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Digital Image Noise Reduction Based on Proposed Smoothing and Sharpening Filters

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Abstract

In order to reduce noise in digital photographs, this paper provides a thorough analysis of sophisticated sharpness enhancement and image smoothing approaches. The research compares and contrasts different approaches, including well-known filters like Gaussian filter, Mean filter, Weighted Averaging filter, Laplacian filters, and Unsharp mask, with suggested strategies aimed at achieving optimal efficiency. The performance of these techniques is evaluated in several circumstances with speckle noise and Gaussian noise corrupted images. The results show how well the suggested strategy performs in terms of reducing noise, preserving image features, and improving overall image quality. The comparative advantage of the suggested technique over conventional filters is highlighted by comparative analysis. The study's conclusion offers information on the possible uses and future developments of these methods in practical image processing situations.

A. Introduction

Handling exterior artefacts on film, such scratches, cracks, and bruising, is a special and challenging task in the field of image processing. In contrast to consistent noise patterns that may be addressed by mathematical analysis, these flaws frequently resist simple algorithmic fixes. As a result, handling these non-uniform artefacts successfully requires manual intervention—a task that is outside the scope of automated systems [1].

The search for a universal filtering algorithm continues despite the abundance of techniques for eliminating noise from images, from features built into photo and video cameras to specialized processing software [2]. The inherent trade-offs in image processing—the fine balance between removing undesired effects like noise and maintaining minute details—are the source of the complexity. There is no one-size-fits-all solution, despite the abundance of filtering algorithms available to us, as deciding between noise reduction and detail retention remains a difficult task [3].

A basic method for removing noise involves averaging pixel values within a spatial neighbourhood. This idea takes advantage of the intrinsic variability of noise across pixels and operates on the notion of noise cancellation from neighbouring pixels when combined [4]. Each pixel in the process is overplayed with a rectangular window, and the value of the central pixel is calculated by examining every other pixel in the window region. The degree of blurring is directly influenced by the size of the window; larger windows provide more noticeable blurring effects [5].

This method's most basic step is figuring out the arithmetic mean of the nearby pixels. However, a numerical threshold can be added to improve the procedure and lessen the impact of pixels from different regions. Subtler noise reduction is possible with this threshold-driven method since it only takes into account neighbor differences that fall within a specific range [6]. This is especially useful in situations when there are contrasting pixel values, such black outlines on light backgrounds. Moreover, this method becomes more sophisticated by adding weighted factors for each neighboring pixel based on how far they are from the center of the area under consideration [7].

Although it is possible to extend this spatial averaging technique into the time domain by averaging pixels over neighboring frames in a video stream, it frequently fails to yield the best results, resulting in a noticeable loss of visual detail. On the other hand, by adding a Gaussian function to control the filtering procedure, the Gaussian filter provides a more sophisticated solution. The Gaussian filter, in contrast to linear averaging filters, selectively includes points depending on a preset threshold value inside a zone of a given radius. This methodical technique efficiently reduces noise in the image while minimizing blurring in places with sharp edges and keeping fine details [8].

In addition, using a Gaussian filter as a low-pass filtering method can produce a rough depiction of the image's lighting. This method offers a balanced way to preserve image details while minimizing undesired effects, substantially improving the sophistication of noise reduction techniques [9].

This examination of noise reduction methods reveals the complex interplay between maintaining image details and minimizing undesirable consequences, providing insights into the complex field of image processing.

B. Related Works

The weighted median filter's (WMF) reliance on weighting coefficients is the main topic of Gupta & Goyal's (2019) study. The preservation of image details, which is largely dependent on the weighting coefficient, is the main focus of the issue statement. Although it is good at conserving details, the challenge is in determining an appropriate weighting coefficient, which in real-world scenarios results in a large computation time [10].

Kumar et al., (2023) in the field emphasize the importance of day-to-day impulse detection owing to the need to successfully remove random-valued impulse noise, particularly when it is densely present in noisy pictures. This form of noise interacts sporadically with the pixels of the image, making it a difficult process. A suggested solution that combines self-organizing migration and adaptive dual-threshold algorithms has shown promise for effectively processing noisy pictures. Through experimentation on numerous noisy photos with varied window widths, this technique has consistently shown excellent results, allowing for the reconstruction of high-quality original images from noisy equivalents. The suggested method's performance was assessed utilizing Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) as primary assessment criteria. PSNR values were measured throughout a wide range of noise levels, from 10% to 70%, indicating the efficacy of the suggested technique [11].

Panda et al., (2022) are investigating 2D histogram-based multilevel threshold selection strategies for picture segmentation, with an emphasis on entropy-based approaches. A unique strategy that employs a PDRCE-based fitness function and OFDA optimization outperforms traditional approaches. Evaluation of the BSDS500 dataset yields promising results for applications such as registration and fusion, improving image analysis research [12].

Manda & Kim, (2020) working to improve object recognition in infrared photos, with image thresholding emerging as an effective technique. Recently published research describes a novel infrared picture thresholding strategy based on histogram functional approximation. This approach approximates the picture histogram to a first-order linear circuit's transient response and uses combinational analogues of conventional operators to calculate segmentation thresholds. Experimental testing on infrared photos from standard databases reveals that the suggested method outperforms current state-of-the-art methodologies. The findings have interesting implications for future study and applications in the field of infrared picture thresholding [13].

In their 2019 evaluation, Khan et al. divide techniques into four categories: hybrid, CS-based, MRA, VO, and pan-sharpening algorithms for image synthesis. The analysis presents the advantages and disadvantages of each strategy, with CS-based approaches exhibiting runtime efficiency and MRA-based methods excelling in spectral quality. On the other hand, MRA and VO techniques appear to require lengthier processing periods [14].

A unique Mean-Median-Gaussian (MMG) hybrid filtering technique is presented by AKSOY & SALMAN (2020) in order to overcome the drawbacks of conventional filters. When it comes to smoothing pictures and drawing boundary lines, the MMG hybrid algorithm performs better than the mean, median, and

Gaussian filters alone. Its application, however, can rely on the context, so more testing with a variety of datasets is necessary[15].

