

1) $\underline{A} \in \mathbb{C}$, $N \times N$ matrix of rank $r \leq \min(M, N)$

a) Show that $\underline{A}^* \underline{A}$ is a Hermitian matrix & is positive semi-definite

$$\underline{A}^* = \overline{A_{ji}} \quad , \quad \underline{A} = A_{ij} \quad \underline{A}^* \quad \underline{A} = \underline{B}$$

$$[N \times M] \quad [M \times N] \quad [N \times N]$$

\underline{B} is hermitian if $\underline{B} = \underline{B}^*$ then prove $\underline{A}^* \underline{A} = (\underline{A}^* \underline{A})^*$

LHS: $\underline{A}^* \underline{A}$

RHS: $(\underline{A}^* \underline{A})^T = \left(\underline{A}^T (\underline{A}^T)^T \right) = \left(\underline{A}^T \underline{A} \right) = \underline{A}^* \underline{A}$

LHS = RHS

\underline{B} or $\underline{A}^* \underline{A}$ is a hermitian matrix

b) $\underline{A}^* \underline{A}$ can be diagonalized by $\underline{U} \Rightarrow \underline{B} = \underline{U} \underline{D} \underline{U}^H$. How many positive eigenvalues does $\underline{A}^* \underline{A}$ have?

$\underline{A}^* \underline{A} = \underline{B} \quad [N \times N]$

can have r positive eigenvalues

bp 2) \underline{Q} = eigenvalues $\sigma_1^2 \geq \sigma_2^2 \geq \dots \geq \sigma_r^2 > 0$ k^{th} column of \underline{V} unitary matrix is \underline{V}_k
find $\|\underline{V}_k\|_2^2$ and why?

$\|\underline{V}_k\|_2^2 = \underline{V}_k^H \underline{V}_k = 1$ because \underline{V}_k is a column of a unitary matrix w/

property $\underline{U} \underline{U}^H = \underline{I}$ which means that $\underline{V}_k^H \underline{V}_k$ will correspond to a diagonal element of

\underline{I} $\|\underline{V}_k\|_2^2 = 1$

c) Consider $\underline{u}_k = \frac{1}{\sigma_k} A \underline{v}_k$ for $k \in 1, 2, \dots, l$, Show that $\|\underline{u}_k\|_2^2 = 1$

$$\|\underline{u}_k\|_2^2 = \underline{u}_k^H \underline{u}_k = \left[\frac{1}{\sigma_k} \underline{v}_k^H A^H \right] \left[\frac{1}{\sigma_k} A \underline{v}_k \right] = \frac{1}{\sigma_k^2} \underline{v}_k^H \underbrace{(A^H A)}_{\underline{B}} \underline{v}_k = \frac{1}{\sigma_k^2} \underline{v}_k^H \underline{B} \underline{v}_k$$

due to diagonalizable by unitary matrices of \underline{B}
 \underline{v}_k is column vector of \underline{V} & \underline{D} is diagonal matrix containing $\sigma_1^2, \dots, \sigma_k^2$

then $\underline{v}_k^H \underline{B} \underline{v}_k = D_{kk}$ & $D_{kk} = \sigma_k^2$

$$[1 \times N][N \times N][N \times 1] = [1 \times 1]$$

then $\|\underline{u}_k\|_2^2 = \frac{1}{\sigma_k^2} (\sigma_k^2) = 1$ $\|\underline{u}_k\|_2^2 = 1 \quad \text{!}$

d) Show that \underline{u}_k is an eigenvector of $\underline{A} \underline{A}^H$ with eigenvalue σ_k^2 ?

Eigenvector & Eigenvalue has a property $\underline{B} \underline{c} = \lambda \underline{c}$

plugging in $\underline{B} = \underline{A} \underline{A}^H$, $\underline{c} = \underline{u}_k$ & $\lambda = \sigma_k^2$

$$\underline{A} \underline{A}^H \underline{u}_k = \sigma_k^2 \underline{u}_k$$

RHS: $\sigma_k^2 \left[\frac{1}{\sigma_k} A \underline{v}_k \right] = \sigma_k A \underline{v}_k$

LHS: $\underline{A} \underline{A}^H \frac{1}{\sigma_k} A \underline{v}_k$

$\frac{1}{\sigma_k} \underline{A} \underline{A}^H A \underline{v}_k = \sigma_k A \underline{v}_k$ True if \underline{v}_k is eigenvector of $A^H A$ w/ eigenvalue σ_k^2
 which is definition of \underline{V} & \underline{U}_k

$\frac{1}{\sigma_k} A (\sigma_k^2 \underline{v}_k) = \sigma_k A \underline{v}_k$ Same

