EE569 Digital Image Processing

HOMEWORK #1

Issued: 01/10/2022 Due: 11:59PM, 01/30/2022

Problem 1: Image Demosaicing and Histogram Manipulation (45%)

1.1 Motivation

The imaging chip is a key part of a digital camera, and manufacturers usually use a single CCD or CMOS image sensor to reduce the production cost and size of digital cameras, and cover its surface with a color filter array CFA, of which Bayer CFA is the most widely used. CFA allows each imaging point to obtain only one color component of the physical three primary colors (red, green, and blue). Therefore, to obtain a full-color image, the remaining two missing components must be interpolated, a process known as color interpolation or demosaicing. The missing color value at each pixel is approximated by simplest demosaicing method based on bilinear interpolation using the average of two or four adjacent pixels of interest depending of the Bayer array/pattern. Image resizing is implemented using bilinear interpolation.

In image processing, the histogram is made up of a collection of pixel values of specific channels of an image as the horizontal coordinate of the histogram, and the number or proportion of occurrences of each value as the vertical coordinate. The image histogram has the characteristics of translation, rotation and scaling invariance. The distribution of the histogram before and after the image operation remains the same for the case of translation and rotation of the image angle, and the distribution of the histogram before and after the image scaling also remains the same for the case of scaling. The histogram of an image can be used to determine whether an image is dark, light, or normally lit by its corresponding histogram. Therefore, the data in the histogram of a darker image is mostly concentrated on the left and middle parts, while the opposite is true for a brighter image with only a few shadows. In order to improve the contrast of an image, Histogram equalization technique is essential, we investigate the method based on transfer function and cumulative probability.

There are some problems with histogram equalization. Histogram equalization is global and does not work well for local areas of the image that are too bright or too dark. Histogram equalization can enhance background noise. To solve these problems, we can use the histogram equalization for each area separately by chunking the image, so that the local information can be used to enhance the image, and the global problem can be solved. And contrast limiting method can be used to solve the background noise enhancement problem. This method is called Contrast Limited Adaptive Histogram Equalization.

1.2 Approach

1.2.1 Bilinear Demosaicing

The main idea behind bilinear demosaicing is that for each color channel of a pixel, we will use the neighbors that obtained intensity information of that color to interpolate the missing color for the current pixel. The neighbors must be adjacent to the current pixel and thus must be in a 3x3 window centered around the pixel of interest.

R_{11}	G_{12}	R_{13}	G_{14}	R_{15}	G_{16}
G_{21}	B_{22}	G_{23}	B_{24}	G_{25}	B_{26}
R_{31}	G_{32}	R_{33}	G_{34}	R_{35}	G_{36}
G_{41}	B_{42}	G_{43}	B_{44}	G_{45}	B_{46}
R_{51}	G_{52}	R_{53}	G_{54}	R_{55}	G_{56}
G_{61}	B_{62}	G_{63}	B_{64}	G_{65}	B_{66}

In the above figure, there is only one corresponding color component at each pixel position, and in the case of B_{44}, where there is only blue information, in order to obtain the full color information, the red and green components at the (4,4) position must be recovered using the red and green components at the adjacent positions. The bilinear interpolation algorithm uses a 3×3 filter and takes the average of the same color components at its adjacent positions, so that it can obtain:

$$R_{44} = \frac{R_{33} + R_{35} + R_{53} + R_{55}}{4}$$

$$G_{44} = \frac{G_{34} + G_{43} + G_{45} + G_{54}}{4}$$

In the case of G_{34}, it can obtain:

$$B_{34} = \frac{B_{24} + B_{44}}{2}$$

$$R_{34} = \frac{R_{33} + B_{35}}{2}$$

1.2.2 Histogram Manipulation

There are two methods can be adopted to enhance the contrast of an image.

Transfer-function-based histogram equalization method: Count the frequency of pixels of each grayscale value (0~255) to obtain the histogram. Divide the histogram by total number of pixels to calculate the normalized probability histogram.

$$n_{kn} = \frac{n_k}{length \times width} = p_r(r_k)$$

Then calculate the CDF.

$$cdf(x) = \sum_{k=-\infty}^{x} P(k)$$

And create the mapping-table.

Cumulative-probability-based histogram equalization method: This method can also be referred to as the "bucket filling" method. Instead of the transfer function method, this one opts to first make the uniform distribution as a sequence of "buckets" and then "fill" each one accordingly. The histogram is arranged into long chain of sequence. Total number of pixels in an image of size N is N^2, the long chain is partitioned into 256 subsets with fixed number of occurrences of pixel intensity.

1.2.3 Contrast Limited Adaptive Histogram Equalization

The CLAHE algorithm process has the following steps:

Pre-processing, such as image chunk filling and so on; For each chunk, a mapping relationship is computed, which is calculated using contrast limits; The final enhanced image is obtained by using interpolation method.

