

Lecture 7: Recall:

Understanding convolution:

Discrete convolution:

$$v(n, m) = \sum_{n'=0}^{N-1} \sum_{m'=0}^{N-1} g(n-n', m-m') I(n', m')$$

$g \times I(n, m)$

Linear combination of pixel values of I

In particular, if $g(k, l)$ is only non-zero around $(0, 0)$, then, $g \times I(n, m)$ is a linear combination of pixel value of I around (n, m) !!

DFT of convolution:

$$\text{Recall: } g * w(n, m) = \sum_{n'=0}^{N-1} \sum_{m'=0}^{M-1} g(n-n', m-m') w(n', m')$$

$$(g, m \in M_{N \times M}(\mathbb{R}))$$

Then, the DFT of $g * w(p, q) = MN \text{DFT}(g)(p, q) \text{DFT}(w)(p, q)$

\therefore DFT of convolution can be reduced to simple multiplication!

Recall: Shift-invariant image transformation = 2D convolution.

\therefore Easy computation/manipulation of shift-invariant transf.
after DFT!!

Image enhancement in the frequency domain:

- Goal:
1. Remove high-frequency components (low-pass filter) for image denoising
↑ noise
 2. Remove low-frequency components (high-pass filter) for the extraction of image details
edges

High/Low frequency components of $\hat{F} \leftarrow \text{DFT}(F)$

Let F be a $N \times N$ image, $N = \text{even}$. Let $\hat{F} = \text{DFT}(F)$.

$$\therefore \hat{F}(k, l) = \frac{1}{N^2} \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} F(m, n) e^{-j2\pi \left(\frac{mk+nl}{N} \right)}$$

Fourier coefficients of F at (k, l)

$$e^{j\theta} = \overline{e^{j(-\theta)}} = \cos\theta - j\sin\theta$$

Observe that: for $0 \leq k, l \leq \frac{N}{2} - 1$

$$\hat{F}\left(\frac{N}{2} + k, \frac{N}{2} + l\right) = \frac{1}{N^2} \sum_m \sum_n F(m, n) e^{-j\frac{2\pi}{N} \left(m\left(\frac{N}{2} + k\right) + n\left(\frac{N}{2} + l\right) \right)}$$

$$= \frac{1}{N^2} \sum_m \sum_n F(m, n) (-1)^{m+n} e^{-j\frac{2\pi}{N} (m(-k) + n(-l))}$$

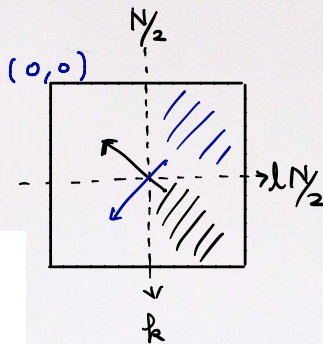
$$= \frac{1}{N^2} \sum_m \sum_n F(m, n) e^{-j \frac{2\pi}{N} (m(\frac{N}{2} - k) + n(\frac{N}{2} - l))}$$

$$\hat{F}(\frac{N}{2} + k, \frac{N}{2} + l) = \hat{F}(\frac{N}{2} - k, \frac{N}{2} - l)$$

$$F(m, n) = \sum_k \sum_l \hat{F}(k, l) e^{j \frac{2\pi}{N} (mk + nl)}$$

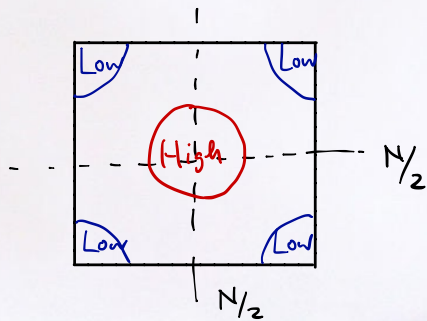
We have:

