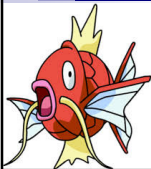


Lecture 12: Fourier Transforms



Definition

- Let f be a $M \times N$ matrix.
- The 2D Discrete Fourier Transform is

$$F(u, v) = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i, j) e^{-2\pi i \left(\frac{ui}{M} + \frac{vj}{N} \right)}$$

- The resulting matrix F also has size $M \times N$ and is complex-valued.
- Inverse Discrete Fourier Transform to recover f from F is

$$f(i, j) = \frac{1}{MN} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u, v) e^{2\pi i \left(\frac{ui}{M} + \frac{vj}{N} \right)}$$

FFT in Matlab

- The Fast Fourier Transform (FFT) implementation is a numerical trick for computing a Fourier Transform very efficiently.
- The FFT of a vector of length N can be computed in $O(N \log N)$ time (which is fast).
- In Matlab, we can compute the FFT of a 1D signal and invert it easily.

$F = \text{fft}(f);$ $f = \text{ifft}(F);$

- For a 2D image, we use the `fft2` command.

$F = \text{fft2}(f);$ $f = \text{ifft2}(F);$

Understanding

- The FFT breaks an image down into a sum of sinusoid functions.

$$F(u, v) = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i, j) e^{-2\pi i \left(\frac{ui}{M} + \frac{vj}{N} \right)}$$

- The **coefficients** of F tell us the **frequencies** of the **sinusoid** waves that appear in the image f .
- We say that f is in the **spatial domain**, while its Fourier Transform F is in the **spectral** or **frequency domain**.

The DC-Term

$$F(u, v) = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i, j) e^{-2\pi i \left(\frac{ui}{M} + \frac{vj}{N} \right)}$$

- Note that when $u=v=0$, we get

$$F(0,0) = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i, j)$$

- So the **zero term of the Fourier Transform** is the **sum of all values** in the matrix.
- Engineers call this the **DC-term**.

1D Example

- Suppose we have a non-negative sine wave.

`x = 0:0.1:2*pi;`

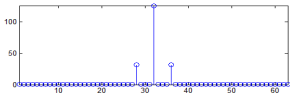
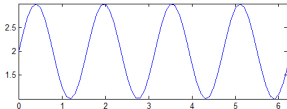
`f = 2 + sin (4*x);`

- Let's compute the FFT.

`F = fft (f);`

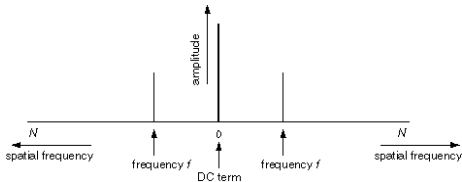
- The vector F is complex-valued, so we plot the absolute value (magnitude) of its coefficients: $|a + bi| = \sqrt{a^2 + b^2}$

`stem(abs(fftshift(F)))`



1D Example

- The 3 peaks represent the DC-term and the \pm frequency of the sine wave.
- We generally see this type of symmetry.



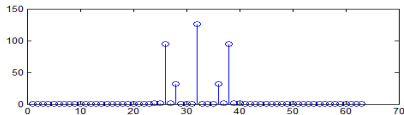
1D Example

- Now let's sum two sine waves.

$$f = 2 + \sin(4 \cdot x) + 3 \cdot \sin(6 \cdot x);$$

- Let's view the FFT.

```
F = fft(f);  
stem( abs(fftshift(F)))
```

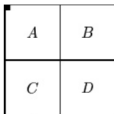


Viewing FFT Images

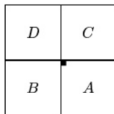
- When viewing a 2D Fourier Transform, it is often helpful to move the DC-term to the center of the image using the `fftshift` command.

```
imagesc( abs( fftshift(F) ) );
```

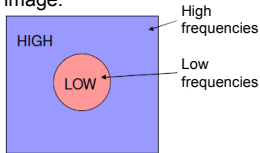
- This helps us understand the image.



An FFT



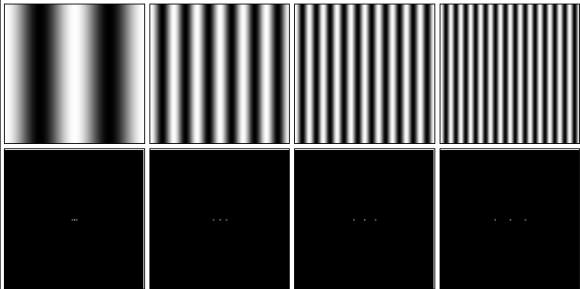
After shifting



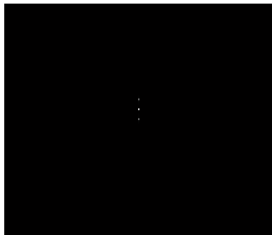
2D Example



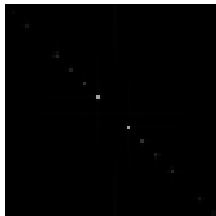
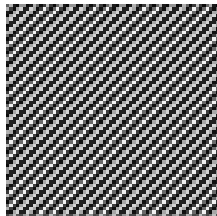
2D Example



2D Example



2D Example



Log Images

- Since the DC-term is much larger than the other values, the FFT image often appears as just a single bright dot.

