Medical Image Enhancement based on CLAHE approach

Submitted

By

B SATISH CHANDRA KUMAR

BU21EECE0100338

AKHIL S

BU21EECE0100411

S ANSAR

BU21EECE0100358

Under the Guidance of

PANKAJ KHANDWAY Asst.professor

Duration:18/12/24 to 12/03/25

Department of Electrical, Electronics and Communication Engineering

GITAM School of Technology

GITAM

(DEEMED TO BE UNIVERSITY)

(Estd. u/s 3 of the UGC act 1956)

NH 207, Nagadenehalli, Doddaballapur taluk, Bengaluru-561203 Karnataka, INDIA.

DECLARATION

We declare that the project work contained in this report is original and it has been done by me under the guidance of my project guide.

Name:
B Satish Chandra Kumar
Akhil S
S Ansar

Date: **Signature of the Student**
12/03/25

Department of Electrical, Electronics and Communication Engineering
GITAM School of Technology, Bengaluru-561203

CERTIFICATE

This is to certify that (Student Name) bearing (Regd. No.:) has satisfactorily completed Mini Project Entitled in partial fulfillment of the requirements as prescribed by University for VIIIth semester, Bachelor of Technology in "Electrical, Electronics and Communication Engineering" and submitted this report during the academic year 2024-2025.

[Signature of the Guide] **[Signature of HOD]**

Table of contents

Chapter 1: Introduction

Image enhancement and noise reduction are crucial steps in many image processing tasks, especially when dealing with images that are corrupted by noise. In real-world scenarios, images captured through digital cameras or other imaging devices often contain noise due to various factors such as low light conditions, sensor imperfections, or transmission errors. One common type of noise is salt-and-pepper noise, where random pixels in the image are set to either black or white, which significantly distorts the original image. Moreover, image enhancement methods such as adaptive histogram equalization can be applied to improve the contrast and sharpness of the image after the noise reduction process. One advanced technique used for combining the benefits of different enhancement methods is Principal Component Analysis (PCA), which allows for the fusion of multiple denoised and enhanced images into a single, high-quality output.

1.1 Overview of the problem statement

The task at hand involves enhancing a noisy RGB image by applying various denoising techniques and fusion methods, aimed at improving the image quality for better clarity and detail retention. The noisy image is assumed to be a salt-and-pepper noise corrupted image, which is a common form of noise where pixels randomly become either black or white, disrupting the visual integrity of the image. The goal is to remove this noise and improve the visual quality of the image through multiple image processing techniques, with an emphasis on preserving essential details while removing noise.

1.2 Objectives and goals

- Denoising of Noisy RGB Images
- Channel-wise Enhancement
- Fusion of Results using PCA
- Enhancement using CLAHE
- Final Output Generation

Chapter 2 : Literature Review

Paper	Objective	Methodology	Key Findings	Limitations
Haddadi et al. (2024) *A novel medical image enhancement algorithm based on CLAHE and pelican optimization*	Improve medical image quality using CLAHE and POA	- CLAHE for contrast enhancement- Pelican Optimization Algorithm (POA) for estimating optimal clip-limit- Text-to-image stable diffusion for medical image generation	- Improved image quality and contrast- Enhanced visibility of medical details- Higher conformity rate in clinical diagnosis	- Noise over-amplification in CLAHE- Computational complexity due to POA
Sonali et al. (2019) *An approach for de-noising and contrast enhancement of retinal fundus image using CLAHE*	Enhance fundus image quality by reducing noise and improving contrast	- Applied CLAHE on RGB channels- Used median, Gaussian, Wiener, and mean filters- Evaluated with PSNR, SSIM, CoC, and EPI	Improvement in PSNR,SSIM. Enhanced edge preservation and detail clarity	- Noise amplification due to CLAHE- Green channel dependency
Rao et al. (2022) *Retinex-Centered Contrast Enhancement Method for Histopathology Images with Weighted CLAHE*	Improve contrast and visibility in histopathology images	- Multiscale Retinex with Adaptive Weighting (MSRAW)- Weighted CLAHE (WCLAHE) on Lab* color space- Combined MSRAW and WCLAHE for	- Enhanced histopathology image details- Preserved color balance and reduced noise- Improved local contrast and overall visibility	- Increased computational cost- Limited performance on certain color channels