$$\begin{aligned} F(m, n) &= \sum_{0 \leq k, l \leq \frac{N}{2} - 1} \left[\hat{F}\left(\frac{N}{2} + k, \frac{N}{2} + l\right) e^{j \frac{2\pi}{N} [(\frac{N}{2} + k)m + (\frac{N}{2} + l)n]} \right] \\ &+ \sum_{1 \leq k, l \leq \frac{N}{2} - 1} \left[\hat{F}\left(\frac{N}{2} + k, \frac{N}{2} + l\right) e^{j \frac{2\pi}{N} [(\frac{N}{2} - k)m + (\frac{N}{2} - l)n]} \right] \\ &+ \sum_{0 \leq k, l \leq \frac{N}{2} - 1} \left[\hat{F}\left(\frac{N}{2} + k, \frac{N}{2} - l\right) e^{j \frac{2\pi}{N} [(\frac{N}{2} + k)m + (\frac{N}{2} - l)n]} \right] \\ &+ \sum_{1 \leq k, l \leq \frac{N}{2} - 1} \left[\hat{F}\left(\frac{N}{2} + k, \frac{N}{2} - l\right) e^{j \frac{2\pi}{N} [(\frac{N}{2} - k)m + (\frac{N}{2} + l)n]} \right] \\ &+ \sum_{0 \leq l \leq \frac{N}{2} - 1} (-1)^m \hat{F}\left(0, \frac{N}{2} + l\right) e^{j \frac{2\pi}{N} [(\frac{N}{2} + l)n]} + \sum_{1 \leq l \leq \frac{N}{2} - 1} \hat{F}\left(0, \frac{N}{2} + l\right) e^{j \frac{2\pi}{N} [(\frac{N}{2} - l)n]} (-1)^m \\ &+ \sum_{0 \leq k \leq \frac{N}{2} - 1} \hat{F}\left(\frac{N}{2} + k, 0\right) e^{j \frac{2\pi}{N} [(\frac{N}{2} + k)m]} + \sum_{1 \leq k \leq \frac{N}{2} - 1} \hat{F}\left(\frac{N}{2} + k, 0\right) e^{j \frac{2\pi}{N} [(\frac{N}{2} - k)m]} + \hat{F}(0, 0) \end{aligned}$$



Observation:

1. When k and l are close to $N/2$, $\hat{F}\left(\underbrace{\frac{N}{2}+k}_{SS}, \underbrace{\frac{N}{2}+l}_{SS}\right)$ is associated to $e^{-j\frac{2\pi}{N}\left(\left(\frac{N}{2}+k\right)m + \left(\frac{N}{2}+l\right)n\right)}$
 \therefore Fourier coefficients at the bottom right are associated to low frequency components!
 $e^{-j\frac{2\pi}{N}\left(\frac{N}{2}m + \frac{N}{2}n\right)} = e^{-j\pi\left(\frac{m}{2} + \frac{n}{2}\right)}$ where $(k', l') = (0, 0)$
 $\cos\left(\frac{2\pi}{N}\left(k'm + l'n\right)\right) + i \sin\left(\frac{2\pi}{N}\left(k'm + l'n\right)\right)$
2. Similarly, we can check that Fourier coefficients at the 4 corners are associated to low frequency components.
3. Fourier coefficients in the middle are associated to high-frequency components



- !!
- \therefore High-pass filtering
Remove coefficients at 4 corners
 - Low-pass filtering
Remove coefficients at the center

Centralisation:

Assume periodic conditions on F .

We can let $\tilde{F}(u, v) = \hat{F}(u - \frac{N}{2}, v - \frac{N}{2})$ where $0 \leq u \leq N-1$
 $0 \leq v \leq N-1$

Then, High-frequency components are located at 4 corners of $\tilde{F}(u, v)$

Low-frequency components are located at center of $\tilde{F}(u, v)$

Mathematically,

Consider the discrete Fourier transform of $(-1)^{x+y}F(x, y)$:

$$\begin{aligned} & \text{DFT}(F(x, y)(-1)^{x+y})(u, v) \quad e^{j2\pi(\frac{N}{2}x + \frac{N}{2}y)} \\ &= \frac{1}{N^2} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x, y) e^{j\pi(x+y)} \exp\left(-j2\pi\left(\frac{ux}{N} + \frac{vy}{N}\right)\right) \\ &= \frac{1}{N^2} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x, y) \exp\left(-j2\pi\left(\frac{(u - N/2)x}{N} + \frac{(v - N/2)y}{N}\right)\right) \\ &= \hat{F}\left(u - \frac{N}{2}, v - \frac{N}{2}\right) = \tilde{F}(u, v) \end{aligned}$$

Therefore, to compute $\tilde{F}(u, v)$, we can compute DFT of $(-1)^{x+y}f(x, y)$.

