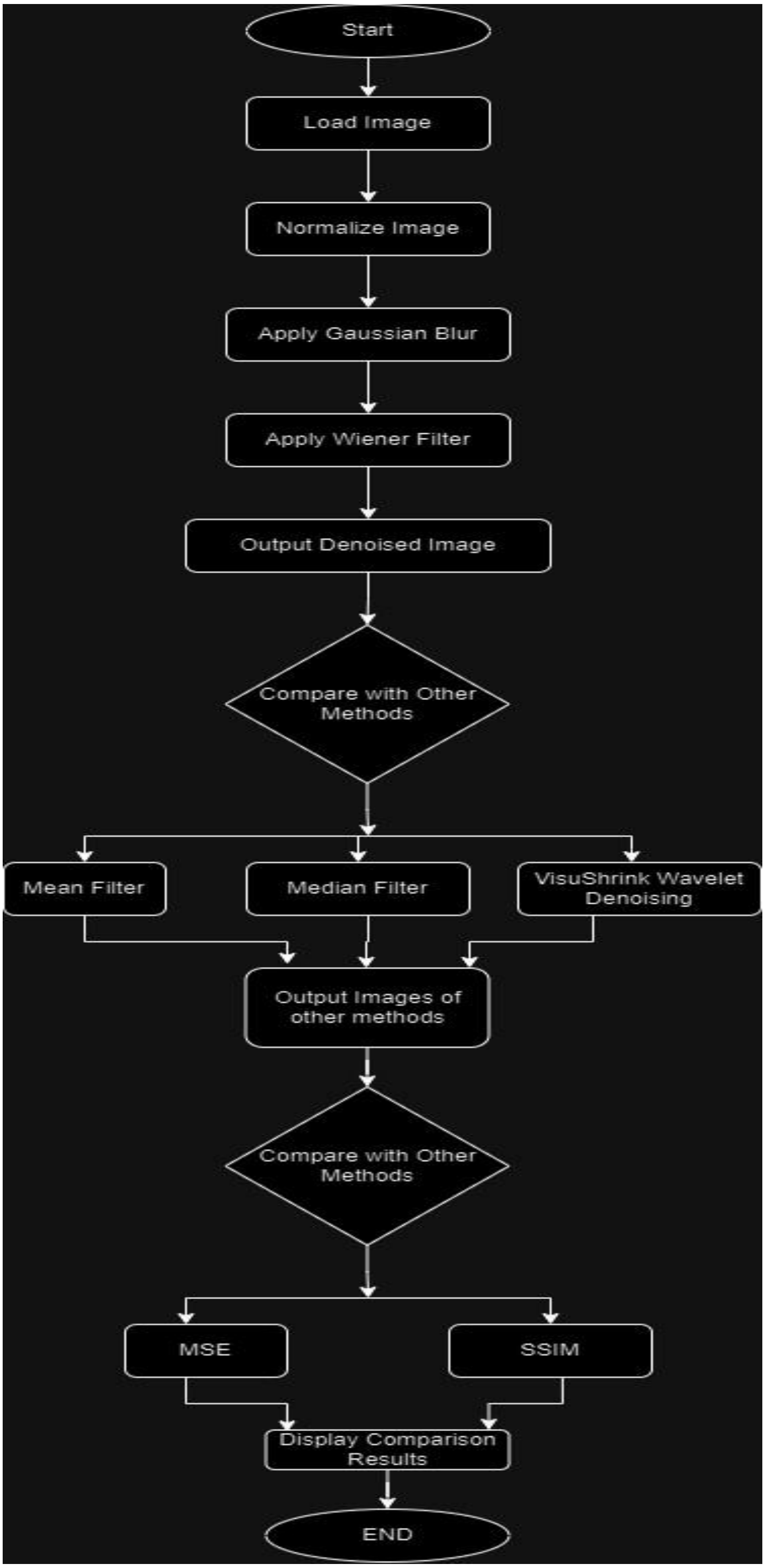

Figure 2.1- Flowchart of the workflow

3. Presentation of the Results

3.1 Dataset Description

The dataset used in this project comprises a collection of 25 original images along with their corresponding noisy versions. These noisy images are generated at three different noise levels, labelled as 'Noisy10', 'Noisy25', and 'Noisy50', representing increasing degrees of noise intensity. The variety in noise levels allows for a comprehensive evaluation of the denoising algorithm under various conditions, making the dataset well-suited for assessing both the effectiveness and robustness of the implemented denoising techniques.