Paper	Objective	Methodology	Key Findings	Limitations
		global and local enhancement		
Dinh et al. (2022) *A new medical image enhancement algorithm using adaptive parameters*	Enhance medical image contrast, noise reduction, and sharpness simultaneously	- Image decomposition into structure, texture, and noise- CLAHE for contrast enhancement- Marine Predators Algorithm (MPA) for parameter tuning	- Improved structural and texture details- Enhanced performance in medical image fusion- Increased image clarity and contrast	- Complexity in decomposition and parameter tuning- Sensitivity to initial parameter settings
Wen et al. (2016) *Medical X-Ray Image Enhancement Based on Wavelet Domain Homomorphic Filtering and CLAHE*	Enhance brightness and contrast of medical X-ray images	- Wavelet transformation to decompose image- Homomorphic filtering on low-frequency components- CLAHE for histogram modification	- Enhanced texture details and contrast- Better noise suppression compared to other methods	- High computational demand- Potential loss of detail in high-frequency regions

Chapter 3 : Strategic Analysis and Problem Definition

3.1 SWOT Analysis

Strengths

- Use of Multiple Filtering Techniques
- PCA-Based Fusion
- Channel-Wise Processing
- Adaptive Contrast Enhancement

Weaknesses

- Computational Complexity
- Noise Amplification
- Green Channel Dependency
- Loss of Detail in High-Frequency Regions

