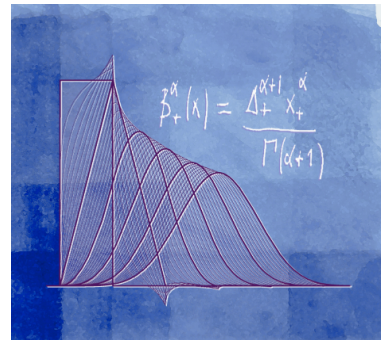


Image Processing

Chapter 1

Characterization of continuous images

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September 2022

CONTENT

■ 1.1 Images as functions

- Hilbert-space formulation
- Two-dimensional systems

■ 1.2 Multidimensional Fourier transform

- Properties
- Dirac impulse, etc...

■ 1.3 Characterization of LSI systems

- Multidimensional convolution
- Modeling of optical systems
- Examples of transfer functions

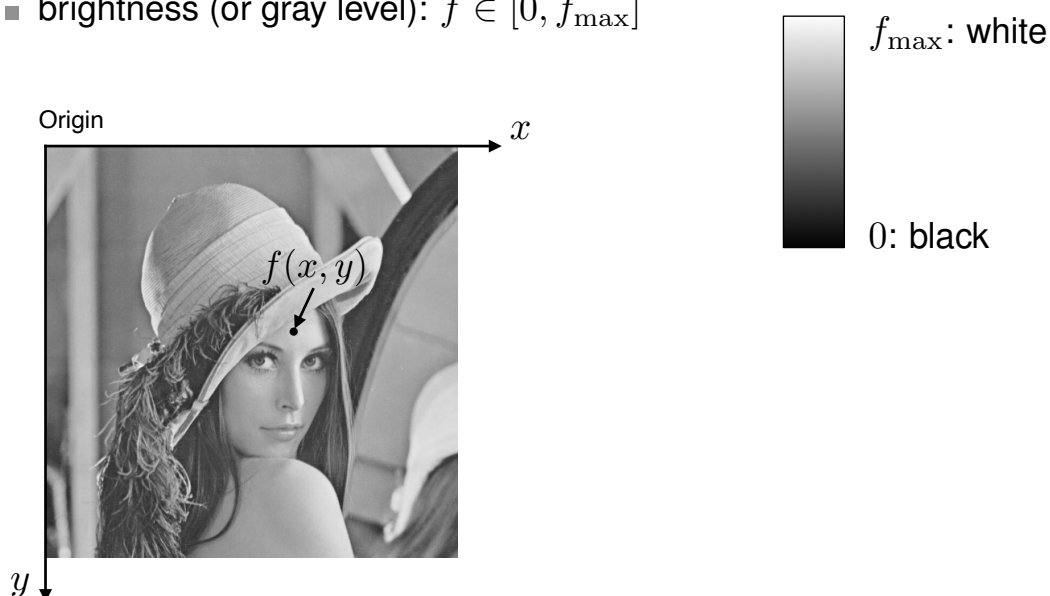
1.1 IMAGES AS FUNCTIONS

- Continuous image representation
- Hilbert-space formulation
- Space of finite-energy images
- Two-dimensional systems
- Linear, shift-invariant systems

Continuous image representation

2D light intensity function: $f(x, y)$

- spatial coordinates: (x, y)
- brightness (or gray level): $f \in [0, f_{\max}]$



Hilbert-space formulation

Hilbert space = infinite-dimensional Euclidean space

Unifying point of view: images as points in a Hilbert space $\mathcal{H}$

■ 1D signals

- Vectors of samples $\mathbb{R}^N$
 $u = (u_1, u_2, \dots, u_N)$
- Discrete signals $\ell_2(\mathbb{Z})$
 $u = (\dots, u_0, u_1, \dots, u_k, \dots)$
- Continuously-defined signals $L_2(\mathbb{R})$
 $u = u(x), x \in \mathbb{R}$

■ 2D images

- Finite arrays of pixels $\mathbb{R}^N$
- Discrete images $\ell_2(\mathbb{Z}^2)$
- Continuously-defined images $L_2(\mathbb{R}^2)$

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1-5

Hilbert space: definition

A Hilbert space $\mathcal{H}$ is a *complete*^{*} vector space with an inner product.

