Lab2 Report

Zepeng Chen

June 21, 2021

Contents

1 Spatial Filtering

1.1 Implemented Function

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

#read image
img = cv2.imread('img1.png',0)
#obtain number of rows and columns
#of the imaage

m,n=img.shape
#develop different filter
k1=np.ones([3,3],dtype=int)
k1=k1/9
k2=np.ones([7,7],dtype=int)
k2=k2/49
#creates gaussian kernel with side length l and a sigma of sig
def gkern(l, sig):
    ax = np.linspace(-(l - 1) / 2., (l - 1) / 2., l)
    xx, yy = np.meshgrid(ax, ax)

    kernel = np.exp(-0.5 * (np.square(xx) + np.square(yy)) / np.square(sig))

    return kernel / np.sum(kernel)
k3=gkern(3,0.5)
k4=gkern(13,1.2)

k6=[[1,0,1],[-2,0,2],[-1,0,1]] #sobel x
k7=[[-1,-2,-1],[0,0,0],[1,2,1]]#sobel y
k8 =[[0.4038,   0.8021,   0.4038]
    [0.8021,  -4.8233,   0.8021]
    [0.4038,   0.8021,   0.4038]]


#convolve the mask over the image

def filter(kx):
    kernel_n=kx.shape[0]
    kn=int((kernel_n-1)/2)
    img_=np.zeros([m,n])
    img_new=np.zeros([m+kernel_n,n+kernel_n])
    for s in range(kn,m+kn):
        for t in range(kn,n+kn):
            img_new[s,t]=img[s-kn,t-kn]
            sum_p=0
            for p in range(0,kernel_n):
               for q in range(0,kernel_n):
                    sum_p=sum_p+img_new[s-kn+p,t-kn+q]*kx[p,q]
                    img_[s-kn,t-kn]=sum_p
    return img_
```

```
'''
#without padding
def filter(kx):
    kernel_n=kx.shape[0]
    kn=int((kernel_n-1)/2)
    img_new=np.zeros([m,n])
    for s in range(kn,m-kn):
        for t in range(kn,n-kn):
            sum_p=0
            for p in range(0,kernel_n):
               for q in range(0,kernel_n):
                    sum_p=sum_p+img[s-kn+p,t-kn+q]*kx[p,q]
                    img_new[s,t]=sum_p
    return img_new
'''
img_one3=filter(k1)
img_one3= img_one3.astype(np.uint8)
#compare the intensities between after padding and origin
print('scale of origin')
print(img.min(), img.max())
print('scale after filter')

print(img_one3.min(), img_one3.max())
cv2.imwrite('ones3.png', img_one3)
cv2.imshow('ones3',img_one3)

img_one7=filter(k2)
img_one7 = img_one7.astype(np.uint8)
cv2.imwrite('ones7.png', img_one7)
cv2.imshow('ones7',img_one7)

img_g3=filter(k3)
img_g3=img_g3.astype(np.uint8)
cv2.imshow('g3',img_g3)

img_g7=filter(k4)
img_g7=img_g7.astype(np.uint8)
cv2.imshow('g7',img_g7)

cv2.imwrite('origin.png',img)
cv2.imshow('origin',img)

cv2.waitKey(0)
cv2.destroyAllWindows()
```

1.2 Outcome Collection I

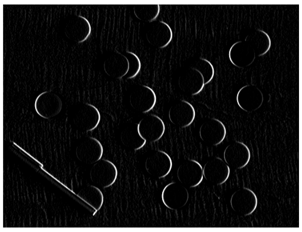

(a) Original Image.


(b) Ones(3)

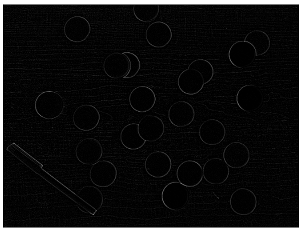

(c) ones(7)


(d) Gaussian3


(e) Gaussian7


(f) Sobel-x


(g) Sobel-y


(h) log3

2 Median Filter

2.1 Code