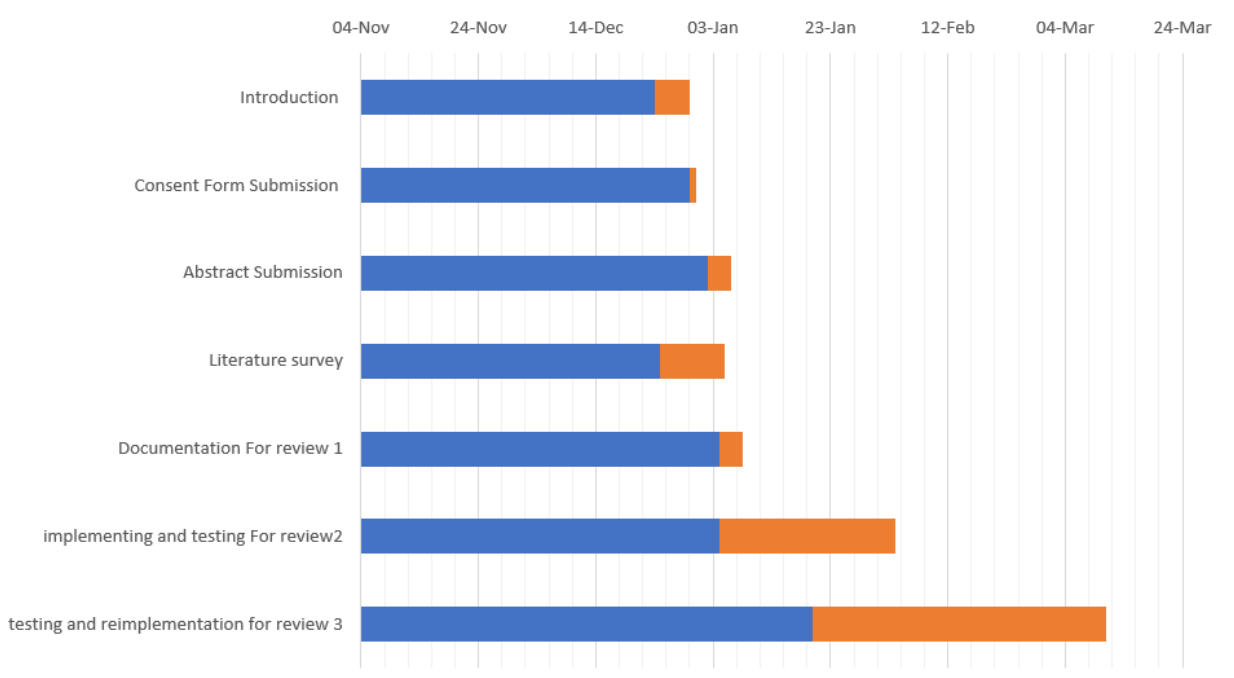
Opportunities

- Integration with Bio-Inspired Algorithms
- Development of Hybrid Models
- Real-Time Processing Capability
- Machine Learning Integration

Threats

- Algorithm Sensitivity
- Variability in Medical Images
- Artifact Formation
- Data Privacy and Security

3.2 Project Plan - GANTT Chart



3.3 Refinement of problem statement

Medical image enhancement is a critical task in image processing, particularly for improving the diagnostic accuracy of medical images such as fundus images, X-rays, and histopathology slides. The presence of noise, low contrast, and uneven illumination significantly affects the quality of these images, thereby complicating accurate diagnosis and clinical decision-making. The existing methods for medical image enhancement, including Contrast Limited Adaptive Histogram Equalization (CLAHE), Retinex-based approaches, and wavelet-based methods, have shown limitations in handling complex noise patterns and maintaining fine details. Moreover, the application of PCA fusion for combining multiple filtering outputs has demonstrated potential for enhancing image quality, but it also introduces challenges related to computational complexity and noise amplification.

Chapter 4 : Methodology

4.1 Description of the Approach

The proposed approach involves a multi-step image enhancement process aimed at improving the quality of medical images by reducing noise and enhancing contrast. The process is applied individually to the red, green, and blue (RGB) color channels of the input image. The steps are as follows:

1. **Input Image**– The input retinal medical image.
2. **Channel Separation** – The three RGB channels (Red, Green, and Blue) are extracted from the input image for independent processing.
3. **Filtering Stage** – Each channel undergoes four different types of filtering to reduce noise and improve clarity:
    - Gaussian Filtering
    - Mean Filtering
    - Median Filtering
    - Wiener Filtering
4. **PCA-Based Fusion** – The outputs from the filtering stage are fused using Principal Component Analysis (PCA) to generate intermediate enhanced channels.
5. **Final Fusion** – The intermediate outputs from PCA fusion are further fused using PCA to produce the final enhanced color channels.
6. **Channel Combination** – The final enhanced RGB channels are combined to form the complete enhanced image.
7. **Output Generation** – The enhanced image is resized to the original dimensions and displayed for evaluation.

4.2 Tools and Techniques Utilized

1. **MATLAB** – MATLAB is used for the implementation and execution of the image enhancement algorithm.
2. **Filtering Techniques** – The following filtering techniques are used:
    - Gaussian Filter
    - Mean Filter
    - Median Filter
    - Wiener Filter
3. **PCA Fusion** – PCA is used to combine the filtered outputs for optimal enhancement.
4. **Adaptive Histogram Equalization** – CLAHE (Contrast Limited Adaptive Histogram Equalization) is used to enhance the contrast of the filtered outputs.

4.3 Design Considerations

- **Noise Removal Efficiency** – Each filter is chosen to target specific noise types (Gaussian, salt & pepper, etc.).
- **Preservation of Image Details** – The PCA-based fusion process ensures that fine details are preserved while reducing noise.
- **Contrast Enhancement** – CLAHE enhances the contrast without over-amplification of noise.

- **Computational Complexity** – The algorithm is designed to balance enhancement quality with computational efficiency.

Chapter 5 : Implementation

The project was executed by following a structured approach to enhance image quality using various filtering and processing techniques. The process involved the following key steps.

