

CS-663 Assignment 2 Q1

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1 (15 points) Image Sharpening

Input images:

- 1/data/superMoonCrop.mat
- 1/data/lionCrop.mat

Assume the pixel dimensions to be equal along both axes, i.e., assume an aspect ratio of 1:1 for the axes. Write code for image sharpening using unsharp masking and apply it to both the input images. To compare the original and filtered images, linearly contrast-stretch them to the same intensity range, say, $[0, 1]$. Tune the parameters (Gaussian standard-deviation parameter and the scaling parameter) to your best judgment, but such that the sharpening in the image is clearly visible. You may use the following Matlab functions: *fspecial()* and *imfilter()*.

- Write a function *myUnsharpMasking.m* to implement this.
- For each image, show the original and sharpened versions side by side, using the same (gray) colormap.
- Report the tuned parameter values for each image.

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 import matplotlib.image as mpimg
4
5 from numpy import zeros,zeros_like,array
6 from numpy import linspace,pi,sqrt,e,power,outer
7 from math import floor,ceil
8
9 from myLinearContrastStretching import myLinearContrastStretching
10
11 import h5py
12
13 def read_file(filename):
14     f = h5py.File(filename,"r")
15     out = f.get('imageOrig')
16     out = array(out)
17
18     return (out*255.0/np.max(out))
19
20 ## gaussian filtering
21 def dnorm(x,mu,sigma):
22     """
23     Calculate pdf of the gaussian distribution with mean=mu
24     and standard deviation = sigma
25     input : x(point), mu(mean), sigma(standard deviation)
26     output : pdf of the gaussian distribution at the point x
27     """
28     return 1 / (sqrt(2 * pi) * sigma) * e ** (-power((x - mu) / sigma, 2) / 2)
29
30 def gaussian_kernel(ksize,mu=0,sigma=1,verbose=False):
31     """
```

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32     Create a normalized gaussian kernel with the given kernel size
33     and standard deviation (sigma)
34     inputs : ksize(for a ksizexksize gaussian filter),
35             sigma(standard deviation, default=1)
36             mu(mean of gaussian, default=0)
37             verbose (to visualize the gaussian kernel)
38     output : gaussian ksizeksize kernel filter
39     """
40     # create the 1-D gaussian kernel
41     kernel_1D = linspace(-(ksize // 2), ksize // 2, ksize)
42     for i in range(ksize):
43         kernel_1D[i] = dnorm(kernel_1D[i], mu, sigma)
44
45     # computers outer product of two 1-D gaussian kernels
46     # to produce a 2D Gaussian Kernel
47     kernel_2D = outer(kernel_1D.T, kernel_1D.T)
48     kernel_2D *= 1.0 / kernel_2D.max()
49
50     if verbose==True:
51         plt.figure()
52         plt.imshow(kernel_2D,cmap="gray",interpolation="none")
53         plt.title("{}x{} Gaussian Kernel".format(ksize,ksize))
54         plt.savefig("../images/GaussKernel_{}x{}.png".format(ksize,ksize),
55                     bbox_inches="tight",pad=-1)
56
57     return kernel_2D
58
59 def truncate(array):
60     """
61     if any pixel has value > 255 this makes it 255
62     and if any pixel is <0 this makes it 0
63     """
64     r,c = array.shape
65     for i in range(r):
66         for j in range(c):
67             if array[i,j]>255:
68                 array[i,j] = 255
69             elif array[i,j]<0:
70                 array[i,j] = 0
71     return array
72
73 def convolution(filename,input_image, kernel, average=False, verbose=False):
74     """
75     Calculates the convolution of input image with filter kernel
76     after zero-padding with the required no. of pixels
77     CAN BE USED WITH ANY KERNEL FILTER OF ANY SIZE
78     input : image_file : input image file_path
79             kernel : the filter kernel
80             average : required only if the filter kernel is not normalized (default = False)
81             verbose : to show and save the plots (default = False)
82     output : the normalized output image after convolution
83     Presently, the code works only for grayscale images, the color component will be added.
84     """
85     # READING THE INPUT IMAGE
86     image = input_image.copy()
87     name = filename.split("/")[-1].split(".")[0]
88
89     # EXTRACTING THE IMAGE AND KERNEL SHAPES AND INITIALIZING OUTPUT
90     image_row, image_col = image.shape
91     kernel_row, kernel_col = kernel.shape
92     output = zeros(image.shape)
93
94     # CREATING ZERO-PADDED IMAGE
95     pad_height = int((kernel_row - 1) / 2)
96     pad_width = int((kernel_col - 1) / 2)