$\underline{u}_k \text{ is eigenvector of } \underline{A} \underline{A}^H \text{ w/ eigenvalue } = \sigma_k^2$

e) let $\underline{V}_e [N \times L]$ matrix whose k^{th} column is \underline{V}_k above, & $\underline{U}_e [M \times L]$

whose k^{th} column is \underline{U}_k above. Let $\underline{\Sigma}_e$ be the diagonal matrix w/ diagonal entry σ_k

Show that $\underline{A} \underline{V}_e = \underline{U}_e \underline{\Sigma}_e$

$$\underline{A} \underline{V}_e = \underline{U}_e \underline{\Sigma}_e$$

Take k^{th} column of \underline{V}_e we have \underline{V}_k
& from previous sections we know that

$$\underline{U}_k = \frac{1}{\sigma_k} \underline{A} \underline{V}_k$$

$$\underline{A} \underline{V}_k = \underline{U}_k \sigma_k$$

$$[M \times L] [N \times L] = [M \times L] [L \times L]$$

$$[M \times L] = [M \times L] \checkmark$$

Concatenating all columns

we get that

$$\boxed{\underline{A} \underline{V}_e = \underline{U}_e \underline{\Sigma}_e} \checkmark$$

f) Now Show that $\underline{\Sigma}_e = \underline{U}_e^* \underline{A} \underline{V}_e$

from above we know that $\underline{A} \underline{V}_e = \underline{U}_e \underline{\Sigma}_e$ then plug in becomes

$$\underline{\Sigma}_e = \underline{U}_e^* \underline{U}_e \underline{\Sigma}_e$$

from part c the proof implied that

$$\underline{U}_e^* \underline{U}_e = \underline{I}$$

then

$$\underline{\Sigma}_e = \underline{I} \underline{\Sigma}_e$$

$$\boxed{\underline{\Sigma}_e = \underline{\Sigma}_e}$$

Grad and Denoise: HW 3

Problem #2: Programming Exercise 1

Image Derivatives a) to c)

The image derivatives were gathered by using a shifting in x and y in order to have a similar property of circulant matrices. This results in the same size output as the input. The figure below shows the image derivative in both directions and the total magnitude. From this the edges of the images can be clearly seen.

