ELEC221 HW4 Problem5 2D FFT

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1 Problem 5: Images: Fourier Transforms & the Value of Phase

Goal of this part In this exercise, you will learn how to:

- 1. compute the 2D FT of an image by calling the FFT algorithm
- 2. compute the inverse FT by calling the iFFT algorithm
- 3. plot the magnitude of the FT of an image

You will also see a demonstration of why the phase information of the fourier transform is important. Specifically, you will learn that the phase of the FT carries most of the information about the image!

1.1 1.1 Fourier Transform of 2D signals

In the lectures, we talked about the Fourier/frequency representation of 1D signals. Specifically, we introduced the Fourier transform as a mapping from the time-domain to the frequency domain, where the values of the Fourier transform are informative of the degree with which the corresponding frequency is "present" in the signal. At its heart, the Fourier transform (FT) of a time-varying signal is a decomposition into simple sinusoids of different frequencies. The output of the FT tells us which frequencies we need to compose our signal.

Can we extend these ideas to 2D signals? Is there a Fourier transform of a spatially-varying 2D signal? If so, what does it mean and how to compute it?

It turns out that the very same ideas that we introduced for 1D time signals extend naturally to 2D spatially-varying signals. First, we now need a decomposition into spatially variying sinusoids, rather than time-varying ones. Second, we need sinusoids that vary in two-dimensions. Such sinusoids can oscilate with different frequencies just like classical time-varying 1D sinusoids. Only now, every such sinusoid is specified by **two frequencies**. This is consistent with the fact that a 2D signal is specified by two independet variables!

In this course we will avoid formalizing this extension further. Instead, we will follow a programming-based approach. We will learn how to compute the FT of a 2D signal (specifically, an image) and how to plot its magnitude and its phase.

Image processing techniques that are based on processing the FT of the image are called **spectral techniques** and are very useful and popular!

Read the image in a 2D array Let us first load the image and store it in a 2D array.

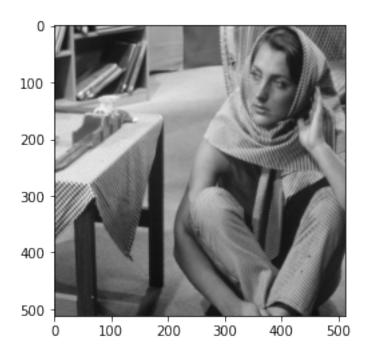
```
[5]: # importing libraries for image import numpy as no
```

```
import matplotlib.image as mpimg
import matplotlib.pyplot as plt
```

```
[6]: # Read the image (Image should be in same folder as jupyter file, otherwise,
     \rightarrow define a proper path to image)
     img = mpimg.imread('test_image.jpg')
     # check the type of image
     print("type of image ", type(img))
     # image is a 2D array
     # Check the Dimension of Image
     print("Dimension of Image ", img.shape)
     rows = img.shape[0]
     cols = img.shape[1]
     # Total No of pixels in the image is 512 X 512
     #Check the Values in the image
     print(img)
     #plot the image
     plt.imshow(img, cmap="gray")
    type of image <class 'numpy.ndarray'>
    Dimension of Image (512, 512)
    [[180 201 201 ... 106 95 94]
     [175 199 199 ... 90 99
     [172 196 193 ... 83 100 96]
```

```
[ 98 95 97 ... 114 116 114]
[ 96 97 98 ... 112 115 114]
[ 93 97 97 ... 109 109 107]]
```

[6]: <matplotlib.image.AxesImage at 0x7fd78d4623d0>



2D Fourier Transform of Image Computing the FT (specifically the Fast Fourier Transform) of a 2D array is very easy in Python and is done as follows:

```
[7]: import numpy as np

FT_img = np.fft.fft2(img)
```

