# A1_P2_Implementation_Task

October 4, 2021

## 1 PART II: Implementation TASK

#### 1.0.1 import necessary library for the assignment

[ ]:
```
import numpy as np
import matplotlib.pyplot as plt
import cv2
```

### 1.1 STEP1: Gaussian Blurring

[ ]:
```
def gaussian_kernel(size: int, sigma: float)-> np.ndarray:
    """This function returns 2-dimentional gaussian kernel

    Parameters
    ----------
    size : int, size of the kernel in square
    sigma : float, standard derivation in gaussian distribution function

    Returns
    -------
    out : np.ndarray, shape = (size, size)
          an square matrix with centered gaussian kernel
    """

    # create equally spaced x which will inputed to gaussian formula
    x = np.linspace(- (size // 2), size // 2, size)

    # gaussian formula (results 1D gaussian kernel)
    gaussian = np.exp(-np.square(x)/(2.*np.square(sigma)))

    # perform outer product to obtain 2D gaussian kernal
    gaussian_2d = np.outer(gaussian, gaussian)

    # normalize and return
    return gaussian_2d / gaussian_2d.sum()
```

- Note: 2D visualization with color map is done on STEP4(testing part)

### 1.2 STEP2: Gradient Magnitude

[ ]:
```
def convolution(image: np.ndarray, filter: np.ndarray)-> np.ndarray:
    """This function returns image that are convolved with filter(kernel)

    Parameters
    ----------
    image: np.ndarray, gray scaled image
    filter: np.ndarray, kernel used to convolved the image with

    Returns
    -------
    out: np.ndarray, shape(image.shape[0], image.shape[1])
         an convolved result from image with filter
    """
    #perform horizontal and vertial flip of a filter.
    kernel = np.flipud(np.fliplr(filter))

    #obtain sub-matrices to speed up the process of convolution␣
↪(size(sub_matrices) = size(kernels))
    sub_matrices = np.lib.stride_tricks.as_strided(image,
                                                   shape=tuple(np.
↪subtract(image.shape, kernel.shape)+1)+kernel.shape,
                                                   strides=image.strides*2)

    #get result of convolution by applying scalr product between kernal and␣
↪sub_matrices
    return np.einsum('ij,klij->kl', kernel, sub_matrices)
```

[ ]:
```
def gradient_magitude(image: np.ndarray) -> np.ndarray:
    """This function return gradient magnitude from the inputed image

    Parameters
    ----------
    image: np.ndarray, gray scaled image

    Returns
    -------
    out: np.ndarray, shape(image.shape[0], image.shape[1])
         gradient magnitude using the Sobel operator
    """

    # sober filters
    s_x = np.array([[-1,0,1], [-2,0,2], [-1,0,1]])
    s_y = np.array([[-1,-2,-1], [0,0,0], [1,2,1]])

    # get derivates
```

```
    d_x = convolution(image, s_x)
    d_y = convolution(image, s_y)

    # get gradient magnitude
    res = np.linalg.norm(np.array([d_x,d_y]), axis=(0)) #same as np.sqrt(d_x**2
↪+ d_y**2)
    return res
```

