

# Fast Fourier Transform (FFT)

( You can visit MIT-13310 lecture notes for more details )

$n = 2m$  is an even integer.

$$\vec{x} = (x_0, x_1, \dots, x_{n-1}) \in \mathbb{C}^n$$

Recall: (ID DFT and ID IDFT)

write  $w_n = e^{2\pi i/n}$

$$\hat{x} = \text{DFT}(\vec{x}) = \frac{1}{\sqrt{n}} \begin{bmatrix} 1 & 1 & \dots & 1 \\ w_n & w_n^2 & \dots & w_n^{n-1} \\ \vdots & \vdots & \ddots & \vdots \\ w_n^{n-1} & w_n^{2(n-1)} & \dots & w_n^{(n-1)^2} \end{bmatrix} \vec{x}$$

$$\vec{x} = \text{IDFT}(\hat{x}) = \begin{bmatrix} 1 & w_n & \dots & w_n^{n-1} \\ \vdots & w_n^2 & \dots & w_n^{2(n-1)} \\ \vdots & \vdots & \ddots & \vdots \\ w_n^{n-1} & w_n^{2(n-1)} & \dots & w_n^{(n-1)^2} \end{bmatrix} \hat{x}$$

Goal: Perform Fourier Transform faster than  
(Also Inverse Fourier Transform)  
matrix multiplication.

$$\begin{bmatrix} y_0 \\ \vdots \\ y_{m-1} \end{bmatrix} = F_n X = \begin{bmatrix} 1 & \omega_n & \omega_n^2 & \dots & \omega_n^{n-1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \omega_n^{2m} & \omega_n^{4m} & \dots & \omega_n^{(n-1)m} \end{bmatrix} X$$

For  $0 \leq h \leq m-1$ ,

$$\begin{aligned} y_h &= \sum_{k=0}^{n-1} (\omega_n)^{kh} x_k \\ &= \sum_{\substack{k=0 \\ k \text{ even}}}^{n-1} (\omega_n)^{kh} x_k + \sum_{\substack{k=0 \\ k \text{ odd}}}^{n-1} (\omega_n)^{kh} x_k \\ &= \sum_{k''=0}^{m-1} (\omega_{2m})^{2k''h} x_{2k''} + \sum_{k''=0}^{m-1} (\omega_{2m})^{(2k''+1)h} x_{2k''+1} \\ &= \sum_{k''=0}^{m-1} (\omega_{2m})^{2k''h} x_{2k''} + \omega_{2m}^h \sum_{k''=0}^{m-1} (\omega_{2m})^{2k''h} x_{2k''+1} \end{aligned}$$

Note  $(\omega_{2m})^{2k''h} = e^{-2\pi i j \frac{2k''h}{2m}}$   
 $= e^{-2\pi i j \frac{k''h}{m}} = (\omega_m)^{k''h}$

write  $\vec{x}' = (x_0, x_2, \dots, x_{2(m-1)}) \in \mathbb{C}^m$

$\vec{x}'' = (x_1, x_3, \dots, x_{2m-1}) \in \mathbb{C}^m$

$$\begin{aligned} &= \sum_{k''=0}^{m-1} (\omega_m)^{k''h} x'_{k''} + \omega_{2m}^h \sum_{k''=0}^{m-1} (\omega_m)^{k''h} x''_{k''} \\ &= \left( F_m \vec{x}' \right)_h + \omega_{2m}^h \left( F_m \vec{x}'' \right)_h \end{aligned}$$

$$\begin{bmatrix} y_0 \\ y_1 \\ \dots \\ y_{m-1} \\ \hline y_m \\ \dots \\ y_{2m-1} \end{bmatrix} \stackrel{NFT}{=} F_m X = \begin{bmatrix} 1 & \dots & 1 \\ \omega_m & \dots & \omega_m^{n-1} \\ \vdots & \ddots & \vdots \\ \omega_m^{n-1} & \dots & \omega_m^{(n-1)^2} \end{bmatrix} X$$

$$0 \leq h \leq m-1$$

$$y_{m+h} = \sum_{k=0}^{n-1} (\bar{\omega}_m)^{k(h+m)} x_k$$

$$= \sum_{\substack{k=0 \\ k \text{ even}}}^{n-1} (\bar{\omega}_m)^{k(h+m)} x_k + \sum_{\substack{k=0 \\ k \text{ odd}}}^{n-1} (\bar{\omega}_m)^{k(h+m)} x_k$$

