

# Lab #4 Post-Lab Report

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## 1 Introduction

In this lab, we tried to do several operations with related to corner, line and circle detection with using Tomasi Kanade cornerness measure and Hough transformation functions. All of the operations have been performed on gray-scale images and has been checked whether if they are gray-scale before each process and if not, they have been transformed. To avoid any confusion, during the rest of the paper, the images that we will use our operations on will be referred as "Original Image", and images we will be creating after processes will be referred as "Resulting Image". Additionally, we used the **tic** and **toc** commands on the **main.m** to calculate the processing time for each function and printed them to console. Initially, the algorithms for each operation that we have done in the lab will be explained with the methods used and accordingly, further trials with different parameters (e.g. different threshold values) or different images will be discussed with my own results.

## 2 In Lab Implementations

### 2.1 Tomasi Kanade Corner Detection

Tomasi Kanade Corner detection algorithm is a method for detecting the corners in the image with getting the use of eigenvalues. For implementing Tomasi Kanade corner detection algorithm, we first initialized the sliding window size as ( $k = 1$ )  $3 \times 3$  and corners array as empty. For corner detection to work better, first we smoothen the image since we wanted to get rid of the possible noises that might have occurred in the original image. We either used the built-in function for Gaussian filtering (`imgaussfilt(I)` where  $I$  is the gray-scale version of the original image) or the Gaussian filter we implemented on the previous labs. I preferred the built in function since the Gaussian function I wrote was padding empty pixels to the edges and the corner detection was detecting them as (false) corners. Then we calculated the directional gradients using another built-in function `imgradientxy(Simg)` (where  $Simg$  is the smoothened version of the gray-scale image) and stored them as **Gx** and **Gy**. After that, in the nested for loops, for each window sliding among the Gradient matrices we implemented the following for each iteration:

We calculated the square (elements-wise) of the window matrix for both gradients in x and y direction (**Gx** and **Gy**) and the (element-wise) multiplication of window matrices of **Gx** and **Gy**. Then we summed all the values in each matrix within self where resulting values are the indices of the co-variance matrix, stored as **H** matrix. Then we calculated the eigen-values of the **H** matrix ( $\lambda_1 = \text{lambda1}$  and  $\lambda_2 = \text{lambda2}$ ) with `eig()` command in MATLAB. Finally, we applied a threshold method again where the minimum of the eigen values of the current pixel that are over a certain threshold are stored in the corners array. At the end, we showed all the corners by plotting them on the image and visualized them.

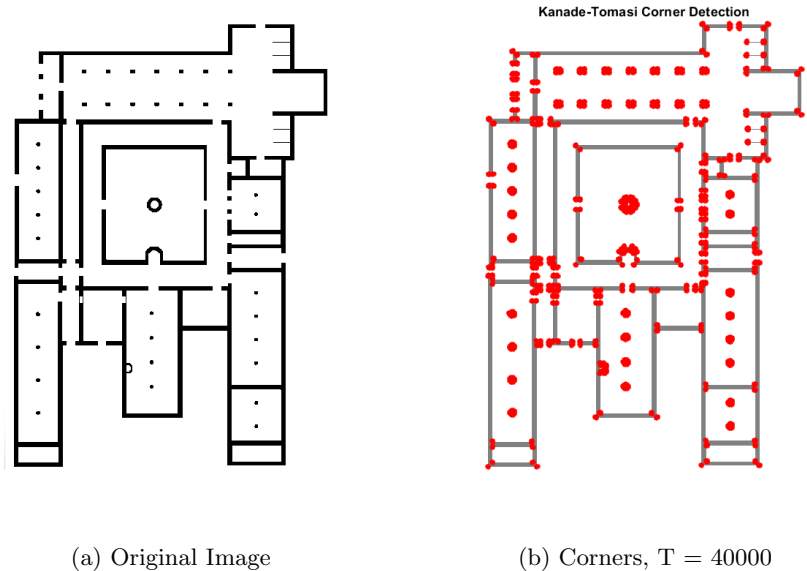


Figure 1: Tomasi Kanade Corner Detection

The threshold value is given by us as a parameter which we used as  $T = 40000$  for this example and as can be seen from the Figure 1 the corner detection algorithm successfully detected all the corners. On the given image, additional to all of the rectangles' corners the dots' edges are detected as well which is also correct.

