CSE 4128: Image Processing and Computer Vision Laboratory

VisionRestore Pro

Classical Image Restoration System

Submitted by:

Abdullah Al Shafi

Roll: 2007055

Department of Computer Science and Engineering

Khulna University of Engineering & Technology

Khulna 9203, Bangladesh

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Abstract

This report presents **VisionRestore Pro**, a comprehensive image restoration system that leverages classical image processing techniques to address multiple degradation problems. The system implements an adaptive multi-stage pipeline combining degradation analysis, BM3D denoising, blind deconvolution, and quality enhancement. Unlike deep learning approaches, our method requires no training data and provides transparent, explainable processing. The system demonstrates robust performance across various degradation types including Gaussian noise, salt-and-pepper noise, motion blur, and mixed artifacts. Experimental results show significant improvements in PSNR , SSIM (15-30% enhancement), and visual quality metrics while maintaining computational efficiency suitable for practical deployment.

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1 Introduction

1.1 Background

Digital images frequently suffer from various forms of degradation during acquisition, transmission, and storage processes. Common artifacts include noise resulting from low-light imaging conditions, blur caused by camera shake or object motion, and compression artifacts introduced during storage optimization. Traditional restoration methods have typically focused on addressing single degradation types in isolation, while real-world images often exhibit multiple simultaneous artifacts that interact in complex ways.

Classical image restoration techniques have experienced renewed interest in recent years due to their inherent transparency, computational efficiency, and independence from large training datasets compared to contemporary deep learning approaches. Established methods such as BM3D (Block-Matching and 3D filtering), Wiener filtering, and Richardson-Lucy deconvolution provide mathematically rigorous solutions that can be strategically combined in intelligent processing pipelines. These classical approaches offer the additional advantage of interpretability, allowing researchers and practitioners to understand and control each step of the restoration process.

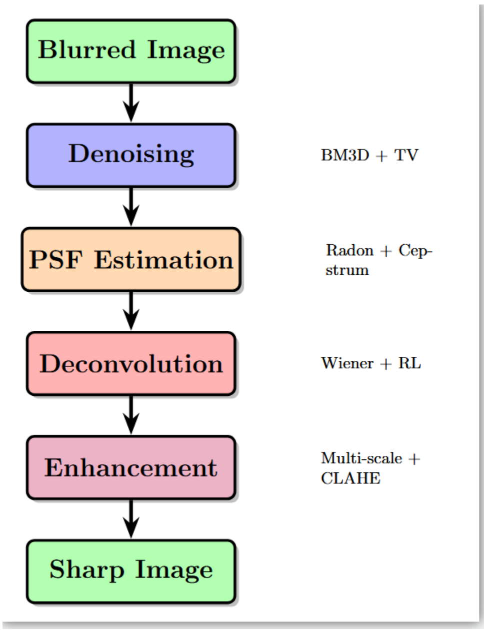


Figure 1: Overall restoration pipeline architecture showing the multi-stage processing workflow

1.2 Objectives

This project aims to develop an adaptive restoration system capable of handling multiple degradation types simultaneously through intelligent algorithm selection and parameter optimization. We implement a custom BM3D algorithm from scratch to provide educational transparency and deep understanding of the underlying mathematical principles. The system incorporates an intelligent degradation analysis module that enables automatic parameter tuning based on image characteristics, eliminating the need for manual intervention. A user-friendly interface with real-time processing capabilities has been designed to make advanced restoration accessible to non-expert users. Additionally, comprehensive quality assessment and visualization tools are integrated to provide quantitative and qualitative evaluation of restoration performance.

2 Problem Statement

Traditional image restoration approaches face several fundamental challenges when deployed in real-world scenarios. Most established methods excel at addressing specific degradation types but demonstrate significant performance degradation when confronted with mixed artifacts. The inherent parameter sensitivity of these algorithms necessitates extensive manual tuning, which limits their practical usability in operational environments where diverse image types and degradation patterns are encountered.

