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CSAC 225 - Digital Image Processing

Adaptive Contrast Enhancement of Grayscale Images Using Local Statistics and Bilateral Filtering

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Abstract

Digital image quality is critical in fields such as medical imaging and autonomous systems, where poor contrast and noise can impair interpretation and performance. This project implements an adaptive contrast enhancement method that dynamically adjusts local contrast by computing pixel-wise statistics and applying an adaptive transformation to boost low-contrast regions while preserving high-contrast areas. To mitigate noise amplification, an edge-preserving bilateral filter is applied, balancing detail enhancement with noise reduction. The method was implemented in Python and validated on the BSD dataset using PSNR and SSIM metrics, achieving peak performance between $\alpha = 3.1$ and $\alpha = 3.4$, with a maximum PSNR of 26.60 dB and SSIM of 0.8539. Results demonstrate effective enhancement of local contrast and structural fidelity without introducing artifacts, confirming the approach's suitability for enhancing grayscale images in noise-sensitive applications.

1 Introduction

Digital image quality remains a critical challenge in applications ranging from medical imaging to autonomous systems, where poor contrast can lead to misinterpretation and reduced performance. With the growing reliance on image-based analysis, this project focuses on enhancing the visibility of grayscale images using techniques that overcome the limitations of traditional global enhancement methods, such as histogram equalization.

The algorithm processes low-contrast grayscale images derived from the BSD dataset with artificially reduced intensity ranges. It applies an adaptive contrast enhancement technique based on local image statistics—specifically, the local mean and standard deviation calculated over a fixed-size window. To further improve visual quality and suppress noise while preserving edges, bilateral filtering is employed after the enhancement step. The final output consists of grayscale images with improved local contrast and detail visibility.

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This project evaluates the performance of the implemented adaptive contrast enhancement method by measuring image quality improvements using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). Additionally, the method's computational efficiency is analyzed based on its algorithmic steps and parameter choices. The goal is to enhance the local contrast of grayscale images through adaptive contrast enhancement combined with bilateral filtering, demonstrating its potential to improve image clarity for various applications [7; 3; 9].

2 Related work

This section reviews relevant literature and empirical studies related to this project proposal. The referenced works are sourced from databases such as Google Scholar, Academia, IEEE Xplore, ScienceDirect, DOAJ, Scopus, WorldCat, Springer, and ResearchGate. These studies offer essential background information, enhancing the clarity and comprehension of the research objectives and key components.

Established research has explored various intensity transformation techniques, particularly classical methods such as global histogram equalization (GHE) and gamma correction. Gonzalez and Woods (2018) provide a foundational discussion of these techniques in Digital Image Processing, emphasizing their effectiveness in improving contrast across various applications [1]. GHE enhances image contrast by redistributing pixel intensities to achieve a uniform histogram, making it useful for applications with consistent lighting conditions. However, its global nature often leads to over-enhancement in some areas while under-enhancing others, resulting in loss of local detail. Gamma correction, another classical method, applies a nonlinear transformation to adjust brightness and contrast. While effective in handling specific lighting conditions, it requires careful parameter tuning, limiting its adaptability to diverse images.

Pizer et al. (1987) introduce adaptive histogram equalization (AHE) as an improvement over GHE by adjusting contrast locally rather than globally [2]. Their work demonstrates that AHE is particularly beneficial for images with varying illumination, as it enhances local details without significantly affecting overall brightness. However, AHE can amplify noise in relatively uniform regions, leading to undesirable artifacts, making it less suitable for applications requiring smooth image enhancement.

