Advanced Image Denoising through Combined Directional Wavelet based NLM and BM3D Technique

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Degree for which the Thesis is submitted: **Bachelor of Technology**

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It is certified that the work contained in this thesis entitled **“Advanced Image Denoising through Combined Directional Wavelet based NLM and BM3D Technique”** submitted by **Anik Das Emon(2012168), Pronab Chandra Roy (2012167), Shazedul Islam (2012163)** for the B.Tech. End Semester Project Examination November, 2023 is absolutely based on their own work carried out under my supervision.

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"You have to dream before your dreams can come true."

A. P. J. Abdul Kalam

Abstract

Wavelet-based Non-Local Means (NLM) and BM3D (Block-Matching 3D) are popular algorithms used in image denoising, each with its approach to reducing noise while preserving image details. Harnessing the directional insights of wavelet transformation, our method dissects image details, applying tailored Non-Local Means (NLM) for noise reduction within each directional subband.By integrating Block Matching 3D (BM3D), our method leverages the 3D contextual understanding of image patches, uncovering hidden details while eradicating noise artifacts. Additionally, adaptive thresholding utilizing wavelet transformation is employed to finely control denoising strength. Experimental results showcase the efficacy of the proposed technique against prevalent benchmarks. Quantitative evaluation using metrics such as Mean Squared Error (MSE), Signal-to-Noise Ratio (SNR), and Peak Signal-to-Noise Ratio (PSNR) was conducted across diverse image types.

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CHAPTER 1

Introduction

The pervasive presence of noise in digital images poses a significant challenge in various applications, including medical imaging, satellite imaging, surveillance, and photography. Addressing this challenge requires sophisticated techniques that not only effectively remove noise but also preserve essential image details. In recent years, significant advancements have been made in the field of image denoising, leveraging the power of both non-local means (NLM) and block-matching 3D (BM3D) techniques. However, conventional approaches often struggle to handle complex noise patterns and preserve fine details, leading to a demand for more robust and advanced denoising methodologies. Advancing image denoising by synergistically combining wavelet-based directional non-local means (NLM) and the block-matching 3D (BM3D) technique. This hybrid approach aims to exploit the strengths of both methodologies while mitigating their individual limitations. The incorporation of wavelet-based directional information enhances the ability to capture image structures in various orientations, enabling a more accurate characterization of the underlying image features. Simultaneously, the integration of BM3D further refines denoising by exploiting similar local patches and effectively exploiting the self-similarity within an image.

1.0.1 Motivation

Image denoising aims to remove unwanted noise from images, leading to clearer and more visually appealing results. Noise can degrade image quality in various applications, such as medical imaging or remote sensing. Different types of noise, such as Gaussian, salt-and-pepper, or speckle noise, affect images differently. The hybrid approach intends to develop a robust denoising methodology capable of handling diverse noise types commonly encountered in practical scenarios, ensuring its applicability across a wide range of image sources.The proposed research aims to address these challenges by combining two powerful denoising methodologies: Non-Local Means (NLM) and Block-Matching 3D (BM3D) algorithms. Integrating these techniques with wavelet-based directional processing offers a comprehensive solution to tackle various noise types and levels while maintaining the integrity of important image features. The ultimate goal of this research is to create a denoising methodology that finds practical application in various fields, such as medical imaging, surveillance, astronomy, or any domain where clean and accurate images are imperative for decision-making or analysis.

1.0.2 Objective

i To enhance Image quality through denoising.

ii To develop a denoising approach capable of handling a wide range of noise types commonly encountered in practical scenarios across various domains, ensuring the methodology's adaptability and effectiveness.

iii To improve the interpretability and analysis of images by boosting their SNR.

iv To Validate the effectiveness and practical utility of the hybrid denoising approach across diverse fields.

