# CAP 4453 PA-1 Discussion

Aayush Rana 2/17/2021

- Image operations (read, write, show)
- Edit images

Image operations (read, write, show)

```
Dimport cv2
import numpy as np
ldef get images():
     # Read image as grayscale
     img1 = cv2.imread('einstein.jpg', 0)
     print("Image size: ", img1.shape)
     print("Image type: ", imgl.dtype)
     print("Min value: ", np.min((img1)))
     print("Max value: ", img1.max())
     cv2.imshow("Input Image", img1)
     cv2.waitKey(0)
     cv2.imwrite('my img1.jpg', img1)
     name == ' main ':
     get images()
```

• Image operations (read, write, show)



#### Output

Image size: (285, 292)

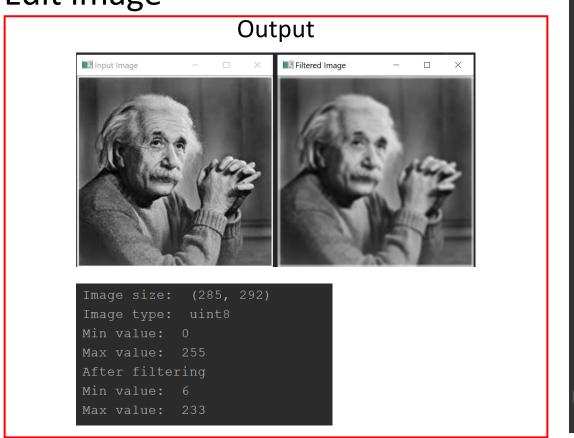
Image type: uint8

Min value: 0

Max value: 255

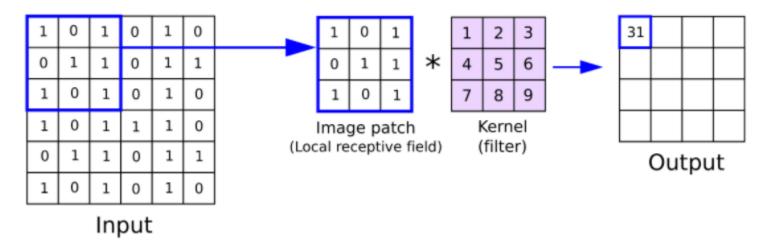
```
Jimport cv2
import numpy as np
|def get images():
     # Read image as grayscale
     img1 = cv2.imread('einstein.jpg', 0)
     print("Image size: ", img1.shape)
     print("Image type: ", img1.dtype)
     print("Min value: ", np.min((img1)))
     print("Max value: ", img1.max())
     cv2.imshow("Input Image", img1)
     cv2.waitKey(0)
     cv2.imwrite('my img1.jpg', img1)
     name == ' main ':
     get images()
```

- Image operations (read, write, show)
- Edit image



```
def read and edit images():
   img1 = cv2.imread('einstein.jpg', 0)
   print("Image size: ", img1.shape)
   print("Image type: ", img1.dtype)
   print("Min value: ", np.min((img1)))
   print("Max value: ", img1.max())
   kernel = np.ones((5, 5), np.float32) / 25
   filtered img = cv2.filter2D(img1, -1, kernel)
   print("After filtering")
   print("Min value: ", np.min((filtered img)))
   print("Max value: ", filtered img.max())
   cv2.imshow("Input Image", img1)
   cv2.imshow("Filtered Image", filtered img)
   cv2.waitKey(0)
   cv2.imwrite('my img1.jpg', filtered img)
```

## Filtering array



$$(1*1) + (0*2) + (1*3) + (0*4) + (1*5) + (1*6) + (1*7) + (0*8) + (1*9) = 31$$

This uses correlation formula: 
$$F \circ I(x,y) = \sum_{j=-N}^{N} \sum_{i=-N}^{N} F(i,j)I(x+i,y+j)$$

