

1st Programming Assignment: Corner Detection

CSE 6239 (July 2020)

Report By:

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Description:

Corner detection executed for 8 images with different criteria is reported below with results.

Image: img1.png

Kernel: Gaussian

```
def dnorm(x, sd):
    return 1 / (np.sqrt(2 * np.pi) * sd) * np.e ** (-np.power(x / sd, 2) / 2)

def myGaussianKernel(size, sigma=1, verbose=False):
    kernel_1D = np.linspace(-(size // 2), size // 2, size)
    for i in range(size):
        kernel_1D[i] = dnorm(kernel_1D[i], sigma)
    print(kernel_1D)

    kernel_2D = np.outer(kernel_1D, kernel_1D)
    kernel_2D **= 1.0 / kernel_2D.max()

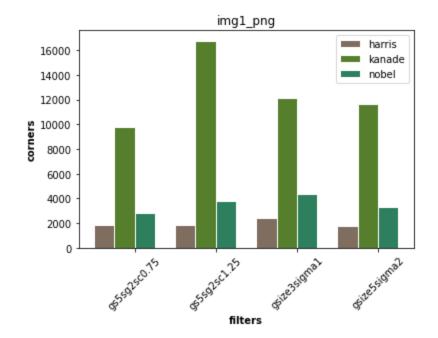
    plt.imshow(kernel_2D, interpolation='none', cmap='gray')
    plt.title("Gaussian Kernel Image")

if verbose:
    plt.show()
    else:
    plt.savefig(os.path.join("output", f"gk{size}_{sigma}.png"))
    return kernel_2D
```

	Size: 3 Sigma: 1	Size: 5 Sigma: 2	Size: 5 Sigma: 2 Scale: 0.75	Size: 5 Sigma: 2 Scale: 1.25
Kernel	-0.1 General Image 60 60 61 63 63 63 64 65 66 66 67 68 68 68 68 68 68 68	Gaussian Kernel Image 1 2 3 6 1 1 1 1 1 1 1 1 1 1 1 1	Caussian formel image Caussian formel image L L L L L L L L L L L L L	Caucation Fernel Images
X Derivative	X derhados Inage 10- 100- 1	X derhados Inage 18- 18- 18- 18- 20- 20- 20- 20- 20- 20- 20- 20	3 - 3 - 5 - 50 - 25 - 250 - 151	3 - 3 - 3 - 3 - 3 - 3 - 3 - 3 - 3 - 3 -
Y Derivative	y derhadha Inage 34- 30- 30- 30- 30- 30- 30- 30- 30	y derhados inage 34- 300- 3	y derhados image 23- 33- 33- 33- 33- 33- 33- 33- 33- 33	y derivative image 34- 350- 350- 350- 350- 350- 350- 350- 350

Harris R Threshold = 10000.00		
Kanade R Threshold = 100.00		
Nobel R Threshold = 1.00		

Bar chart for above Gaussian filter



Comments:

- 1. Harris algorithm has worked well.
- 2. Kanade works very bad
- 3. Scale up detected more accurate corners
- 4. 15.5% corners are found common for 3 algorithms

Kernel: Box

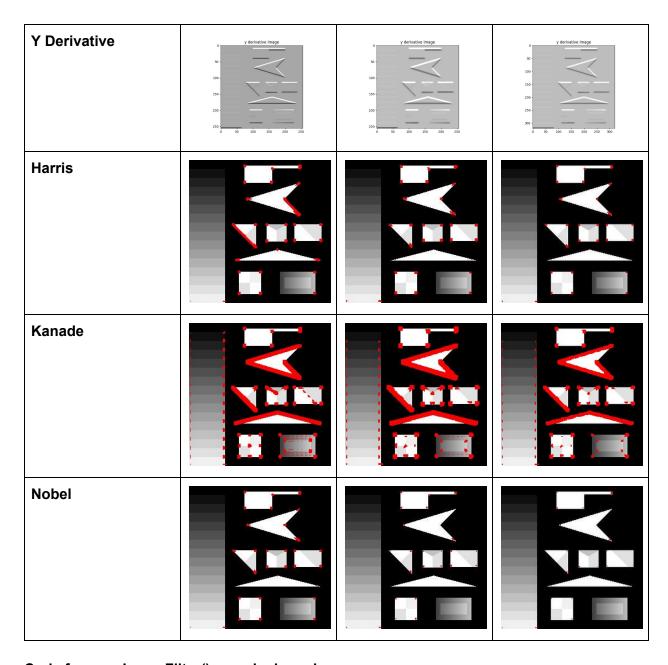
```
def myBoxKernel(size, verbose=False):
    kernel_2D = np.ones((size, size)) / 9

plt.imshow(kernel_2D, interpolation='none', cmap='gray')
plt.title("Box Kernel Image")

if verbose:
    plt.show()
else:
    plt.savefig(os.path.join("output", f"box{size}.png"))

return kernel_2D
```