^{*}Completeness: all Cauchy sequences in $\mathcal{H}$ have a limit in $\mathcal{H}$.

■ $\mathcal{H}$ -inner product: $\langle u, v \rangle$

- (i) Linearity: $\langle a_1 u + a_2 v, w \rangle = a_1 \langle u, w \rangle + a_2 \langle v, w \rangle,$
 $\forall a_1, a_2 \in \mathbb{C}, \forall u, v, w \in \mathcal{H}$
- (ii) Symmetry: $\langle u, v \rangle^* = \langle v, u \rangle, \quad \forall u, v \in \mathcal{H}$
- (iii) Positive definite: $\langle u, u \rangle > 0, \quad \forall u \neq 0, u \in \mathcal{H}$

■ Induced norm

$$\|u\| = \langle u, u \rangle^{1/2}$$

Example: $u = (u_1, u_2, \dots, u_N) \in \mathbb{C}^N$

■ Cauchy-Schwarz inequality

$$|\langle u, v \rangle| \leq \|u\| \cdot \|v\|$$

$$\langle u, v \rangle = \sum_{n=1}^N u_n v_n^*$$

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1-6

Space of finite-energy images

- Images as 2D functions of the space variables

$$f(x, y) \in L_2(\mathbb{R}^2)$$

More compact vector notation: $f(\mathbf{x})$ with $\mathbf{x} = (x, y) \in \mathbb{R}^2$

- 2D L_2 -inner product

$$\langle f, g \rangle_{L_2} \triangleq \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y) g^*(x, y) \, dx dy$$

$$\|f\|_{L_2} = \sqrt{\langle f, f \rangle_{L_2}} = \sqrt{\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} |f(x, y)|^2 \, dx dy}$$

- Space of finite-energy functions

$$L_2(\mathbb{R}^2) \triangleq \{f(\mathbf{x}) : \mathbf{x} \in \mathbb{R}^2, \|f\|_{L_2}^2 < +\infty\}$$

Space of finite energy images (cont'd)

- Extension to higher dimensions

$$f(\mathbf{x}) \text{ with } \mathbf{x} = (x_1, \dots, x_d) \in \mathbb{R}^d$$

$$\langle f, g \rangle_{L_2(\mathbb{R}^d)} \triangleq \int_{\mathbb{R}^d} f(\mathbf{x}) g^*(\mathbf{x}) \, dx_1 \cdots dx_d$$

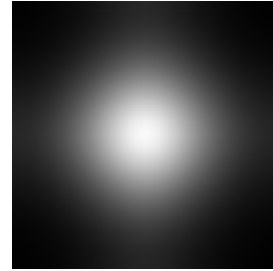
$$L_2(\mathbb{R}^d) \triangleq \left\{ f(\mathbf{x}) : \mathbf{x} \in \mathbb{R}^d, \|f\|_{L_2(\mathbb{R}^d)}^2 < +\infty \right\}$$

Examples of image functions

■ 2D-Gaussian

$$g(x, y) = \frac{1}{2\pi} \exp\left(-\frac{(x^2 + y^2)}{2}\right)$$

$$g(x, y) \in L_2(\mathbb{R}^2)$$



■ Finite support Ω and bounded images

$$\begin{cases} \forall (x, y) \notin \Omega, & f(x, y) = 0 \\ \forall (x, y) \in \mathbb{R}^2, & |f(x, y)| < C_0 \end{cases} \implies \|f\|^2 < C_0^2 \cdot \int \int_{\Omega} dx dy$$

$$\Downarrow$$

$$f \in L_2(\mathbb{R}^2)$$



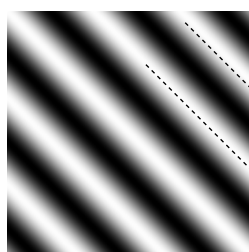
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1-9

Plane waves

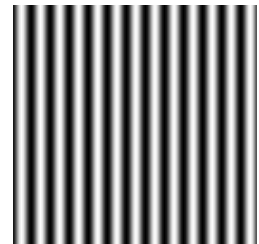
■ Sinusoidal gratings

$$s(x, y) = A \cdot \cos(\omega_1 x + \omega_2 y + \phi) = A \cdot \cos(\langle \boldsymbol{\omega}, \boldsymbol{x} \rangle + \phi)$$



Wave vector
 $\boldsymbol{\omega} = (\omega_1, \omega_2)$

Period: $T = \frac{2\pi}{\sqrt{\omega_1^2 + \omega_2^2}}$



Note that $s(x, y) \notin L_2(\mathbb{R}^2)$

However:

$$s(x, y) \cdot w(x, y) \in L_2(\mathbb{R}^2)$$

where

$w(x, y)$: finite-support and bounded window function.

