

## Lecture 1:

### Image transformation

Let  $\mathcal{I}$  = Collection of images of size  $N$  and range of intensity  $[0, M]$ .

$$= \{ f \in M_{N \times N}(\mathbb{R}) : 0 \leq f(i, j) \leq M ; 1 \leq i, j \leq N \}$$

(for simplicity, assume  $f$  is a square image; can be general  $N_1 \times N_2$  image)

Remark: • Images are matrices (mathematically)

• For the ease of discussion, we assume  $\mathcal{I} = M_{N \times N}(\mathbb{R})$   
(collection of all  $N \times N$  real matrices)

Image transformation =  $O : \mathcal{I} \rightarrow \mathcal{I}$  (transform one image to another)

## Image processing v.s. Image Transformation

Let  $g$  be a "bad" image, which is a distorted version of a good (clean) image  $f$ . Then: we can write  $g = \mathcal{O}(f)$ , where  $\mathcal{O}: M_{N \times N}(\mathbb{R}) \rightarrow M_{N \times N}(\mathbb{R})$  transforms one image to another.

To solve the imaging problem:

(1) Design a suitable  $T: M_{N \times N}(\mathbb{R}) \rightarrow M_{N \times N}(\mathbb{R})$  such that:

$$T(g) = f \quad (\text{i.e. } T \approx \mathcal{O}^{-1})$$

(2) Design mathematical method to solve:

$$g = \underbrace{\mathcal{O}(f)}_{\text{unknown}}$$

(Given  $g$  and  $\mathcal{O}$ , we solve for the unknown  $f$ )

## Definition: (Linear image transformation)

An image transformation  $\mathcal{O}: M_{N \times N}(\mathbb{R}) \rightarrow M_{N \times N}(\mathbb{R})$  is linear if it satisfies:  
 $\mathcal{O}(af + bg) = a\mathcal{O}(f) + b\mathcal{O}(g)$  for all  $f, g \in M_{N \times N}(\mathbb{R}), a, b \in \mathbb{R}$ .

Examples: • Given  $A \in M_{N \times N}(\mathbb{R})$ . Define:  $\mathcal{O}: M_{N \times N}(\mathbb{R}) \rightarrow M_{N \times N}(\mathbb{R})$

by:  $\mathcal{O}(f) = 2f + Af$  for all  $f \in M_{N \times N}(\mathbb{R})$ .

Then:  $\mathcal{O}$  is linear.

• Given  $A, B \in M_{N \times N}(\mathbb{R})$ . Define  $\mathcal{O}$  by:

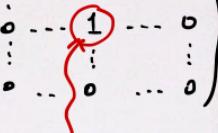
$\mathcal{O}(f) = AfB$  for all  $f \in M_{N \times N}(\mathbb{R})$ .  $\mathcal{O}$  is linear

• Given  $A \in M_{N \times N}(\mathbb{R})$ . Define  $\mathcal{O}$  by:

$\mathcal{O}(f) = fAf$ . Is  $\mathcal{O}$  linear??

## Point Spread Function

Take  $f \in \mathcal{I} = M_{N \times N}(\mathbb{R})$ .

$$\text{Let } f = \begin{pmatrix} f(1,1) & \dots & f(1,N) \\ f(2,1) & \dots & f(2,N) \\ \vdots & \ddots & \vdots \\ f(N,1) & \dots & f(N,N) \end{pmatrix} = \sum_{x=1}^N \sum_{y=1}^N \begin{pmatrix} 0 & \dots & 0 & \dots & 0 \\ \vdots & & \vdots & & \vdots \\ 0 & \dots & f(x,y) & \dots & 0 \\ \vdots & & \vdots & & \vdots \\ 0 & \dots & 0 & \dots & 0 \end{pmatrix} = \sum_{x=1}^N \sum_{y=1}^N f(x,y) \begin{pmatrix} 0 & \dots & 0 & \dots & 0 \\ \vdots & & \vdots & & \vdots \\ 0 & \dots & 1 & \dots & 0 \\ \vdots & & \vdots & & \vdots \\ 0 & \dots & 0 & \dots & 0 \end{pmatrix}$$


Consider a linear image transformation  $\mathcal{O}: M_{N \times N}(\mathbb{R}) \rightarrow M_{N \times N}(\mathbb{R})$ .

Let  $g = \mathcal{O}(f)$ . Then:

$$g(\alpha, \beta) = \left[ \sum_{x=1}^N \sum_{y=1}^N f(x,y) \mathcal{O} \left( \begin{pmatrix} 0 & \dots & 0 & \dots & 0 \\ \vdots & & \vdots & & \vdots \\ 0 & \dots & 1 & \dots & 0 \\ \vdots & & \vdots & & \vdots \\ 0 & \dots & 0 & \dots & 0 \end{pmatrix} \right) \right]_{\alpha, \beta}$$