CHAPTER 2

Literature survey

Barbhuiya et al.[1] Discuss about similarities and dissimilarities between wavelet transform and Fourier transform are also discussed. Furthermore, the applications of wavelet transform in many areas like face recognition, fingerprint analysis, image compression and image denoising are discussed.
Ruikar et al.[2] Wavelet transform in connection with threshold functions for removing noise. Universal, Visu Shrink, Sure Shrink and Bayes Shrink, normal shrink are compared with our threshold function, it improves the SNR efficiently.
Ergen et al.[3]Wavelets gave a superior performance in image denoising because here multi-resolution analysis is possible. Wavelet thresholding is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising.
Kaur et al.[4]An image denoising threshold method that exploits the subband dependency of the wavelet coefficients to estimate the signal variance using the local neighboring coefficients.
Biswas et al.[5]Image denoising has been done by wavelet transform using Visu thresholding techniques for different wavelet families. PSNR (Peak signal to noise ratio) and RMSE (Root Mean Square Error) value is also calculated for different wavelet families.
Koranga et al.[6] proposed that the advanced image denoising algorithm improves upon BM3D by employing adaptive soft-thresholding and total variation filtering, adapting thresholds to noise intensity, and introducing an Adaptive Weight Function based on spatial distances. The method, tested on diverse digital images, surpasses BM3D in

visual quality, PSNR, and SSIM. Keywords: Adaptive filtering, Total variation, Soft-thresholding, K-means clustering, Adaptive weight function.

Yahya et al.[7] proposed that the advanced image denoising algorithm improves upon BM3D by employing adaptive soft-thresholding and total variation filtering, adapting thresholds to noise intensity, and introducing an Adaptive Weight Function based on spatial distances. The method, tested on diverse digital images, surpasses BM3D in visual quality, PSNR, and SSIM. Keywords: Adaptive filtering, Total variation, Soft-thresholding, K-means clustering, Adaptive weight function.

Shreyamsha Kumar et al.[8] proposed that the non-local means filter reduces noise in images by considering self-similarities, but struggles with increased noise, causing blurring. This paper suggests combining it with wavelet-based noise thresholding, outperforming other methods in noise reduction, visual quality, PSNR, and Image Quality Index. The proposed method balances noise suppression and detail preservation.

Li et al.[9] proposed that a new image denoising approach, the Two-Directional Nonlocal (TDNL) model, leverages similarities within image patches both horizontally and vertically. It combines nonlocal-means-like estimations based on column similarities and nonlocal-autoregression-like estimations from row similarities. The TDNL model demonstrates comparable or superior performance to state-of-the-art denoising methods, offering a promising alternative for image enhancement.

Ye et al.[10] proposed that our proposed image denoising method enhances BM3D by introducing adaptive filtering, adjusting thresholds based on noise levels, and employing an Adaptive Weight Function for dissimilarity measurement. This approach, tested on diverse digital images, surpasses BM3D, delivering improved visual quality, higher PSNR, and enhanced SSIM index.

HanminOur et al.[11] proposed that improved denoising method enhances BM3D with adaptive filtering and adjusted thresholds based on noise. Using an Adaptive Weight Function, it surpasses BM3D in visual quality, PSNR, and SSIM index, tested on various digital images.

Zhang et al.[12]This paper tackles the common issue of reducing Gaussian noise in signals and images. It reviews various wavelet denoising methods, highlighting the effectiveness of the Block Matching and 3D Filtering (BM3D) algorithm as a top choice. Additionally, the Non-Local Means and Optimal Spatial Adaptation (OSA) methods prove successful for image denoising.

Thakur et al.[13] proposed that this study taps into natural image similarities for effective denoising. Introducing a Two-Directional Nonlocal (TDNL) model, it leverages similarities in both columns and rows. The model, with three components, achieves denoising through nonlocal-means-like and nonlocal-autoregression-like estimations, showcasing comparable or superior performance to leading denoising methods.
Chen et al.[14] that the paper introduces a method using Rotated Wavelet Filters (RWF) to enhance wavelet-based image denoising, building on Donoho's 1994 work. It surpasses traditional wavelet approaches and advanced transforms like Curvelet, demonstrating improved quality in general and medical images. Notably, it maintains computational efficiency similar to standard wavelet methods and faster execution than BM3D algorithm.
Bin Shen et al.[15] that this paper addresses the common issue of reducing Gaussian noise in signals and images. It reviews various wavelet denoising methods, highlighting the effectiveness of the Block Matching and 3D Filtering (BM3D) algorithm as a top choice. Additionally, the Non-Local Means and Optimal Spatial Adaptation (OSA) methods prove successful for image denoising, offering valuable alternatives.