For convolution, the kernel is rotated by 180 degrees

Image credit: Anh H. Reynolds <a href="https://anhreynolds.com/blogs/cnn.html">https://anhreynolds.com/blogs/cnn.html</a>

### Filtering array – 1D

```
def filter 1d():
    matrix = np.ones((10))
    print("Matrix: ", matrix)
    sigma = 1
    kernel radius = int(np.floor(kernel size / 2))
    kernel gaus = np.linspace(-kernel radius, kernel radius, kernel size)
    kernel gaus = (1 / (np.sqrt(2 * np.pi) * sigma)) * \
                        np.e ** (-np.power((kernel gaus-mean) / sigma, 2) / 2)
    kernel gaus = kernel gaus / np.sum(kernel gaus)
    filtered matrix = np.zeros(matrix.shape)
    for i in range(kernel radius, matrix.shape[0]-kernel radius):
        patch = matrix[i-kernel radius:i+kernel radius+1]
        filtered matrix[i] = np.sum((patch * kernel gaus))
        print(filtered matrix)
    print("cv2 blur: ", cv2.GaussianBlur(matrix, (1, 3), 1).reshape(10))
```

### Filtering array – 1D

```
def filter 1d():
    matrix = np.ones((10))
   matrix[4:7] = 0
    print("Matrix: ", matrix)
    sigma = 1
    kernel radius = int(np.floor(kernel size / 2))
    kernel gaus = np.linspace(-kernel radius, kernel radius, kernel size)
    kernel gaus = (1 / (np.sqrt(2 * np.pi) * sigma)) * \
                        np.e ** (-np.power((kernel gaus-mean) / sigma, 2) / 2)
    kernel gaus = kernel gaus / np.sum(kernel gaus)
    filtered matrix = np.zeros(matrix.shape)
    for i in range(kernel radius, matrix.shape[0]-kernel radius):
        patch = matrix[i-kernel radius:i+kernel radius+1]
        filtered matrix[i] = np.sum((patch * kernel gaus))
        print(filtered matrix)
    print("result: ", filtered matrix)
    print("cv2 blur: ", cv2.GaussianBlur(matrix, (1, 3), 1).reshape(10))
```

#### Question 1: Box Filtering [1 pt]

Implement two box filters (one with 3 by 3, the other one is 5 by 5 kernel size), and apply them to the given images (i.e., image1.png and image2.png) separately. Show the resulting images, and explain the resulting images, and their differences. (For convolution operation, you can use built-in function. Do not use built-in function for box filtering.)

- Prepare box filters as shown before
- Perform 2D convolution for each filter on the image

```
img_height, img_width = img.shape
  filtered_img = np.zeros((img_height, img_width))
  kernel_radius = int(np.floor(kernel.shape[0] / 2.))
  for row in range(kernel_radius, img_height-kernel_radius):
     for col in range(kernel_radius, img_width-kernel_radius):
          # Your code to do convolution operation
          # Write new value to filtered_img
          filtered_img[row, col] = value after_convolution
     return filtered_img
```

#### Question 2: Median Filtering [1 pt]

Implement three median filters (3 by 3, 5 by 5, and 7 by 7 kernel size), and apply these filters to image1.png and image2.png separately. Show (and discuss as comments) the resulting differences for each kernel on the screen, explain where median filters are most effective. (For convolution operation, you can use built-in function. Do not use built-in function for Median filtering.)

- Take image patch
- Sort and find median for each patch

#### Question 3: Gaussian Filtering [1 pt]

Implement a two-dimensional Gaussian kernel with a variation (sigma) equal to 3, 5, and 10. Apply these three Gaussian kernels to image1.png and image2.png separately, show them on the screen, discuss the differences of Gaussian operations with different sigmas (as comments on the code). Also, compare your results with question 1 and question 2: what are the differences between these three filters, what do you observe (as comments on the code)? Which filtering is the most effective in which images? Why? (For convolution operation, you can use built-in function. Do not use built-in function for Gaussian filtering.)