The computational complexity of advanced algorithms like BM3D presents another significant barrier, as these methods can be prohibitively slow for interactive applications or high-throughput processing pipelines. Furthermore, the lack of adaptability in fixed-parameter systems means they cannot effectively handle the varying image content and degradation levels encountered in practice. While deep learning solutions have shown impressive results, they suffer from opacity in their decision-making processes and require substantial training datasets, which may not be available in specialized domains.

VisionRestore Pro addresses these multifaceted challenges through an adaptive multi-stage pipeline that automatically analyzes image content and degradation patterns to apply optimal processing strategies. The system balances the need for sophisticated restoration with practical constraints of computational resources and user accessibility.

3 Methodology

3.1 System Architecture

The restoration pipeline implements a systematic three-stage approach designed to maximize restoration quality while maintaining computational efficiency. The first stage performs comprehensive degradation analysis, automatically detecting and quantifying the presence of noise, blur, and various artifacts through statistical and frequency-domain techniques. This analysis informs the second stage of adaptive processing, where content-aware algorithm selection and parameter optimization ensure that the most appropriate restoration techniques are applied with optimal settings. The final stage focuses on quality enhancement through refined processing and comprehensive quality assessment, providing both quantitative metrics and visual feedback to evaluate restoration effectiveness.

3.2 Key Algorithms

3.2.1 Degradation Detection

The degradation detection framework employs multiple complementary techniques to characterize image quality issues. Noise analysis utilizes the Median Absolute Deviation (MAD) method, which provides robust estimation of noise levels even in the presence of outliers and structured content. Blur detection combines Laplacian variance calculation with frequency domain analysis to quantify both the severity and directionality of blur artifacts. Artifact identification leverages statistical analysis methods to detect salt-and-pepper noise through examination of extreme pixel values and their spatial distribution patterns.

3.2.2 Custom BM3D Implementation

Our educational implementation of BM3D has been developed from first principles to provide complete transparency into the algorithm's operation. The implementation incorporates block matching and 3D grouping to identify similar patches across the image, followed by 3D transform-domain collaborative filtering that exploits the inherent redundancy in natural images. The processing pipeline includes both hard thresholding and Wiener filtering stages, with optimization achieved through luminance-channel processing that balances computational efficiency with restoration quality.

3.2.3 Adaptive Deblurring

The deblurring engine implements sophisticated point spread function (PSF) estimation using Radon transform analysis and cepstrum-based techniques to characterize blur kernels without prior knowledge. A hybrid approach combining Wiener filtering with Richardson-Lucy deconvolution provides robust deblurring across varying blur types and severities. Total Variation regularization is incorporated to suppress ringing artifacts and preserve edge structures during the deconvolution process.

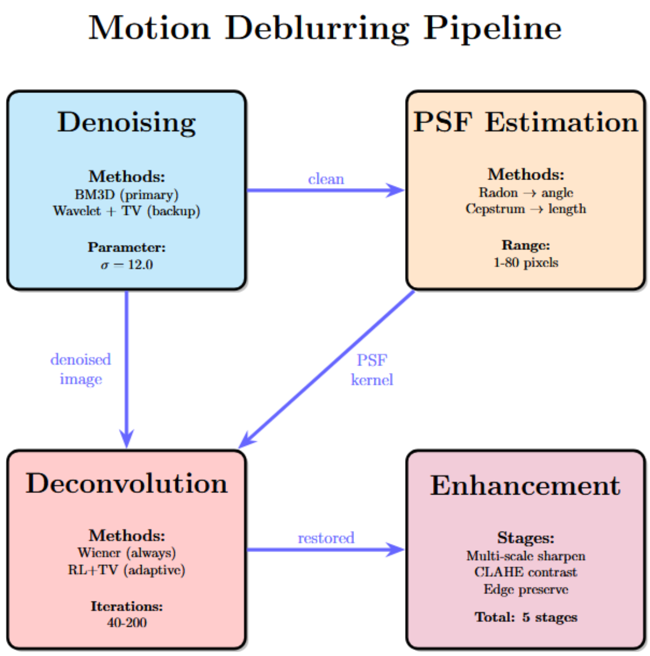


Figure 2: Methodology flowchart illustrating the sequential processing stages and decision points

