

Digital Image Processing

Project report

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Project 1 - Histogram Equalization

Problem

Histogram Equalization (test images: fig1.jpg, fig2.jpg)

(a) Write a computer program for computing the histogram of an image.

(b) Implement the histogram equalization technique.

(c) Your program must be general to allow any gray-level image as its input.

As a minimum, your report should include the original image, a plot of its histogram, a plot of the transformation function, the enhanced image, and a plot of its histogram.

Environment

Matlab R2016a

Atom 1.22 (with language-matlab package)

Principle

This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values.

For discrete values, we deal with probabilities (histogram values) and summations instead of probability density functions and integrals. The probability of occurrence of intensity level r_k in a digital image is approximated by:

$$p_r(r_k) = \frac{n_k}{MN} \quad k = 0, 1, 2, \dots, L - 1$$

And where MN is the total number of pixels in the image, n_k is the number of pixels that have intensity r_k , and L is the number of possible intensity levels in the image. The discrete form of the transformation is:

$$\begin{aligned} s_k &= T(r_k) = (L - 1) \sum_{j=0}^k p_r(r_j) \\ &= \frac{(L - 1)}{MN} \sum_{j=0}^k n_j \quad k = 0, 1, 2, \dots, L - 1 \end{aligned}$$

Implementation

1. Clear the former environments at the beginning:

```
4 % Clear the environment
5 close all;
6 clc;
7 clear;
```

2. Input the image and get the information about the image (There the location of the input image is directly assigned for convenience and it also can be assigned by the function parameter after comment this line) :

```
9 % Set the default location of input image file
10 img_location = '../images/Fig1.jpg';
11 input_img = imread(img_location);
12
13 % Get the relative information of the image
14 info = imfinfo(img_location);
15 MN = info.Width * info.Height;
16
17 % For this program must be general to allow any
18 % gray-level image, so it needs to get the depth
19 % of the image
20 L = info.BitDepth;
```

3. Initial the gray distribution of input and output image arrays , p_r array and T(r) array with zero:

```
22 % Initialize the gray distribution and output image matrix
23 input_gray_distribution = zeros(2^L,1);
24 output_img = zeros(info.Height,info.Width);
25 output_gray_distribution = zeros(2^L,1);
26 transform = zeros(2^L,1);
27
```

4. Get the gray distribution of input image:

```
28 % Calculate the gray distribution of input image
29 for i = 1:2^L
30     input_gray_distribution(i) = length(find(input_img == (i - 1)));
31 end
```

5. Get the pdf of input image by dividing MN:

```
33 % Get the pdf
34 input_img_pdf = input_gray_distribution / MN;
35
```

6. Get the tranformation:

```
36 % Calculate the transformation
37 for i = 1:2^L
38     transform(i) = (2^L - 1) * sum(input_img_pdf(1:i));
39 end
```

7. Get the output image and cast the type from double to uint:

```

41 % Calculate the output image
42 for i = 1:info.Width
43     for j = 1:info.Height
44         output_img(j,i) = transform(double(input_img(j,i)) + 1);
45     end
46 end
47
48 % Format the values of pixels
49 output_img = uint8(output_img);
50

```

8. Calculate the gery histogram of output image:

```

51 % Calculate the gray distribution of output image
52 for i = 1:2^L
53     output_gray_distribution(i) = length(find(output_img == i));
54 end
55

```

9. Draw the bar graphs and show the input and output images:

```

57 % Show pictures & Draw graphs
58 % Show pictures and graphs seperately
59 figure('NumberTitle','off','Name','Histogram Of Input Image')
60 bar(input_gray_distribution,0.7);
61 xlabel('Gray Level','FontSize',16);
62 ylabel('Distribution','FontSize',16);
63 set(gca, 'XLim',[0 2^L]);
64 set(gca, 'YLim',[0 16000]);
65
66 figure('NumberTitle','off','Name','Histogram Of Output Image')
67 bar(output_gray_distribution,0.7);
68 xlabel('Gray Level','FontSize',16);
69 ylabel('Distribution','FontSize',16);
70 set(gca, 'XLim',[0 2^L]);
71 set(gca, 'YLim',[0 16000]);
72
73 figure('NumberTitle', 'off', 'Name', 'Transformation function')
74 plot(1:2^L, transform)
75 xlabel('Original Gray','FontSize',16);
76 ylabel('Transformed Gray','FontSize',16);
77 set(gca, 'XLim',[0 2^L]);
78 set(gca, 'YLim',[0 2^L]);
79
80 figure('NumberTitle','off','Name','Input Image')
81 imshow(input_img);
82
83 figure('NumberTitle','off','Name','Output Image')
84 imshow(output_img);
85

```

10. Compare them in one graph:

```

86 % Show them all together to compare
87 figure('NumberTitle','off','Name','Compare')
88 subplot(2,3,1);
89 imshow(input_img);
90 title('The Input Image');

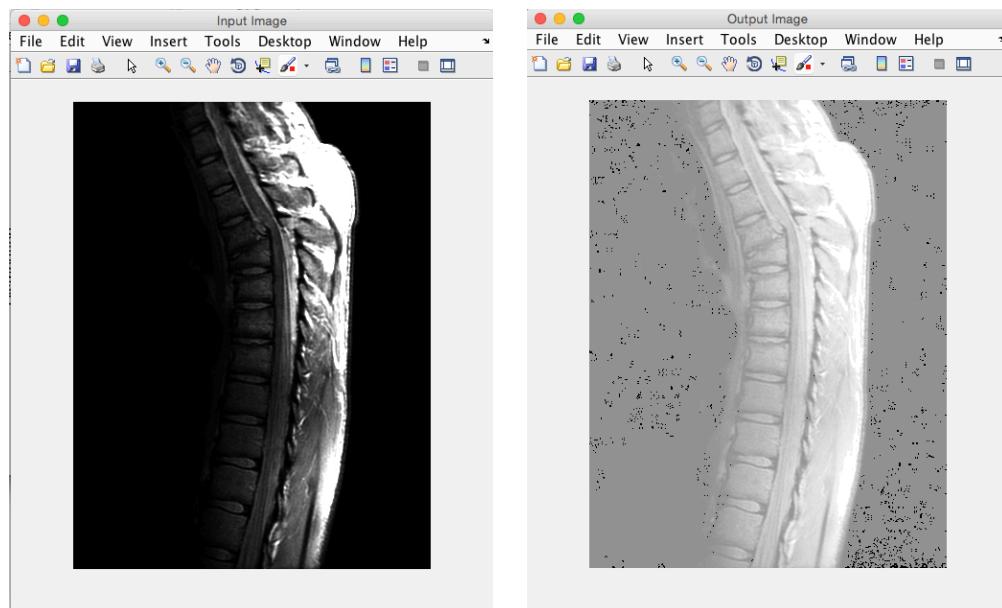
```

```

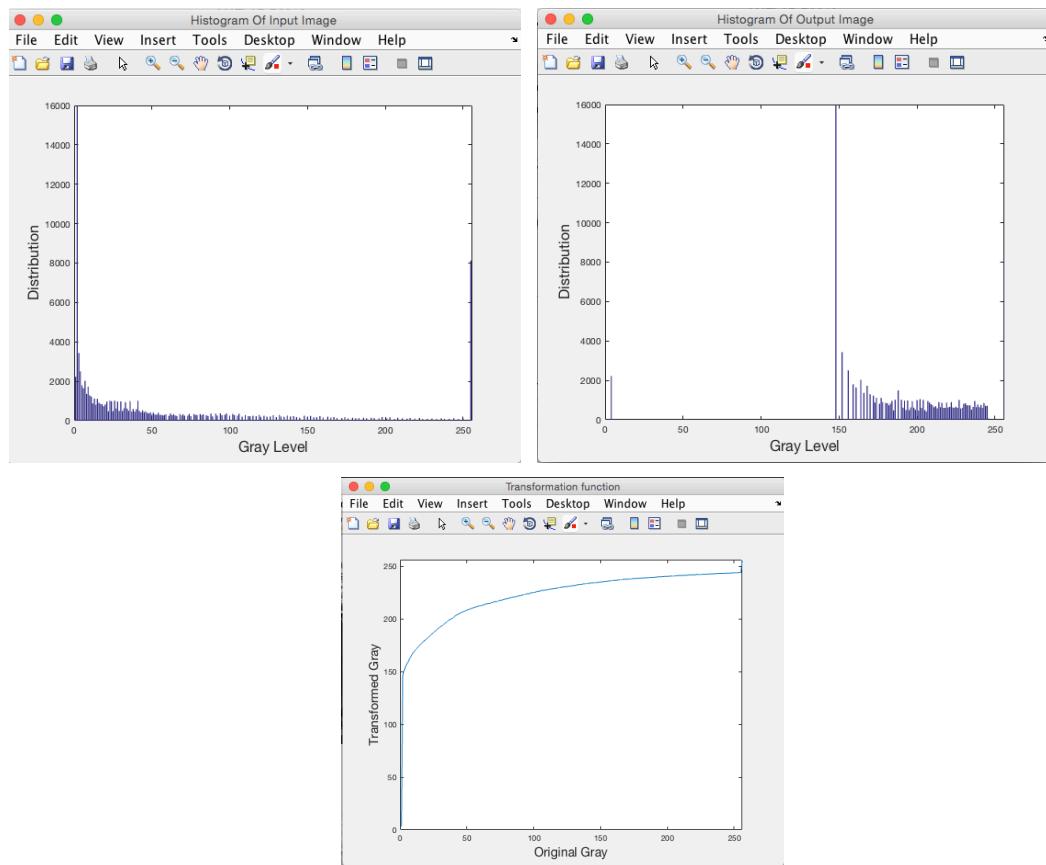
92 subplot(2,3,2);
93 bar(input_gray_distribution,0.7);
94 title('Histogram Of Input Image');
95 xlabel('Gray Level','FontSize',16);
96 ylabel('Distribution','FontSize',16);
97 set(gca, 'XLim',[0 2^L]);
98 set(gca, 'YLim',[0 16000]);
99
100 subplot(2,3,3);
101 plot(1:2^L, transform)
102 title('The Transformation Function')
103 xlabel('Original Gray','FontSize',16);
104 ylabel('Transformed Gray','FontSize',16);
105 set(gca, 'XLim',[0 2^L]);
106 set(gca, 'YLim',[0 2^L]);
107
108 subplot(2,3,4);
109 imshow(output_img);
110 title('The Output Image');
111
112 subplot(2,3,5);
113 bar(output_gray_distribution,0.7);
114 title('Histogram Of Output Image');
115 xlabel('Gray Level','FontSize',16);
116 ylabel('Distribution','FontSize',16);
117 set(gca, 'XLim',[0 2^L]);
118 set(gca, 'YLim',[0 16000]);

```

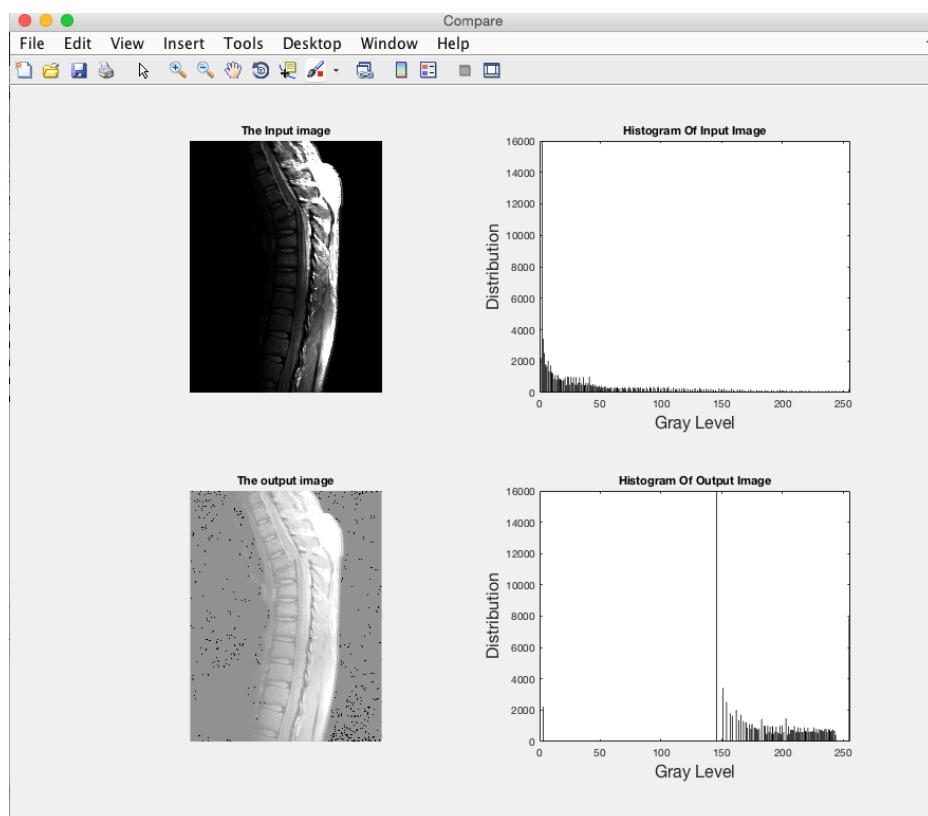
Result



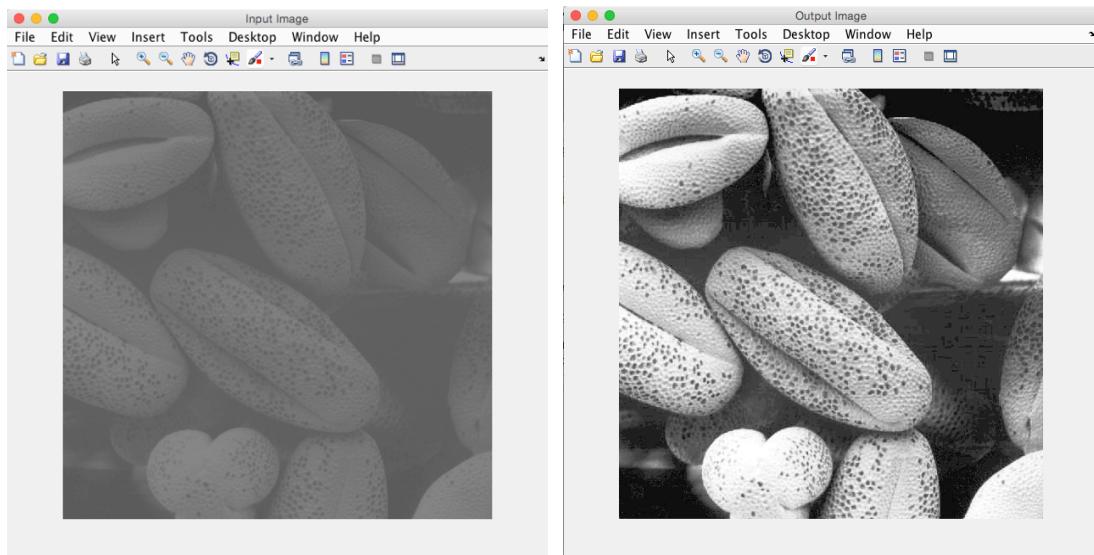
Input Image and output image



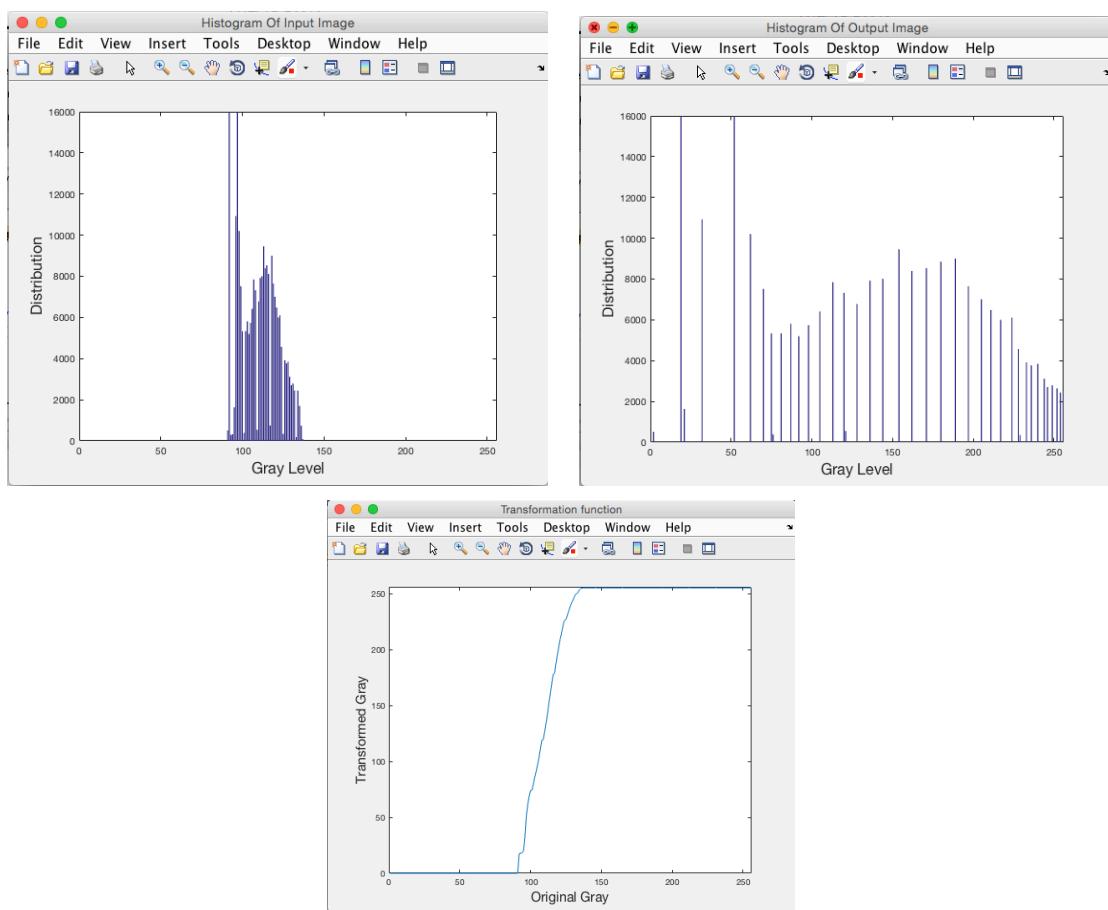
Corresponding histograms and transformation function



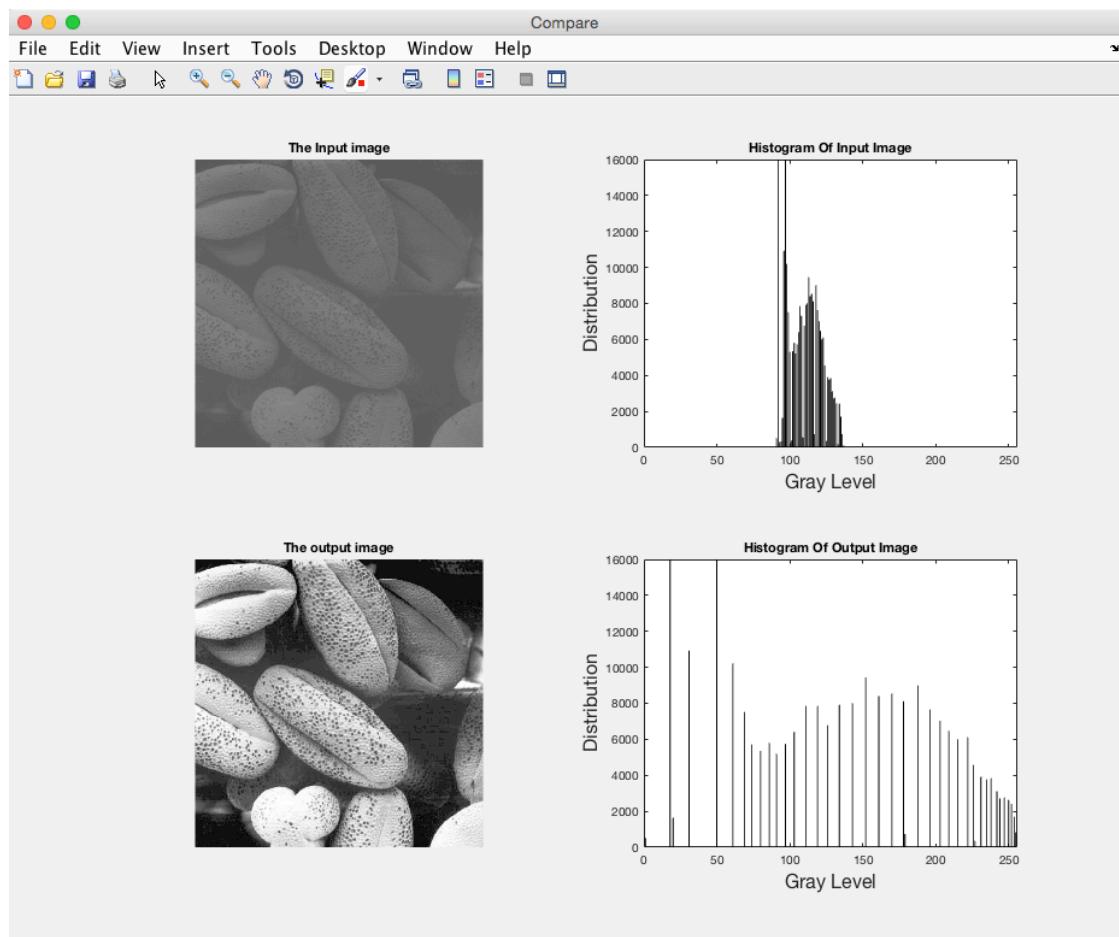
Comparison



Input Image and output image



Corresponding histograms and transformation function



Comparison

Project 2 - Combining spatial enhancement methods

Problem

Combining spatial enhancement methods

Implement the image enhancement task of Section 3.7 (Fig 3.43, page 171). The image to be enhanced is skeleton_orig.tif. You should implement all steps in Figure 3.43. (You are encouraged to implement all functions by yourself, not to directly use Matlab functions such as imfilter or fspecial.)

Environment

Matlab R2016a

Atom 1.22 (with language-matlab package)

Principle

- **The Laplacian:**

We can use the implementation of 2-D, second-order derivatives for image sharpening and the simplest isotropic derivative operator is the Laplacian, which, for a function (image) $f(x, y)$ of two variables, is defined as

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

In the x-direction and y-direction:

$$\frac{\partial^2 f}{\partial x^2} = f(x+1, y) + f(x-1, y) - 2f(x, y)$$

$$\frac{\partial^2 f}{\partial y^2} = f(x, y+1) + f(x, y-1) - 2f(x, y)$$

And the discrete Laplacian of two variables:

$$\begin{aligned}\nabla^2 f(x, y) = & f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1) \\ & - 4f(x, y)\end{aligned}$$

It can be expressed as mask:

0	1	0	1	1	1
1	-4	1	1	-8	1
0	1	0	1	1	1

- **The Sobel gradient:**

First derivatives in image processing are implemented using the magnitude of the gradient. For a function $f(x, y)$, the gradient of f at coordinates (x, y) is defined as the two-dimensional column vector:

$$\nabla f \equiv \text{grad}(f) \equiv \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

The magnitude (length) of vector ∇f , denoted as $M(x, y)$, where:

$$M(x, y) = \text{mag}(\nabla f) = \sqrt{g_x^2 + g_y^2} \approx |g_x| + |g_y|$$

So we can get Sobel gradient:

$$g_x = \frac{\partial f}{\partial x} = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)$$

$$g_y = \frac{\partial f}{\partial y} = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)$$

The masks of Sobel operator:

-1	-2	-1	-1	0	1
0	0	0	-2	0	2
1	2	1	-1	0	1

- **Power-law(Gamma) transformation:**

Power-law transformations have the basic form:

$$s = cr^\gamma$$

where c and γ are positive constants. Sometimes it is written as:

$$s = c(r + \varepsilon)^\gamma$$

to account for an offset.

Implementation

1. Clear the former environments at the beginning:

```
4 % Clear the environment
5 close all;
6 clc
7 clear;
```

2. Input the image and get the information about the image (There the location of the input image is directly assigned for convenience and it also can be assigned by the function parameter after comment this line) :

```
9 % Set the default location of input image file
10 img_location = '../images/skeleton_orig.tif';
11 input_img = double(imread(img_location));
12
13 % For this program must be general to allow any
14 % gray-level image, so it needs to get the depth
15 % of the image
16 info = imfinfo(img_location);
17 L = info.BitDepth;
18
```

3. Set the laplacian mask , the sobel masks in x-direction and y-direction seperately and the smooth mask in 5 x 5 range:

```
19 % Set the laplacian and sobel gradient masks also smooth mask
20 laplacian_mask = [0,-1,0; -1,4,-1; 0,-1,0];
21 sobel_gradient_x_mask = [-1,-2,-1; 0,0,0; 1,2,1];
22 sobel_gradient_y_mask = [-1,0,1; -2,0,2; -1,0,1];
23 smooth_5x5_mask = ones(5,5) * 1/(5*5);
```

4. To filter the input image with the above masks, it needs a new function linear_filter(input_img, mask) to do the linear filter work:

```
1 % Linear filter
2 function [output_img] = linear_filter(input_img, mask)
3 % This function is used to mask to input image
4
```

- a. First we need padding to avoid the error when mask the boundary, it needs get the padding distance from the mask and use zero padding:

```
5 % Get the height and width of the mask
6 [m, n] = size(mask);
7
8 % Calculate the size of padding according to the size of mask
9 padding_m = floor((m - 1) / 2);
10 padding_n = floor((n - 1) / 2);
11 % Use zero padding to mask the boundary
12 padding_input_img = padarray(input_img, [padding_m, padding_n]);
13
```

- b. Then we can mask the input image with the mask “line by line”, and just return the part without padding:

```

13
14 % Get the height and width of the image
15 [M, N] = size(input_img);
16
17 % Initialize and calculate output image
18 output_img = zeros(M, N);
19 for i = padding_m + 1:padding_m + M
20     for j = padding_n + 1:padding_n + N
21         output_img(i - padding_m, j - padding_n) = sum(sum(padding_input_img
22             (i-padding_m:i+padding_m,j-padding_n:j+padding_n) .* mask));
23     end
24 end
25
26 end

```

5. So we can use the linear filter function to mask the image and “combine” them:

```

23
24 % Laplacian of the input image
25 laplacian_img = linear_filter(input_img, laplacian_mask);
26
27 % Use laplacian to sharpen the image
28 sharpen_laplacian_img = input_img + laplacian_img;
29
30
31

```

6. For sobel gradient mask, we use the sum of absolute values of x-direction and y-direction. We can also use the square sum of the value of x-direction and y-direction which maybe takes more calculation:

```

32 % Sobel gradient of the input image of direction x and y
33 sobel_gradient_x_img = linear_filter(input_img, sobel_gradient_x_mask);
34 sobel_gradient_y_img = linear_filter(input_img, sobel_gradient_y_mask);
35
36 % Sobel gradient of the input image it can also use square sum
37 sobel_gradient_img = abs(sobel_gradient_x_img) + abs(sobel_gradient_y_img);
38

```

7. Use 5 x 5 smooth mask to smooth:

```

39 % Use 5x5 mask to smooth
40 smooth_5x5_sobel_img = linear_filter(sobel_gradient_img, smooth_5x5_mask);
41

```

8. The product of sharpened laplacian and smoothed sobel:

```

42 % Calculate the product mask of laplacian and smooth sobel
43 mask_product_img = sharpen_laplacian_img .* smooth_5x5_sobel_img / (2^L - 1);
44 sharpen_smooth_sobel_img = input_img + mask_product_img;
45

```

9. Power-law transformation:

```

45
46 % Calculate the power-law transformation of smooth sobel image
47 power_law_transform_img = (sharpen_smooth_sobel_img * (2^L - 1)).^ 0.5;
48

```

10. To show the pictures we need handle the negative grey values:

```

49 % Increase the gray level to handle the negative gray level
50 laplacian_img = laplacian_img - min(laplacian_img(:));
51 sharpen_laplacian_img = sharpen_laplacian_img - min(sharpen_laplacian_img(:));
52 sobel_gradient_img = sobel_gradient_img - min(sobel_gradient_img(:));
53

