IOSR Journal of Mathematics (IOSR-JM)
e-ISSN: 2278-0661, p-ISSN: 2278-8727, Volume 22, Issue 4, Ser. 1 (July. – August. 2026), PP 10-19
www.iosrjournals.org

Adaptive Multi-Scale FFT-Based Image Denoising And Enhancement Using Frequency Domain Filtering

Puja Kumari[1], Dr. Anita Kumari[2]
(Research Scholar, Department Of Mathematics, Dr. Shyama Prasad Mukherjee University, India)
(Assistant Professor, Department Of Mathematics, Dr. Shyama Prasad Mukherjee University, India)

Abstract:
Image denoising is a fundamental task in image analysis and computer vision applications. Traditional frequency-domain filtering methods often use fixed filter parameters, which may not provide optimal performance for images corrupted with different noise levels. This paper presents an Adaptive Multi-Scale FFT-Based Image Denoising and Enhancement framework. The proposed method decomposes the image into multiple scales, performs Fast Fourier Transform (FFT) at each scale, and adaptively adjusts filtering parameters according to noise characteristics. The filtered images are combined to reconstruct an enhanced image with improved visual quality and preserved edge information. The performance of the proposed method is evaluated using Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). Experimental results demonstrate improved denoising performance compared with conventional FFT-based filtering approaches.
Key Word: *Fast Fourier transformation, Image Denoising, Frequency Domain Filtering, Multi-Scale Analysis, Image Enhancement, PSNR, MSE, SSIM.*

Date of Submission: 06-07-2026 Date of Acceptance: 16-07-2026

I. Introduction

Background

Digital images are frequently affected by noise during acquisition, transmission, storage, and processing operations. Noise degrades image quality and reduces the accuracy of subsequent image analysis tasks such as segmentation, feature extraction, object detection, and pattern recognition [1]. Image denoising has therefore become a fundamental preprocessing step in many applications including medical imaging, satellite image analysis, remote sensing, computer vision, and industrial inspection [2].

Over the past few decades, various image denoising techniques have been developed in both spatial and frequency domains. Among these approaches, frequency-domain processing has attracted considerable attention because of its computational efficiency and ability to separate useful image information from noise components [3]. The Fast Fourier Transform (FFT) is one of the most widely used frequency-domain techniques due to its ability to efficiently compute the Discrete Fourier Transform (DFT) with reduced computational complexity [4]. FFT-based filtering methods have been successfully applied to image enhancement, restoration, denoising, and compression applications [5].

Motivation

Although FFT-based denoising methods have demonstrated promising performance, many existing approaches employ fixed filtering parameters regardless of image characteristics or noise levels [6]. Such fixed-parameter methods may not provide optimal denoising performance for images affected by varying noise conditions. In addition, single-scale image processing techniques often face challenges in maintaining an appropriate balance between noise suppression and detail preservation [7].

Recent studies have shown that multi-scale image processing can improve image quality by analyzing image information at different resolutions while preserving important structural details [8]. Furthermore, adaptive filtering techniques have been reported to provide improved denoising performance by adjusting filtering parameters according to image content and noise characteristics [3],[6]. These observations motivate the development of an adaptive FFT-based denoising framework capable of integrating multi-scale analysis with frequency-domain filtering.

Objectives

The primary objectives of this research are:
a) To develop an adaptive FFT-based image denoising framework.
b) To perform multi-scale frequency-domain analysis for improved image representation.

c) To investigate the effectiveness of FFT-based filtering under different noise conditions.
d) To compare denoising performance using standard image quality metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE), and Structural Similarity Index (SSIM).
e) To provide a computationally efficient framework suitable for future FPGA-based implementation and real-time image processing applications [5].

Organization of the Paper

The remainder of this paper is organized as follows. Section 2 presents a review of related literature on FFT-based image filtering, frequency-domain filters, and multi-scale image processing techniques. Section 3 describes the proposed Adaptive Multi-Scale FFT-Based Filtering Framework. Section 4 presents the mathematical formulation and performance evaluation metrics. Experimental results and comparative analysis are discussed in Section 5. Finally, conclusions and future research directions are presented in Section 6.

II. Literature Review

FFT-Based Image Filtering

Fast Fourier Transform (FFT) has been extensively employed in image processing applications due to its computational efficiency and ability to transform image information from the spatial domain into the frequency domain [4]. The frequency-domain representation allows noise components and useful image information to be analyzed separately, thereby facilitating effective image denoising and enhancement. Gonzalez and Woods [1] highlighted the importance of frequency-domain processing for image restoration and filtering applications. Several researchers have demonstrated that FFT-based techniques provide efficient solutions for image denoising, image enhancement, image compression, and feature extraction tasks [3], [5].