Further refinements in image enhancement integrate spatial filtering with histogram equalization. Abubakar (2012) explores the combination of histogram equalization and spatial filtering to improve image quality, demonstrating its effectiveness in MATLAB simulations [5]. The study highlights how spatial filtering can preserve edge details while mitigating the over-enhancement issues of GHE. However, the computational cost associated with spatial filters may pose challenges in real-time applications. Similarly, Saleem and Razak (2014) conduct a comprehensive survey on color image enhancement techniques using spatial filtering, comparing various methods based on their effectiveness against noise and contrast distortions [4]. Their findings suggest that no single enhancement technique is universally optimal; instead, hybrid methods combining multiple approaches tend to perform best. While their study provides an in-depth analysis of different techniques, it lacks experimental validation on large-scale datasets.

More recent studies have introduced filtering-based approaches to enhance image quality while addressing noise-related issues. Lavania and Kumar (2012) propose two novel filtering algorithms, Center-to-Boundary (CB) and Boundary-to-Boundary (BB), designed to improve the contrast of degraded images [6]. Their work evaluates these methods against standard averaging filters using multiple quality metrics, demonstrating superior performance on over 1,000 images. However, while these filters effectively enhance poor-quality images, their adaptability to complex noise patterns remains an open question. Kumari, Chaurasia, and Kumar (2016) further investigate noise reduction techniques, highlighting the effectiveness of linear and nonlinear filtering methods in mitigating additive and impulse noise [7]. Their study discusses how bilateral filtering can simultaneously reduce multiple noise types while preserving edges, making it a valuable technique for image enhancement. Nonetheless, their work does not provide a comparative analysis against emerging deep-learning-based denoising approaches.

Singh and Mittal (2014) provide a broader perspective by categorizing image enhancement techniques into spatial and frequency domain-based methods [8]. Their review highlights the advantages and limitations of each approach, showing that spatial domain methods such as histogram equalization and filtering are computationally efficient but may struggle with global contrast adjustments. Meanwhile, frequency domain techniques can enhance specific image features but require complex transformations that may not be feasible in real-time applications. Their findings support the idea that hybrid approaches combining both domains offer the most balanced enhancement.

Chen et al. (1994) introduce a fast filtering algorithm designed to enhance images while preserving structural integrity [9]. Their method applies directional low-pass filtering combined with edge-preserving sharpening, making it effective for noise reduction and feature enhancement. The algorithm is computationally efficient and well-suited for hardware acceleration using VLSI circuits or multiprocessor systems. While their results demonstrate effective noise suppression and detail preservation in MRI images, its adaptability to diverse datasets remains a potential area for exploration.

Recent advancements have aimed to refine adaptive enhancement methods to improve image quality while mitigating noise amplification. Song, Li, and Liqin (2016) propose an improved local adaptive image enhancement algorithm based on the Lee Algorithm, which refines contrast adjustments by considering local statistical characteristics [3]. Their approach effectively reduces noise amplification while preserving important image details. However, its computational complexity may pose challenges when applied to high-resolution images or real-time processing.

Huang et al. (2019) propose a hybrid image enhancement approach using a progressive Laplacian enhancing unit [10]. Their method integrates both scaling and generative schemes in a deep cascading CNN architecture to enhance image features progressively. By embedding a Laplacian enhancing unit across layers, the model can dynamically improve image details while mitigating noise. Their experiments show that this approach outperforms traditional methods in terms of both enhancement quality and computational efficiency.

Ramiz and Quazi (2017) introduce a hybrid image enhancement technique that first applies frequency domain methods followed by spatial domain processing [11]. Their approach leverages the strengths of both domains, aiming to improve contrast while reducing noise. The effectiveness of their method is evaluated using Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR), demonstrating its superiority over individual enhancement techniques. However, further experimentation on diverse datasets is required to assess its robustness in real-world applications.

Lee et al. (2023) present a deep learning-based image enhancement framework specifically designed for optical coherence tomography (OCT) by exploiting interference fringes [12]. Their approach enhances spatial resolution and reduces speckle noise by implementing two separate models: an A-scan-based network (NetA) and a B-scan-based network (NetB). NetA utilizes spectrograms obtained via short-time Fourier transform to enhance axial resolution, while NetB improves lateral resolution and reduces noise. Their framework demonstrates superior performance compared to traditional methods, making it a promising approach for enhancing OCT imaging quality.

