

# Template Matching

Aim: To match image with template.

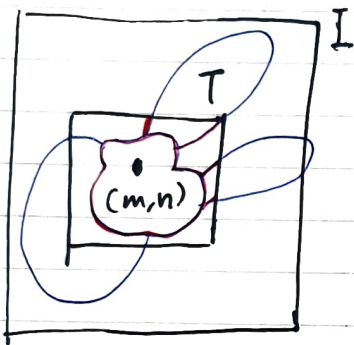
need: ①. space of images.

② distance of images: "norm" / "metric".

→ to measure how similar an given image is ~~compare~~ compared to the template.

Image template:  $T(i, j)$ , the brightness distribution around pixel  $(i, j)$

Given image:  $I(i, j)$



"Distance" between 2 images:

~~Euclidean~~ • Ellidean norm:  $L_2$ -norm

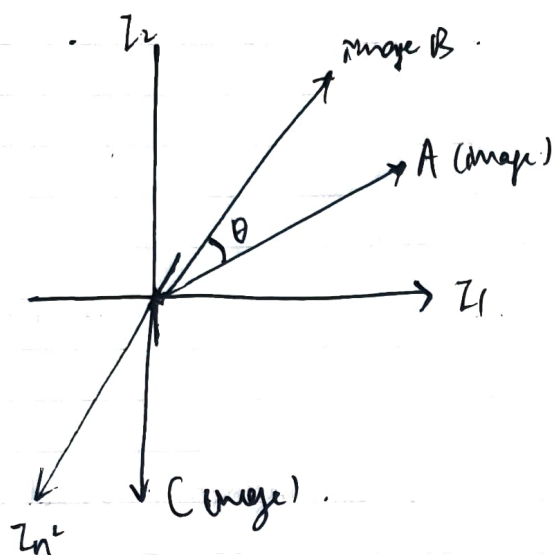
$$\text{Match}_{L_2}(m, n) = \left[ \sum_{i, j \text{ s.t. } (i-m, j-n) \in \text{Dom}(T)} (I(i, j) - T(i-m, j-n))^2 \right]^{\frac{1}{2}}$$

•  $\text{Match}_{L_2}^2(m, n)$   
(MSE) =  $\sum_{i, j \text{ s.t. } (i-m, j-n) \in \text{Dom}(T)} \left( \underbrace{I^2(i, j)}_{\text{image energy}} - 2I(i, j)T(i-m, j-n) + \underbrace{T^2(i-m, j-n)}_{\text{template energy}} \right)$

• Cross Correlation =  $\sum_{i, j \text{ s.t. } (i-m, j-n) \in \text{Dom}(T)} I(i, j) T(i-m, j-n)$

• Normalized Cross Correlation =  $\frac{\text{Cross Correlation}}{\left[ \sum_{i, j \text{ s.t. } (i-m, j-n) \in \text{Dom}(T)} I(i, j)^2 \right]^{\frac{1}{2}}}$

~~Correlation as inner product~~



The more similar the two images  
the smaller the angle,  
i.e. the smaller the inner product

→ This idea gives rise to K-means clustering !

## Lecture 5-6: Linear in Frequency

### The physical domain

$$I(x) = \sum_i (I \cdot \phi_i) \phi_i$$

project onto  $\phi_i$   
 $\phi_i$  is the  $i^{\text{th}}$  basis vector

### The frequency domain

$$a_n = \frac{2}{T} \int_0^T I(t) \cos(n\omega t) dt$$

$$b_n = \frac{2}{T} \int_0^T I(t) \sin(n\omega t) dt$$

project onto sin/cos

$$a_0 = \frac{1}{T} \int_0^T I(t) dt$$

Sinusoids as basis for the frequency domain:

$$\frac{1}{\sqrt{2\pi}}, \frac{\cos x}{\sqrt{\pi}}, \frac{\sin x}{\sqrt{\pi}}, \frac{\cos 2x}{\sqrt{\pi}}, \frac{\sin 2x}{\sqrt{\pi}}, \dots$$

orthogonal:  $\int_{-\pi}^{\pi} \phi_i \phi_j dx = 0 \quad \forall i \neq j$

unit length:  $\int_{-\pi}^{\pi} \phi_i^2 = 1 \quad \forall i$

linking sin & cos:  $(\cos \phi + i \sin \phi) = e^{i\phi}$

### Hilbert space:

- $\infty$  dim
- spanned by complex exponentials
- inner product & norm

Fourier Transform: change in basis.

$$\mathcal{F}(f(x)) = F(\omega) = \int_{-\infty}^{+\infty} f(t) e^{-i\omega t} dt$$

physical domain      freq domain

$$\mathcal{F}^{-1}(F(\omega)) = f(x) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} F(\omega) e^{i\omega t} d\omega$$

(OH MY Prof. is hilarious 00:58:00)

## Action of linear system with sin input:

$$\begin{aligned} \text{Linear operator} \uparrow \quad \text{a sinusoid} \uparrow \quad e^{i\omega t} & \quad = \int_{-\infty}^{+\infty} h(u) e^{i\omega(t-u)} du. \\ & = e^{i\omega t} \int_{-\infty}^{+\infty} h(u) e^{i\omega u} du. \\ & = H(\omega) e^{i\omega t}. \end{aligned}$$

$\uparrow$  a scalar.  $\uparrow$  a sinusoid.  
!!

significance of this: output of a linear operator on sinusoid gives a scalar times sinusoid.