```

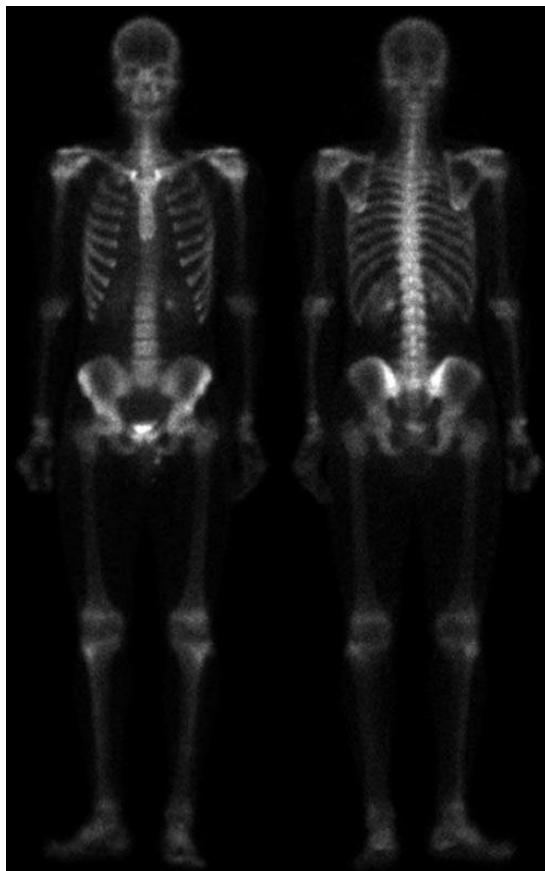
11. Show the pictures and output them:

```

54
55 %%%%%%%%%%%%%% Show pictures %%%%%%%%%%%%%%
56 figure('NumberTitle','off','Name','Combining spatial enhancement methods')
57 subplot(2,4,1);imshow(input_img,[0,2^L-1]);title('(a) Input image');
58 subplot(2,4,2);imshow(laplacian_img,[0,2^L-1]);title('(b) Laplacian of (a)');
59 subplot(2,4,3);imshow(sharpen_laplacian_img,[0,2^L-1]);title('(c) Sum of (a) and (b)');
60 subplot(2,4,4);imshow(sobel_gradient_img,[0,2^L-1]);title('(d) Sobel of (a)');
61 subplot(2,4,5);imshow(smooth_5x5_sobel_img,[0,2^L-1]);title('(e) Smooth (d) with a 5x5 average filter');
62 subplot(2,4,6);imshow(mask_product_img,[0,2^L-1]);title('(f) Product of (c) and (e)');
63 subplot(2,4,7);imshow(sharpen_smooth_sobel_img,[0,2^L-1]);title('(g) Sum of (a) and (f)');
64 subplot(2,4,8);imshow(power_law_tranform_img,[0,2^L-1]);title('(h) Gamma transformation result of (g)');
65
66 %%%%%%%%%%%%%% Output pictures %%%%%%%%%%%%%%
67 imwrite(uint8(input_img), '1_origin_image.jpg');
68 imwrite(uint8(laplacian_img), '2_laplacian_of_image.jpg')
69 imwrite(uint8(sharpen_laplacian_img), '3_sharpen_laplacian_image.jpg')
70 imwrite(uint8(sobel_gradient_img), '4_sobel_gradient_image.jpg')
71 imwrite(uint8(smooth_5x5_sobel_img), '5_smooth_sobel_image.jpg')
72 imwrite(uint8(mask_product_img), '6_product_laplacian_sobel.jpg')
73 imwrite(uint8(sharpen_smooth_sobel_img), '7_sharpen_smooth_sobel.jpg')
74 imwrite(uint8(power_law_tranform_img), '8_power_law_transform.jpg')
75

```

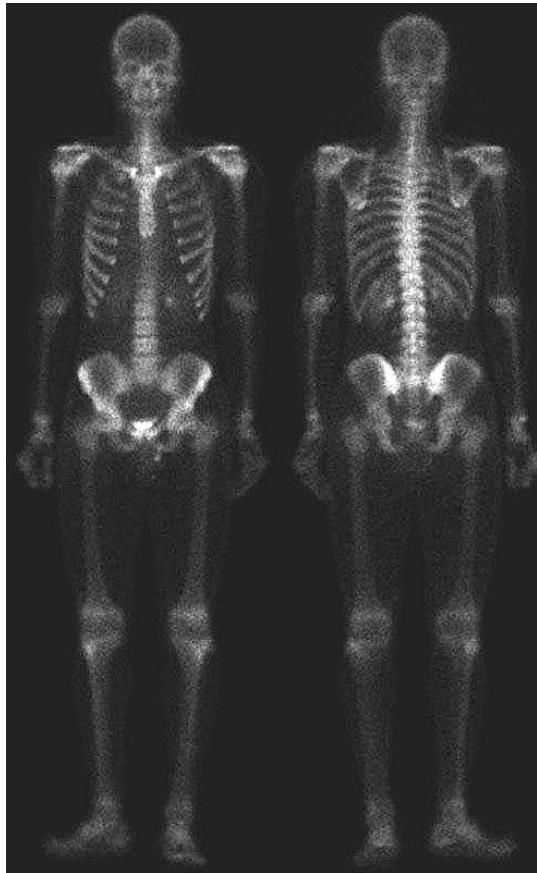
Result



(a) Image of whole body bone scan.



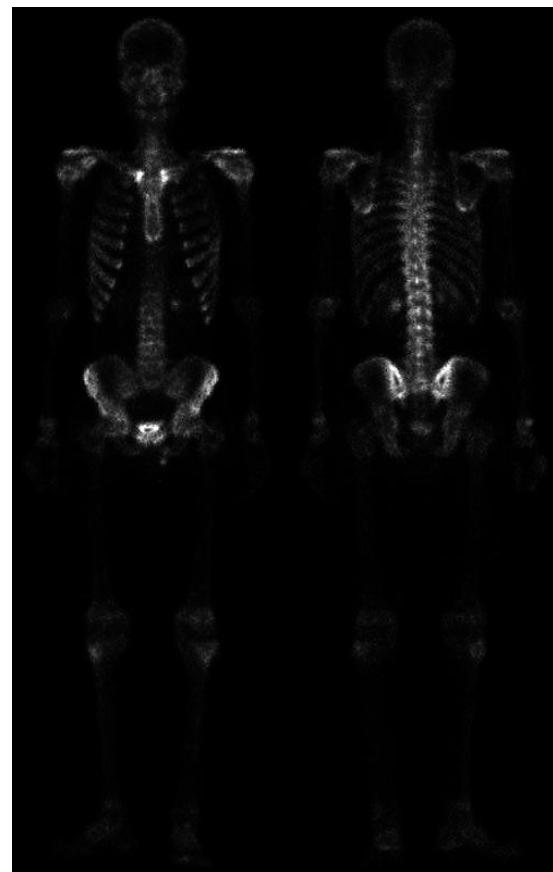
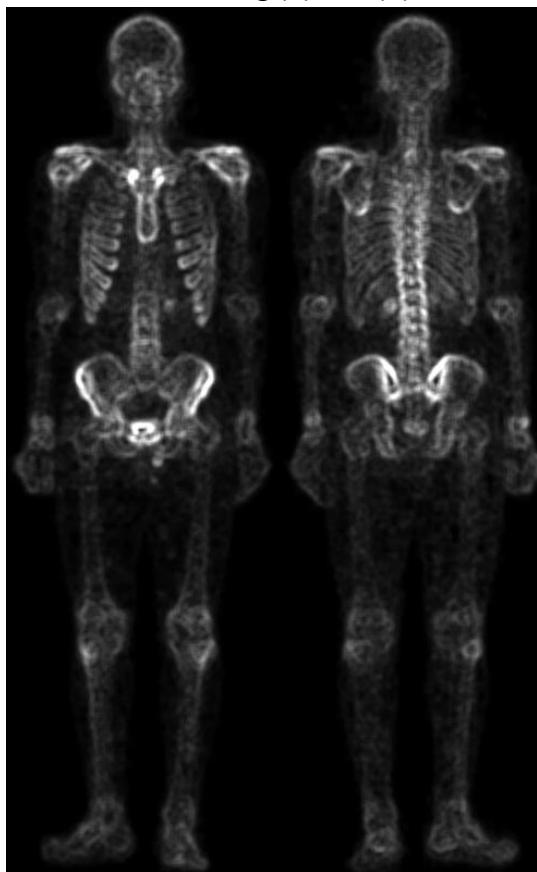
(b) Laplacian of (a)



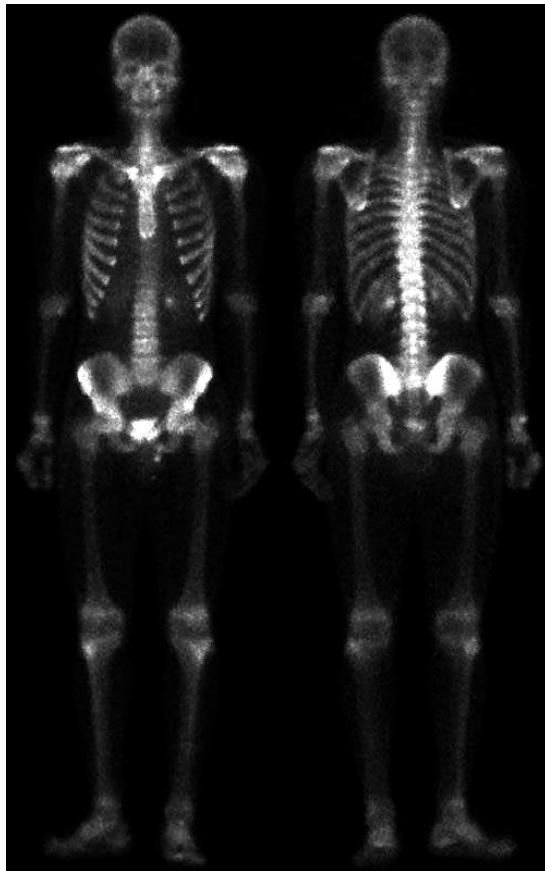
(c) Sharpened image obtained by
adding (a) and (b).



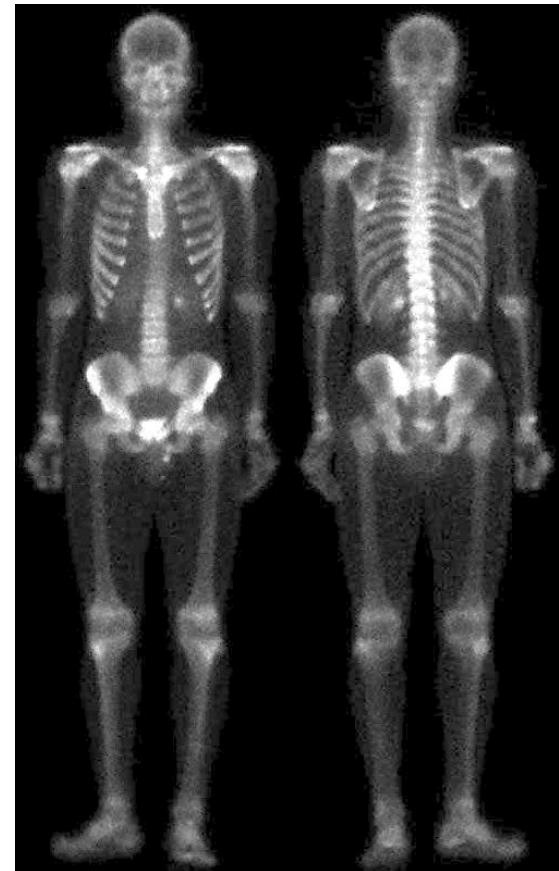
(d) Sobel gradient of (a)



(e) Sobel image smoothed with
a 5×5 averaging filter.

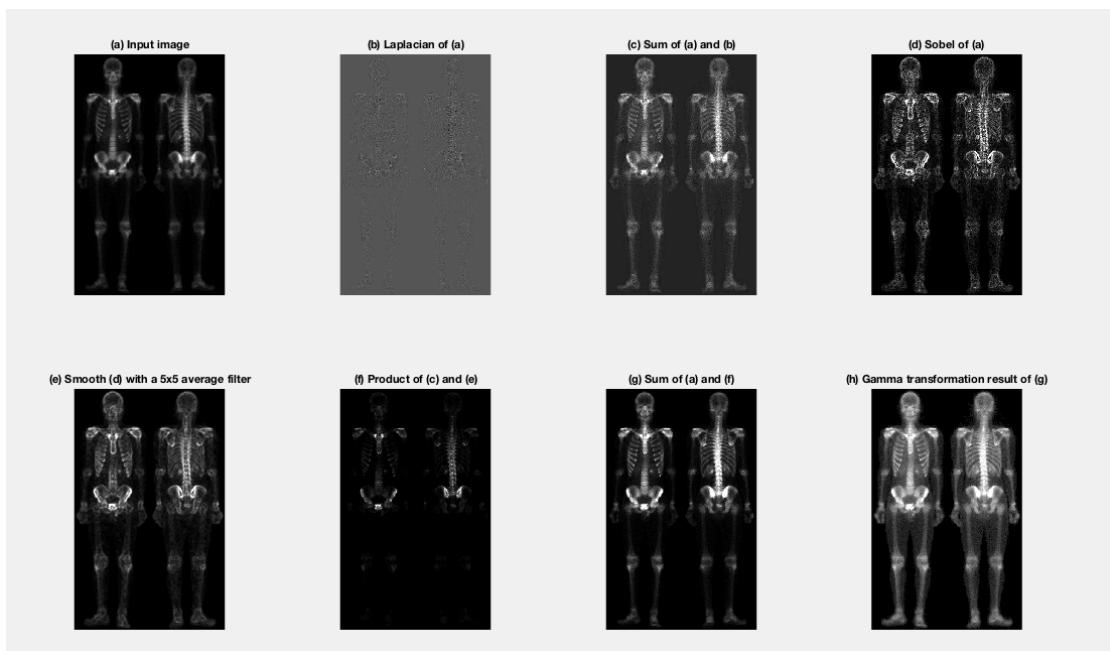


(f) Mask image formed by the
product of (c) and (e).



(g) Sharpened image obtained by
the sum of (a) and (f).

(h) Final result obtained by applying
a power-law transformation to (g).



Project 3 Filtering in frequency domain

Problem

Filtering in frequency domain

Implement the ideal, Butterworth and Gaussian low-pass and high-pass filters and compare the results under different parameters using the image characters_test_pattern.tif (this image file can be found at the ftp server <ftp://ftp.cs.sjtu.edu.cn:990/lu-ht/DIP/images>) as the test pattern.

Environment

Matlab R2016a

Atom 1.22 (with language-matlab package)

Principle

- **The Fourier transform**

We can use the Fourier transform to transform the signal of time domain to frequency domain. The Fourier transform of a continuous function $f(t)$ of a continuous variable, t , denoted $F(\mu)$, is defined by the equation

$$F(\mu) = \int_{-\infty}^{\infty} f(t) e^{-j2\pi\mu t} dt$$

and for the discrete signal:

$$F_m = \sum_{n=0}^{M-1} f_n e^{-j2\pi mn/M} \quad m = 0, 1, 2, \dots, M-1$$

Also the 2-D discrete Fourier transform is defined by

$$F(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) e^{-j2\pi(ux/M + vy/N)}$$

- **ideal low-pass filter**

$$H(u, v) = \begin{cases} 1 & \text{if } D(u, v) \leq D_0 \\ 0 & \text{if } D(u, v) > D_0 \end{cases}$$

$$D(u, v) = [(u - P/2)^2 + (v - Q/2)^2]^{1/2}$$

- **ideal high-pass filter**

$$H(u, v) = \begin{cases} 0 & \text{if } D(u, v) \leq D_0 \\ 1 & \text{if } D(u, v) > D_0 \end{cases}$$

- **Butterworth low-pass filter**

$$H(u, v) = \frac{1}{1 + [D(u, v)/D_0]^{2n}}$$

- **Butterworth high-pass filter**

$$H(u, v) = \frac{1}{1 + [D_0/D(u, v)]^{2n}}$$

- **Gaussian low-pass filter**

$$H(u, v) = e^{-D^2(u, v)/2\sigma^2}$$

- **Gaussian high-pass filter**

$$H(u, v) = 1 - e^{-D^2(u, v)/2D_0^2}$$

Implementation

1. Clear the former environments at the beginning:

```
4 % Clear the environment
5 close all;
6 clc
7 clear;
```

2. Input the image and get the information about the image (There the location of the input image is directly assigned for convenience and it also can be assigned by the function parameter after comment this line) :

```

9 % Set the default location of input image file
10 img_location = '../images/characters_test_pattern.tif';
11 input_img = double(imread(img_location));
12
13 % Get the relative information of the image
14 info = imfinfo(img_location);
15 M = info.Height;
16 N = info.Width;
17

```

3. Set the tested cutoff values, noise patterns and pass type:

```

18 % Set the tested cutoff values, noise patterns and pass type
19 cutoffs = [10, 30, 60, 160, 460];
20 patterns = {'ideal', 'butterworth', 'gaussian'};
21 pass_types = {'lowpass', 'highpass'};
22

```

4. Get the discrete Fourier transform of the input image and shift the dft, in there we use double size of input image for a better precision:

```

24 % Get the Discrete Fourier Transform
25 dft = fft2(input_img, 2*M, 2*N);
26 dft = fftshift(dft);
27

```

5. For each pattern high/low pass with different cutoffs, use function frequency_filter (frequency_filter.m) to filter the dft, then use ifft to convert the filtered dft to the filtered image. Because we use larger-size dft to get better precision, so we need to crop the image converted back. For convenience and clearance, I define a function frequency_filter_figures to show and output the figures together:

```

28 % Test each pattern high/low pass with different cutoffs
29 for pass_type = pass_types
30   for pattern = patterns
31     % Collect the generated figures to show together later
32     figures = {};
33     figures{1} = input_img;
34
35     for i = 1:numel(cutoffs)
36       % Frequency filter
37       filter_dft = frequency_filter(dft, pattern, pass_type, cutoffs(i), 2);
38       filter_img = real(ifft2(fftshift(filter_dft)));
39
40       % For we use bigger dft image so we need to crop the image converted back
41       filter_img = filter_img(1:M,1:N);
42       figures{i+1} = filter_img;
43     end
44
45     % Show and output the generated figures together
46     frequency_filter_figures(figures, {pattern, pass_type}, [0,cutoffs], true)
47   end
48 end
49

```

6. Considering the clear structure and the shortness of main function, I take the filter and figure out from the main function. Compared the codes in Project2, it gets much better to read.

- a. The function frequency_filter() implements all the high/low pass filter patterns, the input needs to be the allowed formats.

```

1 % Frequency filters
2 function [ output_img ] = frequency_filter( input_img, pattern, pass_type, D0, n )
3     % Input:
4     %   input_img - the input image
5     %   pattern - the pattern of filter, it need to be the value of next several values:
6     %             {'ideal', 'butterWorth', 'gaussian'}
7     %   pass_type - high pass or low pass
8     %   D0 - the 'distance' D0
9     %   n - the parameter used in the butterworth pattern
10    % Output:
11    %   the image after filtering
12
13
14 % The allowed patterns and high/low pass
15 patterns = {'ideal', 'butterworth', 'gaussian'};
16 pass_types = {'lowpass', 'highpass'};
17
18 % Convert the data type
19 input_img = double(input_img);
20
21 % Initialize
22 [M,N] = size(input_img);
23 H = zeros(M,N);
24
25
```

Then calculate the H matrix according to the patterns:

```

26 switch lower(char(pattern))
27 case patterns{1}
28     % Ideal
29     for i = 1:M
30         for j = 1:N
31             if sqrt((i - M/2) ^ 2 + (j - N/2) ^ 2) <= D0
32                 H(i,j) = 1;
33             end
34         end
35     end
36 case patterns{2}
37     % Butterworth
38     for i = 1:M
39         for j = 1:N
40             H(i,j) = 1 / (1 + (sqrt((i - M/2) ^ 2 + (j - N/2) ^ 2) / D0) ^ (2 * n));
41         end
42     end
43 case patterns{3}
44     % Gaussian
45     for i = 1:M
46         for j = 1:N
47             H(i,j) = exp(-(sqrt((i - M/2) ^ 2 + (j - N/2) ^ 2) ^ 2) / (2*(D0^2)));
48         end
49     end
50 otherwise
51     error(['The', ' ', pattern, ' ', 'filter pattern can not be found.'])
52 end
53
```

And we can easy to know that the “sum” of high pass and the low pass is equal to 1, so we can just calculate one matrix H and just get the other by $1 - H$:

```

54 switch lower(char(pass_type))
55 case pass_types{1}
56     H = H;
57 case pass_types{2}
58     H = 1 - H;
59 end
60
61 output_img = H .* input_img;
62 end
```

- b. To reduce the repeated codes, the pictures need to frequency_filter_figures() function to show and output, it needs to input the information concerned to get the titles and files name:

```

1 % Figures
2 function [] = frequency_filter_figures( input_imgs, image_info, cutoffs, output_file )
3 % Show the pictures and the figures
4
5 figure('NumberTitle','off','Name', ['The ', ' ', char(image_info{1}), ' ', ...
6 ' ', char(image_info{2}), ' ', 'filter'])
7 column = 2;
8 [temp, num] = size(input_imgs);
9 row = ceil(num / column);
10
11 % Show the pictures in 2 pictures/lines format
12 % If the output_file flag is set, then output to files
13 for i = 1:row
14     for j = 1:column
15         if((i - 1)* column + j) <= num
16             subplot(row, column, (i - 1)* column + j)
17             imshow(uint8((input_imgs{(i - 1) * column + j})),[]);
18             if (i - 1)* column + j == 1
19                 title('Origin input image')
20             else
21                 title(['Cutoff = ', int2str(cutoffs((i - 1) * column + j))]);
22             if output_file
23                 if (i - 1)* column + j > 1
24                     imwrite(uint8(input_imgs{(i - 1) * column + j}), [char(image_info{1}),...
25                     '_', char(image_info{2}), '_', int2str(cutoffs((i - 1) * column + j)), '.jpg']);
26                 end
27             end
28         end
29     end
30 end
31
32 if output_file
33     % Save the whole figure containing six pictures
34     saveas(gcf, [char(image_info{1}), '_', char(image_info{2}), '_', 'filter', '.jpg'])
35 end
36 end
37

```

7. *Some small try with the basic DFT function:

At the beginning I want to implement from the basic dft function like this :

```

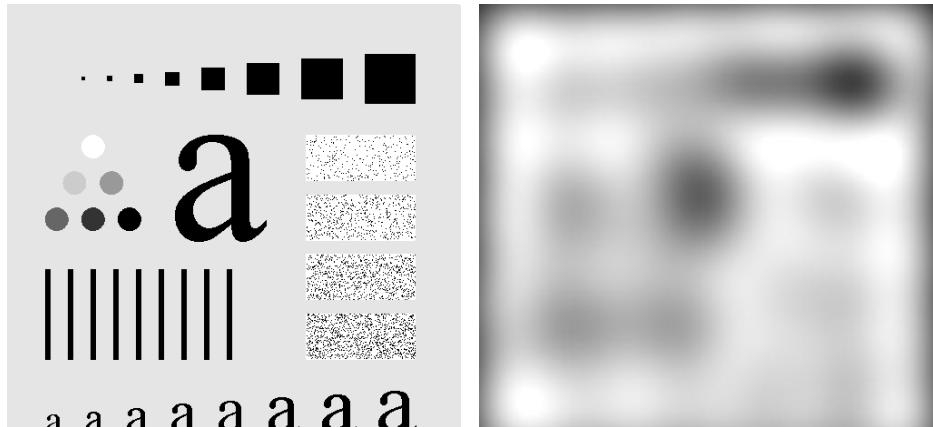
20 % Calculate the F(u,v) according to the 2D dft formula
21 x=@:n*M-1;
22 y=@:n*N-1;
23 [x,u]=meshgrid(x,x);
24 [v,y]=meshgrid(y,y);
25 output_img = exp(-1i * 2 * pi * (u .* x / M)) * extended_input_img * ...
26     exp(-1i * 2 * pi * (v .* y / N));
27
28
29 % For better show the frequency distribution in one picture,
30 % shift the blocks to focus the high frequencies to the center
31 if shift_flag == true
32     temp = output_img;
33     output_img = zeros(M,N);
34     output_img(1:floor(M/2), 1:floor(N/2)) = temp((ceil(M/2) + 1):M, (ceil(N/2) + 1):N);
35     output_img(1:floor(M/2), ceil(N/2):N) = temp((ceil(M/2) + 1):M, 1:(floor(N/2) + 1));
36     output_img(ceil(M/2):M, 1:floor(N/2)) = temp(1:(floor(M/2) + 1), (ceil(N/2) + 1):N);
37     output_img(ceil(M/2):M, ceil(N/2):N) = temp(1:(floor(M/2) + 1), 1:(floor(N/2) + 1));
38 end
39

```

But it's so quite slow compared with the fft() function of the matlab so I didn't use it finally.

