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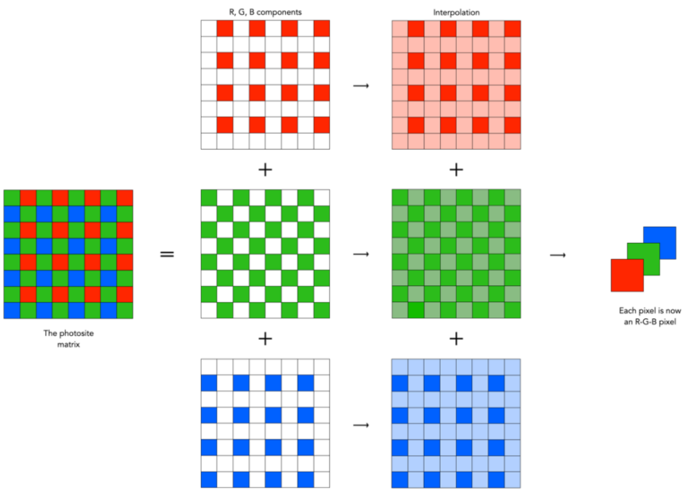
HOMEWORK 1

Problem 1:

1 (a) Image Demosaicing using Bilinear Interpolation.

I. Abstract and Motivation

The common cameras that we use use a color image sensor to capture color images. This sensor stores the intensity levels of three different filters—Red, Green, and Blue. At this stage, the image created by the sensor is a Bayer image. This Bayer image has just one channel and a specific pattern in which these rgb values are stored. To produce an RGB image, or color image, all three color intensities must be divided into three distinct channels.
The process of filling in the missing pixel intesities of the 3 different channels is called demosaicing. And demosaicing is performed using bilinear interpolation. The neighborhood point intensities are used in bilinear interpolation We take the average of the nearby points for a given Bayer pattern by selecting the neighboring points that have the same color. Ultimately, obtaining a fully RGB color image which is our objective.



II. Approach and Procedures.

We have a grayscale image called "House.raw" from the Bayer dataset. Its intensities range from 0 to 255. It is now our task to turn this grayscale picture into an RGB color image. Initially, we store each of these intensities in a two-dimensional matrix. Next, in order to

avoid losing any information when trying to interpolate this image, we apply zero padding to this matrix.
Next, we define another matrix, this one a three-dimensional matrix with three channels: a red channel, a green channel, and a blue channel. We set its proportions to match those of our Bayer image. Now, our Bayer image is shown in the image below.

G	R	G	R
B	G	B	G
G	R	G	R
B	G	B	G
G	R	G	R

This serves as our point of reference, and we record the corresponding intensities for each channel in our RGB image. Next, by averaging the neighborhood intensities, we fill in the missing pixel numbers.
The formulas used are :-

$$\hat{B}_{3,4} = \frac{1}{4}(B_{2,3} + B_{2,5} + B_{4,3} + B_{4,5})$$

$$\hat{G}_{3,4} = \frac{1}{4}(G_{3,3} + G_{2,4} + G_{3,5} + G_{4,4})$$

$$\hat{R}_{3,3} = \frac{1}{2}(R_{3,2} + R_{3,4})$$

$$\hat{B}_{3,3} = \frac{1}{2}(B_{2,3} + B_{4,3})$$

III. Experimental Results.

Figure 1: House.raw

Figure 2: House_rgb.raw

IV. **Discussion**

Figure 1 shows the bayer image. This is shown as a grayscale image as it is a 2d image. Figure 2 is the image that we obtain after image demosaicing process. This is a rgb image an is a representation of 3d matrix. Every camera senor takes the image as the one in figure 1 and it converts in figure 2 that we see on a day to day basis.

1 (b) Histogram Equalization (Grayscale Image, Transfer Function and Bucket Filling)

I. **Abstract and Motivation**

Images with poor contrast, which are frequently defined by uniform pixel intensities, can be visually unpleasant. To address this problem, Histogram Equalization becomes an important image processing approach. By redistributing intensity values, it prevents the dominance of a single tone, thereby enhancing overall clarity. The transfer method and the bucket filling method are the two basic techniques used in histogram equalization.
Transfer function histogram equalization is performed by calculating the cumulative probability of pixel intensities, can be used to improve contrast. An enhanced contrast image is produced by the approach, which redistributes pixel values depending on the cumulative distribution. Bucket filling histogram uses cumulative distribution functions are directly manipulated via equalization. By matching the original and equalized cumulative histograms, it redistributes pixel values and improves image contrast. This technique offers a different strategy for achieving significant contrast enhancement. In the ned of these two procedures, we will get a brighter and a more distributive intensity.

II. **Approach and Procedures.**

The image for DimLight.raw is really dark, thus we must apply the transfer function and bucket filling to increase the contrast of these pictures.

Using the transfer function, we first determine the total number of pixels and their intensities. We next determine the probability of each pixel, compute the cumulative count, and multiply these cumulative values with 255.