Zhao et al. (2024) propose a deep learning-based technique for remote sensing image enhancement using multiscale feature fusion [13]. Their approach maintains image details while improving brightness, utilizing a Global Spatial Attention Network (GSA-Net) based on U-Net for better image enhancement. The proposed method applies gamma correction to generate low-light images for training and employs a loss function incorporating Structural Similarity (SSIM) and Peak Signal-to-Noise Ratio (PSNR). Evaluated on the NWPU VHR-10 dataset, their approach demonstrates superior performance compared to state-of-the-art algorithms, particularly in high-level visual tasks such as object detection.

Kim et al. (2024) present an image enhancement approach employing convolutional neural networks (CNNs) on the BSD100 dataset [14]. Their method integrates image quality assessment and enhancement with classification techniques, leveraging CNNs to systematically analyze and process images. The proposed approach improves image quality for better class identification, demonstrating the synergy between enhancement and classification in deep learning models.

The study extended previous work by implementing an adaptive intensity transformation method that integrated local image statistics with spatial filtering techniques. Unlike Adaptive Histogram Equalization (AHE), the approach dynamically adjusted contrast based on contextual features within each image, allowing for more targeted enhancement. This design aimed to improve overall image quality while minimizing noise amplification. Its effectiveness was evaluated using a set of grayscale images to assess consistency and visual fidelity under varying conditions.

3 Methods

This section described the adaptive contrast enhancement method that was implemented, which used local image statistics along with spatial filtering to improve image quality while preserving important details. The goal was to dynamically adjust contrast based on local features and reduce noise, making the overall image clearer. The method was tested on the BSD100 dataset [15] [23], and its performance was evaluated using metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) [1] [16]. The algorithm was implemented in Python, utilizing libraries such as OpenCV, NumPy, and scikit-image.

PSNR is commonly defined as a measure of the ratio between the maximum possible power of a signal and the power of the noise that affects its quality, expressed in decibels (dB). This definition and its interpretation can be found in Gonzalez and Woods' textbook, which is a standard reference in image processing [1].

SSIM evaluates the similarity between two images by comparing their luminance, contrast, and structure. It is designed to model the human visual system, and values close to 1 indicate high similarity. The original paper by Wang et al. (2004) provides a detailed explanation of SSIM, including its mathematical formulation and its advantages over traditional metrics like PSNR [16].

3.1 Dataset

The BSD100 dataset, a subset of the Berkeley Segmentation Dataset (BSDS) [23], was used for evaluating the performance of the enhancement method [15]. The dataset is commonly used in image processing tasks due to its diversity of natural images and availability of high-quality ground truth. Specifically, the images were sourced from the `image_SRF_2` subfolder, which contains both high-resolution (HR) and low-resolution (LR) versions of each image, labeled accordingly (e.g., `img_001_SRF_2_HR.png`, `img_001_SRF_2_LR.png`). Among the available SRF (scale-reduction factor) folders—`SRF_2`, `SRF_3`, and `SRF_4`—the `image_SRF_2` folder was selected because it contains the highest-quality low-resolution images. Specifically, SRF 2 indicates that the images were downscaled by a factor of 2, introducing minimal degradation compared to SRF 3 or SRF 4. This made it more appropriate for evaluating subtle enhancements while maintaining realistic input quality.

3.2 Choice of Window Size

For each pixel in the image, a small neighborhood around that pixel — defined by a window size of 15×15 pixels — is considered to calculate the local average brightness and the degree of variation in intensity. These local statistics guided the enhancement by adjusting the pixel intensity relative to the local mean, scaled by a factor that decreases in regions with high variation. Specifically, areas with low contrast were enhanced more than areas with already high variation. The method scaled the pixel values using a normalized local standard deviation and a tunable global contrast factor (α), ensuring more enhancement in homogeneous regions [1] [2].