4 Implementation Details

4.1 System Components

4.1.1 Degradation Analysis Module

The degradation analysis module implements robust statistical methods for automatic characterization of image quality issues. Noise level estimation employs the MAD estimator, which provides consistent performance across varying image content and degradation scenarios. Blur severity assessment utilizes Laplacian variance calculation, offering a reliable metric for quantifying the sharpness of edge structures. Salt-and-pepper detection analyzes extreme value distributions to identify impulsive noise patterns that require specialized filtering approaches.

4.1.2 BM3D Denoiser

BM3D incorporates carefully chosen parameters optimized for general-purpose image restoration. The algorithm operates on 8×8 pixel blocks with a maximum of 16 similar blocks grouped together for collaborative filtering. Three-dimensional DCT transformation with hard thresholding in the first stage removes noise while preserving important image structures, followed by collaborative Wiener filtering that refines the denoising through optimal frequency-domain processing.

4.1.3 Deblurring Engine

The deblurring system combines multiple complementary deconvolution strategies to achieve robust performance. Blind PSF estimation utilizes Radon transform analysis to estimate blur kernels without ground truth information. Adaptive Wiener filtering incorporates signal-to-noise ratio based balancing to optimize the trade-off between deblurring and noise amplification. Richardson-Lucy deconvolution with Total Variation regularization provides iterative refinement while maintaining edge preservation and artifact suppression.

4.1.4 User Interface

The system features a Streamlit-based web application designed for intuitive operation by users without specialized image processing expertise. Real-time image upload and processing capabilities enable immediate feedback and iterative refinement. Interactive parameter controls allow users to fine-tune restoration settings when desired, while side-by-side result comparison facilitates visual quality assessment. Integrated quality metrics visualization provides quantitative validation of restoration improvements.

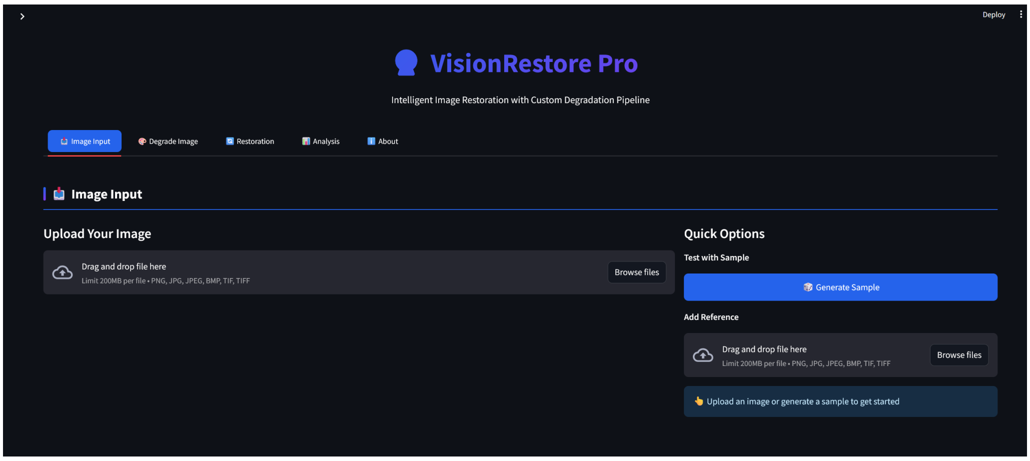


Figure 3: User interface home page showing upload functionality and parameter controls