Exercise 1.1.1 [1pt] Print the output of FT_img to see the content of the FT. Observe that the output is a 2D array (just like the input!). What is the dimension of the array? Are the entries real or complex?

```
[8]: print(type(FT_img))  # print the type of FT_img
print(FT_img.shape)  # print its size
print(FT_img)  # print its values

<class 'numpy.ndarray'>
(512, 512)
```

```
327455.75137714 -860417.10872256j ...
   89592.706793
                  +559212.63509031j -132804.75547397 -960790.56857338j
  642599.17166411 +116266.54863986j]
[ -77127.53398743 -91312.05052342j
                                      -532844.07867579 +198564.21560351j
  378045.82281314 -311084.97919889j ...
 1459197.36323365 -93470.40254699j
                                       487938.31029356 -122056.85916023j
   103382.47131944 +289595.77780842j]
[ -398493.5112166 -990710.60778142j
                                       642599.17166411 -116266.54863986j
 -132804.75547397 +960790.56857338j ...
 -393184.08277997 +990032.6540007j
                                       327455.75137714 +860417.10872256j
 1207498.32043378 -635093.73237648j]
[-1965690.65595536+3213534.44330876j -133404.71407643 +266237.41405963j
  -551250.30501679 +597511.38578556j ...
   636664.75275784+1000032.16391545j -1444045.81899304 -350669.07904033j
 -2010424.97153977-2500354.49628939j]]
```

Just as we did in the case of 1D signals, it is convenient to "center" the FT such that the DC component is at the center. We do this below.

```
[9]:

Now once you got the result, zero frequency component (DC component) will be at 

→ top left corner.

If you want to bring it to center, you need to shift the result by \frac{N}{2}\

→ in both the directions.

This is simply done by the function, np.fft.fftshift(). (It is more easier to 

→ analyze).

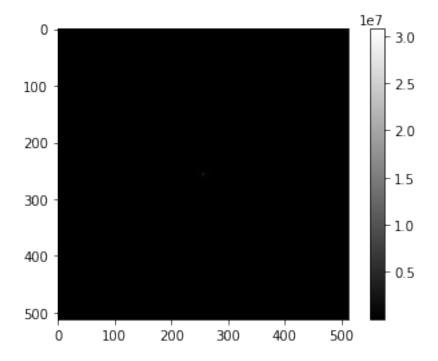
'''

FT_img_shift = np.fft.fftshift(FT_img)
```

Try to plot the **magnitude** of the 2D spectrum

```
[10]: plt.imshow(abs(FT_img_shift), cmap = "gray")
plt.colorbar()
```

[10]: <matplotlib.colorbar.Colorbar at 0x7fd78d3f45e0>



Why is it hard to see anything? What are the min and maximum values of the magnitude?

```
[11]: FT_img_abs = abs(FT_img_shift)
    print('Minimum value of Fourier magnitude is:',np.min(FT_img_abs))
    print('Maximum value of Fourier magnitude is:',np.max(FT_img_abs))
```

Minimum value of Fourier magnitude is: 11.069131790558064 Maximum value of Fourier magnitude is: 30773716.0

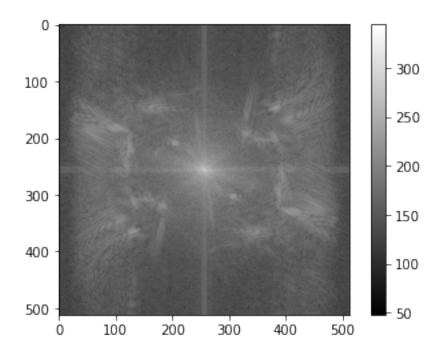
To circumvent the issue above, we will instead plot the magnitude values in decibel (dB) as follows.

```
[12]: magnitude_spectrum = 20*np.log(np.abs(FT_img_shift)) # magnitude of spectrum_

→ in dB

plt.imshow(magnitude_spectrum, cmap = "gray")
plt.colorbar()
```

[12]: <matplotlib.colorbar.Colorbar at 0x7fd78d319a90>

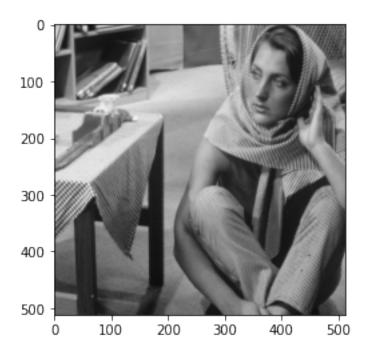


We can now clearly see some pattern on the magnitude of the Fourier transform. Specifically, observe that the larger values (whiter regions) are located at the center of image, which corresponds to low frequencies. In other words, the low-frequencies of this image have high energy.