1.3 Results

(a)

(1)

Figure 1: Bilinear Demosaicing to the *House* image

(2) Yes, I observed clear artifacts on the roof part of the house. The cause is that the interaction of the gray values of the neighboring points is not considered, so it has the nature of low-pass filtering, which leads to the loss of the high-frequency components of the scaled image and the blurring of the image edges to a certain extent. We should consider not only the image of the gray value of the surrounding 4 pixel points, but also the image of the rate of change of their gray value. This can be calculated by using the grayscale values of the 16 pixel points in the vicinity to be sampled for three interpolations.

(b)

(1)

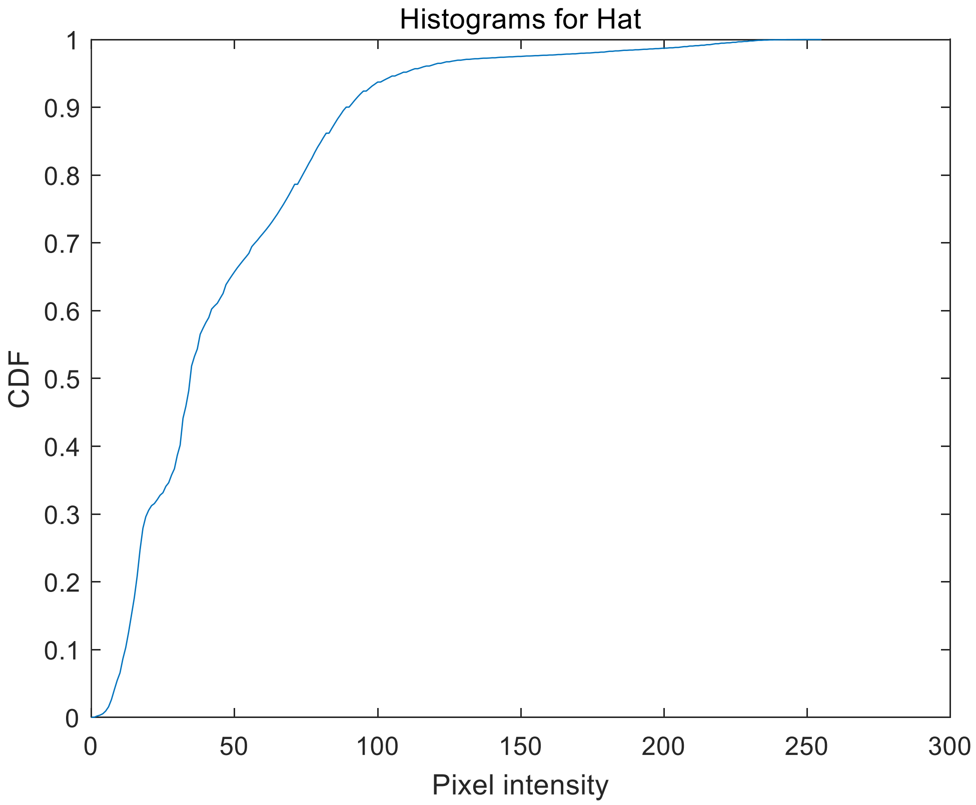

Figure 2: Histograms for *Hat* image

(2)

Figure 3: Transfer function based Histogram equalization enhanced image for *Hat*