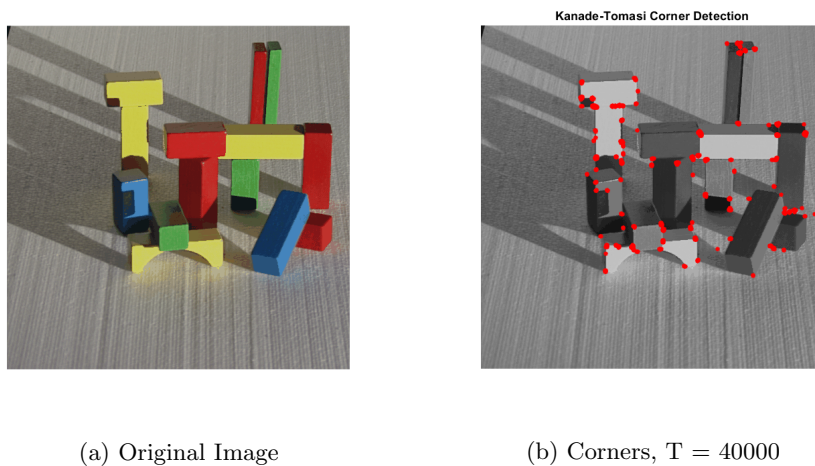


Figure 2: Tomasi Kanade Corner Detection

As it was also given in the lab document and provided us as an image, I also tried this method on another image during the lab which resulted as the Figure 1b with again  $T = 40000$ . After looking closely, even though it succeeded to detect most of the corners, there are still few missing that it failed to identify. It might be the case that it is related to threshold value which we will be seeing in the further trials.

## 2.2 Hough Lines

Here, we implemented a line detection function with using the Hough transform where the points on the image space are mapped into another space called the parameter space. Since the methods we used for edge detection in the previous labs mostly resulted in a disconnection and called as 'edgels', this time we want to detect the lines where there is not interruption of the lines.

To do so, first I chose an edge detector for extracting the b and white version of the image with the detected edges and since my observations were in the favor Canny Edge detector as successful, I the built-in function `edge()` with 'Canny' and stored it `img_edges` (see Appendix lab4houghlines.m) and visualized it with the original image. After that, I used the `hough()` built-in function and calculated the H matrix,  $\theta$  and  $\rho$  values with it which is the new values in the parameter space extracted by using the trigonometric parametric equation of the line in 2D. Then I calculated the Hough peaks and Hough lines with again the built-in functions `houghpeaks(H,20,'threshold',Thresh)` and `houghlines(img_edges,theta,rho,peaks)` where H is the Hough transform matrix and 20 is for returning 20 peak values, and Thresh is for the threshold value we determined (also the default value by MATH LAB). H, theta and rho is returned by the `hough()` function while peaks is returned by the `houghpeaks()` function. After that I visualized the peaks and showed the lines on the original image. Additionally, I calculated the max and min length with determining the line lengths for each element in the lines (using `norm()` function) and comparing with the current max and min line value. Finally I visualized the selected lines with the stored end points of them from `xy_long` and `xy_short` matrices (see Appendix lab4houghlines.m).