III. Experimental Results.

Figure 3: DimLight.raw

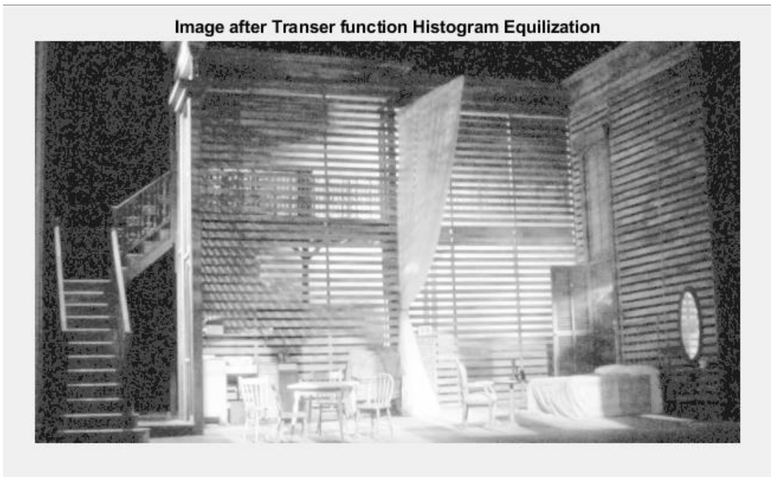


Figure 3: DimLight_tf_equilized.raw

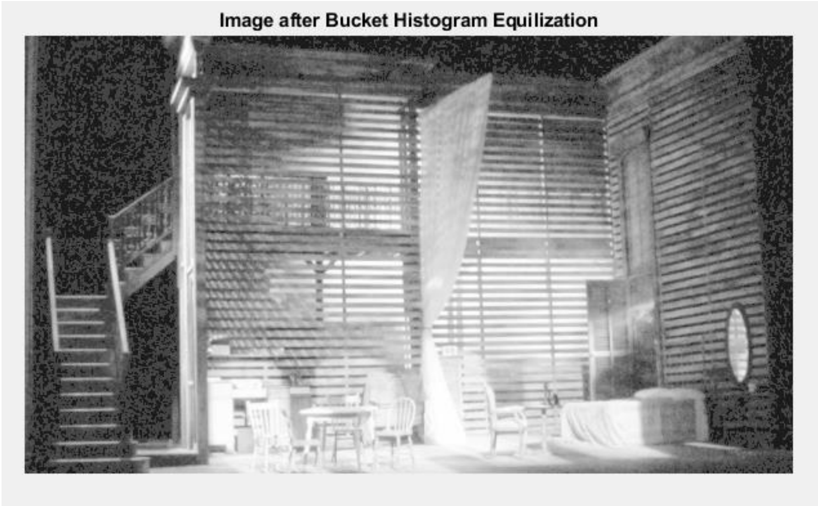


Figure 4: DimLight_bf_equilizedt.raw

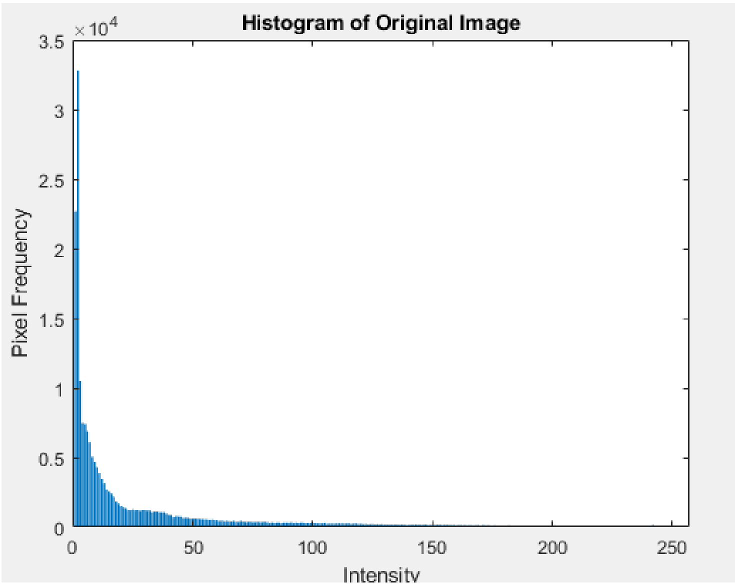


Figure 6: Original Image Histogram

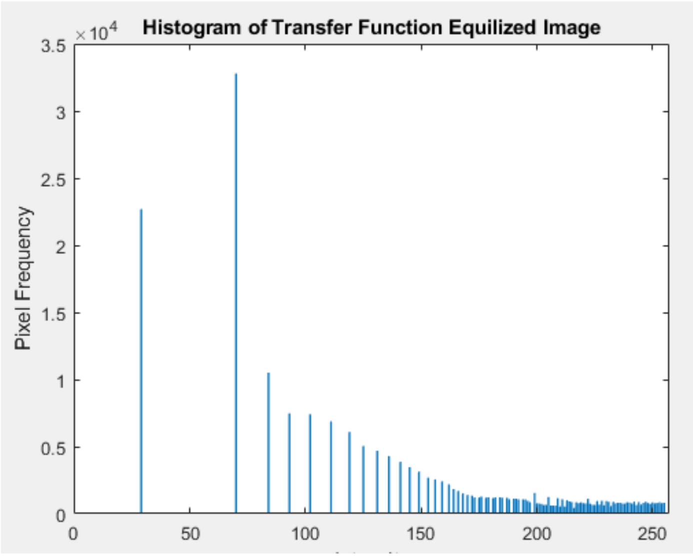


Figure 7: Histogram after Transfer function

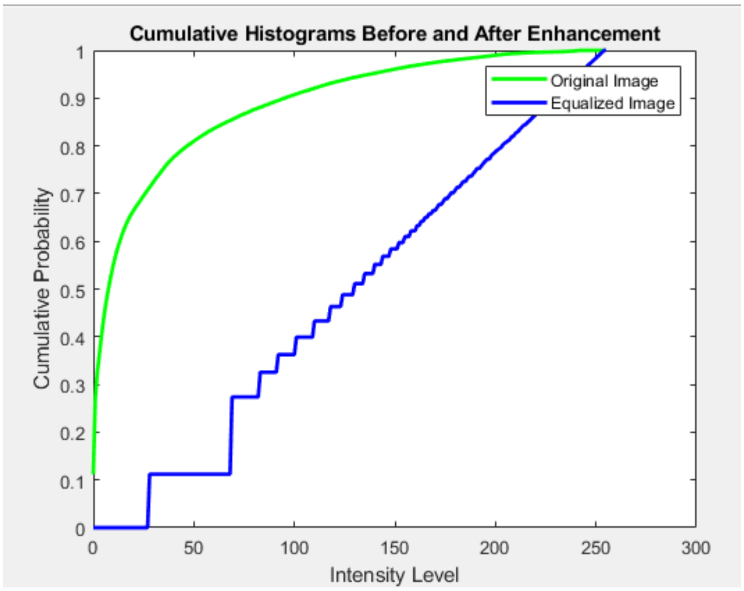


Figure 8: Cumulative Histograms of original vs after bucket filling

IV. Discussion

Figures 3, 4, and 5 illustrate how the three photos differ from one another. Figure 3's photo is quite dark because of the exceedingly low contrast. Both the transfer function and the bucket filling had nearly the same effect on the contrast since they increased the visibility of the image by providing a few pixels with higher intensities, which the first one did not provide. It is evident from the histograms that most of the pixels have intensities that are close to 0, and that by applying equalization, the higher intensities obtained few pixels.

1 (c) CLAHE and Haze Removal

I. Abstract and Motivation

CLAHE .

An excellent advanced image processing method for boosting contrast in images is called Contrast-Limited Adaptive Histogram Equalization (CLAHE). Let's say you have a gorgeous picture, but certain areas are too light, while others are too dark. Rather than making changes to the image all at once, CLAHE divides it into smaller pieces, or "tiles." It is comparable to cutting a canvas into smaller squares. It is more intelligent than simply increasing contrast. It uses histogram to examine each tile's intensities. It's similar to a chart that indicates which intensities are more prevalent and which are less so in that particular area.