Ref. No.	Author & year	Title of the paper	Methodology used	Findings
1	A.H.M. Jaffar Iqbal Barbhuiya, K. Hemachandran Year: 2013	Wavelet Transformations Its Major Applications In Digital Image Processing	A. Image compression B. Image denoising C. Discrete image transforms	A. Fourier methods are not always good tools to recapture the signal or image. B. Wavelet transform provides us with one of the methods for image denoising.
2	R. Guhathakurta Year: 2010	Comparison of BayesShrink and SureShrink for image denoising using DWT	A. Visu Shrink B. Sure Shrink C. Bayes Shrink D. Normal Shrink	Wavelets gave a superior performance in image denoising because here multi-resolution analysis is possible. Wavelet thresholding is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising.

3	B. Ergen Year:2012	Signal and image denoising using wavelet transform	A. Image compression B. Computer graphics C. Pattern recognition.	successfully used in many scientific fields such as signal processing, image compression, computer graphics, and pattern recognition.
4	Dr. S. Ruikar, Dr. D. Dharmpal Year: 2010	Image denoising using wavelet transform	A. Visu Shrink (universal threshold) B. Sure Shrink (Sub-band level)	wavelet transform in connection with threshold functions for removing noise. Universal, Visu Shrink, Sure Shrink and Bayes Shrink, normal shrink are compared with our threshold function, it improves the SNR efficiently.

5	M. Biswas, H. Om, Year:2013	An Image Denoising Threshold Estimation Method	Threshold method	An image denoising threshold method that exploits the wavelet coefficients to estimate the signal variance using the local neighboring coefficients.
6	P. Koranga, G. Singh, D. Verma, Year:2018	Image Denoising Based on Wavelet Transform using Visu Thresholding Technique	A. PSNR (Peak signal to noise ratio) B. RMSE (Root Mean Square Error)	Image denoising has been done by wavelet transform using Visu thresholding techniques for different wavelet families. PSNR (between max power of signal and power of corrupting noise) and RMSE (measure error between two images) value is also calculated for different wavelet families.

7	Ye, Hanmin, Bin Shen, and Shili Yan. Year:2018	Prewitt edge detection based on BM3D image denoising	A. Combines the de-noising of BM3D (block-matching 3D filtering) and Prewitt operator. B. Multi-threshold and read-time edge detection method based on Sobel gradient template	A. Prewitt operator will be detected a lot of false edges during the detection. B. Combines the de-noising of BM3D and Prewitt operator to improve the anti-noise of the algorithm and reduce the misjudgment of the edge of the algorithm. C. Sobel: it creates an image emphasizing edges.
8	G. Chen, W. Xie and Y. Zhao Year: 2013	Wavelet-based denoising: A brief review	A.3D filtering (BM3D) algorithm B. Non-local means and the OSA methods. C. Portilla's method and bivariate thresholding.	Developed block matching and 3D filtering (BM3D) algorithm performs much better than other existing methods. The non-local means method and the optimal spatial adaptation (OSA) method are also very successful methods in image denoising.

9	BM3D image denoising algorithm based on an adaptive filtering Year:2020	Blockchain Based Framework for Educational Certificates Verification	Nonlocal means which was proposed by Buades et al. Dual domain image denoising method. K-means clustering method. soft-thresholding methods. Peak Signal to Noise Ratio (PSNR) index and Structural Similarity (SSIM) index	the optimal value of the threshold is a tremendously difficult task. BM3D and Dual Domain: State-of-the-art methods like block-matching 3D filtering (BM3D) seamlessly combine both spatial and transform domains k-means clustering to reducing the risk of finding poor matching.
10	B. K. Shreyamsha Kumar Year:2012	Image denoising based on non-local means filter and its method noise thresholding	Noise thresholding using wavelets. Non-local means filter and its method noise thresholding. Frequency-based denoising methods adopt low-pass filtering	Finding a universal threshold value known as VisuShrink, which depends on the noise power and the signal size (number of samples in the image). Drawback: smooth texture region. Frequency-Domain Deep Guided Image Denoising. Data Frequency Statistical Characteristics.