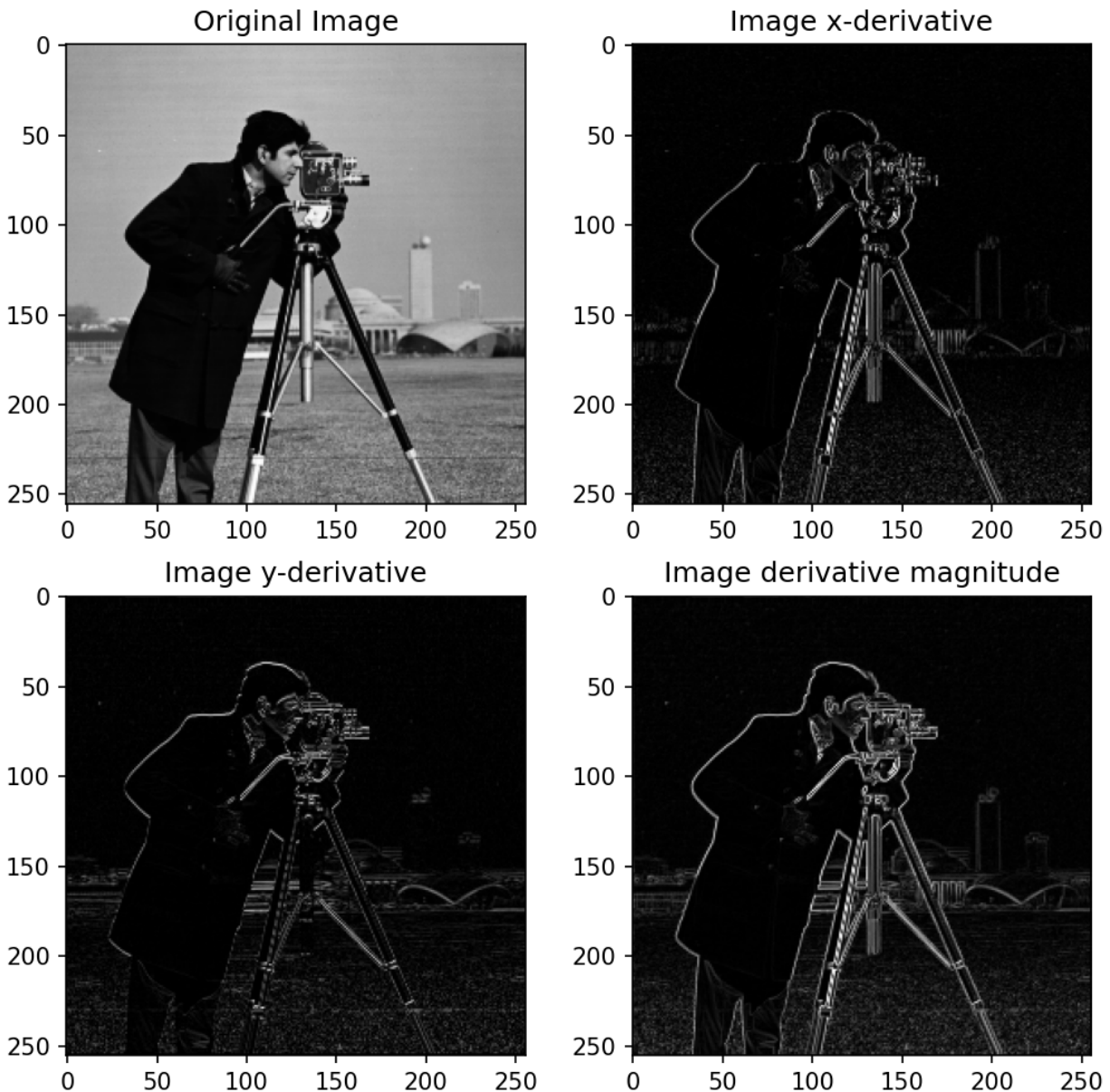


Figure 1: Image Derivative in x,y and magnitude

The whole image has a size of 256 by 256. The DCT of each 8 by 8 block is taken which means that there are a total of 32 by 32 sets of blocks. Although DCT is used, the form of the man can still be seen a bit which

is close to the edge data.

d) Discrete Cosine Transform (DCT)