The computational complexity of FFT is significantly lower than that of the direct Discrete Fourier Transform (DFT), making it suitable for large-scale image processing and real-time applications [4]. Recent studies have further explored the application of FFT in medical image analysis and image enhancement systems, reporting improved processing efficiency and image quality [5], [7].

Frequency Domain Filters

Frequency-domain filtering is one of the most common approaches used in FFT-based image denoising systems. Low-pass filters are widely utilized to suppress high-frequency noise while preserving low-frequency image information [1]. Among the various filtering techniques, the Ideal Low Pass Filter (ILPF), Butterworth Low Pass Filter (BLPF), and Gaussian Low Pass Filter (GLPF) are the most frequently used.

The Ideal Low Pass Filter removes high-frequency components abruptly; however, it often introduces ringing artifacts in the reconstructed image. The Butterworth Low Pass Filter provides a smoother frequency transition and offers improved visual quality. The Gaussian Low Pass Filter is generally considered superior due to its smooth frequency response and better preservation of image structures [1], [6]. Recent image denoising studies have reported that Gaussian-based filtering approaches achieve improved PSNR and SSIM values compared to conventional filtering methods [2], [6].

Although these filtering techniques have demonstrated satisfactory denoising performance, most existing approaches rely on fixed filtering parameters regardless of image content and noise characteristics [3], [6].

Multi-Scale Image Processing

Multi-scale image processing has emerged as an effective approach for analyzing image information at different resolutions. The fundamental idea behind multi-scale analysis is to represent an image at multiple levels, allowing both global structures and local image details to be processed simultaneously [12]. Techniques such as image pyramids, scale-space representation, and multi-resolution analysis have been widely used in image enhancement, denoising, segmentation, and feature extraction applications [13].

Recent Advances in Image Denoising

Recent research indicates that multi-scale processing improves edge preservation and detail retention while effectively reducing noise [8]. Rani and Bhogal [8] demonstrated the effectiveness of multi-scale Gaussian pyramid techniques for real-world image denoising applications. Similarly, modern image enhancement frameworks have shown that integrating multi-scale information can significantly improve image quality and structural preservation [7]. Despite these advancements, the combined application of adaptive FFT-based filtering and multi-scale analysis remains relatively unexplored.

Summary of Existing Research

A review of the existing literature reveals that FFT-based filtering techniques provide computationally efficient solutions for image denoising and enhancement [3], [4], [5]. Frequency-domain filters such as ILPF, BLPF, and GLPF have been widely adopted for noise suppression [1], [6]. Furthermore, multi-scale image processing techniques have demonstrated promising results in preserving image details and enhancing image quality [7], [8]. However, most studies focus either on FFT-based filtering with fixed parameters or on independent multi-scale processing approaches.

Author(s)	Methods	Advantages	Limitations
Gonzalez and Woods [1]	FFT-Based Filtering	Efficient frequency-domain processing	Fixed filtering parameters
Uddin et al. [10]	Prior-Based Denoising	Improved image restoration	No multi-scale analysis
Ullah et al. [11]	Adaptive Hybrid Filtering	Better denoising quality	No FFT-based multi-scale processing
Rani and Bhogal [12]	Multi-scale Gaussian Pyramid	Improved detail preservation	No adaptive FFT filtering
Pei et al. [13]	FFT Former	Effective feature extraction	High computational complexity
Pham et al. [14]	FFT-Based Medical Framework	Efficient frequency-domain analysis	Focused on segmentation

Table 1. Summary of Existing Research

Research Gap

Despite significant progress in FFT-based image denoising, several limitations still exist. Most existing methods employ fixed filtering parameters and single-scale image analysis techniques [3], [6], [8]. Such approaches may not effectively adapt to varying noise levels and often face difficulties in maintaining a balance between noise suppression and detail preservation. Furthermore, limited research has investigated the integration of adaptive filtering mechanisms with multi-scale FFT-based image analysis.

Proposed Contribution

To address the identified research gap, this work proposes an Adaptive Multi-Scale FFT-Based Filtering Framework for image denoising and enhancement. The proposed framework performs image analysis at multiple scales, applies FFT-based frequency-domain filtering, and adaptively adjusts filtering parameters according to image characteristics and noise levels. The filtered outputs obtained from different scales are subsequently fused to reconstruct an enhanced image. The proposed approach aims to achieve improved denoising performance, better preservation of image details, and enhanced computational efficiency. Furthermore, the framework is designed to support future FPGA-based implementation for real-time image processing applications.

III. Proposed Methodology

Overview

This work proposes an Adaptive Multi-Scale FFT-Based Filtering Framework for image denoising and enhancement. The framework combines multi-scale image analysis with frequency-domain filtering to improve noise suppression while preserving important image details. Unlike conventional FFT-based methods, the proposed approach adaptively adjusts filtering parameters according to image noise characteristics.