3.2 Evaluation Metrics

Two key metrics are employed to evaluate the performance of the denoising algorithm:

- **Mean Squared Error (MSE)**: MSE quantifies the average squared difference between the original and denoised images. It is a measure of the extent to which the denoising process alters the pixel values from the original. Lower MSE values indicate better performance, as they suggest less deviation from the original image.

- **Structural Similarity Index (SSIM)**: SSIM is used to assess the similarity between the original and denoised images in terms of luminance, contrast, and structure. Unlike MSE, SSIM is more aligned with human visual perception. It ranges from -1 to 1, where higher values indicate greater similarity and thus better denoising performance.

These metrics provide a dual perspective, combining the error-based evaluation of MSE with the perceptual evaluation of SSIM, offering a comprehensive understanding of the denoising quality.

3.3 Results with Visualizations

The results are presented through a series of tables and graphs, visually depicting the MSE and SSIM values for each noise level. The data clearly demonstrate how the denoising algorithm performs under different noise intensities. Key observations include:

MSE Trends:

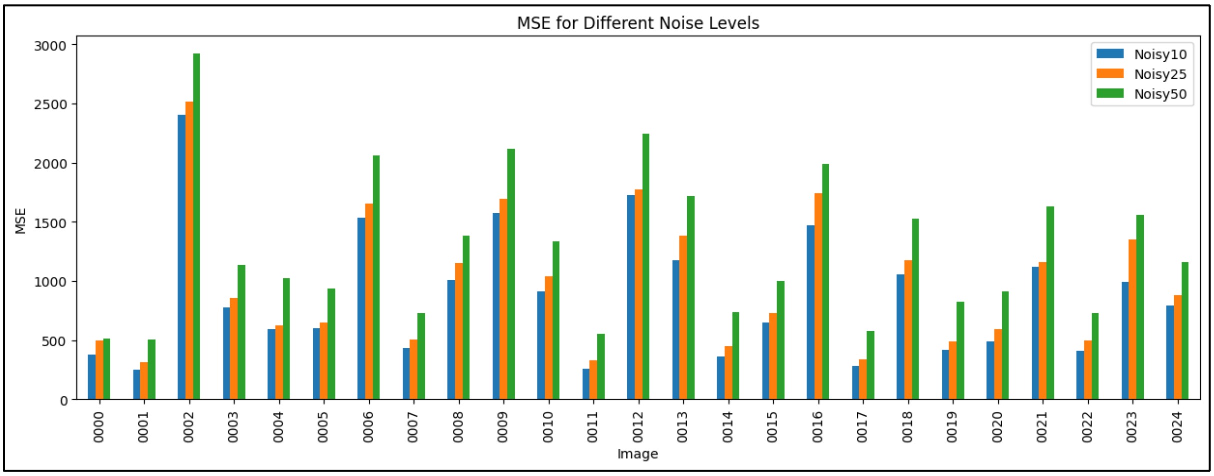

Figure 3.1- Graph Visualization of MSE Values

The chart shows algorithm performance assessed through Mean Squared Error (MSE) on images with three noise levels: Noisy10, Noisy25, and Noisy50. MSE increases with higher noise levels, indicating greater challenges for accurate image processing. Notably, Noisy50 consistently has the highest MSE, signifying its impact on the algorithm's performance. Conversely, Noisy10 yields the lowest MSE, showcasing the algorithm's best performance. MSE variations across images imply noise impact varies depending on the specific image.

SSIM Trends:

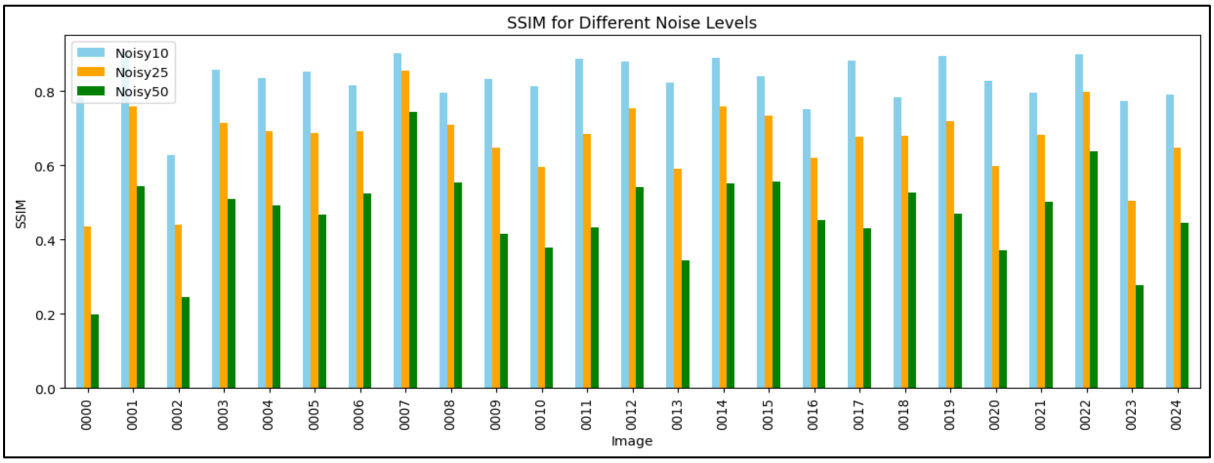

Figure 3.2- Graph Visualization of SSIM Values

The chart exhibits the Structural Similarity Index (SSIM) for images with three noise levels: Noisy10, Noisy25, and Noisy50. Higher SSIM values for Noisy10 suggest better structural integrity is retained at lower noise levels. In contrast, Noisy50, with lower SSIM values, indicates more structural detail loss. The trend suggests increased noise levels correlate with reduced image structure preservation, although variations across images imply the influence of individual image characteristics.

Sample Images:

A selection of sample images is included to visually demonstrate the impact of the denoising process. For each noise level ('Noisy10', 'Noisy25', 'Noisy50'), the following images are presented side by side:

Figure 3.3- Sample Image Comparison

4. Key Findings and Discussions

4.1 Performance Analysis

The analysis of the denoising algorithm across three noise levels (Noisy10, Noisy25, Noisy50) revealed distinct performance trends. For Noisy10, the algorithm demonstrated a generally effective noise reduction, reflected in relatively low Mean Squared Error (MSE) values and high Structural Similarity Index (SSIM) scores. This indicates successful preservation of image details with minimal deviation from the original images.

As the noise level increased to Noisy25, a noticeable increase in MSE and decrease in SSIM was observed. This trend suggests that while the algorithm remains effective at a moderate noise level, its ability to maintain the structural integrity of the images diminishes slightly.

The most challenging scenario was presented at the Noisy50 level, where both MSE and SSIM values indicated a significant impact on image quality. High MSE values at this level suggest that the denoising process altered the pixel values considerably from the original image, while the low SSIM scores reflect a substantial loss in image structure and detail.

4.2 Comparison with Noise Levels

The results indicate a clear correlation between noise intensity and the performance of the denoising algorithm. The algorithm is more capable of handling lower levels of noise, maintaining a balance between noise reduction and detail preservation. However, as noise intensity increases, this balance is disrupted, leading to either over-smoothing or inadequate noise removal.

4.3 Strengths and Limitations

The main strength of the algorithm lies in its robustness at low to moderate noise levels, where it effectively reduces noise without significantly compromising image details. This makes it suitable for applications where noise levels are relatively controlled or predictable. However, the algorithm's limitations become apparent at high noise levels, where it struggles to distinguish between noise and important image features.

5. Conclusion

This project's development and evaluation of an image denoising algorithm yielded notable results:

- **Effective at Low to Moderate Noise Levels**: As shown by MSE and SSIM metrics, the algorithm effectively reduced noise in images with lower noise intensities (Noisy10 and Noisy25), maintaining image quality.

- **Problems with High Noise Levels**: The algorithm had trouble preserving details at the Noisy50 level, which resulted in a major modification of the image and a loss of structural integrity.

- **Robust and Versatile**: Demonstrated versatility across different noise types and images, suggesting potential for diverse applications.

- **Understanding Denoising Techniques**: The experiment demonstrated the benefits of different denoising techniques, such as spatial domain filters and Wiener filtering based on the Fourier Transform, highlighting the necessity for a multifaceted approach.

In summary, the method exhibits potential in situations with low to moderate noise levels, but more optimization is needed for high noise levels. Subsequent research endeavours may involve the incorporation of sophisticated methodologies to enhance the discernment between extraneous elements and crucial image information, hence broadening the algorithm's scope in domains necessitating superior image processing.

References

[1] Richard Wenzhe Xu. "Techniques and Applications of Image Denoising". Retrieved from [l1j2b-richard-wenzhe_xu.pdf]

[2] Naveen, S., & Aiswarya, V. A. (2015). Image Denoising by Fourier Block Processing and Wiener Filtering. Procedia Computer Science, 58, 84-91. https://doi.org/10.1016/j.procs.2015.08.011

[3] Navarro, L., & Molimard, J. (2019). Directional Denoising Using Fourier Spectrum Cloning. In G. S. Nikolić & D. Z. Marković-Nikolić (Eds.), Fourier Transforms (Ch. 4). IntechOpen. https://doi.org/10.5772/intechopen.85519