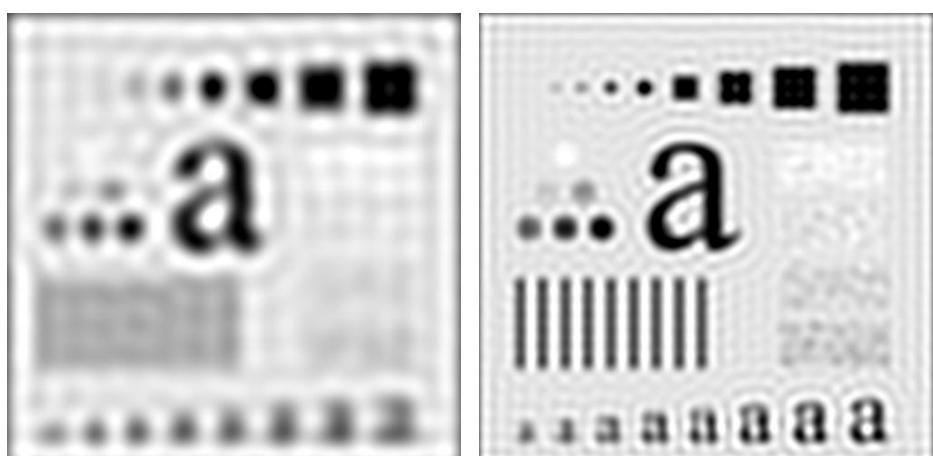
Result

1. Ideal lowpass



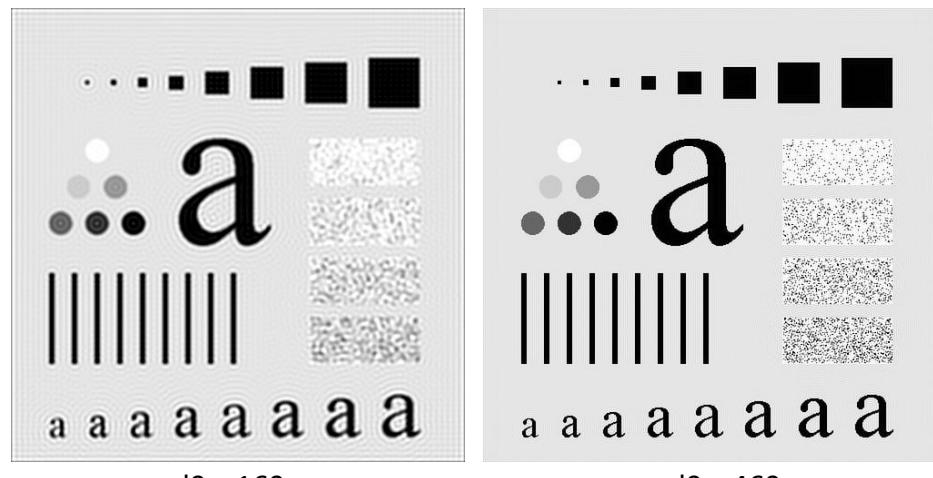
Original input image

d0 = 10



d0 = 30

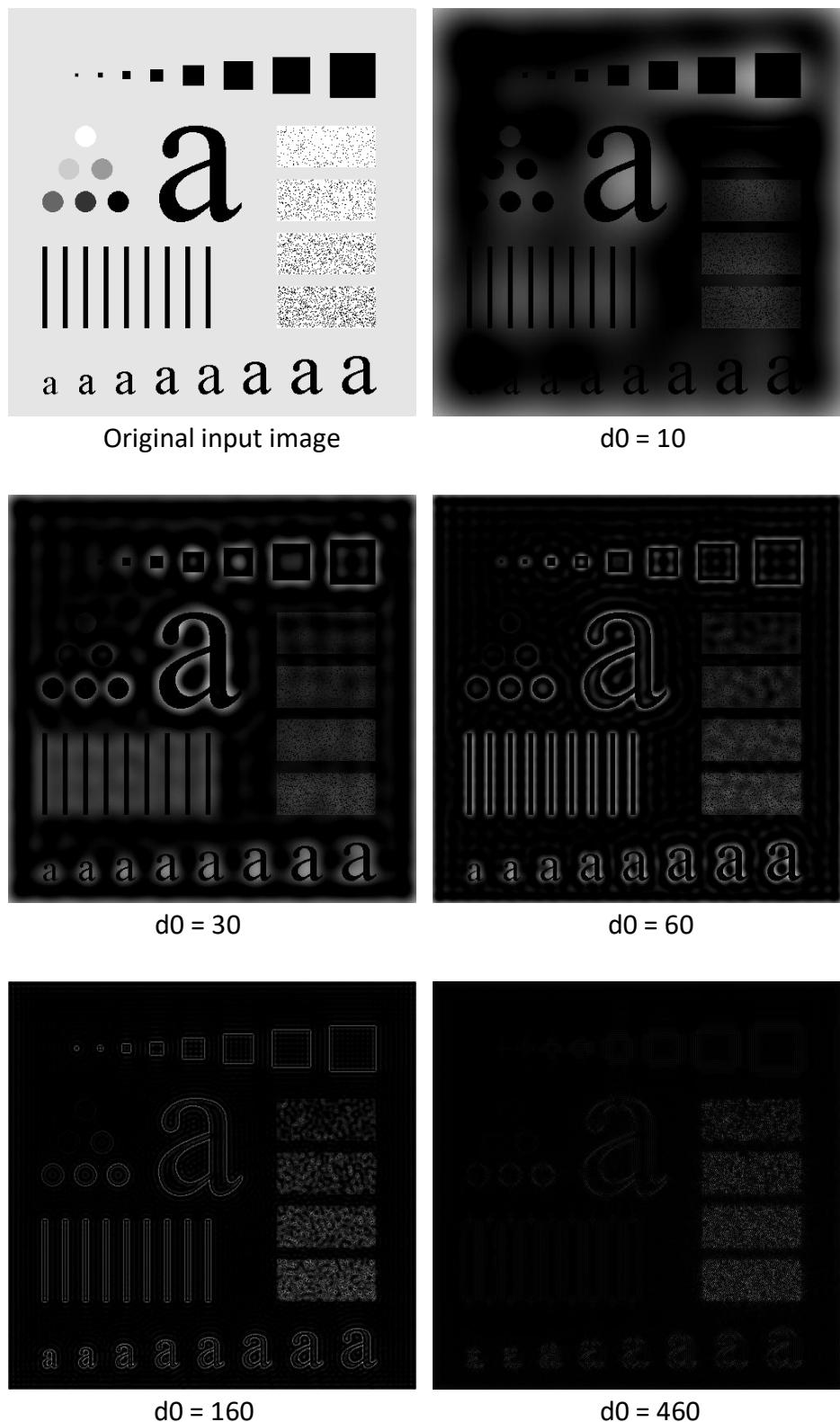
d0 = 60



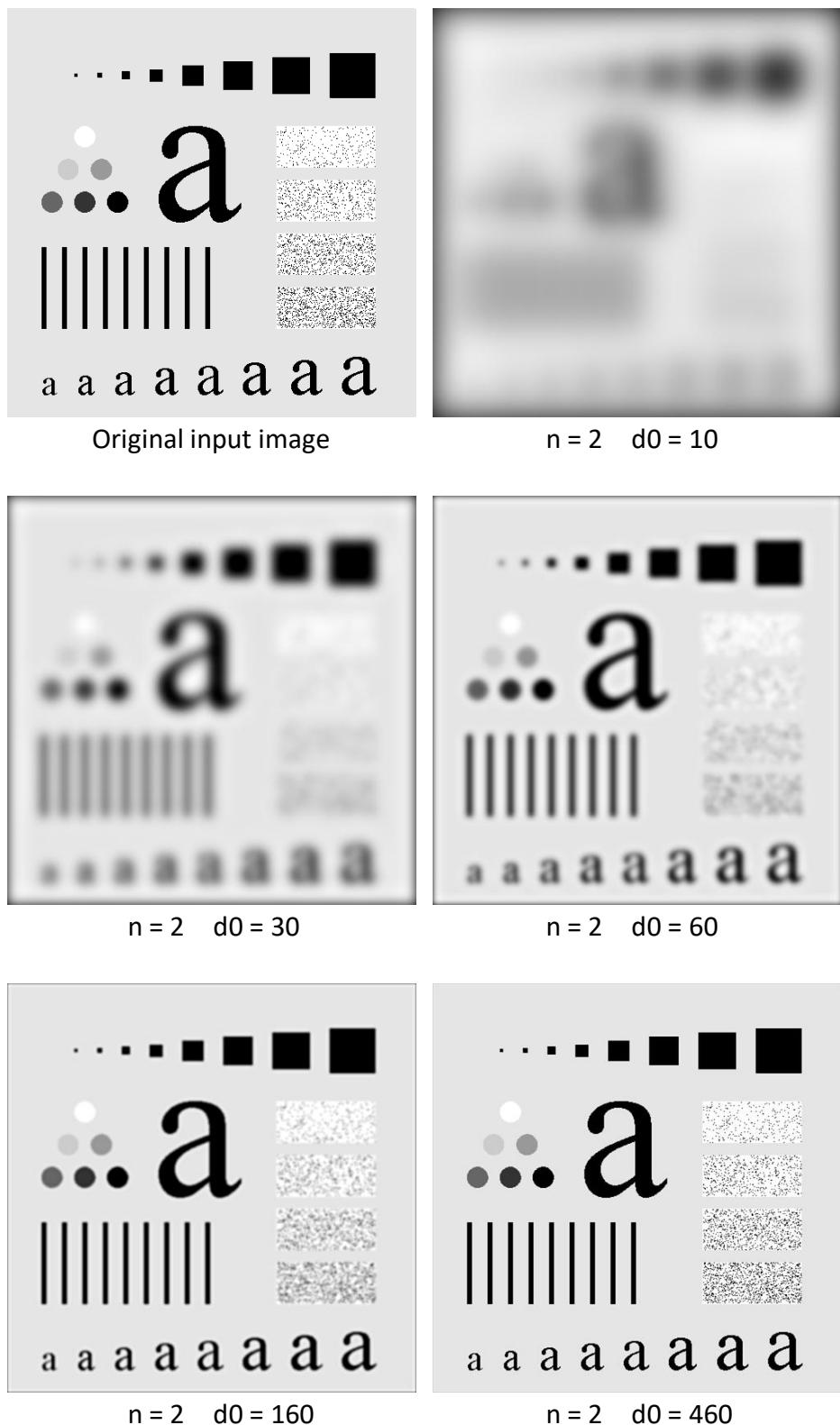
d0 = 160

d0 = 460

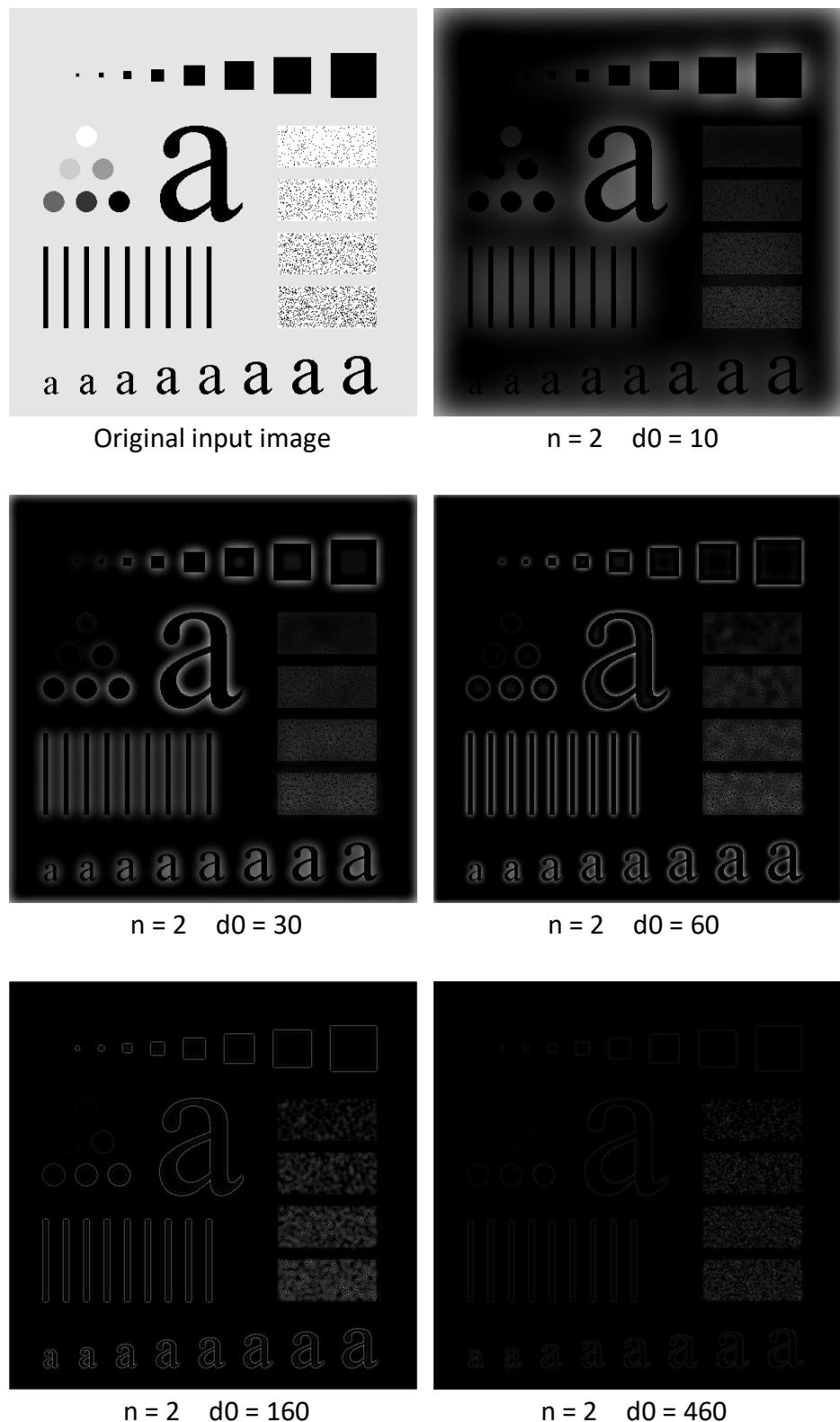
2. Ideal highpass



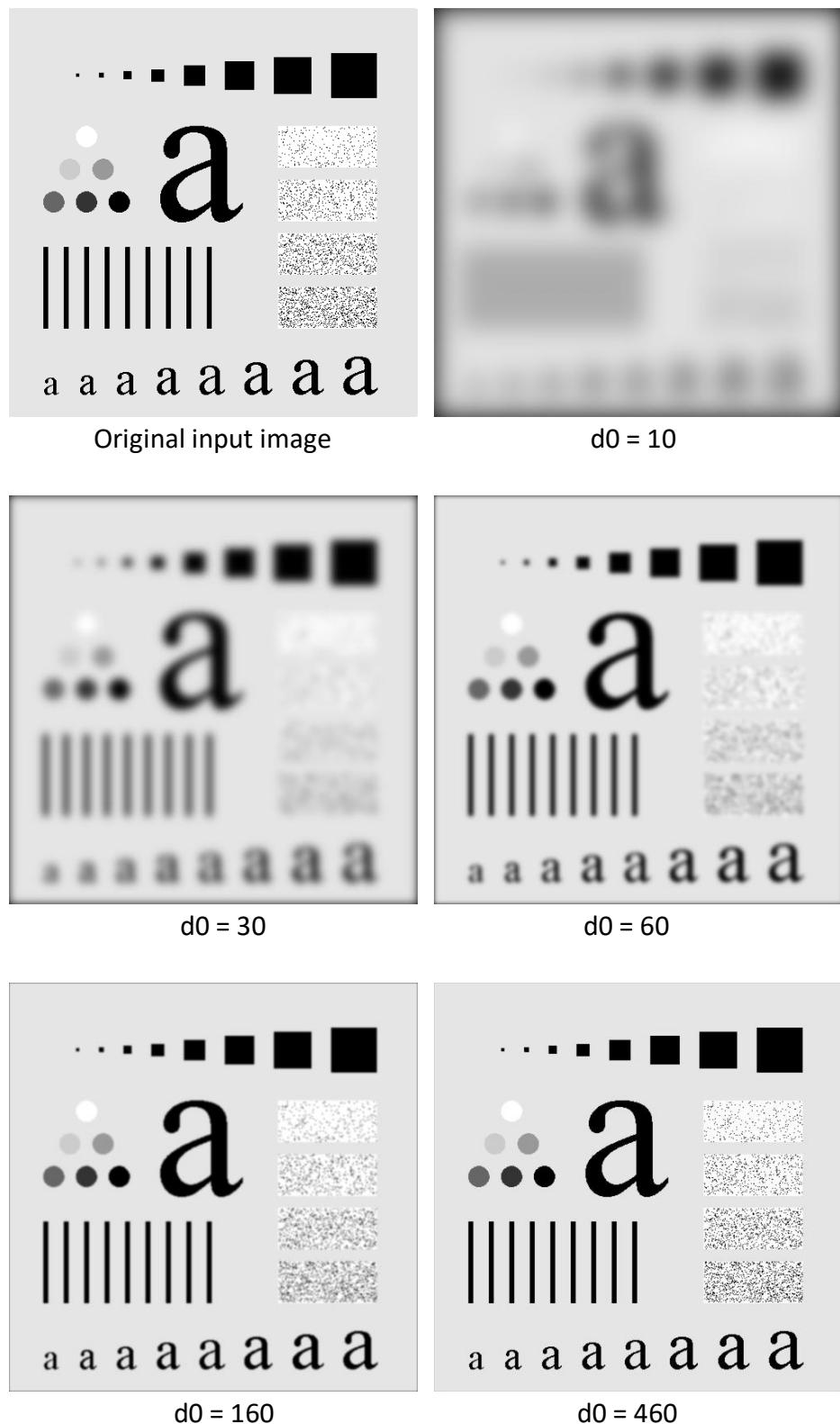
3. Butterworth lowpass



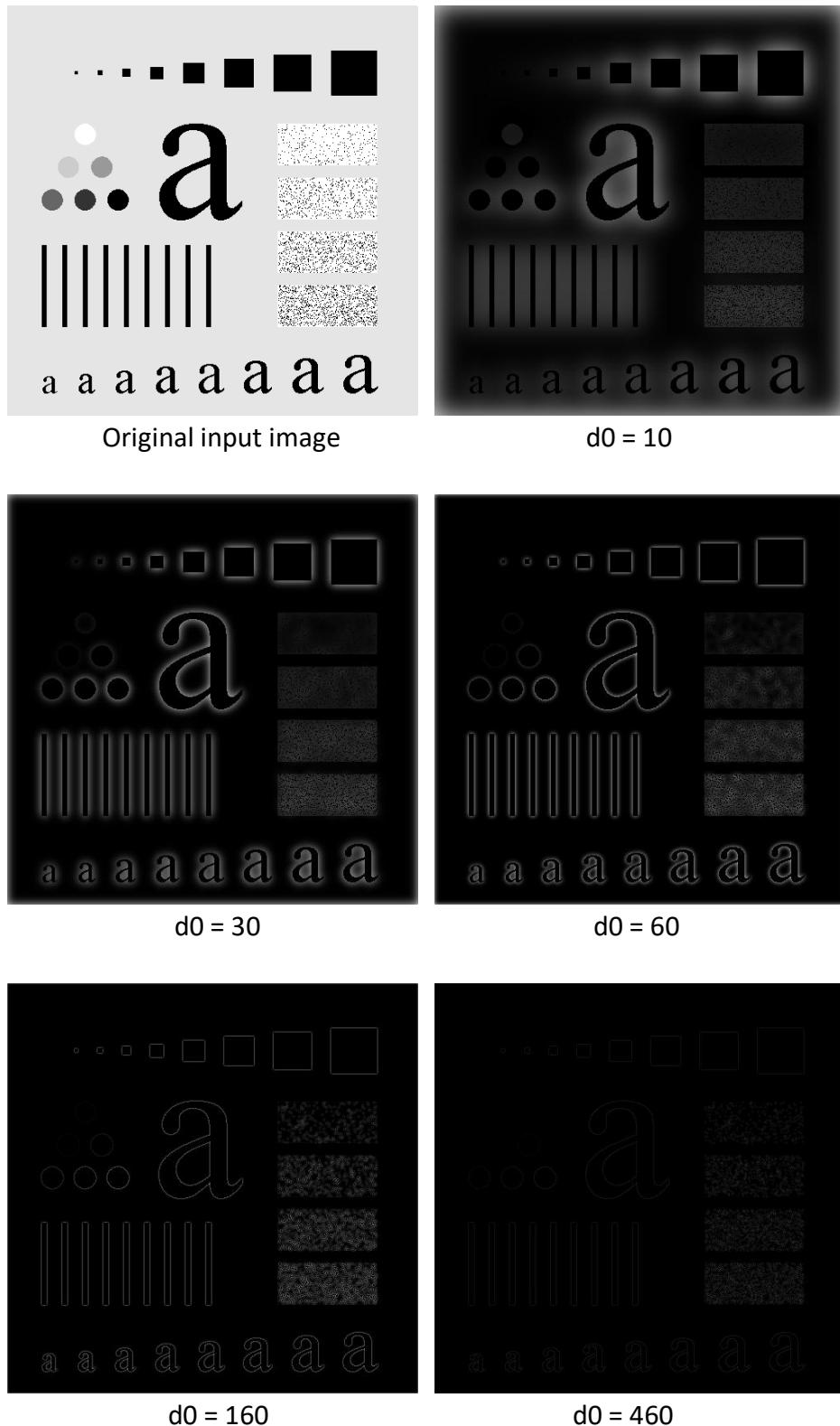
4. Butterworth highpass



5. Gaussian lowpass



6. Gaussian highpass



Project 4 - Generating different types of noise and comparing different noise reduction methods

Problem

Generating different types of noise and comparing different noise reduction methods
In this problem, you are required to write a program to generate different types of random noise (Uniform, Gaussian, Rayleigh, Gamma, Exponential and Impulse, first started from the uniform noise and then use some functions to convert the uniform noise to Gaussian, Rayleigh, Gamma and Exponential; Impulse noise is generated in a different way, consulting the textbook and some other references) and then add these noises to the test pattern image Fig0503(original_pattern).tif to compare the visual results of the noisy images. Add some of these noises to the circuit image Circuit.tif (images can be found at <ftp://ftp.cs.sjtu.edu.cn:990/lu-ht/DIP/images>) and investigate the noise reduction results using different mean filters and order statistics filters as the textbook did at pages 344-352 (Pages 322-329 in the electronic version of the textbook).

Environment

Matlab R2016a
Atom 1.22 (with language-matlab package)

Principle

- **Noise Probability Density Functions**

- **Gaussian noise**

The PDF of a Gaussian random variable, z , is given by

$$p(z) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(z-\bar{z})^2/2\sigma^2}$$

where z represents intensity, \bar{z} is the mean[†] (average) value of z , and σ is its standard deviation. In matlab, we can use the `randn()` function to get the Gaussian distribution random numbers so we can get Gaussian noise in this way:

$$z = \bar{z} + \sigma * \text{randn}(M, N)$$

- **Rayleigh noise**

The PDF of Rayleigh noise is given by:

$$p(z) = \begin{cases} \frac{2}{b}(z - a)e^{-(z-a)^2/b} & \text{for } z \geq a \\ 0 & \text{for } z < a \end{cases}$$

The mean and variance of this density are given by:

$$\bar{z} = a + \sqrt{\pi b/4}$$

and

$$\sigma^2 = \frac{b(4 - \pi)}{4}$$

- **Erlang (gamma) noise**

The PDF of Erlang noise is given by :

$$p(z) = \begin{cases} \frac{a^b z^{b-1}}{(b-1)!} e^{-az} & \text{for } z \geq 0 \\ 0 & \text{for } z < 0 \end{cases}$$

The mean and variance of this density are given by:

$$\bar{z} = \frac{b}{a}$$

and

$$\sigma^2 = \frac{b}{a^2}$$

- **Exponential noise**

The PDF of exponential noise is given by :

$$p(z) = \begin{cases} ae^{-az} & \text{for } z \geq 0 \\ 0 & \text{for } z < 0 \end{cases}$$

The mean and variance of this density are given by:

$$\bar{z} = \frac{1}{a}$$

and

$$\sigma^2 = \frac{1}{a^2}$$

- **Uniform noise**

The PDF of uniform noise is given by :

$$p(z) = \begin{cases} \frac{1}{b-a} & \text{if } a \leq z \leq b \\ 0 & \text{otherwise} \end{cases}$$

The mean and variance of this density are given by:

$$\bar{z} = \frac{a+b}{2}$$

and

$$\sigma^2 = \frac{(b-a)^2}{12}$$

- **Impulse (salt-and-pepper) noise**

The PDF of (bipolar) impulse noise is given by :

$$p(z) = \begin{cases} P_a & \text{for } z = a \\ P_b & \text{for } z = b \\ 0 & \text{otherwise} \end{cases}$$

- **Spatial Filtering**

- **Mean Filters**

- **Arithmetic mean filter**

$$\hat{f}(x, y) = \frac{1}{mn} \sum_{(s,t) \in S_{xy}} g(s, t)$$

- **Geometric mean filter**

$$\hat{f}(x, y) = \left[\prod_{(s,t) \in S_{xy}} g(s, t) \right]^{\frac{1}{mn}}$$

- **Harmonic mean filter**

$$\hat{f}(x, y) = \frac{mn}{\sum_{(s, t) \in S_{xy}} \frac{1}{g(s, t)}}$$

- **Contraharmonic mean filter**

$$\hat{f}(x, y) = \frac{\sum_{(s, t) \in S_{xy}} g(s, t)^{Q+1}}{\sum_{(s, t) \in S_{xy}} g(s, t)^Q}$$

- **Order-Statistic Filters**

- **Median filter**

$$\hat{f}(x, y) = \operatorname{median}_{(s, t) \in S_{xy}} \{g(s, t)\}$$

- **Max and min filters**

$$\hat{f}(x, y) = \max_{(s, t) \in S_{xy}} \{g(s, t)\}$$

$$\hat{f}(x, y) = \min_{(s, t) \in S_{xy}} \{g(s, t)\}$$

- **Midpoint filter**

$$\hat{f}(x, y) = \frac{1}{2} \left[\max_{(s, t) \in S_{xy}} \{g(s, t)\} + \min_{(s, t) \in S_{xy}} \{g(s, t)\} \right]$$

- **Alpha-trimmed mean filter**

$$\hat{f}(x, y) = \frac{1}{mn - d} \sum_{(s, t) \in S_{xy}} g_r(s, t)$$

Implementation

1. The noise pattern part:

a. First clean the environment:

```
7  
8 %%%%%%%%%%%%%% The noise patterns part %%%%%%%%%%%%%%  
9  
10 % Clear the environment  
11 clc  
12 clear;
```

b. Then input the image file and get the relative information:

```
14 % Set the default location of input image file that needs to add noise  
15 noise_img_location = '../images/Fig0503 (original_pattern).tif';  
16 input_noise_img = double(imread(noise_img_location));  
17  
18 % Get the relative information of the image  
19 noise_img_info = imfinfo(noise_img_location);  
20 M = noise_img_info.Height;  
21 N = noise_img_info.Width;  
22 % For this program must be general to allow any  
23 % gray-level image, so it needs to get the depth  
24 % of the image  
25 L = noise_img_info.BitDepth;  
26
```

c. For each pattern, assign the corresponding parameters a and b, and use function noise_generator() to add the noise to the input image. To show the histogram of the noise image, use histogram drawing function in the Project1:

```
27  
28 % Generating the noise and add them to the image that needs to add noise  
29 a = 0; b = 20;  
30 uniform_noise_img = noise_generator(input_noise_img, 'uniform', L,a,b);  
31 uniform_noise_histogram = histogram(uniform_noise_img, L);  
32  
33 a = 0; b = 100;  
34 gaussian_noise_img = noise_generator(input_noise_img, 'gaussian', L,a,b);  
35 gaussian_noise_histogram = histogram(gaussian_noise_img, L);  
36  
37 a = 0; b = 400;  
38 rayleigh_noise_img = noise_generator(input_noise_img, 'rayleigh', L,a,b);  
39 rayleigh_noise_histogram = histogram(rayleigh_noise_img, L);  
40  
41 a = 0.1; b = 0.1;  
42 impulse_noise_img = noise_generator(input_noise_img, 'impulse', L,a,b);  
43 impulse_noise_histogram = histogram(impulse_noise_img, L);  
44  
45 a = 0.1; b = 1;  
46 exponential_noise_img = noise_generator(input_noise_img, 'exponential', L,a,b);  
47 exponential_noise_histogram = histogram(exponential_noise_img, L);  
48  
49 a = 0.1; b = 5;  
50 gamma_noise_img = noise_generator(input_noise_img, 'gamma', L,a,b);  
51 gamma_noise_histogram = histogram(gamma_noise_img, L);  
52  
53 input_img_histogram = histogram(input_noise_img, L);  
54
```

d. Use the function noise_figure() to show the pictures and figures:

```

55 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% Show pictures & Draw graphs %%%%%%
56
57 noise_figure(input_noise_img, input_img_histogram, 'Input Image', L, true);
58 noise_figure(uniform_noise_img, uniform_noise_histogram, 'Uniform noise', L, true);
59 noise_figure(gaussian_noise_img, gaussian_noise_histogram, 'Gaussian noise', L, true);
60 noise_figure(rayleigh_noise_img, rayleigh_noise_histogram, 'Rayleigh noise', L, true);
61 noise_figure(impulse_noise_img, impulse_noise_histogram, 'Impulse noise', L, true);
62 noise_figure(exponential_noise_img, exponential_noise_histogram, 'Exponential noise', L, true);
63 noise_figure(gamma_noise_img, gamma_noise_histogram, 'Gamma noise', L, true);
64
65

```

2. The noise generator function:

- a. First define the permitted pattern values:

```

14
15 % Define the noise patterns can be generated
16 patterns = {'uniform', 'gaussian', 'rayleigh', 'gamma', 'exponential', 'impulse'};
17

```

- b. Then get the height and width of the input image, and initialize the noise and output image:

```

17
18 % Get the height and width of the input image
19 [M,N] = size(input_img);
20
21 % Initialize the noise and output image matrice
22 noise = zeros(M,N);
23 output_img = zeros(M,N);
24

```

- c. According to the pattern, calculate the noise to be added to the input image. To avoid the negative values in the impulse image, there use some preprocessing on the output image matrix to make sure that the minimum value is zero not negative:

```

25 % Generate the noise according to the pattern and the random matrice rand(M,N)
26 switch lower(pattern)
27 case patterns{1}
28   % The uniform noise
29   noise = a + (b - a) * rand(M, N);
30 case patterns{2}
31   % The Gaussian noise
32   noise = a + sqrt(b) * randn(M, N);
33 case patterns{3}
34   % The Rayleigh noise
35   noise = a + sqrt(-b * log(1 - rand(M, N)));
36 case patterns{4}
37   % The Gamma or we say Erlang noise
38   for i = 1:b
39     noise = noise + (-1 / a) * log(1 - rand(M, N));
40   end
41 case patterns{5}
42   % The Exponential noise
43   noise = (-1 / a) * log(1 - rand(M, N));
44 case patterns{6}
45   % The impulse or we say Salt and Pepper noise
46   random = rand(M, N);
47   noise(random < a) = 1;
48   noise(random >= a & random < (a + b)) = 2^depth - 1;
49   output_img(random < a) = -input_img(random < a);
50   output_img(random >= a & random < (a + b)) = -input_img(random >= a & random < (a + b));
51 otherwise
52   error(['The', ' ', pattern, ' ', 'noise pattern can not be found.'])
53 end
54 output_img = input_img + noise + output_img;
55

```

3. The histogram function:

```

1 % Histogram of input images
2 function [ img_histogram ] = histogram(input_img, depth)
3 % Used to generate the histogram of the input image
4 % Similiar with the project 1
5 input_img = uint8(input_img);
6 img_histogram = zeros(2^depth,1);
7 for i = 1:2^depth
8     img_histogram(i) = length(find(input_img == i));
9 end
10
11 end % function
12

```

4. The noise figure function:

```

1 % Show the noise image and draw its histogram graph
2 function [] = noise_figure( input_img, histogram, img_title, depth, output_file)
3 % If needs output the image file, set the output_file to be True
4
5 figure('NumberTitle', 'off', 'Name', ['The ', ' ', lower(img_title)])
6 subplot(1,2,1)
7 imshow(uint8(input_img));
8 title(img_title)
9 subplot(1,2,2)
10 bar(histogram, 0.7);
11 xlabel('Gray Level','FontSize',16);
12 ylabel('Distribution','FontSize',16);
13 axis square
14 set(gca, 'XLim',[0 2^depth]);
15 set(gca, 'YLim',[0 3000]);
16 if (output_file == true)
17     saveas(gcf, [img_title, '.jpg'])
18 end
19 end
20

```

5. The reduciton filter part:

- a. First clean the formal environment and get the image and informations:

```

66
67 % %% %%%%%%%%%%%%%% The reduction filter part %%%%%%%%%%%%%%
68
69 % Clear the environment
70 clc
71 clear;
72
73 % the image that that to show the result of noise reduction
74 reduction_img_location = '../..//images/Circuit.tif';
75 input_reduction_img = double(imread(reduction_img_location));
76
77 % Get the relative information of the i
78 reduction_img_info = imfinfo(reduction_img_location);
79 M = reduction_img_info.Height;
80 N = reduction_img_info.Width;
81 % For this program must be general to allow any
82 % gray-level image, so it needs to get the depth
83 % of the image
84 L = reduction_img_info.BitDepth;

```

- b. Then we need to add the some noise to the image, and use the function *spatial_filter()* to reduce the noise use different spatial filters. Also use *figure* function *noise_reduction_figure()* to show the pictures and figures.