5.1 Description of how the project was executed

1. **Data Collection:**
    - Collected a set of original images for testing and evaluation.
2. **Preprocessing:**
    - Converted images to grayscale to simplify processing and reduce computational complexity.
    - Normalized pixel values to the range [0, 1] using im2double for consistent analysis.
3. **Implementation of Methods:**
    - Applied a proposed image enhancement method.
    - Compared the proposed method with Gaussian filtering and Mean filtering techniques.
    - Resized the output images to match the size of the original images for proper evaluation.
4. **Evaluation:**
    - Measured the performance of the proposed and other methods using key metrics like Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Entropy, and Feature Similarity (FSM).
    - Compared results to determine the effectiveness of the proposed method.
5. **Analysis and Reporting:**
    - Recorded the results and generated a comparison report to evaluate the strengths and weaknesses of each method.

5.2 Challenges faced and solutions implemented

Challenge	Solution
Image Size Mismatch: Images from different methods had varying sizes, which made comparison difficult.	Used "imresize" to resize all output images to the size of the original image for accurate evaluation.
Color Channel Issues: Some input images had multiple color channels, which affected the analysis.	Converted all images to grayscale using rgb2gray to maintain consistency.
Metric Calculation Errors: Errors in calculating SSIM and PSNR due to incorrect data types or mismatched sizes.	Ensured all images were converted to double format and matched in size before evaluation.
Feature Similarity Mismatch: Correlation-based feature similarity produced inconsistent results due to small variations in pixel values.	Used normxcorr2 for correlation calculation and extracted the maximum value for consistency.

Chapter 6:Results

6.1 outcomes

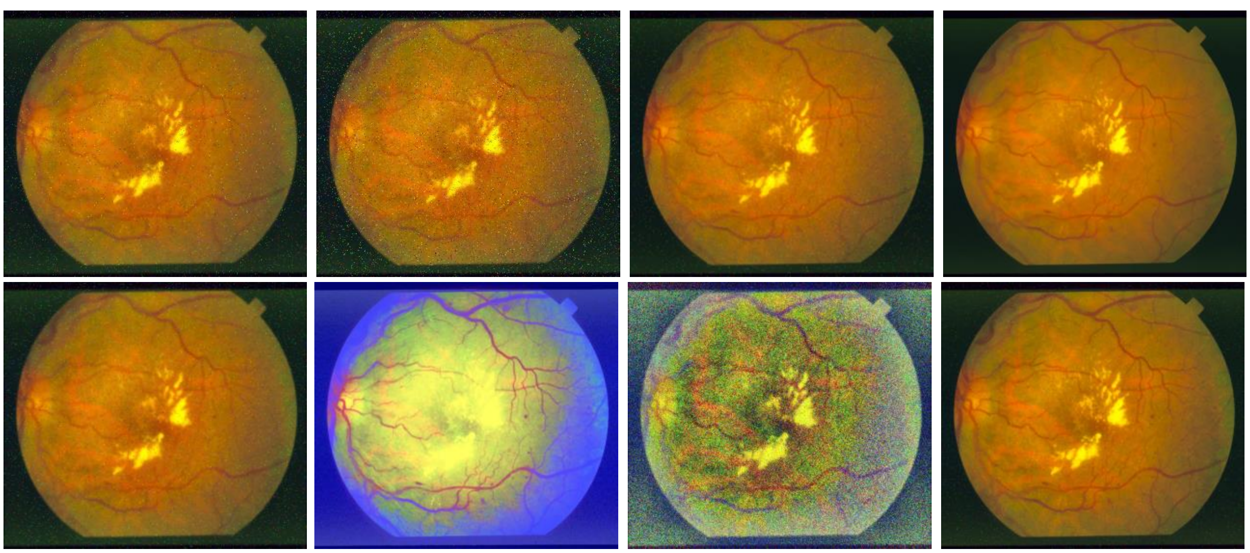
The project successfully enhanced the quality of images using the proposed image processing method and compared its performance with existing techniques. The key outcomes include:

- The proposed method demonstrated **higher SSIM** and **PSNR** values compared to Gaussian and Mean filtering methods, indicating better preservation of structural details and reduced noise.