Two-dimensional systems

- Mapping of an image function into another

$$\mathcal{T} : L_2(\mathbb{R}^2) \longrightarrow L_2(\mathbb{R}^2)$$

$$g(x, y) = \mathcal{T}\{f\}(x, y)$$

More (or less) pedantic notations:

$$g(\mathbf{x}) = \mathcal{T}\{f(\cdot)\}(\mathbf{x})$$

$$g = \mathcal{T}\{f\}$$

- Linear operators

$$\mathcal{T}\{a_1 f_1 + a_2 f_2\}(\mathbf{x}) = a_1 \mathcal{T}\{f_1\}(\mathbf{x}) + a_2 \mathcal{T}\{f_2\}(\mathbf{x})$$

$$\forall f_1, f_2 \in \mathcal{H} \text{ and } \forall a_1, a_2 \in \mathbb{C}$$

Examples

- Gradient operator is linear

$$\mathcal{T}_1\{f\} = f_x = \frac{\partial f(x, y)}{\partial x} \quad \text{and} \quad \mathcal{T}_2\{f\} = f_y = \frac{\partial f(x, y)}{\partial y}$$

- Geometric operators are linear (warping)

$$\mathcal{T}_3\{f\}(x, y) = f(G_1(x, y), G_2(x, y))$$

where $G_1(x, y)$ and $G_2(x, y)$ are arbitrary (non-linear)

- Threshold operator is non-linear

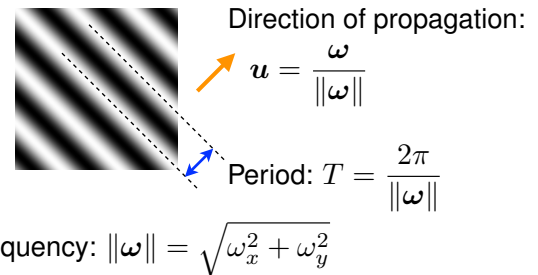
$$\mathcal{T}_4\{f\}(x, y) = \begin{cases} 1, & |f(x, y)| \geq T_0 \\ 0, & \text{otherwise} \end{cases}$$

Linear, shift-invariant systems

- **Definition.** $\mathcal{T}$ is shift-invariant iff: $\mathcal{T}\{f(\cdot - \mathbf{x}_0)\}(\mathbf{x}) = \mathcal{T}\{f(\cdot)\}(\mathbf{x} - \mathbf{x}_0)$
- Linear, shift-invariant system (LSI): model of most physical imaging devices
- **Complex sinusoids:** $s(\mathbf{x}, \mathbf{y}) = \exp\{j(\omega_x x + \omega_y y)\}$

Compact vector notation: $s(\mathbf{x}) = e^{j\langle \boldsymbol{\omega}, \mathbf{x} \rangle}$

with $\boldsymbol{\omega} = (\omega_x, \omega_y)$, $\mathbf{x} = (x, y)$

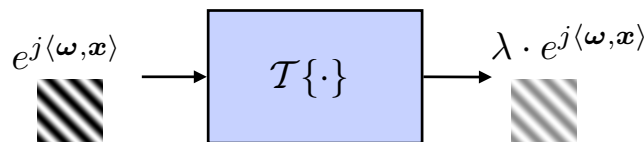


Theorem. The complex sinusoid $e^{j\langle \boldsymbol{\omega}, \mathbf{x} \rangle}$ is an *eigenfunction* of the LSI system $\mathcal{T}$ with eigenvalue $\lambda = \lambda(\boldsymbol{\omega}) = \mathcal{T}\{e^{j\langle \boldsymbol{\omega}, \cdot \rangle}\}(\mathbf{0})$.