For this part, it is asked to investigate the noise reduction results using different mean filters and order statistics filters as the textbook did at pages 322-329, so I implemented the process according to the book and show the results according to the figures in the book as following:

i. Figure 5.7

```

91 %%%%%%%%%%%%%% Mean filters %%%%%%%%%%%%%%
92
93 % FIGURE 5.7 -
94 % (a) Original input image.
95 % (b) Image corrupted by additive Gaussian noise.
96 % (c) Filtering with an arithmetic mean filter of size 3 * 3.
97 % (d) Filtering with a geometric mean filter of size 3 * 3.
98 a = 0; b = 400;
99 gaussian_noise_img_400 = noise_generator(input_reduction_img, 'gaussian', L,a,b);
100 arithmetic_mean_reduction = spatial_filter(gaussian_noise_img_400, 'arithmetic_mean', 3, 3, 0);
101 geometric_mean_reduction = spatial_filter(gaussian_noise_img_400, 'geometric_mean', 3, 3, 0);
102
103 noise_reduction_figure('Figure 5.7',...
104 {input_reduction_img, gaussian_noise_img_400, arithmetic_mean_reduction, geometric_mean_reduction},...
105 {'Input image', 'Gaussian noise', 'Arithmetric mean', 'Geometric mean'},...
106 true);
107

```

ii. Figure 5.8

```

108
109 % FIGURE 5.8 - P325
110 % (a) Image corrupted by pepper noise with a probability of 0.1.
111 % (b) Image corrupted by salt noise with a probability of 0.1.
112 % (c) Filtering (a) with a 3 * 3 contraharmonic filter of order 1.5.
113 % (d) Filtering (b) with a 3 * 3 contraharmonic filter of order -1.5.
114 a = 0.1; b = 0;
115 pepper_noise_img = noise_generator(input_reduction_img, 'impulse', L,a,b);
116 a = 0; b = 0.1;
117 salt_noise_img = noise_generator(input_reduction_img, 'impulse', L,a,b);
118 contraharmonic_mean_reduction_pepper = spatial_filter(pepper_noise_img, 'contraharmonic_mean', 3, 3, 1.5);
119 contraharmonic_mean_reduction_salt = spatial_filter(salt_noise_img, 'contraharmonic_mean', 3, 3, -1.5);
120 noise_reduction_figure('Figure 5.8',...
121 {pepper_noise_img, salt_noise_img, contraharmonic_mean_reduction_pepper, contraharmonic_mean_reduction_salt},...
122 {'Pepper noise', 'Salt noise', 'Contraharmonic mean Q=1.5', 'Contraharmonic mean Q=-1.5'},...
123 true);
124

```

iii. Figure 5.9

```

125
126 % FIGURE 5.9 - P326
127 % Results of selecting the wrong sign in contraharmonic filtering.
128 % (a) Filtering Fig. 5.8(a) with a contraharmonic filter of size 3 * 3 and Q = -1.5.
129 % (b) Filtering Fig. 5.8(b) with a contraharmonic filter of size 3 * 3 and Q = 1.5.
130 wrong_contraharmonic_mean_reduction_pepper = spatial_filter(pepper_noise_img, 'contraharmonic_mean', 3, 3, -1.5);
131 wrong_contraharmonic_mean_reduction_salt = spatial_filter(salt_noise_img, 'contraharmonic_mean', 3, 3, 1.5);
132 noise_reduction_figure('Figure 5.9',...
133 {wrong_contraharmonic_mean_reduction_pepper, wrong_contraharmonic_mean_reduction_salt},...
134 {'Wrong contraharmonic mean Q=-1.5', 'Wrong contraharmonic mean Q=1.5'},...
135 true);
136

```

iv. Figure 5.10

```

139 % FIGURE 5.10 - P328
140 % (a) Image corrupted by salt-and-pepper noise with probabilities Pa=Pb=0.1.
141 % (b) Result of one pass with a median filter of size 3 * 3.
142 % (c) Result of processing (b) with this filter.
143 % (d) Result of processing (c) with the same filter.
144 a = 0.1; b = 0.1;
145 impulse_noise_img = noise_generator(input_reduction_img, 'impulse', L,a,b);
146 median_reduction_1times = spatial_filter(impulse_noise_img, 'median', 3, 3, 0);
147 median_reduction_2times = spatial_filter(median_reduction_1times, 'median', 3, 3, 0);
148 median_reduction_3times = spatial_filter(median_reduction_2times, 'median', 3, 3, 0);
149 noise_reduction_figure('Figure 5.10',...
150 {impulse_noise_img, median_reduction_1times, median_reduction_2times, median_reduction_3times},...
151 {'Pepper and salt noise', 'Median filter 1 times', 'Median filter 2 times', 'Median filter 3 times'}...
152 true);
153

```

v. Figure 5.11

```

53
54 % FIGURE 5.11 - P328
55 % (a) Result of filtering Fig. 5.8(a) with a max filter of size 3 * 3.
56 % (b) Result of filtering 5.8(b) with a min filter of the same size.
57 max_reduction = spatial_filter(pepper_noise_img, 'max', 3, 3, 0);
58 min_reduction = spatial_filter(salt_noise_img, 'min', 3, 3, 0);
59 noise_reduction_figure('Figure 5.11',...
60 {max_reduction, min_reduction},...
61 {'Max filter', 'Min filter'},...
62 true);

```

vi. Figure 5.12

```

164 % FIGURE 5.12 - P329
165 % (a) Image corrupted by additive uniform noise.
166 % (b) Image additionally corrupted by additive salt-and-pepper noise. Image (b) filtered with a 5 * 5:
167 % (c) arithmetic mean filter;
168 % (d) geometric mean filter;
169 % (e) median filter;
170 % (f) alpha-trimmed mean filter with d = 5.
171 a = -20; b = 20;
172 uniform_noise_img = noise_generator(input_reduction_img, 'uniform', L,a,b);
173 a = 0.1; b = 0.1;
174 impulse_uniform_noise_img = noise_generator(uniform_noise_img, 'impulse', L,a,b);
175 arithmetic_mean_reduction_5x5 = spatial_filter(impulse_uniform_noise_img, 'arithmetic_mean', 5, 5, 0);
176 geometric_mean_reduction_5x5 = spatial_filter(impulse_uniform_noise_img, 'geometric_mean', 5, 5, 0);
177 median_reduction_5x5 = spatial_filter(impulse_uniform_noise_img, 'median', 5, 5, 0);
178 alpha_trimmed_mean_reduction_5x5 = spatial_filter(impulse_uniform_noise_img, 'alpha_trimmed_mean', 5, 5, 5);
179 noise_reduction_figure('Figure 5.12',...
180 {uniform_noise_img, impulse_uniform_noise_img, arithmetic_mean_reduction_5x5, ...
181 geometric_mean_reduction_5x5, median_reduction_5x5, alpha_trimmed_mean_reduction_5x5},...
182 {'Uniform noise', 'Impulse noise added to uniform noise', 'Arithmetic mean 5x5', ...
183 'Geometric mean 5x5', 'Median filter 5x5', 'Alpha trimmed mean 5x5'},...
184 true);

```

6. The spatial filter function:

- First get the height and width of the input image also the mask, and padding the image with 0:

```

18
19 % Calculate the size of padding according to the size of mask
20 padding_m = floor((m - 1) / 2);
21 padding_n = floor((n - 1) / 2);
22
23 % Use zero padding to mask the boundary
24 padding_input_img = padarray(input_img, [padding_m, padding_n]);
25
26 % Get the height and width of the image
27 [M, N] = size(input_img);
28

```

- Then mask the padding input image with assigned pattern mask:

```

29 % Initialize and calculate output image
30 output_img = zeros(M, N);
31 for i = padding_m + 1:padding_m + M
32     for j = padding_n + 1:padding_n + N
33         img_in_mask = padding_input_img(i - padding_m:i + padding_m, j - padding_n:j+padding_n);
34         output_img(i - padding_m, j - padding_n) = mask(img_in_mask, pattern, m, n, parameter);
35     end
36 end
37 end
38

```

for the clear structure of the code, I take the mask process out from the main function to be a separate function mask(), it implements the detailed procession of the pixels in the mask according to the pattern:

```

patterns = {'arithmetic_mean', 'geometric_mean', 'harmonic_mean', 'contraharmonic_mean',...
    'alpha_trimmed_mean', 'median', 'max', 'min', 'midpoint'};

switch lower(pattern)
    case patterns{1}
        mask_result = sum(sum(img_in_mask)) / (m * n);
    case patterns{2}
        mask_result = prod(prod(img_in_mask)) ^ (1 / (m * n));
    case patterns{3}
        mask_result = (m * n) / (sum(sum(1 ./ img_in_mask)));
    case patterns{4}
        % mask_result = sum(img_in_mask .^ (parameter + 1)) / sum(img_in_mask .^ parameter);
        mask_result = sum(sum(img_in_mask .^ (parameter + 1))) / sum(sum(img_in_mask .^ parameter));
    case patterns{5}
        sorted_pixels = sort(img_in_mask);
        low = round(parameter / 2);
        high = parameter - low;
        sorted_pixels = sorted_pixels(low : m * n - high - 1);
        mask_result = sum(sum(sorted_pixels)) / (m * n - parameter);
    case patterns{6}
        mask_result = median(median(img_in_mask));
    case patterns{7}
        mask_result = max(max(img_in_mask));
    case patterns{8}
        mask_result = min(min(img_in_mask));
    case patterns{9}
        mask_result = (max(max(img_in_mask)) + min(min(img_in_mask))) / 2;
    otherwise
        error(['The', ' ', pattern, ' ', 'filter can not be found.'])
end
end

```

7. The noise reduction figure function:

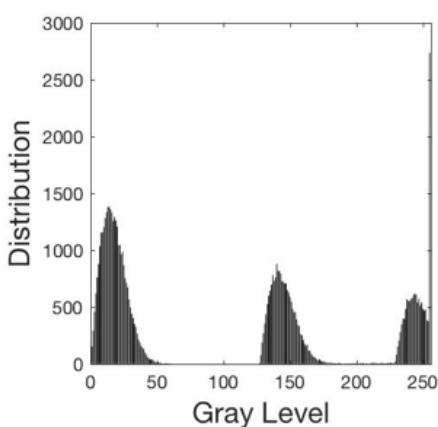
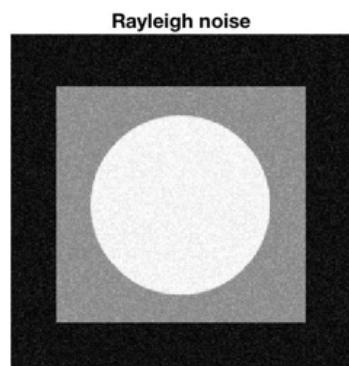
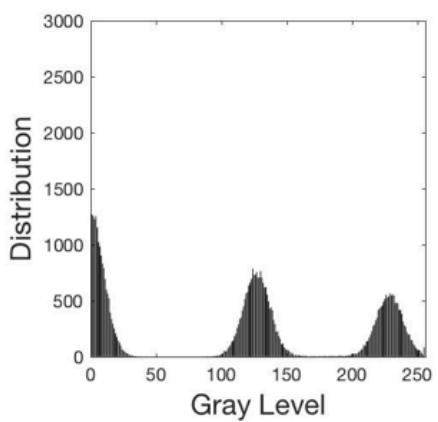
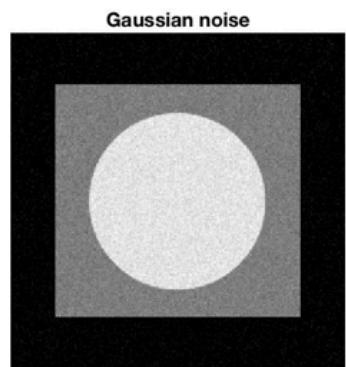
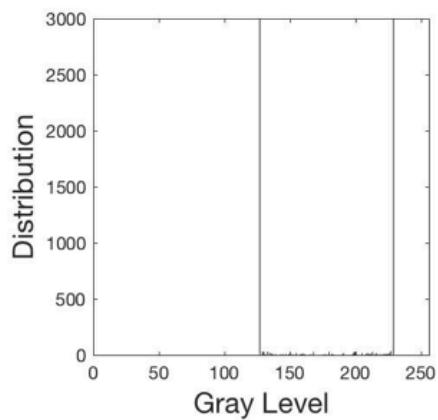
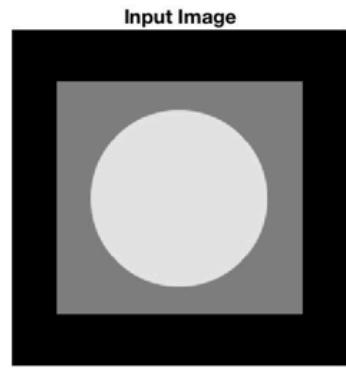
```

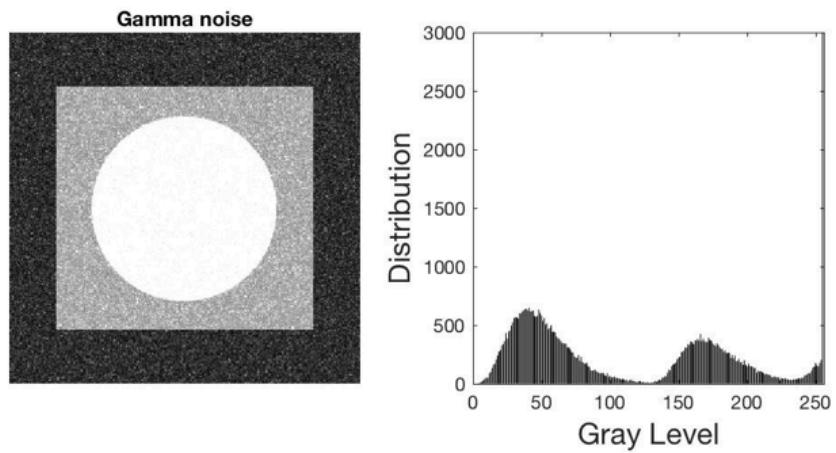
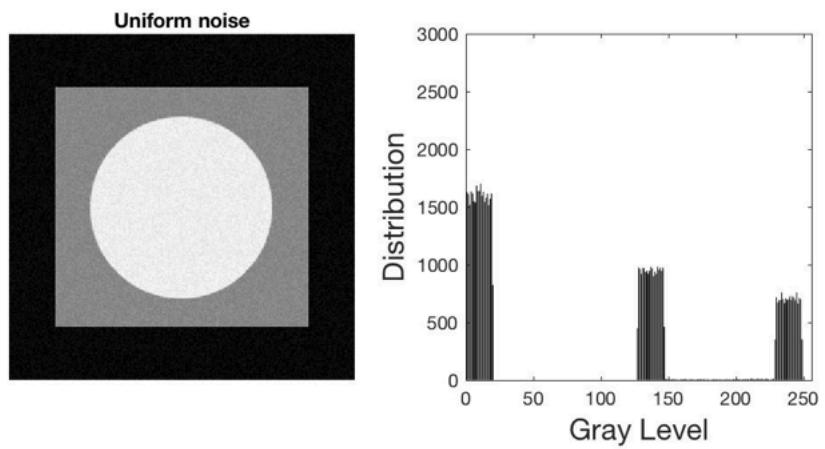
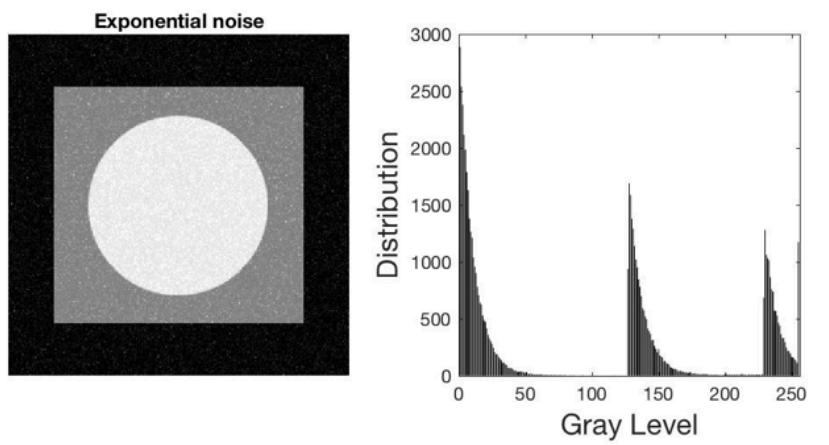
1 % Show the noise images before and after spatial filter
2 function [] = noise_reduction_figure.figure_title, images, titles, output_file)
3 % If needs output the image file, set the output_file to be True
4
5 [temp, num] = size(images);
6
7 column = 2;
8 row = floor((num + 1)/ column);
9
10 figure('NumberTitle','off','Name',figure_title)
11 for i = 0:row-1
12     for j = 1:column
13         if (i * column + j <= num)
14             subplot(row, column, i * column + j );
15             imshow(uint8(images{i * column + j}));
16             title(titles{i * column + j});
17             if (output_file == true)
18                 imwrite(uint8(images{i * column + j}), [figure_title, '-', titles{i * column + j}, '.jpg']);
19             end
20         end
21     end
22 end
23 if (output_file == true)
24     saveas(gcf, [figure_title, '.jpg']);
25 end
26 end
27

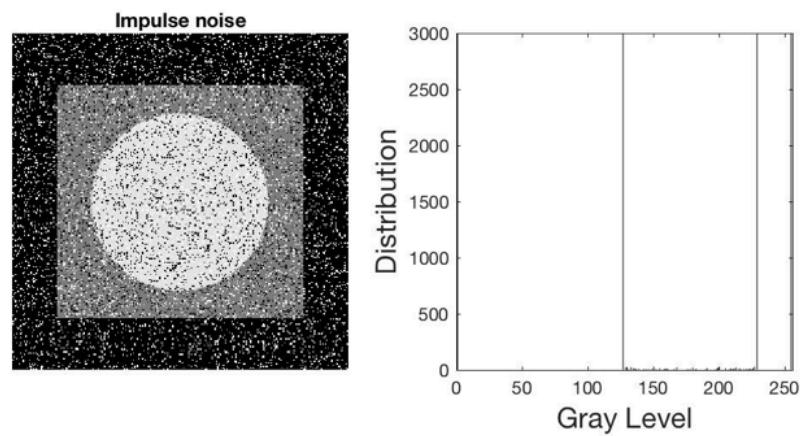
```

Result

The different-pattern noises:







The spatial filter reduction:

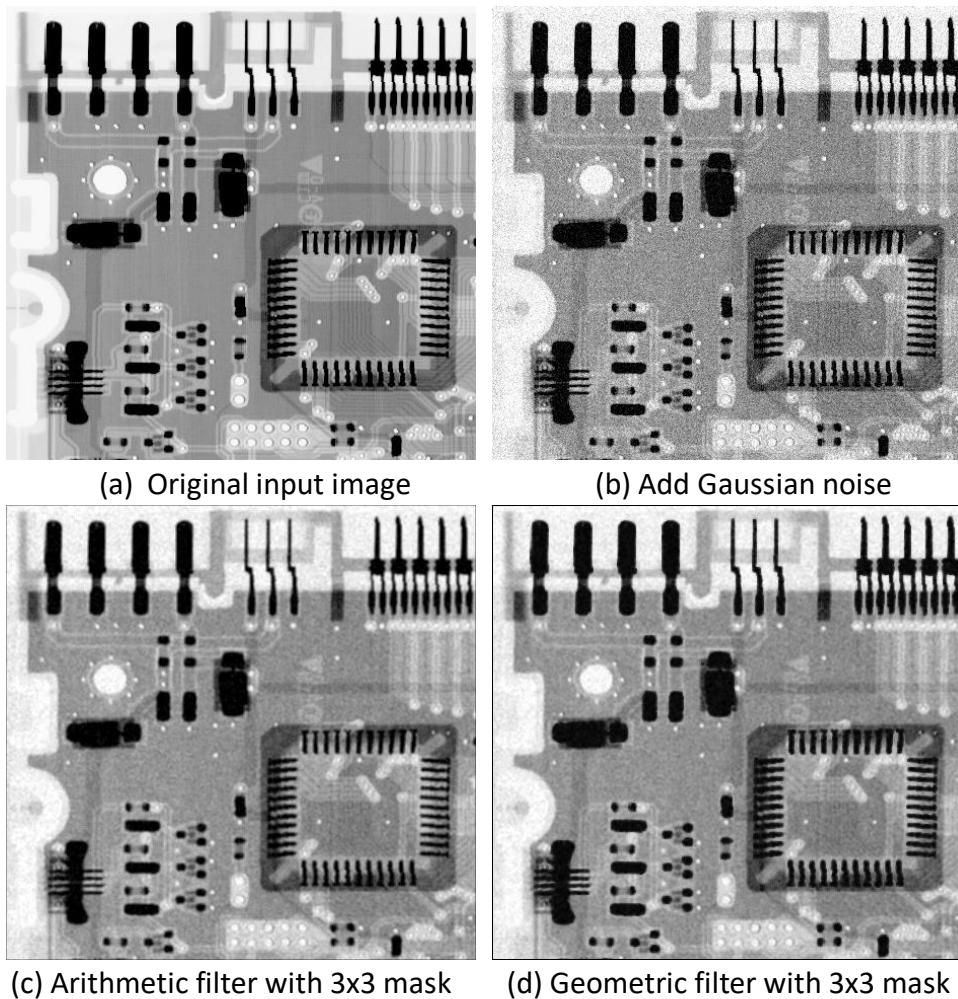


Figure 5.7 (P324)

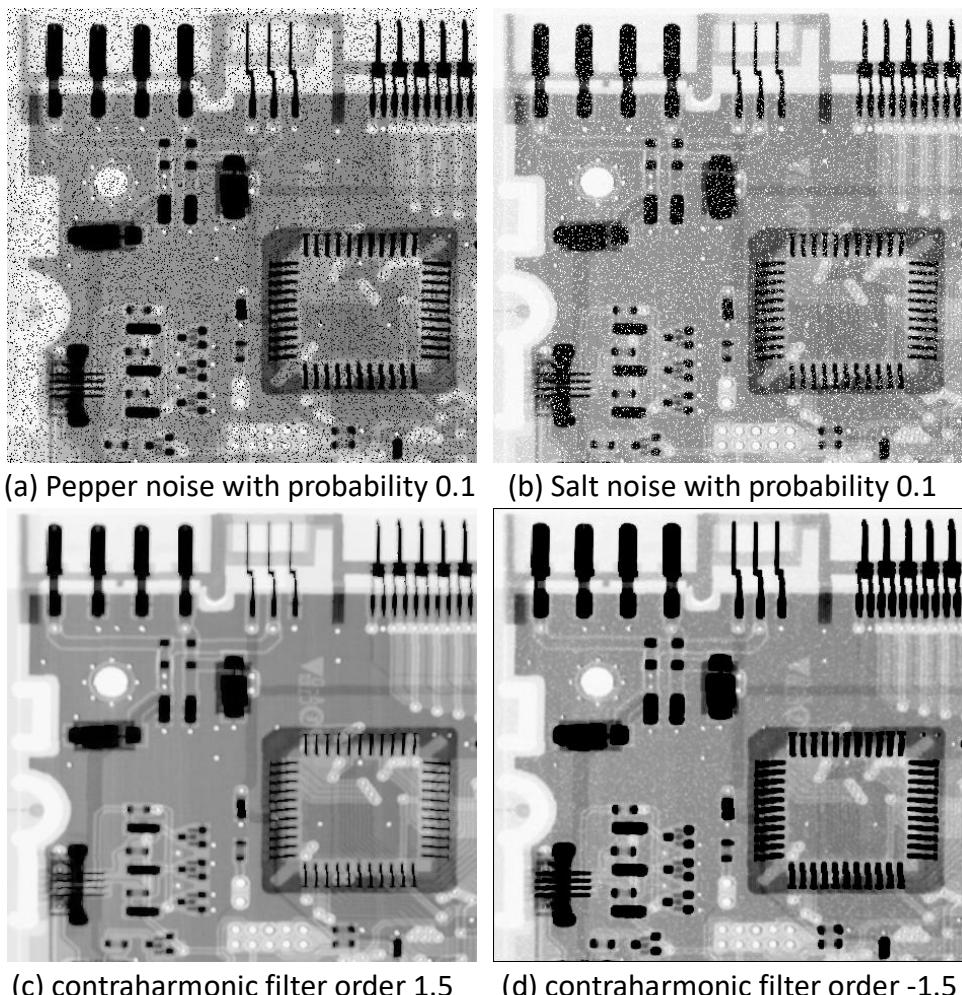


Figure 5.8 (P325)

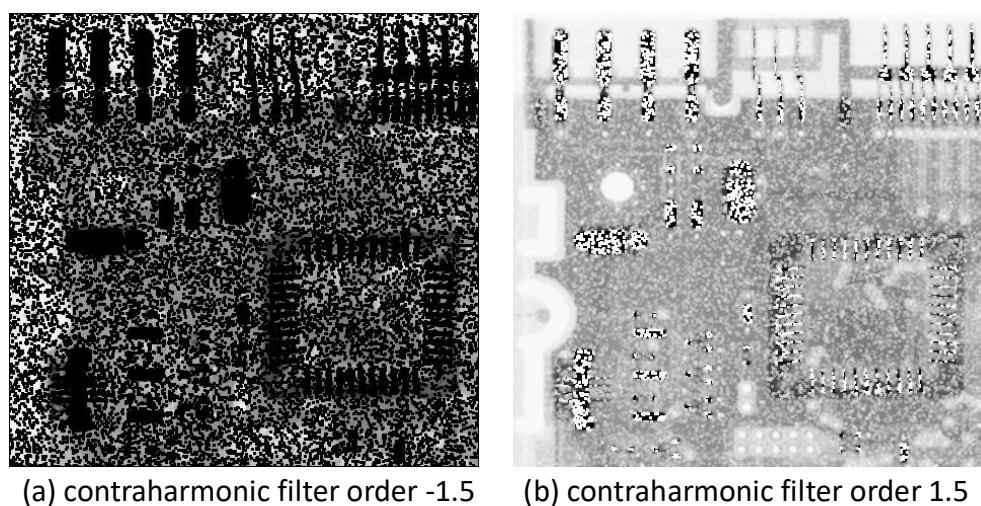


Figure 5.9 (P326)