Definition 3.5: A **low-pass filter (LPF)** (LPF) leaves low frequencies unchanged, while attenuating the high frequencies.

A **high-pass filter (HPF)** leaves high frequencies unchanged, while attenuating the low frequencies.

Basic steps of filtering in the frequency domain

1. Multiply $f(x, y)$ by $(-1)^{x+y}$.
2. Compute $\tilde{F}(u, v) = DFT(f(x, y)(-1)^{x+y})(u, v)$.
3. Multiply \tilde{F} by a real "filter" function $H(u, v)$ to get

$$G(u, v) = H(u, v)\tilde{F}(u, v)$$

(point-wise multiplication, but not matrix multiplication)

4. Compute inverse DFT of $G(u, v)$.
5. Take real part of the result in Step 4.
6. Multiply the result in Step 5 by $(-1)^{x+y}$.

Example of Low-pass filters for image denoising

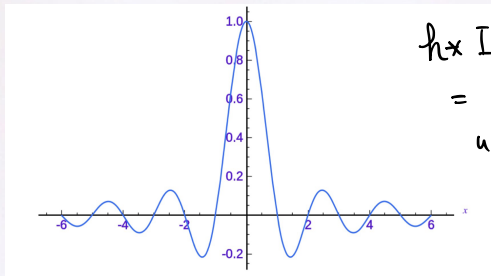
Assume that we work on the centered spectrum!

That is, consider $\hat{F}(u, v)$ where $-\frac{N}{2} \leq u \leq \frac{N}{2} - 1$, $-\frac{N}{2} \leq v \leq \frac{N}{2} - 1$.

1 Ideal low pass filter (ILPF):

$$H(u, v) = \begin{cases} 1 & \text{if } D(u, v) := u^2 + v^2 \leq D_0^2 \\ 0 & \text{if } D(u, v) > D_0^2 \end{cases}$$

In 1-dim cross-section, $\mathcal{F}^{-1}(H(u, v))$ looks like:



$$h \times I(x, y)$$

$$= \sum_{u, v} h(x-u, y-v) I(u, v)$$

every pixel values of I has an effect on $h \times I(x, y)$!!

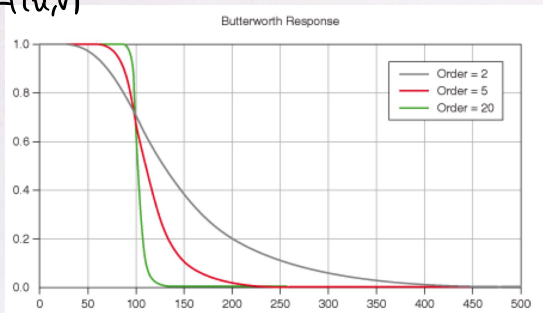
Good: Simple

Bad: Produce ringing effect!

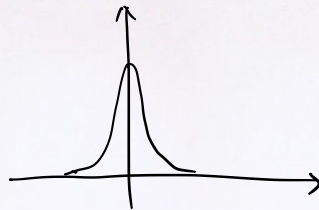
2. Butterworth low-pass filter (BLPF) of order n ($n \geq 1$ integer):

$$H(u, v) = \frac{1}{1 + (D(u, v)/D_0)^n}$$

$H(u, v)$ in 1-dim



$\mathcal{F}^{-1}(H(u, v))$ in 1-dim

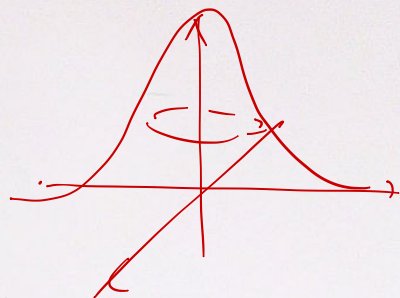


Good: Produce less / no visible ringing effect if n is carefully chosen!!

3. Gaussian low-pass filter

$$H(u, v) = \exp\left(-\frac{D(u, v)}{2\sigma^2}\right)$$

σ = spread of the Gaussian function



F.T. of Gaussian is also Gaussian!!

Good: No visible ringing effect!!

