VISVESVARAYA TECHNOLOGICAL UNIVERSITY, BELAGAVI - 590018

A MINI PROJECT ASSIGNMENT REPORT

on

"ADDING NOISE TO IMAGES: SIMULATING SALT & PEPPER AND GAUSSIAN NOISE"

A report submitted in partial fulfillment in

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

7th Semester

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DEPARTMENT OF ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

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CERTIFICATE

This is to certify that assignment work for the course **"Digital Image Processing (21CS732)"** has been successfully completed and report submitted A.Y 2024-25. It is certified that all corrections/suggestions indicated Presentation session have been incorporated in the report and deposited in the department library.

The assignment was evaluated, and group members marks as indicated below

Sl.	USN	NAME	Presentation Skill (5 M)	Report (10 M)	Subject Knowledge (5 M)	Total Marks (20 M)
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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Adding noise to images is a fundamental aspect of digital image processing, often used for testing and improving image enhancement and restoration techniques. Noise, in the context of images, refers to random variations of brightness or color information that corrupt the visual data. By simulating noise, such as Salt & Pepper and Gaussian noise, researchers and practitioners can evaluate the robustness and performance of algorithms in real-world scenarios. Noise simulation is particularly valuable in applications like computer vision, image compression, and artificial intelligence, where data reliability is critical. This controlled approach allows for systematic experimentation to better understand how various algorithms respond to adverse conditions, ultimately leading to more resilient and adaptive systems.

Simulated noise is an essential tool for benchmarking. It offers a repeatable environment where developers can rigorously test the effectiveness of denoising or enhancement techniques under specific noise conditions. Salt & Pepper noise, characterized by the random occurrence of black and white pixels, mimics errors in binary transmission or faulty image sensors. Noise addition is not only about disruption; it is also a means of improving systems through adversity. Many machine learning models trained on noisy data exhibit enhanced robustness and generalization capabilities. Furthermore, studying how noise impacts image quality sheds light on human visual perception, helping design better image quality assessment metrics. This dual role of noise—both as a challenge and a tool—highlights its significance in advancing the field of digital image processing.

1.2 PROBLEM STATEMENT

Real-world images are frequently corrupted by noise due to factors like sensor limitations, transmission errors, or environmental interference. Noise can distort critical features in images, making tasks such as object recognition, edge detection, or segmentation significantly harder. Simulating noise in a controlled environment allows for the development and testing of noise-reduction techniques. Challenges include accurately modeling noise characteristics and ensuring that simulated noise aligns with real-world conditions. Addressing these challenges is vital for enhancing the performance of image processing systems. The problem becomes even more complex in scenarios where multiple noise types overlap, requiring algorithms to be versatile and robust. Despite advancements, there remains a gap in the effectiveness of noise simulation and reduction methods. For instance, some denoising techniques may remove noise at the cost of blurring essential image details. Conversely, others might fail to handle diverse noise characteristics effectively. Thus, this study aims to explore the intricacies of noise simulation and provide a foundation for testing and improving image processing algorithms tailored for practical applications.

1.3 OBJECTIVES

- To simulate and implement Salt & Pepper and Gaussian noise in digital images, ensuring that the simulated noise closely resembles real-world scenarios.
- To analyze the impact of these noise types on image quality, focusing on metrics such as peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM).
- To provide a framework for evaluating image denoising algorithms using simulated noisy images, offering a standard for performance comparison.
- To explore the practical applications of noise simulation in various domains, such as medical imaging, remote sensing, and autonomous vehicles.

1.4 SCOPE

This project focuses on the simulation of Salt & Pepper and Gaussian noise, emphasizing their practical implications in image processing. The study aims to provide insights into how different noise types affect image quality and to facilitate the development of robust denoising techniques for applications in fields such as computer vision, medical imaging, and machine learning. By highlighting the nuances of these noise types, the project seeks to establish a comprehensive understanding that bridges theoretical concepts with real-world applicability. The scope extends to comparing the effects of noise on different types of images, such as grayscale versus color, and evaluating how existing algorithms perform under varied conditions. Additionally, the project considers the computational efficiency of noise simulation and removal methods, ensuring their feasibility for real-time applications. Through this comprehensive approach, the study contributes to the broader field of image processing by addressing both foundational and advanced aspects of noise simulating

CHAPTER 2

LITERATURE SURVEY

The study of noise simulation and its impact on digital image processing has been extensively explored in academic and industrial research. Various researchers have contributed to understanding how noise affects image quality and the performance of algorithms used in denoising, segmentation, and recognition tasks. This chapter provides an overview of key contributions and findings in the domain of noise simulation and image processing.