Table 3.1: Literature survey with summarized findings

CHAPTER 3

Proposed System

3.1 Basics of Directional Wavelet Transform, Adaptive Thresholding, NLM Filtering, BM3D and the proposed algorithm

3.1.1 Directional Wavelet Transform

In our denoising methodology, the utilization of the Directional Wavelet Transform serves as a pivotal step in extracting essential structural information from noisy images. The Directional Wavelet Transform extends the traditional wavelet transform by providing a decomposition that captures not only the frequency content but also the directional characteristics inherent in images.

1. Transforming Image Structure: The process begins with the conversion of the input image to a floating-point representation, denoted as img_float32. This allows for precision in the subsequent wavelet transformation. The 'bior1.3' wavelet is employed due to its balanced frequency and directional selectivity, making it well-suited for capturing both high and low-frequency components along various orientations.

2. Decomposition into Directional Subbands: The resulting coefficients consist of four subbands: cA capturing the approximation, and cH, cV, and cD capturing the horizontal, vertical, and diagonal details, respectively. These subbands represent different directional components of the image, enabling a more nuanced analysis of image structure.

3. Directional NLM Filtering on Subbands: Each directional subband undergoes the Directional Non-Local Means (NLM) filtering process. This involves applying a customized NLM filter that considers both pixel intensities and directional information during patch matching and averaging. The goal is to preserve structural details while effectively suppressing noise.

4. Inverse Wavelet Transform: Reconstructing the Image: Following the denoising of individual directional subbands, the Inverse Directional Wavelet Transform is applied to reconstruct the final denoised image. This step completes the directional wavelet denoising process, resulting in an enhanced representation of the original image with preserved structural details and reduced noise.

In essence, the Directional Wavelet Transform enriches our denoising methodology by providing a multi-scale and multi-directional analysis of image structure. This comprehensive approach allows us to selectively denoise components based on their directional characteristics, contributing to the overall effectiveness of the denoising pipeline.

3.1.2 Directional NLM Filtering

In the first stage of our denoising pipeline, we harness the capabilities of Directional Non-Local Means (NLM) filtering to elevate the quality of noisy images. NLM is a powerful denoising technique that exploits the redundancy in natural images by comparing and averaging similar patches. Traditionally, NLM operates in the spatial domain, searching for similar patches based on pixel intensities. In our approach, we extend this concept to the directional domain by first applying a directional wavelet transform to the input image. This transform decomposes the image into directional subbands, capturing information along various orientations. The directional NLM filter is then applied to these subbands, where the comparison of patches considers both intensity and directional characteristics.

The key to the effectiveness of NLM lies in its ability to distinguish between signal and noise through patch similarity metrics. The filtering process is governed by the following formula:

$$\hat{I}(\mathbf{x}) = \frac{\sum_{\mathbf{p}\in\Omega} w(\mathbf{p}) \cdot I(\mathbf{x}+\mathbf{p})}{\sum_{\mathbf{p}\in\Omega} w(\mathbf{p})}, \tag{3.1}$$

where $\hat{I}(\mathbf{x})$ represents the denoised intensity at pixel $\mathbf{x}, I(\mathbf{x}+\mathbf{p})$ is the intensity of a similar patch at position $\mathbf{x}+\mathbf{p}, \Omega$ is the search window, and $w(\mathbf{p})$ is a weight term based on the similarity between patches. This adaptation of NLM to directional subbands enhances its denoising capabilities, allowing us to preserve intricate image details while effectively suppressing noise. The directional NLM filtering stage serves as a foundational step, setting the stage for subsequent refinement through the Block Matching 3D (BM3D) process.

3.1.3 Block Matching 3D (BM3D)

In our denoising methodology, the integration of the Block Matching 3D (BM3D) algorithm plays a crucial role in further refining the denoised image obtained from the Directional Non-Local Means (NLM) filtering process. BM3D is a state-of-the-art denoising technique that leverages collaborative filtering and 3D transform-domain processing to achieve superior results.

1. Collaborative Denoising with BM3D: BM3D operates on the principle of collaborative denoising, where similar blocks within the image are grouped together for joint processing. This collaborative approach enables the exploitation of redundancies across similar structures, enhancing the denoising performance.

2. 3D Transform-Domain Processing: BM3D incorporates a 3D transform-domain processing step, where blocks are transformed into a sparse representation in a transform domain, typically using a 3D Discrete Cosine Transform (3D DCT). The sparsity in

this transform domain allows for efficient thresholding, distinguishing between signal and noise components.