Zhang et al. (2023) suggest a high-low pass hybrid filtering technique for improving infrared images. The technique enhances detail and suppresses background infrared pictures by combining Butterworth high-pass and Gaussian low-pass filters. Additional verification is required to evaluate its efficacy in various circumstances and applications [16].

Pham (2022) presents an innovative technique for anisotropic averaging combined with Laplacian kernels for enhancing grayscale images. Without requiring input statistical parameters, the approach shows advantages over conventional sharpening filters in terms of sharpness and natural visualization balance [17].

Deng et al. (2021) use unsharp masking to address the link between these procedures and provide a single smoothing and sharpening filter for image processing. With its guided filtering and Laplacian-based formulation, the suggested filter performs well in adaptive smoothing and sharpening applications, among other uses [18].

To improve real-time picture recognition in cloudy settings, Liang et al. (2021) provide a quick defogging approach based on bilateral hybrid filtering. The approach achieves high-speed picture recognition and promising defogging effects while reducing computing complexity and image execution time [19].

Wangno & Pichai (2020) use a hybrid algorithm that combines guided filter and dark channel prior (DCP) in order to remove haze and improve image quality. Although the method works well in hazing instances, its performance could change depending on the context and some aspects of the image [20].

C. Background Theory

Digital images, which are commonplace in contemporary civilization, are representations of visual information encoded in a digital format, usually made up of grid-organized pixels. Digital cameras, scanners, or computer algorithms are used to create these images. Red, green, and blue (RGB) channels are frequently used to express the numerical values that reflect the color information found in each pixel [21]. A digital image's level of detail is determined by its resolution; images with greater resolutions offer crisper and more detailed representations. Numerous software tools and formats are available for manipulating, processing, and storing digital images, opening up a plethora of applications in fields like scientific research, healthcare, entertainment, and photography. To achieve the best possible image quality and fidelity, sophisticated methods for noise reduction, augmentation, and restoration must be developed because digital images are prone to noise, artefacts, and degradation during acquisition, transmission, and processing [22].

1. Digital Image Filters

Gaussian Filter: The Gaussian filter is a popular image processing filter for reducing noise and blurring pictures. It works by convolving the picture with a Gaussian kernel, which gives larger weights to pixels near the kernel's center and lower weights to those farther away. This weighting system produces a smoothing effect that maintains the general structure of the image while decreasing noise. The standard deviation (σ) of the Gaussian distribution determines the efficacy of the Gaussian filter. Higher values result in stronger smoothing effects [23].

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{\frac{z^2+y^2}{2\sigma^2}} \quad (1)$$

Weighted Average Filter: The weighted average filter, also known as the weighted smoothing filter, is a linear filter used to reduce noise in photographs. It calculates the average intensity of neighboring pixels inside a specified window, giving each pixel a distinct weight based on its closeness to the center. This weighting approach enables the filter to maintain edges and fine features while significantly lowering noise. The weighted average filter is especially effective in cases where maintaining picture clarity is critical, such as in medical imaging or satellite data analysis [24].

$$I_{smoothed}(x,y) = \frac{\sum_{i=-k}^{k}\sum_{j=-k}^{k} w(i,j) I(x+i,y+j)}{\sum_{i=-k}^{k}\sum_{j=-k}^{k} w(i,j)} \quad (2)$$

Laplacian Filter: The Laplacian filter is a popular edge detection filter that highlights fast intensity changes or edges in a picture. It computes the second spatial derivative of picture intensity, emphasizing areas with high spatial frequency. The Laplacian filter successfully identifies edges and other critical elements in a picture by recognizing sudden changes in pixel values. Despite its susceptibility to noise, the Laplacian filter remains a useful tool in several image processing applications, such as picture segmentation and feature extraction [25].

$$\nabla^2 I(x,y) = I(x-1,y) + I(x+1,y) + I(x+1,y) + I(x,y+1) - 4I(x,y) \quad (3)$$

where$\nabla^2 I(x,y)$ represents the Laplacian of I at position (x,y).

Unsharp masking: is a method of image processing that improves edge contrast and sharpness. To produce a mask, first a blurry version of the original image is created, then the mask is subtracted and added back to the original image. The image appears sharper as a result of this technique, which brings out edges and minute details. The threshold (minimum difference for edge detection), quantity (strength of sharpening), and radius (amount of blur) are important factors. Although it works well to enhance visual clarity, excessive use might result in noise and artificial halos. It is frequently utilised in printing, medical imaging, and photography.

2. Digital Noise

Various types of noise provide problems for the integrity and clarity of digital images in the field of image processing. Common types of noise seen in digital images include Gaussian noise, impulse noise, Poisson noise, and speckle noise. Each has unique properties and affects image processing techniques. Blurred details and decreased sharpness are often the result of Gaussian noise, which is defined as random changes that follow a Gaussian distribution. It is sometimes caused by sensor limits, gearbox faults, or electronic interference [26]. Impulse noise is characterized by abrupt, discrete spikes in pixel values that might result from data transmission problems or malfunctioning technology. These spikes can generate localized distortions and possible artefacts [27].

Poisson noise, with a Poisson distribution, is common in low-light and sparse photon events. It affects visibility and contrast in images, particularly in situations with low light. Speckle noise distorts image textures and makes correct feature extraction more difficult by introducing granular patterns that seem like grains or speckles during image collection. These patterns might originate from textured backdrops, reflective surfaces, or uneven lighting. Comprehending the characteristics of every kind of noise is crucial for formulating efficient strategies for mitigating noise, customized to particular imaging circumstances and demands [28].