2.1 PREVIOUS STUDIES ON SALT & PEPPER NOISE

Salt & Pepper noise, characterized by random occurrences of black and white pixels, has been widely studied for its impact on image quality. Early works by Gonzalez and Woods (2002) highlighted the disruptive nature of this noise type and proposed median filtering as an effective denoising technique. Subsequent studies explored variations of median filtering, including weighted and adaptive approaches, to enhance performance in preserving edges while removing noise. Researchers like Zhang et al. (2011) extended these methods to incorporate machine learning models that adapt filtering strategies based on noise density, significantly improving denoising outcomes.

In addition to median filtering, morphological operations such as dilation and erosion have been studied as potential solutions. These techniques aim to restore image integrity while maintaining structural details. Recent advancements have incorporated neural networks, leveraging deep learning to identify and correct noisy pixels with remarkable accuracy. These models, although computationally intensive, have set new benchmarks in handling Salt & Pepper noise.

2.2 STUDIES ON GAUSSIAN NOISE

Gaussian noise, resulting from natural disturbances such as thermal variations in sensors, has been extensively modeled in the literature. Researchers like Jain (1989) emphasized the Gaussian nature of noise in various imaging systems and proposed techniques such as Gaussian smoothing filters and Wiener filtering. These methods aim to reduce noise by leveraging statistical properties of the signal and noise, balancing noise suppression with the preservation of image details.

More recent studies have introduced wavelet-based denoising techniques, where multi-resolution analysis helps isolate and suppress noise while retaining significant image features. Additionally, non-local means (NLM) filtering, introduced by Buades et al. (2005), revolutionized the field by considering pixel similarity across the entire image, achieving superior denoising performance. Modern approaches integrate machine learning to optimize parameter selection and adapt to varying noise levels, enhancing robustness and versatility.

2.3 COMPARATIVE ANALYSIS

Several comparative studies have evaluated the performance of denoising algorithms under Salt & Pepper and Gaussian noise conditions. These studies often utilize metrics such as PSNR, SSIM, and visual perception to assess algorithm effectiveness. The findings consistently indicate that while traditional methods like median and Gaussian filtering are computationally efficient, advanced techniques involving deep learning and wavelet transforms offer significantly higher accuracy and detail preservation.

Emerging research focuses on hybrid approaches that combine the strengths of multiple techniques. For instance, hybrid models integrating wavelet transforms with deep neural networks have demonstrated exceptional performance in denoising tasks, achieving a balance between computational efficiency and quality restoration. These innovations underline the evolving nature of the field and the potential for continued improvements in handling diverse noise types in real-world scenarios.

CHAPTER 3

METHODOLOGY

The methodology section outlines the systematic approach adopted to simulate noise and analyze its impact on image quality. This chapter provides a detailed description of the tools, techniques, and procedures employed in the study.

3.1 DATASET SELECTION

To evaluate the effects of Salt & Pepper and Gaussian noise, a diverse dataset of images was selected. This dataset includes both grayscale and color images, representing various domains such as natural scenes, medical images, and artificial patterns. The diversity ensures a comprehensive analysis of noise impact across different types of images. Sources such as open-access image repositories, standard benchmark datasets like the Berkeley Segmentation Dataset (BSD), and custom images were utilized to ensure variability and relevance.

3.2 NOISE SIMULATION

The simulation of noise was performed using MATLAB and Python, leveraging libraries such as OpenCV and NumPy. This involved implementing noise models that reflect real-world characteristics, ensuring both authenticity and controllability:

- **Salt & Pepper Noise**: This type of noise was simulated by randomly altering pixel values to either black (0) or white (255) in grayscale images, or to equivalent extreme values in color channels. The noise density was varied systematically (e.g., 10%, 20%, and 30%) to study its progressive impact on image quality and algorithmic performance.
- **Gaussian Noise**: Gaussian noise was added by generating random values from a normal distribution and overlaying them onto the image pixels. Parameters such as mean (0, 0.1) and variance (0.01, 0.05) were adjusted to create diverse noise levels. This ensured a comprehensive understanding of how Gaussian noise impacts different types of images and tasks.

