



Visión Computacional para imágenes y video (Gpo 10)

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7. Harris Edge & Corner Detection

Table of Contents

1. [Libraries](#)
2. [Color image to Grayscale conversion](#)
3. [Spatial derivative calculation](#)
4. [Structure tensor setup](#)
5. [Harris response calculation](#)
6. [Find edges and corners using R](#)
7. [Application and analysis](#)
8. [References](#)

Importing Libraries

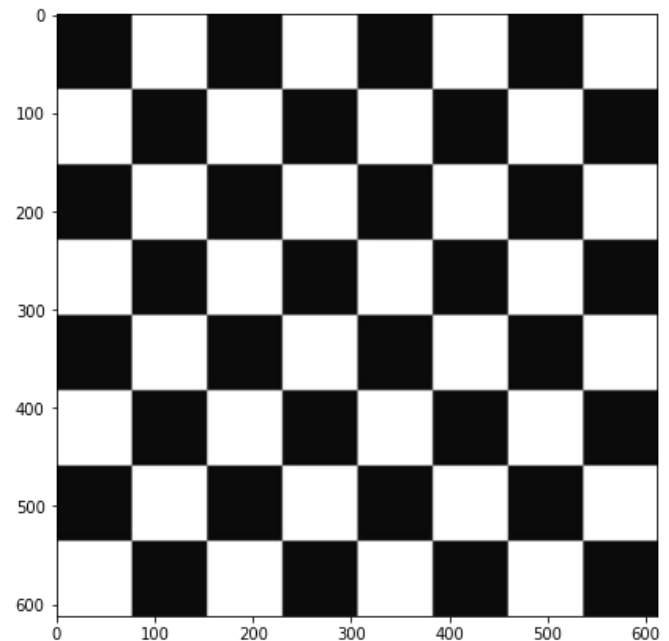
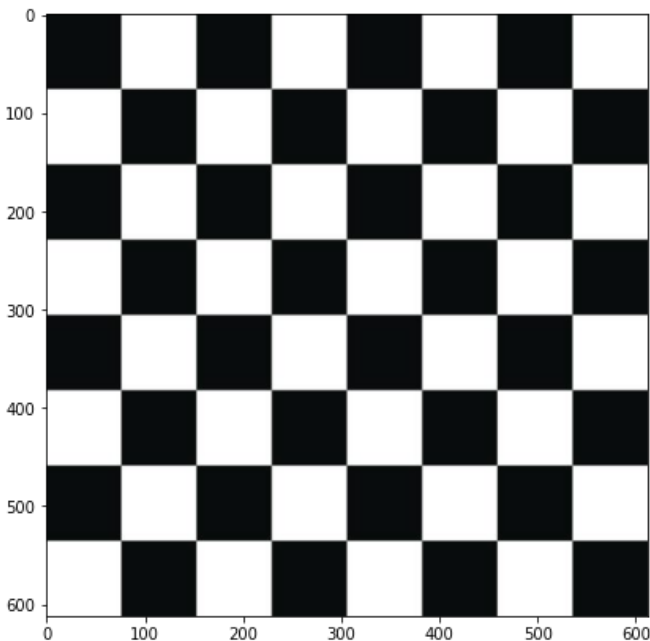
```
In [126.. import cv2
import matplotlib.pyplot as plt
from scipy import signal as sig
import numpy as np
from scipy.ndimage.filters import convolve
```

1. Color to Grayscale

```
In [127... img = cv2.imread('data/chessboard.jpg')
img_color = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
img_gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_color)
plt.subplot(1, 2, 2)
plt.imshow(img_gray, cmap="gray")
```

Out[127]: <matplotlib.image.AxesImage at 0x1e605f61c40>



2. Spatial derivative calculation

```
In [128... def gradient_x(imggray):
    ##Sobel operator kernels.
    kernel_x = np.array([[-1, 0, 1], [-2, 0, 2], [-1, 0, 1]])
    return sig.convolve2d(imggray, kernel_x, mode='same')

def gradient_y(imggray):
    kernel_y = np.array([[1, 2, 1], [0, 0, 0], [-1, -2, -1]])
    return sig.convolve2d(imggray, kernel_y, mode='same')

I_x = gradient_x(img_gray)
I_y = gradient_y(img_gray)
```

3. Structure tensor setup

```
In [129... def gaussian_kernel(size, sigma=1):
    size = int(size) // 2
    x, y = np.mgrid[-size:size+1, -size:size+1]
    normal = 1 / (2.0 * np.pi * sigma**2)
    g = np.exp(-((x**2 + y**2) / (2.0*sigma**2))) * normal
    return g

Ixx = convolve(I_x**2, gaussian_kernel(3, 1))
```

```
Ixy = convolve(I_y*I_x, gaussian_kernel(3, 1))
Iyy = convolve(I_y**2, gaussian_kernel(3, 1))
```

4. Harris response calculation

```
In [130...] k = 0.05

# determinant
detA = Ixx * Iyy - Ixy ** 2

# trace
traceA = Ixx + Iyy

harris_response = detA - k * traceA ** 2
```

```
In [131...] img_gray.shape
```

```
Out[131]: (612, 612)
```

```
In [132...] window_size = 3
offset = window_size//2
width, height = img_gray.shape

for y in range(offset, height-offset):
    for x in range(offset, width-offset):
        Sxx = np.sum(Ixx[y-offset:y+1+offset, x-offset:x+1+offset])
        Syy = np.sum(Iyy[y-offset:y+1+offset, x-offset:x+1+offset])
        Sxy = np.sum(Ixy[y-offset:y+1+offset, x-offset:x+1+offset])
```

```
In [133...] #Find determinant and trace, use to get corner response
det = (Sxx * Syy) - (Sxy**2)
trace = Sxx + Syy
r = det - k*(trace**2)
```