- Prepare 2D Gaussian filter (similar to before)
  - Option 1
    - Prepare 1D Gaussian and reshape [np.reshape(kernel\_gaus, (3,1))]
    - Do dot product [ np.dot(kernel\_gaus, kernel\_gaus.T) ]
  - Option 2
    - Use the Gaussian formula for two variables (x, y)
- Apply filter similar to filter\_1d function from before
  - Patch and filter will be 2D

#### Question 4: Gradient Operations [1 pt]

Write a derivative operations (forward, backward, and central difference) that can be applied to any given image (f) and produces two images: gradient x, and gradient y images (i.e.,  $f_x$ ,  $f_y$ ). Also, calculate gradient magnitude as  $\sqrt{(f_x^2 + f_y^2)}$ . The image that you should use for this problem is called image3.png. Show the results on the screen (Do not use built-in gradient functions, create difference operator yourself as stated clearly in the question.)

- Make three 1D filters [-1, +1], [+1, -1], [-1, 0, +1]
- Apply horizontally (similar to filter\_1d). Gives f\_x
- Get transpose of those filters, apply vertically. Gives f\_y
- Get magnitude
  - Use element-wise matrix operation as np.sqrt(f\_x\*f\_x + f\_y\*f\_y)
- Scale image
  - Get max value of magnitude -> np.max((magnitude))
  - Divide magnitude by max value -> Makes between 0-1
  - Multiply by 255 -> Makes between 0-255
  - Convert to integer and save/show magnitude image

#### Question 5: Sobel Filtering [1 pt]

Implement Sobel filtering with 3 by 3 kernel size. Apply it to image1.png and image2.png. Show the results on the screen, and discuss the resulting images (as comments on the code). (For convolution operation, you can use built-in function. Do not use built-in function for Sobel filtering.)

- Prepare Sobel kernel
  - For x and y direction (S\_x and S\_y)

 $\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$ 

- Similar to Q3 and Q4
  - Apply S\_x and S\_y to image
  - Combine to get final gradient -> np.sqrt(S\_x\*S\_x + S\_y\*S\_y)

#### Question 6: Fast Gaussian Filtering [1 pt]

Implement question 3, but this time, use only 1D Gaussian to do filtering in 2D. The trick is the following: since Gaussians are separable, you can use 1D Gaussian to filter the image in one direction first, and then the other direction can be filtered. Show the results on the screen and compare the efficiency of both methods (question 3 and question 6) as comments on the code. Use image1.png and image2.png for smoothing and show results too. (For convolution operation, you can use built-in function. Do not use built-in function for fast Gaussian filtering.)

#### • Similar to Q3

- Use only 1D filter
- Apply in first direction
- Transpose the filter, apply in another direction
- Combine using magnitude formula

#### Question 7: Histogram [2 pt]

Implement histogram function from scratch, and show the resulting bar-graph (histogram). Use 256, 128, and 64 bins to visualize histograms. Comment on the resulting differences with respect to bins. Use image4.png to conduct this experiment. (Do not use built-in histogram function, create it yourself.)

- Loop through each pixel
- Find bin for that pixel and add 1 to that bin

#### Question 7: Histogram [2 pt]

Implement histogram function from scratch, and sho bins to visualize histograms. Comment on the resulting this experiment. (Do not use built-in histogram func

- Loop through each pixel
- Find bin for that pixel and add
   1 to that bin

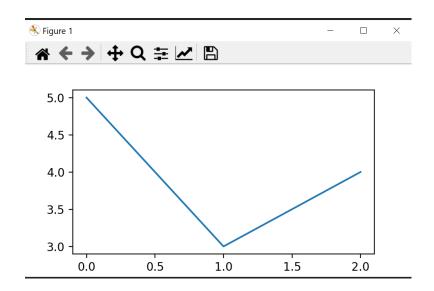
```
Edef plot hist():
     import matplotlib.pyplot as plt
     bins = 3
     mat range = 12
     bin size = int(mat range / bins)
     matrix = np.random.randint(0, 11, mat range_)
     print("Matrix: ", matrix)
     bin count = np.zeros((bins))
     for i in range(matrix.shape[0]):
         this bin = matrix[i] // bin size
         bin count[this bin] += 1
     print("Bin count: ", bin count)
     plt.figure()
     plt.bar(np.arange(bins),bin count)
     plt.show()
```