$$= \sum_{k'=0}^{m-1} (\bar{\omega}_{2m})^{2k'(h+m)} x_{2k'} + \sum_{k''=0}^{m-1} (\bar{\omega}_{2m})^{(2k''+1)(h+m)} x_{2k''+1}$$

$$= \sum_{k'=0}^{m-1} (\bar{\omega}_{2m})^{2k'(h+m)} x_{2k'} + \sum_{k''=0}^{m-1} (\bar{\omega}_{2m})^{(2k''+1)(h+m)} x_{2k''+1}$$

$$= \sum_{k'=0}^{m-1} (\bar{\omega}_{2m})^{2k'(h+m)} x_{2k'} + \bar{\omega}_{2m}^{h+m} \sum_{k''=0}^{m-1} (\bar{\omega}_{2m})^{2k''(h+m)} x_{2k''+1}$$

$$= \sum_{k'=0}^{m-1} (\bar{\omega}_m)^{k'(h+m)} x_{k'} + \bar{\omega}_{2m}^{h+m} \sum_{k''=0}^{m-1} (\bar{\omega}_m)^{k''(h+m)} x_{k''}$$

Note

$$\begin{aligned}
 \bar{\omega}_m^{km} &= e^{-2\pi i j \frac{km}{m}} = e^{-2\pi i j k} = 1 \\
 \bar{\omega}_{2m}^m &= e^{-2\pi i j \frac{m}{2m}} = e^{-\pi i j} = -1
 \end{aligned}$$

$$= \left( \bar{F}_m \vec{X}' \right)_h - \bar{\omega}_{2m}^h \left( \bar{F}_m \vec{X}'' \right)_h$$

In vector Form :

$$\begin{bmatrix} -y_0 \\ \vdots \\ y_{m-1} \end{bmatrix} = \underline{\underline{F_m}} \underline{\underline{x'}} + \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} \odot \underline{\underline{F_m}} \underline{\underline{x''}}$$

$$\begin{bmatrix} -y_m \\ \vdots \\ y_{2n-1} \end{bmatrix} = \underline{\underline{F_m}} \underline{\underline{x'}} - \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} \odot \underline{\underline{F_m}} \underline{\underline{x''}}$$

Originally, we need to compute  $\underline{\underline{F_n}} \underline{\underline{x''}}$ ,  
 $\begin{matrix} \uparrow & \uparrow \\ \mathbb{C}^{n \times n} & \mathbb{C}^n \end{matrix}$

Now, we only need to compute  $\underline{\underline{F_m}} \underline{\underline{x''}}$ ,  
 $\begin{matrix} \uparrow & \uparrow \\ \mathbb{C}^{m \times m} & \mathbb{C}^m \end{matrix}$   
 and  $\underline{\underline{F_m}} \underline{\underline{x''}}$ ,  
 $\begin{matrix} \uparrow & \uparrow \\ \mathbb{C}^{m \times m} & \mathbb{C}^m \end{matrix}$

reduce a large matrix multiplication  
 to 2 smaller matrix multiplication.

If  $n = n/2$  is also even, we can further reduce  
 the 2 smaller matrix multiplication  
 to 4 much smaller matrix multiplication

If  $n = 2^l$ ,

$$n \rightarrow \frac{n}{2} \rightarrow \frac{n}{4} \rightarrow \dots \rightarrow \underline{\underline{1}}$$

# Image Blurring

$g$ : observation, blurry image

$f$ : true, clean image.

Write  $g = D(f) + n$

$D$ : Degradation operator,  $n$ : noise

Suppose:

1.  $D$  is position invariant:

$$\tilde{f}(x, y) = f(x - \alpha, y - \beta)$$

$$(D\tilde{f})(x, y) = g(x - \alpha, y - \beta)$$

2.  $D$  is linear:

$$D(af_1 + bf_2)$$

$$= aD(f_1) + bD(f_2).$$

$\forall f_1, f_2$  image  
 $a, b$  scalar.