System Architecture

The proposed framework consists of the following stages:

a) Input Image Acquisition
b) Noise Estimation
c) Multi-Scale Decomposition
d) FFT Transformation
e) Adaptive Frequency-Domain Filtering
f) Inverse FFT Reconstruction
g) Image Fusion
h) Performance Evaluation

The proposed framework consists of eight sequential stages. First, the input image is acquired and its noise level is estimated. The image is then decomposed into multiple scales for detailed analysis. FFT transforms each scale into the frequency domain, where adaptive filtering suppresses noise while preserving important features. The filtered images are reconstructed using Inverse FFT (IFFT), fused into a final enhanced image, and evaluated using MSE, PSNR, and SSIM metrics.

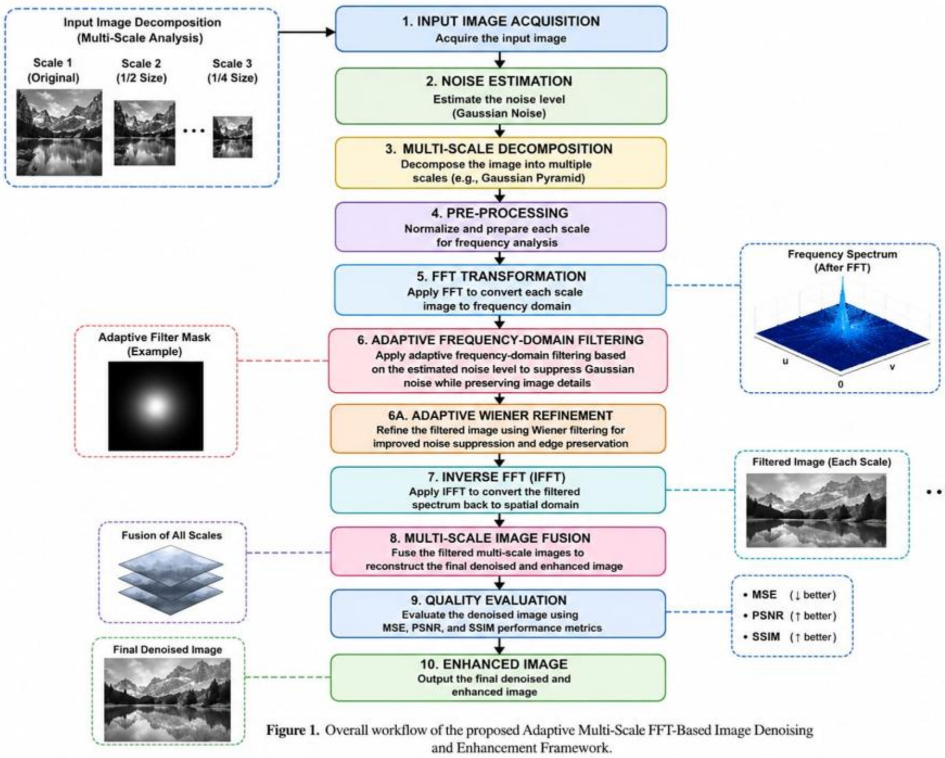

Figure 1. Overall workflow of the proposed Adaptive Multi-Scale FFT-Based Image Denoising and Enhancement Framework.

Multi-Scale Image Decomposition

To improve denoising performance while preserving important image details, the input image is decomposed into multiple resolution levels using a Gaussian Pyramid, as illustrated in Figure 2. At each level, Gaussian smoothing is first applied to suppress high-frequency noise, followed by down sampling by a factor of two. This process generates a sequence of progressively smaller images representing different spatial scales.

The first level retains the original image resolution and contains the finest image details. The subsequent levels capture progressively coarser image structures while reducing computational complexity. Processing the image at multiple scales enables effective noise suppression without significantly degrading important edges and textures. The resulting multi-scale representations are then used for FFT-based frequency-domain filtering and subsequent image fusion.