```
import cv2
import numpy as np

img=cv2.imread('img1.png',0)
m,n=img.shape

def medf(size):
    #listK=np.zeros([size,size])
    listK=np.zeros([size,size],dtype=np.uint8)
    kn=int((size-1)/2)
    img_=np.zeros([m,n],dtype=np.uint8)
    img_new=np.zeros([m+size-1,n+size-1],dtype=np.uint8)
    for s in range(kn,kn+m):
        for t in range(kn,kn+n):
            img_new[s,t]=img[s-kn,t-kn]
            for p in range(0,size):
                for q in range(0,size):
                    listK[p,q]=img_new[s-kn+p,t-kn+q]
                    listK=listK.flatten()
                    listKsort=np.sort(listK)
                    med=listKsort[int((size*size-1)/2)]
                    img_[s-kn,t-kn]=med
    return img_

m3=medf(3)
m3=m3.astype(np.uint8)
cv2.imshow(m3)
cv2.waitKey(0)
cv2.destroyAllWindows
```

2.2 Figure Collection II

(a) Median3X3 (b) Median5X5

3 Thresholding

3.1 Code for fingding threshold

```
import cv2
import numpy as np

def findTh(fig):
    img=cv2.imread(fig,0)
    global L
    L=img.max()
    m, n=img.shape
        #cnt is the number of intensity, pt is the probability accordingly
    cnt=np.zeros(L+1)
    pt=np.zeros(L+1)
    for pixel in img:
        cnt[pixel]+=1
        pt[pixel]=cnt[pixel]/(m*n)

    def sigma(t):
        wt0=wt1=ut0=ut1=0
        for x in range(0,t):
            wt0=wt0+pt[x]
        for y in range(t,L+1):
            wt1=wt1+pt[y]
        for p in range(0,t):
            ut0=ut0+x*pt[p]/wt0
        for q in range(t,L+1):
            ut1=ut1+q*pt[q]/wt1
        sigmaSqr=wt0*wt1*(ut0-ut1)**2
        return sigmaSqr

    maxInit=0
    for k in range(0,L+1):
        s=sigma(k)
        if s>maxInit:
            maxInit=s
            th=k
    return th
#binarize the iamge using threshold found by above function
def biImag(fig,th):
    img=cv2.imread(fig,0)
    L=img.max()
    m,n=img.shape
    for x in range(0,m):
        for y in range(0,n):
            if img[x,y]<th:
                img[x,y]=0
            else:
```

```
                img[x,y]=L
    return img

th3=findTh('img3.png')
print('Threshold of img3 is', th3)
th4=findTh('img4.png')
print('Threshold of img4 is', th4)