3. Image Smoothing

Image filtering is a fundamental approach in image processing that enhances picture quality, reduces noise, and extracts relevant information. Various filtering methods, including as mean filtering, median filtering, adaptive median filtering, Gaussian filtering, and bilateral filtering, are frequently used for these reasons. Mean filtering, a simple spatial domain approach, replaces each pixel with the average value of its neighbors, successfully decreasing noise but potentially creating image blurring, especially around edges and details [29]. To address this, weighted domain average approaches are frequently used. Median filtering is a non-linear method that replaces a pixel's value with the median of its surrounding pixels, allowing for noise reduction while retaining edges. For specific picture elements, a weighted median filtering technique may be required for optimal processing efficiency [30].

The adaptive median filtering technique dynamically adapts the filter window size based on specified criteria, efficiently controlling impulsive noise and retaining more picture information than classic median filtering. Gaussian filtering, which uses a weighted average based on the Gaussian function, is effective for smoothing pictures but can blur edges and features. It is frequently used in the preprocessing step to improve photos of various sizes. Bilateral filtering is an anisotropic filter that includes both spatial and value domains, keeping picture edges while filtering noise using a locally weighted average of the input image. This approach successfully smoothest photos while preserving edge information [31].

4. Image Sharpening

Edge sharpening is an important image processing method that improves the clarity and definition of edges in a two-dimensional image. Its applications range from increasing visual attractiveness to emphasizing key characteristics. One frequent way is to utilize convolution filters, such as the Laplacian or Sobel filters, which emphasize intensity shifts and so effectively enhance edges. The Laplacian filter, which is commonly used for edge detection and sharpening, shows areas with fast intensity variations, suggesting the existence of edges [32].

Similarly, the Sobel filter is useful, especially for identifying vertical and horizontal edges. It uses convolution with two 3x3 kernels, one for vertical changes and the other for horizontal changes. Another technique, unsharp masking, involves removing a blurred version of the picture from the original in order to improve tiny details and edges. High-pass filtering is also used to emphasize high-frequency components, which frequently correlate to picture edges [33].

5. Anti Bee Colony

The Anti Bee Colony Algorithm is a metaheuristic optimization algorithm based on bee foraging behaviour and the idea of "anti-pheromones." Unlike traditional bee-inspired algorithms like the Artificial Bee Colony (ABC) Algorithm, which focuses on the exploration-exploitation balance of employed and onlooker bees, the Anti Bee Colony Algorithm introduces the notion of "anti-pheromones" to discourage bees from revisiting unpromising food sources. This strategy tries to increase the variety of search space exploration while avoiding early convergence to local optima. By adopting this principle, the Anti Bee Colony Algorithm aims to increase the overall efficiency and efficacy of optimization tasks in a variety of fields, including engineering, logistics, and machine learning [34].

D. Methodology

1. Smoothing Process

We use an approach to do the smoothing process that combines image improvement and noise removal techniques. The input image, which forms the foundation of our case study, was first read. We next add noise to the picture to mimic real-world situations and assess how well our smoothing technique worked. Since Gaussian noise is a frequently encountered type of noise in numerous imaging applications, it is introduced to the image. After adding the noise, we go ahead and filter the image using a Gaussian filter. The Gaussian filter is used due to its ability to effectively reduce noise while maintaining the details of the image.

After removing the noise, we want to use a weighted average filter to improve the image. Using a weighted combination, two copies of the image, designated as f_1 and f_2, are blended during the enhancing process.

$$H = xf_2 + (1 - x)f_1 \tag{4}$$

The improved image is represented by (H), the weight assigned to f_2 is indicated by f_2 and the weight allocated to $f_2$is indicated by (1 - x). We can modify the contribution of each image version to the final improved result using this equation.

To summarize, our approach to smoothing entails reading the input image, simulating real-world conditions with Gaussian noise, applying a Gaussian filter to remove noise while maintaining image details, and then enhancing the image using a weighted averaging filter based on the given enhancement equation. By employing this methodology, we hope to show how well our strategy works to concurrently achieve noise reduction and image enhancement. Figure (1) shows the process flow chart.

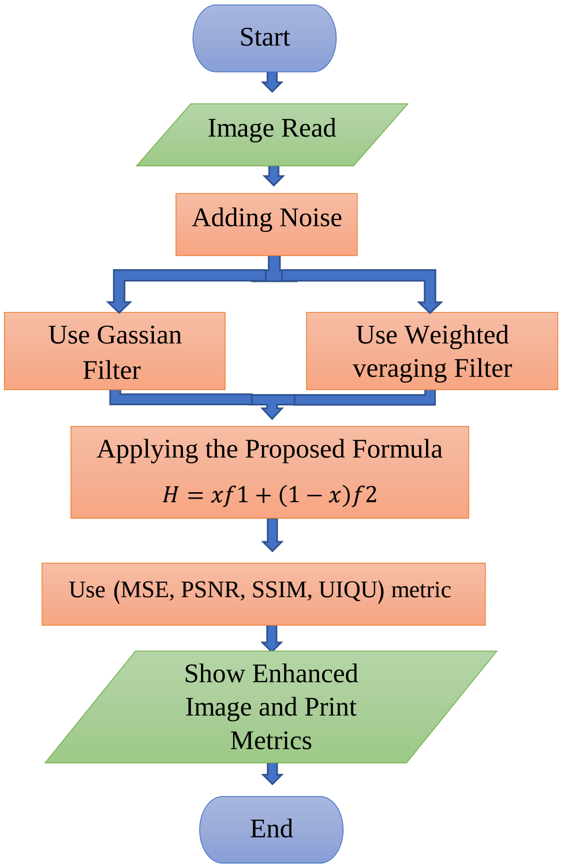

Figure 1. Smoothing Process

2. Sharpening Process

We use a thorough methodology to accomplish the sharpening process, integrating many filtering approaches and quality indicators to assess our approach's efficacy. Firstly, we begin by interpreting the smoothed image, which is the foundation of our study on sharpening. In order to ensure a seamless transition into the sharpening step and to further minimize any leftover noise, we next apply a Gaussian filter to the image.