Then:  $\exists h$

$$\text{s.t. } D(f) = f * h.$$

$$\text{Then } \hat{g} = c \hat{h} \odot \hat{f} + \hat{n}$$

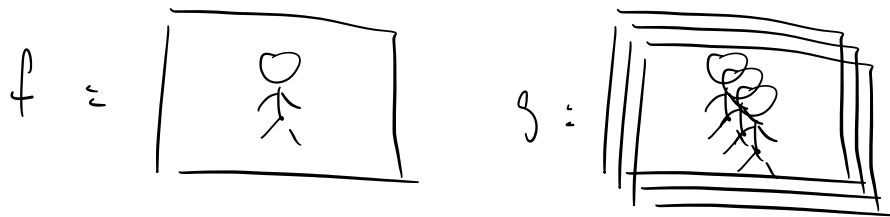
Remove the noise and inverse the  $\hat{h}$  can get back the clean image.

## Example

Assuming periodicity.

Suppose  $g \in \mathbb{R}^{N \times N}$ ,  $0 \leq m, n \leq N-1$ ,  $c > 0$   
 $g = D(f)$  given by:

$$g(m, n) = \sum_{j=0}^T f(m - cj, n - cj)$$



$$\tilde{f}(x, y) = f(x - \alpha, y - \beta)$$

$$\text{Then } D(\tilde{f})(m, n) = \sum_{j=0}^T \tilde{f}(m - cj, n - cj)$$

$$= \sum_{j=0}^T f(m - cj - \alpha, n - cj - \beta)$$

$$= \sum_{j=0}^T f((m - \alpha) - cj, (n - \beta) - cj)$$

$$= g(m - \alpha, n - \beta)$$

$\therefore$  Position Invariant.

$$D(a f_1 + b f_2)$$

$$= \sum_{j=0}^T (a f_1 + b f_2)(m - cj, n - cj)$$

$$\begin{aligned}
&= \sum_{j=0}^T a f_1(m - c_j, n - c_j) + b f_2(m - c_j, n - c_j) \\
&= a \sum_{j=0}^T f_1(m - c_j, n - c_j) + b \sum_{j=0}^T f_2(m - c_j, n - c_j) \\
&= a D(f_1) + b D(f_2).
\end{aligned}$$

$\therefore$  linear.

$$h = D(\delta), \text{ where}$$

$$\delta(m, n) = \begin{cases} 1, & \text{if } m = n = 0 \\ 0, & \text{else.} \end{cases}$$

$$h(m, n) = \sum_{j=0}^T \delta(m - c_j, n - c_j)$$

$$\therefore h(m, n) = \begin{cases} 1, & \text{if } m = n = c_j, 0 \leq j \leq T. \\ 0, & \text{else} \end{cases}$$

$$\hat{g} = c \hat{h} \odot \hat{f} + \hat{u}$$

$$\hat{g}(k, l) = c \hat{h}(k, l) \cdot \hat{f}(k, l) + \hat{u}(k, l)$$

Construct  $\tilde{f}(k, l) = \bar{T}(k, l) \hat{g}(k, l)$   
by a suitable  $\bar{T}(k, l)$ .

Direct Inverse Filtering:

$$\bar{T}(k, l) = \frac{1}{c \hat{h}(k, l) + \varepsilon \operatorname{sign}(\hat{h}(k, l))}$$

$$\tilde{f}(k, l) = \frac{\hat{g}(k, l)}{c \hat{h}(k, l) + \varepsilon \operatorname{sign}(\hat{h}(k, l))}$$

$$= \frac{c \hat{h}(k, l) \hat{f}(k, l)}{c \hat{h}(k, l) + \varepsilon \operatorname{sign}(\hat{h}(k, l))} + \frac{\hat{u}(k, l)}{c \hat{h}(k, l) + \varepsilon \operatorname{sign}(\hat{h}(k, l))}$$

usually large in high frequency

↑  
usually small in high frequency

→ Increase noise.



Modified Inverse filtering:

$$T(k, l) = \frac{B(k, l)}{c \hat{h}(k, l) + \varepsilon \operatorname{sign}(\hat{h}(k, l))}$$

Butterworth LPF

Then

$$\begin{aligned} \tilde{f}(k, l) &= T(k, l) \hat{y}(k, l) \\ &= T(k, l) \hat{h}(k, l) \hat{f}(k, l) + \frac{\hat{h}(k, l) B(k, l)}{c \hat{h}(k, l) + \varepsilon \operatorname{sign}(\hat{h}(k, l))} \end{aligned}$$

close to zero in high frequency  
large in high frequency

→ Reduce Noise.