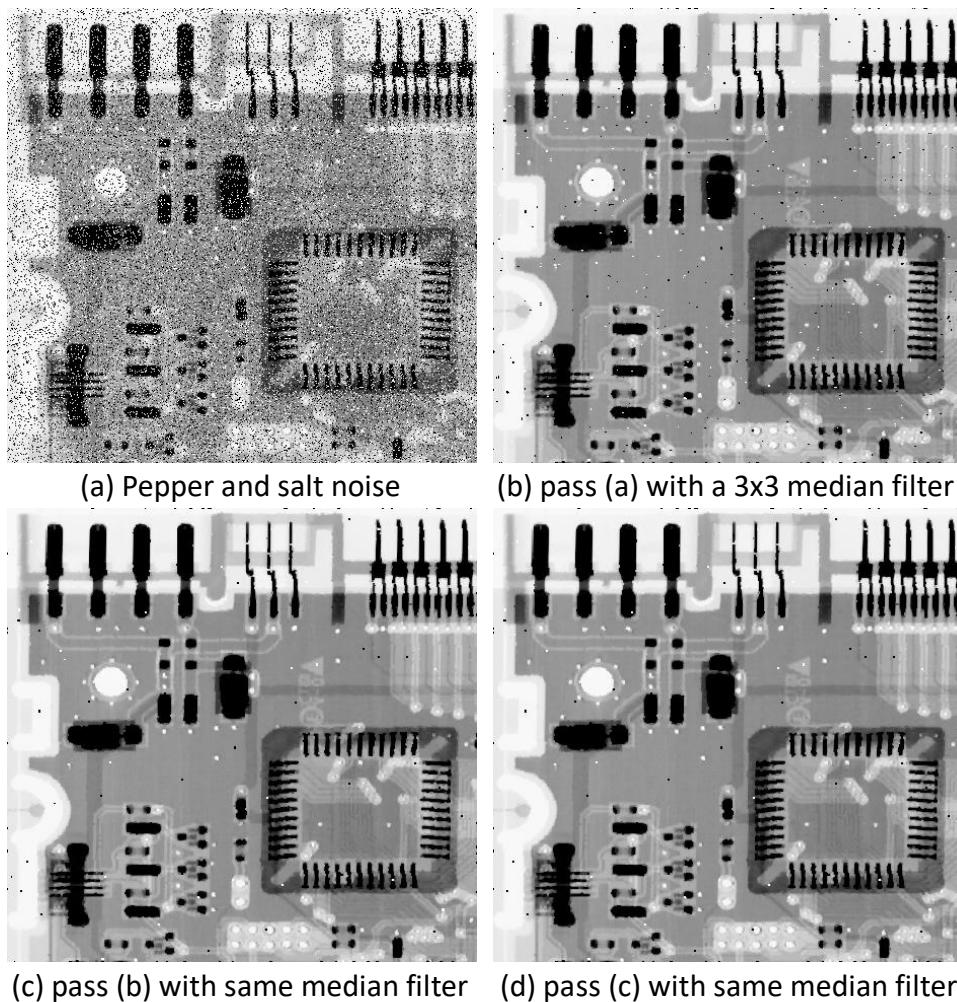


Figure 5.10 (P328)

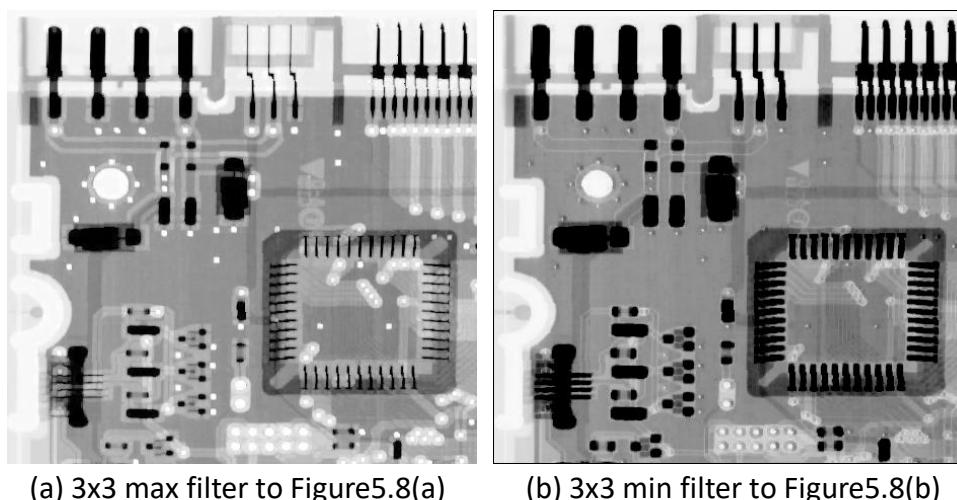


Figure 5.11 (P328)

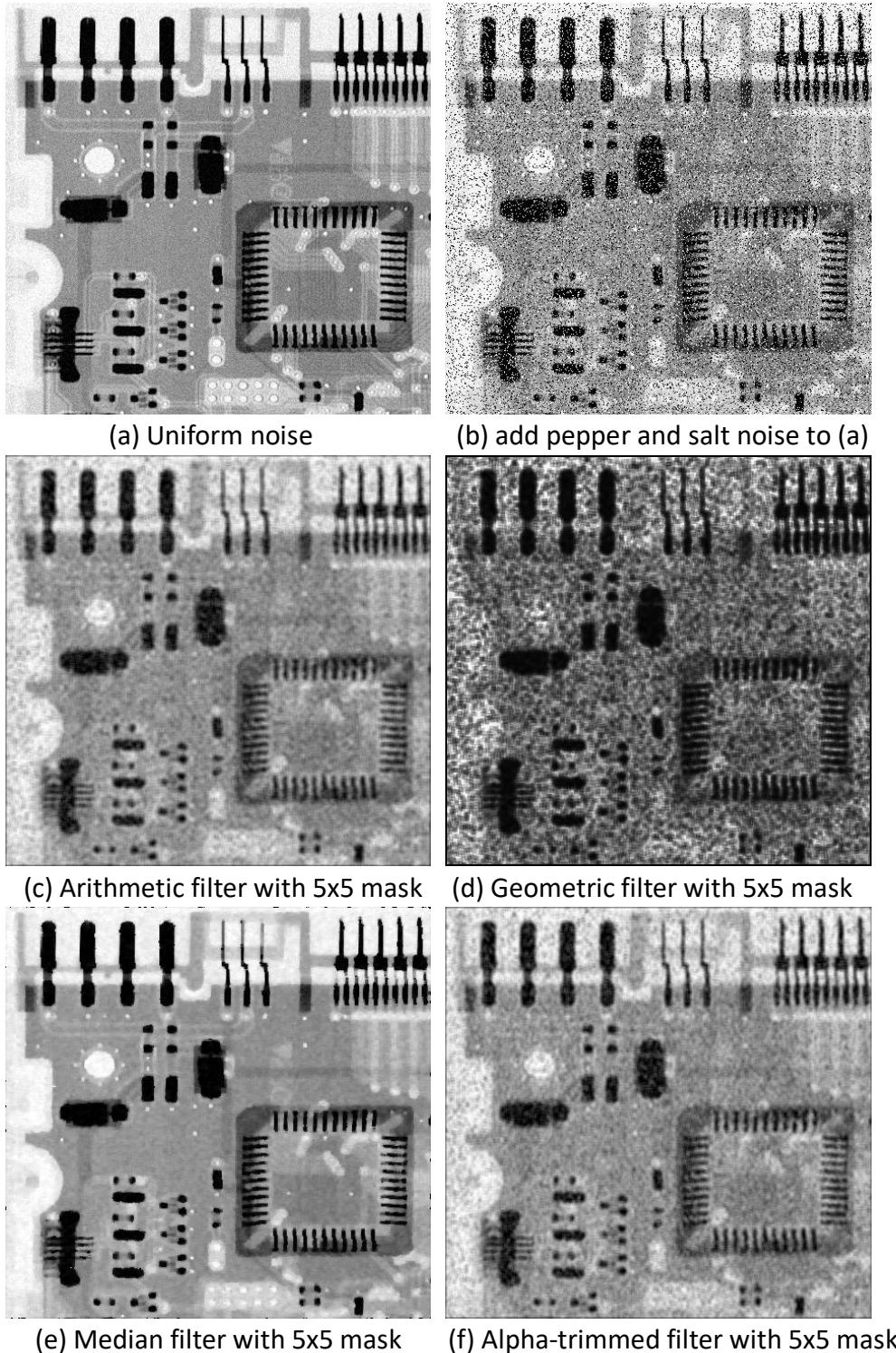


Figure 5.12 (P329)

Conclusion

We can see from the results that:

- 1) The mean filters are nice ways to reduce the noises of which the pattern has random distribution, such as uniform noise, Gaussian noise and Rayleigh noise, while, for pepper and salt noise, it is much better to use the min/max filters or the contraharmonic filter.
- 2) For exponential noise and Gamma noise, the min filter and contraharmonic are nice ways for these two noise will make the image turns to be a little bit of white.
- 3) We can use median filter many times on pepper and salt noise to get a better result compared with use it only once.

Project 5 - Image restoration

Problem

Image restoration (the test image book_cover.jpg can be found at
<ftp://ftp.cs.sjtu.edu.cn:990/lu-ht/DIP/images>)

Suppose a blurring degradation function as

$$H(u, v) = \frac{T}{\pi(ua + vb)} \sin[\pi(ua + vb)] e^{-j\pi(ua + vb)} \quad (1)$$

- (a) Implement a blurring filter using Eq. (1).
- (b) Blur the test image book_cover.jpg using parameters $a=b=0.1$ and $T = 1$.
- (c) Add Gaussian noise of 0 mean and variance of 650 to the blurred image.
- (d) Restore the blurred image and the blurred noisy image using the inverse filter, Wiener filter, respectively.
- (e) Add Gaussian noise of 0 and different variances to the blurred image and repeat
- (d) Investigate the performance of the Wiener filter .

Environment

Matlab R2016a

Atom 1.22 (with language-matlab package)

Principle

- **Blurring degradation function**

$$H(u, v) = \frac{T}{\pi(ua + vb)} \sin[\pi(ua + vb)] e^{-j\pi(ua + vb)}$$

- **Inverse filter**

The simplest approach to restoration is direct inverse filtering, where we compute an estimate, $\hat{F}(u, v)$, of the transform of the original image simply by dividing the transform of the degraded image, $G(u, v)$, by the degradation function:

$$\hat{F}(u, v) = \frac{G(u, v)}{H(u, v)}$$

But when the $H(u, v)$ turns to be very small, the result will be too large to get the output picture show normally, so we need to set a minimum for $H(u, v)$ to avoid this condition.

- **Wiener deconvolution filter (Minimum Mean Square Error Filter)**

To solve the problem caused by small $H(u, v)$ and to deal with blurred image added noise, Wiener deconvolution filter is used. The basic idea is to assume that the noise and the image are uncorrelated; that one or the other has zero mean; and that the intensity levels in the estimate are a linear function of the levels in the degraded image. Based on these conditions, the minimum of the error function is given in the frequency domain by the expression

$$\begin{aligned}\hat{F}(u, v) &= \left[\frac{H^*(u, v)S_f(u, v)}{S_f(u, v)|H(u, v)|^2 + S_\eta(u, v)} \right] G(u, v) \\ &= \left[\frac{H^*(u, v)}{|H(u, v)|^2 + S_\eta(u, v)/S_f(u, v)} \right] G(u, v) \\ &= \left[\frac{1}{H(u, v)} \frac{|H(u, v)|^2}{|H(u, v)|^2 + S_\eta(u, v)/S_f(u, v)} \right] G(u, v)\end{aligned}$$

When we are dealing with spectrally white noise, the spectrum $|N(u, v)|^2$ is a constant, which simplifies things considerably. However, the power spectrum of the undegraded image seldom is known. An approach used frequently when these quantities are not known or cannot be estimated is to approximate the formula by the expression

$$\hat{F}(u, v) = \left[\frac{1}{H(u, v)} \frac{|H(u, v)|^2}{|H(u, v)|^2 + K} \right] G(u, v)$$

Implementation

1. Clear the former environments at the beginning:

```
4 % Clear the environment
5 close all;
6 clc
7 clear;
```

2. Input the image and get the information about the image (There the location of the input image is directly assigned for convenience and it also can be assigned by the function parameter after comment this line) :

```

8
9 % Set the default location of input image file
10 img_location = '../../images/book_cover.jpg';
11 input_img = double(imread(img_location));
12
13 % Get the relative information of the image
14 info = imfinfo(img_location);
15 M = info.Height;
16 N = info.Width;
17 depth = info.BitDepth;
18

```

- First we get the dft of the input image and blur the frequency image using blurring() function. Then convert the blurred image back to the normal image:

```

19 % Blurring the input image
20 dft_input_img = fftshift(fft2(input_img));
21 blur_img = zeros(M, N);
22 for i = 1:M
23     for j = 1:N
24         % Use the H(u,v) to get the blurring with motion effects
25         H = blurring(i - M/2, j - N/2, 0.1, 0.1, 1);
26         blur_img(i,j) = dft_input_img(i,j) * H;
27     end
28 end
29 blur_img = ifft2(ifftshift(blur_img));
30 % Show the pictures and output them
31 figures...
32 {input_img, blur_img},...
33 'Bluring degradation with a=b=0.1 & T=1',...
34 {'Origin input image', 'Blurred image'},...
35 true)

```

- For the blurring function, it just need calculate the output according to the formula and avoid infinity and NaN appears in the output:

```

1 % Blurring degradation function
2 function [ output ] = blurring(u, v, a, b, T)
3 % blurring degradation function.
4
5 t = u * a + v * b;
6 output = (T / (pi * t)) * sin(pi * t) * exp(-1i * pi * t);
7
8 % when the output gets infinity or NaN, we just do nothing
9 output(isinf(output)) = 1;
10 output(isnan(output)) = 1;
11
12 end
13

```

- Then we need add the Gaussian noise to the blurred image, there I choose to add the Gaussian noise which has the variance 650, 65, 6.5 respectively to get the compare. The generation of Gaussian noise is same with the Project4 so I just use the noise_generator function in the Project4 to get the noise:

```

37 % For different variance gaussian noises
38 for variance = [650, 65, 6.5]
39     % Add gaussian noises to the blurred image
40     gaussian_img = noise_generator(blur_img, 'gaussian', 0, variance);
41

```

6. To restore the image by inverse filter, first get the dft of the image and calculate the H according to the formula, if we just directly divide H it may get very large in some condition when H is quite small. So we set a minimum threshold to avoid the H getting too small. To get the pictures similar with the textbooks we show the direct inverse result and the threshold inverse result both:

```

42 % Restore the image using the inverse filter.
43 dft.blur_img = fftshift(fft2(blur_img));
44 direct_inverse_img = zeros(M, N);
45 inverse_img = zeros(M, N);
46 for i = 1:M
47     for j = 1:N
48         H = blurring(i - M/2, j - N/2, 0.1, 0.1, 1);
49         direct_inverse_img(i,j) = (dft.blur_img(i,j) / H);
50         % For there with be conditions H = 0
51         % we need to set a threshold such as 0.001
52         if abs(H) < 0.001
53             H = 0.001;
54         end
55         inverse_img(i,j) = (dft.blur_img(i,j) / H);
56     end
57 end
58 direct_inverse_img = uint8(real(ifft2(ifftshift(direct_inverse_img))));
59 inverse_img = uint8(real(ifft2(ifftshift(inverse_img))));
60

```

7. It's similar for the process of restoring by wiener filter:

```

61 % Restore the image using wiener deconvolution filters.
62 dft.gaussian_img = fftshift(fft2(gaussian_img));
63 wiener_img = zeros(M, N);
64 for i = 1:M
65     for j = 1:N
66         H = blurring(i - M/2, j - N/2, 0.1, 0.1, 1);
67         wiener_img(i,j) = (dft.gaussian_img(i,j) / H) * (abs(H)^2 / (abs(H)^2 + 0.01));
68     end
69 end
70 wiener_img = uint8(real(ifft2(ifftshift(wiener_img))));
71

```

8. At last we show them all:

```

71 % Show the pictures and output them
72 figures...
73 {gaussian_img, direct_inverse_img, inverse_img, wiener_img},...
74 ['Restore the image with gaussian noise(var=', int2str(variance), "')'],...
75 {[['Gaussian noise image(var=', int2str(variance), "')'], ['Direct inverse restore (var=',...
76     int2str(variance), "')'], ['Inverse restore (var=', int2str(variance), "')'], ['Wiener restore...',...
77     K = 0.01(variance, int2str(variance), "')']},...
78     true)
79 end
80
81

```

9. To investigate the performance of the wiener filter, I choose K = 0.1, 0.01, 0.001 and 0.0001 to restore a blurred image adding Gaussian noise with variance 65. By comparing the result of these result we can investigate the performance of the wiener filter:

```

81
82 % Investigate the performance of wiener filter
83 % Add gaussian noises to the blurred image
84 gaussian_img = noise_generator(blur_img, 'gaussian', depth, 0, 65);
85
86 for K = [0.1, 0.01, 0.001, 0.0001]
87 % Restore the image using wiener deconvolution filters.
88 dft_gaussian_img = fftshift(fft2(gaussian_img));
89 wiener_img = zeros(M, N);
90 for i = 1:M
91 for j = 1:N
92 H = blurring(i - M/2, j - N/2, 0.1, 0.1, 1);
93 wiener_img(i,j) = (dft_gaussian_img (i,j) / H) * (abs(H)^2 / (abs(H)^2 + K));
94 end
95 end
96 wiener_img = uint8(real(ifft2(ifftshift(wiener_img))));
97
98 % Show the pictures and output them
99 figures({wiener_img}, {'Restore the image using wiener filter(K=', num2str(K), "')"}, ...
100 {[['Wiener filter(K=', num2str(K), ')']]}, true)
101 end

```

10. For all the pictures and figures, I use the figure function similar with the former project to show:

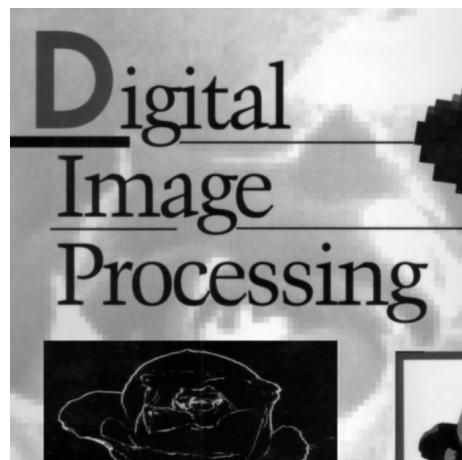
```

5 figure('NumberTitle','off','Name', figure_title)
6 column = 2;
7 [temp, num] = size(input_imgs);
8 row = ceil(num / column);
9
10 for i = 1:row
11 for j = 1:column
12 if((i - 1)* column + j) <= num
13 subplot(row, column, (i - 1)* column + j)
14 imshow(uint8(input_imgs{(i - 1) * column + j}),[])
15 title(char(image_titles{(i - 1) * column + j}))
16 if output_file
17 imwrite(uint8(input_imgs{(i - 1) * column + j}), [char(image_titles{(i - 1) * column + j}), '.jpg']);
18 end
19 end
20 end
21 end

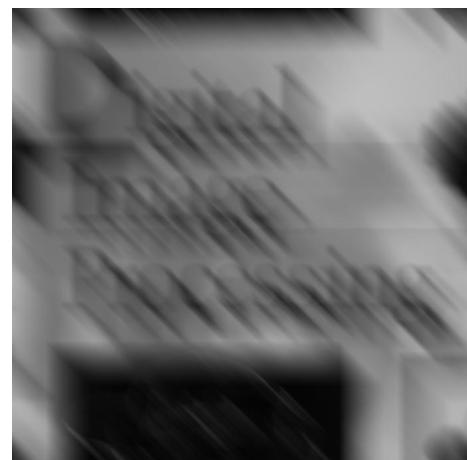
```

Result

- Blur the test image:

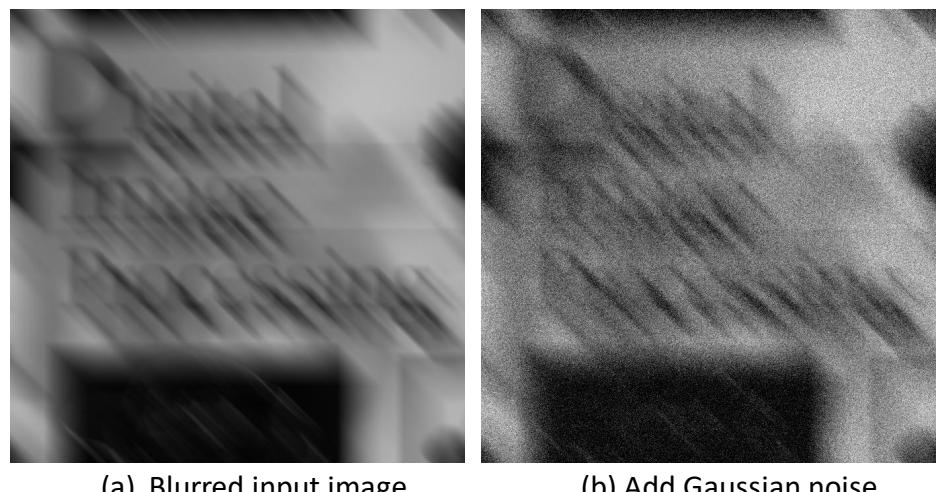


(a) Original input image

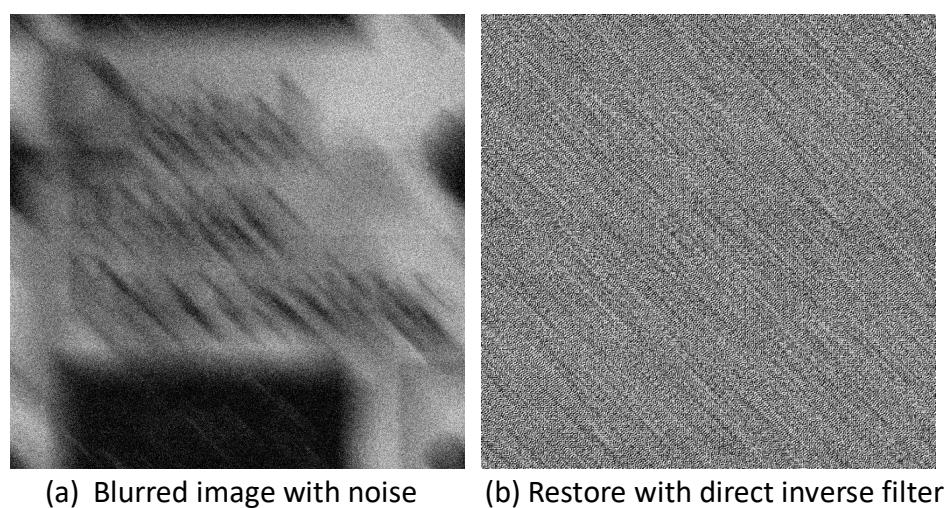


(b) Motion blurring (a)

- Add Gaussian noise with variance 650



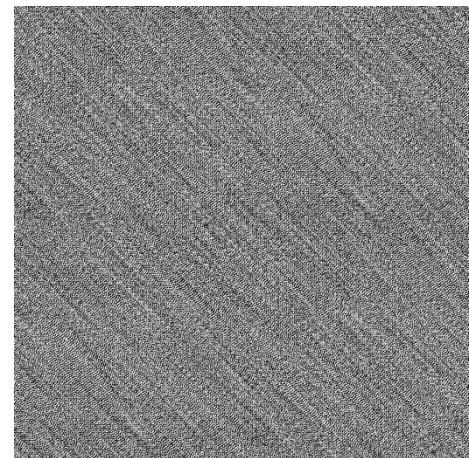
- Restore the variance 650 Gaussian noise image using different filters



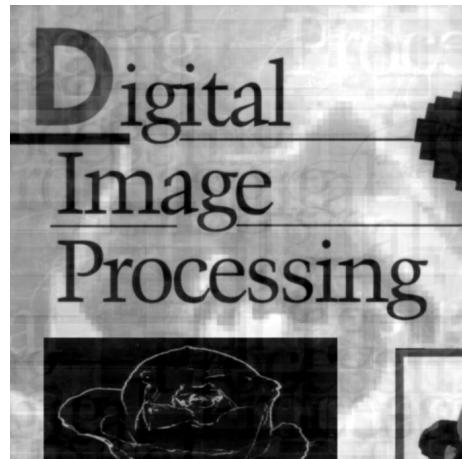
- Restore the variance 65 Gaussian noise image using different filters



(a) Blurred image with noise



(b) Restore with direct inverse filter

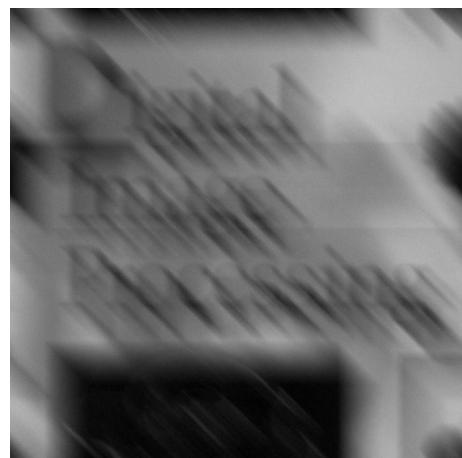


(c) Restore with threshold inverse filter

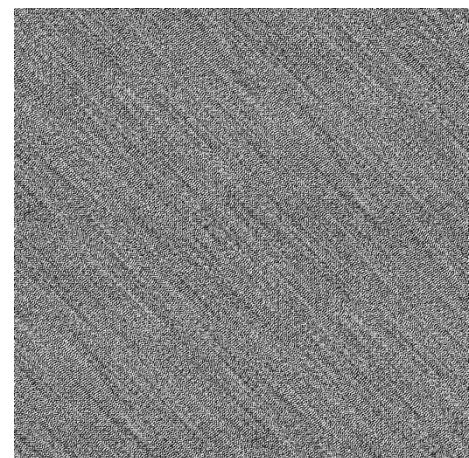


(d) Restore with wiener filter

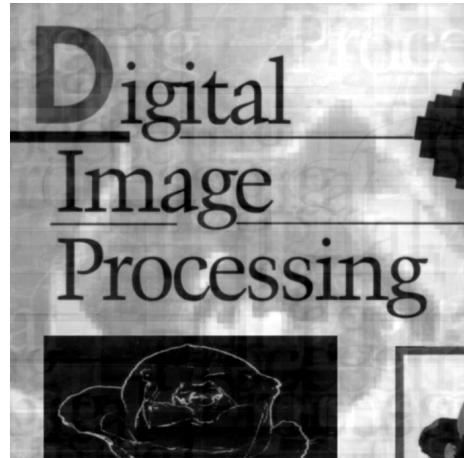
- Restore the variance 6.5 Gaussian noise image using different filters



(a) Blurred image with noise



(b) Restore with direct inverse filter



(c) Restore with threshold inverse filter



(d) Restore with wiener filter

- **Restore the variance 65 Gaussian noise image using wiener filter with different K value**



(a) $K = 0.1$



(b) $K = 0.01$



(c) $K = 0.001$



(d) $K = 0.0001$

Conclusion

We can see from the results that:

- 1) The direct inverse filter will totally damage the process of restoring because of the small H, after setting a threshold, this problem can be avoided but the restore effect is not very nice.
- 2) The wiener filter can get a better result relatively. But if the value of K gets too small there still will be a lot of noise, while if the value of K gets too big the image will still be blurred. Therefore the K needs to be adjusted according to actual conditions.

Project 6 - Geometric transform

Problem

Develop a geometric transform program that will rotate, translate, and scale an image by specified amounts, using the nearest neighbor and bilinear interpolation methods, respectively.

Environment

Matlab R2016a
Atom 1.22 (with language-matlab package)

Principle

- **Spatial transformation**

The spatial transformation defines the spatial relationship between points in the input image and points in the output image.

$$g(x, y) = f(x', y') = f[a(x, y), b(x, y)]$$

- **Translate**

$$a(x, y) = x + x_0 \quad b(x, y) = y + y_0$$

Can be expressed in homogeneous coordinates as

$$\begin{bmatrix} a(x, y) \\ b(x, y) \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & x_0 \\ 0 & 1 & y_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

- **Scale**

$$a(x, y) = x/c \quad b(x, y) = y/d$$

Homogeneous form

$$\begin{bmatrix} a(x, y) \\ b(x, y) \\ 1 \end{bmatrix} = \begin{bmatrix} 1/c & 0 & 0 \\ 0 & 1/d & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

When $c = -1, d = 1$: reflection about the y-axis

$$a(x, y) = -x \quad b(x, y) = y$$

- **Rotate**

$$a(x, y) = x \cos(\theta) - y \sin(\theta)$$

$$b(x, y) = x \sin(\theta) + y \cos(\theta)$$

$$\begin{bmatrix} a(x, y) \\ b(x, y) \\ 1 \end{bmatrix} = \begin{bmatrix} \cos(\theta) & -\sin(\theta) & 0 \\ \sin(\theta) & \cos(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

- **Gray-level interpolation methods**

Gray-level interpolation is necessary because the gray-level values are defined only at integral values of x and y , however, spatial transformation may make the output image $g(x, y)$ taking values at fractional positions of $a(x, y)$ and $b(x, y)$

- **Nearest neighbor interpolation**

The gray level of the output pixel is taken to be that of the input pixel nearest the location to which the output pixel maps.