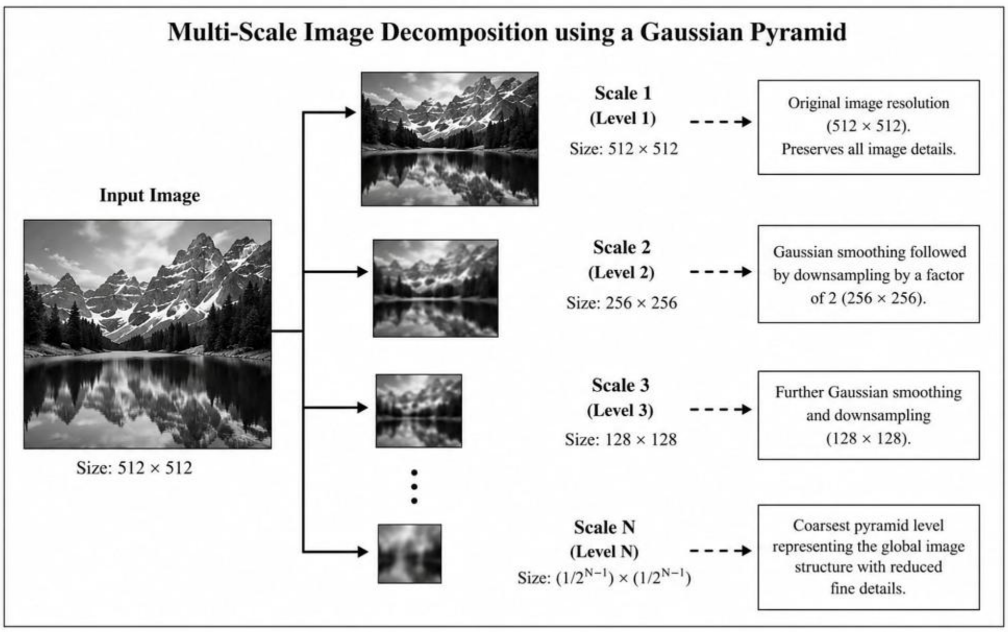

Figure 2. Multi-Scale Image Decomposition using a Gaussian Pyramid.

FFT-Based Filtering Process

After multi-scale decomposition, each image scale is transformed into the frequency domain using the Fast Fourier Transform (FFT). An adaptive frequency-domain filter is then applied to suppress noise while preserving important image details. The filtered frequency components are reconstructed using the Inverse Fast Fourier Transform (IFFT). Finally, the reconstructed images from different scales are fused to obtain the enhanced output image. The denoised image is evaluated using Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM). Figure 3 illustrates the complete FFT-based frequency-domain filtering process used in the proposed framework.

The major steps involved in the proposed FFT-based filtering process are summarized below:
a) Transform each multi-scale image into the frequency domain using FFT.
b) Analyze the frequency spectrum and estimate the noise characteristics.
c) Apply an adaptive frequency-domain filter (Gaussian or Butterworth) to suppress noise while preserving image details.
d) Perform the Inverse Fast Fourier Transform (IFFT) to reconstruct the filtered image in the spatial domain.
e) Fuse the reconstructed images obtained from different scales to generate the final enhanced image.
f) Evaluate the performance of the proposed method using MSE, PSNR, and SSIM metrics.

Figure 3. FFT-Based Frequency Domain Filtering Process used in the proposed framework.

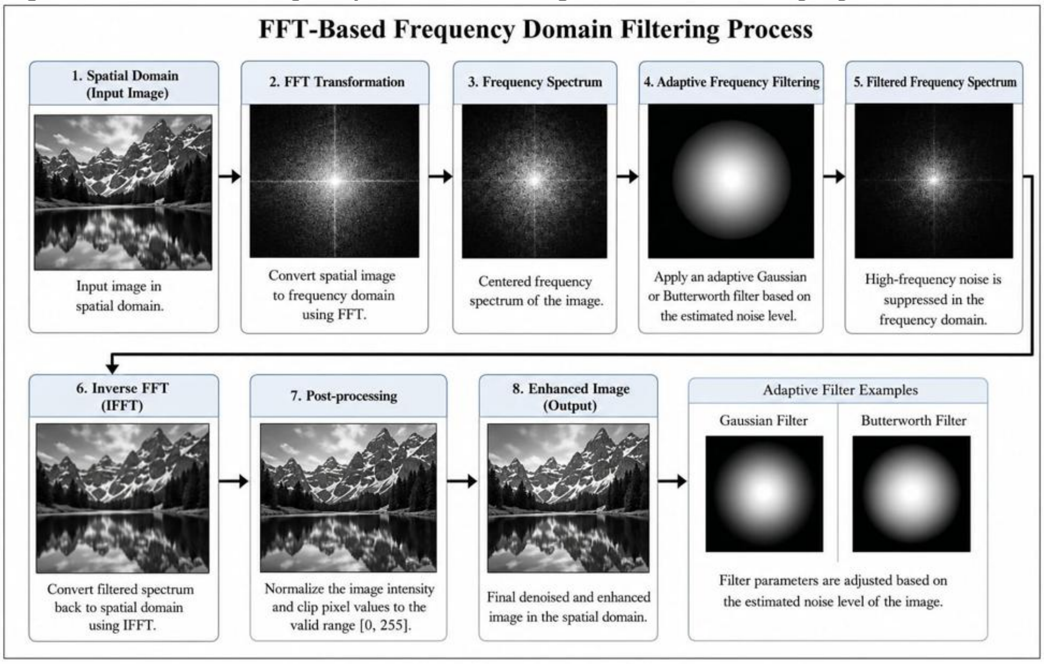

Figure 3. FFT-Based Frequency Domain Filtering Process.

Performance Evaluation

The effectiveness of the proposed framework is evaluated using Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). These metrics are used to assess denoising performance and image quality preservation.