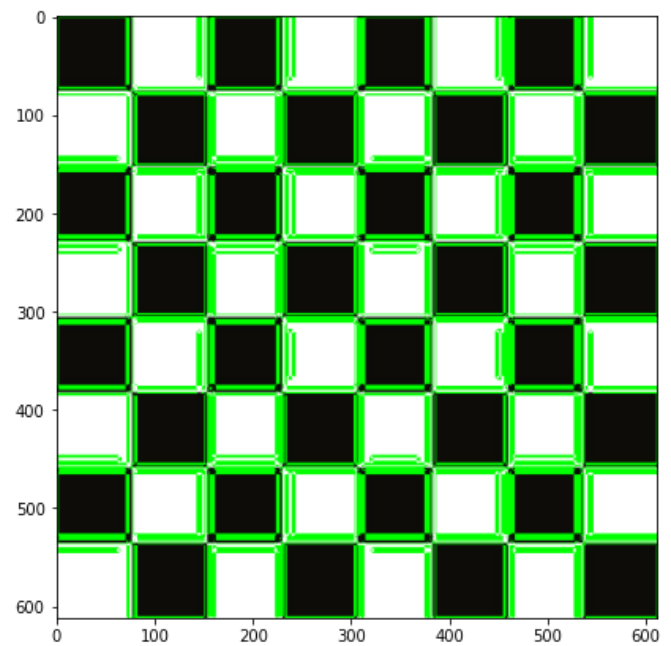
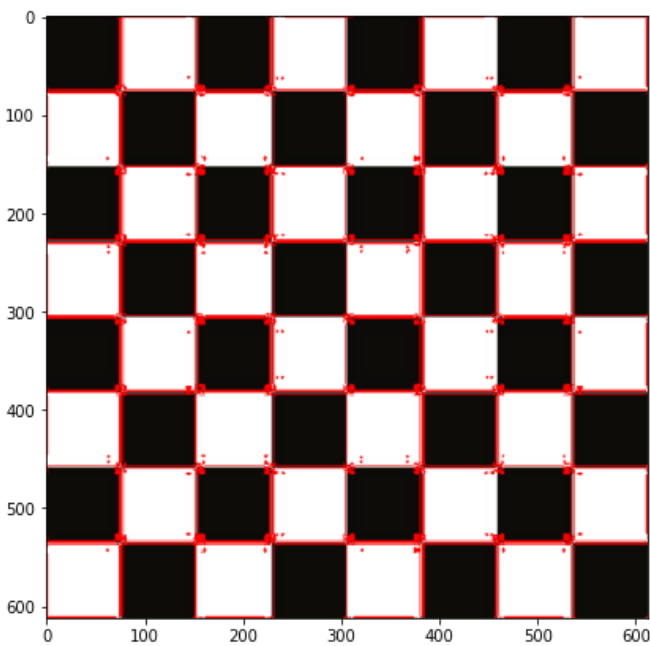
5. Find edges and corners using R

```
In [134...] img_copy_for_corners = np.copy(img)
img_copy_for_edges = np.copy(img)

for rowindex, response in enumerate(harris_response):
    for colindex, r in enumerate(response):
        if r > 0:
            # this is a corner
            img_copy_for_corners[rowindex, colindex] = [255,0,0]
        elif r < 0:
            # this is an edge
            img_copy_for_edges[rowindex, colindex] = [0,255,0]
```

```
In [135...] plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_copy_for_corners, cmap="gray")
plt.subplot(1, 2, 2)
plt.imshow(img_copy_for_edges, cmap="gray")
```

```
Out[135]: <matplotlib.image.AxesImage at 0x1e6058513a0>
```



Applications and Analysis

For this exercise we are going to take three sets of photos, a very simple pokemon, one of a bust with different lighting and finally a third one of a bunny plush also with different light and slightly different angle. Using these two sets of images we will present how the Harris Corner Detection algorithm performs.

Let's first see the images of the bust with different lighting scenarios, original image from [1].

```
In [189... print("Image of a pokemon")
Image.open('./data/pikachu.jpg')
```

Image of a pokemon

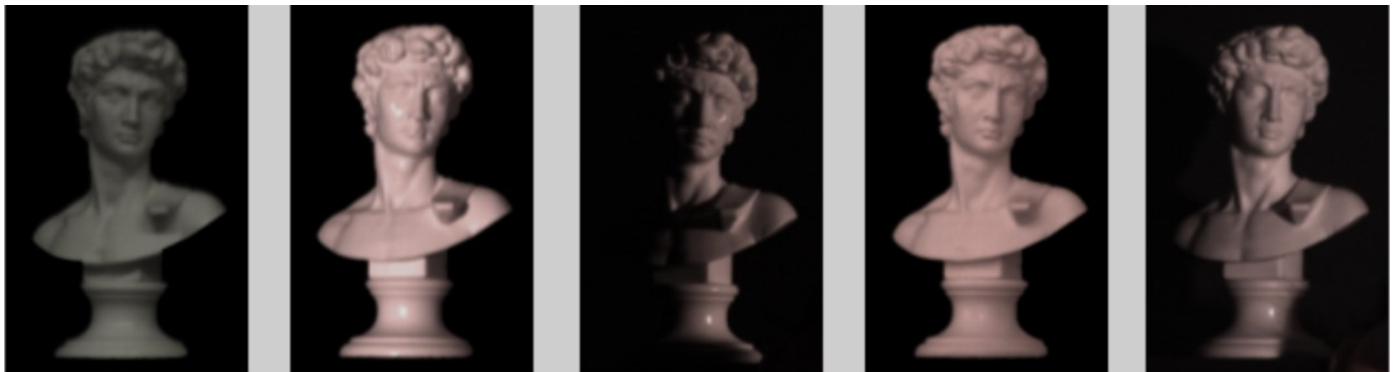
Out[189]:



```
In [177... print("Images of bust under different lighting ")  
Image.open('./data/invariant_images.jpg')
```

