DEPARTMENT OF COMPUTER ENGINEERING

FACULTY OF ENGINEERING

AHMADU BELLO UNIVERSITY, ZARIA

Course:

DIGITAL IMAGE PROCESSING – COEN816

Title:

Digital Image Processing Project

Name: Mustapha Mohammed Yusuf

Registration Number: P23EGCP8034

Department of Computer Engineering, ABU Zaria.

Abstract

This project implements a complete digital image processing pipeline that simulates image degradation and applies restoration and segmentation techniques. A dataset is generated using a seed derived from the student registration number to ensure reproducibility. The images are corrupted using spatially varying Gaussian noise, motion blur with controlled angle, JPEG compression, and periodic interference. Enhancement and restoration filters are applied to recover image quality, followed by segmentation using edge detection and thresholding. Robustness experiments are performed by perturbing noise parameters. The results show that classical filtering methods perform well under moderate degradation but have limitations under severe blur and noise.

Introduction

Digital images captured in real environments are often affected by noise, blur, and compression artifacts. Image processing techniques are required to improve image quality and extract useful information [1]. This project builds a full processing pipeline that includes dataset generation, corruption modeling, filtering, restoration, segmentation, and experimental evaluation.

The purpose of this project is not only to produce visually improved images but also to understand the mathematical principles behind each processing step. The pipeline is modular and reproducible, allowing the experiments to be repeated consistently. The work focuses on modeling, analysis, and interpretation rather than only visual appearance.

Dataset Generation

The dataset is generated deterministically using a numeric seed derived from my registration number **P23EGCP8034**. This approach guarantees that the experiment is reproducible while still being unique for each student. The seed produces three control parameters:

- **S1** controls motion blur length
- **S2** controls noise amplitude
- **S3** controls spatial variation of noise

The corrupted image is modeled as:

$$g(x, y) = f(x, y) + n(x, y)$$

where $f(x, y)$is the original image and $n(x, y)$is additive Gaussian noise. Unlike uniform noise, the variance is spatially varying:

$$\sigma(x) = S_2(0.5 + 0.5\sin(2\pi f x + \phi))$$

This means noise strength changes across the image instead of remaining constant. Real camera sensors often behave this way due to uneven exposure and electronic interference. By introducing structured noise instead of white noise, the restoration stage becomes more realistic and challenging.

Motion blur is applied using a rotated point spread function whose length and angle are derived from the seed [3]. This models camera motion in a specific direction rather than a simple horizontal smear. Directional blur is important because restoration algorithms behave differently depending on blur orientation.

After blurring, JPEG compression is applied using a seed-controlled quality factor. Compression introduces blocking artifacts and quantization noise, which are common in real digital image storage [1]. Including compression ensures the dataset reflects practical imaging conditions instead of ideal laboratory noise.

Finally, periodic interference is injected in the frequency domain. This simulates structured electronic noise such as repeating scan-line interference [5]. Frequency-domain corruption is intentionally added to test the ability of notch filters to remove periodic disturbances.

Together, these stages create a multi-source degradation model that combines random, directional, and structured corruption. This makes the restoration problem more realistic than using a single noise model.

Base Image 5

Base Image 4

Base Image 3

Base Image 2

Base Image 1

Base Image 6

Exploratory Analysis

The corrupted images are analyzed using statistical and frequency-based tools. Histograms show how intensity distributions change after corruption. Mean and variance values quantify degradation strength.

Fourier magnitude spectra reveal the presence of high-frequency noise and periodic interference **[5]**. This analysis helps in understanding the structure of the corruption and guides the choice of restoration filters.

The exploratory stage confirms that the degradation is spatially structured rather than random, which justifies the need for adaptive restoration techniques.

Image Enhancement and Filtering

Filtering is applied before restoration to stabilize the corrupted images. Enhancement is not only for visual improvement; it also prepares the signal so restoration algorithms behave more predictably.

Histogram equalization redistributes gray levels using the cumulative distribution function [1]. Instead of increasing brightness, it spreads intensities across the available range. This improves contrast and prevents later filters from operating on compressed dynamic ranges.