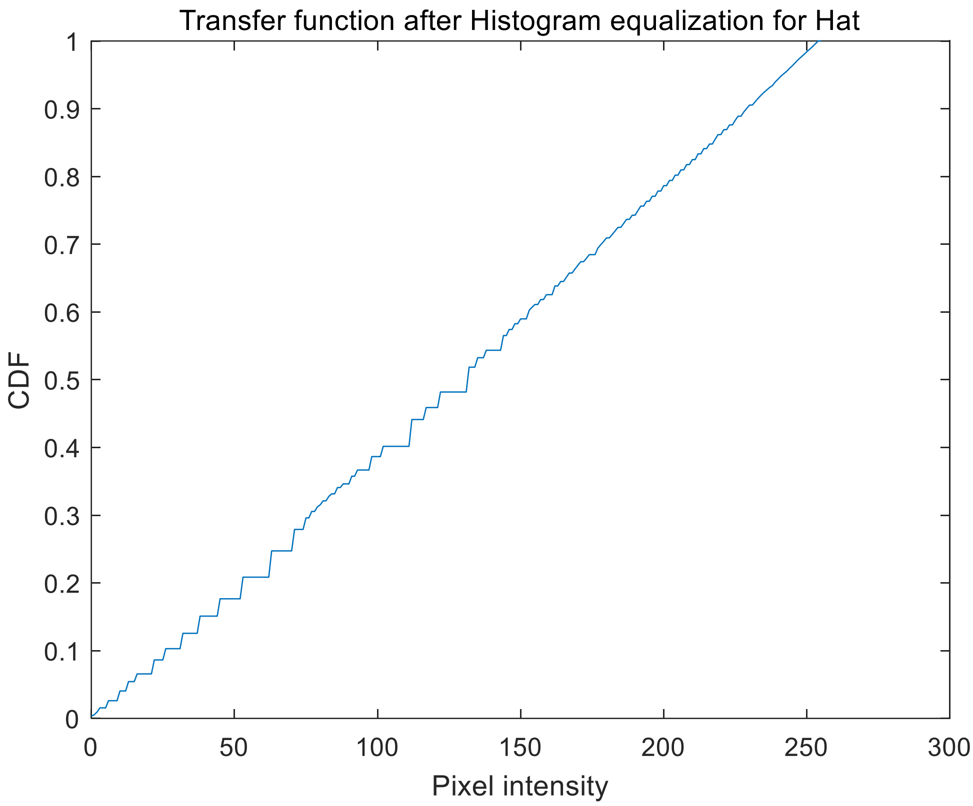

Figure 4: Transfer function after Histogram equalization for *Hat*

(3)