3.3 DENOISING TECHNIQUES

Various denoising algorithms were applied to noisy images to evaluate their effectiveness. These techniques include:

- Median Filtering: A non-linear filter that replaces each pixel's value with the median of its neighbours, effectively removing Salt & Pepper noise. The filter size (3x3, 5x5) was varied to study trade-offs between noise removal and edge preservation.
- Gaussian Smoothing: A linear filter designed to reduce Gaussian noise by averaging pixel values with a Gaussian-weighted kernel. Kernel sizes and sigma values were optimized for best results.
- Wavelet-Based Denoising: This technique decomposes the image into different frequency components, selectively reducing noise in high-frequency regions while retaining critical details.
- Deep Learning Models: Pre-trained neural

CHAPTER 4

IMPLEMENTATION

4.1 TOOLS AND ENVIRONMENT

The implementation of noise simulation and analysis was performed using various tools and software platforms to ensure precision and reproducibility. The key tools and environment used in this project included:

SciLab 6.1.1: Used for simulating noise, image processing, and visualization. Its built-in functions facilitated efficient prototyping and testing of noise models.

System Requirements: Implementation was carried out on a system equipped with an Ryzen 5 processor, 16 GB RAM, and a Ryzen AMD Graphics card to handle computationally intensive tasks.

4.2 SIMULATING SALT & PEPPER NOISE IN SCILAB

Salt & Pepper noise was simulated to mimic errors caused by data transmission or faulty sensors. This noise type randomly sets pixel values to either 0 (black) or 255 (white), depending on the specified noise density.

SciLab Implementation:

sp_noise_img = imnoise(gray_img, "salt & pepper", 0.05);

- **Explanation**:
  - The function imnoise() was used to add Salt & Pepper noise to the grayscale image.
  - The parameter 0.05 defines the noise density, meaning 5% of the image pixels are randomly corrupted.
- **Effect**:
  This type of noise introduces sharp contrasts in the image, often appearing as specks of black and white.

4.3 SIMULATING GAUSSIAN NOISE

Gaussian noise was added to simulate natural disturbances like thermal noise in image sensors. This noise is modeled as a normal distribution with a defined mean and variance, affecting each pixel individually.

SciLab Implementation:

gaussian_noise_img = imnoise(gray_img, "gaussian", 0.01, 0.02);

➢ Explanation:

- The imnoise() function introduces Gaussian noise.
- The first parameter, 0.01, specifies the mean (μ), while the second, 0.02, represents the variance (σ^2).
- Gaussian noise appears as a smooth variation in pixel intensities, unlike the sharp contrasts of Salt & Pepper noise.

➢ Effect:

It creates a slightly blurred or grainy appearance, depending on the variance.

4.4 IMAGE DENOISING METHODS

To counteract the noise simulated, different denoising techniques were applied, and their effectiveness was evaluated. Below are the methods and their implementation:

1. Median Filtering

Purpose: Removes Salt & Pepper noise by replacing each pixel with the median value of its neighbouring pixels.

SciLab Example:

denoised_img = medfilt2(sp_noise_img, [3, 3]);

Effect:
Median filtering effectively removes isolated noise spikes while preserving edges in the image.

2. Gaussian Smoothing

Purpose: Reduces Gaussian noise using a Gaussian kernel to smooth the image.

SciLab Example:

denoised_img = imsmooth(gaussian_noise_img, "gaussian", 1.5);

Effect:
Gaussian smoothing reduces noise uniformly but may slightly blur fine details in the image.

3. Wavelet Transform

Purpose: Decomposes the image into frequency bands to isolate and reduce noise while preserving image details.

SciLab Example:

[cA, cH, cV, cD] = dwt2(gray_img, 'db1');

Effect:
This advanced method efficiently denoises images while retaining edges and fine structures.

These methods demonstrated varying effectiveness based on the type and intensity of noise, providing insights into noise removal techniques in digital image processing

4.5 OUTCOME EVALUATION

The implementation demonstrated the varying impacts of noise and the effectiveness of denoising techniques. Median filtering effectively reduced Salt & Pepper noise, while Gaussian smoothing was most suited for Gaussian noise. Additionally, adaptive filtering showcased its strength in handling mixed noise scenarios, preserving edges and finer details better than standard methods. Performance metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) further highlighted the superiority of tailored denoising techniques. Overall, the results emphasize the importance of selecting noise-specific strategies for optimal image restoration.