#### Question 7: Histogram [2 pt]

Implement histogram function from scratch, and show the resulting bar-graph (histogram). Use 256, 128, and 64 bins to visualize histograms. Comment on the resulting differences with respect to bins. Use image4.png to conduct this experiment. (Do not use built-in histogram function, create it yourself.)

- Loop through each pixel
- Find bin for that pixel and add
   1 to that bin

```
plt.figure()
plt.plot(bin_count)
plt.show()
```

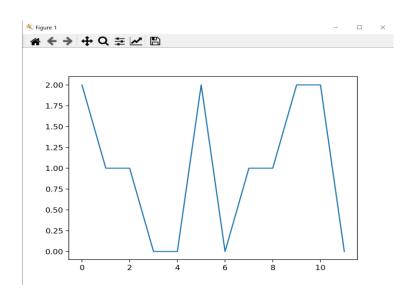


#### Question 7: Histogram [2 pt]

Implement histogram function from scratch, and show the resulting bar-graph (histogram). Use 256, 128, and 64 bins to visualize histograms. Comment on the resulting differences with respect to bins. Use image4.png to conduct this experiment. (Do not use built-in histogram function, create it yourself.)

- Loop through each pixel
- Find bin for that pixel and add
   1 to that bin
- bins=12

```
plt.figure()
plt.plot(bin_count)
plt.show()
```



#### Question 8: Canny Edge Detection [7 pt]

#### Your tasks:

- 0 pt Use two different images (canny1.jpg and canny2.jpg) to perform the following steps for getting Canny edges of the input image.
- 1 pts Use 1-dimensional Gaussians to implement 2D Gaussian filtering yourself (do not use built-in functions).
- 1 pts Obtain gradient images (x-dim, y-dim, gradient magnitude, and gradient orientation) by following the Canny algorithm that we have seen in the class. Show resulting gradient images on screen and in the report.
- 2 pts Implement non-max suppression algorithm to reduce some of the falsely detected edges in the gradient images (from the previous step). Show the improved edge map on the screen and in the report.
- 1 pts Implement hysteresis thresholding algorithm and use it to further enhance the edge map obtained from the previous step. Show the final Canny edge map on the screen and in the report.
- 1 pt Show the effect of  $\sigma$  in edge detection by choosing three different  $\sigma$  values when smoothing. Note that you need to indicate which  $\sigma$  works best as a comment in your assignment.
- 1 pt Discuss about the different filtering approaches you took for four pictures. Since pictures are the same scene but different noise and smoothing patterns, you need to adjust your Canny edge filtering parameters to show similar results to Canny edges of the output-canny1.png and output-canny2.png.

#### Question 8: Canny Edge Detection [7 pt]

#### Your tasks:

- 0 pt Use two different images (canny1.jpg and canny2.jpg) to perform the following steps for getting Canny edges of the input image.
- 1 pts Use 1-dimensional Gaussians to implement 2D Gaussian filtering yourself (do not use built-in functions).
- 1 pts Obtain gradient images (x-dim, y-dim, gradient magnitude, and gradient orientation) by following the Canny algorithm that we have seen in the class. Show resulting gradient images on screen and in the report.