Images of bust under different lighting

Out[177]:



We will implement a simple script to split the images into 4 tiles to then use it for the Harris-Corner algorithm.

```
In [166... from PIL import Image  
  
# Open the image  
img = Image.open('./data/invariant_images.jpg')  
  
# Define the tile size  
tile_width = img.width // 5  
tile_height = img.height
```

```

# Loop through the tiles
for j in range(5):
    # Calculate the coordinates of the tile
    correction_left = [10, 10, 20, 30, 32]
    correction_right = [30, 20, 10, 5, 0]
    left = j * tile_width + correction_left[j]
    upper = 0
    right = (j + 1) * tile_width - correction_right[j]
    lower = tile_height

    # Crop and resize the tile
    tile = img.crop((left, upper, right, lower))
    tile.resize((200,200))

    tile.save(f'./data/tile_{j}.jpg')
    print(f"tile image saved in /data/tile_{j}.jpg")

    # Show the tile in the corresponding subplot

```

```

tile image saved in /data/tile_0.jpg
tile image saved in /data/tile_1.jpg
tile image saved in /data/tile_2.jpg
tile image saved in /data/tile_3.jpg
tile image saved in /data/tile_4.jpg

```

Now, let's take a look at the two images we will use of the bunny plush

```

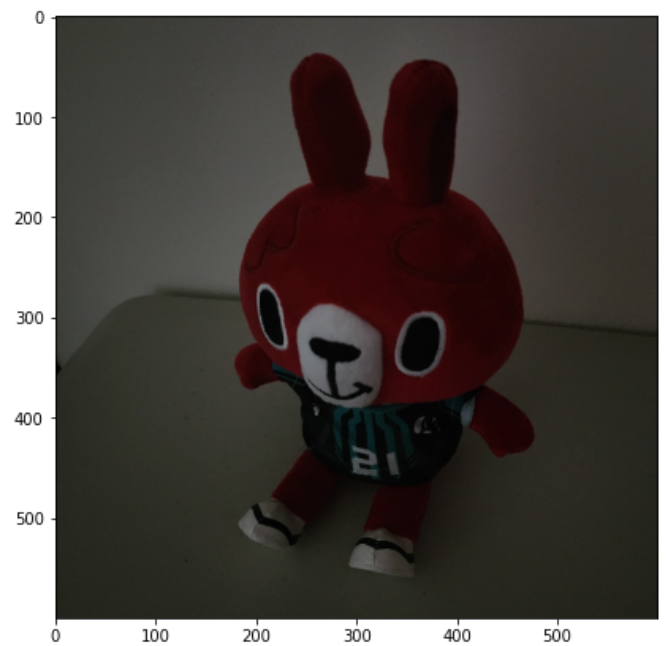
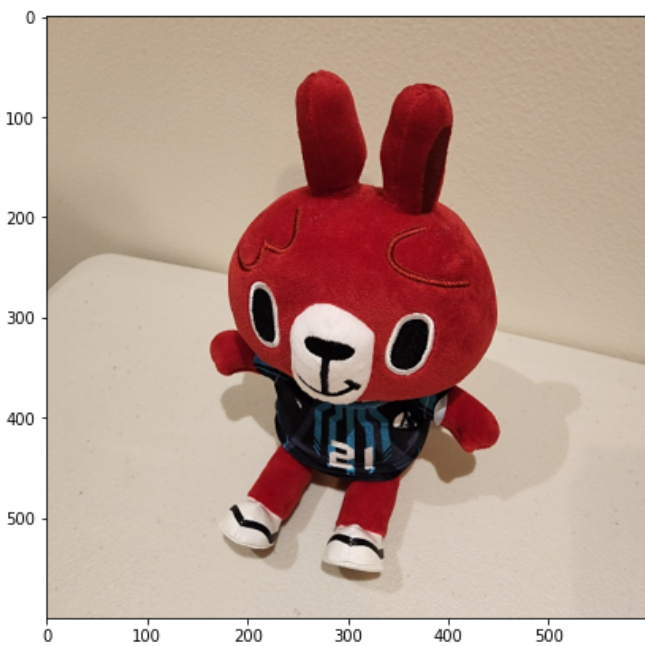
In [178... # First image
img_0 = cv2.imread('data/bunny_5.jpg')
img_0 = cv2.cvtColor(img_0, cv2.COLOR_BGR2RGB)
img_0 = cv2.resize(img_0, (600, 600))

# Second image
img_1 = cv2.imread('data/bunny_11.jpg')
img_1 = cv2.cvtColor(img_1, cv2.COLOR_BGR2RGB)
img_1 = cv2.resize(img_1, (600, 600))

# Canvas for output
print("Images of bunny plush")
plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_0)
plt.subplot(1, 2, 2)
plt.imshow(img_1)
plt.show()