Just like the FT of an 1D time-signal is an **invertible** transformation, the same is true for the FT of a 2D signal. Namely, we can go back and forth between the original image and its FT!

```
[13]: # Reconstructing Image using both Magnitude and Phase Information
img_back = np.fft.ifft2(FT_img_shift)
img_back = np.abs(img_back)
plt.imshow(img_back, cmap="gray")
```

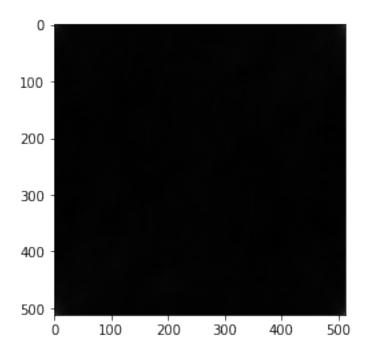
[13]: <matplotlib.image.AxesImage at 0x7fd78d307310>



Remember: There is information both in the magnitude and in the phase of the FT! Here is what happens if we ignore the phase! Not good, eh? :)

```
[14]: # Reconstructing Image just using Magnitude Information
  img_back_mag = np.fft.ifft2(np.abs(FT_img_shift))
  img_back_mag = np.abs(img_back_mag)
  plt.imshow(img_back_mag, cmap = "gray")
```

[14]: <matplotlib.image.AxesImage at 0x7fd78d254a60>



Next, let us convert the grayscale image to a binary image and plot the Fourier transform of the binary image. The following piece of code will do this for us.

```
(512, 512)

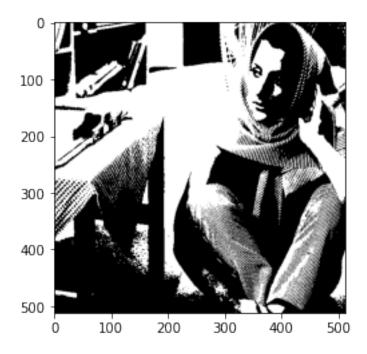
[[0 0 0 ... 0 0 0]

[0 0 0 ... 0 0 0]

[0 0 0 ... 0 0 0]
```

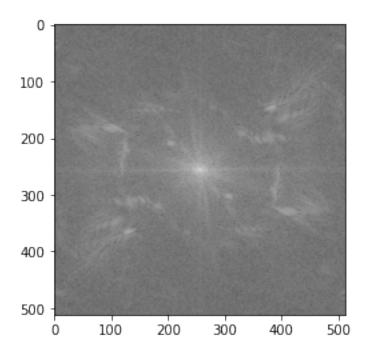
... [0 0 0 ... 0 0 0] [0 0 0 ... 0 0 0] [0 0 0 ... 0 0 0]

[15]: <matplotlib.image.AxesImage at 0x7fd78d232b80>



Exercise 1.1.2[1pt] Compute the Fourier transform of the binary image img_binary, shift the content as above and plot the magnitude of the fourier transform in dB.

[16]: <matplotlib.image.AxesImage at 0x7fd78d207a30>



Observe that the magnitude content is different to that of the grayscale image.

Exercise 1.1.3 [1pt] Write a function that takes as argument an image and returns an array of the same size with entries equal to the shifted coefficients of the Fourier transform.

```
[17]: def my_img_fft(img_in):
    fft_img = np.fft.fft2(img_in)
    fft_img = np.fft.fftshift(fft_img) # shift
    return fft_img
```

1.2 1.3 Phase is important

In this part, we will demonstrate that the phase information of the Fourier Transform is important, especially so for images!

To demonstrate this, we will perform the following experiment. We will load two images, compute their FTs and swap their phases. Then, we will use the inverse Fourier transform to map the FTs with swaped phases back to the original domain. We will plot the new images and see that they are highly distorted!

To begin with, go through and execute the following piece of code. Make sure that you understand how to go back and forth from the original image domain to the fourier transform domain. The FFT transform is invertible (i.e., there is no loss of information).

```
[18]: # load the two images
img1 = mpimg.imread('test_image.jpg')
```

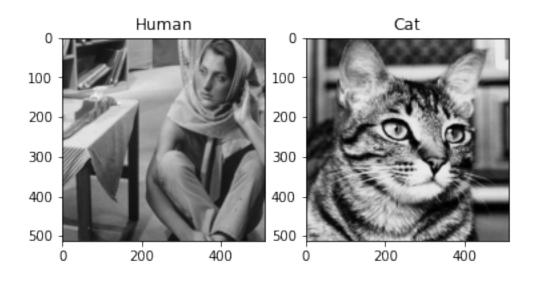
```
img2 = mpimg.imread('cat.jpg')
# plot the two images
fig = plt.figure()
fig.suptitle("Original images")
fig.add_subplot(1,2,1)
plt.imshow(abs(img1), cmap="gray")
plt.title("Person")
fig.add_subplot(1,2,2)
plt.imshow(abs(img2), cmap="gray")
plt.title("Cat")
# compute Fourier transforms of the images
FT1 = my_img_fft(img1)
FT2 = my_img_fft(img2)
# compute the *inverse* Fourier transforms of the images
img1_new = np.fft.ifft2(FT1)
img2_new = np.fft.ifft2(FT2)
fig = plt.figure()
fig.suptitle("Images after inverse FT")
fig.add_subplot(1,2,1)
plt.imshow(abs(img1_new), cmap="gray")
plt.title("Human")
fig.add_subplot(1,2,2)
plt.imshow(abs(img2_new), cmap="gray")
plt.title("Cat")
```