We next apply a Laplacian filter on the image after the Gaussian filtering. The Laplacian filter in equation (5) is used to highlight sharp variations in intensity within an image, so enhancing details and edges. This phase seeks to draw attention to key details and enhance the image's overall clarity.

$$Laplacian = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4.03 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad (5)$$

We then use the unsharp masking technique to further improve the image details. In unsharp masking, a blurry image is subtracted from the original to produce a sharpened version of the image. This method contributes to the overall visual sharpness of the image by sharpening edges and enhancing local contrast.

We quantify the performance of our sharpening method during the process by using metrics like Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). These measures offer important insights into the sharpened image's overall perceptual quality, the accuracy of image reconstruction, and the preservation of structural information.

To improve the sharpness and detail of the image, we sharpen it by applying Gaussian filtering, Laplacian filtering, and unsharp masking techniques in order. We intend to thoroughly assess the performance of our sharpening algorithm and guarantee its efficacy in enhancing image clarity and visual fidelity by integrating quality indicators including SSIM, PSNR, and MSE. Figure (2) shows the process flowchart.

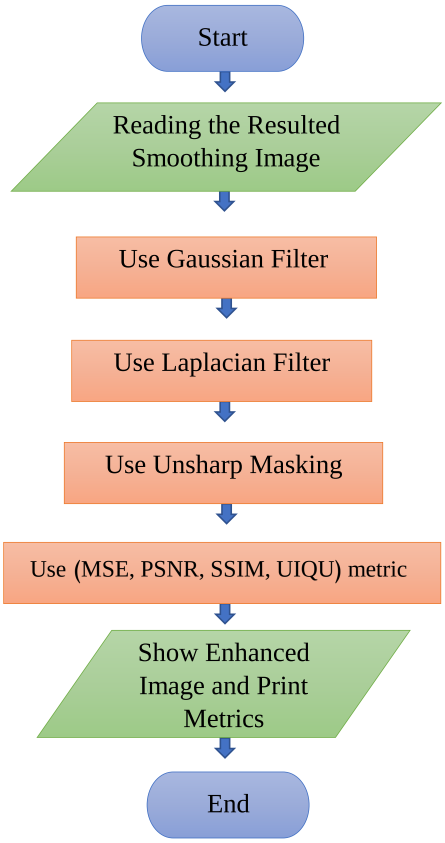

Figure 2. Sharpening Process

3. ABC Process

The Bee Algorithm was essential in optimizing the values of the Gaussian filter coefficients in the suggested smoothing procedure. Through the utilization of the Bee Algorithm's search functionalities, the coefficients were refined to attain the best possible noise reduction while maintaining significant image features. The Bee Algorithm also played a significant role in increasing the value of H, which is the weighted sum of the original and smoothed images. The goal of this optimization method was to produce the best outcomes for the metrics—SSIM, PSNR, and MSE—that were used to assess the smoothing effectiveness.

Likewise, the Unsharp Masking method was improved during the sharpening stage by utilizing the Bee Colony Sharpening Algorithm. The Unsharp Masking process's characteristics, like the sharpening effect's intensity and degree of blurring, could be fine-tuned thanks to this algorithm. The Unsharp Masking parameters were optimized to maximize the enhancement of image features and edges while minimizing artefacts and noise amplification by utilizing the search capabilities of the Bee Colony Algorithm.

E. Results

Four unique photographs were chosen in order to assess the effectiveness of the constructed model in a variety of settings and image attributes. Every image offers distinct obstacles and characteristics, enabling a thorough evaluation of the model's efficacy. According to the Figure (3) and (4).