```

Images of bunny plush



We will use the algorithm of the code below to analyze the pictures to find corners and edges.

```
In [179... # Required libraries
import cv2
import matplotlib.pyplot as plt
from scipy import signal as sig
import numpy as np
from scipy.ndimage.filters import convolve

# Main function
def harris_corner(imgpath, k, resize=False):
    """
    This function takes the path of an image, a parameter k for the Harris Corner algorithm.
    It returns the image in a 4-tile where we can see the original image, that image in
    """

    # Open the image
    img = cv2.imread(imgpath)

    # If we require to resize
    if resize:
        img = cv2.resize(img, (600, 600))

    # To show the original image (cv2 is BGR for some reason...)
    orig_img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

    # Change the image to gray scale
    img_gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    # Function to take the gradient of x  $I_x = df/dx$ 
    def gradient_x(img):
        kernel_x = np.array([
            [-1, 0, 1],
            [-2, 0, 2],
            [-1, 0, 1]
        ])
        return sig.convolve2d(img, kernel_x, mode='same')

    # Function to take the gradient of y  $I_y = df/dy$ 
    def gradient_y(img):
        kernel_y = np.array([
            [1, 2, 1],
            [0, 0, 0],
            [-1, -2, -1]
        ])
        return sig.convolve2d(img, kernel_y, mode='same')
```

```

        [0, 0, 0],
        [-1, -2, -1]
    ])
    return sig.convolve2d(img, kernel_y, mode='same')

# Gaussian kernel to smooth the image
def gaussian_kernel(size, sigma=1):
    size = int(size) // 2
    x, y = np.mgrid[-size:size+1, -size:size+1]
    normal = 1 / (2.0 * np.pi * sigma**2)
    g = np.exp(-((x**2 + y**2) / (2.0*sigma**2))) * normal
    return g

# We take the derivatives and product of those derivatives
I_x = gradient_x(img_gray)
I_y = gradient_y(img_gray)

Ixx = convolve(I_x**2, gaussian_kernel(3, 1))
Ixy = convolve(I_y*I_x, gaussian_kernel(3, 1))
Iyy = convolve(I_y**2, gaussian_kernel(3, 1))

# We then create the determinant measure
detA = Ixx * Iyy - Ixy ** 2

# We then creat the trace measure
traceA = Ixx + Iyy

# This creates our Harris Response for an isoquant K
harris_response = detA - k * traceA ** 2

# We want an image for corners and one for edges
img_copy_for_corners = np.copy(orig_img)
img_copy_for_edges = np.copy(orig_img)

# Using the harris response we can color the edges and corners in different colors
for rowindex, response in enumerate(harris_response):
    for colindex, r in enumerate(response):
        if r > 0:
            # this is a corner
            img_copy_for_corners[rowindex, colindex] = [255,0,0]
        elif r < 0:
            # this is an edge
            img_copy_for_edges[rowindex, colindex] = [0,255,0]

# Canvas for output
plt.figure(figsize=(15, 8))

# Original Image
a = plt.subplot(2, 2, 1)
a.set_title('Original')
plt.imshow(orig_img)

# Image in gray scale
b = plt.subplot(2, 2, 2)
b.set_title('Gray image')
plt.imshow(img_gray, cmap='gray')

# Corners
c = plt.subplot(2, 2, 3)
c.set_title('Corners')
plt.imshow(img_copy_for_corners, cmap='gray')

# Edges
d = plt.subplot(2, 2, 4)
d.set_title('Edges')

```

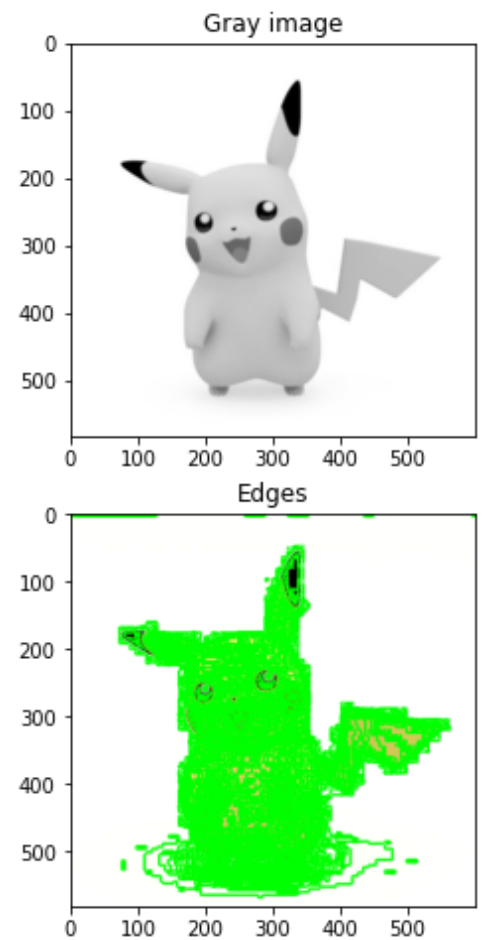
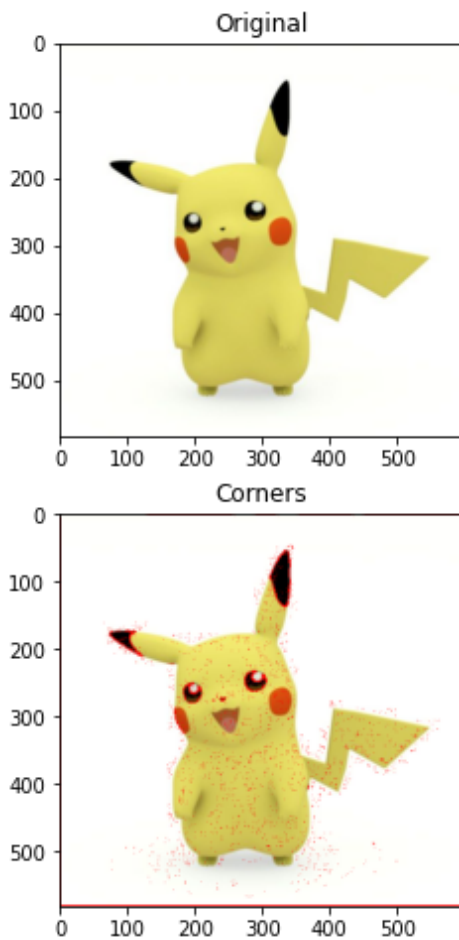


```
plt.imshow(img_copy_for_edges, cmap='gray')

# Show all plots
plt.show()
```

