

## Lecture 8:

### Recall: Discrete Fourier Transform:

Definition: The 1D discrete Fourier Transform (DFT) of a function  $f(k)$ , defined at discrete points  $k=0, 1, 2, \dots, N-1$  is defined as:

$$\hat{f}(m) = \frac{1}{N} \sum_{k=0}^{N-1} f(k) e^{-j \frac{2\pi m k}{N}} \quad (\text{where } j = \sqrt{-1}, e^{j\theta} = \cos \theta + j \sin \theta)$$

The 2D DFT of a  $M \times N$  image  $g = (g(k, l))_{k, l}$ , where  $0 \leq k \leq M-1$ ,  $0 \leq l \leq N-1$  is defined as:

$$\hat{g}(m, n) = \frac{1}{MN} \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} g(k, l) e^{-j 2\pi \left( \frac{k m}{M} + \frac{l n}{N} \right)}$$

Remark: The inverse of DFT is given by:

$$g(p, q) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \hat{g}(m, n) e^{j 2\pi \left( \frac{p m}{M} + \frac{q n}{N} \right)}$$

$\uparrow$  (no  $\frac{1}{Mn}$ !)       $\uparrow$  DFT of  $g$        $\uparrow$  (no -ve sign)

## Why is DFT useful in imaging:

### 1. 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  $g * w(p, \xi) = MN \text{DFT}(g)(p, \xi) \text{DFT}(w)(p, \xi)$

$\therefore$  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!!

## 2. Average value of image

$$\text{Average value of } g = \bar{g} = \frac{1}{N^2} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} g(k, l) = \frac{1}{N^2} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} g(k, l) e^{-j2\pi(0)}$$

$\hat{g}(0, 0)$

## 3. DFT of a shifted image

Let  $g = (g(k', l'))$  be a  $N \times N$  image, where the indices are taken as:  
 $-k_0 \leq k' \leq N-1-k_0$  and  $-l_0 \leq l' \leq N-1-l_0$

Let  $\tilde{g}$  be shifted image of  $g$  defined as:

$$\tilde{g}(k, l) = g(k - k_0, l - l_0) \text{ where } 0 \leq k \leq N-1 \\ 0 \leq l \leq N-1.$$

Then:

$$\therefore \hat{\tilde{g}}(m, n) = \hat{g}(m, n) e^{-j2\pi \left( \frac{k_0 m + l_0 n}{N} \right)}$$

#### 4. DFT of a rotated image

Consider a  $N \times N$  image  $g$ .

$$\text{Then: } \hat{g}(m, n) = \frac{1}{N^2} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} g(k, l) e^{-j2\pi \left( \frac{km+ln}{N} \right)}$$

Write  $k$  and  $l$  in polar coordinates:

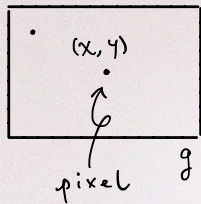
$$k \equiv r \cos \theta ; \quad l \equiv r \sin \theta$$

Similarly, write  $m \equiv w \cos \phi ; \quad n = w \sin \phi$ .

Note that:  $km + ln = rw (\cos \theta \cos \phi + \sin \theta \sin \phi) = rw \cos(\theta - \phi)$ .

Denote  $\mathcal{P}(g) = \{(r, \theta) : (r \cos \theta, r \sin \theta) \text{ is a pixel of } g\}$   
(Polar coordinate set of  $g$ )





If  $\begin{cases} x = r \cos \theta \\ y = r \sin \theta \end{cases}$ , then  $(r, \theta) \in \mathcal{P}(g)$ .

$$\text{Then: } \underbrace{\hat{g}(m, n) = \hat{g}(\omega, \phi)}_{\substack{\text{Identify } \hat{g}(m, n) \text{ with} \\ \hat{g}(\omega, \phi)}} = \frac{1}{N^2} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} \underbrace{g(r, \theta)}_{\substack{\text{Identify} \\ g(k, l) \text{ with } g(r, \theta)}} e^{-j2\pi \left( \frac{r\omega \cos(\theta - \phi)}{N} \right)}$$

Consider a rotated image  $\tilde{g}(r, \theta) = g(r, \theta + \theta_0)$  where  $\theta$  is defined between  $-\theta_0$  to  $\frac{\pi}{2} - \theta_0$ .

$\therefore$  image  $g$  is rotated clockwise by  $\theta_0$ .