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1-13

Complex sinusoids and LSI systems



Proof: (in d dimensions)

- Input signal: $s(\mathbf{x}) = e^{j\langle \boldsymbol{\omega}, \mathbf{x} \rangle}$

- Shift $\Rightarrow$ Multiplication

$$s(\mathbf{x} - \mathbf{x}_0) = e^{j\langle \boldsymbol{\omega}, \mathbf{x} \rangle - j\langle \boldsymbol{\omega}, \mathbf{x}_0 \rangle} = e^{-j\langle \boldsymbol{\omega}, \mathbf{x}_0 \rangle} \cdot e^{j\langle \boldsymbol{\omega}, \mathbf{x} \rangle}$$

- If $\mathcal{T}$ is *linear* and *shift-invariant*

$$\text{SI: } \mathcal{T}\{s(\cdot - \mathbf{x}_0)\}(\mathbf{x}) = \mathcal{T}\{s(\cdot)\}(\mathbf{x} - \mathbf{x}_0)$$

$$\text{Lin: } \mathcal{T}\{s(\cdot - \mathbf{x}_0)\}(\mathbf{x}) = \mathcal{T}\{e^{-j\langle \boldsymbol{\omega}, \mathbf{x}_0 \rangle} \cdot e^{j\langle \boldsymbol{\omega}, \cdot \rangle}\}(\mathbf{x}) = e^{-j\langle \boldsymbol{\omega}, \mathbf{x}_0 \rangle} \cdot \mathcal{T}\{s(\cdot)\}(\mathbf{x})$$

$$\text{Set } \mathbf{x}_0 = \mathbf{x}: \quad \lambda = \mathcal{T}\{s\}(\mathbf{0}) = e^{-j\langle \boldsymbol{\omega}, \mathbf{x} \rangle} \mathcal{T}\{s\}(\mathbf{x}) \quad \Rightarrow \quad \lambda \cdot e^{j\langle \boldsymbol{\omega}, \mathbf{x} \rangle} = \mathcal{T}\{s\}(\mathbf{x})$$

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1-14

1.2 MULTI-D FOURIER TRANSFORM

- Definition
- Separability
- Properties
- Dirac impulse
- Dirac related Fourier transforms
- Application: finding the orientation
- Importance of the phase

2D Fourier transform: definition

- 2D Fourier transform:
$$\hat{f}(\omega_x, \omega_y) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y) e^{-j(\omega_x x + \omega_y y)} dx dy$$
- Inverse Fourier transform:
$$f(x, y) = \frac{1}{(2\pi)^2} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \hat{f}(\omega_x, \omega_y) e^{j(\omega_x x + \omega_y y)} d\omega_x d\omega_y$$

(a.e. = almost everywhere)
- Sufficient condition for existence:
$$\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} |f(x, y)| dx dy < +\infty \quad \Leftrightarrow \quad f \in L_1(\mathbb{R}^2)$$

Vector notation

Spatial variables: $\mathbf{x} = (x, y) \in \mathbb{R}^2$

Frequency variables: $\boldsymbol{\omega} = (\omega_x, \omega_y) \in \mathbb{R}^2$

Equivalent phase: $\langle \boldsymbol{\omega}, \mathbf{x} \rangle = \boldsymbol{\omega}^T \mathbf{x} = \omega_x x + \omega_y y$

$$\begin{array}{c} \hat{f}(\boldsymbol{\omega}) = \int_{\mathbb{R}^2} f(\mathbf{x}) e^{-j\langle \boldsymbol{\omega}, \mathbf{x} \rangle} d\mathbf{x} dy \\ \updownarrow \mathcal{F} \\ f(\mathbf{x}) = \frac{1}{(2\pi)^2} \int_{\mathbb{R}^2} \hat{f}(\boldsymbol{\omega}) e^{j\langle \boldsymbol{\omega}, \mathbf{x} \rangle} d\omega_x d\omega_y \\ \text{(a.e.)} \end{array}$$

Mathematical extensions

■ Multidimensional Fourier transform (d dimensions)