3. Collaborative Wiener Filtering: After the transformation, a collaborative Wiener filtering process is applied to attenuate the noise while preserving the signal. This involves adaptively adjusting the weights of the transform coefficients based on their statistical properties and the collaborative information from similar blocks.

4. Aggregation of Denoised Blocks: The denoised blocks are then aggregated to reconstruct the final denoised image. This aggregation process ensures a seamless integration of information obtained from different blocks, resulting in a coherent and visually pleasing denoised output.

5. Parameter Tuning for Optimal Performance: Parameters such as sigma_psd (power spectral density of the noise) are crucial in BM3D and may require fine-tuning based on the characteristics of the input image and the noise present. Experimentation with these parameters allows for optimization and ensures the adaptability of the algorithm across diverse datasets.

Incorporating BM3D into our denoising pipeline enhances the overall performance by exploiting collaborative filtering in the transform domain. This collaborative and transform-based strategy, coupled with the earlier directional wavelet denoising, contributes to a comprehensive and effective denoising methodology.

3.1.4 Adaptive Thresholding:

In the denoising pipeline, the incorporation of Adaptive Thresholding stands as a critical stage, fine-tuning the denoising process to achieve a balance between noise reduction and preservation of essential image features. This section elucidates the principles behind Adaptive Thresholding, its role in the methodology, and its impact on enhancing denoising precision.

1. Basics of Adaptive Thresholding: Adaptive Thresholding is a technique that dynamically adjusts the threshold for denoising based on the characteristics of the input image. Unlike fixed thresholding, this adaptive approach allows for selective denoising in different regions, accommodating variations in noise intensity.

2. Application on Wavelet Coefficients- Wavelet Coefficient Thresholding: In our denoising methodology, Adaptive Thresholding is applied to the wavelet coefficients obtained from the Block Matching 3D (BM3D) denoising step. The goal is to control the amount of denoising applied to different frequency components, tailoring the denoising process to the local characteristics of the image.

3. Working Principles - Dynamic Threshold Computation: The threshold is dynamically computed based on a factor (threshold_factor) multiplied by the median absolute value of the wavelet coefficients. This factor allows for flexibility in controlling the denoising strength, making the process adaptive to different noise levels and image structures.

4. Localized Denoising Control - Region-Specific Adjustment: Adaptive Thresholding enables localized denoising control, ensuring that regions with higher noise levels receive a more aggressive denoising treatment, while regions with important image details are subject to a more conservative threshold.

5. Mathematical Notation - Adaptive Thresholding Equation:

While not explicitly implemented in the code, the adaptive thresholding process can be represented conceptually as:

$\text{threshold} = \text{threshold\_factor} \times \text{median}\ (abs(\text{coefficients})\ )$

Algorithm 1 Combining Directional NLM & BM3D

```
procedure MAIN
    DIRECTIONAL_NLM_FILTER
    BM3D_DENOISING
    ADAPTIVE_THRESHOLDING
end procedure
procedure DIRECTIONAL_NLM_FILTER
    coeffs = DWT(noisy_image)
    for each subband in [cH, cV, cD] do
        subband = NLM(subband, sigma_nlm, patch_size_nlm, search_window_nlm)
    end for
    denoised_image = IDWT(coeffs)
end procedure
procedure BM3D_DENOISING
    denoised_image = BM3D(denoised_image, sigma_bm3d)
end procedure
procedure ADAPTIVE_THRESHOLDING
    coeffs = WaveletDecomposition(denoised_image, 'bior1.3', level=3)
    for i = 1 to length(coeffs) do
        coeffs[i] = thresholding(MedianCoeffs[i], threshold_factor)
    end for
    denoised_image = WaveletReconstruction(coeffs, 'bior1.3')
end procedure
```

Definition:

- coeffs : The coefficients include the approximation coefficients (cA) and the three directional subbands (cH, cV, cD).
- NLM(subband, sigma nlm, patch size nlm, search window nlm): Applies Fast Non-Local Means Denoising to the subband. This step helps remove noise from each directional component independently.
- BM3D(denoised image, sigma_bm3d): The denoised image obtained from NLM filtering (nlm_denoised_img) is then further processed using the bm3d_denoising() function, applying the BM3D denoising algorithm to the directional components.
- WaveletDecomposition(denoised image, 'bior1.3', level=3): Performs a 2D wavelet transform (level 3) on the BM3D denoised image.
- thresholding(MedianCoeffs[i], threshold factor): Applies adaptive thresholding using the adaptive_thresholding() function to each level of wavelet coefficients.
- WaveletReconstruction(coeffs, 'bior1.3'): Performs the inverse 2D wavelet transform to reconstruct the final denoised image.