Advantages of the Proposed Framework
a) Adaptive filtering according to noise characteristics.
b) Improved noise suppression and detail preservation.
c) Multi-scale image analysis for enhanced performance.
d) Computational efficiency through FFT processing.
e) Potential suitability for future FPGA implementation.

IV. Mathematical Model

The proposed image denoising framework is mathematically represented using the Fast Fourier Transform (FFT), Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM). These mathematical formulations are used for frequency-domain processing and quantitative performance evaluation.

Fast Fourier Transform (FFT) Formula:

$$\mathbf{X(k)}=\sum_{n=0}^{N-1} x(n)e^{-j2\pi kn}/_{N}$$

Where:
- X(k) is the frequency-domain representation (FFT output).
- X(n) is the input signal (or image intensity values).
- N is the total number of samples.
- k is the frequency index.
- n is the sample index.
- J= $\sqrt{-1}$ is the imaginary unit.

Mean Square Error (MSE) Formula:

$$\mathbf{MSE}=\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[I(i,j)-K(i,j)]^2$$

Where:
- I (i, j) is the pixel intensity of the original image.
- K (i, j) is the pixel intensity of the denoised (reconstructed) image.
- M is the number of rows in the image.
- N is the number of columns in the image.
- i and j represent the row and column indices, respectively.

A lower MSE value indicates better image restoration quality and smaller reconstruction error.

Peak Signal-to-Noise Ratio (PSNR) Formula:

$$\text{PSNR}=10log_{10}(\frac{255^2}{MSE})$$

Where:
- PSNR is the Peak Signal-to-Noise Ratio (in dB).
- MSE is the Mean Square Error between the original and denoised images.
- 255 is the maximum possible pixel value for an 8-bit grayscale image.
- $\log_{10}$ denotes the base-10 logarithm.

Structural Similarity Index Measure (SSIM) Formula:

$$\mathbf{SSIM\ (x, y)} = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)}$$

Where:
- μ_x, μ_y: The mean pixel intensities of the original image x and the denoised image y.
- σ_x^2, σ_y^2: The variance (standard deviation squared) of the original image x and the denoised image y.
- σ_{xy} : The covariance between the original image and the denoised images.
- C_1, C_2 : Small stabilization constants included to avoid division by zero. (e.g., when the denominator is near zero. They are typically defined as $C_1 = \langle K_1L\rangle^2$ and $C_2 = \langle K_2L\rangle^2$,where L is the dynamic range of the pixel values and $K_{1,}K_2 << 1$.

The SSIM index measures the structural similarity between the original and denoised images. Its value ranges from 0 to 1, where values closer to 1 indicate better preservation of structural information and higher visual quality.

V. Experimental Results And Discussion

Experimental Setup

The proposed Adaptive Multi-Scale FFT-Based Filtering Framework was implemented in MATLAB and evaluated using standard grayscale images. Gaussian noise was artificially added to the test images to evaluate the denoising performance of the proposed framework. The effectiveness of the proposed method was quantitatively assessed using Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM).

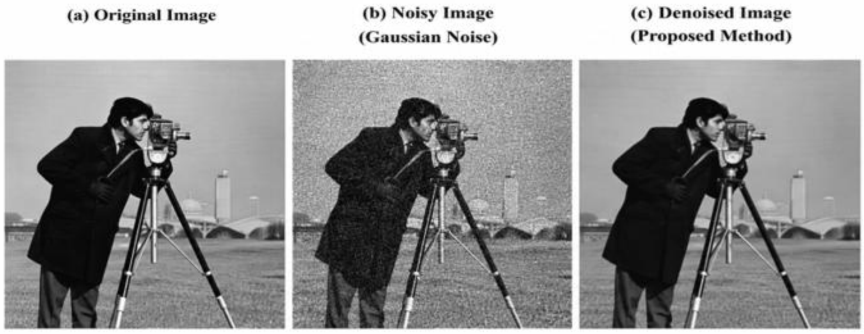

Figure 4. Visual comparison of (a) original image, (b) noisy image corrupted with Gaussian noise, and (c) denoised image obtained using the proposed Adaptive Multi-Scale FFT-Based Filtering Framework.

Visual Analysis

The visual performance of the proposed Adaptive Multi-Scale FFT-Based Filtering Framework was evaluated by comparing the original, noisy, and denoised images. As shown in Figure 4, the addition of Gaussian noise significantly degrades the image quality and obscures important structural details. The proposed framework effectively suppresses the noise while preserving edges and fine image details. The denoised image exhibits improved visual clarity and structural preservation compared with the noisy image, demonstrating the effectiveness of the proposed adaptive frequency-domain filtering approach.