CLAHE then adapts to the local conditions of each tile. If one tile has a lot of dark colors, it enhances the dark ones to bring out details. But it doesn't go overboard – there's a built-in control called "contrast-limiting." This prevents extreme adjustments, so your image doesn't look artificial or noisy. Assume you have a picture of a beach under a bright blue sky. The sky won't become an insanely vivid blue thanks to CLAHE. It maintains the natural feel of the scene while ensuring that the clouds and waves have striking features.

CLAHE’s key goals are to preserve spatial coherence and avoid over-amplification. On the other hand, a transfer function is a global adjustment that is applied consistently throughout the picture. It changes pixel values using a mathematical function or curve to modify brightness, contrast, or color balance on a large scale.

II. Approach and Procedures.

The City.raw image is a color image which has a lot of haze, unlike the above dmlight image which has most f the intensities near 0 this has most of the intensities which are leading to white colour in the image, so what we need to do here is to increase the contrast in the top part of the Haze image and the bottom of the image to remove almost same. We try with both the transfer function and the CLAHE method.

For Clahe we used `adapthisteq()` function. Adapthisteq() in MATLAB divides an image into smaller tiles, computes histograms for each, and modifies pixel values adaptively to improve contrast. This procedure guarantees that contrast enhancements are customized to specific local picture features. The image that has to be improved is the main input. Extra options like 'ClipLimit' define a maximum limit for contrast improvement, while 'NumTiles' regulates the tile size, affecting the granularity of the enhancement. Adapthisteq() is a flexible tool for boosting visual attractiveness in a variety of applications since it processes small regions intelligently, bringing out details and improving overall image clarity.