Figure 5: Cumulative Probability based Histogram equalization for *Hat*

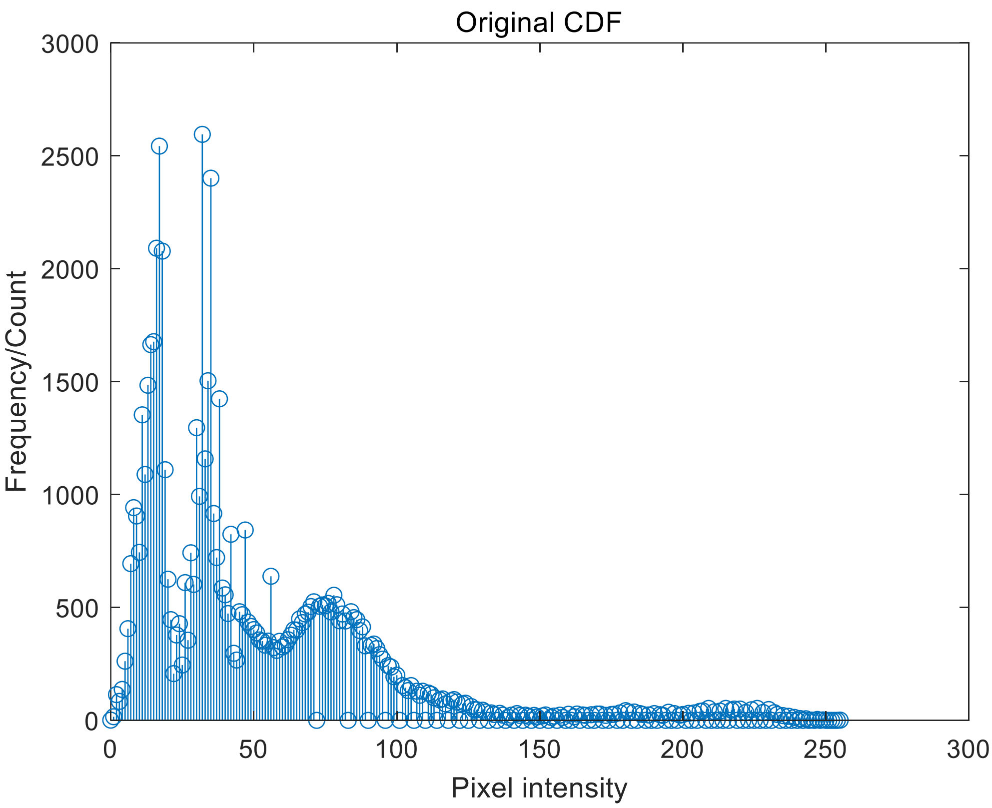

Figure 6: Cumulative Histograms before enhancement

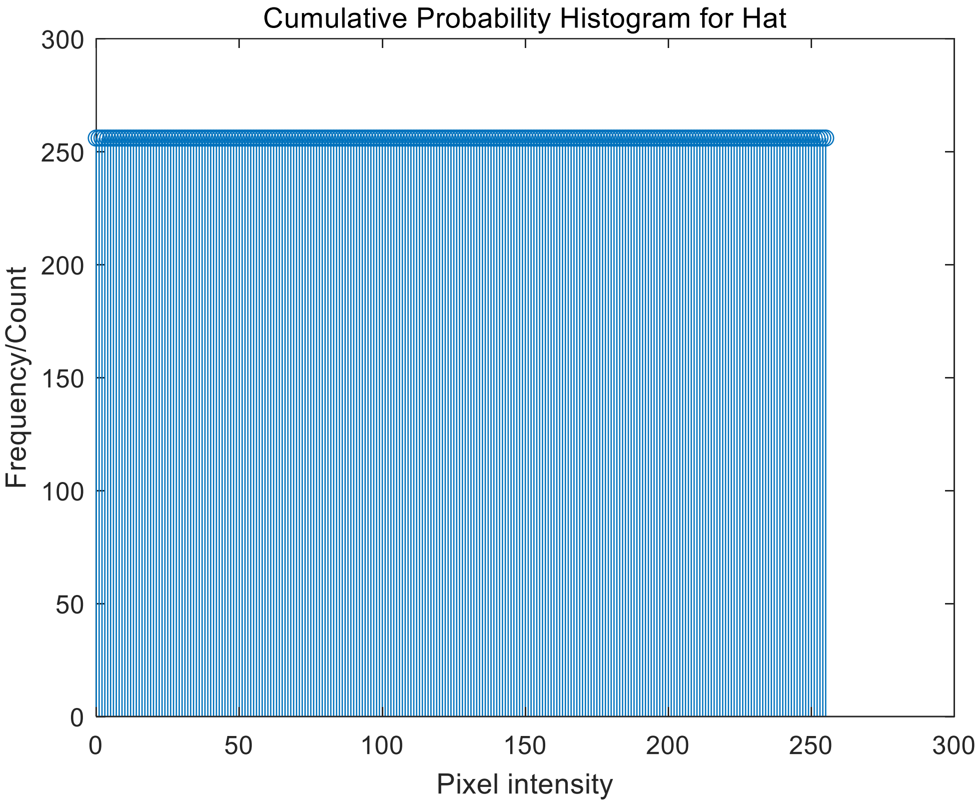

Figure 7: Cumulative Histogram after enhancement

(4) I think the cumulative-probability-based histogram equalization method is better. We can find in a large area with little gradient change, method B can give us a smoother surface than method A.

(c)

(1) CLAHE is to use the histogram equalization for each area separately by chunking the image, so that the local information can be used to enhance the image to solve the global problem. And using contrast limiting method to solve the background noise enhancement problem.

(2)

After Removing Haze with Transfer-function-based Histogram Equalization

Figure 8: Transfer-Function-Based Histogram equalization for *Taj_Mahal*

After Removing Haze with Cumulative-probability-based Histogram Equalization

Figure 9: Cumulative Probability based Histogram equalization for *Taj_Mahal*

After Removing Haze with CLAHE Algorithm

Figure 10: CLAHE for *Taj_Mahal*

(4) The comparison results show that CLAHE not only achieves the enhancement of image details, but also suppresses the background noise.

1.4 Discussion

The bilinear demosaicing algorithm calculates the gray value of the four points around the sampling point in a bilinear way. This algorithm does not consider the interaction of the gray values of the neighboring points, so it has the nature of low-pass filtering, which leads to the loss of the high-frequency components of the scaled image and the blurring of the image edges to a certain extent. We can use the bicubic interpolation algorithm to calculate the grayscale value of the sampled point based on the bilinear relationship of the 16-pixel values around the sampled point and the pixel change rate. It is able to produce smoother edges than the bilinear demosaicing algorithm, with high computational accuracy and the best results with the least loss of image quality after processing.

To improve Transfer-Function-Based histogram, instead of distributing nearby or local neighborhood pixel intensities, it is better to redistribute the highest occurrence of any pixel intensity to many other occurrences causing many to one mapping. To improve Cumulative Probability based histogram equalization and to retain uniqueness in the enhanced/contrast image, probability or weighted functions needs to be introduced.

The main difference between CLAHE and normal adaptive histogram equalization is its contrast limiting. This feature can also be applied to the global histogram equalization, which constitutes the so-called Contrast-Limited Histogram Equalization (CLAHE), but this is rarely used in practice. In CLAHE, contrast limiting must be used for each small area. CLAHE is mainly used to overcome the problem of over-amplified noise in AHE. The main advantage of the CLAHE transform is that it uses only one parameter - crop limit, and it gives better image processing results. CLAHE also has disadvantages, since the goal of this method is to make the contrast optimal, the original image is not in a 1-to-1 relationship with the CLAHE processing result, however, the CLAHE image is not a normalized calculation, it relies mainly on the pixel values of the image for its calculation.

Problem 2: Image Denoising (40 %)

2.1 Motivation

Image noise is the unnecessary or superfluous interference information present in the image data. The various factors in an image that prevent people from accepting its information can be called image noise. Noise can be defined theoretically as "unpredictable random errors that can only be recognized by probabilistic statistical methods" (image noise can be described as different types, and its categorization is based on statistical methods). Therefore, it is appropriate to consider image noise as a multidimensional random process, and thus the method of describing noise can be borrowed from the description of random processes, i.e., using its probability distribution function and probability density distribution function. The image sensor CCD and CMOS image acquisition process is affected by the sensor material properties, working environment, electronic components and circuit structure, etc., which can introduce various noises. The imperfections of transmission media and recording equipment, etc., digital images are often contaminated by a variety of noises during their transmission and recording.

The ability to suppress potential noise is a very important issue. That said, there are many great techniques available for dealing with noise. In our project, we focus on three. They are linear filters including uniform and gaussian, bilateral filters, and non-local means (NLM) filter.