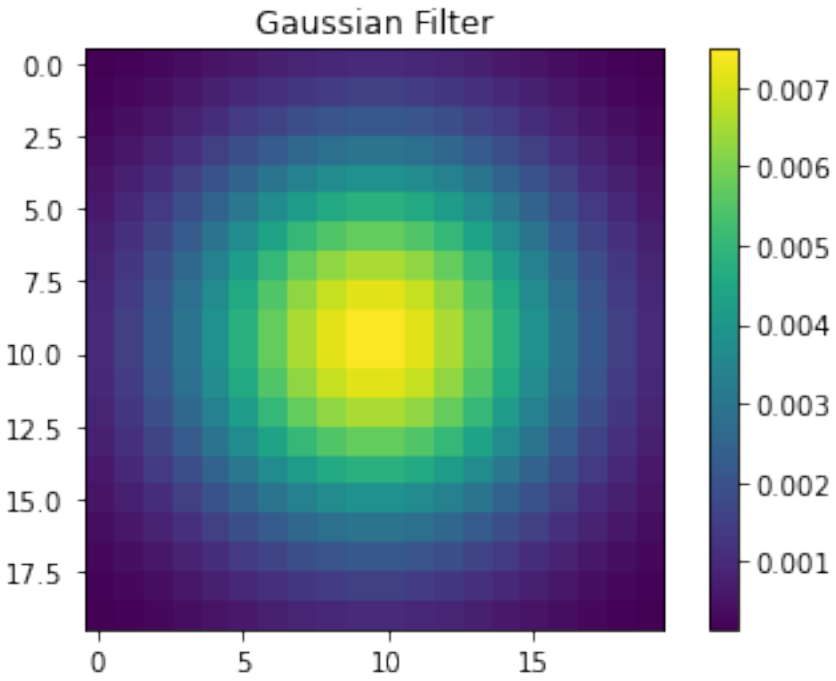
### 1.3 STEP3: Threshold Algorithm

[ ]:
```
def threshold(grad_image: np.ndarray, epsilon=0.1)->np.ndarray:
    """This function returns black and white edge-mapped image

    Parameters
    ----------
    grad_image: np.ndarray
    epsilon: variable for setting the threshold

    Returns
    -------
    out: np.ndarray, shape(grad_image[0], grad_image[1])
         edge-mapped image with pixel value of either 0 or 255
    """

    # calculate average intensity of grad image
    i_t = grad_image.mean()
    i_t_new = float('inf')

    #create loop that sets the threshold
    while np.abs(i_t- i_t_new) > epsilon:
        i_t_new  = i_t
        l_class = grad_image.mean(where=grad_image < i_t_new)
        u_class = grad_image.mean(where=grad_image >= i_t_new)
        i_t = (l_class + u_class)/2

    # for all the pixels in grad_image, if pixel is larger than threshold make
↪that
    # pixel 255 otherwise 0
    res = np.where(grad_image > i_t, 255, 0)

    return res
```

### 1.4 STEP4: TEST

[ ]:
```
#generate gaussian_kernel (step1)
g_kernel = gaussian_kernel(20, 5)
plt.imshow(g_kernel, interpolation='none')
plt.colorbar()
plt.title('Gaussian Filter')
```