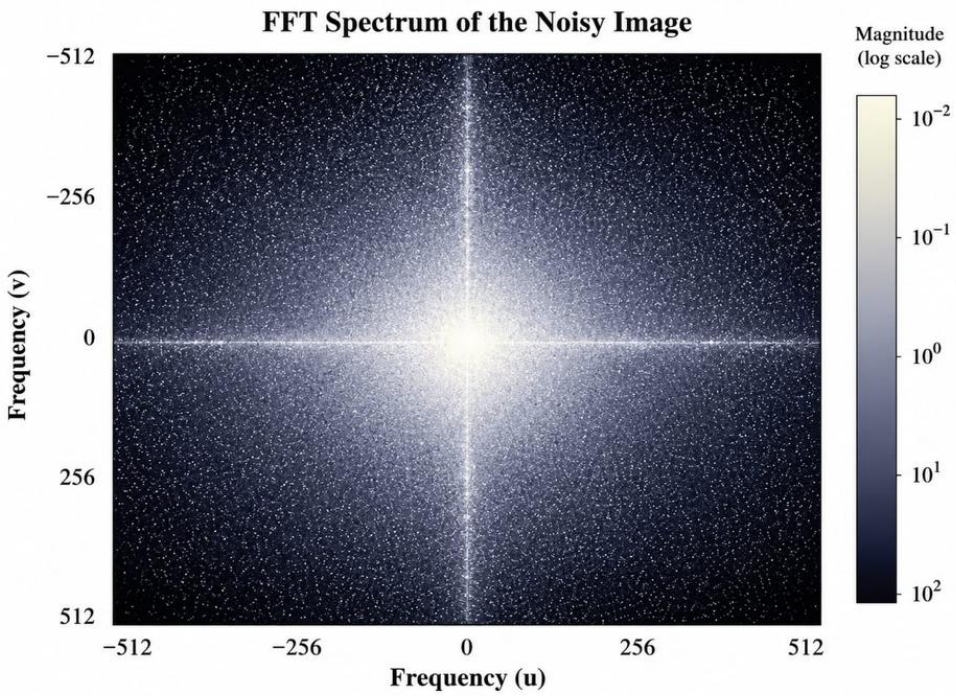

Figure 5. Log-magnitude FFT spectrum of the Gaussian noise-corrupted image.

Figure 5 illustrates the logarithmic magnitude spectrum of the noisy image after applying the Fast Fourier Transform (FFT). The bright central region represents the low-frequency components containing the major structural information, whereas the scattered high-frequency components correspond to noise. This frequency-domain representation facilitates adaptive filtering for effective noise suppression while preserving important image details.

Quantitative Analysis

The denoising performance of the proposed methods was evaluated using Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). Table 2 summarizes the quantitative comparison obtained from MATLAB simulations. Among the evaluated methods, the Hybrid FFT + Wiener Filtering approach achieved the lowest MSE (0.002500) and the highest PSNR (26.02 dB), indicating excellent noise suppression. The Proposed Adaptive Multi-Scale FFT + Wiener Filtering method achieved the highest SSIM (0.7202), demonstrating superior preservation of structural information and image details. These results confirm that integrating multi-scale FFT analysis with adaptive Wiener filtering significantly improves denoising performance while maintaining image quality.

Method	MSE	PSNR(Db)	SSIM
Multi-Scale FFT Fusion	0.004305	23.66	0.6873
Hybrid FFT + Wiener Filtering (Proposed)	0.002500	26.02	0.7142
Proposed Multi-Scale Adaptive Wiener Filtering	0.005002	23.01	0.7038
Proposed Adaptive Multi-Scale FFT_ + Wiener Filtering	0.003729	24.28	0.7202

Table 2. Quantitative performance comparison of the implemented denoising methods.

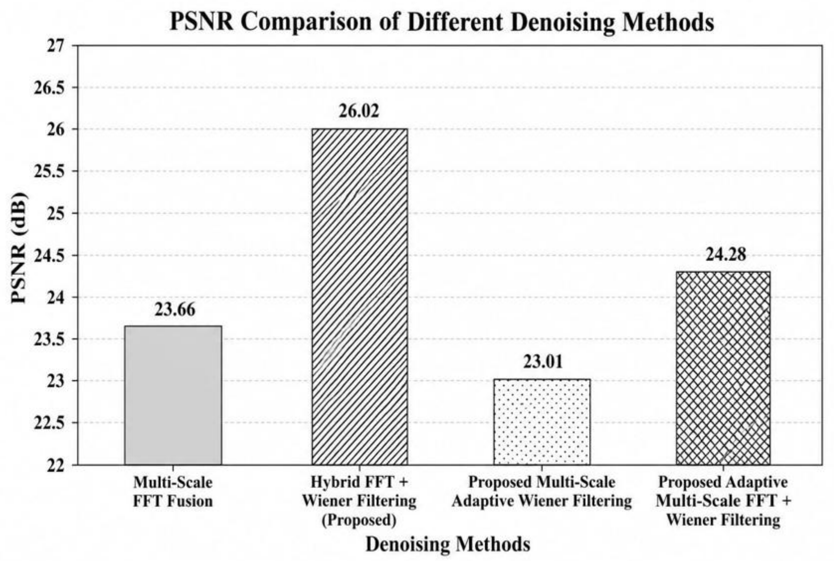

Figure 6. Comparison of PSNR values obtained using different image denoising methods. The proposed Hybrid FFT + Wiener Filtering method achieves the highest PSNR (26.02 dB), indicating superior reconstruction quality.