Spatial variables: $\mathbf{x} = (x_1, \dots, x_d) \in \mathbb{R}^d$

Frequency variables: $\boldsymbol{\omega} = (\omega_1, \dots, \omega_d) \in \mathbb{R}^d$

$$\hat{f}(\boldsymbol{\omega}) = \mathcal{F}\{f\} \triangleq \int_{\mathbb{R}^d} f(\mathbf{x}) e^{-j\langle \boldsymbol{\omega}, \mathbf{x} \rangle} dx_1 \cdots dx_d$$

$$\updownarrow \mathcal{F}$$

$$\mathcal{F}^{-1}\{\hat{f}\} \triangleq \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} \hat{f}(\boldsymbol{\omega}) e^{j\langle \boldsymbol{\omega}, \mathbf{x} \rangle} d\omega_1 \cdots d\omega_d = f(\mathbf{x}) \quad (\text{a.e.})$$

Sufficient condition for existence:

$$f \in L_1(\mathbb{R}^d) \Rightarrow \hat{f}(\boldsymbol{\omega}): \text{bounded, continuous} \\ \text{and tends to 0 when } \boldsymbol{\omega} \rightarrow +\infty$$

(Riemann-Lebesgue Lemma)

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1-17

Finite-energy functions

■ Fourier analysis in L_2 (Plancherel's extension)

$$f \in L_2(\mathbb{R}^d) \Leftrightarrow \hat{f} \in L_2(\mathbb{R}^d)$$

■ Parseval's formula: $\langle f, g \rangle_{L_2} \propto \langle \hat{f}, \hat{g} \rangle_{L_2}$

$$\int_{\mathbb{R}^d} f(\mathbf{x}) g^*(\mathbf{x}) dx_1 \cdots dx_d = \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} \hat{f}(\boldsymbol{\omega}) \hat{g}^*(\boldsymbol{\omega}) d\omega_1 \cdots d\omega_d$$

■ 2π -isometry (energy conservation)

$$\|f\|_{L_2}^2 = \frac{1}{(2\pi)^d} \|\hat{f}\|_{L_2}^2$$

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1-18

Separability

- Separability of Fourier kernel: $e^{j(\omega_x x + \omega_y y)} = e^{j\omega_x x} \cdot e^{j\omega_y y}$

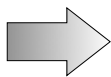
Equivalent sequence of 1D calculations:

- (1) 1D Fourier transform along x ($y = \text{Const}$)

$$\hat{f}_y(\omega_x; y) = \int_{-\infty}^{+\infty} f(x, y) e^{-j\omega_x x} dx$$

- (2) 1D Fourier transform along y ($x = \text{Const}$)

$$\hat{f}(\omega_x, \omega_y) = \int_{-\infty}^{+\infty} \hat{f}_y(\omega_x; y) e^{-j\omega_y y} dy$$



Multidimensional Fourier transform inherits most properties of 1D Fourier transform!

- Separable signals (or transfer functions)

$$f(x, y) = f_1(x) \cdot f_2(y) \quad \Leftrightarrow \quad \hat{f}(\omega_x, \omega_y) = \hat{f}_1(\omega_x) \cdot \hat{f}_2(\omega_y)$$

In d dimensions:

$$f(\mathbf{x}) = \prod_{i=1}^d f_i(x_i) \quad \Leftrightarrow \quad \hat{f}(\boldsymbol{\omega}) = \prod_{i=1}^d \hat{f}_i(\omega_i)$$