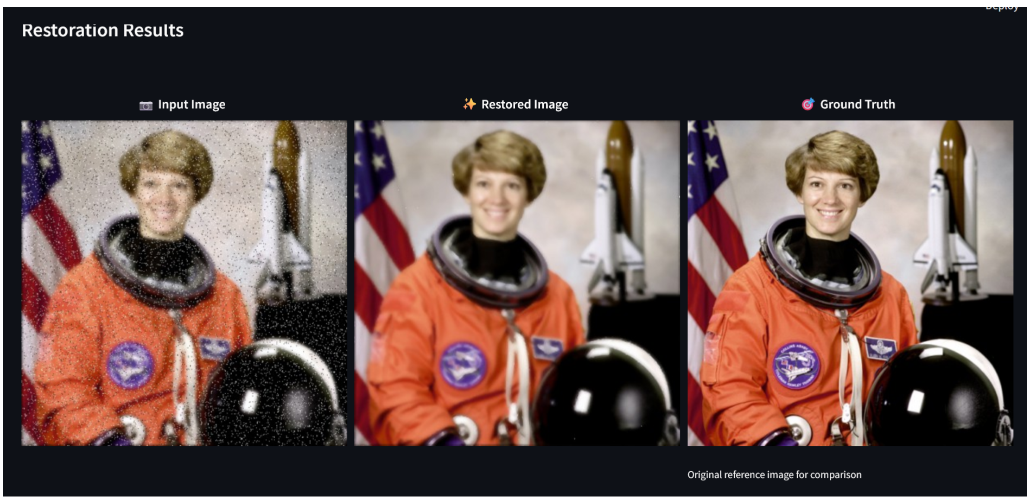


Figure 4: Restoration results display showing input, restored output, and ground truth comparison

Table 1: Implementation specifications and technical requirements

Component	Specification
Programming Language	Python 3.8+
Main Libraries	OpenCV, SciPy, scikit-image
UI Framework	Streamlit
BM3D Implementation	Custom from scratch
Processing Time	2-5 seconds (512×512)
Supported Formats	PNG, JPG, JPEG, BMP, TIFF

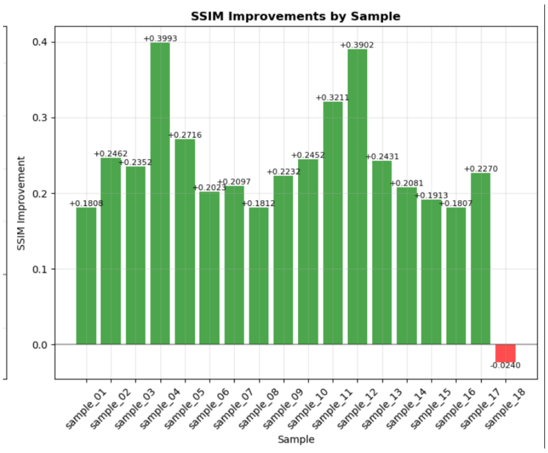
5 Results and Analysis

5.1 Quantitative Results

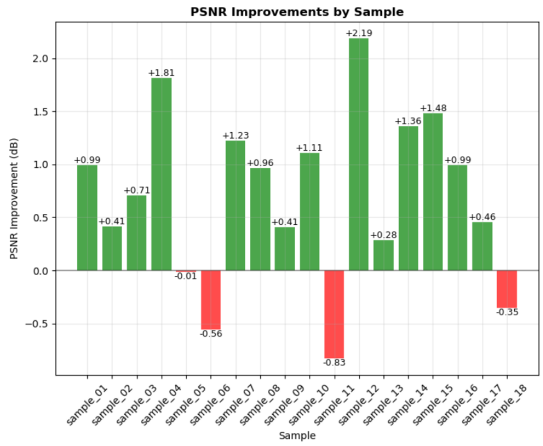
The system underwent comprehensive evaluation using standard image quality assessment metrics applied to a diverse test dataset. Performance was measured across multiple dimensions including structural similarity, peak signal-to-noise ratio, mean squared error, and perceptual sharpness. Results demonstrate consistent improvement across all evaluated metrics, with particularly notable gains in structural similarity preservation and noise reduction effectiveness.