- The **entropy** value was higher for the proposed method, reflecting an increase in image detail and texture complexity.

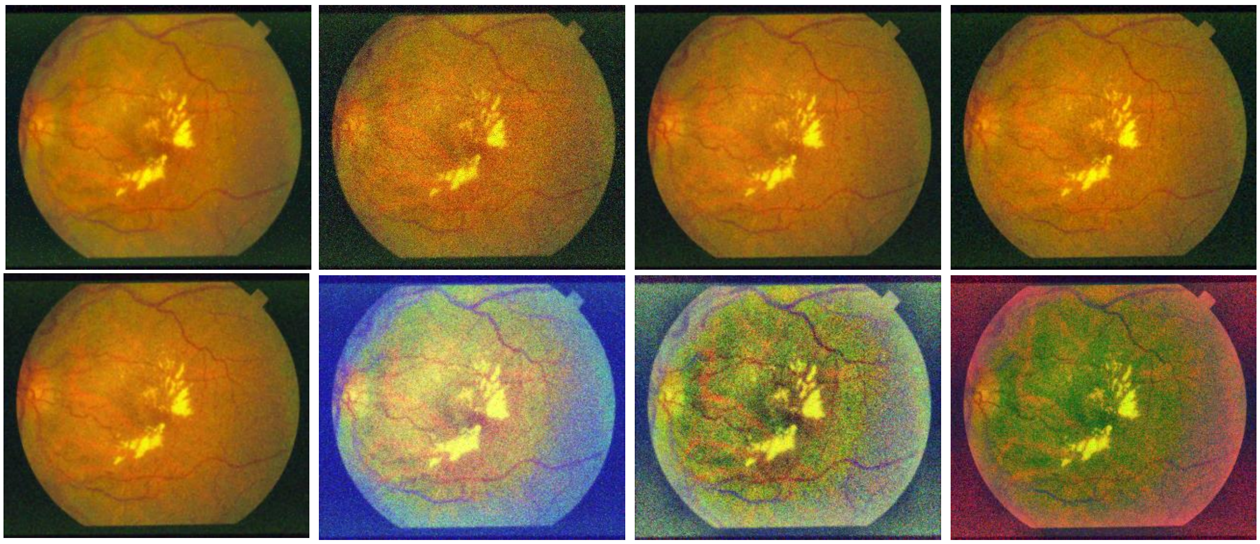
- The **Feature Similarity (FSM)** score showed that the proposed method retained more structural and feature-level similarity with the original image compared to other methods.