`imagesc(abs(fftshift(F)));`

- Sometimes it helps to view the log image.

`imagesc(log(1 + abs(fftshift(F))));`

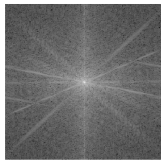
Original



$\text{abs}(F)$

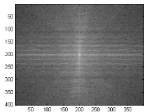
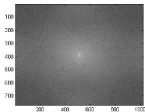
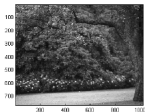


Log image



Man vs. Nature

- Manmade objects tend to have stronger edges, especially in the vertical and horizontal directions. Usually we see a cross in the Fourier transform.
- The edges in natural scenes are not as sharp and not as straight, so the Fourier transform is more diffuse.



Spectral Filtering

- We learned how to apply filters to the image pixel values to perform spatial filtering (e.g. mean filter, median filter).
- Spectral filtering is an operation applied to the frequencies, rather than the pixel values.

$$F = \text{fft}(A);$$

- We can create a 0-1 mask D for the Fourier Transform.
- Applying this to the FFT will keep some frequencies, but throw away others.

$$F2 = \text{fftshift}(F) .* D;$$

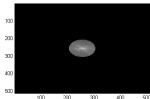
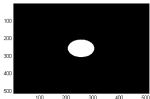
- We can then go back to the spatial domain.

$$A2 = \text{ifft2}(F2);$$

Low-pass Filter

- A low-pass filter allows the low frequencies to pass through, but stops (*attenuates*) the high frequencies.
- A low-pass filter smooths the image (denoising).

Mask D



$$F2 = F \cdot D$$

Original A

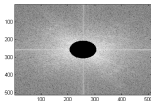
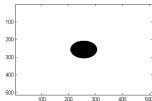


$$A2 = \text{ifft2}(F2)$$

High-pass Filter

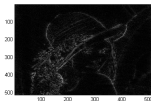
- A high-pass filter allows only the high frequencies to pass through.
- A high-pass filter keeps image details.

Mask D



$$F2 = F \cdot D$$

Original A

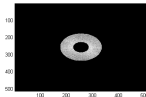
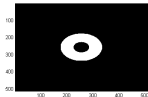


$$A2 = \text{ifft2}(F2)$$

Band-pass Filter

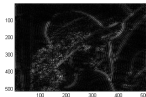
- A **band-pass filter** allows only frequencies in a **narrow band** to pass through.
- It is useful for **edge and feature** detection.

Mask D



$$F2 = F * D$$

Original A

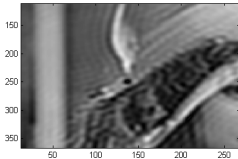
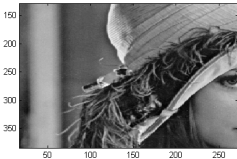


$$A2 = \text{ifft2}(F2)$$

- A **band-stop** filter has the **opposite** shape.

Ringling Artifacts

- The ideal low-pass filter smooths out the image, which is good for removing noise.
- The edges remain fairly sharp (better than mean filter).
- But it creates "ringing" or "halo" artifacts around edges.
- This is due to the sharp 0-1 transition in the filter and is called the *Gibbs phenomenon*.



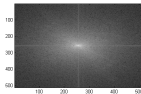
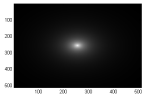
Butterworth Filter

- The Butterworth Filter creates a smooth image mask, rather than a sharp 0-1 transition:

$$H(x,y) = \frac{1}{(1 + d(x,y)/R_0)^2}$$

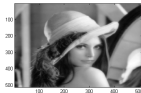
where $d(x,y)$ is the distance from (x,y) to center of image.

Mask H
 $R_0 = 50$



$F2 = F.*H$

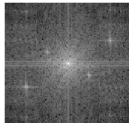
Original A



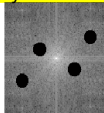
$A2 = \text{ifft2}(F2)$

Notch Filtering

- We might decide to **remove specific frequencies**. This is called notch filtering.
- Looking at the FFT of the striped clown image, we see 4 bright spots.



- Guessing that these 4 bright spots correspond to the periodic stripes, **we could manually create a mask to remove the spots.**



Structured Noise Removal

- Spectral filtering is good at removed *structured* noise.
- Stationary (striped) noise

(Fehrenbach-Weiss-Lorenzo, 2011)



Structured Noise Removal

- Snow / rain removal

(Barnum-Kanade-Narasimhan, 2007)