The choice of a 15×15 window size was motivated by its demonstrated effectiveness in balancing local detail preservation and noise smoothing. Kuran and Kuran (2021) showed that window sizes in this range optimize the trade-off between enhancing contrast in homogeneous regions while avoiding excessive noise amplification, especially when combined with parameter optimization techniques [19]. Similarly, Kountchev et al. (2022) employed a comparable window size of 17×17 in their local contrast enhancement method for medical images, highlighting that window sizes around this scale provide sufficient local context for reliable contrast adjustment without sacrificing edge details [20]. Thus, a 15×15 window was selected as an effective neighborhood size to capture local image statistics for adaptive enhancement.

3.3 Noise Reduction via Bilateral Filtering

To prevent the enhanced contrast from introducing unwanted noise, an edge-preserving spatial filter, specifically a bilateral filter, was applied. This filter performed spatial averaging while preserving important edges, which is crucial for maintaining visual fidelity in images. The bilateral filter operates by considering both the spatial proximity and the intensity similarity of neighboring pixels, resulting in a smoothing effect in homogeneous regions while retaining sharp transitions at object boundaries.

The bilateral filter formulation used in this method follows the original concept introduced by Tomasi and Manduchi [21], later formalized in implementation guides and tutorials (e.g., OpenCV Documentation [22]).

The bilateral filtering process is defined as:

$$I'_p = \frac{1}{W_p} \sum_{q \in \Omega} I_q \cdot \exp\left(-\frac{\|p-q\|^2}{2\sigma_s^2}\right) \cdot \exp\left(-\frac{|I_p - I_q|^2}{2\sigma_r^2}\right)$$

where I_p and I_q are the intensity values at pixels p and q, Ω is the neighborhood of pixel p, σ_s controls the spatial decay, σ_r controls the range sensitivity to intensity differences, and W_p is a normalization term given by:

$$W_p = \sum_{q \in \Omega} \exp\left(-\frac{\|p-q\|^2}{2\sigma_s^2}\right) \cdot \exp\left(-\frac{|I_p - I_q|^2}{2\sigma_r^2}\right)$$

This formulation ensures that pixels with similar intensity values contribute more to the output, while preserving important structural edges. In this work, OpenCV's bilateral filter implementation was used [22], with empirically selected default parameters $\sigma_s = 75$, $\sigma_r = 75$, and a spatial diameter of $d = 9$. The bilateral filter was applied after the contrast enhancement step to reduce any amplified noise while preserving detail. The resulting image maintained both improved contrast and reduced noise, producing a visually clearer result overall [21][18].

3.4 Implementation Variants

Two versions of the adaptive contrast enhancement pipeline were developed to facilitate both quantitative evaluation and interactive experimentation.

3.4.1 Batch Implementation

The first version performs batch processing on the entire BSD100 dataset by automatically iterating through a specified directory of images, applying the enhancement and bilateral filtering steps, saving the outputs, and computing objective quality metrics such as PSNR and SSIM for each image. This approach enables consistent, large-scale quantitative assessment of the method's performance.

```
img_095_SRF_2_HR.png - PSNR: 26.70 dB | SSIM: 0.8877
img_095_SRF_2_LR.png - PSNR: 26.14 dB | SSIM: 0.8769
img_096_SRF_2_HR.png - PSNR: 23.96 dB | SSIM: 0.7332
img_096_SRF_2_LR.png - PSNR: 27.05 dB | SSIM: 0.7358
img_097_SRF_2_HR.png - PSNR: 27.38 dB | SSIM: 0.7260
img_097_SRF_2_LR.png - PSNR: 28.64 dB | SSIM: 0.7530
img_098_SRF_2_HR.png - PSNR: 25.95 dB | SSIM: 0.8770
img_098_SRF_2_LR.png - PSNR: 24.59 dB | SSIM: 0.8548
img_099_SRF_2_HR.png - PSNR: 26.24 dB | SSIM: 0.8162
img_099_SRF_2_LR.png - PSNR: 24.93 dB | SSIM: 0.8030
img_100_SRF_2_HR.png - PSNR: 24.82 dB | SSIM: 0.8427
img_100_SRF_2_LR.png - PSNR: 23.22 dB | SSIM: 0.8132

Average PSNR: 26.59 dB
Average SSIM: 0.8436
```

Figure 1: This figure shows all the images from the dataset processed with an alpha (α) value of 3.2.