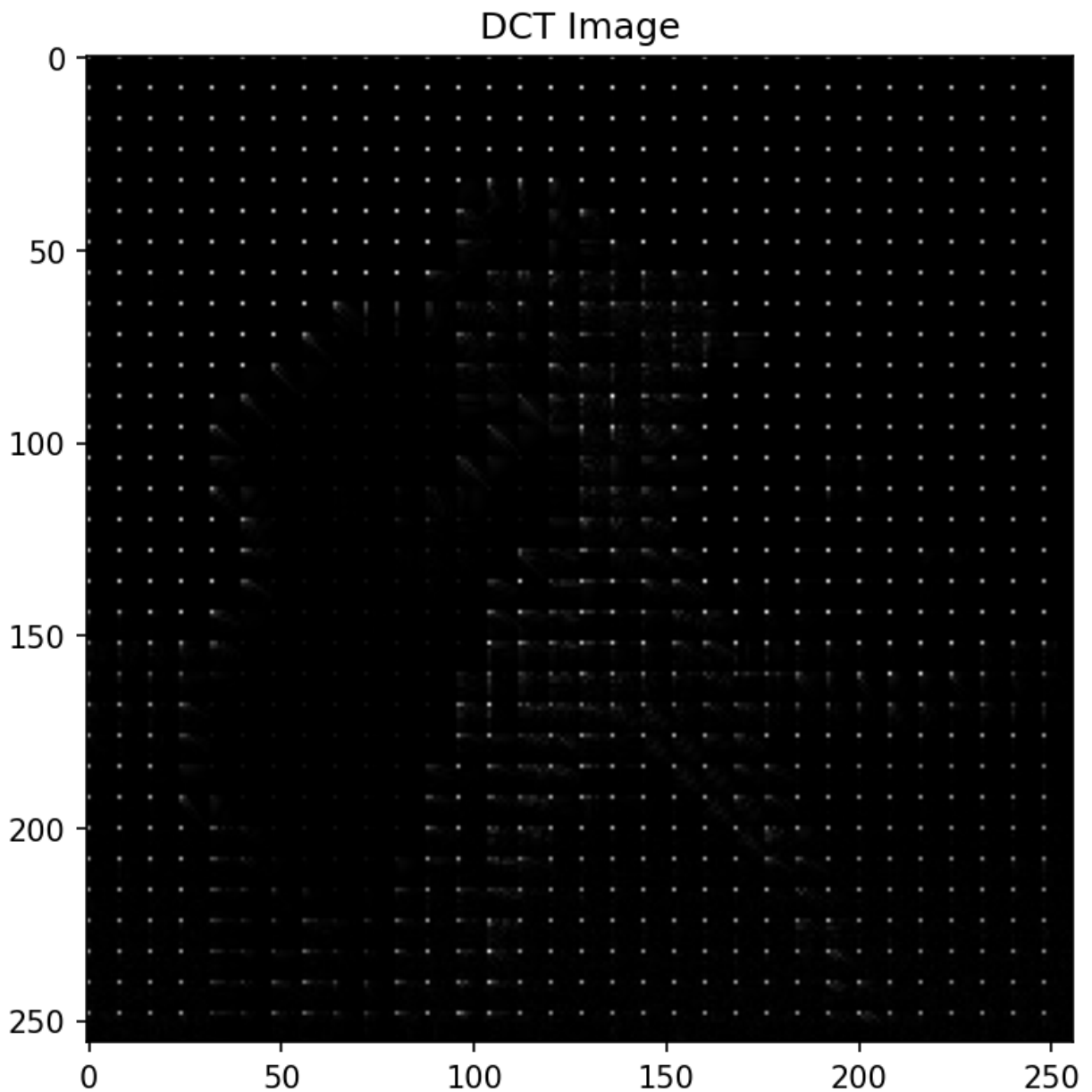


Figure 2: DCT on each 8x8 block

Problem #3: Programming Exercise 2

a) Proximal Gradient Descent

This is the result of the blurry image after 7500 iterations. It can be seen that the deblurred image looks fairly nice.

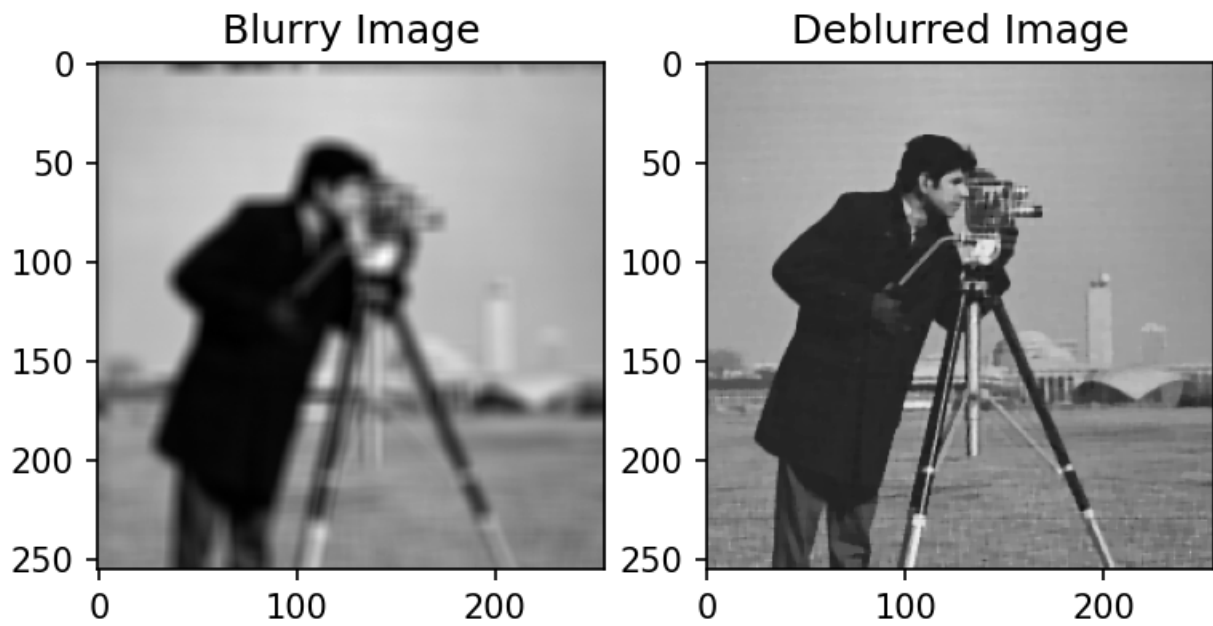


Figure 3: Denoising using PGD

However from the image below, it can be seen that a substantial result doesn't come until the 5000th iteration. The picture isn't as bad as the original image but the first few shots still look like a basic blurred image.