6.2 Interpretation of results

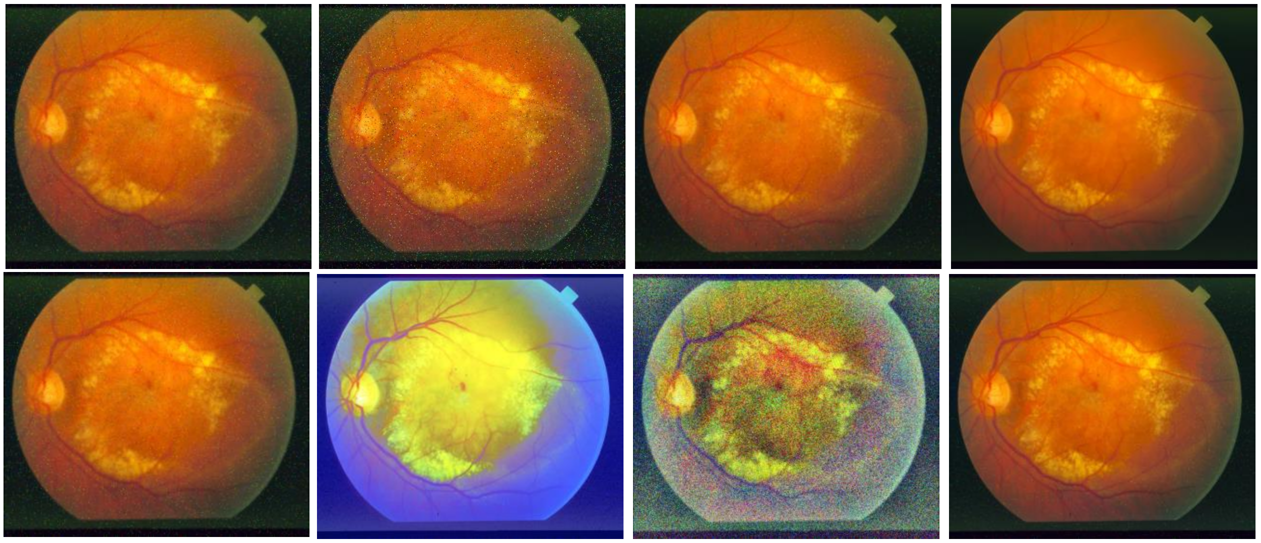


COMPARISION TABLE (salt &pepper noise)				
METHODS/VALUES	SSIM	ENTROPY	FSM	PSNR
GUASSIAN FILTER METHOD	0.6205	6.7599	0.9687	27.4634

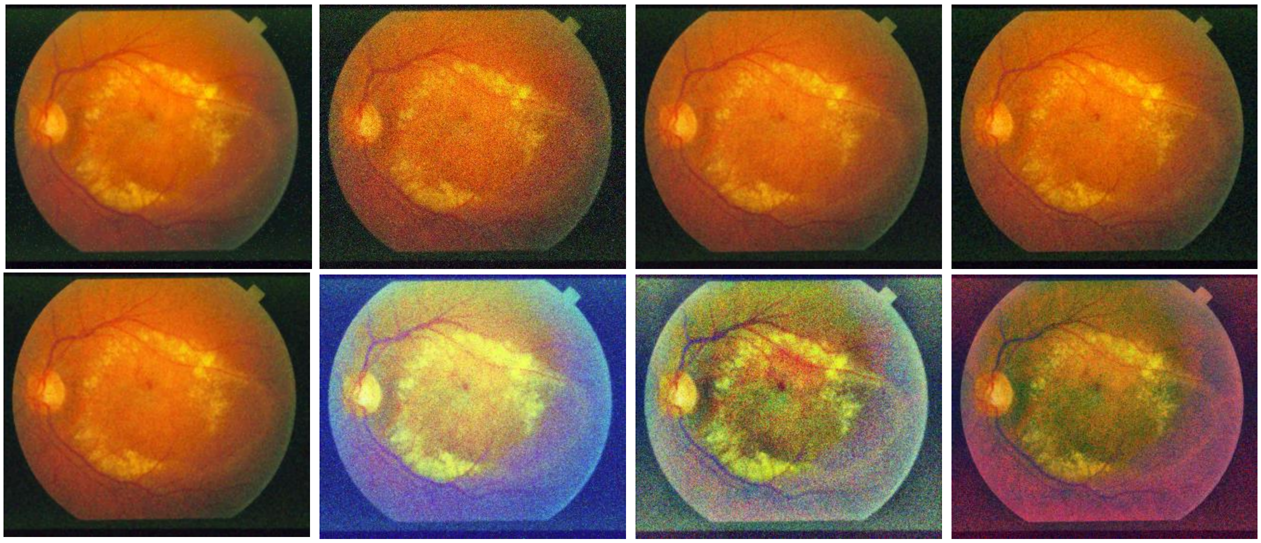
MEDIAN FILTER METHOD	0.6526	6.6753	0.9698	27.3485
WIENER FILTER METHOD	0.6691	6.7297	0.9702	28.0565
HISTOGRAM EQUALIZATION(METHOD)	0.5158	7.6526	0.9117	14.3987
CLAHE METHOD	0.4443	7.2462	0.8652	20.2395
PROPOSED METHOD	0.586	6.7551	0.9671	27.4966