	Size: 3	Size: 5	Size: 5 Scale: 1.25
Kernel	-03 Box Kernel Image 05- 10- 15- 28- 28- 28- 28- 28- 28- 28- 28- 28- 28	Box Kernel Image 1- 2- 3- 4- 6 1 3 3 4	Box Kernel Image 0- 1- 2- 3- 4- 0 1 2 3 4
X Derivative	x derivative image 20 - 100 -	x derivative image 20 - 100 - 100 - 100 - 200 -	x derivative image 50 100 150 200 250 50 150 150

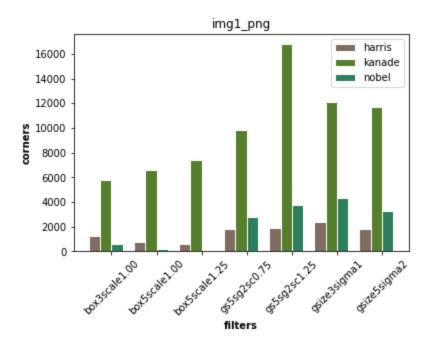


Code from mylmageFilter() conv by kernel:

```
for row in range(image_row):
    for col in range(image_col):
        output[row, col] = np.sum(kernel * padded_image[row:row + kernel_row, col:col + kernel_col])
        if average:
             output[row, col] /= kernel.shape[0] * kernel.shape[1]

print("Output Image Size : {}".format(output.shape))
```

Bar chart for above Gaussian + Box filter



Comments:

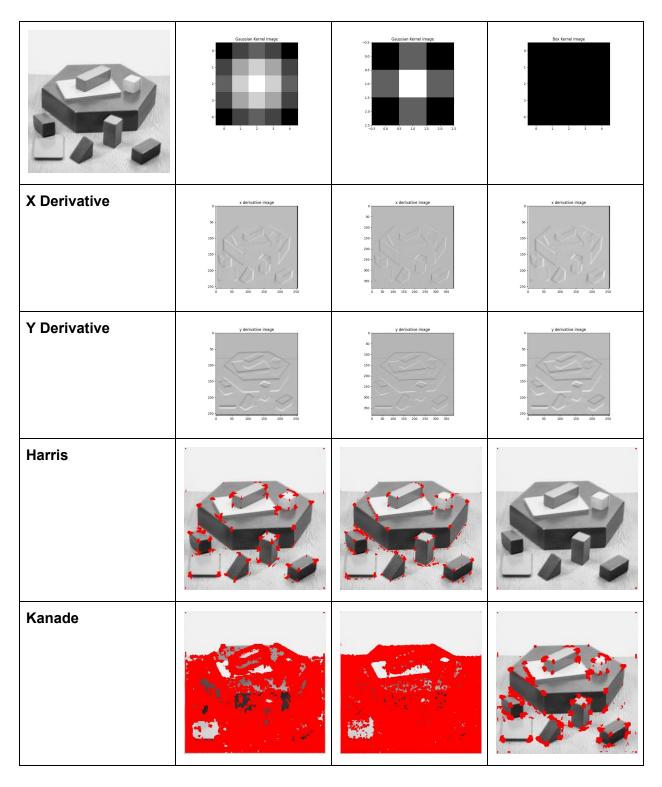
- Less corner detected in box filter
- 6. Again scaling up detect more corners

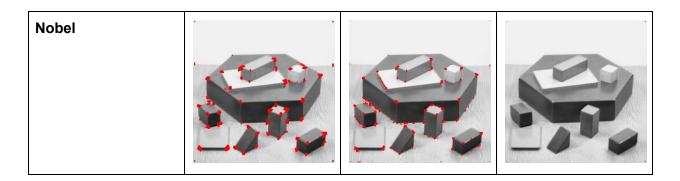
Code for R calculation:

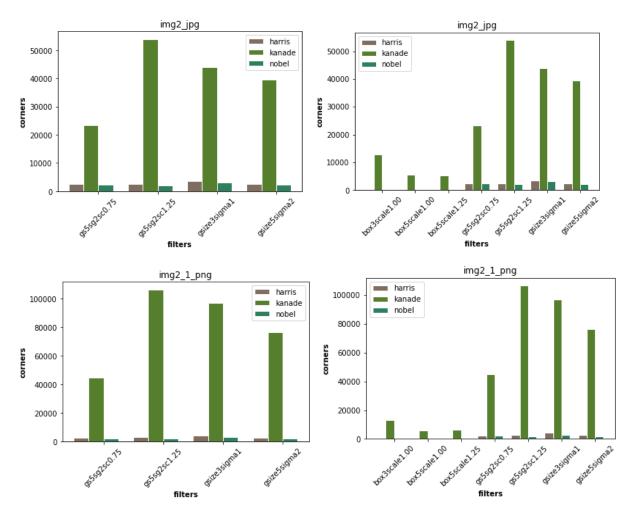
```
# Calculate r for Harris Corner equation
title = "Harris"
k = 0.04
r = det - k * (trace ** 2)
threshold = 10000.00
if r > threshold:
    harris_corner_list.append([x, y, r])
# cv2.circle(output_img, (x, y), 1, 255, -1)
harris_output_img[y, x] = (0, 0, 255)
# Calculate r for Kanade & Tomasi Corner equation
title = "Kanade & Tomasi"
# Lamda1 * Lamda2 = det
# Lamda1 + Lamda2 = trace
w, v = np.linalg.eig(M)
r = np.min(w)
threshold = 1.00
if r > threshold:
     kanade_corner_list.append([x, y, r])
kanade_output_img[y, x] = (0, 0, 255)
# Calculate r for Nobel Corner equation
title = "Nobel"
e = 1
r = det / (trace + e)
threshold = 100.00
if r > threshold:
     nobel_corner_list.append([x, y, r])
     nobel_output_img[y, x] = (0, 0, 255)
```

Similar process applied for all other provided images and For more programming reference please visit here.

Image: img2.jpg







Comments:

- 1. Harris and Nobel algorithms do not perform well with the box kernel but work well with the gaussian kernel.
- 2. So much noise is found in the Kanade algorithm with the gaussian kernel. But with the box kernel Kanade algorithm works well.
- 3. Here 95% corners are common for kernel size difference

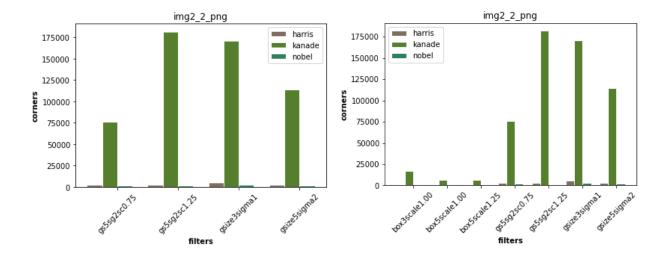
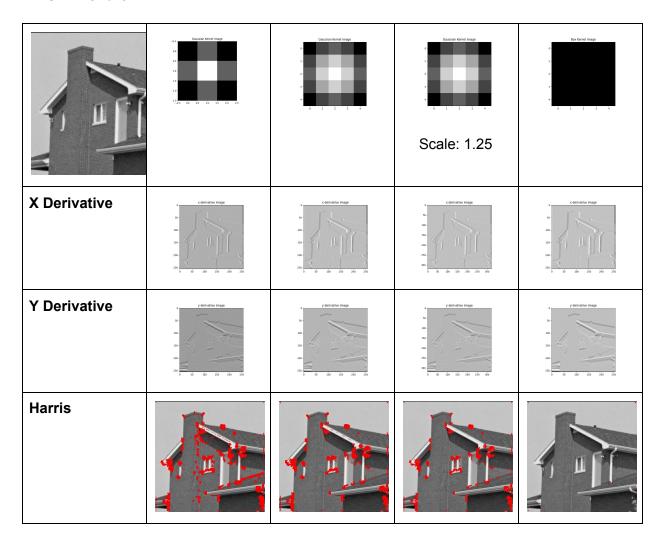
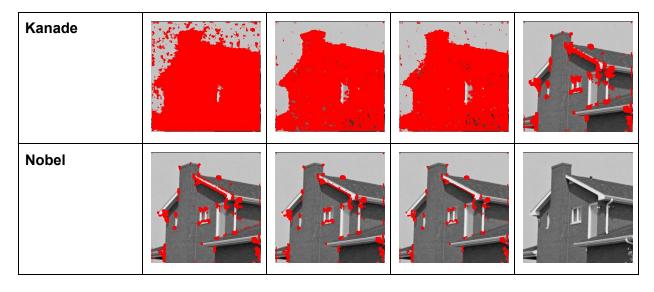


Image: img3.jpg





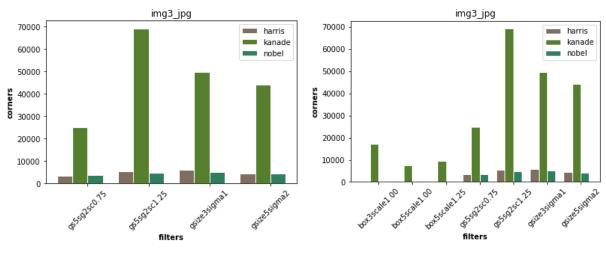


Image: img4.png