In order to perform Haze removal we first convert our RGB image to a YUV image. We then equitize the Y channel and adjust the other channel according to the Y Channel. For haze removal, it is preferable to convert an RGB image to YUV since YUV distinguishes between color (chrominance, U and V) and brightness (luminance, Y). The main effect of haze is to reduce brightness, making distant things appear less distinct. Algorithms that isolate luminance in the Y channel can concentrate on improving contrast and visibility, which are essential for reducing haze. This division makes computations easier and makes dehazing methods more potent. The YUV color space offers a useful way to deal with the particular difficulties caused by haze, even though it is not the only technique for removing it. This allows for crisper and more detailed imagery even in hazy situations.

III. Experimental Results.

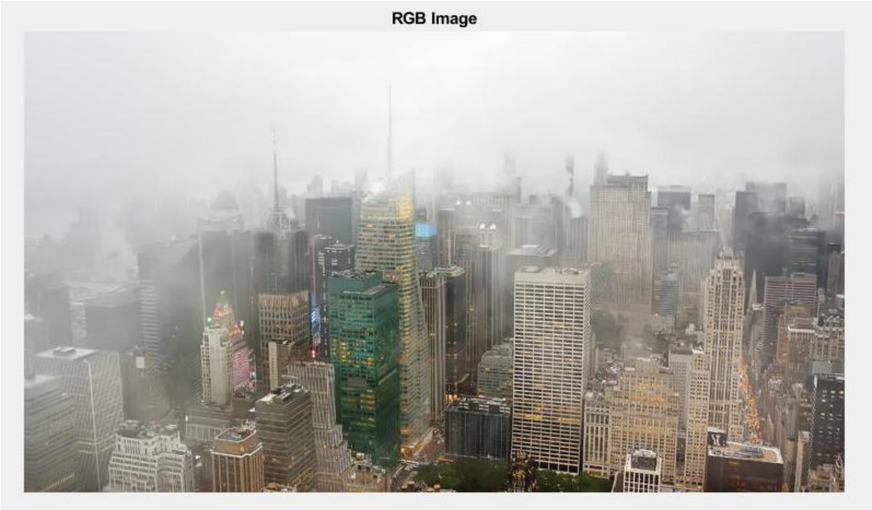


Figure 9: City.raw

Figure 10: YUV Image

Figure 11: Haze_Removed_Tf.raw

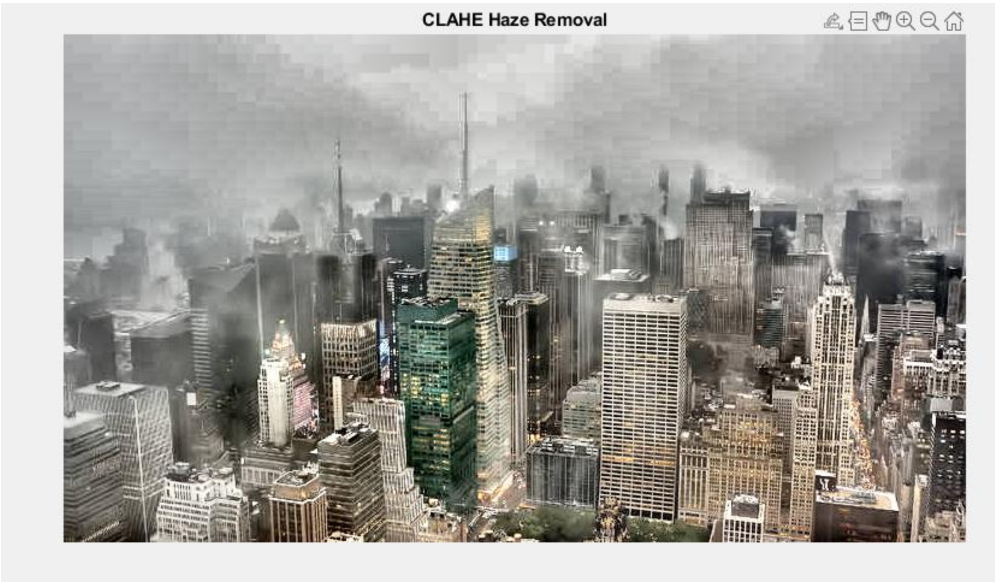


Figure 12: Haze_Removed_Clahe.raw

IV. Discussion

In the initial City image, noticeable high-intensity pixels dominated the upper frame, indicating the presence of haze. To address this, a conversion to the YUV color space was performed, as depicted in Figure 10. This transformation separates brightness (Y) from color information (U and V), aiding in haze removal. Upon comparing two haze removal techniques, namely the transfer function and Contrast-Limited Adaptive Histogram Equalization (CLAHE), distinct differences emerge. In the transfer function method, the image experiences a subtle darkening effect. The overall tone appears slightly dimmed, aiming to counteract the haze by adjusting pixel intensities globally. On the other hand, the CLAHE-based haze removal showcases a nuanced improvement. Instead of a mere darkening, CLAHE enhances clarity without significant overall darkening. This localized approach, working with adaptive histograms in small regions, prevents the image from becoming excessively dim while effectively combating the haze. The result is a picture that not only appears clearer but maintains a balanced brightness, demonstrating the efficacy of CLAHE in targeted contrast enhancement for haze removal in comparison to the more global adjustment seen in the transfer function method.