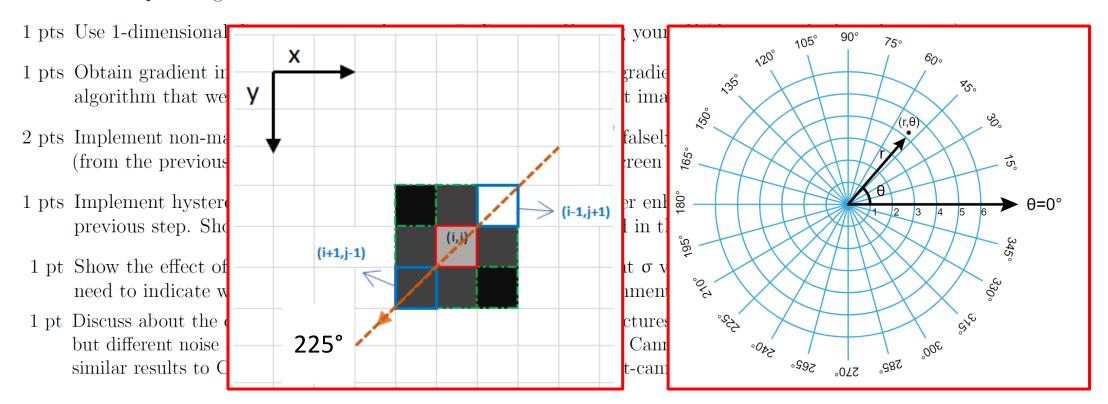
```
# Compute orientation
gradient_orientation = np.degrees(np.arctan2(I_yy, I_xx)_)
the report.
```

- 1 pts Implement hysteresis thresholding algorithm and use it to further enhance the edge map obtained from the previous step. Show the final Canny edge map on the screen and in the report.
- 1 pt Show the effect of  $\sigma$  in edge detection by choosing three different  $\sigma$  values when smoothing. Note that you need to indicate which  $\sigma$  works best as a comment in your assignment.
- 1 pt Discuss about the different filtering approaches you took for four pictures. Since pictures are the same scene but different noise and smoothing patterns, you need to adjust your Canny edge filtering parameters to show similar results to Canny edges of the output-canny1.png and output-canny2.png.

#### Question 8: Canny Edge Detection [7 pt]

#### Your tasks:

0 pt Use two different images (canny1.jpg and canny2.jpg) to perform the following steps for getting Canny edges of the input image.



#### Question 8: Canny Edge Detection [7 pt]

#### Your tasks:

- 0 pt Use two different images (canny1.jpg and canny2.jpg) to perform the following steps for getting Canny edges of the input image.
- 1 pts Use 1-dimensional Gaussians to implement 2D Gaussian filtering yourself (do not use built-in functions).
- 1 pts Obtain gradient images (x-dim, y-dim, gradient magnitude, and gradient orientation) by following the Canny algorithm that we have seen in the class. Show resulting gradient images on screen and in the report.
- 2 pts Implement non-max suppression algorithm to reduce some of the falsely detected edges in the gradient images (from the previous step). Show the improved edge map on the screen and in the report.
- 1 pts Implement hysteresis thresholding algorithm and use it to further enhance the edge map obtained from the previous step. Show the final Canny edge map on the screen and in the report.
- 1 pt Show the effect of  $\sigma$  in edge detection by choosing three different  $\sigma$  values when smoothing. Note that you need to indicate which  $\sigma$  works best as a comment in your assignment.
- 1 pt Discuss about the different filtering approaches you took for four pictures. Since pictures are the same scene but different noise and smoothing patterns, you need to adjust your Canny edge filtering parameters to show similar results to Canny edges of the output-canny1.png and output-canny2.png.

#### Question 9: Image segmentation [5 pts]

In this question you goal is to implement Otsu thresholding to perform image segmentation. The algorithm was discussed during a class lecture.

#### Your tasks:

- First implement a simple thresholding based image binarization algorithm. Plot the histogram for three different input image. Now based on the plot, perform binarization at three different threshold levels.
- Implement a Otsu thresholding. Use the determined threshold to perform segmentation on the three input image.

NOTE: You are free to choose any 3 images. If the images are colored, you can convert them to greyscale by averaging the RGB values at each pixel. You can also use any library function to convert it to greyscale.