Example one

```
In [209... harris_corner('data/pikachu.jpg', 0.24)
```

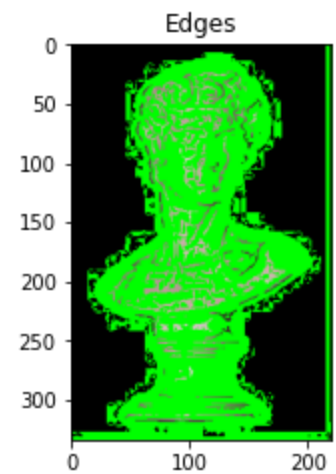
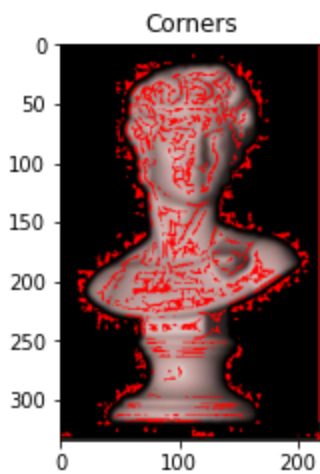
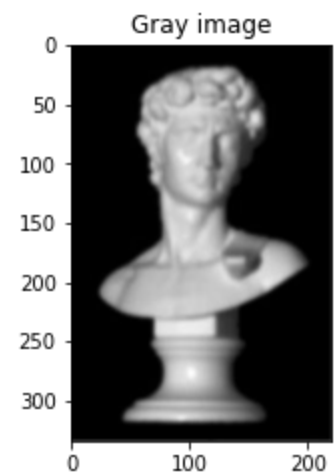
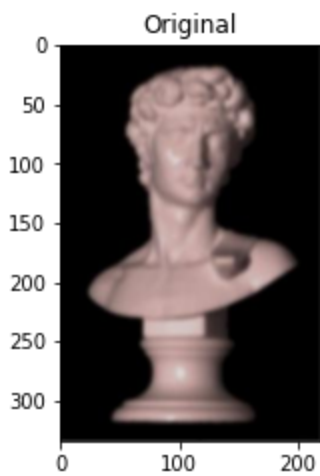
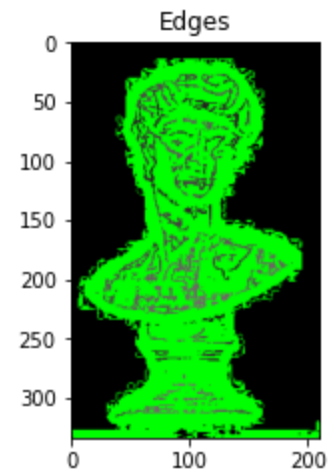
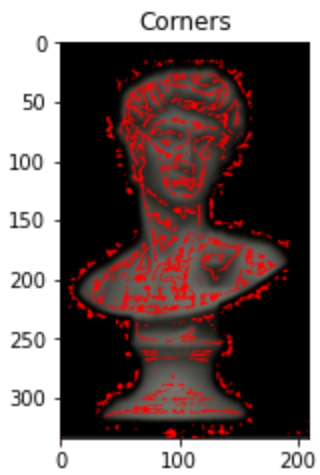
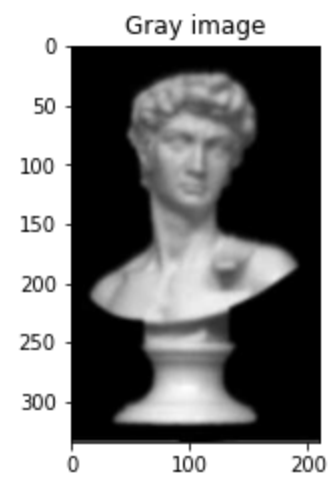
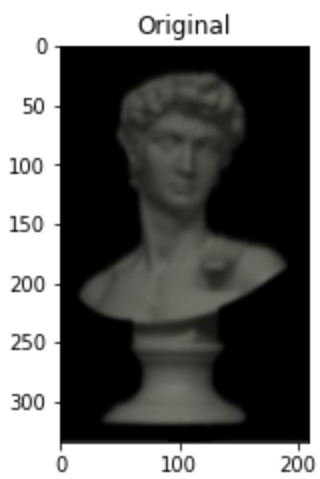