Problem 2: Image Denoising

1 (a) Basic Denoising. (Linear Filtering)

I. Abstract and Motivation

In image processing, the presence of noise often manifests as high-frequency variations in pixel intensity, introducing undesirable distortions to the visual content. Addressing this challenge involves the application of low-pass filters, which selectively permit low-frequency components to pass through while suppressing higher frequencies. Two widely utilized filters for noise reduction are the mean linear filter and the Gaussian low-pass filter.

The mean filter operates by convolving a kernel with the main image, wherein each pixel is replaced by the average value of its neighbouring pixels according to the kernel size. This process effectively diminishes high-frequency noise, providing a smoother representation of the image. On the other hand, the Gaussian filter employs a kernel normalized to a Gaussian distribution. The convolution with this weighted kernel results in a more nuanced attenuation of high-frequency noise, with greater emphasis on the central pixels. The Gaussian filter's design allows for a gradual transition in intensity, producing a more visually pleasing and natural smoothing effect.

II. Approach and Procedures.

The flower image is a grayscale image with a little noise added to it. Now in order to undertand how mcuh noise is present in that image we compare the acture flowe image with the noise image. Now this performance is measured using Peak signal to noise ratio. Given by:

$$PSNR = 10\log_{10}(R^2 / MSE)$$

- $R = 255$
- Expressed as db

To then improve the picture quality we use the mean and gaussian filter which are given by:

Mean Filter :

$$Y(i,j) = \frac{\sum_{k,l} I(k,l)w(i,j,k,l)}{\sum_{k,l} w(i,j,k,l)}$$

$$w(i,j,k,l) = \frac{1}{w_1 \times w_2}$$

Gaussian Filter :

$$Y(i,j) = \frac{\sum_{k,l} I(k,l) w(i,j,k,l)}{\sum_{k,l} w(i,j,k,l)}$$

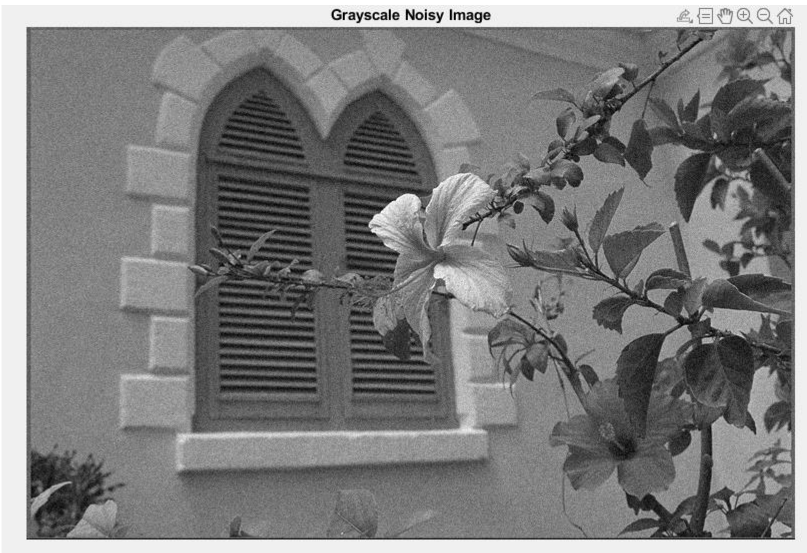
$$w(i,j,k,l) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(k-i)^2 + (l-j)^2}{2\sigma^2}\right)$$

Here Y is the output image I is input image and w are the convulsion weights.

In or problem we implemented the filter with kernel sizes of 3x3 and 5x5 for both the filters.

The images were zero padded before they could be convoluted. And for each experiment the PSNR ratio was calculated

III. Experimental Results.



3x3 Average Linear Filter Denoised Image

5x5 Average Linear Filter Denoised Image

Figure 2: House_rgb.raw

IV. Discussion

The experimental results provide valuable insights into image denoising techniques, particularly through the lens of Peak Signal-to-Noise Ratio (PSNR). The baseline PSNR between the original and noisy images is established at 28.1249, serving as a reference point for subsequent analyses. The application of a 3x3 average filter significantly improves PSNR to 30.7978, indicating effective noise reduction. Similarly, a 5x5 average filter maintains a high PSNR of 27.6249, emphasizing sustained improvement. Gaussian filters follow a similar pattern, with a 3x3 kernel achieving a notable PSNR of 31.7441, and a 5x5 kernel maintaining a commendable 28.4854. The consistent trend underscores the success of both average and Gaussian filters in enhancing image quality by mitigating noise. Smaller filter kernels generally yield higher PSNR values, emphasizing the critical role of filter size selection in image denoising applications.