Examples for high-pass filtering for feature extraction

1. Ideal high-pass filter: (IHPF)

$$H(u, v) = \begin{cases} 0 & \text{if } D(u, v) \leq D_0^2 \\ 1 & \text{if } D(u, v) > D_0^2 \end{cases}$$

Bad: Produce ringing

2. Butterworth high-pass filter:

$$H(u, v) = \frac{1}{1 + \left(\frac{D_0}{D(u, v)}\right)^{2n}}$$

($H(u, v) = 0$ if $D(u, v) = 0$)

Choose the right n

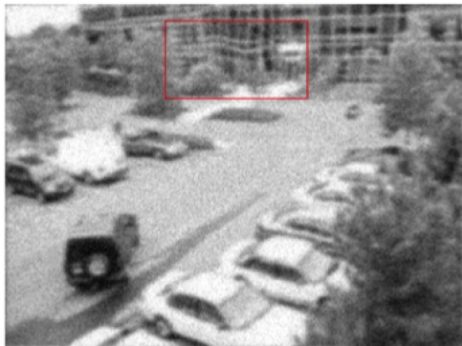
Good: Less ringing

3. Gaussian high-pass filter

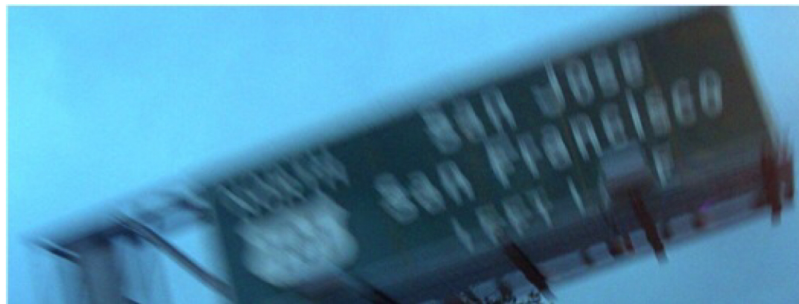
$$H(u, v) = 1 - e^{-\left(\frac{D(u, v)}{2\sigma^2}\right)^2}$$

Good: No visible ringing!

Image deblurring



Atmospheric turbulence



Motion Blur



Speeding problem

Image deblurring in the frequency domain:

Mathematical formulation of image blurring

Let g be the observed (blurry) image.

Let f be the original (good) image.

$$\text{Model } g \text{ as: } g = H(f) + n$$

where H is the degradation function/operator and n is the additive noise.

Assumption on H :

1. H is position invariant:

$$\text{Let } g(x, y) = H(f)(x, y) \text{ and let } \tilde{f}(x, y) := f(x - \alpha, y - \beta).$$

$$\text{Then: } H(\tilde{f})(x, y) = g(x - \alpha, y - \beta)$$

2. Linear: $H(f_1 + f_2) = H(f_1) + H(f_2)$

$$H(\alpha f) = \alpha H(f) \text{ where } \alpha \text{ is a scalar multiplication.}$$

3. Linearity can be extended to integral:

$$H\left(\iint \alpha(u, v) f(x-u, y-v) du dv\right) = \iint \alpha(u, v) H(f)(x-u, y-v) du dv$$

With the above assumption, consider an impulse signal:

$$\delta(x, y) = \begin{cases} 1 & \text{if } (x, y) = (0, 0) \\ 0 & \text{if } (x, y) \neq (0, 0) \end{cases}$$

$$\text{Then: } f(x, y) = f * \delta(x, y) = \sum_{\alpha=-M/2}^{M/2-1} \sum_{\beta=-N/2}^{N/2-1} f(\alpha, \beta) \delta(x-\alpha, y-\beta)$$

$$\therefore g(x, y) = H(f)(x, y)$$

$$= \sum_{\alpha=-M/2}^{M/2-1} \sum_{\beta=-N/2}^{N/2-1} f(\alpha, \beta) H(\delta)(x-\alpha, y-\beta) \quad (\text{by linearity and position-invariant})$$

$$= \sum_{\alpha=-M/2}^{M/2-1} \sum_{\beta=-N/2}^{N/2-1} f(\alpha, \beta) h(x-\alpha, y-\beta) \quad \text{where } h(x, y) = H(\delta)(x, y)$$

$$= f * h(x, y)$$

\therefore With the above assumption,

Degradation/Blur = Convolution