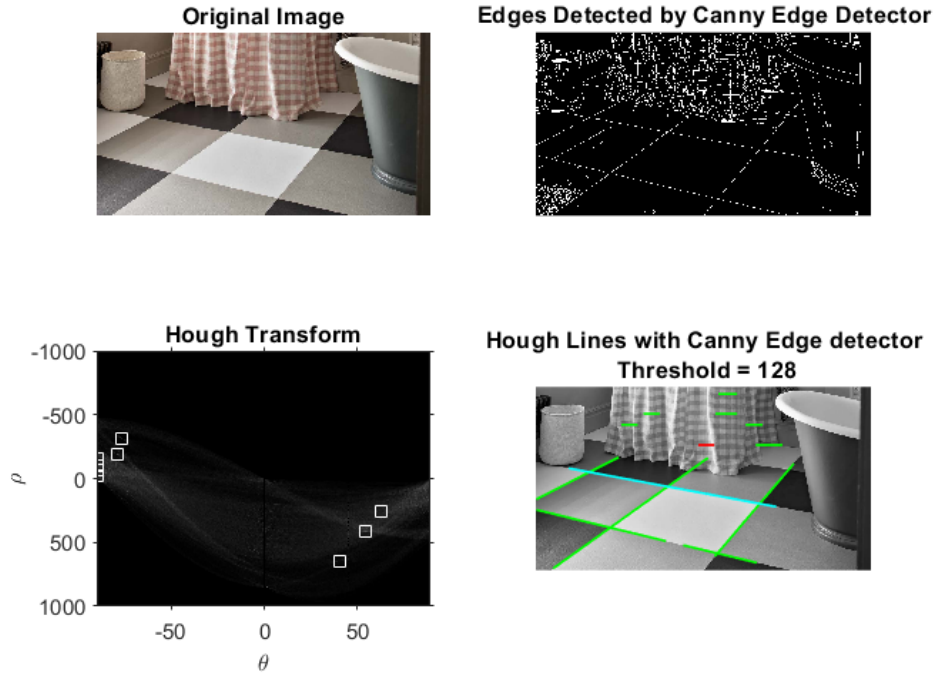


Figure 3: Hough Lines

As it can be seen from the Figure 3 that the Hough Transform resulted in sinusoidal waves which represent every possible line candidate in the image. And as we selected the peak values that are pointed out with boxes, the corresponding lines are the following depicted with green color and also the longest and shortest lines are signified with cyan and red respectively.

## 2.3 Hough Circles

For this last experiment, we used Hough transformation again but this time with circle equation for circle detection. To do so, with the given values for minimum and maximum radius I initialized the radius range as  $rmin$ ,  $rmax = [20,60]$ . Since the functions we used and their parameters are all explained in the lab document I won't be explaining the details but I used the circle detection function `imfindcircles()` 4 times to try it with different sensitivity parameters and also for detecting the circles darker or brighter than the background. Then I visualized all four different trials (see Appendix `lab4houghcircles.m`).