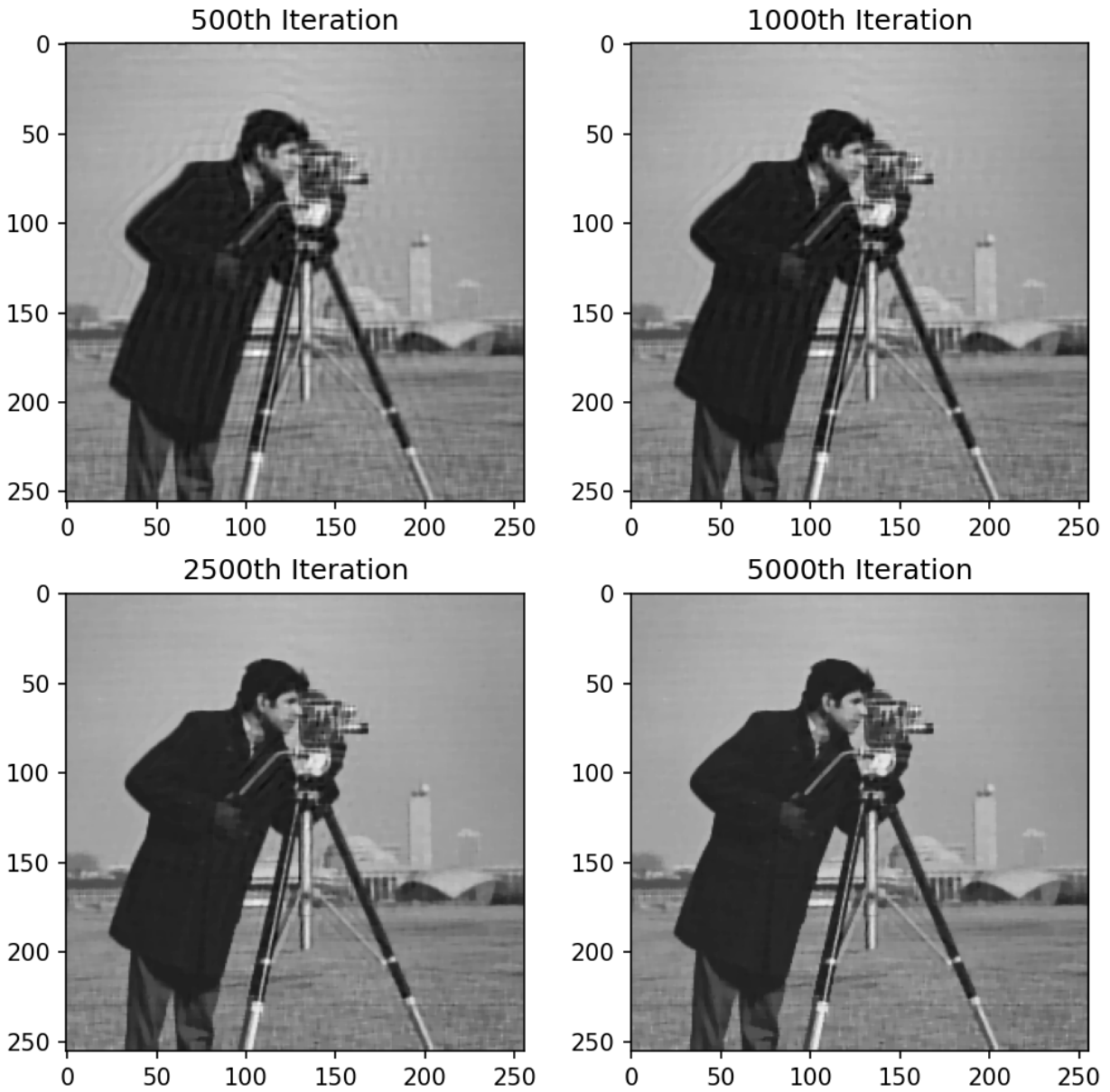


Figure 4: Intermediate Values of PGD Denoising

a) Proximal Gradient Descent

Using proximal gradient descent is lowkey interesting and there are a bit of extra steps to be done. However, I can say that the time needed is lower than PGD. At the same time the deblurred image looks pretty good aside from the small waves that can be seen.