[18]: Text(0.5, 1.0, 'Cat')

Original images



Images after inverse FT



Next, we want to swap the phase information between the FTs of two images, i.e., between the arrays FT1 and FT2. Follow the steps below.

Exercise 1.2.1[1pt] Write a function swap_phase that takes as argument two complex numbers

z1 and z2 and returns complex numbers z3 and z4, such that

$$|z_3| = |z_1|$$
, $\arg(z_3) = \arg(z_2)$,

and

$$|z_4| = |z_2|$$
, $\arg(z_4) = \arg(z_1)$.

You may need to use the following function that converts polar to cartesian coordinates.

```
[19]: def pol2cart(rho, phi):
    x = rho * np.cos(phi)
    y = rho * np.sin(phi)
    z = x + y*1j
    return z
```

Test the function works properly:

```
[20]: print(pol2cart(1,0))
    print(pol2cart(1,np.pi/2))
    print(pol2cart(1,-np.pi/2))
    print(pol2cart(1,-np.pi))
    print(pol2cart(1,-np.pi/4))
```

```
(1+0j)
(6.123233995736766e-17+1j)
(6.123233995736766e-17-1j)
(-1-1.2246467991473532e-16j)
(0.7071067811865476-0.7071067811865475j)
```

Now use the function pol2cart to define the function swap_phase.

```
[21]: def swap_phase(z1,z2):
    z3 = pol2cart(np.abs(z1), np.angle(z2))
    z4 = pol2cart(np.abs(z2), np.angle(z1))
    return (z3,z4)
```

Make sure that your function works properly:

```
[22]: z1 = 1 + 1j
z2 = 1 - 1j
print(swap_phase(z1,z2))
```

```
((1.0000000000000002-1j), (1.000000000000002+1j))
```

Also, observe that the function works properly if it is passed as arguments arrays rather than scalars.

```
[23]: z1 = np.array([1 + 1j, 1-1j])
z2 = np.array([1 - 1j, 1+1j])
```

```
(z3,z4) = swap_phase(z1,z2)
print(z3)
print(z4)
```

```
[1.-1.j 1.+1.j]
[1.+1.j 1.-1.j]
```

Exercise 1.2.2[1pt] Use the function that you defined above to swap the phases of FT1 and FT2. Then, call the inverse fourier transform on the new Fourier transform arrays. Plot the new images. What do you observe?

```
[24]: # load the two images
     img1 = mpimg.imread('test_image.jpg')
     img2 = mpimg.imread('cat.jpg')
     # plot the two images
     fig = plt.figure()
     fig.suptitle("Original images")
     fig.add_subplot(1,2,1)
     plt.imshow(abs(img1_new), cmap="gray")
     plt.title("Person")
     fig.add_subplot(1,2,2)
     plt.imshow(abs(img2_new), cmap="gray")
     plt.title("Cat")
     # ****** #
     # swap phases
     # ****** #
     # compute Fourier transforms of the images
     FT1 = my img fft(img1)
     FT2 = my_img_fft(img2)
     (FT1_new,FT2_new) = swap_phase(FT1, FT2) # swap phases
     # compute the *inverse* Fourier transforms of the images
     img1_new = np.fft.ifft2(FT1_new)
     img2_new = np.fft.ifft2(FT2_new)
     fig = plt.figure()
     fig.suptitle("Images after inverse FT")
     fig.add_subplot(1,2,1)
     plt.imshow(abs(img1_new), cmap="gray")
     plt.title("Person")
     fig.add_subplot(1,2,2)
```

```
plt.imshow(abs(img2_new), cmap="gray")
plt.title("Cat")
```

[24]: Text(0.5, 1.0, 'Cat')

Original images



Images after inverse FT