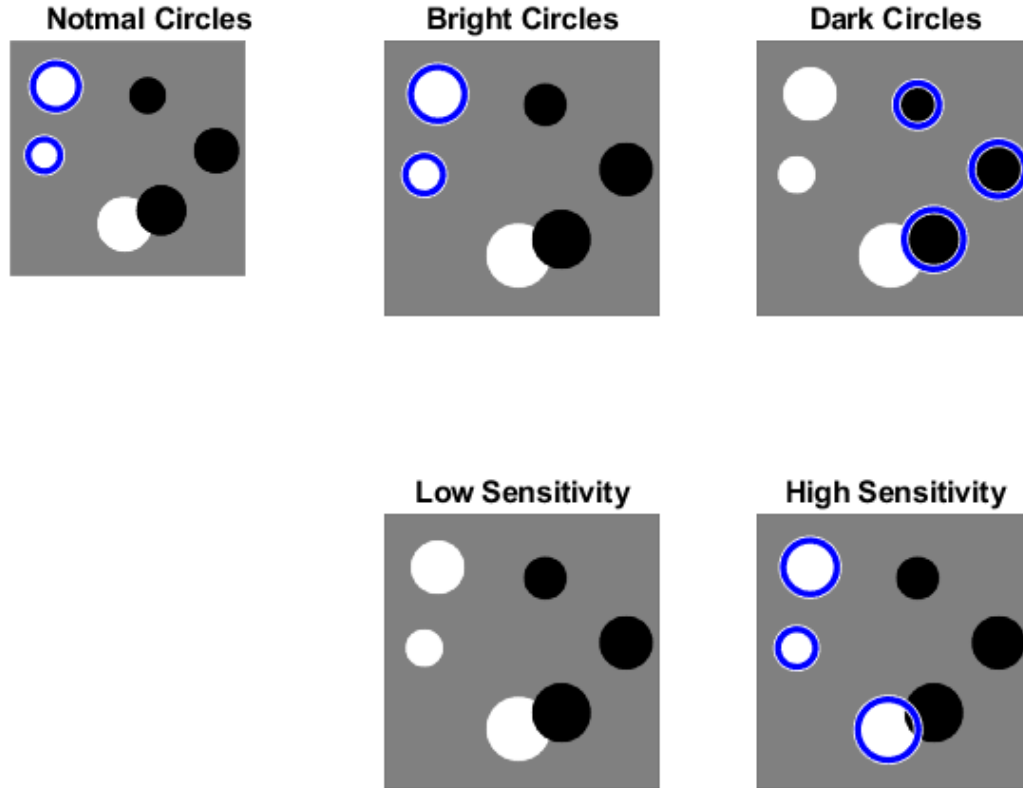


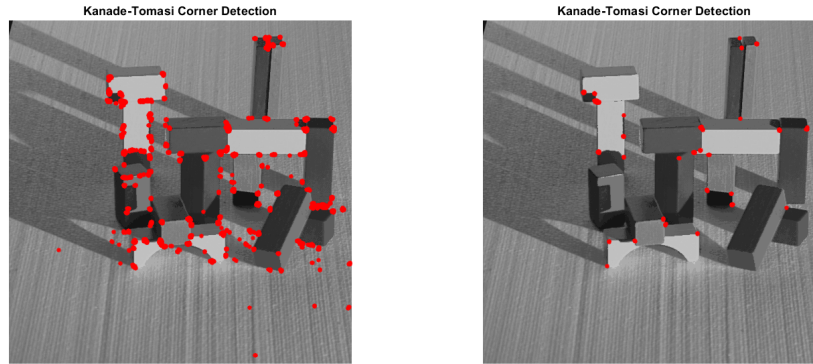
Figure 4: Hough Circles

As can be seen in the Figure 4 "Normal Circles" when I called the function without specifying any parameters with only the radius range it only detected the left 2 circles. However, when I called the function with specifying 'Object Polarity' parameter, it successfully found the circles which are darker and brighter. On the other hand, low sensitivity with 0.4 failed to detect any of the circles but high sensitivity with value 0.9 only detected the brighter circles.

### 3 Post Lab Experiments

#### 3.1 Tomasi Kanade Corner Detection

Since for the image in Figure 1 we achieved to detect all the corners, I will now try to find a better detection for the second image that we tried which was on the Figure 2 to see whether changing the threshold value will affect the results or not.



(a) Corners,  $T = 20000$

(b) Corners,  $T = 100000$

Figure 5: Tomasi Kanade Corner Detection

As can be seen from the Figure 5a, when I tried a smaller threshold value, the corners appeared to be even less than the actual one so I also tried another high threshold value which can also be seen from the Figure 5b. However, this time, wrong corners started to appear on the places where our eyes wouldn't see as corners which also ended up in a worse result. Thus, it is possible to say that either it should have tried many more values to see the optimum threshold value and might expect more corners to be detected or put the blame on the detection algorithm and accept the fact that it didn't turn out to be that successful for this image.

#### 3.2 Hough Lines

For the Hough lines, as the resulting lines were successful enough I wanted to try another image where the lines are not that clear (e.g. checker on the floor) compared to the image in the Figure 3. And I kept all the other parameters the same such as the threshold.

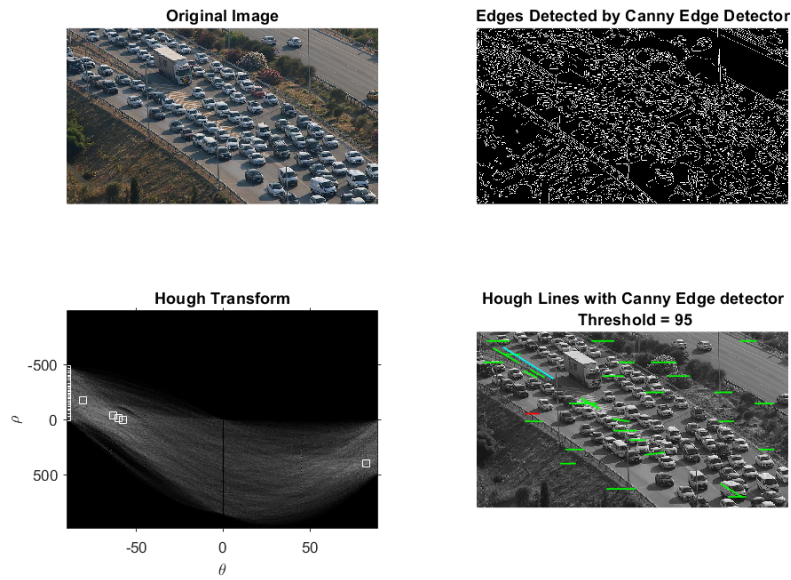


Figure 6: Hough Lines

Since one of the places that the line detection might be seen and be useful in real life is detecting the lines on the road for the automated cars to follow, I wanted to see its performance on a road. However, as can be seen from the Figure 6 that it failed to detect any of the lines of the road but rather detected the barriers on where the road broke apart into two. And also some of the lines were arbitrary when I observed it with my eyes. While the longest line indicated with blue was actually line but the actual longest, red line was barely significant on the original image to be a line. Thus, I tried another image where there is clearly lines in the seen that has been captured.