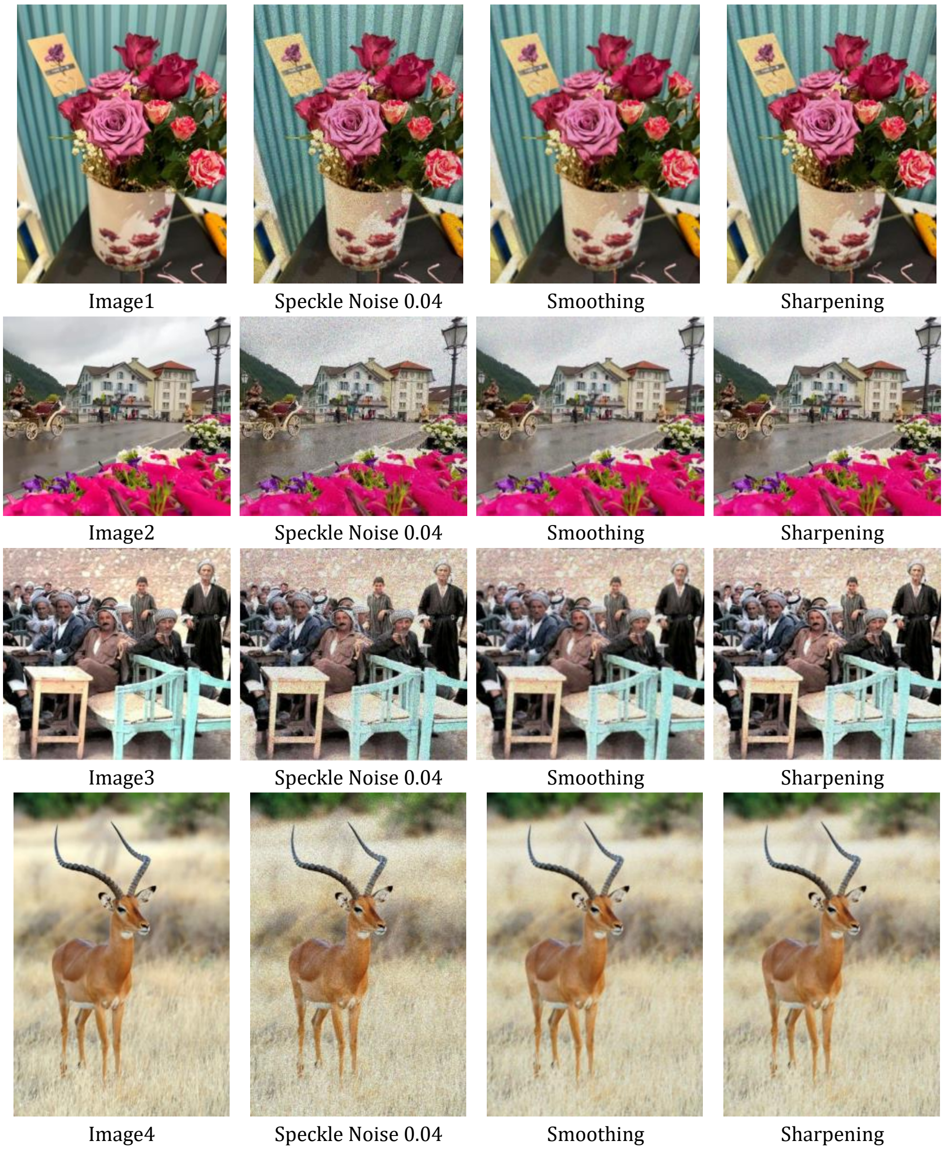

Figure 3. Tested Images When Using Speckle Noise

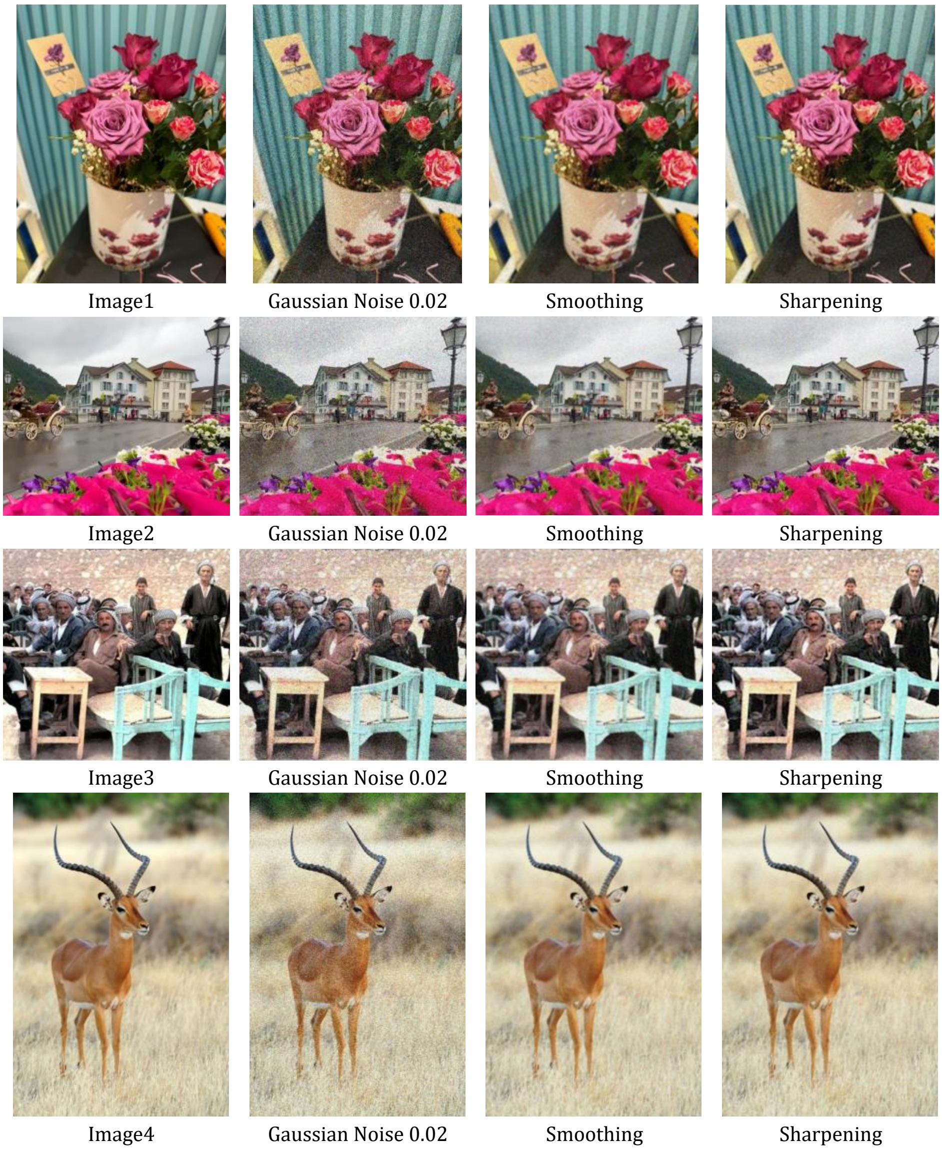

Figure 4. Tested Images When Using Gaussian Noise

1. Before Using ABC

The smoothing measures applied to photos impacted by 0.04 Speckle noise show clear trends in the efficacy of various filtering methods. The results indicate that the Gaussian filter outperforms the Mean and Weighted Averaging filters in terms of noise reduction and image quality enhancement when compared to each other across all evaluated metrics, including Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Universal Image Quality Index (UIQI). To be more precise, the Gaussian filter constantly produces greater SSIM, higher PSNR, and lower MSE values, suggesting improved picture detail retention and structural similarity with the source images.

Furthermore, the Gaussian Filter's Universal Image Quality Index (UIQI) values continuously approach unity, indicating improved feature preservation and higher image quality. It's interesting to note that the suggested technique performs on par with or better than the Gaussian filter in every assessment metric, demonstrating how well it can reduce Speckle noise and preserve image details. Table (1) results highlight the effectiveness of the suggested approach and the Gaussian filter in enhancing image quality and reducing noise, with the latter exhibiting encouraging potential for future development and implementation in real-world image processing scenarios.