DFT of  $\tilde{g}$  is:

$$\hat{\tilde{g}}(\omega, \phi) = \frac{1}{N^2} \sum_{(r, \theta) \in \mathcal{P}(\tilde{g})} \tilde{g}(r, \theta) e^{-j2\pi \left( \frac{r\omega \cos(\theta - \phi)}{N} \right)} = \frac{1}{N^2} \sum_{(r, \tilde{\theta}) \in \mathcal{P}(g)} g(r, \tilde{\theta}) e^{-j2\pi \left( \frac{r\omega \cos(\tilde{\theta} - \theta_0 - \phi)}{N} \right)}$$

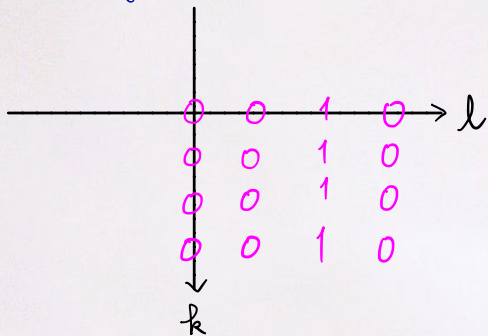
$\tilde{\theta}$

$\therefore \hat{\tilde{g}}(\omega, \phi) = \hat{g}(\omega, \phi + \theta_0)$ . ( $\phi$  is also defined between  $-\theta_0$  to  $\frac{\pi}{2} - \theta_0$ )

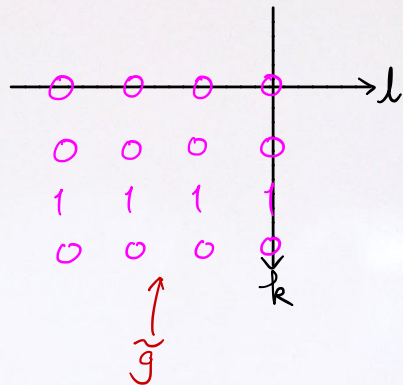
DFT of an image rotated by  $\theta_0$  = DFT of the original image and then rotated by  $\theta_0$ .

Example: Let  $g = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}$ . Then:  $\hat{g} = \begin{pmatrix} \frac{1}{4} & -\frac{1}{4} & \frac{1}{4} & -\frac{1}{4} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$

Note that  $g$  in the coordinate system:



Rotated  
by  $90^\circ$   
clockwisely



Note that indices of  $\tilde{g}$  are taken as:  $\begin{cases} -3 \leq l \leq 0 \\ 0 \leq k \leq 3 \end{cases}$ .

Now, DFT of  $\tilde{g} = \hat{\tilde{g}}$  (given by:  $\sum_{k=0}^3 \sum_{l=-3}^0 \tilde{g}(k,l) e^{-j2\pi(\frac{km+ln}{4})}$ )

$$= \begin{pmatrix} 0 & 0 & 0 & 1/4 \\ 0 & 0 & 0 & -1/4 \\ 0 & 0 & 0 & 1/4 \\ 0 & 0 & 0 & -1/4 \end{pmatrix} \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \end{matrix}$$

$\xrightarrow{l \quad -3 \quad -2 \quad -1 \quad 0}$

$$\therefore \begin{matrix} 0 \leq k \leq 3 \\ -3 \leq l \leq 0 \end{matrix}$$

## How to compute DFT fast?

Goal: Convert image  $I$  to  $\hat{I}$  (Fast?)  $\xrightarrow{\text{DFT}}$  Manipulate / adjust  $\hat{I}$  (Fourier coefficients) to get a new  $\hat{I}^{\text{new}}$   
 $\downarrow$   
Convert  $\hat{I}^{\text{new}}$  into the spatial domain (Fast?)

## Fast Fourier Transform

Recall: DFT is separable  $\Rightarrow$  2D DFT = Two 1D DFT!

$$\hat{I}(m, n) = \frac{1}{N} \sum_{k=0}^{N-1} \underbrace{\left( \frac{1}{N} \sum_{l=0}^{N-1} I(k, l) e^{-j2\pi(\frac{ln}{N})} \right)}_{\text{1D DFT}} e^{-j2\pi(\frac{km}{N})}$$

ID DFT

Suffices to consider how to compute 1D DFT fast!!



ID DFT is:  $\hat{f}(u) = \frac{1}{N} \sum_{x=0}^{N-1} f(x) \underbrace{e^{-j2\pi(\frac{ux}{N})}}_{W_N^{ux}}$  where  $W_N = e^{-j\frac{2\pi}{N}}$

Assume  $N = 2^n = 2M$  ( $\therefore M = 2^{n-1}$ ).