[ ]:
```
Text(0.5, 1.0, 'Gaussian Filter')
```

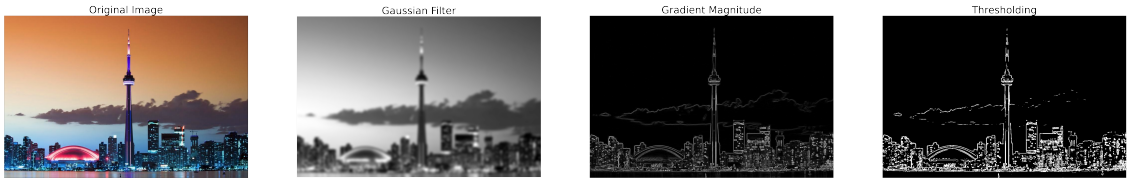



#### 1.4.1 For image1

[ ]:
```
fig_1 = plt.figure(figsize=(200, 160))
ax1 = fig_1.add_subplot(141)
ax2 = fig_1.add_subplot(142)
ax3 = fig_1.add_subplot(143)
ax4 = fig_1.add_subplot(144)


#original image
image_1 = cv2.imread('./a1_image/image1.jpg')
gray_1 = cv2.cvtColor(image_1, cv2.COLOR_BGR2GRAY) #generate gray-scaled image
ax1.imshow(image_1)
ax1.set_title("Original Image", fontsize=100)
ax1.set_xticks([]), ax1.set_yticks([])
```

```
#apply gaussian filter on image
g_image_1 = convolution(gray_1, g_kernel)
ax2.imshow(g_image_1, interpolation='none', cmap='gray')
ax2.set_title("Gaussian Filter", fontsize=100)
ax2.set_xticks([]), ax2.set_yticks([])

#generate gradient magnitude of the image
image_grad_mag_1 = gradient_magitude(gray_1)
ax3.imshow(image_grad_mag_1, cmap='gray')
ax3.set_title("Gradient Magnitude", fontsize=100)
ax3.set_xticks([]), ax3.set_yticks([])

#Show black and white edge-mapped image
threshold_1 = threshold(image_grad_mag_1)
ax4.imshow(threshold_1, cmap='gray')
ax4.set_title("Thresholding", fontsize=100)
ax4.set_xticks([]), ax4.set_yticks([])
```

[ ]: ([], [])




```
[ ]: fig_2 = plt.figure(figsize=(200, 160))
bx1 = fig_2.add_subplot(141)
bx2 = fig_2.add_subplot(142)
bx3 = fig_2.add_subplot(143)
bx4 = fig_2.add_subplot(144)


#original image
image_2 = cv2.imread('./a1_image/image2.jpg')
gray_2 = cv2.cvtColor(image_2, cv2.COLOR_BGR2GRAY) #generate gray-scaled image
bx1.imshow(image_2)
bx1.set_title("Original Image", fontsize=100)
bx1.set_xticks([]), bx1.set_yticks([])

#apply gaussian filter on image
g_image_2 = convolution(gray_2, g_kernel)
bx2.imshow(g_image_2, interpolation='none', cmap='gray')
```

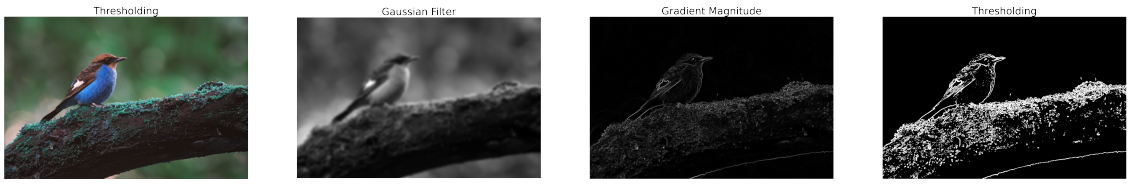
```
bx2.set_title("Gaussian Filter", fontsize=100)
bx2.set_xticks([]), bx2.set_yticks([])

#generate gradient magnitude of the image
image_grad_mag_2 = gradient_magitude(gray_2)
bx3.imshow(image_grad_mag_2, cmap='gray')
bx3.set_title("Gradient Magnitude", fontsize=100)
bx3.set_xticks([]), bx3.set_yticks([])

#Show black and white edge-mapped image
threshold_2 = threshold(image_grad_mag_2)
bx4.imshow(threshold_2, cmap='gray')
bx4.set_title("Thresholding", fontsize=100)
bx4.set_xticks([]), bx4.set_yticks([])
```

[ ]:
```
([], [])
```


[ ]:
```
fig_3 = plt.figure(figsize=(200, 160))
cx1 = fig_3.add_subplot(141)
cx2 = fig_3.add_subplot(142)
cx3 = fig_3.add_subplot(143)
cx4 = fig_3.add_subplot(144)


#original image
image_3 = cv2.imread('./a1_image/image3.jpg')
gray_3 = cv2.cvtColor(image_3, cv2.COLOR_BGR2GRAY) #generate gray-scaled image
cx1.imshow(image_3)
cx1.set_title("Thresholding", fontsize=100)
cx1.set_xticks([]), cx1.set_yticks([])

#apply gaussian filter on image
g_image_3 = convolution(gray_3, g_kernel)
cx2.imshow(g_image_3, interpolation='none', cmap='gray')
cx2.set_title("Gaussian Filter", fontsize=100)
cx2.set_xticks([]), cx2.set_yticks([])

#generate gradient magnitude of the image
image_grad_mag_3 = gradient_magitude(gray_3)
```

```
cx3.imshow(image_grad_mag_3, cmap='gray')
cx3.set_title("Gradient Magnitude", fontsize=100)
cx3.set_xticks([]), cx3.set_yticks([])

#Show black and white edge-mapped image
threshold_3 = threshold(image_grad_mag_3)
cx4.imshow(threshold_3, cmap='gray')
cx4.set_title("Thresholding", fontsize=100)
cx4.set_xticks([]), cx4.set_yticks([])
```

