

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

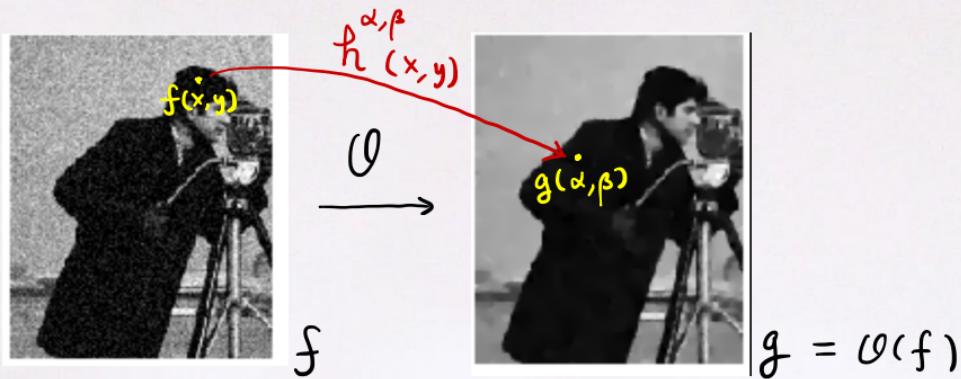
y^{th}

↓

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

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

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



Definition: (Point spread function)

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