3.1.5 Description of the diagram:

The original grayscale image is uploaded and displayed.

Gaussian noise with a specified sigma value is added to the original image, resulting in a noisy image.

The noisy image undergoes a directional wavelet transform using the 'bior1.3' wavelet. The horizontal (cH), vertical (cV), and diagonal (cD) components are separately processed using fast non-local means denoising (NLM). The denoised subbands are combined to obtain a partially denoised image.

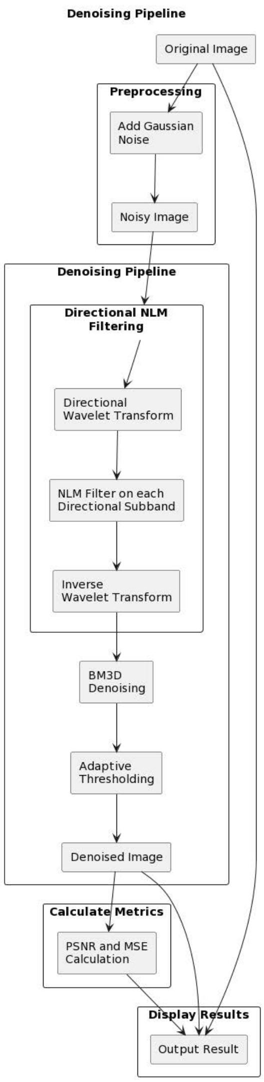


FIGURE 3.1: Combining directional NLM & BM3D

This denoising pipeline combines the strengths of directional NLM, BM3D, and wavelet thresholding to effectively reduce noise in the input image. The use of adaptive thresholding allows for more flexible noise suppression across different frequency bands. The SNR provides a quantitative measure of the denoising effectiveness.

CHAPTER 4

Experimental Results and Discussions

Our proposed algorithm has explored different quality measuring techniques for Gaussian noise, specifically focusing on MSE (Mean Squared Error), SNR (Signal-to-Noise Ratio), and PSNR (Peak Signal-to-Noise Ratio) metrics for evaluation in different types of images. Our approaches Show a moderate MSE (53.62), suggesting a relatively higher average squared difference compared to the Wiener filter but better performance than the Wavelet Transform. For Image(tulip) The highest SNR (25.15), indicates higher quality denoising and better preservation of the signal against the noise, compared to the other techniques. On the other hand, the highest PSNR (30.84), indicates higher fidelity in preserving image quality compared to the other methods. Other image analyses are given in the below table. Overall the proposed method combining wavelet-based Directional NLM and BM3D showcases better denoising effectiveness in terms of SNR and PSNR compared to the other techniques.

a) Original Image b) Noisy Image(Gaussian) c) Proposed Method

a) Original Image b) Noisy Image(Gaussian) c) Wiener Filter

a) Original Image b) Noisy Image(Gaussian) c) Wavelet Transform

Figure 4.1: Output comparison of the proposed method with Wiener Filter and Wavelet Transform method - Lena Image

Image :lena	**MSE**	**SNR**	**PSNR**
Wiener Filter	5388	-0.03	10.82
Wavelet Transform	54.70	22.08	30.75
Proposed Method	22.61	25.92	34.59

Table 4.1: Results of MSE, SNR and PSNR for the lena Image.