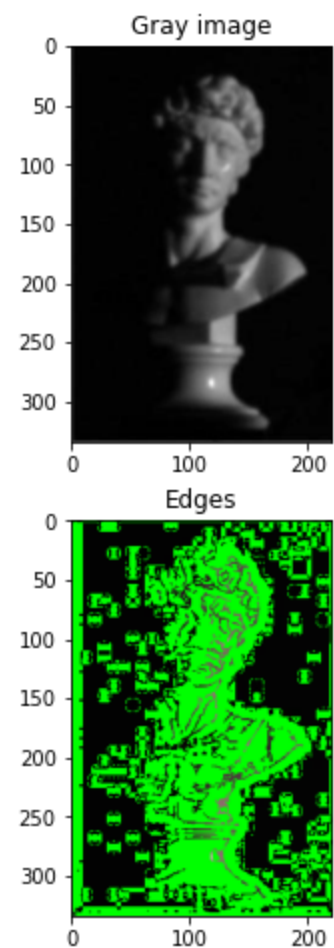
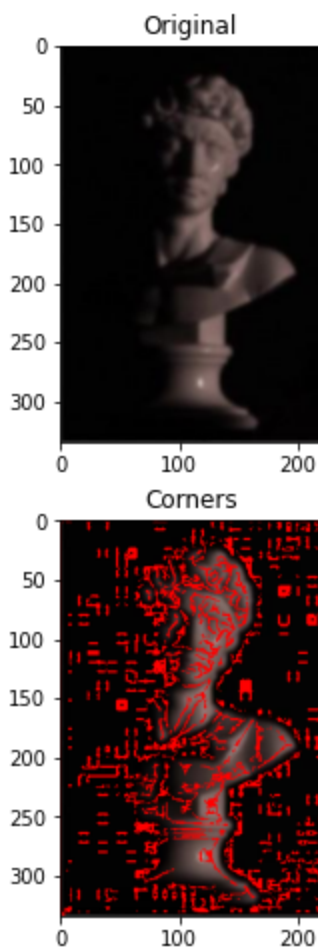
In this example we can easily see how features like the ears, the eyes, the tail are being recognized by the algorithm and although there is some noise also in the body, it give us a general good idea of where the corners are

Example two

For the example one we will take 3 shots of the bust image

```
In [182... harris_corner('data/tile_0.jpg', 0.1)
harris_corner('data/tile_1.jpg', 0.1)
harris_corner('data/tile_2.jpg', 0.1)
```





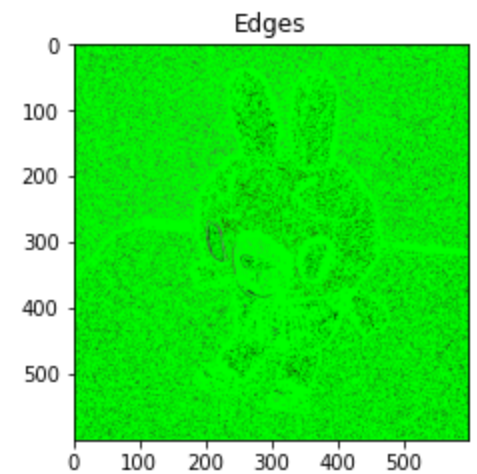
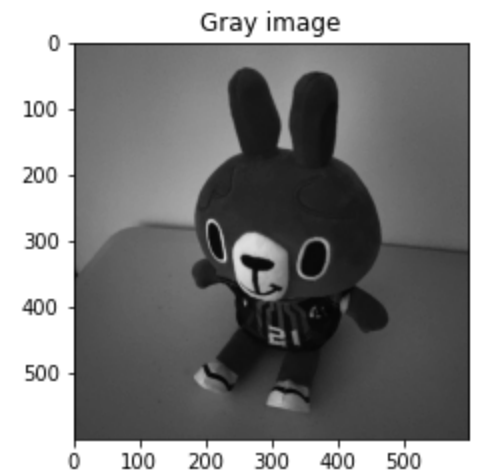
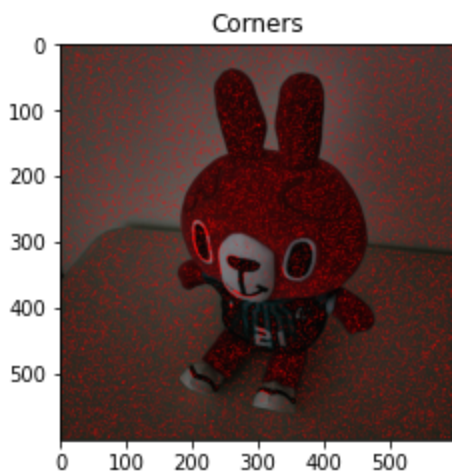
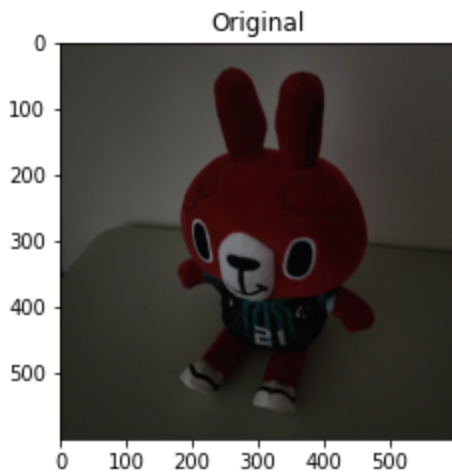
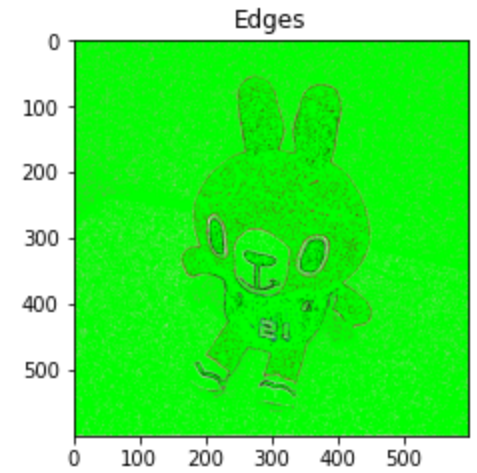
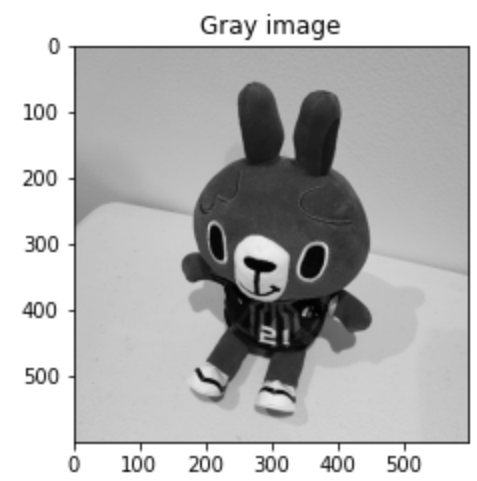
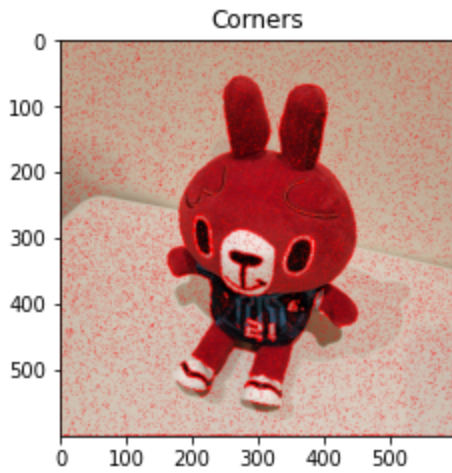
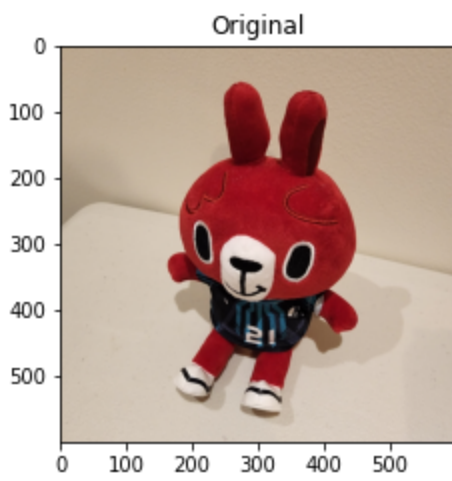
Between the first and second image we notice slight differences, lighting here although distinct, has a negligible effect in the detection algorithm. When we look at the third picture, we start to see something different as the corners are detecting more noise; the general image is there but the effect is different; this suggest to us that the algorithm of Harris is somehow resistant to different lights, but it might be indeed affected.