2(b) Denoising Color Images

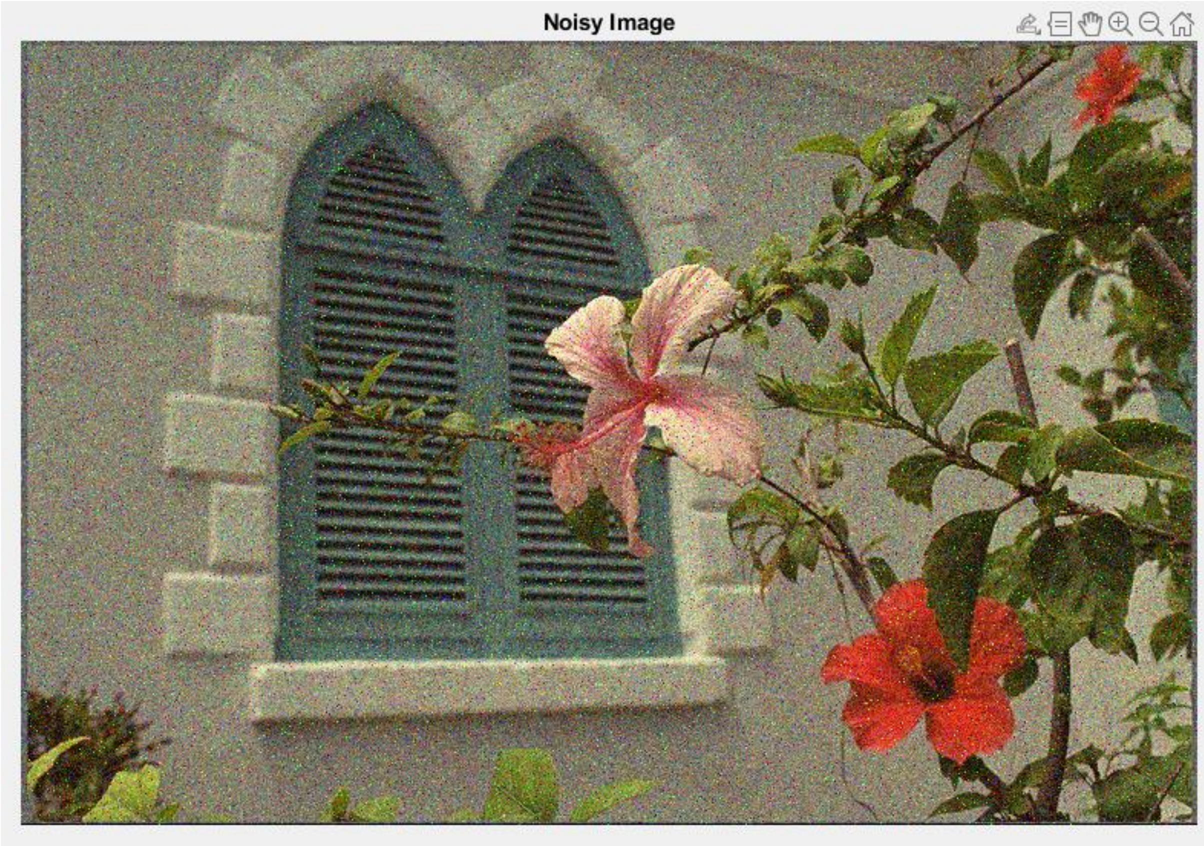
I. Abstract and Motivation.

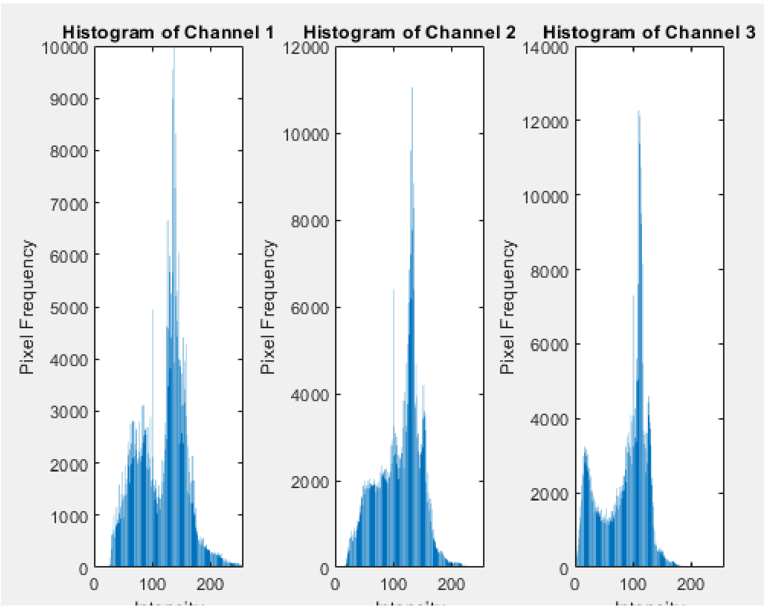
In image processing, diverse types of noise—such as impulse noise, mixed noise, and Gaussian noise—require distinct filtering techniques for effective removal. Each noise type presents unique challenges, necessitating tailored approaches for optimal denoising outcomes. Impulse noise, characterized by sudden, isolated intensity spikes, often responds well to median filtering, which replaces outlier pixels with the median value of their neighborhood. Mixed noise, a combination of various noise types, may benefit from adaptive filtering methods capable of adjusting to different noise characteristics within the image. Gaussian noise, with a probability distribution resembling a Gaussian curve, is commonly addressed using linear filters like the Gaussian filter itself. To identify and characterize these noises, histogram analysis proves instrumental. Analyzing the distribution of pixel intensities through histograms aids in recognizing noise patterns and selecting appropriate filtering strategies. Thus, a comprehensive denoising strategy involves understanding the specific noise types present, utilizing corresponding filtering techniques, and leveraging histogram analysis to tailor the approach for optimal noise reduction in image processing applications.