- **Bilinear interpolation**

For a function $f(x, y)$ of two variables, given its values at four vertices of the unit square $f(0,0)$, $f(0,1)$, $f(1,0)$ and $f(1,1)$, we desire to determine the value of $f(x, y)$ at an arbitrary point inside the square. This can be done by a hyperbolic paraboloid defined by the bilinear equation

$$f(x, y) = ax + by + cxy + d$$

$$f(x, y) = (f(1,0) - f(0,0))x + [f(0,1) - f(0,0)]y + [f(1,1) + f(0,0) - f(0,1) - f(1,0)]xy + f(0,0)$$

Implementation

1. Clear the former environments at the beginning:

```
4 % Clear the environment
5 close all;
6 clc
7 clear;
```

2. Input the image and get the information about the image (There the location of the input image is directly assigned for convenience and it also can be assigned by the function parameter after comment this line) :

```

9 % Set the default location of input image file
10 img_location = '.../images/ray_trace_bottle.tif';
11 input_img = double(imread(img_location));
12
13 % Get the relative information of the image
14 info = imfinfo(img_location);
15 M = info.Height;
16 N = info.Width;
17

```

3. Define the allowed patterns of spatial transformations and interpolation methods, also assign the parameters will be tested:

```

17
18 % Define the spatial transformation and interpolation patterns
19 transform_patterns = { 'translate', 'rotate', 'scale' };
20 interpolate_patterns = {'nearest', 'bilinear'};
21
22 % Get all the parameters according to the order of the patterns
23 all_parameters = {...
24 {[200,300], [-200,300]}, ...
25 {[90,0],[30,0],[45,0]}, ...
26 {[1,1.2],[2,1],[3,3]}...
27 };
28

```

4. For each spatial transformation and interpolation methods, we test with the a set of parameters using function spatial_transform:

```

29
30 % All three spatial transformation patterns and two interpolation patterns
31 % Get the output image and resize the output image to avoid cropping
32 for i = 1:3
33     transform_pattern = transform_patterns{i};
34     parameters = all_parameters{i};
35     for parameter = parameters
36         nearest_img = spatial_transform(input_img, transform_pattern, 'nearest', false, parameter{1});
37         resize_nearest_img = spatial_transform(input_img, transform_pattern, 'nearest', true, parameter{1});
38         bilinear_img = spatial_transform(input_img, transform_pattern, 'bilinear', false, parameter{1});
39         resize_bilinear_img = spatial_transform(input_img, transform_pattern, 'bilinear', true, parameter{1});
40

```

5. The spatial transform function

- a. we first get the transformation matrix T according to the pattern. Because for some transformations, the image size will change so it needs to resize the output image size according to the resize flag.

```

25 switch lower(char(transform_pattern))
26 case transform_patterns{1}
27     % Translate
28     T = [1, 0, 0;
29           0, 1, 0;
30           parameters(1), parameters(2), 1];
31
32     % Calculate inverse matrix of T.
33     T = inv(T);
34
35     % Resize the image to avoid the crop
36     if resize
37         H = M + abs(parameters(1));
38         W = N + abs(parameters(2));
39     end
40
41 case transform_patterns{2}
42     % Rotate
43

```

```

44     parameter = (parameters(1) / 180) * pi;
45     % For positive x-axis points down in matlab coordinates, and rotating
46     % from x to y means counter clockwise, so there needs to inverse T.
47     T = [cos(parameter), sin(parameter), 0;
48           -sin(parameter), cos(parameter), 0;
49           0, 0, 1];
50
51     % Resize the image to avoid the crop
52     if resize
53         H = ceil(sqrt(M^2 + N^2) + 2);
54         W = H;
55     end
56     parameter(1) = 0;
57     parameter(2) = 0;
58
59     case transform_patterns{3}
60         % Scale
61
62         T = [parameters(1), 0, 0;
63               0, parameters(2), 0;
64               0, 0, 1];
65
66         T = inv(T);
67
68         % Resize the image to avoid the crop
69         if resize
70             H = ceil(M * parameters(1));
71             W = ceil(N * parameters(2));
72         end
73
74         parameters(1) = 0;
75         parameters(2) = 0;

```

- b. Then we get the output image by multiply the transform matrix T and use function interpolation() to interpolate:

```

81
82     % Get the output image by the matrix T
83     output_img = zeros(H, W);
84     for i = -H/2 + 1:H/2
85         for j = -W/2 + 1:W/2
86             p = [i j 1] * T;
87             % Add the offset
88             u = p(1) + (M + parameters(1))/2;
89             v = p(2) + (N + parameters(2))/2;
90             if u >= 1 && u <= M && v >= 1 && v <= N
91                 output_img(i + H/2, j + W/2) = interpolation(input_img, interpolate_pattern, u, v);
92             end
93         end
94     end
95
96     % Transform the data type to be uint8
97     output_img = uint8(output_img);
98

```

- c. For rotate transformation, it will generate invalid black border, so we remove it at last:

```

99     % Cut off invalid black border.
100    if (strcmp(char(transform_pattern), 'rotate') && resize)
101        fy = find(max(output_img));
102        fx = find(max(output_img, [], 2));
103        output_img = output_img(min(fx):max(fx), min(fy):max(fy));
104    end

```

6. The interpolation function

We can just calculate according to the formula, there we directly use (round(x), round(y)) to find the nearest point:

```

16 % Get the interpolation result according to the pattern
17 switch lower(char(pattern))
18 case patterns{1}
19 % nearest
20 % There use the round(x), round(y) to find the nearest point
21 output = input_img(round(x), round(y));
22 case patterns{2}
23 % bilinear
24 xm = floor(x);
25 ym = floor(y);
26 if x == xm && y == ym
27     output = input_img(x, y);
28 elseif x == xm && y ~= ym
29     output = (y - ym) * input_img(x, ym + 1) + (ym + 1 - y) * input_img(x, ym);
30 elseif x ~= xm && y == ym
31     output = (x - xm) * input_img(xm + 1, y) + (xm + 1 - x) * input_img(xm, y);
32 else
33     t1 = (x - xm) * input_img(xm + 1, ym) + (xm + 1 - x) * input_img(xm, ym);
34     t2 = (x - xm) * input_img(xm + 1, ym + 1) + (xm + 1 - x) * input_img(xm, ym + 1);
35     output = (y - ym) * t2 + (ym + 1 - y) * t1;
36 end
37 otherwise
38     error(['The', ' ', pattern, ' ', 'interpolation pattern can not be found.'])
39 end

```

7. For the output is relatively regular so just direct show the pictures and output the file:

```

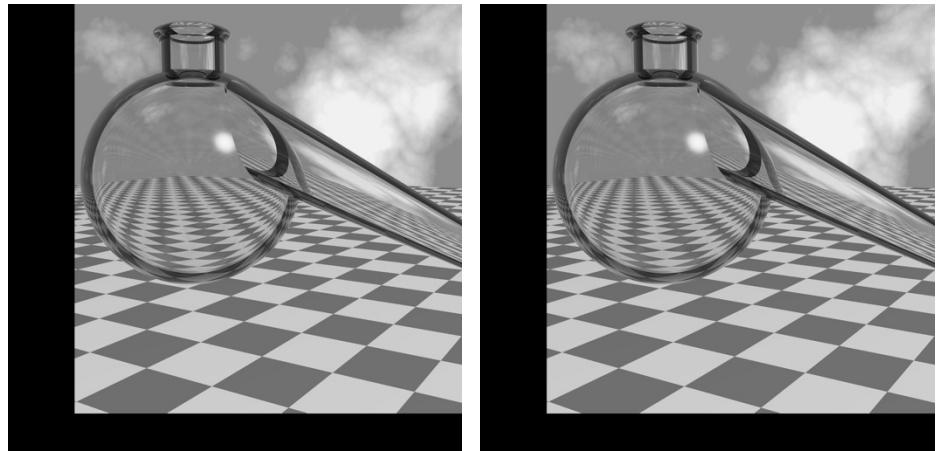
41 %%%%%%%%%%%%%% Show pictures %%%%%%%%%%%%%%
42 figure('NumberTitle', 'off', 'Name', ['The ', ' ', char(transform_pattern), ' transform'])
43 if strcmp(char(transform_pattern), 'rotate')
44     img_title = [int2str(parameter{1}(1)), ' degree'];
45 else
46     img_title = [int2str(parameter{1}(1)), ',', int2str(parameter{1}(2))];
47 end
48 subplot(2,2,1);
49 imshow(nearest_img);
50 title(['nearest - ', img_title]);
51 subplot(2,2,2);
52 imshow(resize_nearest_img);
53 title('After resize');
54 subplot(2,2,3);
55 imshow(bilinear_img);
56 title(['bilinear - ', img_title]);
57 subplot(2,2,4);
58 imshow(resize_bilinear_img);
59 title('After resize');

60 %%%%%%%%%%%%%% Output the file %%%%%%%%%%%%%%
61 imwrite(nearest_img, ['nearest - ', img_title, '.jpg']);
62 imwrite(resize_nearest_img, ['resize nearest - ', img_title, '.jpg']);
63 imwrite(bilinear_img, ['bilinear - ', img_title, '.jpg']);
64 imwrite(resize_bilinear_img, ['resize bilinear - ', img_title, '.jpg']);
65
66 end

```

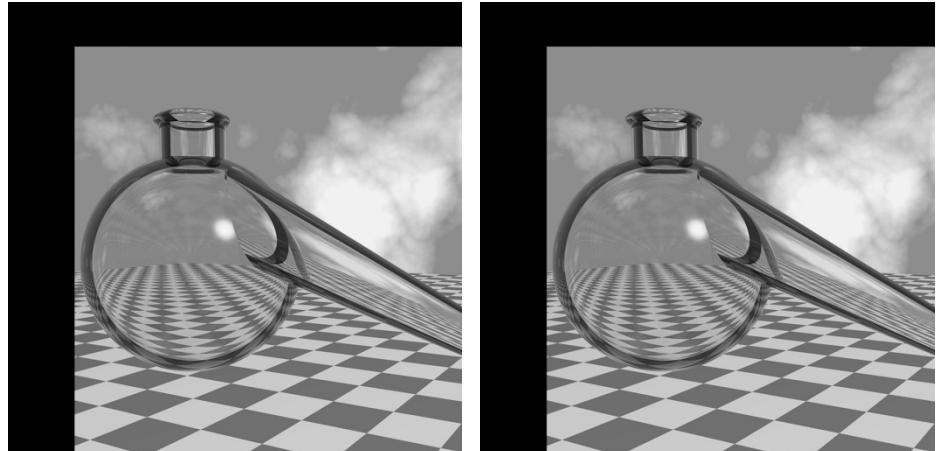
Result

- **Translate**



(a) Translate (300,200) - nearest

(b) Translate (300,200) - bilinear

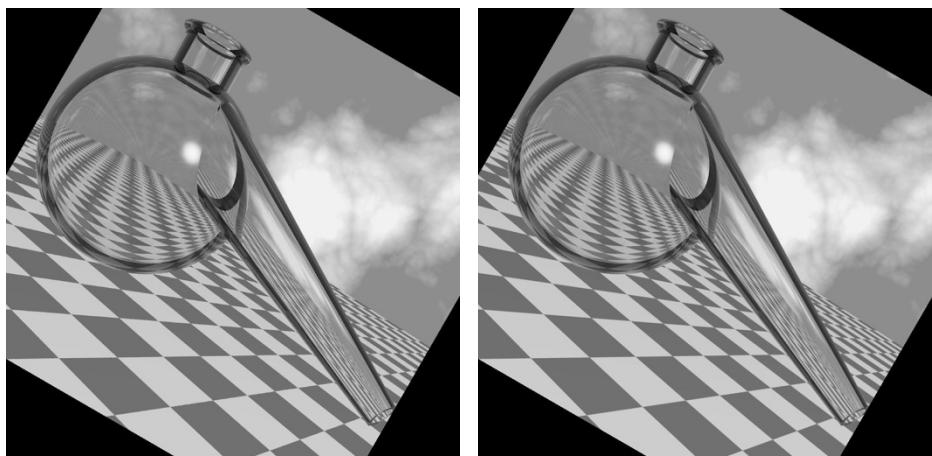


(c) Translate (300,-200) - nearest

(d) Translate (300,-200) - bilinear

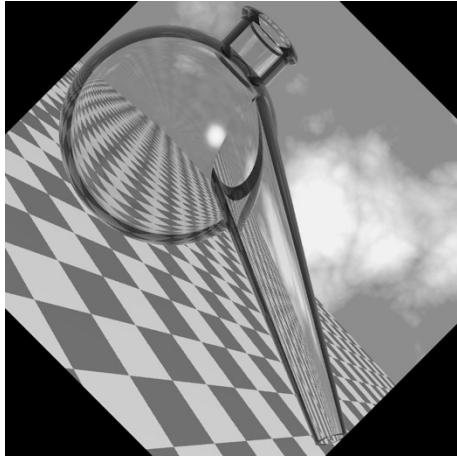
- **Rotate**

- **Cropped**

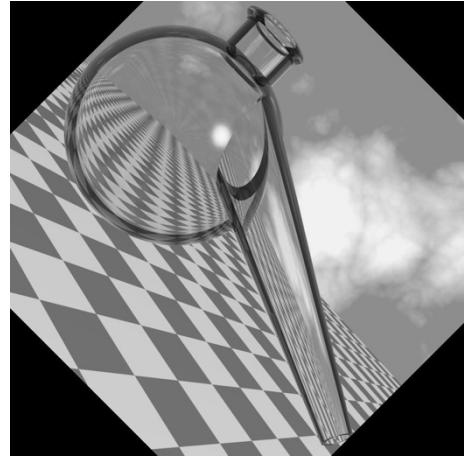


(a) Rotate 30 degree - nearest

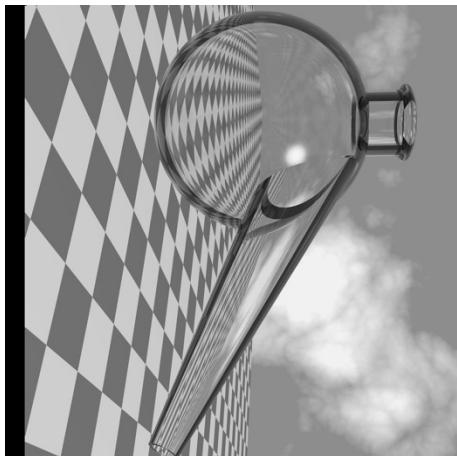
(b) Rotate 30 degree - bilinear



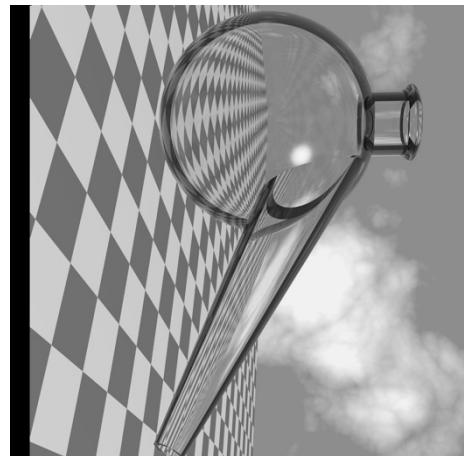
(c) Rotate 60 degree - nearest



(d) Rotate 60 degree - bilinear

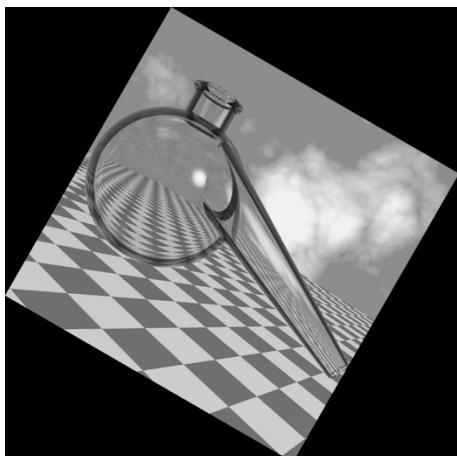


(e) Rotate 90 degree - nearest

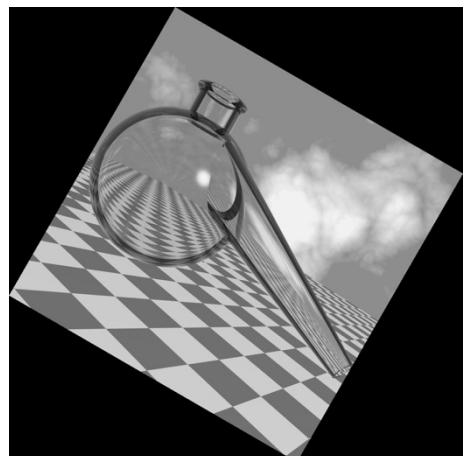


(f) Rotate 90 degree - bilinear

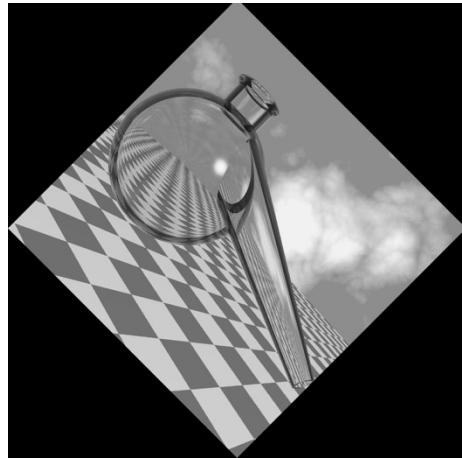
- **Resized**



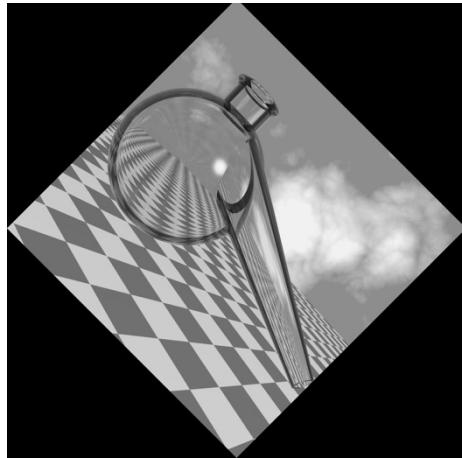
(a) Rotate 30 degree - nearest



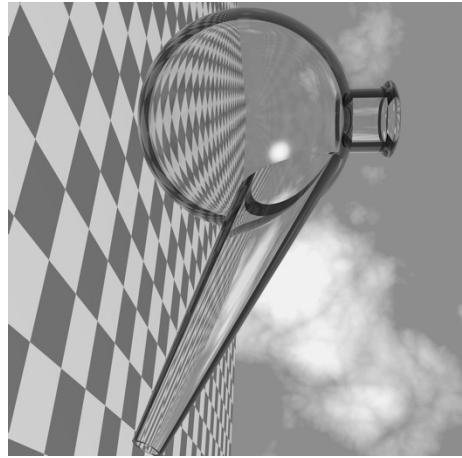
(b) Rotate 30 degree - bilinear



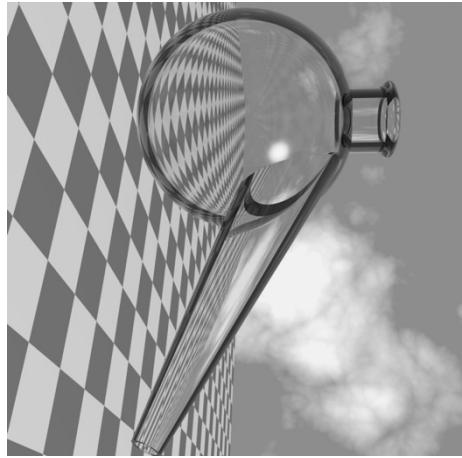
(c) Rotate 60 degree - nearest



(d) Rotate 60 degree - bilinear



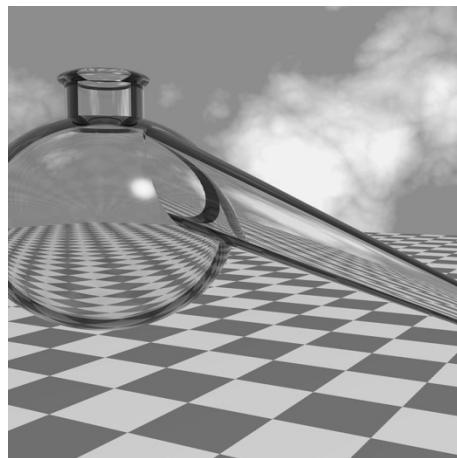
(e) Rotate 90 degree - nearest



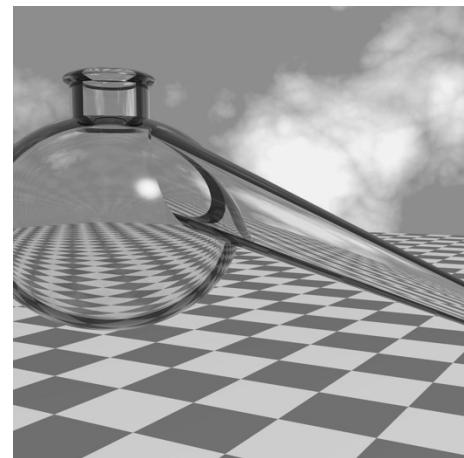
(f) Rotate 90 degree - bilinear

- **Scale**

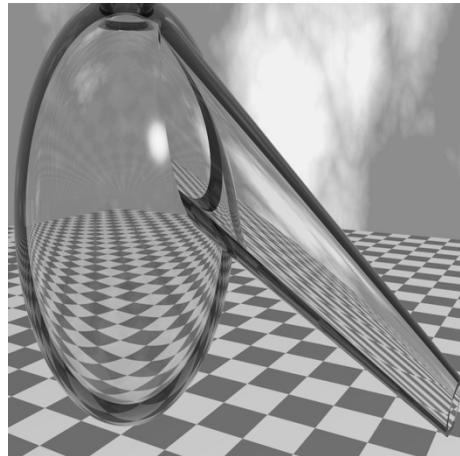
- **Cropped**



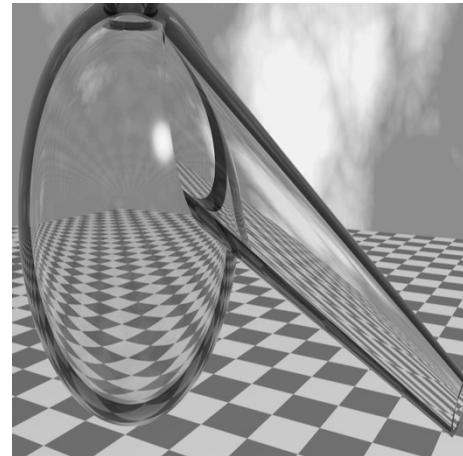
(a) Scale (1,1.2) - nearest



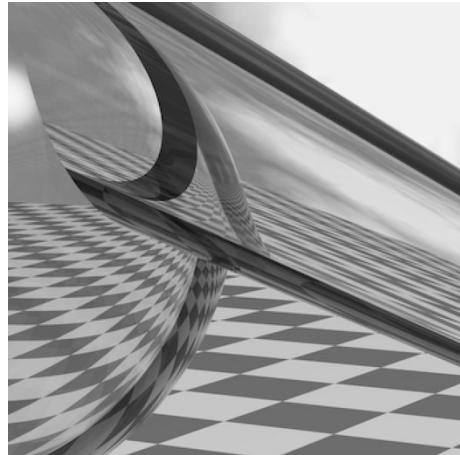
(b) Scale (1,1.2) - bilinear



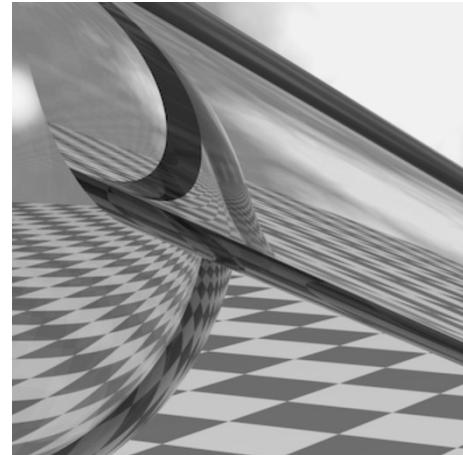
(c) Scale (2,1) - nearest



(d) Scale (2,1) - bilinear

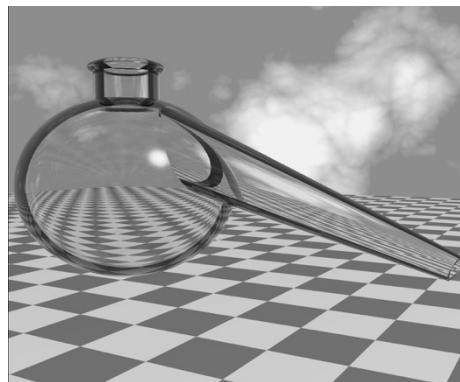


(e) Scale (3,3) - nearest

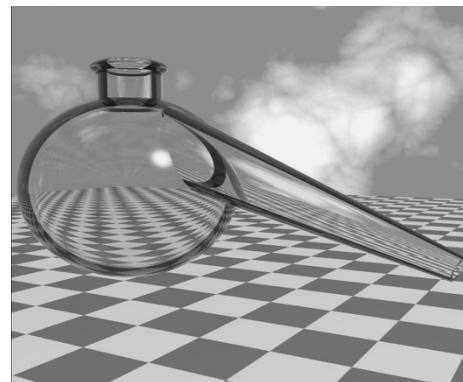


(f) Scale (3,3) - bilinear

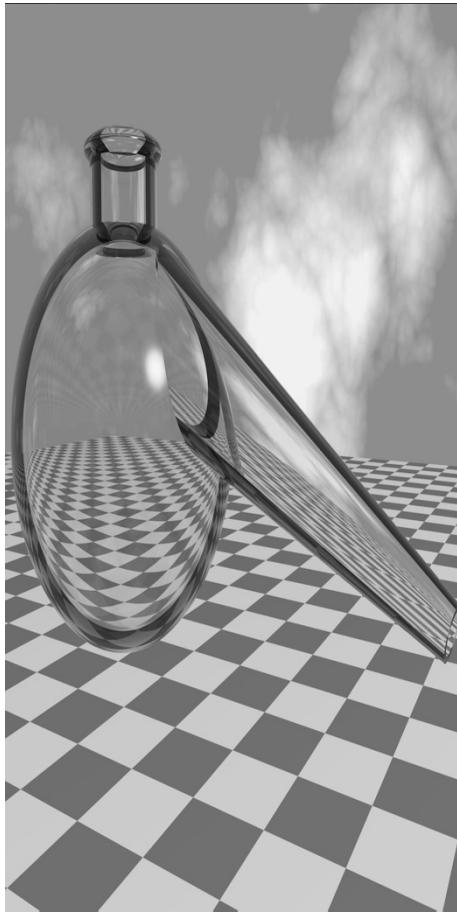
○ **Resized**



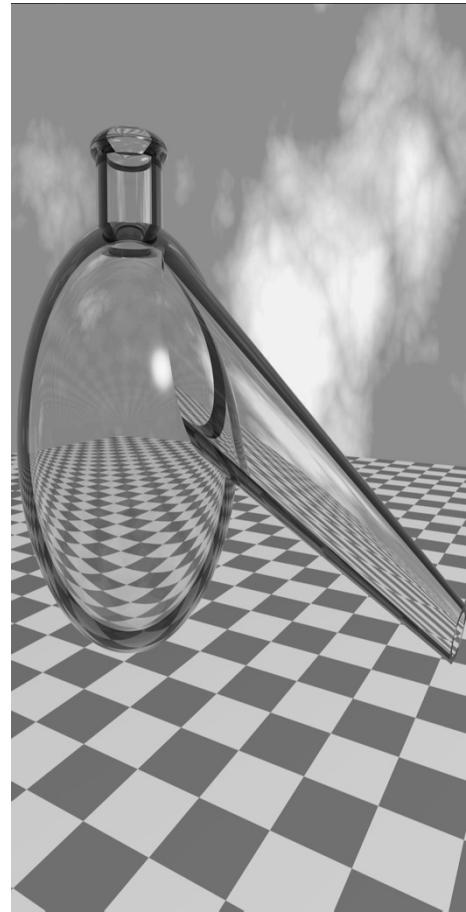
(a) Scale (1,1.2) - nearest



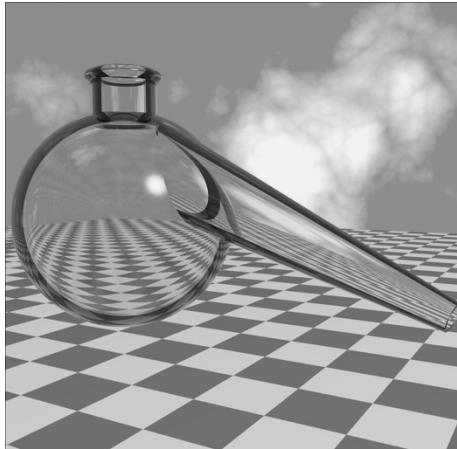
(b) Scale (1,1.2) - bilinear



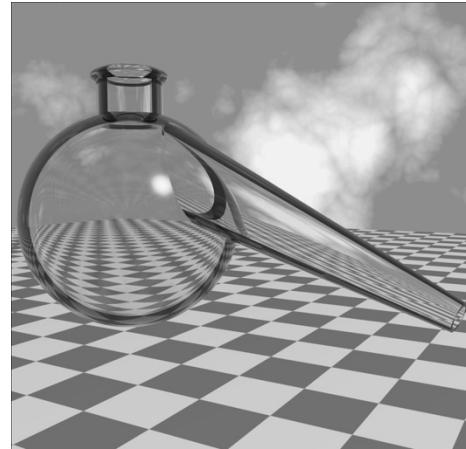
(c) Scale (2,1) - nearest



(d) Scale (2,1) - bilinear



(e) Scale (3,3) - nearest



(f) Scale (3,3) - bilinear

Project 8 - Morphological Processing

Problem

Implement the “Opening by reconstruction”, “Filling holes” and “Border clearing” operations on pages 681-683 (pp.659-661 for the electronic textbook), and reproduce the results in Figure 9.29, Figures 9.31, and Figure 9.32. (The images fig9.29(a) and fig9.31(a) can be found at <ftp://ftp.cs.sjtu.edu.cn:990/lu-ht/DIP/images>)