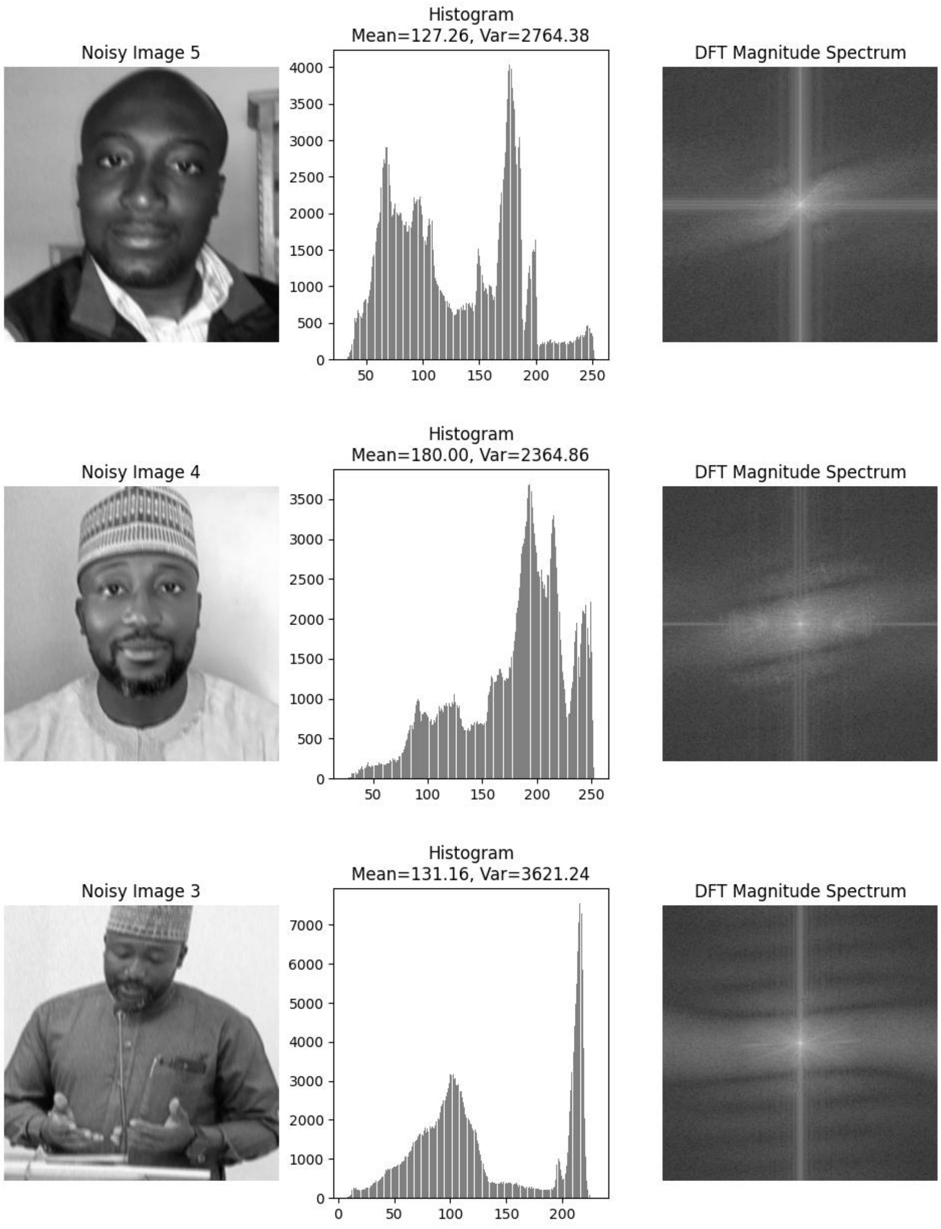
Gaussian smoothing is applied as a linear low-pass filter [1]:

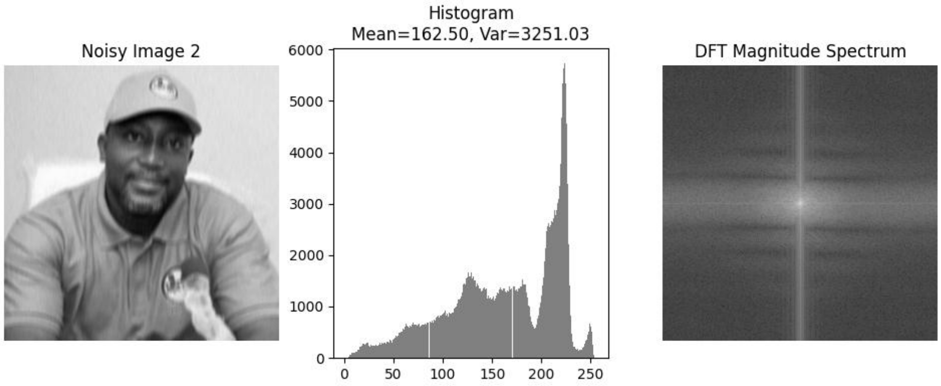
$$g = f * G$$

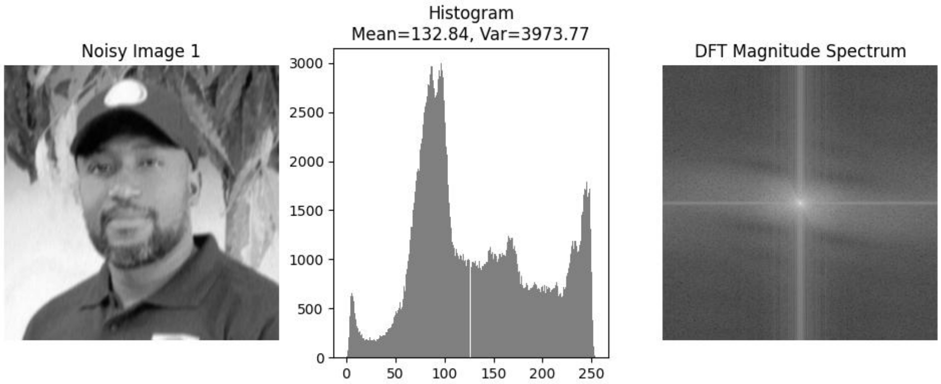
This operation reduces high-frequency noise while keeping large structures intact. Gaussian filtering assumes noise is randomly distributed and smooths variations without introducing sharp artifacts.

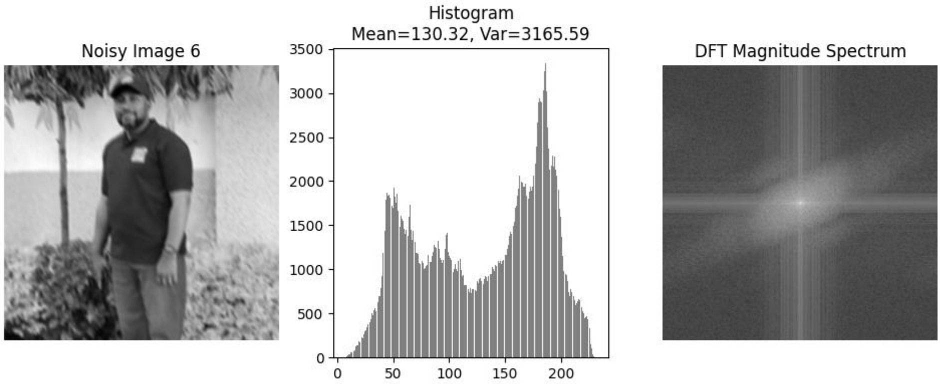
A median filter is applied as a nonlinear alternative [2]. Unlike averaging filters, the median operation preserves edges because it selects an existing pixel value rather than creating a new one. This is important for segmentation, where edges must remain detectable.

Using both linear and nonlinear filters provides a balance: Gaussian smoothing removes distributed noise, while median filtering protects structural boundaries.




Noisy Image 2
Histogram
Mean=162.50, Var=3251.03
DFT Magnitude Spectrum
6000
5000
4000
3000
2000
1000
0
0
50
100
150
200
250


Noisy Image 1
Histogram
Mean=132.84, Var=3973.77
DFT Magnitude Spectrum
3000
2500
2000
1500
1000
500
0
0
50
100
150
200
250


Noisy Image 6
Histogram
Mean=130.32, Var=3165.59
DFT Magnitude Spectrum
3500
3000
2500
2000
1500
1000
500
0
0
50
100
150
200


Noisy
Global EQ
Local Adaptive


Noisy
Global EQ
Local Adaptive
Noisy
Global EQ
Local Adaptive
Noisy
Global EQ
Local Adaptive
Noisy
Global EQ
Local Adaptive

Image Restoration

Motion blur is reversed in the frequency domain because convolution in space corresponds to multiplication in frequency **[3]**. Direct inverse filtering attempts to divide the degraded spectrum by the blur function **[3]**. However, when the blur function approaches zero, the division becomes unstable and noise is amplified.