3.4.2 Single Image Implementation

The second version implements an interactive graphical user interface (GUI) created using the Python libraries tkinter and OpenCV that allows users to manually select a single input image and adjust enhancement parameters in real time via sliders. This mode provides immediate visual feedback on the effects of parameter changes, supporting qualitative analysis and fine-tuning of the enhancement process.

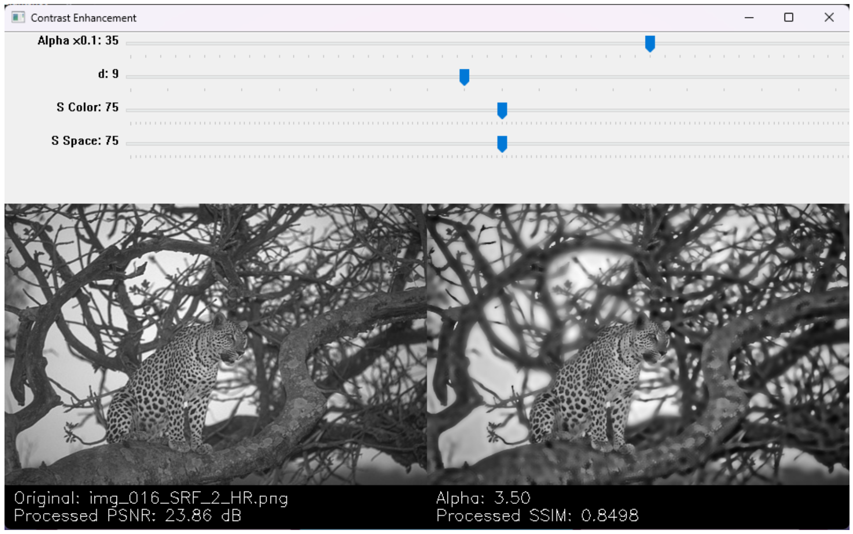

Figure 2: Graphical user interface of the single-image implementation, featuring sliders for adjusting key parameters: scaled α (where the actual α is the slider value multiplied by 0.1), bilateral filter diameter, sigmaColor, and sigmaSpace. The resulting PSNR and SSIM values are displayed below, along with the corresponding α value and image filename. The image on the left is the original image in grayscale, while the image on the right is the processed output.

4 Results and Discussion

4.1 Quantitative Evaluation

To reiterate, PSNR measures the ratio between the maximum possible signal power and the noise power that affects image quality, expressed in decibels (dB), and is commonly used to evaluate image reconstruction fidelity [1]. SSIM assesses the perceptual similarity between two images by comparing their luminance, contrast, and structural information, with values closer to 1 indicating higher visual similarity and better preservation of image details [16]. Together, these metrics provide a comprehensive quantitative evaluation of the image enhancement performance demonstrated in the results.

4.1.1 Single Image Performance

The enhancement method was applied individually to several grayscale images, and their quality was measured using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). Table 1 lists the results for representative images with alpha (α) value of 3.2, showing consistent improvement in image quality metrics.