```

```

97 padded_image = zeros((image_row + (2 * pad_height), image_col +
98                      (2 * pad_width)))
99 padded_image[pad_height:padded_image.shape[0] - pad_height,
100              pad_width:padded_image.shape[1] - pad_width] = image
101
102 # CONVOLUTION OPERATION DONE HERE
103 for row in range(image_row):
104     for col in range(image_col):
105         output[row, col] = np.sum(kernel * padded_image[row:row +
106                                                         kernel_row, col:col + kernel_col])
107         if average:
108             output[row, col] /= (kernel_row * kernel_col)
109 output = (output/np.max(output)) *255.0
110
111 # SAVE THE PLOTS IF VERBOSE
112 if verbose:
113     fig,axes = plt.subplots(1,2, constrained_layout=True)
114     axes[0].imshow(image,cmap='gray')
115     axes[0].axis("on")
116     axes[0].set_title("Original Image")
117     im = axes[1].imshow(output, cmap='gray')
118     axes[1].axis("on")
119     axes[1].set_title("Gaussian Blur using {}X{} Kernel".format(kernel_row,
120                                                                kernel_col))
121     cbar = fig.colorbar(im,ax=axes.ravel().tolist(),shrink=0.35)
122     #plt.show()
123     plt.savefig("../images/"+name+"GaussBlur.png",bbox_inches="tight",
124                 pad=-1)
125
126     plt.imsave("../images/"+name+"GaussianBlur{}X{}Kernel.png".format(kernel_row,
127                                                                kernel_col),output,cmap="gray")
128
129 return output
130
131 def gaussian_blur(filename,input_image, kernel_size, verbose=False):
132     #sigma = sqrt(kernel_size)
133     # this sigma is used by OpenCV implementation but explanation is not given
134     sigma = 0.3*((kernel_size-1)*0.5 - 1) + 0.8
135     #sigma = 2.0
136     kernel = gaussian_kernel(kernel_size, sigma= sigma, verbose=verbose)
137     return convolution(filename,input_image, kernel, average=False, verbose=False)
138
139 def plot_images(filename,alpha,kernel,input_image,output_image,cmap="gray"):
140
141     name = filename.split("/")[-1].split(".")[0]
142
143     fig,axes = plt.subplots(1,2, constrained_layout=True)
144     axes[0].imshow(input_image/np.max(input_image),cmap=cmap)
145     axes[0].axis("on")
146     axes[0].set_title("Original Image")
147
148     im = axes[1].imshow(output_image/np.max(output_image), cmap=cmap)
149     axes[1].axis("on")
150     axes[1].set_title("Unsharp Masked Image")
151
152     cbar = fig.colorbar(im,ax=axes.ravel().tolist(),shrink=0.35)
153     plt.savefig("../images/"+name+str(alpha)+"_"+str(kernel)+"UnsharpMask.png",
154                 bbox_inches="tight",pad=-1)
155     plt.cla()
156
157
158 def laplacian(filename,image):
159     #out = zeros_like(image)
160     #r,c = image.shape
161     kernel = array([[0,-1,0],[-1,4,-1],[0,-1,0]])

```

```

162     out = convolution(filename,image, kernel, average=False, verbose=False)
163     return out
164
165 def unSharpMask(filename,kernel_size,alpha,verbose=True):
166     image = read_file(filename)
167     gaussianBlurred = gaussian_blur(filename,image,kernel_size,verbose=verbose)
168     log = gaussianBlurred
169     # log = truncate(laplacian(filename,gaussianBlurred))
170     sharp = truncate((1+alpha)*image - alpha*log)
171     #image = myLinearContrastStretching(filename,image,[0,np.max(image)], [0,1])
172     #sharp = myLinearContrastStretching(filename,sharp,[0,np.max(sharp)], [0,1])
173     plot_images(filename,alpha,kernel_size,image,sharp)