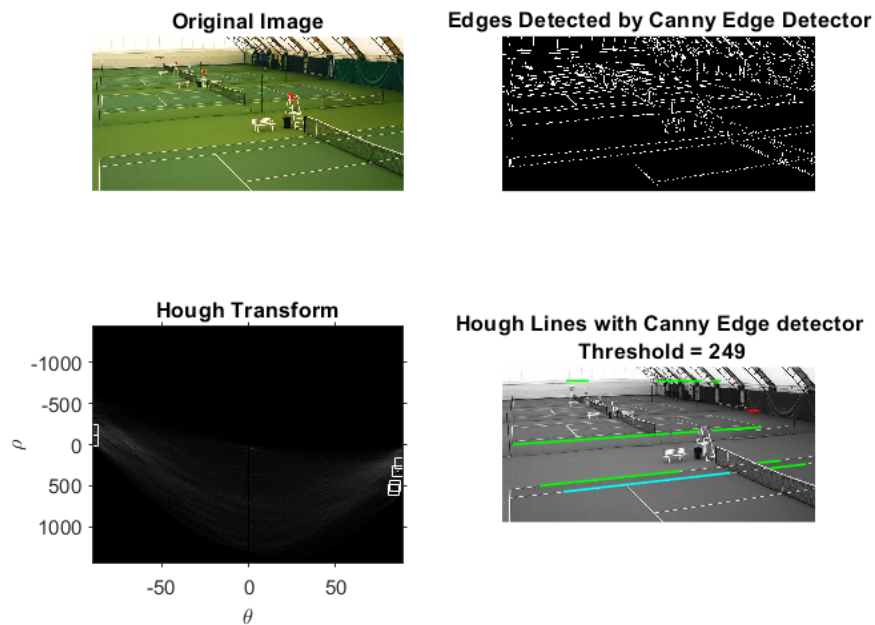


Figure 7: Hough Lines

As it can be seen from the Figure 7 the transform was able to detect few lines as the lines of the borders of the tennis court but it failed to detect all of them. It might be related to the threshold value that has been used or other parameters initialized so to achieve better results a deeper analysis should be done with trying to find the optimal values for each unique image.

Finally, when compared the results of the graphs for Hough transforms from Figure 3, 6, 7, it is possible to conclude that when the lines are more visible and easier to detect by the algorithm the resulting lines are less visible since the candidates are lower. When looked at the resulting graph on 6, the lines and the waves are quite complicated.

### 3.3 Hough Circles

Since the algorithm did not detect all the circles when I didn't insert any parameters and failed to detect any circles when the sensitivity is low (0.4) I wanted to do more trial with experimenting on the sensitivity parameter to see how it affects the results.

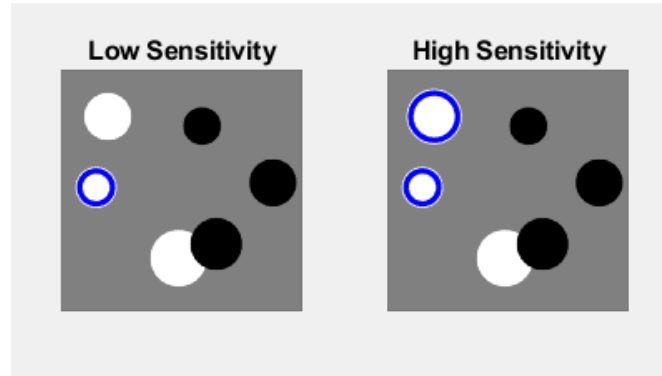


Figure 8: Hough Circles with Sensitivity 0.6 and 0.8

Since the default value for sensitivity is 0.85 (according to MATH LAB documentation) and max is 0.9 and we already tried both of them, I tried two different values in between the values I already tried (0.4 and 0.9). And as can be seen from the Figure 8, the resulting detecting were not any better than the previous trials and they both only found the brighter circles. Thus, based on my observations, we can conclude than the function performs better with higher sensitivity (0.9 optimal) on this image and detect bright circles. However, it is important to note that, it has been achieved to detect all the circles with specifically using the parameters 'bright' or 'dark' and can be combined to achieve a total result of detected circles as can be seen from Figure 9, so it might be a better idea to use two functions instead of one and merge them.