Environment

Matlab R2016a
Atom 1.22 (with language-matlab package)

Principle

- **Erosion and Dilation**

- **Erosion**

With A and B as sets in Z^2 , the erosion of A by B, denoted $A \ominus B$, is defined as:

$$A \ominus B = \{z | (B)_z \subseteq A\}$$

Because the statement that B has to be contained in A is equivalent to B not sharing any common elements with the background, we can express erosion in the following equivalent form:

$$A \ominus B = \{z | (B)_z \cap A^c = \emptyset\}$$

- **Dilation**

With A and B as sets in Z^2 , the dilation of A by B, denoted $A \oplus B$, is defined as:

$$A \oplus B = \{z | (\hat{B})_z \cap A \neq \emptyset\}$$

This equation is based on reflecting B about its origin, and shifting this reflection by z. The dilation of A by B then is the set of all displacements, z, such that BN and A overlap by at least one element. Based on this interpretation, Equation above can be written equivalently as:

$$A \oplus B = \{z | [(\hat{B})_z \cap A] \subseteq A\}$$

- **Duality**

Erosion and dilation are duals of each other with respect to set complementation and reflection. That is:

$$(A \ominus B)^c = A^c \oplus \hat{B}$$

and

$$(A \oplus B)^c = A^c \ominus \hat{B}$$

- **Opening by reconstruction**

The opening of set A by structuring element B, denoted $A \circ B$, is defined as

$$A \circ B = (A \ominus B) \oplus B$$

The opening by reconstruction of size n of an image F is defined as the reconstruction by dilation of F from the erosion of size n of F; that is,

$$O_R^{(n)}(F) = R_F^D[(F \ominus nB)]$$

- **Filling holes**

Let $I(x, y)$ denote a binary image and suppose that we form a marker image F that is 0 everywhere, except at the image border, where it is set to $1 - I$; that is,

$$F(x, y) = \begin{cases} 1 - I(x, y) & \text{if } (x, y) \text{ is on the border of } I \\ 0 & \text{otherwise} \end{cases}$$

Then

$$H = [R_{I^c}^D(F)]^c$$

is a binary image equal to I with all holes filled.

- **Border clearing**

In this application, we use the original image as the mask and the following marker image:

$$F(x, y) = \begin{cases} I(x, y) & \text{if } (x, y) \text{ is on the border of } I \\ 0 & \text{otherwise} \end{cases}$$

The border-clearing algorithm first computes the morphological reconstruction $R_I^D(F)$ (which simply extracts the objects touching the border) and then computes the difference:

$$X = I - R_I^D(F)$$

to obtain an image, X, with no objects touching the border.

Implementation

1. The opening by reconstruction part

- First clear the former environments and get the input image :

```
7 %%%%%%%%%%%%%% Opening by reconstruction %%%%%%%%%%%%%%
8 % Clear the environment
9 clc
10 clear;
11
12 % Set the default location of input image file
13 img_location = '../images/Fig0929(a)(text_image).tif';
14 input_img = double(imread(img_location));
15
16 % Get the relative information of the image
17 info = imfinfo(img_location);
18 M = info.Height;
19 N = info.Width;
```

- Use function operations() to get the erosion input image and dilation image:

```
21 % Get the erosion image and dilation image
22 erosion_img = operations(input_img, 'erosion', 51,1);
23 dilation_img = operations(erosion_img, 'dilation', 51,1);
24
```

- To get the reconstruction image, just do dilation operations on dilation input image until it doesn't change any more, then we can get the final result :

```
25 % First assign the dilation image to reconstruction image
26 % Then use dilation operation on reconstruction image
27 % Until the reconstruction image doesn't change any more
28 reconstruction_img = dilation_img;
29 while(true)
30     new_img = operations(reconstruction_img, 'dilation', 3, 3);
31     new_img = new_img & input_img;
32     if all(all(new_img == reconstruction_img))
33         break;
34     end
35     reconstruction_img = new_img;
36 end
37
38 % Show the pictures and output them
39 figures...
40 {input_img, erosion_img, dilation_img, reconstruction_img},...
41 'FIG9.29 Opening by reconstruction',...
42 {'FIG9.29(a) Origin input image', 'FIG9.29(b) Erosion', 'FIG9.29(c) Opening', ...
43 'FIG9.29(d) Reconstruction'},...
44 true)
```

2. The operations function

- First we get the height and width of the input image and zero padding it:

```
11 [M,N] = size(input_img);
12 H = (m - 1)/2;
13 W = (n - 1)/2;
14
15 % Zero padding
16 im_padded = zeros(M + m - 1, N + n - 1);
17 im_padded(H + 1:H + M,W + 1:W + N) = input_img;
18
```

- Then do the erosion or the dilation operation according to the pattern to

get the output image:

```
19  output_img = zeros(M, N) == 1;
20 v switch lower(operation)
21 v   case 'erosion'
22 v     for i = H + 1:H + M
23 v       for j = W + 1:W + N
24 v         % Considering the efficiency, use the square mask with 1s
25 v         if all(all(im_padded(i - H:i + H, j - W:j + W)))
26         output_img(i - H, j - W) = 1;
27     end
28   end
29 end
30 v case 'dilation'
31 v   for i = H + 1:H + M
32 v     for j = W + 1:W + N
33 v       if any(any(im_padded(i - H:i + H, j - W:j + W)))
34       output_img(i - H, j - W) = 1;
35     end
36   end
37 end
38 v otherwise
39   error(['The ', ' ', operation, ' ', 'operation pattern can not be found.'])
40 v end
41 end
```

3. The filling holes part

- First clear the former environments and get the input image :

```
46 %%%%%%%%%%%%%% Filling holes %%%%%%%%%%%%%%
47 % Clear the environment
48 clc
49 clear;
50
51 % Set the default location of input image file
52 img_location = '../images/Fig0929(a)(text_image).tif';
53 input_img = double(imread(img_location));
54
55 % Get the relative information of the image
56 info = imfinfo(img_location);
57 M = info.Height;
58 N = info.Width;
59
```

- Then we get the complement of the input image also the erosion and dilation image:

```
59
60 % Get the complement of the input image
61 complement_img = ~input_img;
62
63 % Get the erosion image and dilation image
64 erosion_img = operations(complement_img, 'erosion', 51, 3);
65 dilation_img = operations(erosion_img, 'dilation', 51, 3);
66
```

- To get the marker image we need add edges to the dilation image:

```
67 % First assign the dilation image to filling image
68 % And add edges to it
69 filling_img = dilation_img;
70 filling_img([1, end], :) = 1;
71 filling_img(:, [1, end]) = 1;
72 filling_img = filling_img & complement_img;
73
74 marker_img = zeros(M,N);
75 marker_img([1, end], :) = input_img([1, end], :) == 1;
76 marker_img(:, [1, end]) = input_img(:, [1, end]) == 1;
77
```

- d. Similar to the former part, also repeat the dilation operations until it doesn't change any more:

```

77
78 % Then use dilation operation on filling image
79 % Until the filling image doesn't change any more
80 while(true)
81     new_img = operations(filling_img, 'dilation', 3, 3);
82     new_img = new_img & complement_img;
83 if all(all(new_img == filling_img))
84     break;
85 end
86 filling_img = new_img;
87 end
88
89 filling_img = ~filling_img;
90
91 % Show the pictures and output them
92 figures...
93 {input_img, complement_img, marker_img, filling_img},...
94 'FIG9.31',...
95 {'FIG9.31(a) Origin input image', 'FIG9.31(b) Complement', 'FIG9.31(c) Marker',...
96 'FIG9.31(d) Hole-filling'},...
97 true
98

```

4. The border clearing part

- a. First also clear the former environments and get the input image:

```

100
101 % Clear the environment
102 clc
103 clear;
104
105 % Set the default location of input image file
106 img_location = '../images/Fig0929(a)(text_image).tif';
107 input_img = double(imread(img_location));
108
109 % Get the relative information of the image
110 info = imfinfo(img_location);
111 M = info.Height;
112 N = info.Width;
113
114 % First get the border of the input image
115 border_img = zeros(M,N);
116 border_img([1, end], :) = input_img([1, end], :);
117 border_img(:, [1, end]) = input_img(:, [1, end]);
118

```

- b. Also to get the marker image we need add edges to the dilation image:

```

113
114 % First get the border of the input image
115 border_img = zeros(M,N);
116 border_img([1, end], :) = input_img([1, end], :);
117 border_img(:, [1, end]) = input_img(:, [1, end]);
118

```

- c. Also repeat the dilation operations until no changes:

```

119 % Then use dilation operation on filling image
120 % Until the filling image doesn't change any more
121 while(true)
122     new_img = operations(border_img, 'dilation', 3, 3);
123     new_img = new_img & input_img;
124     imshow(new_img);
125     if all(all(new_img == border_img))
126         break;
127     end
128     border_img = new_img;
129 end
130 border_clearing_img = input_img - border_img;
131

```

- d. Then we can get the border image after reduced by the original input image:

```

130 border_clearing_img = input_img - border_img;
131
132 % Show the pictures and output them
133 figures...
134 {border_img, border_clearing_img, input_img},...
135 'FIG9.32',...
136 {'FIG9.32(a) Marker', 'FIG9.32(b) Border clearing', 'FIG9.32 Origin input image'},...
137 true)
138 ...

```

5. The figure function

Also use the similar function to show the pictures and figures:

```

2 function [] = figures( input_imgs, figure_title, image_titles, output_file)
3 % Show the pictures and the figures
4
5 figure('NumberTitle','off','Name', figure_title)
6 column = 2;
7 [temp, num] = size(input_imgs);
8 row = ceil(num / column);
9
10 for i = 1:row
11     for j = 1:column
12         if((i - 1)* column + j) <= num
13             subplot(row, column, (i - 1)* column + j)
14             imshow(uint8(input_imgs{ (i - 1) * column + j}),[]);
15             title(char(image_titles{ (i - 1) * column + j}))
16             if output_file
17                 imwrite(uint8(input_imgs{ (i - 1) * column + j} * 255), [char(image_titles{ (i - 1) * column + j}), '.jpg']);
18             end
19         end
20     end
21 end
22
23 end
24

```

Result

- **Opening by reconstruction**

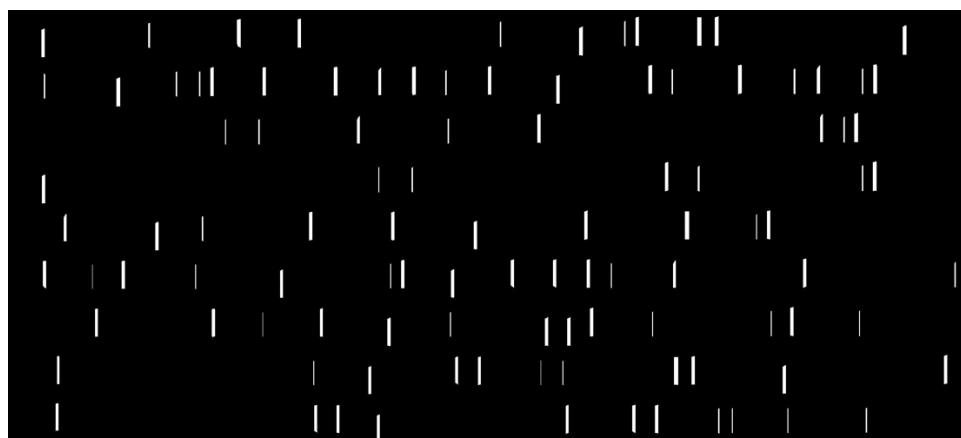
ponents or broken connection paths. There is no point in going beyond this level of detail required to identify those components.

Segmentation of nontrivial images is one of the most difficult tasks in image processing. Segmentation accuracy determines the effectiveness of computerized analysis procedures. For this reason, considerable care must be taken to improve the probability of rugged segmentation. In such applications as industrial inspection applications, at least some degree of tolerance to the environment is possible at times. The experienced image processing designer invariably pays considerable attention to such factors.

Original input image



Erosion using 51*1 mask



Dilation using 51*1 mask

p	t	b	k		t	p	th	Th	p				
t	p	t th	l	l	f d	t	l	q	d t	d	t f	th	
				t t	f	t	l					f th	
p					t	t			d	t		th	
f		p	t		d	l	p	d	F	th			
b	t	k	t	p		th	p	b	b l	t	f	d	t
h			d	t	l	p	t	ppl	t		tl	t	
h					t	p	bl	tt	Th	p		d	
d					bl	p		d	bl	tt	t	t	

Final Result

- **Filling holes**

ponents or broken connection paths. There is no point past the level of detail required to identify those components.

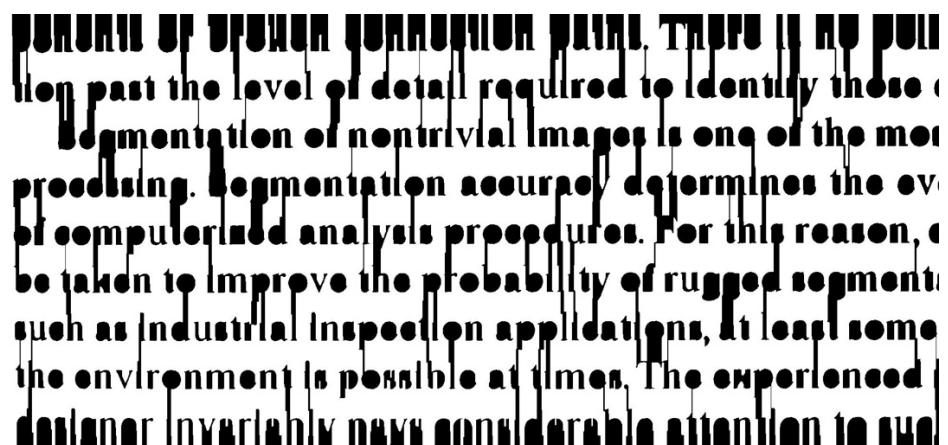
Segmentation of nontrivial images is one of the most difficult tasks in computer vision processing. Segmentation accuracy determines the effectiveness of computerized analysis procedures. For this reason, care must be taken to improve the probability of rugged segmentation, such as industrial inspection applications, at least some of the time. The environment is possible at times. The experienced image designer invariably pays considerable attention to such

Original input image

ponents or broken connection paths. There is no point past the level of detail required to identify those components.

Segmentation of nontrivial images is one of the most difficult tasks in computer vision processing. Segmentation accuracy determines the effectiveness of computerized analysis procedures. For this reason, care must be taken to improve the probability of rugged segmentation, such as industrial inspection applications, at least some of the time. The environment is possible at times. The experienced image designer invariably pays considerable attention to such

Complement of the input image



Dilation using 51*1 mask



Marker image

ponents or broken connection paths. There is no point past the level of detail required to identify those components.

Segmentation of nontrivial images is one of the most difficult tasks in computer vision processing. Segmentation accuracy determines the effectiveness of computerized analysis procedures. For this reason, care must be taken to improve the probability of rugged segmentation in applications such as industrial inspection applications, at least some of the time. The environment is possible at times. The experienced image processing designer invariably pays considerable attention to such problems.

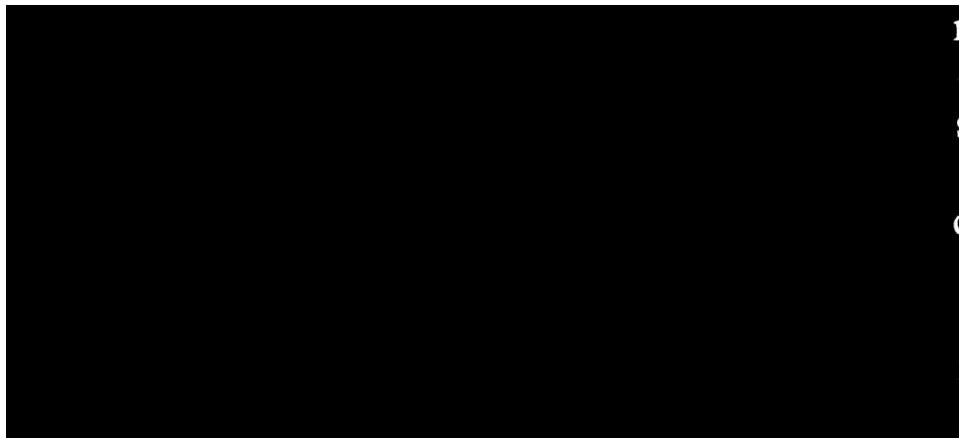
Final Result

- **Border clearing**

ponents or broken connection paths. There is no point past the level of detail required to identify those components.

Segmentation of nontrivial images is one of the most difficult tasks in computer vision processing. Segmentation accuracy determines the effectiveness of computerized analysis procedures. For this reason, care must be taken to improve the probability of rugged segmentation in applications such as industrial inspection applications, at least some of the time. The environment is possible at times. The experienced image processing designer invariably pays considerable attention to such problems.

Original input image



Border image

ponents or broken connection paths. There is no poi
tion past the level of detail required to identify those

Segmentation of nontrivial images is one of the mo
processing. Segmentation accuracy determines the ev
of computerized analysis procedures. For this reason,
be taken to improve the probability of rugged segment
such as industrial inspection applications, at least some
the environment is possible at times. The experienced
designer invariably pays considerable attention to suc

Final result

Project 9 - Image segmentation

Problem

(a). Develop a program to implement the Roberts, Prewitt, Sobel, the Marr-Hildreth and the Canny edge detectors. Use the image ‘building.tif’ to test your detectors. (For technique details of Marr-Hildreth and Canny, please refer to pp.736-747 (3rd edition, Gonzalez DIP, or pp.705-725 for the electronic textbook) or MH-Canny.pdf at the same address of the slides.)

(b). Develop a program to implement the Otsu’s method of thresholding segmentation, and compare the results with the global thresholding method using test image ‘polymersomes.tif’. (For technique details, please refer to pp.763-770 (3rd edition, Gonzalez DIP, or pp.742-747 for the electronic textbook, or Otsu.pdf at the same ftp address of slides.)

Environment

Matlab R2016a

Atom 1.22 (with language-matlab package)

Principle

- **Edge detection**

- **Basic**

As illustrated in the previous section, detecting changes in intensity for the purpose of finding edges can be accomplished using first- or second-order derivatives.

$$\nabla f = \text{grad}(f) = \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

- **Roberts cross-gradient operators**

The Roberts operators are based on implementing the diagonal differences:

$$g_x = \frac{\partial f}{\partial x} = (z_9 - z_5)$$

and:

$$g_y = \frac{\partial f}{\partial y} = (z_8 - z_6)$$

-1	0
0	-1
1	0
0	1

Roberts

- **Prewitt operators**

The simplest digital approximations to the partial derivatives using masks of size $3 * 3$ are given by:

$$g_x = \frac{\partial f}{\partial x} = (z_7 + z_8 + z_9) - (z_1 + z_2 + z_3)$$

and

$$g_y = \frac{\partial f}{\partial y} = (z_3 + z_6 + z_9) - (z_1 + z_4 + z_7)$$

-1	-1	-1
0	0	0
1	1	1

Prewitt

0	1	1
-1	0	1
-1	-1	0

Prewitt

- **Sobel cross-gradient operators**

A slight variation of the preceding two equations uses a weight of 2 in the center coefficient:

$$g_x = \frac{\partial f}{\partial x} = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)$$

and

$$g_y = \frac{\partial f}{\partial y} = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)$$

-1	-2	-1
0	0	0
1	2	1

Sobel

0	1	2
-1	0	1
-2	-1	0

Sobel

- **Mill-Hildreth edge detection**

The Laplacian of a Gaussian (LoG):

$$\nabla^2 G(x, y) = \left[\frac{x^2 + y^2 - 2\sigma^2}{\sigma^4} \right] e^{-\frac{x^2+y^2}{2\sigma^2}}$$

The Marr-Hildreth algorithm consists of convolving the LoG filter with an input image, $f(x, y)$:

$$g(x, y) = [\nabla^2 G(x, y)] \star f(x, y)$$

and then finding the zero crossings of $g(x, y)$ to determine the locations of edges in $f(x, y)$. Because these are linear processes, $g(x, y)$ can be written also as

$$g(x, y) = \nabla^2 [G(x, y) \star f(x, y)]$$

The Marr-Hildreth edge-detection algorithm may be summarized as follows:

- Filter the input image with an $n * n$ Gaussian low-pass filter obtained by sampling:

$$G(x, y) = e^{-\frac{x^2+y^2}{2\sigma^2}}$$

- Compute the Laplacian of the image resulting from Step1 using mask.
- Find the zero crossings of the image from Step 2.

○ Canny edge detection

- **Smooth the input image with a Gaussian filter**

Let $f(x, y)$ denote the input image and $G(x, y)$ denote the Gaussian function:

$$G(x, y) = e^{-\frac{x^2+y^2}{2\sigma^2}}$$

We form a smoothed image, $f_s(x, y)$, by convolving G and f :

$$f_s(x, y) = G(x, y) \star f(x, y)$$

- **Compute the gradient magnitude and angle images.**

This operation is followed by computing the gradient magnitude and direction (angle):

$$M(x, y) = \sqrt{g_x^2 + g_y^2}$$

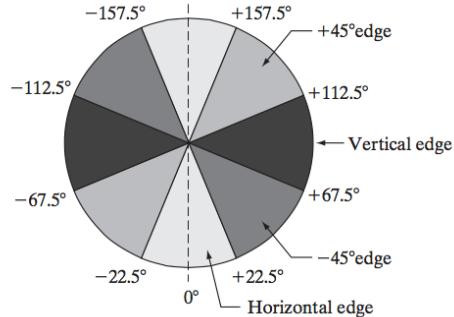
and

$$\alpha(x, y) = \tan^{-1} \left[\frac{g_y}{g_x} \right]$$

- **Apply nonmaxima suppression to the gradient magnitude image.**

Let d_1, d_2, d_3, d_4 denote the four basic edge directions just discussed for a $3 * 3$ region: horizontal, -45° , vertical, and $+45^\circ$.

- Find the direction d_k that is closest to $a(x, y)$.
- If the value of $M(x, y)$ is less than at least one of its two neighbors along d_k , let $g_n(x, y) = 0$ (suppression); otherwise, let $g_n(x, y) = M(x, y)$



- Use double thresholding and connectivity analysis to detect and link edges.

$$g_{NH}(x, y) = g_N(x, y) \geq T_H$$

$$g_{NL}(x, y) = g_N(x, y) \geq T_L$$

$$g_{NL}(x, y) = g_{NL}(x, y) - g_{NH}(x, y)$$

- Thresholding segmentation

- Global thresholding segmentation

- Select an initial estimate for the global threshold, T .
 - Segment the image using T :

$$g(x, y) = \begin{cases} 1 & \text{if } f(x, y) > T \\ 0 & \text{if } f(x, y) \leq T \end{cases}$$

This will produce two groups of pixels: G_1 consisting of all pixels with intensity values $> T$, and G_2 consisting of pixels with values $\leq T$.

- Compute the average (mean) intensity values m_1 and m_2 for the pixels in G_1 and G_2 , respectively.
 - Compute a new threshold value:

$$T = \frac{1}{2}(m_1 + m_2)$$

- Repeat Steps 2 through 4 until the difference between values of T in successive iterations is smaller than a predefined parameter ΔT .

- **Otsu's method of thresholding segmentation**

The basic idea is that well-thresholded classes should be distinct with respect to the intensity values of their pixels and, conversely, that a threshold giving the best separation between classes in terms of their intensity values would be the best (optimum) threshold.

Otsu's algorithm may be summarized as follows:

- Compute the normalized histogram of the input image. Denote the components of the histogram by p_i , $i = 0, 1, 2, \dots, L - 1$.
- Compute the cumulative sums, $P_1(k)$, for $k = 0, 1, 2, \dots, L - 1$, using

$$P_1(k) = \sum_{i=0}^k p_i$$

- Compute the cumulative means, $m(k)$, for $k = 0, 1, 2, \dots, L - 1$, using

$$m(k) = \sum_{i=0}^k i p_i$$

- Compute the global intensity mean, m_G , using

$$m_G = \sum_{i=0}^{L-1} i p_i$$

- Compute the between-class variance, $\sigma_B^2(k)$, for $k = 0, 1, 2, \dots, L - 1$, using

$$\sigma_B^2(k) = \frac{[m_G P_1(k) - m(k)]^2}{P_1(k)[1 - P_1(k)]}$$

- Obtain the Otsu threshold, k^* , as the value of k for which $\sigma_B^2(k)$ is maximum. If the maximum is not unique, obtain k^* by averaging the values of k corresponding to the various maxima detected.
- Obtain the separability measure, η^* , by evaluating

$$\eta(k) = \frac{\sigma_B^2(k)}{\sigma_G^2}$$

at $k = k^*$.