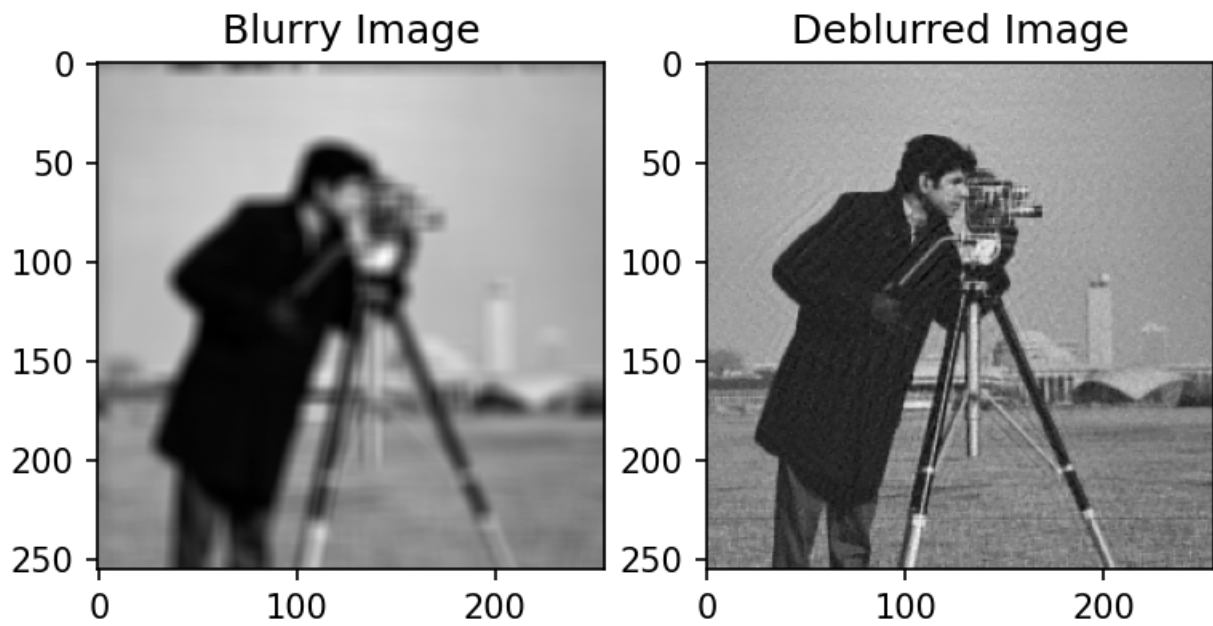


Figure 5: Denoising using ADMM

This is especially more amazing, when one notes that this is just done within 500 iterations which is much less than the 7500 iterations for PGD. At the same time, the first few shots aren't as good but the jump from 250 to 500 iterations is a big one which shows the speed of convergence of the ADMM method.