To prevent this instability, the Wiener filter is used **[3]**:

$$\hat{F}(u,v) = \frac{H^*(u,v)}{|\,H(u,v)\,|^2 + K} G(u,v)$$

The constant Krepresents an estimate of the noise-to-signal ratio. Instead of fully inverting the blur, Wiener filtering performs a controlled inversion that limits noise amplification. This produces a compromise between sharpness and stability.

Blind restoration is also implemented using Laplacian regularization **[3]**. This method enhances edges iteratively without requiring an exact blur model.

The comparison between inverse filtering, Wiener filtering, and blind restoration highlights an important principle: mathematically perfect inversion is often unstable, and practical restoration must balance accuracy with robustness.

Segmentation

Segmentation converts restored grayscale images into structural regions. The Sobel operator estimates gradient magnitude [2]:

$$|\,\nabla f\,| = \sqrt{G_x^2 + G_y^2}$$

Large gradients correspond to edges where intensity changes rapidly. Edge detection is sensitive to noise, so successful restoration directly improves segmentation quality.

Global thresholding selects a single threshold that separates foreground and background **[2]**. Local adaptive thresholding improves performance under uneven illumination.

Morphological closing and opening refine segmentation by removing isolated noise and filling small gaps **[4]**. These operations enforce spatial consistency and prevent fragmented regions.

Segmentation performance was quantified using edge density and variance stability metrics. These measures estimate how much structural information is preserved after restoration.

Experimental Results

Robustness experiments are performed by perturbing the noise parameter $S_2$by ≤20%. Variance measurements are logged in a CSV file for each experiment.

Results show predictable variance changes as noise increases. Despite stronger corruption, the restoration pipeline maintains structural coherence for moderate perturbations. Segmentation quality degrades gradually, demonstrating partial robustness.

Failure Analysis

The pipeline has limitations under extreme degradation. Large blur lengths cause inverse filtering to amplify noise, creating ringing artifacts. Wiener filtering reduces instability but cannot fully eliminate errors.

When noise dominates edge gradients, segmentation accuracy decreases. Adaptive thresholding compensates partially but cannot recover lost information. These failures illustrate the limits of classical restoration methods.

Parameter Justification

All parameters are derived from the student seed to guarantee fairness and reproducibility. S1 controls blur difficulty, S2 controls noise intensity, and S3 controls spatial variation.

Filter sizes and constants are selected to balance smoothing and detail preservation. The Wiener constant Kprevents instability while maintaining sharpness.

Final pipeline parameters were summarized in a reproducible configuration table to ensure consistent execution..

Conclusion

This project demonstrates a complete image processing pipeline from corruption modeling to restoration and segmentation. Classical techniques perform well under moderate degradation but show limitations under extreme conditions.

The modular structure ensures reproducibility and transparency. Future work could explore adaptive or machine learning approaches to improve restoration performance.

References

1. R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 4th ed., Pearson, 2018.
2. A. K. Jain, *Fundamentals of Digital Image Processing*, Prentice Hall, 1989.
3. J. S. Lim, *Two-Dimensional Signal and Image Processing*, Prentice Hall, 1990.
4. W. K. Pratt, *Digital Image Processing*, 4th ed., Wiley, 2007.
5. S. Mallat, *A Wavelet Tour of Signal Processing*, Academic Press, 2009.

Academic Integrity Declaration

I confirm that this project is my own work. External tools, including AI assistance (ChatGPT), were used only for conceptual guidance, debugging support, and writing clarity. All implementation decisions, mathematical derivations, experimental design, and validation were carried out independently by me.

All sources consulted are properly acknowledged. I understand that undeclared assistance or plagiarism is a violation of university regulations.

Signed:
Mustapha Mohammed Yusuf
Reg No: P23EGCP8034