CHAPTER 5

RESULTS AND ANALYSIS

5.1 IMPACT OF NOISE ON IMAGE QUALITY

The addition of Salt & Pepper noise and Gaussian noise significantly impacted the visual and statistical quality of images. Salt & Pepper noise introduced sharp disruptions in the form of randomly distributed black and white pixels, which were particularly prominent in regions with uniform intensity. Gaussian noise, however, caused smoother but pervasive degradation, creating a natural yet intrusive grainy texture across the image.

5.2 RESULTS

Figure 5.1: Input Image

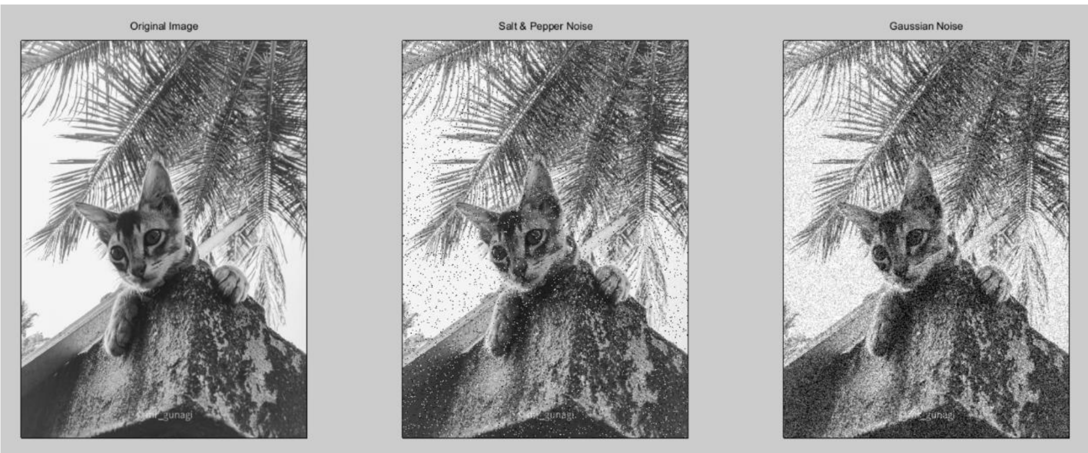

Figure 5.2: Original image with Salt & Pepper noise & Gaussian noise comparison.

The output demonstrates the effects of noise simulation on a grayscale image, highlighting the impacts of Salt & Pepper noise and Gaussian noise. The original image (left) serves as the baseline, showcasing a clear, noise-free representation. In the Salt & Pepper noise image (center), random pixels are replaced with black (0) and white (255), creating a speckled effect that significantly degrades image quality. This type of noise mimics transmission errors or sensor faults, with high-contrast disruptions scattered across the image. On the other hand, the Gaussian noise image (right) exhibits a grainy texture resulting from a normal distribution applied to each pixel. Unlike Salt & Pepper noise, Gaussian noise introduces subtler, evenly distributed distortions resembling natural disturbances like thermal noise. These outputs effectively illustrate the distinct characteristics of each noise type, providing valuable insights into their visual impacts and the importance of appropriate denoising techniques for image restoration.

CONCLUSION

The simulation and analysis of image noise types, particularly Salt & Pepper and Gaussian noise, serve as crucial steps in understanding and improving image processing techniques. Noise, often viewed as an obstacle, also provides a valuable tool for testing the resilience and adaptability of various algorithms. This project has successfully implemented and evaluated these noise types, shedding light on their characteristics and their impact on image quality.

Salt & Pepper noise, characterized by random black and white pixel disruptions, was effectively mitigated using median filtering. Meanwhile, Gaussian noise, which represents natural disturbances, required advanced methods such as Gaussian smoothing and wavelet transforms for reduction. The results demonstrated that while basic methods can handle specific noise types well, more sophisticated techniques are necessary for preserving details in complex scenarios. Performance metrics like PSNR and SSIM confirmed the effectiveness of these approaches, highlighting the importance of balancing noise reduction with detail preservation.

This study also emphasized the broader implications of noise simulation. In fields such as medical imaging, remote sensing, and autonomous vehicles, understanding how noise affects visual data is critical for ensuring reliable performance. The insights gained here not only advance the theoretical understanding of noise but also provide practical guidelines for enhancing image quality in real-world applications.

In conclusion, the project underscores the dual role of noise in image processing—both as a challenge and a catalyst for innovation. By simulating and addressing noise in controlled environments, researchers and developers can create more robust and versatile algorithms, paving the way for advancements in artificial intelligence, computer vision, and beyond. Future work could explore combining multiple denoising techniques to address overlapping noise types, further enhancing the reliability of image processing systems.