It is important to recognize that the images analyzed here have the same angle and they tell little about how the algorithm responds to those changes, hence we will create a second analysis with a second set of pictures.

Example three

We will now work with the image of the bunny plush

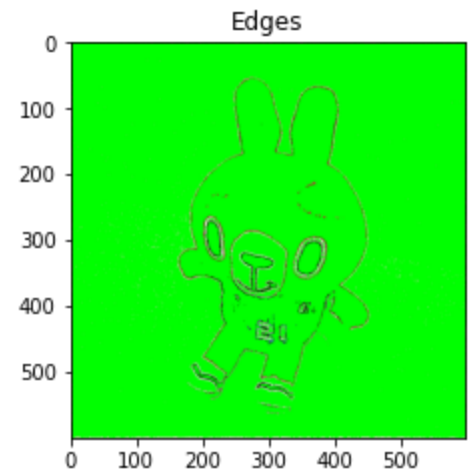
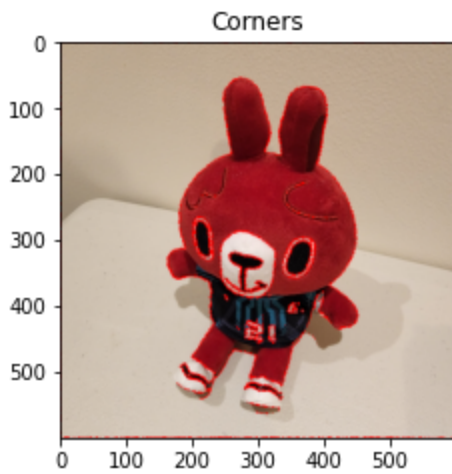
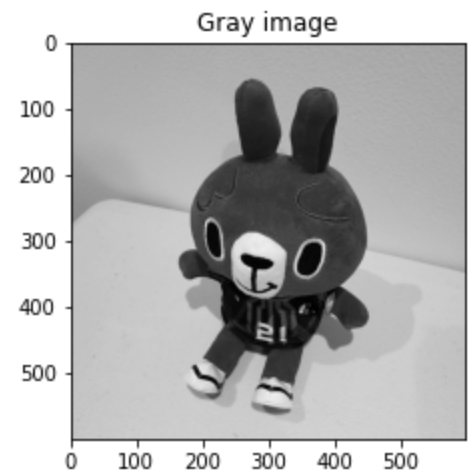
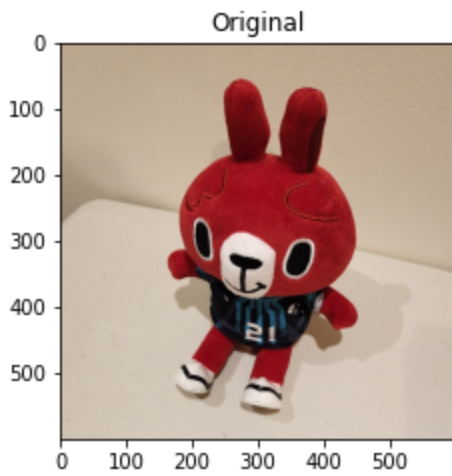
```
In [187... harris_corner('data/bunny_5.jpg', 0.24, True)
harris_corner('data/bunny_11.jpg', 0.24, True)
```