Implementation

1. The edge detection part

- First clear the former environments and get the input image :

```
6 %% %%%%%%%%%%%%%% Edge detection %%%%%%%%%%%%%%
7 clc;
8 clear;
10
11 % Set the default location of input image file
12 img_location = '../images/building.tif';
13 input_img = double(imread(img_location));
14
15 % Get the relative information of the image
16 info = imfinfo(img_location);
17 M = info.Height;
18 N = info.Width;
19
20
```

- Implement the Robert edge detection using function filters():

```
21 %% Roberts edge detection
22 roberts_x_img = abs(filters(input_img, 'roberts', 'x'));
23 roberts_y_img = abs(filters(input_img, 'roberts', 'y'));
24 roberts_img = (roberts_x_img + roberts_y_img);
25
26 % Show the pictures and output them
27 figures(..., ...
28 {input_img, roberts_x_img, roberts_y_img, roberts_img}, ...
29 'Roberts ', ...
30 {'Origin input image', 'Roberts |gx|', 'Roberts |gy|', 'Roberts |gx|+|gy|'}, ...
31 true)
```

- Also the Prewitt edge detection:

```
34 %% Prewitt edge detection
35 prewitt_x_img = abs(filters(input_img, 'prewitt', 'x'));
36 prewitt_y_img = abs(filters(input_img, 'prewitt', 'y'));
37 prewitt_img = (prewitt_x_img + prewitt_y_img);
38
39 % Show the pictures and output them
40 figures(..., ...
41 {input_img, prewitt_x_img, prewitt_y_img, prewitt_img}, ...
42 'Prewitt ', ...
43 {'Origin input image', 'Prewitt |gx|', 'Prewitt |gy|', 'Prewitt |gx|+|gy|'}, ...
44 true)
45
```

- The Sobel edge detection:

```
47 %% Sobel edge detection
48 sobel_x_img = abs(filters(input_img, 'sobel', 'x'));
49 sobel_y_img = abs(filters(input_img, 'sobel', 'y'));
50 sobel_img = (sobel_x_img + sobel_y_img);
51
52 % Show the pictures and output them
53 figures(..., ...
54 {input_img, sobel_x_img, sobel_y_img, sobel_img}, ...
55 'Sobel ', ...
56 {'Origin input image', 'Sobel |gx|', 'Sobel |gy|', 'Sobel |gx|+|gy|'}, ...
57 true)
58
```

- Smooth the result of Sobel edge detection using 5x5 mask:

```

59  %% Smooth the result of sobel
60  smooth_input_img = filters(input_img, 'smooth');
61  sobel_smooth5x5_x_img = abs(filters(smooth_input_img, 'sobel', 'x'));
62  sobel_smooth5x5_y_img = abs(filters(smooth_input_img, 'sobel', 'y'));
63  sobel_smooth5x5_img = (sobel_smooth5x5_x_img + sobel_smooth5x5_y_img);
64
65  % Show the pictures and output them
66  figures(...).
67  {smooth_input_img, sobel_smooth5x5_x_img, sobel_smooth5x5_y_img, sobel_smooth5x5_img}
68  'Sobel smoothed input image with 5x5 mask',...
69  {'Smoothed input image', 'Sobel Smoothed |gx|', 'Sobel Smoothed |gy|', 'Sobel Smoothed |g|'}
70  true)
71

```

- f. To implement the Marr-Hildreth edge detection, we need first get the Laplacian of Gaussian (LoG) matrix and a matrix used to record the negative or posotive of LoG matrix:

```

72
73  %% Marr-Hildreth edge detection.
74  % The Laplacian of Gaussian
75  LoG_img = filters(input_img, 'log', [25,4]);
76  sign = zeros(M, N);
77  sign(LoG_img > 0) = 1;
78  sign(LoG_img < 0) = -1;
79

```

Then find zero crossings with a threshold of 0:

```

80  % Find zero crossings with a threshold of 0.
81  zero_crossing_0 = zeros(M, N);
82  for i = 2:M-1
83      for j = 2:N-1
84          if sign(i-1, j-1) * sign(i+1, j+1) < 0 || ...
85              sign(i-1, j) * sign(i+1, j) < 0 || ...
86              sign(i, j-1) * sign(i, j+1) < 0 || ...
87              sign(i+1, j-1) * sign(i-1, j+1) < 0
88          zero_crossing_0(i, j) = 1;
89      end
90  end
91
92

```

Also with a threshold of 0.04:

```

93  % Find zero crossings with threshold of 4%
94  zero_crossing_04 = zeros(M, N);
95  threshold = 0.04 * (max(LoG_img(:)) - min(LoG_img(:)));
96  for i = 2:M-1
97      for j = 2:N-1
98          if sign(i-1, j-1) * sign(i+1, j+1) < 0 && ...
99              abs(LoG_img(i-1, j-1) - LoG_img(i+1, j+1)) > threshold
100         zero_crossing_04(i, j) = 1;
101     elseif sign(i, j-1) * sign(i, j+1) < 0 && ...
102         abs(LoG_img(i, j-1) - LoG_img(i, j+1)) > threshold
103         zero_crossing_04(i, j) = 1;
104     elseif sign(i-1, j) * sign(i+1, j) < 0 && ...
105         abs(LoG_img(i-1, j) - LoG_img(i+1, j)) > threshold
106         zero_crossing_04(i, j) = 1;
107     elseif sign(i+1, j-1) * sign(i-1, j+1) < 0 && ...
108         abs(LoG_img(i+1, j-1) - LoG_img(i-1, j+1)) > threshold
109         zero_crossing_04(i, j) = 1;
110     end
111  end
112

```

To show the pictures there needs to do some scaling :

```

114 % To show the image seems like in the book, do some scaling
115 LoG_img = LoG_img - min(LoG_img(:));
116 output_LoG_img = LoG_img / max(LoG_img(:));
117 output_LoG_img = output_LoG_img * 255;
118 zero_crossing_0 = zero_crossing_0 * 255;
119 zero_crossing_04 = zero_crossing_04 * 255;
120
121 % Show the pictures and output them
122 figures...
123 {input_img, output_LoG_img, zero_crossing_0, zero_crossing_04},...
124 'Marr-Hildreth edge detection',...
125 {'Origin input image', 'LoG ', 'Zero crossings with threshold 0', ...
126 'Zero crossings with threshold 0.04'},...
127 true)
128

```

- g. To implement the Canny edge detection, we need to use Gaussian blur to handle the image, there using filter() function:

```

125
126 %% Canny edge detection.
127 % Gaussian blur.
128 gaussian_img = filters(input_img, 'gaussian', [25, 4]);
129

```

Then calculate the gradient magnitude and angle images:

```

130 % Calculate the gradient magnitude and angle images.
131 magnitude_x_img = filters(gaussian_img, 'sobel', 'x');
132 magnitude_y_img = filters(gaussian_img, 'sobel', 'y');
133 magnitude_img = sqrt(magnitude_x_img.^2 + magnitude_y_img.^2);
134
135 angle = zeros(M, N);
136 % For different direction set different number:
137 % Horizontal edge - 1
138 % Vertical edge - 2
139 % -45 degree edge - 3
140 % +45 degree edge - 4
141 for i = 1:M
142     for j = 1:N
143         if magnitude_y_img(i, j) == 0
144             angle(i, j) = 1;
145         else
146             t = magnitude_x_img(i, j) / magnitude_y_img(i, j);
147             if abs(t) >= tan(0.375 * pi)
148                 angle(i, j) = 1;
149             elseif abs(t) <= tan(0.125 * pi)
150                 angle(i, j) = 2;
151             elseif t > 0
152                 angle(i, j) = 3;
153             else
154                 angle(i, j) = 4;
155             end
156         end
157     end

```

Then apply nonmaxima suppression to the gradient magnitude image:

```

161 suppression_img = zeros(M, N);
162 for i = 2:M-1
163     for j = 2:N-1
164         t = angle(i, j);
165         m = magnitude_img(i - 1:i + 1, j - 1:j + 1);
166         if (t == 1 && m(2, 2) > m(3, 2) && m(2, 2) > m(1, 2)) || ...
167             (t == 2 && m(2, 2) > m(2, 3) && m(2, 2) > m(2, 1)) || ...
168             (t == 3 && m(2, 2) > m(1, 1) && m(2, 2) > m(3, 3)) || ...
169             (t == 4 && m(2, 2) > m(1, 3) && m(2, 2) > m(3, 1)))
170             suppression_img(i,j) = m(2, 2);
171     end
172 end
173 end
174

```

For the convenience of thresholding process, scale the suppression matrix:

```

174
175 % Scale the suppression image to [0,1]
176 suppression_img = suppression_img - min(suppression_img(:));
177 suppression_img = suppression_img / max(suppression_img(:));
178

```

Then use double thresholding and connectivity analysis to detect and link edges and use queue to store high pixel positions:

```

179 % Use double thresholding and connectivity analysis to detect and link edges
180 low_threshold_img = zeros(M, N);
181 high_threshold_img = zeros(M, N);
182 low_threshold_img(suppression_img > 0.04) = 1;
183 high_threshold_img(suppression_img > 0.10) = 1;
184
185 % Use queue to store high pixel positions.
186 [x, y] = find(high_threshold_img);
187 head = 1;
188 tail = length(x);
189 canny_edge_img = high_threshold_img;
190 while(head <= tail)
191     x0 = x(head);
192     y0 = y(head);
193     for i = x0 - 1:x0 + 1
194         for j = y0 - 1:y0 + 1
195             if low_threshold_img(i, j) && ~canny_edge_img(i, j)
196                 tail = tail + 1;
197                 x(tail) = i;
198                 y(tail) = j;
199                 canny_edge_img(i, j) = 1;
200             end
201         end
202     end
203     head = head + 1;
204 end
205

```

For show the pictures better we scale the images back to [0,255], and show them:

```

205 % To show the image seems like in the book, do some scaling
206 suppression_img = suppression_img * 255;
207 low_threshold_img = low_threshold_img * 255;
208 high_threshold_img = high_threshold_img * 255;
209 canny_edge_img = canny_edge_img * 255;
210
211
212
213 % Show the pictures and output them
214 figures...
215 {input_img, gaussian_img, magnitude_img, suppression_img},...
216 'Canny edge detection',...
217 {'Origin input image', 'Gaussian blur', 'Gradient magnitude', 'Nonmaxima suppression'},...
218 true)
219 figures...
220 {input_img, low_threshold_img, high_threshold_img, canny_edge_img},...
221 'Canny edge detection use double thresholding',...
222 {'Origin input image', 'Low threshold 0.04', 'High threshold 0.10', 'Canny edge detection'},...
223 true)
224
225

```

** Actually for the final result of Robert, Prewitt, Sobel and smoothed Sobel, it should be the $(|gx| + |gy|)/2$, but when represent on this word/pdf report the effect is not that good for the pictures are scaled small, so I just let the result to be $|gx| + |gy|$.*

2. The filters function

- First we need to calculate the mask according to the filter pattern:

```

18 % Get the mask
19 switch lower(pattern)
20 case patterns{1}
21     mask = [-1, 0; 0, 1];
22     if strcmp(parameters, 'y')
23         mask = [0, -1; 1, 0];
24     end
25 case patterns{2}
26     mask = [-1, -1, -1; 0, 0, 0; 1, 1, 1];
27     if strcmp(parameters, 'y')
28         mask = mask';
29     end
30 case patterns{3}
31     mask = [-1, -2, -1; 0, 0, 0; 1, 2, 1];
32     if strcmp(parameters, 'y')
33         mask = mask';
34     end
35 case patterns{4}
36     mask = ones(5,5) / 25;
37 case patterns{5}
38     r = (parameters(1) - 1)/2;
39     [x, y] = meshgrid(-r:r, -r:r);
40     mask = exp(-(x .* x + y .* y)/(2 * parameters(2) * parameters(2)));
41     if sum(mask(:)) ~= 0
42         mask = mask/sum(mask(:));
43     end
44 case patterns{6}
45     r = (parameters(1) - 1)/2;
46     [x, y] = meshgrid(-r:r, -r:r);
47     mask = exp(-(x .* x + y .* y)/(2 * parameters(2)^2));
48     mask = mask .* (x .* x + y .* y - 2 * parameters(2)^2)/(parameters(2)^4);
49     mask = mask - sum(mask(:))/numel(mask);
50 otherwise
51     error(['The', ' ', pattern, ' ', 'filter pattern can not be found.'])
52 end

```

- b. Then we use zero padding to pad the input image, for the size of mask maybe even so we need some handling to left and right shift:

```

57 % Zero padding
58 padding_m = floor((m - 1)/2);
59 padding_m_ = m - padding_m - 1;
60 padding_n = floor((n - 1)/2);
61 padding_n_ = n - padding_n - 1;
62
63 padding_img = padarray(input_img, [padding_m, padding_n]);
64 padding_img = zeros(M + m - 1, N + n - 1);
65 padding_img(padding_m + 1:padding_m + M, padding_n + 1:padding_n + N) = input_img;
66

```

- c. At last we can just mask the output image:

```

67 output_img = zeros(M, N);
68 for i = padding_m + 1:padding_m + M
69     for j = padding_n + 1:padding_n + N
70         temp = padding_img(i - padding_m:i + padding_m_, j - padding_n:j + padding_n_) .* mask;
71         output_img(i - padding_m, j - padding_n) = sum(temp(:));
72     end
73 end

```

3. The thresholding segmentation part

- a. Also first clear the former environments and get the input image:

```

225
226 %% ##### Thresholding segmentation #####
227 clc;
228 clear;
229
230 % Set the default location of input image file
231 img_location = '../images/polymersomes.tif';
232 input_img = double(imread(img_location));
233
234 % Get the relative information of the image
235 info = imfinfo(img_location);
236 M = info.Height;
237 N = info.Width;
238

```

- b. Implement the global thresholding method according to the formula:

```

242 % global thresholding method.
243 t = mean(mean(input_img));
244 delta = 0.1;
245 delta_t = 255;
246
247 while(delta_t > delta)
248     delta_t = t;
249     G1 = input_img(input_img > t);
250     G2 = input_img(input_img <= t);
251     mG1 = mean(G1);
252     mG2 = mean(G2);
253     t = (mG1 + mG2) / 2;
254     delta_t = abs(delta_t - t);
255 end
256
257 global_threshold_img = zeros(M, N);
258 global_threshold_img(input_img > t) = 1;
259 global_threshold_img = global_threshold_img * 255;
260 figures(...);
261 {input_img, global_threshold_img},...
262 'Global thresholding',...
263 {'Original input image', 'Global thresholding'},...
264 true)
265

```

c. Implement the Otsu's method in similar way:

```
267 % Otsu's method
268 L = 256;
269 Pi = zeros(L, 1);
270 P1k = zeros(L, 1);
271 mk = zeros(L, 1);
272
273 for i = 1:L
274     Pi(i) = sum(sum(input_img == (i - 1))) / (M * N);
275     if i == 1
276         P1k(i) = Pi(i);
277     else
278         P1k(i) = P1k(i - 1) + Pi(i);
279         mk(i) = mk(i - 1) + i * Pi(i);
280     end
281 end
282 mG = mk(L);
283
284 sigma = ((mG * P1k - mk) .^ 2) ./ (P1k .* (1 - P1k));
285 sigma(isnan(sigma)) = 0;
286 k = mean(find(sigma == max(sigma))) - 1;
287
288 otsu_img = zeros(M, N);
289 otsu_img(input_img > k) = 1;
290 otsu_img = otsu_img * 255;
291 figures...
292 {input_img, otsu_img},...
293 'Otsu's method',...
294 {'Original input image', 'Otsu's method'},...
295 true)
```

4. The figures function

Use the same funciton in the former projects to show the pictures and figures also output to files:

```
1 % Figures
2 function [] = figures( input_imgs, figure_title, image_titles, output_file)
3 % Show the pictures and the figures
4
5 figure('NumberTitle','off','Name', figure_title)
6 column = 2;
7 [temp, num] = size(input_imgs);
8 row = ceil(num / column);
9
10 ~ for i = 1:row
11 ~   for j = 1:column
12 ~     if((i - 1)* column + j) <= num
13 ~       subplot(row, column, (i - 1)* column + j)
14 ~       imshow(uint8(input_imgs{(i - 1) * column + j}),[1]);
15 ~       title(char(image_titles{(i - 1) * column + j}))
16 ~     if output_file
17 ~       imwrite(uint8(input_imgs{(i - 1) * column + j}), [char(image_titles{(i - 1) * column + j})])
18 ~     end
19 ~   end
20 ~ end
21 ~ end
22
23 end
24
```

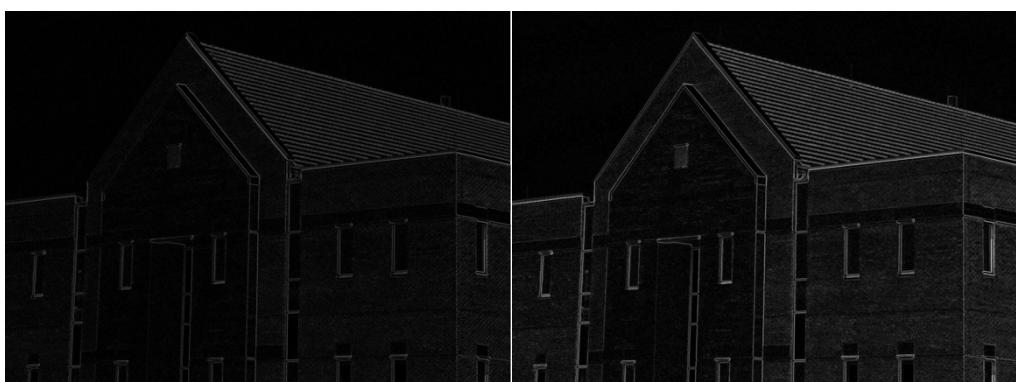
Result

- Edge detection
 - Robert edge detection



Original input image

$|gx|$



$|gy|$

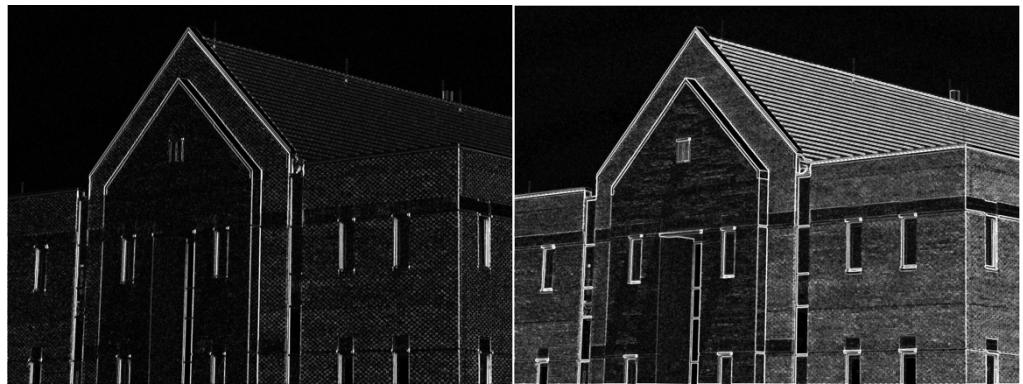
$|gx| + |gy|$

- Prewitt edge detection



Original input image

$|gx|$



$|gy|$

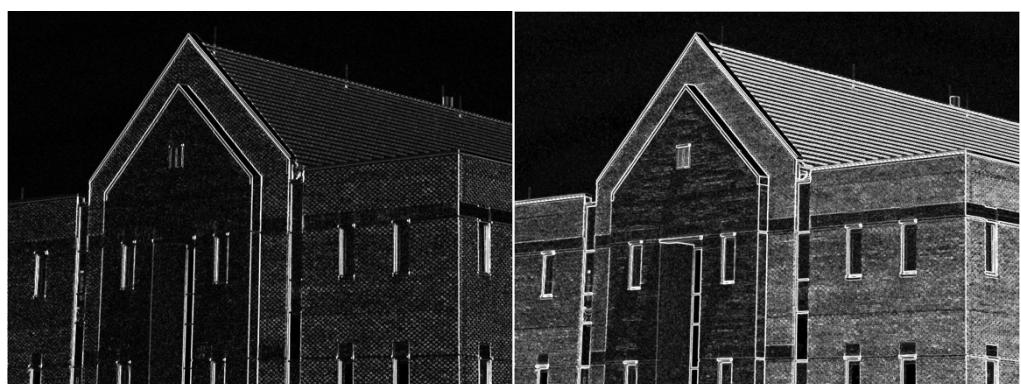
$|gx| + |gy|$

- **Sobel edge detection**



Original input image

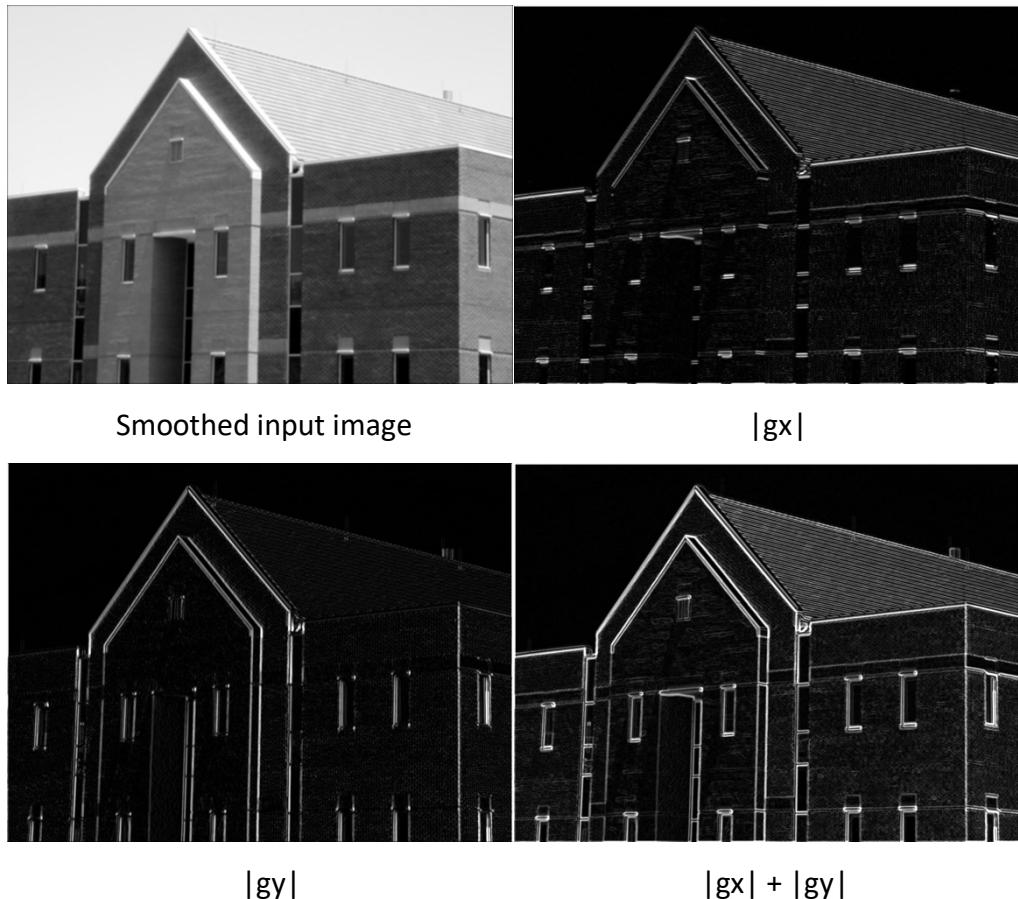
$|gx|$



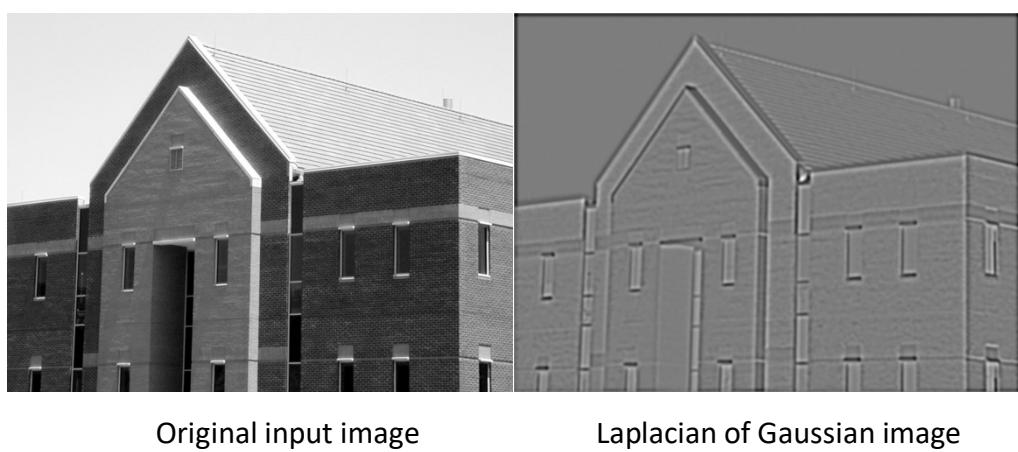
$|gy|$

$|gx| + |gy|$

- **Sobel smoothed edge detection**



- **Marr-Hildreth edge detection**

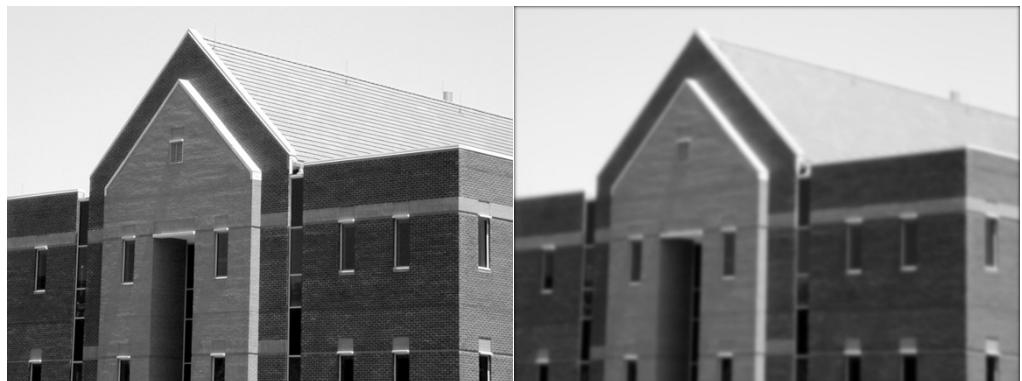




Zero crossing with threshold 0

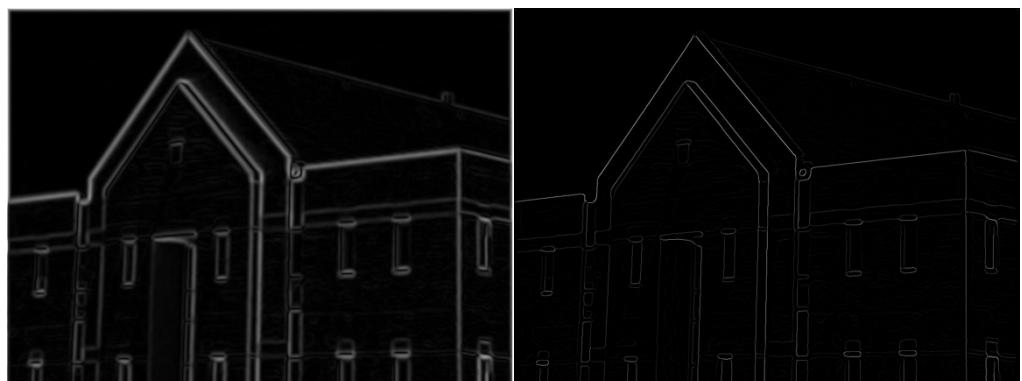
Zero crossing with threshold 0.04

- **Canny edge detection**



Original input image

Gaussian blurred image



Gradient magnitude image

Nonmaxima suppression image



Low threshold 0.04

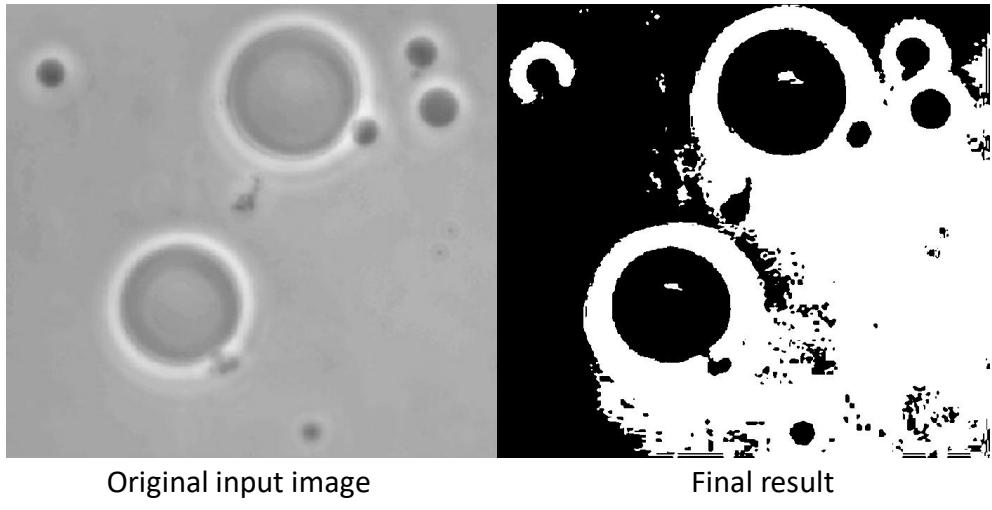
High threshold 0.10



Final result

- **Thresholding segmentation**

- **Global thresholding method**



- **Otsu's method**