$$= \sum_{x=1}^N \sum_{y=1}^N f(x,y) h^{\alpha, \beta}(x, y)$$

where

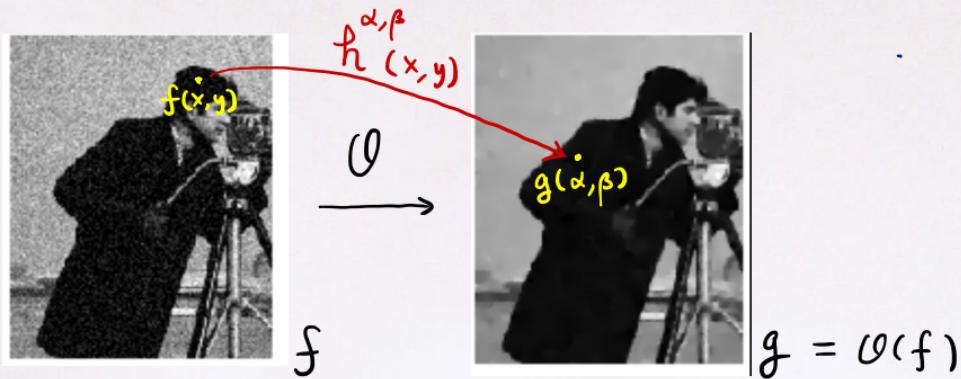
$y^{th}$

↓

$$h^{\alpha, \beta}(x, y) = [\mathcal{O}(P_{xy})]_{\alpha, \beta}; P_{xy} = \begin{pmatrix} 0 & \dots & 0 & \dots & 0 \\ \vdots & & \vdots & & \vdots \\ 0 & \dots & 1 & \dots & 0 \\ \vdots & & \vdots & & \vdots \\ 0 & \dots & 0 & \dots & 0 \end{pmatrix} \leftarrow x^{th}$$

$$h^{\alpha, \beta}(x, y) = [\mathcal{O}(P_{xy})]_{\alpha, \beta}; P_{xy} = \begin{pmatrix} 0 & \dots & 0 & \dots & 0 \\ \vdots & & \vdots & & \vdots \\ 0 & \dots & 1 & \dots & 0 \\ \vdots & & \vdots & & \vdots \\ 0 & \dots & 0 & \dots & 0 \end{pmatrix} \leftarrow x^{th}$$

Remark:  $h^{\alpha, \beta}(x, y)$  determines how much the pixel value of  $f$  at  $(x, y)$  influences the pixel value of  $g$  at  $(\alpha, \beta)$ .



Definition: (Point spread function)

$h^{\alpha, \beta}(x, y)$  is usually called the point spread function (PSF)

Example: Let  $A = \begin{pmatrix} 1 & 0 \\ 2 & 1 \end{pmatrix}$ . Define:  $\mathcal{O}: M_{2 \times 2}(\mathbb{R}) \rightarrow M_{2 \times 2}(\mathbb{R})$  by:

$$\mathcal{O}(f) = Af \quad \text{for all } f \in M_{2 \times 2}(\mathbb{R}).$$

Consider:  $f = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$ . Then:  $f = a \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} + b \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} + c \begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix} + d \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}$

$$\text{Then: } g = \mathcal{O}(f) = a \mathcal{O}\left(\begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}\right) + b \mathcal{O}\left(\begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix}\right) + c \mathcal{O}\left(\begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix}\right) + d \mathcal{O}\left(\begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}\right)$$

$$= a \begin{pmatrix} 1 & 0 \\ 2 & 0 \end{pmatrix} + b \begin{pmatrix} 0 & 1 \\ 0 & 2 \end{pmatrix} + c \begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix} + d \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}$$

$$\therefore \mathcal{O}(f)(1,2) = \underbrace{a \mathcal{O}\left(\begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}\right)(1,2)}_{h^{1,2}(1,1)} + \underbrace{b \mathcal{O}\left(\begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix}\right)(1,2)}_{h^{1,2}(1,2)} + \underbrace{c \mathcal{O}\left(\begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix}\right)(1,2)}_{h^{1,2}(2,1)} + \underbrace{d \mathcal{O}\left(\begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}\right)(1,2)}_{h^{1,2}(2,2)} = 0$$

## Separable linear image transformation

Definition: An image transformation  $\mathcal{O}: M_{N \times N}(\mathbb{R}) \rightarrow M_{N \times N}(\mathbb{R})$  is said to be **separable** if there exists matrices  $A \in M_{N \times N}(\mathbb{R})$  and  $B \in M_{N \times N}(\mathbb{R})$  such that:  $\mathcal{O}(f) = AfB$  for all  $f \in M_{N \times N}(\mathbb{R})$ .

Example:

- $\mathcal{O}(f) = \alpha f \quad \text{for } \alpha \in \mathbb{R}$   
 $= (\alpha I) f (I)$

- Discrete Fourier Transform is Separable
- Discrete Haar Wavelet Transform is Separable.

Remark: Separable image transformation is linear.

Theorem: Let  $\mathcal{O}$  be a separable image transformation given by :  $\mathcal{O}(f) = AfB$  for all  $f \in M_{N \times N}(\mathbb{R})$ , where  $A, B \in M_{N \times N}(\mathbb{R})$ . Then, the point spread function of  $\mathcal{O}$  is given by :

$$h^{\alpha, \beta}(x, y) = A(\alpha, x) B(y, \beta)$$

where  $A(\alpha, x)$  is the  $(\alpha, x)$  entry of  $A$ ,  $B(y, \beta)$  is the  $(y, \beta)$  entry of  $B$ .

Proof: Let  $g = \mathcal{O}(f) = AfB$ . Then, the  $(\alpha, \beta)$  entry of  $g$  is

$$\text{given by : } g(\alpha, \beta) = \sum_{x=1}^N A(\alpha, x) (fB)(x, \beta)$$

$$\begin{aligned}
 & A(gB)(\alpha, \beta) \\
 & " \\
 & \left( \begin{array}{c} A(\alpha, 1) \\ \vdots \\ A(\alpha, 2) \dots A(\alpha, N) \end{array} \right) \left( \begin{array}{c} (gB)(1, \beta) \\ (gB)(2, \beta) \\ \vdots \\ (gB)(N, \beta) \end{array} \right) = \sum_{x=1}^N A(\alpha, x) \sum_{y=1}^N f(x, y) B(y, \beta) \\
 & = \sum_{x=1}^N \sum_{y=1}^N A(\alpha, x) B(y, \beta) f(x, y) \\
 & \quad h^{\alpha, \beta}(x, y)
 \end{aligned}$$