2.2 Approach

2.2.1 Basic denoising methods

Uniform filter replaces the value of a pixel by the mean value of an area centered at the pixel.

1	1	1
1	1	1
1	1	1

3x3 Mean kernel

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

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

where $(k,\ l)$ is the neighboring pixel location within the window of size $w_1 \times w_2$

centered around (i, j), I is the noisy image, Y is the output image.

Gaussian filter is similar to the uniform filter but weighted in favor of pixels closer to the center.

1	4	7	4	1
4	16	26	16	4
7	26	41	26	7
4	16	26	16	4
1	4	7	4	1

5x5 Gaussian kernel

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

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

where σ is the standard deviation of Gaussian distribution.

2.2.2 Bilateral Filtering

Bilateral filter is a filter that allows edge-preserving denoising. The reason for this denoising effect is that the filter is composed of two functions. One function is determined by the geometric spatial distance of the filter coefficients. The other one is determined by the pixel difference of the filter coefficients.

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

$$w(i,j,k,l) = \exp\left(-\frac{(i-k)^2 + (j-l)^2}{2\sigma_c^2} - \frac{\left\|I(i,j) - I(k,l)\right\|^2}{2\sigma_s^2}\right)$$

where σ_c and σ_s are parameters of your choice.

2.2.3 Non-Local Means (NLM) Filtering

The non-local means (NLM) is an effective and popular denoising method that adjusts each pixel value with a weighted average of all pixels in the entire image. The non-locality assures less loss of detail and thus greater preservation of edges.

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

$$w(i,j,k,l) = \exp\left(-\frac{\left\|I(N_{i,j}) - I(N_{k,l})\right\|_{2,a}^2}{h^2}\right)$$

$$\left|\left|I(N_{i,j}) - I(N_{k,l})\right|\right|_{2,a}^2 = \sum_{n_1,n_2 \in \aleph} G_a(n_1,n_2)(I(i-n_1,j-n_2) - I(k-n_1,l-n_2))^2$$

$$G_a(n_1,n_2) = \frac{1}{\sqrt{2\pi a}} \exp\left(-\frac{n_1^2+n_2^2}{2a^2}\right)$$

where $N_{x,y}$ is the window centered around location (x,y), and h is the filtering parameter. $\aleph$ denotes the local neighborhood centered at the origin, $n', n! \in \aleph$ denotes the relative position in the neighborhood window. a is the standard deviation of the Gaussian kernel.

2.3 Results

(a)

(1) Gaussian is the noise embedded in *Flower_gray.raw*.

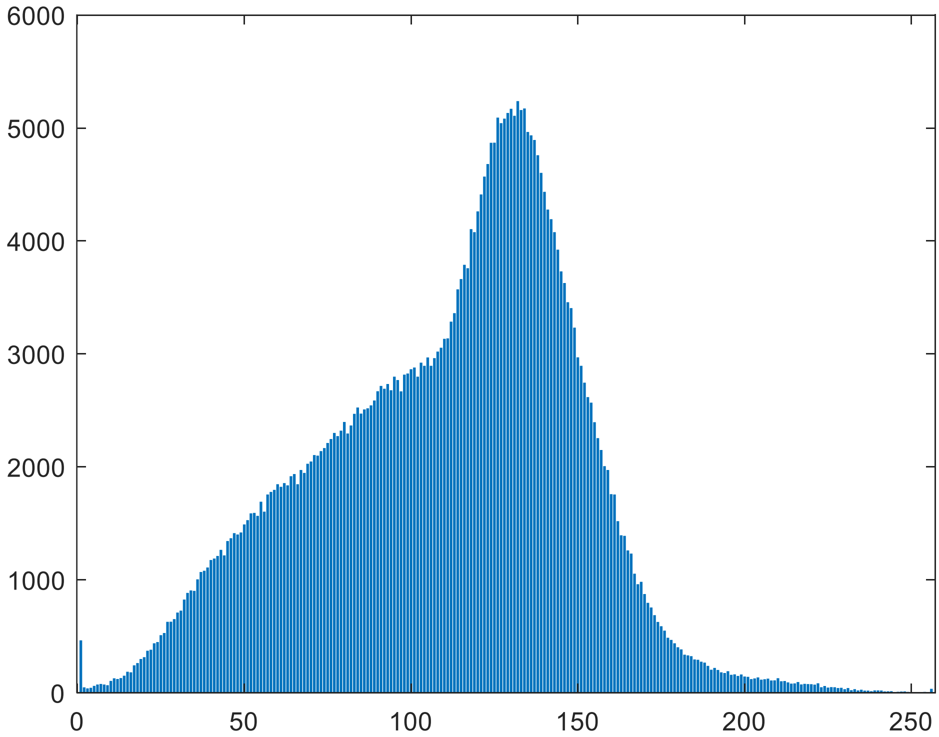

Figure 11: Noise of Flower images

(2)