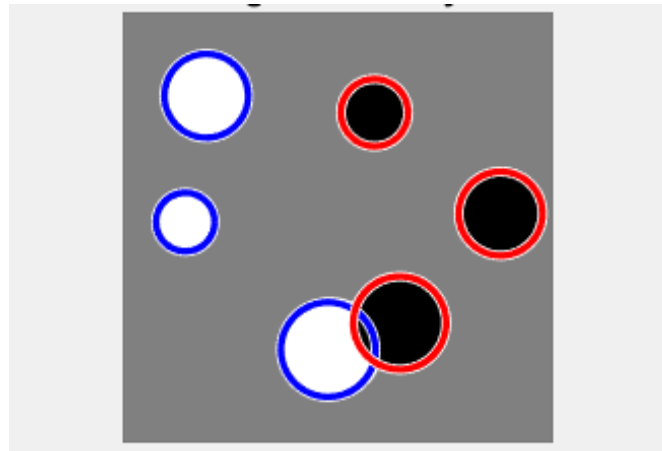


Figure 9: Hough Circles

# Appendix

## 3.4 main.m

```
1 %% Corner detection
2 clear all; close all; clc;
3 tic
4
5 img = imread('blocks.png');
6 imshow(img);
7 Corners_Filtered = lab4ktcorners(img);
8 toc
9
10 %% Hough Lines
11 clear all; close all; clc;
12 tic
13 img = imread('checker.jpg');
14 [H,theta,rho] = lab4houghlines(img);
15 toc
16 %% Hough Circles
17 clear all; close all; clc;
18 tic
19 img = imread('circlesBrightDark.png');
20 [centersBright, radiiBright, centersDark, radiiDark] = lab4houghcircles(img);
21 toc
```

## 3.5 lab4ktcorners.m

```
1 function [corners] = lab4ktcorners(I)
2
3 [r,c,ch] = size(I);
4 if (ch ==3)
5     I = rgb2gray(I);
6 end
7
8 img = I;
9
10 % Corners_Filtered = zeros(size(img));
11
12 % Transforming to double (preparation for calculations)
13 img = double(img);
14 %Corners_Filtered = double(Corners_Filtered);
15
16 % Initializations of corners, threshold, window size
17 corners = [];
18 T = 40000;
19 k = 1;
20
21 % Smoothing
22 Simg = imgaussfilt(img);
23
24 % Finding H for each Pixel using windows
25 [Gx,Gy] = imgradientxy(Simg);
26
27 for i = k+1:1:r-k-1
28     for j=k+1:1:c-k-1
29         Gx_window = Gx(i-k:i+k,j-k:j+k);
30         Gy_window = Gy(i-k:i+k,j-k:j+k);
31
32         I_x2 = Gx_window .* Gx_window;
33         I_xy = Gx_window .* Gy_window;
34         I_y2 = Gy_window .* Gy_window;
35
36         I_x2= sum(I_x2(:));
37         I_xy= sum(I_xy(:));
38         I_y2= sum(I_y2(:));
```



```

39     H = [I_x2, I_xy;
40          I_xy, I_y2];
41
42     e = eig(H);
43
44     lambda1 = e(1);
45     lambda2 = e(2);
46
47     % Finding eigen values and thresholding to get corners
48
49     if (min(lambda1,lambda2) > T)
50         corners = [corners; i,j];
51     end
52
53 end
54
55 end
56
57 % Visualization
58 img = uint8(img);
59
60 figure
61 imshow(I);
62 hold on;
63 plot(corners(:,2),corners(:,1),'r*', 'MarkerSize', 4, 'Linewidth', 1);
64 title('Kanade-Tomasi Corner Detection');
65 end