Then:  $\hat{f}(u) = \frac{1}{2M} \sum_{x=0}^{2M-1} f(x) W_{2M}^{ux}$

Separate the summation into odd and even parts:

$$\hat{f}(u) = \frac{1}{2} \left\{ \frac{1}{M} \sum_{y=0}^{M-1} f(2y) \underbrace{W_{2M}^{u(2y)}}_{W_M^{uy}} + \frac{1}{M} \sum_{y=0}^{M-1} f(2y+1) \underbrace{W_{2M}^{u(2y+1)}}_{W_{2M}^{u(2y)} W_{2M}^u} \right\}$$

Let  $f_{\text{even}} = (f(0), f(2), \dots, f(2M-2))^T$  — even part of  $f$

$f_{\text{odd}} = (f(1), f(3), \dots, f(2M-1))^T$  — odd part of  $f$

Then:  $\hat{f}(u) = \frac{1}{2} \left\{ \hat{f}_{\text{even}}(u) + \hat{f}_{\text{odd}}(u) W_{2M}^u \right\}$  for  $u = 0, 1, 2, \dots, M-1$

only defined for  $u = 0, 1, 2, \dots, M-1$

For  $u \geq M$ , consider:  $\hat{f}(u+M) = \frac{1}{2} \left\{ \frac{1}{M} \sum_{y=0}^{M-1} f(2y) W_M^{uy+My} + \frac{1}{M} \sum_{y=0}^{M-1} f(2y+1) W_M^{uy+My} W_{2M}^{u+M} \right\}$

$$\therefore \hat{f}(u+M) = \frac{1}{2} \{ \hat{f}_{\text{even}}(u) - \hat{f}_{\text{odd}}(u) \omega_{2M}^u \} \quad \text{for } u=0, 1, 2, \dots, M-1$$

FFT algorithm: Let  $N = 2^n$  and  $f \in \mathbb{R}^N$

Step 1: Split  $f$  into:  $f_{\text{even}} = [f(0), f(2), \dots, f(2M-2)]^T$   
 $f_{\text{odd}} = [f(1), f(3), \dots, f(2M-1)]^T$

Step 2: Compute  $\hat{f}_{\text{even}} = F_M f_{\text{even}}$  and  $\hat{f}_{\text{odd}} = F_M f_{\text{odd}}$   
 $M = 2^{n-1}$  DFT matrix

$$F_M = (W_M^{ux})_{0 \leq u, x \leq M-1}$$

"  $M \times M$  matrix!

Step 3: For  $u = 0, 1, 2, \dots, M-1$ , compute

$$\hat{f}(u) = \frac{1}{2} [ \hat{f}_{\text{even}}(u) + \hat{f}_{\text{odd}}(u) \omega_{2M}^u ]$$

$$\hat{f}(u+M) = \frac{1}{2} [ \hat{f}_{\text{even}}(u) - \hat{f}_{\text{odd}}(u) \omega_{2M}^u ]$$

$\therefore$  Reduce the matrix multiplication by  $\frac{1}{2}$ !

For step 2, we can apply the splitting idea again to compute  $\hat{f}_{\text{even}}$  and  $\hat{f}_{\text{odd}}$ !

## Computational cost of FFT:

Let  $C_m$  be the computational cost of  $F_M \vec{x}$ . Then:  $C_1 = 1!!$

Clearly,  $C_N = 2C_{N/2} + 3M$  (2 matrix multiplication by  $F_M$ ,  $M$  multiplication,  $M$  additions and  $M$  subtractions)

$$\begin{aligned} \therefore C_{2^n} &= 2C_{2^{n-1}} + 3M \Rightarrow 2^{-n} C_{2^n} = 2^{-(n-1)} C_{2^{n-1}} + \frac{3}{2} \\ &= 2^{-(n-2)} C_{2^{n-2}} + 2\left(\frac{3}{2}\right) \\ &= \vdots \\ &= \underset{\substack{1 \\ 1}}{C_1} + n\left(\frac{3}{2}\right) \end{aligned}$$

$$\therefore C_{2^n} = 2^n + n2^n\left(\frac{3}{2}\right)$$

We conclude that the computational cost  $C_N$  is bounded by  $K N(\log_2 N)$  (or  $\mathcal{O}(N \log_2 N)$ )

e.g. If  $N = 2^{10}$ , then  $N^2 = 2^{20}$  (Computational cost for conventional matrix multiplication)

For FFT,  $N \log_2 N = 2^{10} \cdot 10 < 2^{14} \Rightarrow 2^6$  times faster!!