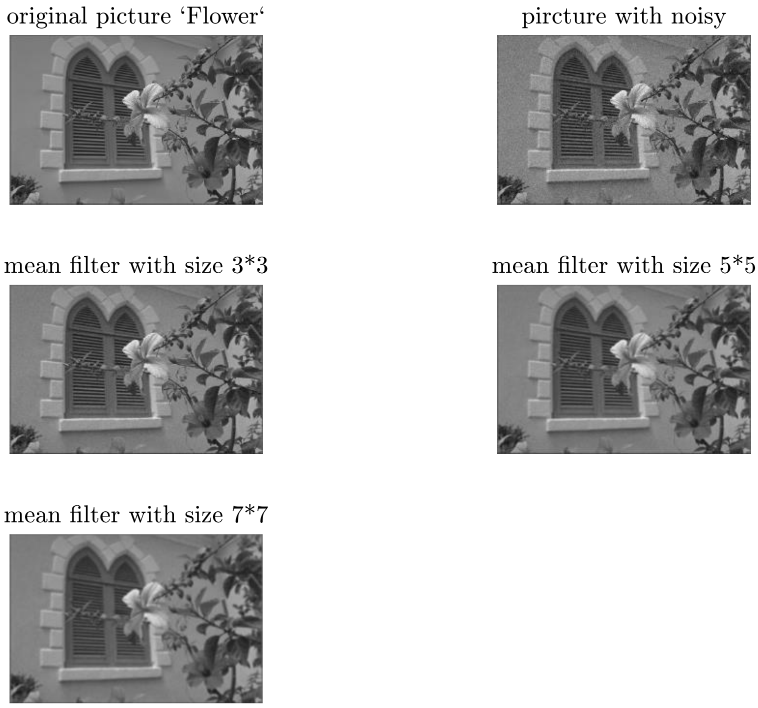

Figure 12: The uniform weight function

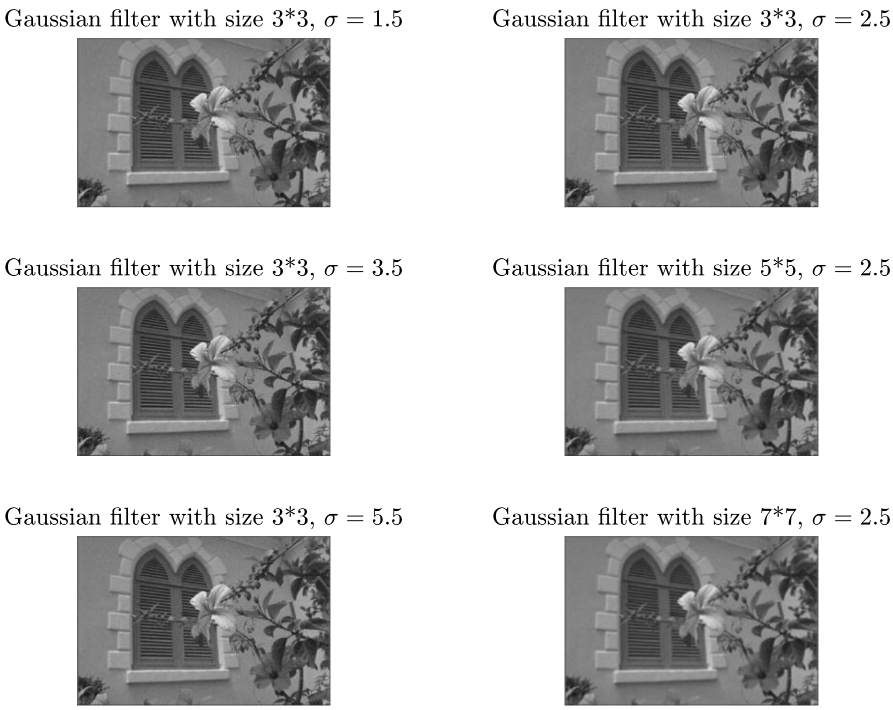

Figure 13: The Gaussian weight function

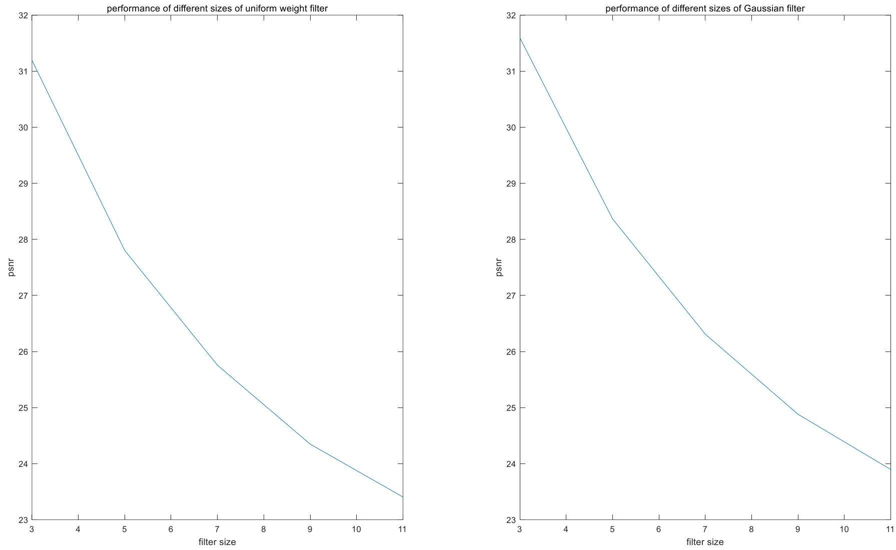

Figure 14: Comparison of performance

(b)