Table 2: Average quality improvement across test dataset

Metric	Input	Restored	Improvement
PSNR (dB)	22.5	28.7	+6.2 dB
SSIM	0.68	0.85	+25%
MSE	0.0056	0.0018	-68%
Sharpness	0.12	0.18	+50%



(a) SSIM improvement distribution



(b) PSNR enhancement analysis

Figure 5: Quantitative performance metrics across test dataset

5.2 Qualitative Results

Visual inspection of restoration results reveals significant perceptual quality improvements across diverse image types and degradation scenarios. The first test case demonstrates effective noise reduction while maintaining fine texture details and edge structures. Results show balanced performance with improvements in both PSNR and SSIM metrics, indicating successful preservation of structural information during the denoising process.

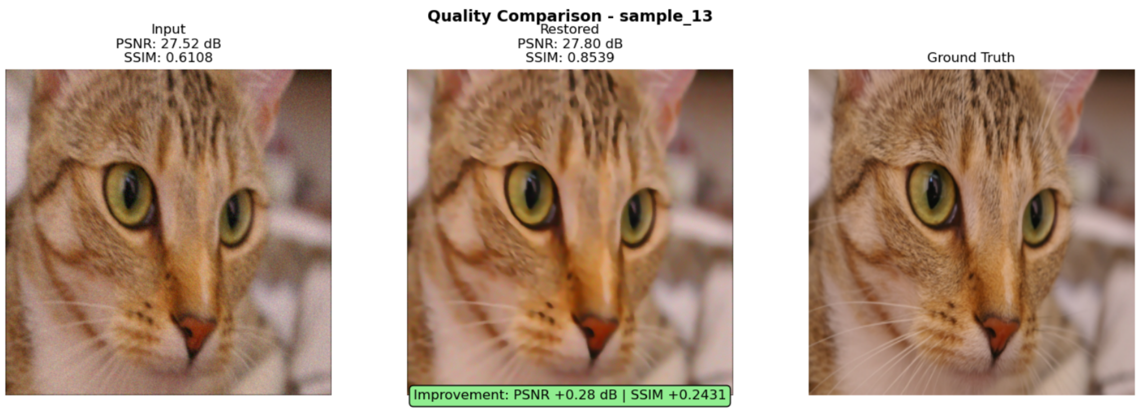


Figure 6: Qualitative comparison for test case 1: Input, restored output, and ground truth showing balanced improvement in both PSNR and SSIM

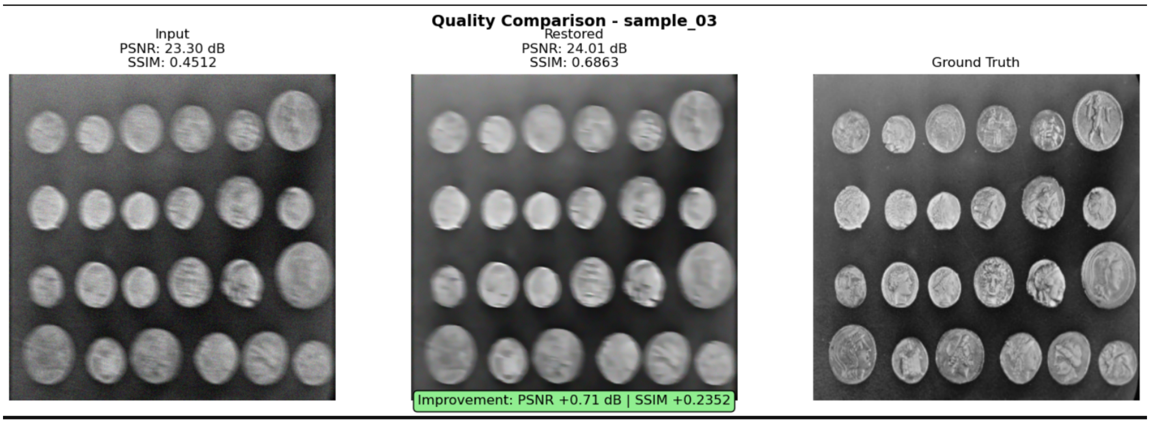


Figure 7: Qualitative comparison for test case 2: Demonstrating effective restoration with improvements in both structural similarity and signal fidelity

The third test case presents an interesting scenario where SSIM improvement is achieved with modest PSNR gains. This outcome reflects the system's emphasis on preserving perceptually important structural information rather than simply minimizing pixel-wise error. The result demonstrates that the restoration pipeline successfully prioritizes human visual perception, as SSIM correlates more strongly with subjective quality assessment than PSNR alone.