⇒ ① Sinusoids are eigenfunctions of a linear system !!

↓  
Link back to RLU.

② The Fourier transform of the input response,  $H(\omega)$  are the eigenvalues associated with the eigenfunctions

## Filtering in the frequency domain

convolution in the physical domain is multiplication in the frequency domain.

$$\mathcal{F}(\underbrace{I * h}_{\text{filtered image}}) = \int_{-\infty}^{+\infty} e^{-i\omega t} \left( \int_{-\infty}^{+\infty} I(t-u) h(u) du \right) dt$$

$$(t, u) \mapsto (v = t-u, u)$$

$$= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} e^{-i(u+v)\omega} I(v) h(u) du dv.$$

$$= \left( \int_{-\infty}^{+\infty} e^{-i v \omega} I(v) dv \right) \cdot \left( \int_{-\infty}^{+\infty} e^{-i u \omega} h(u) du \right)$$

$$= I(\omega) \cdot \underbrace{H(\omega)}_{\text{modulation transfer function}}$$

Fourier's duality theorem:

$$I(x) * h(x) \xleftrightarrow[\text{inv. FT}]{\text{FT}} I(\omega) \cdot H(\omega)$$

$$I(x) \cdot h(x) \longleftrightarrow I(\omega) * H(\omega)$$

low-pass filter = blur operator  
 high-pass filter = sharpening operator  
 band-pass filter



"~~understand~~ learning how to think in the frequency domain is really important for understanding perception & life in general!"

## Fourier Transform in 1D.

$$\begin{cases} F(\xi) = \int_{-\infty}^{\infty} f(t) e^{-2\pi i \xi t} dt. \\ f(t) = \int_{-\infty}^{\infty} F(\xi) e^{2\pi i \xi t} d\xi. \end{cases}$$

Property	$f(t)$ physical domain	$F(\xi)$ frequency domain.
Linearity	$a f_1(t) + b f_2(t)$	$a F_1(\xi) + b F_2(\xi)$
Duality	$F(t)$	$f(-\xi)$
Convolution	$(f * g)(t)$	$F(\xi) G(\xi)$
Product	$f(t) g(t)$	$(F * G)(\xi)$
Time shift	$f(t - t_0)$	$e^{-2\pi i \xi t_0} F(\xi)$
Freq shift	$e^{2\pi i \xi_0 t} f(t)$	$F(\xi - \xi_0)$
Differentiation	$\frac{df(t)}{dt}$	$2\pi i \xi F(\xi)$
Mult. by $t$	$t f(t)$	$\frac{i}{2\pi} \frac{dF(\xi)}{d\xi}$
Time scaling	$f(at)$	$\frac{1}{ a } F(\xi/a)$

+ Parseval's Identity  $\int_{-\infty}^{\infty} |f(t)|^2 dt = \int_{-\infty}^{\infty} |F(\xi)|^2 d\xi$ .

f energy = F energy

## Discrete FT in 1D

$$\begin{cases} F(k) \equiv \sum_{n=0}^{N-1} f(n) e^{-\frac{2\pi i}{N} kn} \\ f(n) \equiv \frac{1}{N} \sum_{k=0}^{N-1} F(k) e^{\frac{2\pi i}{N} kn} \end{cases}$$

$n$  analogous to  $t$ .

$k$  analogous to  $\xi$



## Fourier Transform in 2D

The idea: To decompose the image function  $f(x, y)$  to a linear combination of harmonic functions (weights given by  $F(u, v)$ )  
(sin & cos, or more generally orthogonal functions).

$u, v$  are spatial frequencies:

$$\begin{cases} F(u, v) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) e^{-2\pi i(xu + yv)} dx dy, \\ f(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} F(u, v) e^{2\pi i(xu + yv)} du dv. \end{cases}$$

(linear systems are like gates that control how much power at each frequency is passed through)

Because of Euler's formula,  $e^{iz} = \cos z + i \sin z$

$$e^{2\pi i(xu + yv)} = \cos(-2\pi i x u) + i \sin(2\pi i x u)$$

$\uparrow$  real part                       $\uparrow$  imaginary part.

$F(u, v)$  gives the weights of harmonic components in the linear combination.

## Discrete FT in 2D

$$\begin{cases} F(u, v) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m, n) \exp\left[-2\pi i\left(\frac{mu}{M} + \frac{nv}{N}\right)\right], \\ f(m, n) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u, v) \exp\left[2\pi i\left(\frac{mu}{M} + \frac{nv}{N}\right)\right]. \end{cases}$$

$u = 0, 1, \dots, M-1, v = 0, 1, \dots, N-1.$   
 $m = 0, 1, \dots, M-1, n = 0, 1, \dots, N-1.$