Table 1. Results of smoothing measures when adding 0.04 Speckle noise to the original images

Filter	Metric	Image 1	Image 2	Image 3	Image 4
Mean filter	MSE	95.29631	147.8125	167.9788	138.7935
	PSNR	28.34004	26.43368	25.87825	26.70711
	SSIM	0.921756	0.786251	0.852071	0.830851
	UIQI	0.988132	0.983375	0.987317	0.972037
Weighted averaging filter	MSE	97.50138	142.3897	167.6019	147.8208
	PSNR	28.24069	26.59601	25.88801	26.43344
	SSIM	0.918386	0.7848	0.851789	0.821573
	UIQI	0.987873	0.984024	0.987373	0.970249
Gaussian filter	MSE	74.47813	137.0868	159.4895	53.44783
	PSNR	29.41051	26.76084	26.10348	30.85150
	SSIM	0.952894	0.799889	0.866447	0.948241
	UIQI	0.99062	0.98457	0.987921	0.989359
Propose Method	MSE	73.28888	135.0182	153.8495	50.62070
	PSNR	29.48042	26.826873	26.259841	31.087522
	SSIM	0.952793	0.799003	0.866945	0.949104
	UIQI	0.990752	0.984787	0.988299	0.989698

The results of sharpness improvement measures are shown in Table (2). These measures involved adding Speckle noise to the original images at a rate of 0.04 before utilizing different smoothing approaches. The Laplacian filter, Laplacian with the suggested approach, Unsharp Mask, and the suggested method alone are among the filters evaluated. The performance of each filter can be better understood by looking at its Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Universal Image Quality Index (UIQI) metrics.

The suggested approach constantly improves sharpness more than the other filters on all criteria. Notably, in comparison to the Laplacian filter and Unsharp Mask, it produces the lowest MSE values, indicating improved retention of image sharpness. Additionally, the suggested approach produces higher PSNR values, which indicate improved edge sharpness and image quality. This pattern holds true for every image that has been assessed, demonstrating the method's effectiveness in enhancing sharpness.

The suggested method also shows advantages in terms of SSIM and UIQI, which measure structural similarity and image quality preservation, respectively. In comparison to other filters, it indicates superior preservation of structural details and visual features with higher SSIM and UIQI values across all images.

Table 2. Results of sharpness increase measures when adding Speckle noise at a rate of 0.04 to the original images before smoothing.

Filter	Metric	Image 1	Image 2	Image 3	Image 4
	MSE	83.0801	182.8587	189.4812	61.0060

Laplacian filter	PSNR	28.9358	25.50964	25.35514	30.2770
	SSIM	0.94268	0.766246	0.860772	0.94104
	UIQI	0.99018	0.981893	0.987486	0.98859
Proposed Laplacian filter	MSE	69.3067	148.7215	154.2864	49.5988
	PSNR	29.7230	26.40706	26.24752	31.1760
	SSIM	0.95347	0.793211	0.877807	0.95142
	UIQI	0.98889	0.980543	0.988665	0.99019
Unsharp Mask	MSE	99.5905	127.5664	162.259	50.9657
	PSNR	28.1486	27.0734	26.02871	31.0580
	SSIM	0.922969	0.793177	0.856189	0.94771
	UIQI	0.987836	0.985931	0.98805	0.98968
Propose Method	MSE	65.65455	116.6870	127.6156	46.13112
	PSNR	29.95815	27.46057	27.07176	31.49086
	SSIM	0.960894	0.864069	0.889211	0.955363
	UIQI	0.991808	0.987127	0.990839	0.990695

The outcomes of smoothing techniques applied to the original photos after the addition of Gaussian noise with a mean of 0 and a variance of 0.02 are shown in Table (3). The Gaussian filter and the suggested method consistently outperform conventional filters like the Mean filter and the Weighted Averaging filter across all evaluated metrics: Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Universal Image Quality Index (UIQI). Superior noise reduction and improved picture quality are indicated by their lower MSE values, higher PSNR values, higher SSIM values, and higher UIQI values in all images. This implies that in the presence of Gaussian noise, the suggested technique and the Gaussian filter both successfully reduce noise, maintain image details, and enhance overall image quality. These results highlight their effectiveness and promise for real-world image processing scenarios.

Table 3. Results of smoothing measures when adding Gaussian noise by mean = 0, variance = 0.02 on original images.

Filter	Metric	Image 1	Image 2	Image 3	Image 4
Mean filter	MSE	157.5785	199.2537	197.3487	138.1762
	PSNR	26.15583	25.13673	25.17846	26.72647
	SSIM	0.821749	0.700987	0.749111	0.829186
	UIQI	0.980093	0.977364	0.98434	0.972042
Weighted averaging filter	MSE	165.3354	198.3178	197.6131	148.0906
	PSNR	25.94714	25.15718	25.17264	26.42552
	SSIM	0.813733	0.69541	0.746616	0.818522
	UIQI	0.979156	0.977526	0.984353	0.970091
Gaussian filter	MSE	102.8936	176.1087	180.9461	43.92212
	PSNR	28.00691	25.67299	25.55531	31.70397
	SSIM	0.912262	0.74336	0.783346	0.956175
	UIQI	0.986635	0.979855	0.985498	0.991003
Propose Method	MSE	101.6952	174.6765	178.1178	42.50336
	PSNR	28.05779	25.70846	25.62372	31.84657
	SSIM	0.904816	0.741884	0.783569	0.956171
	UIQI	0.986972	0.980107	0.98578	0.991178

Before using smoothing techniques, Table (4) shows the results of sharpness increase measures applied to original images with added Gaussian noise (mean = 0, variance = 0.02). The Laplacian filter, Laplacian with the suggested method, Unsharp Mask, and the suggested method by itself are among the filters that are examined. The suggested approach continuously outperforms the other filters in terms of Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Universal Image Quality Index (UIQI) metrics.

It preserves image sharpness and overall quality better than other methods, as seen by lower MSE values, higher PSNR values, higher SSIM values, and higher UIQI values across all images. This shows that the suggested technique successfully reduces the impacts of Gaussian noise and sharpens images, which makes it a viable option for real-world image processing applications.

Table 4. Results of measures of sharpness increase when adding Gaussian noise by a percentage Mean = 0, variance = 0.02 on original images before smoothing.