I3=biImag('img3.png',th3)
I4=biImag('img4.png',th4)
cv2.imshow('img3',I3)
cv2.imshow('img4',I4)
cv2.waitKey(0)
cv2.destroyAllWindows
cv2.imwrite('img3bi.png',I3)
cv2.imwrite('img4bi.png',I4)
```

3.2 Outcome

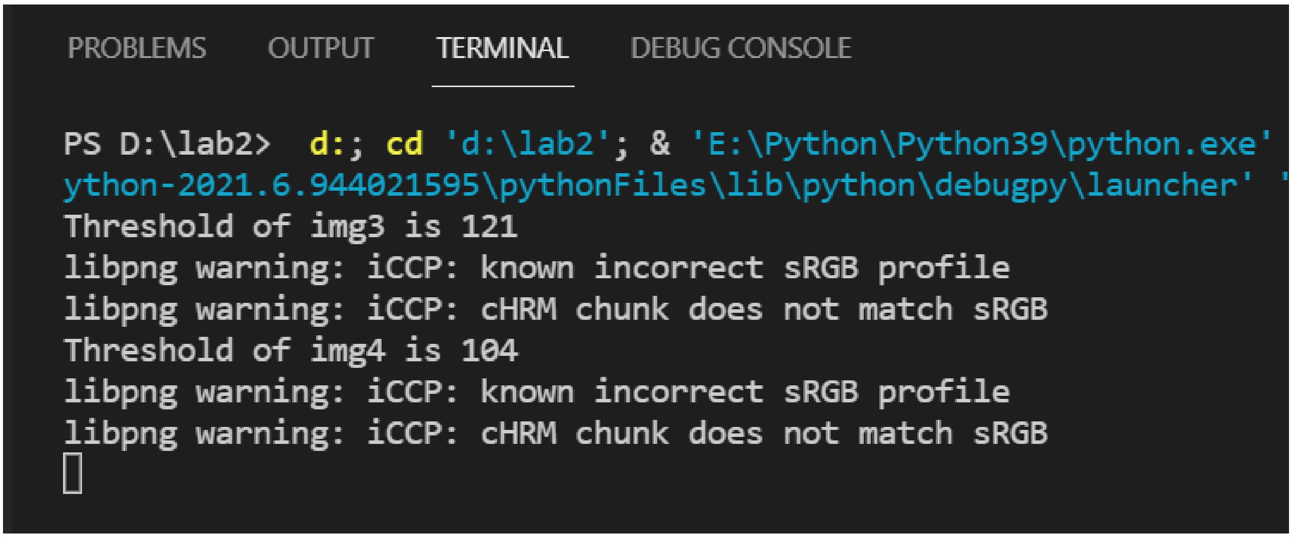
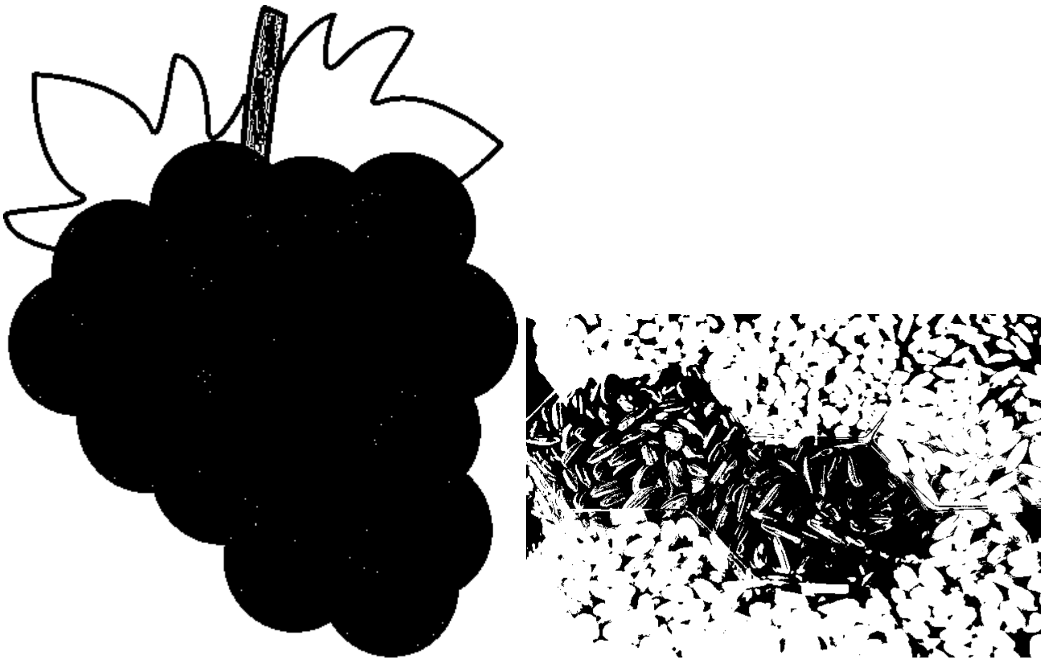


Figure 3: Threshold of img3 and img4 executed from function.



(a) Binarized img3

(b) Binarized img4

4 Discussion

1.Kernel1 and kerne5 are avaraging filter and gaussian filter. Compared to averaging filter, guassian filter weighs the pixel within the kernel which give higher weight to the closer pixel. So Gaussian highlight more importance for the colse pixel.
2. The bigger the kernel size is, the vaguer the image is. Becasue with a bigger size kernel, more pixels far from the origin which are less relevant to the origin pixel will be convolved.
3.Kernel6 is sobel filter for x axis, which sharpens the x direction edge. Kernel7 is a rotationally symmetric Laplacian of Gaussian filter, which sharpens the edge without direction feature.
4. Edges in an image represents a swift change in the intensity of an image and noise in an image also signifies the same. so when noise is abundant in an image, it can interfere the edge detection.
5.Adaptive thresholding typically takes a grayscale or color image as input and, in the simplest implementation, outputs a binary image representing the segmentation. For each pixel in the image, a threshold has to be calculated. If the pixel value is below the threshold it is set to the background value, otherwise it assumes the foreground value.