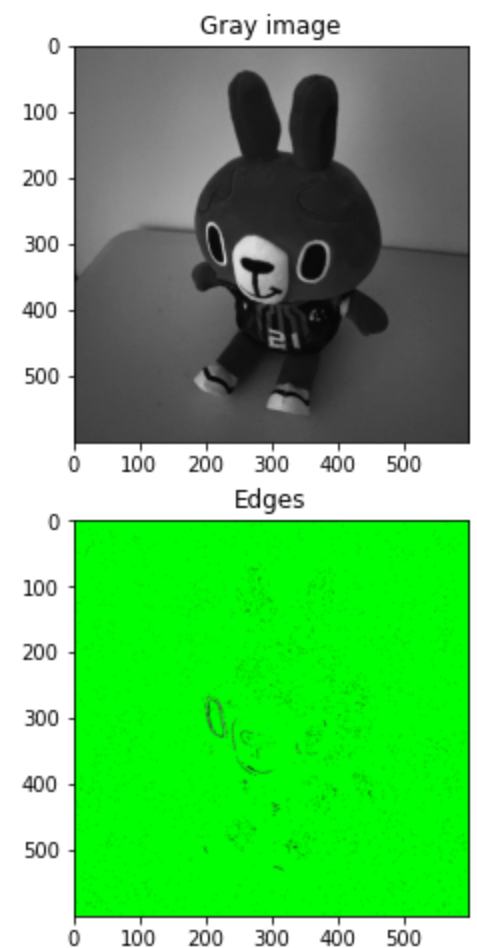
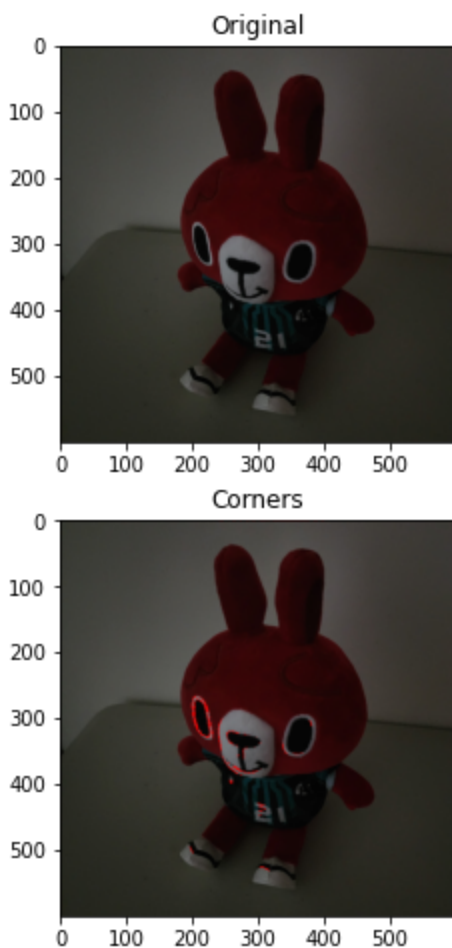


On this exercise we have the pictures of a bunny in a texturized background, this is, the walls and floor have an architecture feature that creates little bumps that the algorithm is detecting as corners; this is telling us a

lot about the capacities of the algorithm. We will see next that by increasing by 0.1 from 0.24 to 0.25 our parameter K some of those features will stop being recognized as corners.

```
In [188... harris_corner('data/bunny_5.jpg', 0.25, True)  
harris_corner('data/bunny_11.jpg', 0.25, True)
```





On this exercise we have the pictures of a bunny in a textured background, this is, the walls and floor have an architecture feature that creates little bumps that the algorithm is detecting as corners; this is telling us a lot about the capacities of the algorithm. We will see next that by increasing by 0.1 from 0.24 to 0.25 our parameter K some of those features will stop being recognized as corners.

Conclusions

Corners are an important part in computer vision, while edges appear an obvious choice they alone might lead to misinterpretations; corners, on the other hand, tend to have a better ability to capture characteristics of an image. In the exercise we used the Harris Corner Algorithm that uses the derivatives of X and Y to capture rapid movement in both directions to interpret a corner, we saw that it has resilience to illumination also to angles but, unfortunately, we also saw that it is by no means a silver bullet as noise can also be interpreted as corners.

We can say that the algorithm is good but there might be better methods nowadays we can use to find these corners and characteristics of images.

References

- [1] S. G. Narasimhan, V. Ramesh and S. K. Nayar (2003). A Class of Photometric Invariants: Separating Material from Shape and Illumination In Proc. International Conference on Computer Vision (ICCV)
- [2] Gonzalez, R. C., & Woods, R. E. (2008). Digital Image Processing (3rd ed.). Pearson Education.