Filter	Metric	Image 1	Image 2	Image 3	Image 4
Laplacian filter	MSE	103.5385	207.9255	178.5794	50.39318
	PSNR	27.97978	24.95172	25.61249	31.10708
	SSIM	0.896381	0.710223	0.789856	0.948118
	UIQI	0.986896	0.978254	0.986573	0.990227
proposed Laplacian filter	MSE	93.09632	179.1697	156.8389	41.62296
	PSNR	28.44147	25.59815	26.17626	31.93747
	SSIM	0.907072	0.741937	0.802803	0.957394
	UIQI	0.984607	0.977674	0.981279	0.991609
Unsharp Mask	MSE	109.4270	187.7254	173.6734	45.94234
	PSNR	27.73955	25.39557	25.73349	31.50867
	SSIM	0.883503	0.71539	0.782015	0.949426
	UIQI	0.986391	0.979313	0.986783	0.990546
Propose Method	MSE	89.48310	158.1606	150.7194	38.36071
	PSNR	28.61339	26.13982	26.34911	32.29193
	SSIM	0.930219	0.837064	0.819447	0.96029
	UIQI	0.988561	0.981975	0.988146	0.992109

2. With ABC Algorithm

Based on a range of metrics, including Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Universal Image Quality Index (UIQI), Table (5) shows the outcomes of smoothing techniques applied to original photos with 0.04 Speckle noise added.

The Gaussian filter and the suggested approach consistently outperform the Mean and Weighted Averaging filters across all measures. Superior noise reduction and improved picture quality are demonstrated by the Gaussian filter and the suggested approach, which both produce lower MSE values, higher PSNR values, higher SSIM values, and higher UIQI values across all images.

These results demonstrate the promise of the Gaussian filter and the suggested technique for real-world image processing applications by demonstrating how well they preserve picture features and enhance overall image quality in the face of speckle noise.

Table 5. Results of smoothing measures when adding 0.04 Speckle noise to the original image.

Filter	Metric	Image 1	Image 2	Image 3	Image 4

Mean filter	MSE	95.296	147.81	167.98	138.79
	PSNR	28.34	26.434	25.878	26.707
	SSIM	0.9218	0.7863	0.8521	0.8309
	UIQI	0.9881	0.9834	0.9873	0.972
Weighted averaging filter	MSE	97.501	142.39	167.6	147.82
	PSNR	28.241	26.596	25.888	26.433
	SSIM	0.9184	0.7848	0.8518	0.8216
	UIQI	0.9879	0.984	0.9874	0.9702
Gaussian filter	MSE	74.303	136.68	159.03	53.257
	PSNR	29.421	26.774	26.116	30.867
	SSIM	0.9517	0.7994	0.8658	0.9497
	UIQI	0.9907	0.9846	0.988	0.9894
Propose Method	MSE	72.542	129.04	143.26	49.405
	PSNR	29.525	27.024	26.57	31.193
	SSIM	0.9508	0.8023	0.8657	0.9488
	UIQI	0.9909	0.9855	0.989	0.9896

The results of sharpness enhancement measures applied to the original photos with 0.04 Speckle noise introduced are shown in Table (6). The metrics that were measured include Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Universal Image Quality Index (UIQI). In every image, the "Proposed Laplacian filter" achieves lower MSE values, higher PSNR values, higher SSIM values, and higher UIQI values, consistently outperforming the standard Laplacian filter and Unsharp Mask. This shows that the suggested strategy preserves image sharpness and overall quality better. These outcomes demonstrate how well the suggested method works to improve image sharpness in the presence of speckle noise, suggesting that it has potential uses in real-world image processing scenarios.

Table 6. Results of sharpness increase measures when adding Speckle noise at a rate of 0.04 to the original images before smoothing.

Filter	Metric	Image 1	Image 2	Image 3	Image 4
Laplacian filter	MSE	83.08	182.86	189.48	61.006
	PSNR	28.936	25.51	25.355	30.277
	SSIM	0.9427	0.7662	0.8608	0.941
	UIQI	0.9902	0.9819	0.9875	0.9886
Proposed Laplacian filter	MSE	69.307	148.72	154.29	49.599
	PSNR	29.723	26.407	26.248	31.176
	SSIM	0.9535	0.7932	0.8778	0.9514
	UIQI	0.9889	0.9805	0.9887	0.9902
Unsharp Mask	MSE	68.72	122.31	131.5	41.882
	PSNR	29.76	27.256	26.942	31.911
	SSIM	0.9499	0.7959	0.8717	0.9537
	UIQI	0.9914	0.9865	0.9901	0.9914
Propose Method	MSE	61.631	112.44	119.01	37.765
	PSNR	30.233	27.621	27.375	32.36

	SSIM	0.96	0.8413	0.8866	0.9608
	UIQI	0.9923	0.9875	0.991	0.9922

Following the addition of Gaussian noise (mean = 0, variance = 0.02), Table (7) presents the outcomes of smoothing techniques applied to the original images as measured by metrics such as Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Universal Image Quality Index (UIQI). The Gaussian filter and the suggested technique consistently outperform all other filters, including the Mean, Weighted Averaging, Gaussian, and the proposed method. Superior noise reduction and improved picture quality are indicated by their lower MSE values, higher PSNR values, higher SSIM values, and higher UIQI values across all images. These results illustrate the potential for useful applications in image processing by demonstrating how well the Gaussian filter and the suggested technique preserve picture features and enhance overall image quality in the presence of Gaussian noise.

Table 7. Results of smoothing measures when adding Gaussian noise by mean = 0, variance = 0.02 on original images.