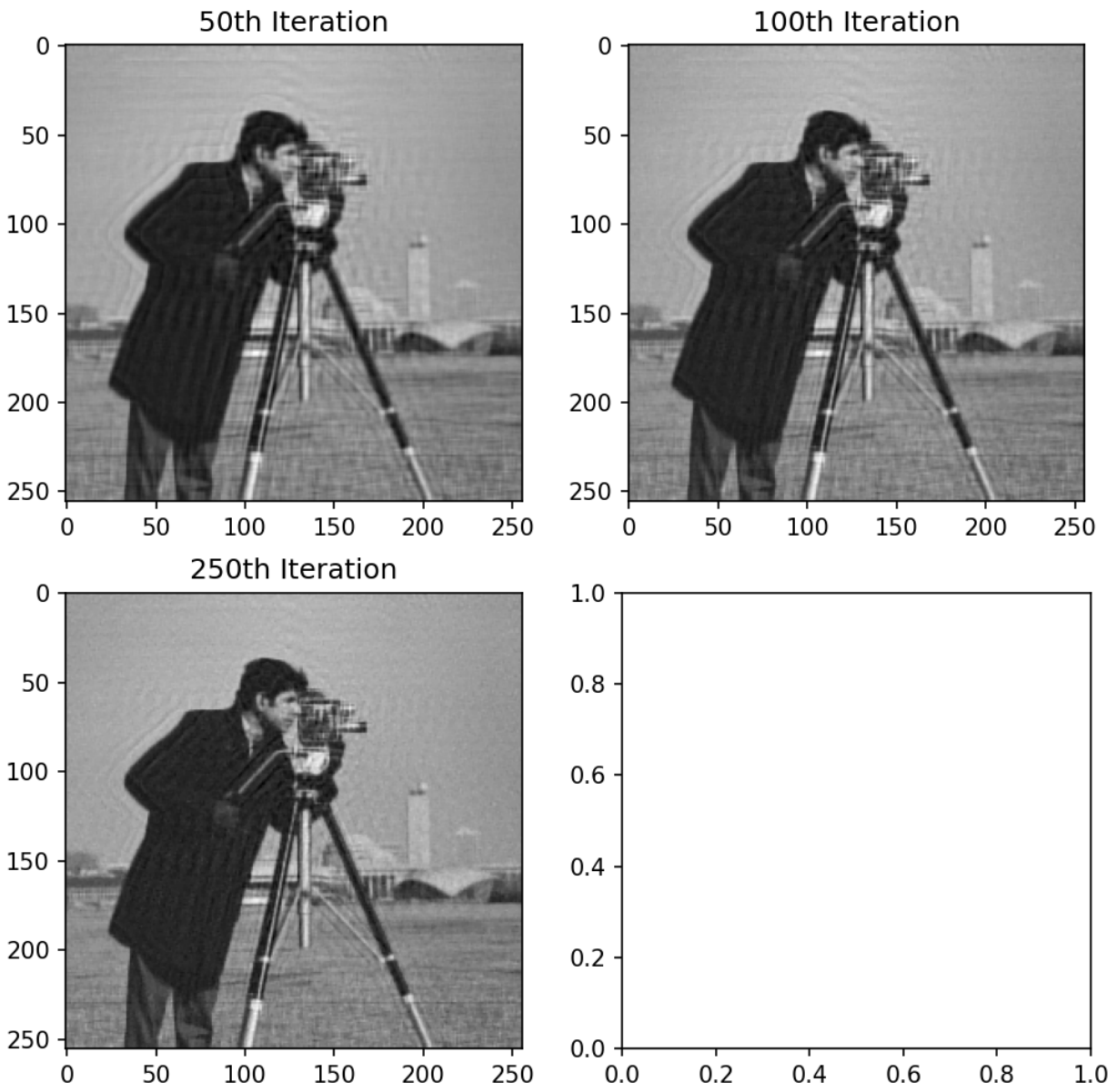


Figure 6: Intermediate Values of ADMM Denoising

Appendix

Problem 2

```
1 '''
2 Justine Serdoncillo
3 EE 5561 - Image Processing
4 Problem Set 3
5 November 7, 2023
6 '''
7
8
9 # %% Problem Statement
10 """
11     2) [9 pts] Programming Exercise 1: In this exercise, you will familiarize yourself with
12     function handles. Write function handles to calculate the following:
13     a) The image derivative in x direction (the built-in function numpy.diff(Python)/diff(
14     MATLAB)
15     may be useful),
16     b) the image derivative in y direction,
17     c) the magnitude of the gradient vector in (x, y) directions,
18     d) discrete cosine transform (you may use the scipy.fftpack.dct(Python)/dct2(MATLAB)
19     function for this) of each 8 x 8 distinct block in the image.
20     For a, b, and c make the derivative operator circulant. Thus, the output should be the
21     same
22     size as the image. Verify all 4 function handles on the cameraman image.
23 """
24 # %%
25
26 import numpy as np
27 import matplotlib.pyplot as plt
28 import matplotlib.image as img
29 import scipy
30 import imageio as iio
31 from scipy.fftpack import dct, idct
32 from scipy.signal import convolve2d
33
34 # %% Function Handles
35 def gradX(image):
36     shift = np.roll(image, 1, axis=1)
37     x = image - shift
38     return x
39
40 def gradY(image):
41     shift = np.roll(image, 1, axis=0)
42     y = image - shift
43     return y
44
45 def gradMag(image):
46     x = gradX(image)
47     y = gradY(image)
48     mag = np.sqrt(x**2 + y**2)
49     return mag
50
51 def dct2c(img):
52     return dct(dct(img, axis=0, norm = 'ortho'), axis=1, norm = 'ortho')
53
54 def DCT(image, size):
55     [Nx,Ny] = image.shape
56     dct = np.zeros_like(image)
57     for x in range(0,Nx,size):
58         for y in range(0,Ny,size):
59             dct[x:x+8,y:y+8] = dct2c(image[x:x+8,y:y+8])
60     return dct
61
62 # %% Importing Images
63 man_img = np.complex64(iio.imread('cameraman.tif'))
64
65 # %% Problem 2
66 def prob2():
```

```

66 print(f"Cameraman has size {man_img.shape}")
67 x = gradX(man_img)
68 y = gradY(man_img)
69 M = gradMag(man_img)
70 D = DCT(man_img, 8)
71 print(f"Derivatives has size {x.shape}")
72
73 # Plot the figures
74 fig, ax = plt.subplots(2,2, figsize=(8,8), dpi=150)
75 ax[0,0].imshow(np.abs(man_img), cmap="gray")
76 ax[0,0].set_title("Original Image")
77 ax[0,1].imshow(np.abs(x), cmap="gray")
78 ax[0,1].set_title("Image x-derivative")
79 ax[1,0].imshow(np.abs(y), cmap="gray")
80 ax[1,0].set_title("Image y-derivative")
81 ax[1,1].imshow(np.abs(M), cmap="gray")
82 ax[1,1].set_title("Image derivative magnitude")
83
84 fig, ax = plt.subplots(figsize=(6,6), dpi=150)
85 ax.imshow(np.abs(D), cmap="gray")
86 ax.set_title("DCT Image")
87
88 # %% Main Function
89 if __name__ == "__main__":
90     prob2()