(1)

Figure 15: The bilateral denoising filter

(2) First, the two sigma values are the variance of the kernel. The larger the variance, the smaller the difference in weights, thus indicating that the influence of this factor is not emphasized, and conversely, the more emphasis is placed on the imbalance in weights due to this factor. Thus. A relatively smaller sigma for one of the two aspects indicates that this aspect is relatively more important and is emphasized. If σ_c becomes smaller, it means that more values of the nearest neighbors are used for smoothing, indicating that the spatial information of the image is more important, i.e., similar to each other. If σ_s becomes smaller, it indicates that the condition of being in

the same class as oneself becomes harsh, thus emphasizing the similarity of the value domain.

Secondly, σ_c indicates smoothing of the null domain, and thus is more appropriate for the part without edges and with slow changes; σ_s indicates the difference in the value domain, and thus emphasizes this difference, i.e., decreasing σ_s can highlight the edges. With larger σ_c, the weight of each region of the image basically originates from the weight of the value domain filtering, so it is not very sensitive to the spatial neighborhood information; with larger σ_s, the value domain is not considered much, and the weight mostly comes from the spatial distance, so it is close to the ordinary Gaussian filtering, and the edge-preserving performance of the image decreases. Therefore, if one wants to remove more noise from the smoothed area, σ_c should be increased, and if one wants to preserve the edges, σ_s should be decreased. In the extreme case, if σ_c is infinitely large, it is equivalent to value domain filtering; σ_s is infinitely large, it is equivalent to null domain Gaussian filtering.

(3) Yes. Bilateral filter as the name implies is more than Gaussian filtering with a Gaussian variance σ_c, it is based on the Gaussian filtering function of spatial distribution, so near the edges, the pixels farther away will not affect too much the pixel values on the edges, which ensures the preservation of pixel values near the edges.

(c)
(1)

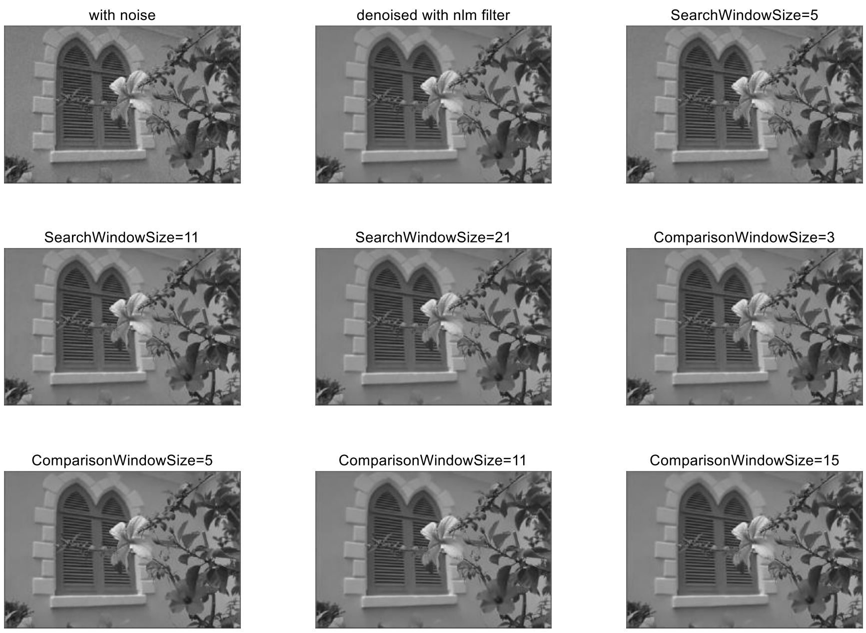

Figure 16: The NLM filter

By comparing the PSNR and complexity of the calculation with different parameters, I finally choose the big search window size to be 21×21, the small neighbor window size to be 7×7. The Gaussian smoothing parameter for the search window h to be 21×21, the Gaussian smoothing parameter for the neighbor window a to be 7×7.

(2) These methods performed very well with the NLM filter achieving the highest PSNR score. However, looking at the images, even though the gaussian filter got a higher PSNR score than the bilateral filter (albeit ever so slightly). The bilateral filter appears more visually appealing to me as it is less grainy.