```

### 3.6 lab4houghlines.m

```

1 function [H,theta,rho] = lab4houghlines(I);
2
3 [r,c,ch] = size(I);
4 if (ch ==3)
5     img = rgb2gray(I);
6 end
7
8 % Edge Detection: the selection of the edge detector is very significant!
9 % Hint use edge built-in function
10 img_edges = edge(img,'Canny');
11
12 % Hough Transform + Display
13 [H,theta,rho] = hough(img_edges, 'RhoResolution',0.5,'Theta',-90:0.5:89);
14
15 figure('Name','Hough Transform','NumberTitle','off');
16 subplot(2,2,1)
17 imshow(I);
18 title('Original Image');
19
20 subplot(2,2,2)
21 imshow(img_edges);
22 title(sprintf('Edges Detected by %s Edge Detector', 'Canny'));
23
24 subplot(2,2,3)
25
26 imshow(H,[],'XData',theta,'YData',rho,'InitialMagnification','fit');
27 title('Hough Transform');
28 xlabel('\theta'), ylabel('\rho');
29 axis on, axis normal, hold on;
30
31 Thresh = ceil(0.5*max(H(:)));
32
33 %Hough peak points and hough lines, find 20 peaks and threshold value is Thresh
34 peaks = houghpeaks(H,20,'threshold',Thresh);
35 x = theta(peaks(:,2)); y = rho(peaks(:,1));
36 plot(x,y,'s','color','white');
37

```

```

38 % Hough Lines
39 lines = houghlines(img_edges,theta,rho,peaks,'FillGap',10,'MinLength',40);
40
41 % Plotting All Lines and Highlighting Longest and Shortest Lines
42
43 subplot(2,2,4);
44     imshow(img),title(sprintf('Hough Lines with %s Edge detector\n Threshold = %d', 'Canny',
45                               Thresh)), hold on
46
47     max_length = 40;
48     min_length = 2000;
49
50 %% Plotting the lines
51
52 for k = 1:length(lines)
53     xy = [lines(k).point1; lines(k).point2];
54     plot(xy(:,1),xy(:,2),'LineWidth',1,'Color','green');
55
56     len = norm(lines(k).point1 - lines(k).point2);
57     % for determining the longest line segment
58     if ( len > max_length)
59         max_length = len;
60         xy_long = xy;
61     elseif (len < min_length)
62         min_length = len;
63         xy_short = xy;
64     end
65 end
66
67 plot(xy_long(:,1),xy_long(:,2),'LineWidth',1,'Color','cyan');
68 plot(xy_short(:,1),xy_short(:,2),'LineWidth',1,'Color','red');

```

### 3.7 lab4houghcircles.m

```

1 function [centersBr, radiiBright, centersD, radiiDark] = lab4houghcircles(I)
2
3 [r,c,ch] = size(I);
4 if (ch ==3)
5     img = rgb2gray(I);
6 end
7
8 % Radius Range
9 rmin = 20;
10 rmax = 60;
11
12 % Circle detection with different parameters
13
14 [centerN, radiiNormal] = imfindcircles(I,[rmin rmax]);
15 [centersBr, radiiBright] = imfindcircles(I,[rmin rmax],'ObjectPolarity','bright');
16 [centersD, radiiDark] = imfindcircles(I,[rmin rmax],'ObjectPolarity','dark');
17 [centerL, radiiLow] = imfindcircles(I,[rmin rmax],'Sensitivity',0.6);
18 [centerH, radiiHigh] = imfindcircles(I,[rmin rmax],'Sensitivity',0.9);
19
20 %Visualisation
21
22 figure
23     subplot(2,3,1)
24         hold
25         imshow(I)
26         viscircles(centerN, radiiNormal,'Color','b');
27         title("Normal Circles")
28
29     subplot(2,3,2)
30         imshow(I)
31         hold
32         viscircles(centersBr, radiiBright,'Color','b');
33         title("Bright Circles");

```

```

34
35     subplot(2,3,3)
36     imshow(I)
37     hold
38     viscircles(centersD, radiiDark,'Color','b');
39     title("Dark Circles");
40
41     subplot(2,3,5)
42     imshow(I)
43     hold
44     viscircles(centerL, radiiLow,'Color','b');
45     title("Low Sensitivity")
46
47     subplot(2,3,6)
48     imshow(I)
49     hold
50     viscircles(centerH, radiiHigh,'Color','b');
51         viscircles(centersD, radiiDark,'Color','r');
52
53     title("High Sensitivity")

```