```

Problem 3

```
1 from scipy.io import loadmat
2 import matplotlib.pyplot as plt
3 import numpy as np
4 from cg_solve import cg_solve
5 try:
6     from skimage.restoration import denoise_tv_chambolle as TV_denoise
7 except ImportError:
8     from skimage.filters import denoise_tv_chambolle as TV_denoise
9
10 # example usage of the functions:
11 # ----cg_solve-----
12 #     x_recon = A^-1.b
13 #     no_iter: numver of iterations
14 #     x_recon = cg_solve(b,A,no_iter)
15 # ----TV_denoise-----
16 #     weight: Weight of the TV penalty term
17 #     x_denoised = TV_denoise(x_noisy, weight)
18
19
20 # %% Load the image
21 I = plt.imread('cameraman.tif').astype(np.float64) # original image
22 y = loadmat('Assignment3_blurry_image.mat')['y']    # blurred image
23
24 # Blur Kernel
25 ksize = 9
26 kernel = np.ones((ksize,ksize)) / ksize**2
27
28 [h, w] = I.shape
29 kernelimage = np.zeros((h,w))
30 kernelimage[0:ksize, 0:ksize] = np.copy(kernel)
31 fftkernel = np.fft.fft2(kernelimage)
32
33 sigm = np.sqrt(0.1)
34 alpha = np.sqrt(sigm**2/ np.max(np.abs(fftkernel)))
35
36 def H(x):
37     return np.real(np.fft.ifft2(np.fft.fft2(x) * fftkernel))
38
39 def HT(x):
40     return np.real(np.fft.ifft2(np.fft.fft2(x) * np.conj(fftkernel)))
41
42 def A(x):
43     return HT(H(x)) + rho*x
44
45 # %% Here, implement proximal gradient
46 step_size = alpha**2/sigm**2
47 # JJ's code starts here
48 x = np.copy(y)
49 aTV = 1e-2
50 save = [500, 1000, 2500, 5000]
51 saves = []
52 for ind in range(7500):
53     x_n = x + step_size * HT(y - H(x))
54     x = TV_denoise(x_n, weight=aTV)
55     if ind in save:
56         saves.append(x)
57
58 fig, ax = plt.subplots(1,2, figsize=(6,6), dpi=150)
59 ax[0].imshow(y, cmap="gray")
60 ax[0].set_title("Blurry Image")
61 ax[1].imshow(x, cmap="gray")
62 ax[1].set_title("Deblurred Image")
63
64 fig, ax = plt.subplots(2,2, figsize=(8,8), dpi=150)
65 ax[0,0].imshow(saves[0], cmap="gray")
66 ax[0,0].set_title("500th Iteration")
67 ax[0,1].imshow(saves[1], cmap="gray")
68 ax[0,1].set_title("1000th Iteration")
69 ax[1,0].imshow(saves[2], cmap="gray")
70 ax[1,0].set_title("2500th Iteration")
```

```

71 ax[1,1].imshow(saves[3], cmap="gray")
72 ax[1,1].set_title("5000th Iteration")
73
74 # %% Here, implement ADMM
75 # JJ's code starts here
76 z = np.zeros_like(y)
77 u = np.zeros_like(y)
78 aTV = 1e-2
79 rho = 0.1
80 no_iter=20
81 save = [50, 100, 250]
82 saves = []
83 x = np.copy(z)
84 for ind in range(500):
85     b = HT(y) + rho*(z-u)
86
87     # cg_solve equivalent
88     x0 = np.zeros_like(b)
89     xcg = np.copy(x0)
90     r = b - A(xcg)
91     p = np.copy(r)
92     rsold = np.sum(r * np.conj(r))
93     for i in range(no_iter):
94         Ap = A(p)
95         alpha = rsold/np.sum(p * Ap)
96         xcg = xcg + alpha * p
97         r = r - alpha * Ap
98         rsnew = np.sum(r * np.conj(r))
99         p = r + rsnew / rsold * p
100        rsold = np.copy(rsnew)
101    x = xcg.copy()
102
103    z = TV_denoise(x + u, weight=aTV)
104    u += x - z
105    if ind in save:
106        saves.append(x)
107
108 fig, ax = plt.subplots(1,2, figsize=(6,6), dpi=150)
109 ax[0].imshow(y, cmap="gray")
110 ax[0].set_title("Blurry Image")
111 ax[1].imshow(x, cmap="gray")
112 ax[1].set_title("Deblurred Image")
113
114 fig, ax = plt.subplots(2,2, figsize=(8,8), dpi=150)
115 ax[0,0].imshow(saves[0], cmap="gray")
116 ax[0,0].set_title("50th Iteration")
117 ax[0,1].imshow(saves[1], cmap="gray")
118 ax[0,1].set_title("100th Iteration")
119 ax[1,0].imshow(saves[2], cmap="gray")
120 ax[1,0].set_title("250th Iteration")

```