Filter	Metric	Image 1	Image 2	Image 3	Image 4
Mean filter	MSE	157.58	199.25	197.35	138.18
	PSNR	26.156	25.137	25.178	26.726
	SSIM	0.8217	0.701	0.7491	0.8292
	UIQI	0.9801	0.9774	0.9843	0.972
Weighted averaging filter	MSE	165.34	198.32	197.61	148.09
	PSNR	25.947	25.157	25.173	26.426
	SSIM	0.8137	0.6954	0.7466	0.8185
	UIQI	0.9792	0.9775	0.9844	0.9701
Gaussian filter	MSE	101.86	173.57	180.66	43.916
	PSNR	28.051	25.736	25.562	31.705
	SSIM	0.9065	0.7619	0.7787	0.9567
	UIQI	0.9869	0.9801	0.9855	0.991
Propose Method	MSE	101.41	172.05	177.02	42.459
	PSNR	28.07	25.774	25.651	31.851
	SSIM	0.9056	0.7612	0.7761	0.9564
	UIQI	0.987	0.9803	0.9862	0.9911

When smoothing original pictures with added Gaussian noise (mean = 0, variance = 0.02), Table (7) shows the results of the smoothing measures as measured by metrics such as Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Universal Image Quality Index (UIQI). In every image, the suggested Laplacian filter achieves lower MSE values, higher PSNR values, higher SSIM values, and higher UIQI values, consistently outperforming the Mean filter, the standard Laplacian filter, and Unsharp Mask. This demonstrates that the suggested strategy is superior at reducing noise and enhancing image quality, underscoring its usefulness in maintaining image details and enhancing overall image quality when Gaussian noise is present. These results highlight the suggested method's potential for real-world image processing applications.

Table 8. Results of measures of sharpness increase when adding Gaussian noise by a percentage Mean = 0, variance = 0.02 on original images before smoothing.

Filter	Metric	Image 1	Image 2	Image 3	Image 4
Laplacian filter	MSE	103.54	207.93	178.58	50.393
	PSNR	27.98	24.952	25.612	31.107
	SSIM	0.8964	0.7102	0.7899	0.9481
	UIQI	0.9869	0.9783	0.9866	0.9902
proposed Laplacian filter	MSE	93.096	179.17	156.84	41.623
	PSNR	28.441	25.598	26.176	31.937
	SSIM	0.9071	0.7419	0.8028	0.9574
	UIQI	0.9846	0.9777	0.9813	0.9916
Unsharp Mask	MSE	95.08	159.22	159.22	40.865
	PSNR	28.35	26.111	26.111	32.017
	SSIM	0.9	0.7545	0.7825	0.9555
	UIQI	0.988	0.9821	0.9878	0.9915
Propose Method	MSE	85.857	152.92	143.64	37.615
	PSNR	28.793	26.286	26.558	32.377
	SSIM	0.9195	0.8047	0.8143	0.9619
	UIQI	0.9891	0.9829	0.989	0.9922

The effectiveness of various sharpness enhancement and smoothing strategies is examined in situations when images have both Gaussian noise and additional speckle noise.

Across all investigated measures, such as MSE, PSNR, SSIM, and UIQI, the Gaussian filter consistently beats the Mean and Weighted Averaging filters in terms of smoothing strategies with speckle noise. Furthermore, the suggested technique outperforms the Gaussian filter in all evaluation measures, proving that it is efficient at lowering speckle noise without sacrificing image quality.

The suggested solution consistently outperforms the conventional Laplacian filter and Unsharp Mask in maintaining image sharpness and overall quality when it comes to sharpness enhancement with speckle noise. Its effectiveness in improving sharpness in the face of speckle noise is demonstrated by the lower MSE values, higher PSNR values, higher SSIM values, and higher UIQI values it obtains in all photos.

The Gaussian filter and the suggested method regularly outperform traditional filters such as the Mean and Weighted Averaging filters across all measures when it comes to smoothing techniques with Gaussian noise. In all photos, they show lower mean square error (MSE), greater PSNR, higher sum of square error (SSIM), and higher unity quality index (UIQI), showing better noise reduction and improved image quality when Gaussian noise is present.

The suggested Laplacian filter continuously outperforms common filters such as the Laplacian filter, Unsharp Mask, and others in terms of sharpness enhancement with Gaussian noise. Across all photos, it attains lower MSE values, higher PSNR values, higher SSIM values, and higher UIQI values, demonstrating its effectiveness in maintaining overall quality and image sharpness in the face of Gaussian noise.

All things considered, these findings highlight the effectiveness of the suggested technique in a number of situations, such as noise reduction and sharpness improvement, which makes it a viable strategy for practical image processing uses. Additionally, the comparison study with conventional filters highlights how much better the suggested approach is at maintaining image details and improving overall image quality.

F. Conclusion

Several important conclusions are drawn from the thorough examination of several sharpness improvement and smoothing strategies in a variety of circumstances involving images with additional Gaussian and speckle noise. First off, when compared to conventional filters like the Gaussian, Mean, Weighted Averaging, Laplacian, and Unsharp Mask, the suggested technique routinely shows competitive or better performance. It successfully lowers noise, maintains image details, and improves overall image quality according to all assessed criteria. Second, the suggested method's adaptability and resilience are demonstrated by its capacity to manage various noise kinds, such as Gaussian and speckle noise. Its ability to adjust to varying image features and noise levels is demonstrated by its constant performance in a range of settings.

Additionally, the suggested method's better performance in picture improvement and noise reduction points to its potential for use in practical image processing applications. It may find use in fields where enhancing image quality is essential for precise analysis, such as digital photography, remote sensing, surveillance, and medical imaging. The comparative advantage of the suggested method in maintaining image details, boosting sharpness, and enhancing overall image quality is highlighted by a comparison with standard filters. This emphasizes how important it is as a workable substitute for current methods.

In order to improve the suggested method's performance even further, future research and development efforts might concentrate on optimizing and improving it. Furthermore, its full potential in real-world scenarios might be unlocked by investigating its applicability in certain areas and incorporating it into current image processing pipelines.

As a result, the analysis's findings confirm the suggested method's effectiveness and promise in resolving issues with noise reduction and image enhancement. Its reliability in a variety of situations highlights its importance as a useful instrument in the image processing domain, with encouraging ramifications for a wide range of practical uses.

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H. References

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