[ ]: ([], [])




### 1.4.2 How does the edge detection algorithm works?

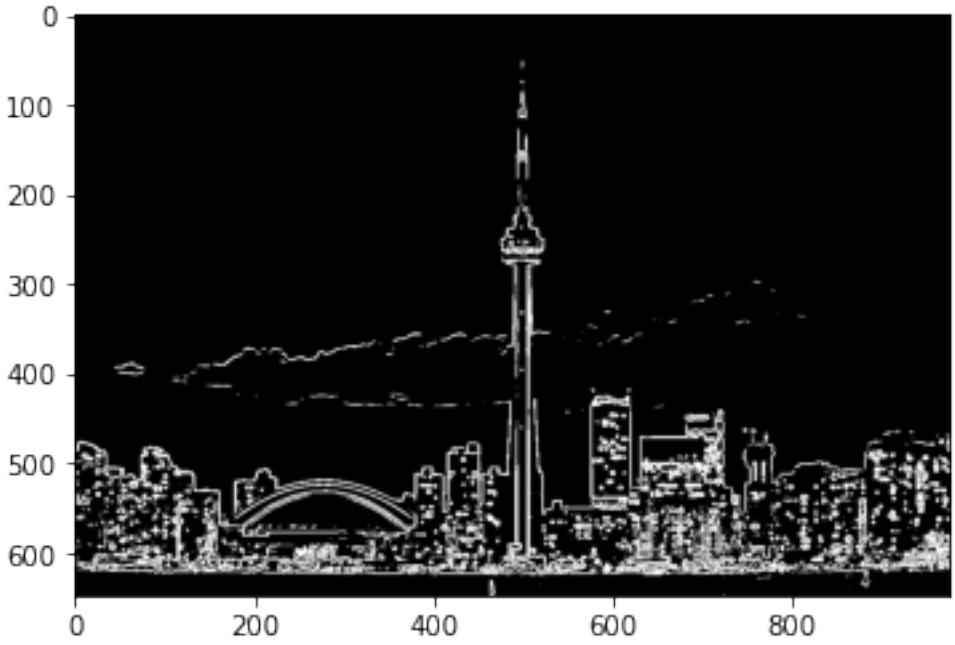
The four different images in the order of original, gaussian blur, gradient magnitude, thresholding were shown for each image we had. In order to detect the edge, we took the grayscale of the original image and applied convolution with a Sobel filter which produce a derivative of the image. Then we tool the results from the convolution to obtain the image of gradient magnitude. Finally, we adopted the thresholding algorithm to filter out the points below the computed threshold to obtain the edge detected image.

### 1.4.3 Highlight our edge detecting algorithm's strength and weakness

As you see from the 3 different edges detected images from the implemented algorithm, it does indeed produce perceivable edges. Without knowing how the original image looks like, we could still tell what each image is about. However, there are two weaknesses I could point out from looking at the result. First of all, some of the edges were lost (ex. edges on the CN tower due to cloud). It seems that the edges from the gradient magnitude were too weak to win the thresholds. Secondly, there were lots of noises in the edge detected images. However, trying to remove them would induce losing the important information about the edge. More detailed results of the edge detected image are shown below.