a) Original Imgae   b) Noisy Image(Gaussian)   c) Proposed Method

a) Original Imgae   b) Noisy Image(Gaussian)   c) Wiener Filter

a) Original Imgae   b) Noisy Image(Gaussian)   c) Wavelet Transform

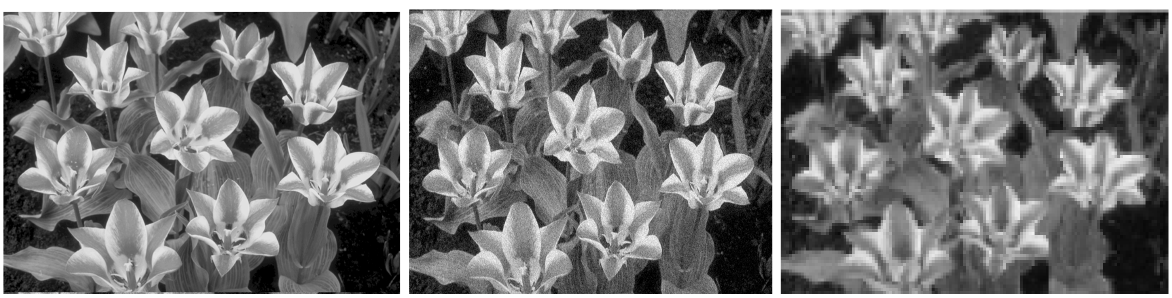
Figure 4.2: Output comparison of the proposed method with Wiener Filter and Wavelet Transform method - Pepper Image

Image : Peppers	**MSE**	**SNR**	**PSNR**
Wiener Filter	3225.55	0.76	10.81
Wavelet Transform	164.28	20.28	25.98
Proposed Method	53.62	25.15	30.84

Table 4.2: Results of MSE, SNR and PSNR for the Peppers Image.

a) Original Imgae b) Noisy Image(Gaussian) c) Proposed Method

a) Original Imgae b) Noisy Image(Gaussian) c) Wiener Filter



a) Original Imgae b) Noisy Image(Gaussian) c) Wavelet Transform

Figure 4.3: Output comparison of the proposed method with Wiener Filter and Wavelet Transform method - Tulip Image

Image: Tulip	**MSE**	**SNR**	**PSNR**
Wiener Filter	6969.26	-0.17	9.70
Wavelet Transform	121.33	20.79	27.29
Proposed Method	62.69	23.99	30.16

Table 4.3: Results of MSE, SNR and PSNR for the Tulip Image.

a) Original Image b) Noisy Image(Speckle) c) Proposed Method

a) Original Image b) Noisy Image(Speckle) c) Wiener Transform

Figure 4.1: Output comparison of the proposed method with Wiener Filter and Wavelet Transform method - Lena Image

Image :lena	MSE	SNR	PSNR
Wiener Filter	5388	0.03	10.82
Proposed Method	45.32	3.04	31.57

Table 4.1: Results of MSE, SNR and PSNR for the lena Image.

a) Original Imgae b) Noisy Image(Speckle) c) Proposed Method

a) Original Imgae b) Noisy Image(Speckle) c) Wiener Filter

Figure 4.2: Output comparison of the proposed method with Wiener Filter and Wavelet Transform method - Pepper Image

Image : Peppers	**MSE**	**SNR**	**PSNR**
Wiener Filter	3225.55	0.76	10.81
Proposed Method	15.70	3.04	36.17

Table 4.2: Results of MSE, SNR and PSNR for the Peppers Image

a) Original Imgae b) Noisy Image(Speckle) c) Proposed Method

a) Original Imgae b) Noisy Image(Speckle) c) Wiener Filter

Figure 4.3: Output comparison of the proposed method with Wiener Filter and Wavelet Transform method - Tulip Image

Image: Tulip	**MSE**	**SNR**	**PSNR**
Wiener Filter	6969.26	0.17	9.70
Proposed Method	49.75	3.05	31.16

Table 4.3: Results of MSE, SNR and PSNR for the Tulip Image.

CHAPTER 5

Conclusion and Future Work

In this research project, we introduced an innovative method for advanced image denoising through a combined approach using wavelet-based directional Non-Local Means (NLM) and Block-Matching 3D (BM3D) techniques. Our results demonstrate significant advancements in image denoising, particularly with Gaussian noise. This combined approach has showcased superior performance compared to traditional Wiener filters and wavelet transformation methods. The integration of directional NLM and BM3D techniques has effectively addressed noise reduction challenges, providing enhanced image quality and preserving important image features.the successful implementation of our combined wavelet-based directional NLM and BM3D technique for Gaussian noise reduction paves the way for extensive research aimed at expanding its capabilities, optimizing performance, and fostering its adoption in diverse real-world applications.

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