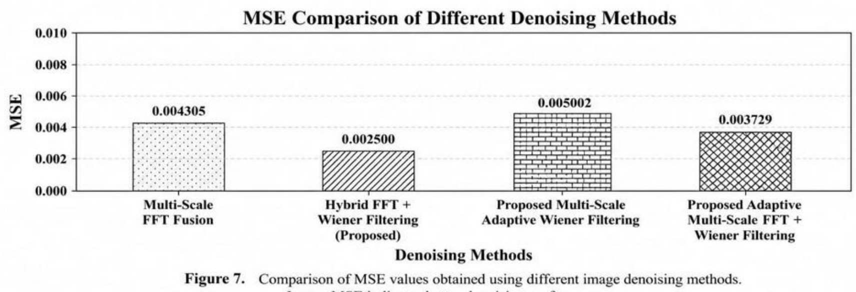

Figure 7. Comparison of MSE values obtained using different image denoising methods. Lower MSE indicates better denoising performance.

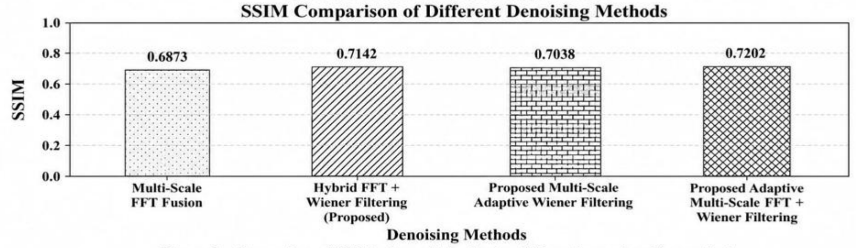

Figure 8. Comparison of SSIM values obtained using different image denoising methods. Higher SSIM values indicate better structural similarity and visual quality.

Discussion

The experimental results demonstrate the effectiveness of the proposed Adaptive Multi-Scale FFT-Based Filtering framework for image denoising. The quantitative results presented in Table 2 demonstrate that the proposed methods effectively reduce image noise while preserving important structural details and improving overall image quality.

Among the evaluated techniques, the Hybrid FFT + Wiener Filtering (Proposed) method achieved the lowest Mean Square Error (MSE = 0.002500) and the highest Peak Signal-to-Noise Ratio (PSNR = 26.02 dB), indicating superior noise suppression and image reconstruction performance. Meanwhile, the Proposed Adaptive Multi-Scale FFT + Wiener Filtering method obtained the highest Structural Similarity Index (SSIM = 0.7202), demonstrating better preservation of image structures, edges, and fine details. The Proposed Multi-Scale Adaptive Wiener Filtering method achieved a PSNR of 23.01 dB and an SSIM of 0.7038, while the Proposed Adaptive Multi-Scale FFT + Wiener Filtering produced a PSNR of 24.28 dB with the highest SSIM value, confirming its effectiveness in preserving structural information.

The multi-scale processing strategy enables the framework to preserve both coarse and fine image structures, resulting in improved visual quality compared with conventional FFT-based denoising techniques.

Overall, the experimental results validate the effectiveness of the proposed Adaptive Multi-Scale FFT-Based Filtering Framework for image denoising. The framework achieves an effective balance between noise suppression, edge preservation, and structural similarity, making it suitable for practical image enhancement applications.

VI. Conclusion And Future Scope

Conclusion

In this research, an Adaptive Multi-Scale FFT-Based Image Denoising and Enhancement Framework was proposed and implemented using MATLAB. The framework integrates frequency-domain Fast Fourier Transform (FFT) analysis, multi-scale image decomposition, adaptive filtering, and Wiener filtering to effectively suppress Gaussian noise while preserving important image structures and fine details.

The proposed methods were evaluated using standard image quality metrics, including Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). The experimental results demonstrated that the Hybrid FFT + Wiener Filtering method achieved the lowest reconstruction error (MSE = 0.002500) and the highest PSNR (26.02 dB), whereas the Proposed Adaptive Multi-Scale FFT + Wiener Filtering method achieved the highest SSIM (0.7202), indicating superior preservation of structural information and visual quality.