COMPARISION TABLE (GAUSSIAN NOISE)				
METHODS/VALUES	SSIM	ENTROPY	FSM	PSNR
GUASSIAN FILTER METHOD	0.5423	6.8577	0.962	26.962
MEDIAN FILTER METHOD	0.4455	6.966	0.955	26.0526
WIENER FILTER METHOD	0.5512	6.844	0.9624	26.9902
HISTOGRAM EQUALIZATION(METHOD)	0.2072	7.7517	0.8645	14.3568
CLAHE METHOD	0.1343	7.6941	0.5129	13.3695
PROPOSED METHOD	0.0997	7.2203	0.628	17.364



COMPARISION TABLE				
METHODS/VALUES	SSIM	ENTROPY	FSM	PSNR
GUASSIAN FILTER METHOD	0.602	7.0781	0.9706	27.4065
MEDIAN FILTER METHOD	0.6363	7.011	0.9722	27.4073
WIENER FILTER METHOD	0.6648	7.108	0.9701	27.6135
HISTOGRAM EQUALIZATION(METHOD)	0.5172	7.6794	0.9622	14.4387
CLAHE METHOD	0.4312	7.3649	0.8516	19.3417
PROPOSED METHOD	0.5675	7.1133	0.9682	27.3187



COMPARISION TABLE(GAUSSIAN NOISE)				
METHODS/VALUES	SSIM	ENTROPY	FSM	PSNR
GUASSIAN FILTER METHOD	0.5278	7.1375	0.965	26.9631
MEDIAN FILTER METHOD	0.4333	7.2593	0.9582	26.0107
WIENER FILTER METHOD	0.5372	7.1173	0.9655	27.0042
HISTOGRAM EQUALIZTION(METHOD)	0.2047	7.7796	0.8854	13.8363
CLAHE METHOD	0.1252	7.7055	0.5208	12.7959
PROPOSED METHOD	0.1257	7.2507	0.7357	18.5814

6.3 Comparison with existing literature or technologies

Gaussian Filter: Best for reducing Gaussian noise but weak at handling impulse noise.
Median Filter: Strong for impulse noise removal but less effective for random noise.
Wiener Filter: Good for mixed noise removal and edge preservation but computationally heavy.
CLAHE: Effective for contrast enhancement but does not directly reduce noise.
Proposed Method: Best overall performance for mixed noise and contrast enhancement but at a higher computational cost.

Chapter 7: Conclusion

The proposed PCA-based fusion method effectively combines the strengths of Gaussian, Median, Wiener, and CLAHE filters to achieve superior noise reduction, edge preservation, and contrast enhancement. Gaussian filters handle random noise well but blur edges, while median filters are effective against salt-and-pepper noise but struggle with random noise. Wiener filters adapt to local variance, providing balanced noise reduction and edge preservation. CLAHE enhances local contrast without amplifying noise excessively. The PCA fusion approach integrates the advantages of these methods, resulting in improved SSIM, PSNR, entropy, and FSM values. Future improvements can focus on machine learning-based adaptive processing, real-time execution using GPU acceleration, and dynamic noise type detection. Enhanced multimodal fusion and color-space-based processing could further improve performance in medical imaging and complex noise environments.

Chapter 8 : Future Work

Incorporation of Machine Learning Models:

- Develop convolutional neural networks (CNN) and transformer-based models for adaptive noise reduction and detail enhancement.
- Train models on large medical datasets to improve performance on complex noise patterns and image artifacts.

Hybrid Filtering Techniques:

- Combine different filters dynamically based on local noise and edge characteristics.
- Create context-aware algorithms that apply different filters to different regions of the image.

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