(d)

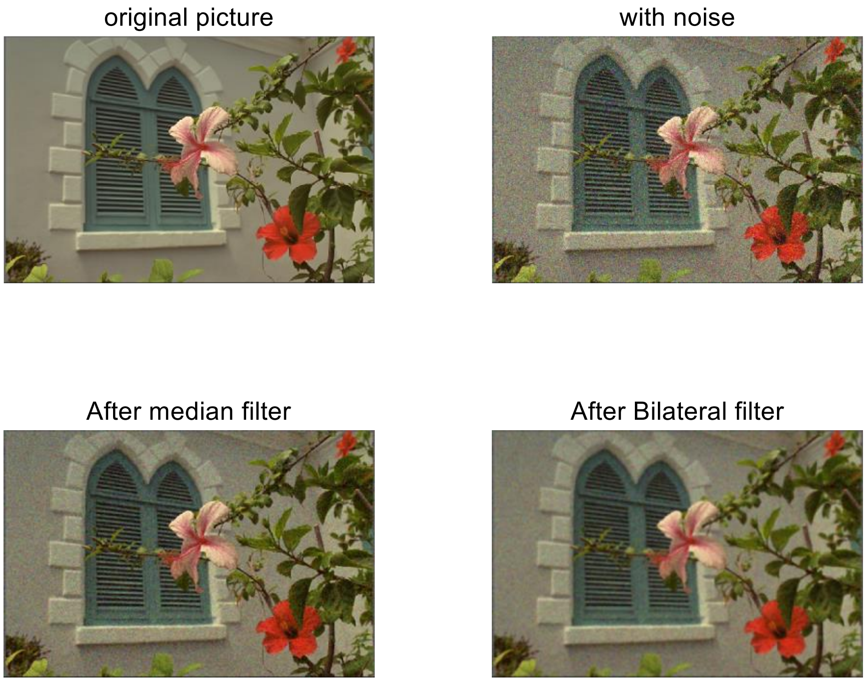

Figure 17: Different filters

(1) The noisy color image corrupted with impulse and shot noises.

(2) Since impulse noise can be filtered out with median filter effectively, we should first apply a median filter. Otherwise, after we use a linear or nonlinear filter to handle Poisson(shot) noise, pixel with impulse noise will affect the neighbors around them.

(3) After trying Linear/Gaussian/Bilateral/NLM filter, the best result is given by

Bilateral filter with σ_c=1, σ_s=300, window size=7. The shortcoming of this method: it cannot fully remove Poisson noise of the picture. To improve its performance. Thus, to improve its performance, we can apply more powerful shot noise denoising method, such as Block-matching and 3D filtering or deep learning algorithm like PURE-LET.

2.4 Discussion

Mean filtering has the advantages of simple operation, high efficiency and easy implementation, and can obtain a rough description of object features. However, mean filtering does not protect the image details well, and it destroys the image details and loses the image feature information while denoising the image.

When Gaussian filtering smooths the pixels in the image neighborhood, the pixels in different positions in the neighborhood are given different weights, so that the image can be smoothed while retaining more of the overall grayscale distribution of the image.

The advantage of the bilateral filter is that it can do edge preservation. Generally, the Wiener filter or Gaussian filter used in the past to reduce noise will blur the edges more obviously, and the protection of high frequency details is not obvious. Bilateral filter is a Gaussian filter function based on spatial distribution, so the pixels near the edges, which are farther away, will not affect the pixel values on the edges too much, which ensures the preservation of pixel values near the edges. However, because too much high-frequency information is preserved, the bilateral filter cannot cleanly filter out the high-frequency noise in the color image and can only filter the low-frequency information better.

The advantage of non-local mean filter is that it can remove noise while preserving image edge details. The disadvantage is that it is very slow to compute.

Problem 3: Special Effect Image Filters: Creating Frosted Glass Effect (15%)

3.1 Motivation

Image filters can be used not only for noise removal, but also sometimes for effects on images, such as creating frosted glass effects.

3.2 Approach

Replacing the color at each pixel with the color at a random pixel in its local neighborhood of size NxN.

1	2	3
8	0	4
7	6	5

Generate a random number for coordinate change.

3.3 Results

(1) (2)

Figure 18: The frosted glass filtering

The frosted glass filter has less effect on noisy images.

(3)

Figure 19: The Bilateral filtering denoising and the frosted glass filtering

Perform denoising first, then apply the frosted-glass filtering will be a visible frosted glass effect. In contrast, apply the frosted-glass filter first then perform denoising, frosted glass effect is not as obvious.

3.4 Discussion

In this experiment, to achieve the frosted glass effect, I first expand the image according to the window size, then create an empty array, then iterate through each pixel of the original image, for example, when the iteration reaches G(i,j), put all the pixel points in the window centered on pixel point (i,j) into the pixel list, and randomly select a pixel in the pixel list as the pixel value of the new image G2(i,j).

According to the experimental results, noise affects the display of the frosted glass effect. To get the ideal display effect, the image should be denoised first.