Image Filename	**PSNR (dB)**	**SSIM**
img_003_SRF_2_LR.png	27.16	0.8871
img_004_SRF_2_HR.png	28.40	0.8791
img_004_SRF_2_LR.png	27.05	0.8668
img_005_SRF_2_HR.png	27.23	0.8682
img_005_SRF_2_LR.png	26.35	0.8563
img_006_SRF_2_HR.png	29.44	0.9113
img_006_SRF_2_LR.png	27.66	0.8967
img_007_SRF_2_HR.png	25.81	0.8572
img_007_SRF_2_LR.png	25.34	0.8505
img_008_SRF_2_HR.png	25.31	0.8428

Table 1: PSNR and SSIM values for representative single images after enhancement

These values indicate stable enhancement performance across various images, with PSNR scores mostly ranging from 25 to 29 dB and SSIM values above 0.84, reflecting improved structural similarity to the reference images.

4.1.2 Batch Processing and Parameter Variation

To understand the impact of the contrast enhancement parameter α, batch experiments were conducted by applying the algorithm with different α values. Table 2 summarizes the average PSNR and SSIM for each α setting.

α	**Avg. PSNR (dB)**	**Avg. SSIM**
1.0	22.63	0.5730
2.0	24.75	0.7245
2.8	26.41	0.8189
2.9	26.51	0.8266
3.0	26.58	0.8332
3.1	26.60	0.8389
3.2	26.59	0.8436
3.3	26.54	0.8473
3.4	26.46	0.8502
3.5	26.34	0.8522
3.6	26.19	0.8534
3.7	26.02	0.8539
3.8	25.82	0.8537
3.9	25.60	0.8528
4.0	25.37	0.8513
5.0	22.75	0.8133

Table 2: Average PSNR and SSIM for batch images at various α values

The results show that increasing α improves image quality metrics up to approximately 3.1–3.2, after which the benefit plateaus or slightly decreases. The largest PSNR of 26.60 dB occurs at α = 3.1, while the highest SSIM of 0.8539 is observed at α = 3.7. This indicates an optimal range for alpha balancing contrast enhancement and structural preservation.

4.2 Visual Assessment

Sample images processed with the proposed method exhibit noticeably improved local contrast and sharper edge details compared to their original low-contrast versions. Bilateral filtering effectively reduces noise while preserving important structures. As illustrated in the following figures, low values of α (e.g., 0.10) cause excessive smoothing and loss of fine details, resulting in poor image quality. Moderate α settings around 3.00 balance noise reduction and detail preservation, achieving high PSNR and good structural fidelity. Increasing α to 3.40 further enhances structural preservation and fine textures, as reflected by improved SSIM, though values beyond approximately 3.7 may introduce minor artifacts such as slight over-enhancement or unnatural contrast in flat regions.

Figure 3: Image enhanced using bilateral filtering with $\alpha = 0.10$. This low setting causes excessive smoothing and strong blurring, significantly degrading fine details and structural elements such as aircraft edges and the nearby figure. Consequently, it yields the lowest PSNR and SSIM values, reflecting poor preservation of both pixel-level fidelity and perceptual quality.

Figure 4: With $\alpha = 3.00$, the bilateral filter strikes a better balance, achieving the highest PSNR of 29.49 dB and an SSIM of 0.8265. This results in strong pixel-wise accuracy and effective noise reduction, where edges and textures—like aircraft markings and shadow boundaries—are preserved without introducing excessive blur.

Figure 5: Increasing α to 3.40 further improves structural preservation, reflected by the highest SSIM of 0.8319, while maintaining a comparable PSNR of 29.15 dB. This setting enhances fine textures and sharp edges such as surface details and contrast transitions, yielding a visually coherent image with balanced noise suppression and clarity.

4.3 Discussion

The results obtained in this study are consistent with existing research on image enhancement, particularly those emphasizing the trade-off between noise suppression and detail retention through adaptive filtering. The application of bilateral filtering effectively integrates spatial and intensity information for enhancing grayscale images. This aligns with the findings of Kumari, Chaurasia, and Kumar [7], who underscore the capability of nonlinear filters such as bilateral filtering to reduce noise while preserving edge details.