Overall, the proposed Adaptive Multi-Scale FFT-Based Image Denoising and Enhancement Framework provides an efficient and reliable solution for image denoising. By integrating FFT-based frequency-domain analysis, multi-scale decomposition, adaptive filtering, and Wiener filtering, the framework effectively suppresses Gaussian noise while preserving image edges, fine details, and structural information. The obtained experimental results demonstrate that the proposed framework improves image quality and is suitable for practical image enhancement applications.

Future Scope

The proposed framework can be extended in several directions to further improve its performance and applicability:

- The algorithm can be implemented on FPGA and GPU platforms for real-time image processing applications.
- Artificial Intelligence and Deep Learning techniques can be integrated to automatically estimate noise levels and optimize filtering parameters.
- The proposed framework can be extended to process color images, hyperspectral images, and video sequences.
- Future work may evaluate the proposed method on medical image analysis, satellite imagery, remote sensing, industrial inspection, and biometric applications.
- The integration of FFT-based processing with Wavelet Transform, Non-Local Means (NLM), BM3D, or deep neural networks may further improve denoising performance.
- Additional optimization techniques can be developed to reduce computational complexity while maintaining high image quality for large-scale datasets.
- The proposed framework can also be extended to image registration, image segmentation, image restoration, feature extraction, and other computer vision applications.

References

[1]. R. C. Gonzalez And R. E. Woods, Digital Image Processing, 4th Edition, Pearson Education, 2018.
[2]. A. V. Oppenheim And R. W. Schafer, Discrete-Time Signal Processing, 3rd Edition, Pearson Education, 2010.
[3]. J. W. Cooley And J. W. Tukey, "An Algorithm For The Machine Calculation Of Complex Fourier Series," Mathematics Of Computation, Vol. 19, No. 90, Pp. 297–301, 1965.
[4]. B. Zitová And J. Flusser, "Image Registration Methods: A Survey," Image And Vision Computing, Vol. 21, No. 11, Pp. 977–1000, 2003.
[5]. H. Foroosh, J. B. Zerubia, And M. Berthod, "Extension Of Phase Correlation To Subpixel Registration," Ieee Transactions On Image Processing, Vol. 11, No. 3, Pp. 188–200, 2002.
[6]. S. Mallat, A Wavelet Tour Of Signal Processing, 3rd Edition, Academic Press, 2009.
[7]. R. Szeliski, Computer Vision: Algorithms And Applications, Springer, 2022.
[8]. A. Rani And R. K. Bhogal, "Efficient Real-World Image Denoising Using Multi-Scale Gaussian Pyramids," Scientific Reports, Vol. 15, Article 40086, 2025.
[9]. T. Wang, Z. Hu, And Y. Guan, "An Efficient Lightweight Network For Image Denoising Using Progressive Residual And Convolutional Attention Feature Fusion," Scientific Reports, Vol. 14, Article 9554, 2024.
[10]. A. F. M. S. Uddin Et Al., "Give Me A Hint: An Explicit Prior-Based Image Denoising Method," Signal, Image And Video Processing, Vol. 18, Pp. 9451–9463, 2024.
[11]. F. Ullah, K. Kumar, T. Rahim Et Al., "A New Hybrid Image Denoising Algorithm Using Adaptive And Modified Decision-Based Filters For Enhanced Image Quality," Scientific Reports, Vol. 15, Article 8971, 2025.
[12]. M. Sonka, V. Hlavac, And R. Boyle, Image Processing, Analysis, And Machine Vision, Cengage Learning, 2014.
[13]. X. Pei, Y. Huang, W. Su Et Al., "Fft Former: A Spatial-Frequency Noise Aware Cnn-Transformer For Low-Light Image Enhancement," Knowledge-Based Systems, Vol. 314, Article 113055, 2025.
[14]. V. T. Pham, M. H. Ha, B. V. Q. Bui Et Al., "Fft Med: Leveraging Fast Fourier Transform For A Lightweight Medical Image Segmentation Framework," Scientific Reports, Vol. 15, Article 37879, 2025.
[15]. Y. Lecun, Y. Bengio, And G. Hinton, "Deep Learning," Nature, Vol. 521, Pp. 436–444, 2015.
[16]. K. He, X. Zhang, S. Ren, And J. Sun, "Deep Residual Learning For Image Recognition," Proceedings Of Cvpr, Pp. 770–778, 2016.
[17]. D. L. Donoho, "De-Noising By Soft Thresholding," Ieee Transactions On Information Theory, Vol. 41, No. 3, Pp. 613–627, 1995.
[18]. R. Jain, R. Kasturi, And B. G. Schunck, Machine Vision, Mcgraw-Hill Education, 1995.
[19]. M. Nixon And A. Aguado, Feature Extraction And Image Processing For Computer Vision, 4th Edition, Academic Press, 2020.
[20]. A. K. Jain, Fundamentals Of Digital Image Processing, Prentice Hall, 1989.