II. Approach and Procedures.

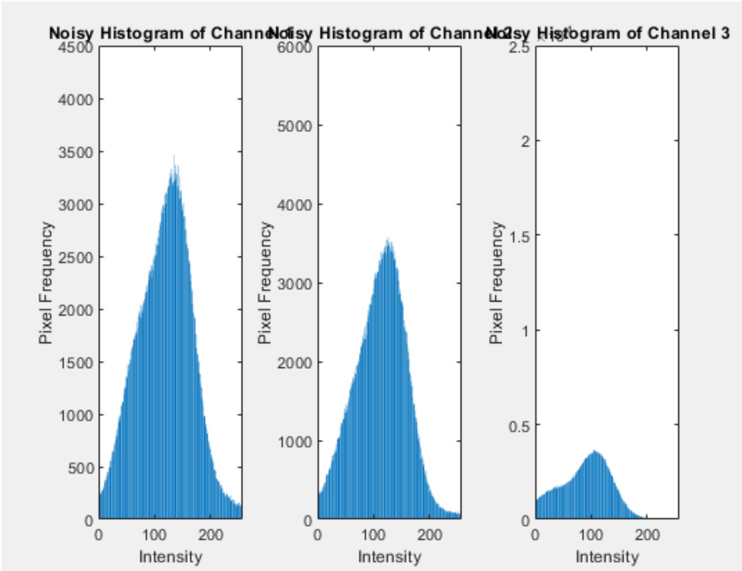
Our approach involved a thorough analysis of image histograms, comparing the original and noisy image histograms across all three color channels. This examination aimed to identify noise patterns and determine suitable filtering strategies. High-intensity noise, indicative of impulse noise, led to the application of the median filter, effectively eliminating isolated spikes. Additionally, experimentation involved the bilateral filter, chosen for its efficacy in preserving edges while reducing noise. The bilateral filter's adaptability to different noise characteristics and its ability to distinguish between genuine image features and noise made it a valuable tool in our denoising efforts.