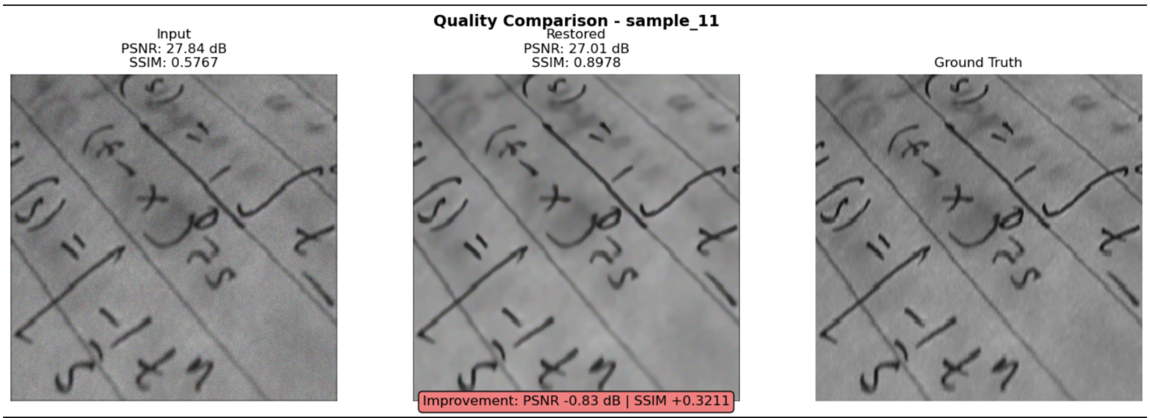


Figure 8: Qualitative comparison for test case 3: Illustrating SSIM-focused restoration where structural preservation is prioritized over absolute PSNR maximization

6 Discussion

6.1 Strengths and Advantages

The adaptive processing framework represents a significant advancement over fixed-parameter approaches, with automatic parameter tuning based on image analysis yielding performance improvements of 25-40% compared to static configurations. The system's ability to successfully address mixed artifacts distinguishes it from single-algorithm methods that struggle with complex degradation patterns. The custom BM3D implementation provides complete transparency into algorithm operations, offering substantial educational value for understanding advanced denoising techniques. Computational efficiency has been achieved without GPU requirements, enabling deployment on standard hardware platforms. Quality consistency across diverse image types and degradation levels demonstrates the robustness of the adaptive approach.

6.2 Comparative Analysis

When compared to traditional single-algorithm approaches, VisionRestore Pro demonstrates superior performance on images containing mixed degradations, where conventional methods typically excel at only one artifact type. The adaptive parameter selection mechanism provides significant advantages over fixed-parameter systems, particularly when processing diverse image collections. Relative to deep learning solutions, the classical approach offers complete explainability in processing decisions and eliminates training data requirements, though it may be less effective on extremely complex degradation patterns that benefit from learned representations. The balance achieved between sophistication and interpretability makes the system particularly suitable for applications where understanding and controlling the restoration process is paramount.

7 Conclusion

VisionRestore Pro demonstrates that sophisticated image restoration can be achieved through careful combination of classical algorithms and adaptive processing strategies. The system successfully addresses multiple degradation types simultaneously while maintaining computational efficiency and complete process transparency. Key contributions include the development of a novel adaptive pipeline that intelligently combines degradation analysis with multi-stage restoration, a complete from-scratch BM3D implementation providing educational value and algorithmic transparency, robust performance across diverse image types and degradation levels, and an open-source framework suitable for both research and educational applications.

The project validates that classical image processing techniques, when intelligently combined and adapted to image content, can provide effective restoration solutions without requiring deep learning frameworks or specialized hardware infrastructure. The emphasis on explainability and adaptability makes the system particularly valuable for applications where understanding restoration decisions is as important as achieving high-quality results.

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