```

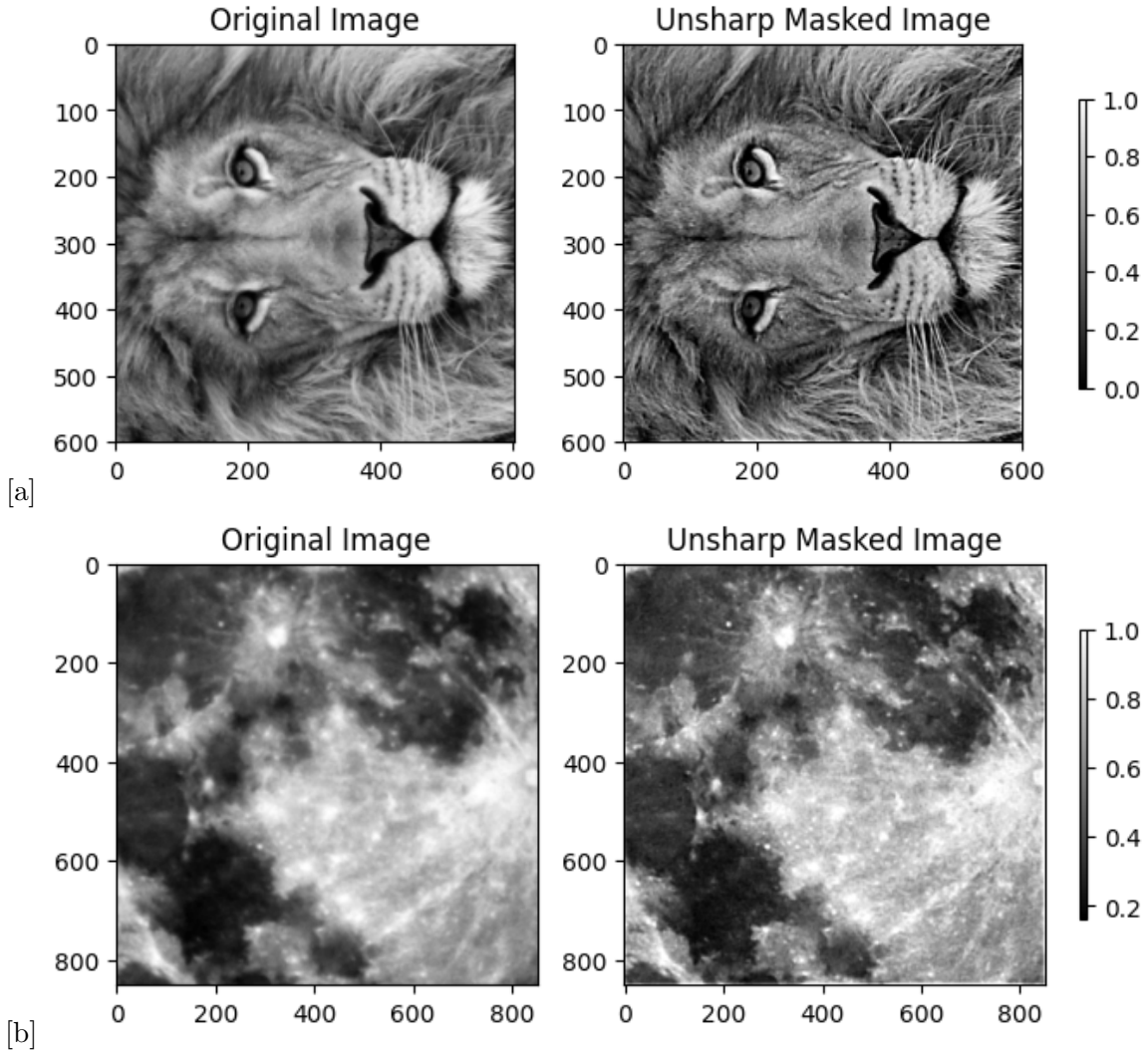


Figure 1: (a) LionCrop Image Unsharp Masking with $\alpha=1.6$ and GaussianStd = 2.6 (b) super-MoonCrop Image Unsharp Masking with $\alpha=2.2$ and GaussianStd = 3.2

Tuned Parameters

For the *lionCrop.mat* image, we found the optimum scaling parameter(α) = 1.6 and the Gaussian Standard deviation = 2.6.

For the *superMoonCrop.mat* image, we found the optimum scaling parameter(α) = 2.2 and the Gaussian Standard deviation = 3.2.

myMainScript.py :

```
1  from myUnsharpMasking import unSharpMask
2
3  files = ["../data/superMoonCrop.mat", "../data/lionCrop.mat"]
4  for file_name in files:
5      if "lion" in file_name:
6          alpha = 1.6
7          kernel = 15
8      elif "superMoon" in file_name:
9          alpha = 2.2
10         kernel = 19
11
12     unSharpMask(file_name, kernel, alpha)
```