III. Experimental Results.

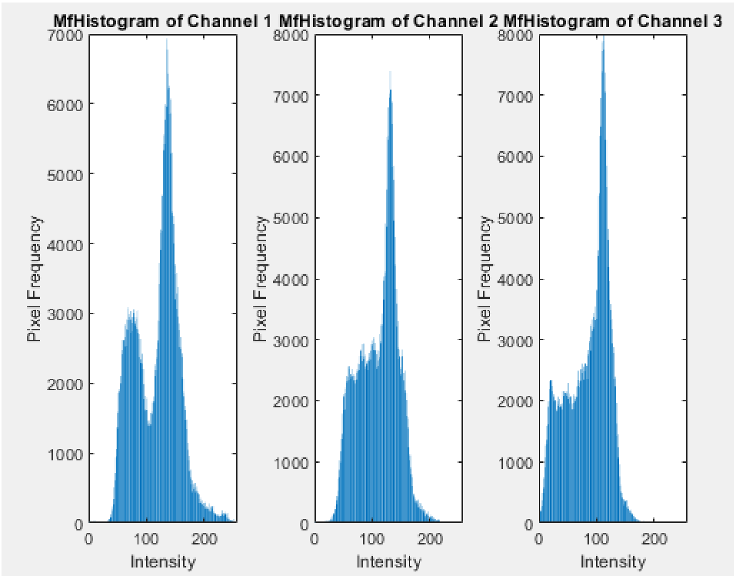




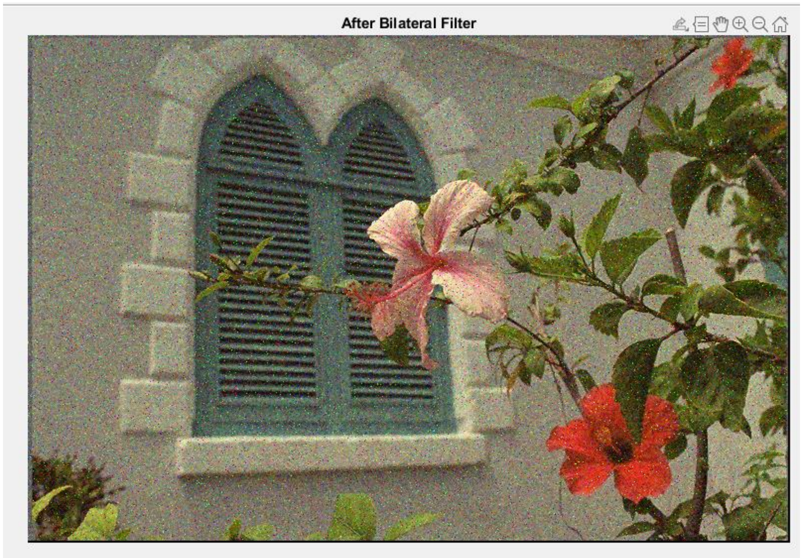
Original image histogram



Noisy Image Histogram



Median filtered image histogram



IV. Discussion

Examining the histogram of the original image revealed a predominant low-frequency signal, with a noticeable spike representing high-intensity components. Conversely, the noise signal exhibited a Gaussian curve, indicating Gaussian noise characteristics. Leveraging this insight, we opted for a low-pass filter to address the Gaussian noise, choosing a median filter with a kernel size of 7. The application of the median filter effectively reduced the impact of high-intensity noise, resulting in a visually improved image compared to the noisy counterpart. Despite the success with the median filter, experimentation with the bilateral filter did not yield favorable outcomes. The bilateral filter, known for its edge-preserving capabilities, failed to achieve the desired denoising effect in this scenario. The discrepancy highlights the importance of tailoring filter choices to the specific noise characteristics revealed by the image histogram. In this instance, recognizing the Gaussian nature of the noise and employing a suitable filter led to successful noise reduction, emphasizing the significance of informed filter selection in enhancing image quality. As the image seems to have a mixed noise signal we can try mixing different filters and experiment with denoising.

Problem 3: Water Colour Painting

I. Abstract and Motivation.

Linear combinations of filters constitute a versatile toolkit in image processing, serving dual roles of technical refinement and artistic expression. While their primary applications involve noise removal, distortion correction, and precise edge detection, the true marvel lies in their potential for creative manipulation. Through judicious combinations, photographers and digital artists can craft a rich variety of image patterns, elevating the visual narrative to unprecedented levels.

In the realm of technical enhancement, these filters act as digital surgeons, delicately removing noise and correcting distortions with precision. Edge detection becomes a refined art, revealing intricate details that might otherwise be obscured. However, the allure of linear combinations extends beyond the realm of technicalities. Creative minds harness these filters to breathe life into their visions. By blending and adjusting filters, artists orchestrate symphonies of effects, transforming ordinary images into captivating visual tales. Whether it's the controlled blur that imparts a dreamlike quality or the fusion of color gradients that evokes a specific mood, the power of linear combinations lies in their capacity to merge the technical and the artistic, offering a canvas where noise reduction converges with creative expression. In this nuanced dance between precision and imagination, linear combinations emerge as a transformative force, shaping images with both technical finesse and artistic ingenuity.

II. Approach and Procedures.

In this image enhancement process, we began by applying median filtering to the original color image, creating a new representation (IM) by selecting median values in local neighborhoods. Subsequently, we refined this output using bilateral filtering, iteratively enhancing details while maintaining smoothness. Gaussian filtering was then applied to the original image, introducing a controlled blur effect.

The culmination involved a linear combination of the bilateral filter output (Ib) and the Gaussian filter output (IG). By assigning weights (1.4 for Ib and -0.4 for IG) and combining these filtered results, a final enhanced image came. This method made thoughtful use of each filter's advantages, producing a composition that was both artistically and aesthetically pleasing. The procedure sought to improve the image by minimizing noise, maintaining details, and striking a pleasing balance between smoothness and sharpness. The result was an improved image that showed a meticulous synthesis of different filtering techniques.

III. Experimental Results.


Median filtered image 5x5


step2 Bilateral filter

step3 gaussian filter

Final

IV. Discussion

In this experiment, distinct filters were systematically applied to enhance an image, each imparting its unique impact. The median filter introduced a subtle painting effect by selecting median pixel values, contributing to a smoother representation. The bilateral filter, with carefully tuned parameters, heightened edge definition, accentuating contours and adding depth. Gaussian filtering, on the other hand, introduced a controlled blurring effect, imbuing the image with a soft, dreamlike quality.

By strategically combining these filtered outputs in a linear manner, the final image achieved a delicate balance. Notably, the weighted combination reduced blurriness, creating a refined yet slightly smudged painting effect. The experiment showcased how the judicious integration of diverse filters can yield a nuanced synthesis, transforming the original image into an artistically enhanced composition with varying tones, textures, and visual aesthetics.