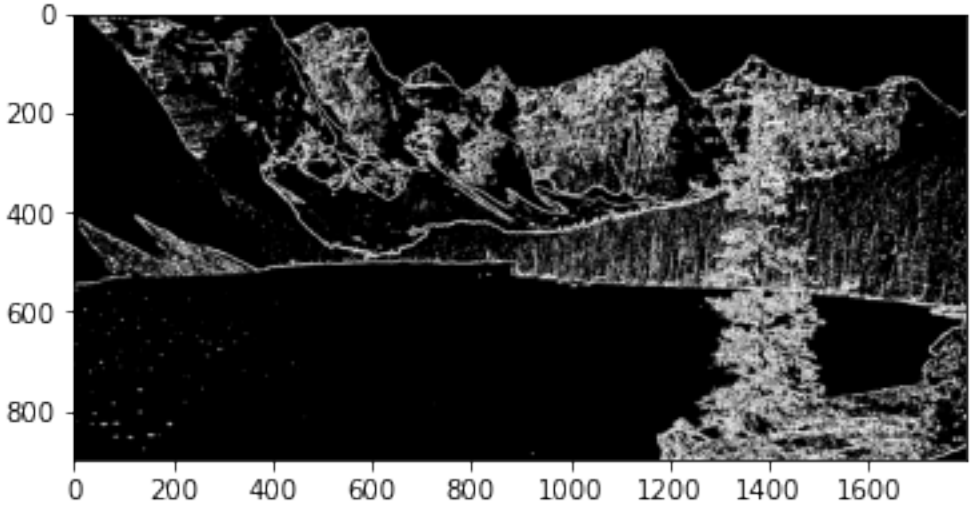
[ ]:
```
plt.imshow(threshold_1, cmap='gray')
```

[ ]: <matplotlib.image.AxesImage at 0x7f3d3cc92a60>



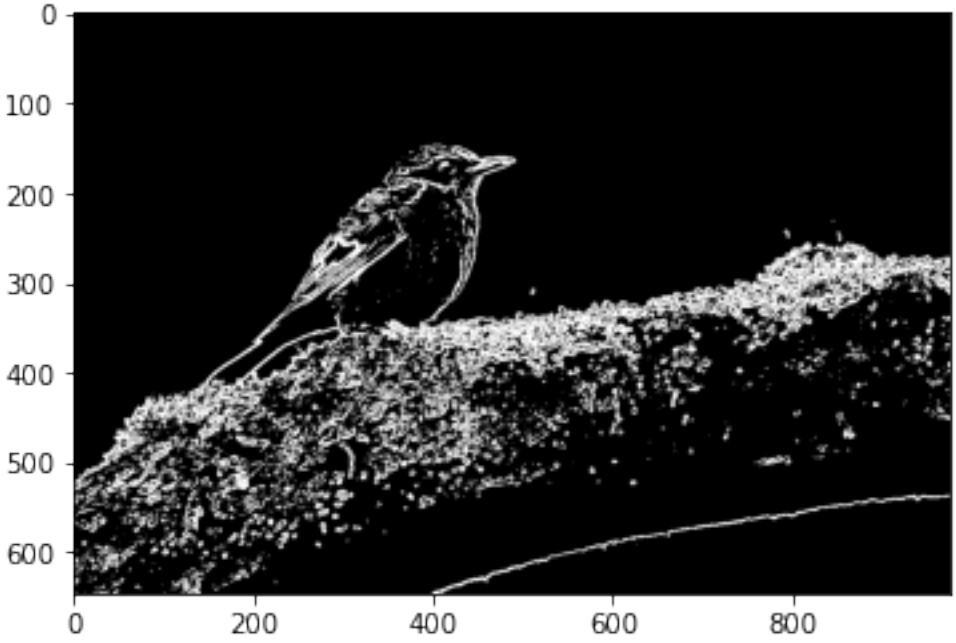

[ ]:
```
plt.imshow(threshold_2, cmap='gray')
```

[ ]:
```
<matplotlib.image.AxesImage at 0x7f3d3dc9e3d0>
```




[ ]:
```
plt.imshow(threshold_3, cmap='gray')
```

[ ]:
```
<matplotlib.image.AxesImage at 0x7f3d3cdec400>
```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