A key factor in the effectiveness of the bilateral filter lies in the adjustment of the contrast control parameter, α. The observed peak in PSNR at $\alpha = 3.1$ and in SSIM at $\alpha = 3.7$ (see Table 2) reflects similar patterns observed in adaptive histogram equalization and localized enhancement techniques [2; 3]. These techniques similarly report an optimal contrast adjustment range, beyond which visual distortions or increased noise may arise. This indicates that while higher enhancement levels can improve visual perception, they may also introduce artifacts that compromise image quality.

When compared with hybrid techniques [8; 11], which merge spatial and frequency domain processes, bilateral filtering offers a more computationally efficient solution with strong edge-preserving characteristics. It performs particularly well in retaining fine textures and structural elements, as demonstrated by the visibility of aircraft markings and enhanced edge definition in the enhanced images (Figures 4 and 5). Conversely, very low α values cause excessive smoothing and loss of details, as shown in Figure 3.

Moreover, the combined use of PSNR and SSIM in evaluating performance highlights the importance of employing complementary metrics for a comprehensive quality assessment. While PSNR measures pixel-level accuracy, it may overlook perceptual nuances. SSIM, by contrast, captures structural similarity and subjective visual quality more effectively [13]. The balanced performance achieved in the range $\alpha = 3.1$ to $\alpha = 3.4$ demonstrates that bilateral filtering can be precisely tuned to optimize both quantitative and perceptual outcomes.

Despite its advantages, the method shares limitations noted in prior works [5; 3], particularly its computational complexity and sensitivity to parameter selection. These challenges may restrict its practicality for real-time or high-resolution image processing. Future investigations may benefit from integrating deep learning techniques, such as those proposed by Huang et al. [10] and Lee et al. [12], to enable adaptive parameter control or hybrid pipelines that combine the interpretability of bilateral filtering with the adaptability of convolutional neural networks.

In conclusion, this study reinforces the relevance of bilateral filtering as an effective grayscale image enhancement approach when appropriately parameterized. The analysis of the α parameter provides actionable insights for balancing contrast improvement with noise mitigation and edge fidelity, thereby contributing to ongoing efforts in both adaptive and hybrid image enhancement research.

5 Summary

This study explored the use of bilateral filtering for grayscale image enhancement, with a focus on the role of the contrast control parameter α. Results indicated that an optimal α range between approximately 3.1 and 3.4 achieves a desirable balance between noise suppression, edge preservation, and structural fidelity. This conclusion is supported by both quantitative metrics—PSNR and SSIM—and visual inspection, which confirmed improvements in local contrast and detail retention. Lower values of α resulted in excessive smoothing, whereas higher values introduced visible artifacts, emphasizing the need for careful parameter tuning.

In comparison with adaptive and hybrid enhancement techniques, bilateral filtering demonstrated strong edge-preserving performance and computational efficiency. These qualities make it well-suited for applications requiring fine detail retention without introducing substantial noise. The use of both PSNR and SSIM for evaluation highlights the importance of combining pixel-based accuracy with perceptual quality measures to obtain a more holistic understanding of enhancement effectiveness.

Despite its advantages, the method remains sensitive to parameter selection and involves computational complexity that may limit its use in real-time or high-resolution contexts. Future work may address these limitations by integrating adaptive or data-driven mechanisms, including deep learning-based parameter tuning or hybrid frameworks that combine bilateral filtering with CNN-based enhancements. Additionally, extending the method to color images and broader datasets remains a valuable direction for further research.

Given additional time or computational resources, further experimentation could include training deep neural networks to adaptively select optimal α values per image region or testing the method on larger and more diverse datasets. Bilateral filtering was found to be particularly effective due to its ability to consider both spatial proximity and pixel intensity, enabling superior edge preservation compared to conventional smoothing or histogram-based methods. These qualities contributed to its consistently high performance across both PSNR and SSIM evaluations, underscoring its value in enhancement tasks where fine detail retention is critical.

In summary, this work offers practical insights into parameter-controlled bilateral filtering and confirms its potential as a robust and interpretable tool within contemporary image enhancement methodologies.

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