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1-19

Fourier properties

- Duality: $\hat{f}(\mathbf{x}) \xleftrightarrow{\mathcal{F}} (2\pi)^d f(-\boldsymbol{\omega})$
- Symmetry: $f(\mathbf{x}) \text{ real} \quad \Leftrightarrow \quad \hat{f}^*(\boldsymbol{\omega}) = \hat{f}(-\boldsymbol{\omega})$
- Isometry: $\|f\| = (2\pi)^{-d/2} \|\hat{f}\|$
- Shift: $f(\mathbf{x} - \mathbf{x}_0) \xleftrightarrow{\mathcal{F}} e^{-j\langle \boldsymbol{\omega}, \mathbf{x}_0 \rangle} \hat{f}(\boldsymbol{\omega})$
- Modulation: $e^{j\langle \boldsymbol{\omega}_0, \mathbf{x} \rangle} f(\mathbf{x}) \xleftrightarrow{\mathcal{F}} \hat{f}(\boldsymbol{\omega} - \boldsymbol{\omega}_0)$
- Scaling: $f(\mathbf{x}/a) \xleftrightarrow{\mathcal{F}} |a|^d \hat{f}(a\boldsymbol{\omega})$
- Affine transformation: $f(\mathbf{A}\mathbf{x}) \xleftrightarrow{\mathcal{F}} |\det \mathbf{A}|^{-1} \hat{f}((\mathbf{A}^{-1})^T \boldsymbol{\omega})$
 $\mathbf{A}$: non-singular matrix
- Differentiation: $\frac{\partial^n f(\mathbf{x})}{\partial x_i^n} \xleftrightarrow{\mathcal{F}} (j\omega_i)^n \hat{f}(\boldsymbol{\omega})$
- Moments: $\mu_f^{m,n} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x^m y^n f(x, y) dx dy = j^{m+n} \left. \frac{\partial^{m+n} \hat{f}(\boldsymbol{\omega})}{\partial \omega_x^m \partial \omega_y^n} \right|_{\boldsymbol{\omega}=0}$
 In particular: $\int_{\mathbb{R}^d} f(\mathbf{x}) dx_1 \cdots dx_d = \hat{f}(\mathbf{0})$
- Convolution: $(f * g)(\mathbf{x}) \xleftrightarrow{\mathcal{F}} \hat{f}(\boldsymbol{\omega}) \cdot \hat{g}(\boldsymbol{\omega})$
- Multiplication: $f(\mathbf{x}) \cdot g(\mathbf{x}) \xleftrightarrow{\mathcal{F}} \frac{1}{(2\pi)^d} (\hat{f} * \hat{g})(\boldsymbol{\omega})$

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1-20

Example of computation

■ 2D Gaussian

$$g(x, y) = e^{-(x^2+y^2)/2}$$

1. Use separability

$$g(x, y) = e^{-x^2/2} \cdot e^{-y^2/2} \Rightarrow \hat{g}(\omega_x, \omega_y) = \hat{f}(\omega_x) \cdot \hat{f}(\omega_y)$$

$$\text{where } f(x) = e^{-x^2/2} \xleftrightarrow{\mathcal{F}} \hat{f}(\omega) = \int_{-\infty}^{+\infty} f(x) e^{-j\omega x} dx$$

2. Determine 1D Fourier transform

Table or explicit calculation

$$e^{-x^2/2} \xleftrightarrow{\mathcal{F}} \sqrt{2\pi} e^{-\omega^2/2}$$

$$\Rightarrow \hat{g}(\omega_x, \omega_y) = 2\pi \cdot e^{-(\omega_x^2 + \omega_y^2)/2}$$

Dirac impulse

Abstract definition: $\forall f \in C^0(\mathbb{R}), \langle f, \delta \rangle = \int_{-\infty}^{+\infty} f(x) \delta(x) dx = f(0)$

$C^0(\mathbb{R})$: the space of continuous functions over $\mathbb{R}$

■ Properties

- Normalized integral: $\int_{-\infty}^{+\infty} \delta(x) dx = 1$ $(f(x) = 1)$
- Fourier transform: $\delta(x) \xleftrightarrow{\mathcal{F}} \int_{-\infty}^{+\infty} \delta(x) e^{-j\omega x} dx = 1$ $(f(x) = e^{-j\omega x})$
- Convolution: $\forall g \in C^0, (g * \delta)(x) = g(x)$ $(f(\cdot) = g(x - \cdot))$

■ Explicit construction

- Window function $\varphi(x) \in L_1(\mathbb{R})$ such that $\int_{-\infty}^{+\infty} \varphi(x) dx = 1$
e.g., $\varphi(x) = \frac{1}{\sqrt{2\pi}} \exp(-x^2/2)$
- Integral-preserving dilation/contraction: $\int_{-\infty}^{+\infty} \frac{1}{|a|} \varphi\left(\frac{x}{a}\right) dx = 1$
- $\delta(x) = \lim_{a \rightarrow 0} \left(\frac{1}{|a|} \varphi\left(\frac{x}{a}\right) \right)$

Multidimensional Dirac impulse

Abstract definition: $\forall f \in C^0(\mathbb{R}^d), \langle f, \delta \rangle = \int_{\mathbb{R}^d} f(\mathbf{x}) \delta(\mathbf{x}) \, dx_1 \cdots dx_d = f(\mathbf{0})$

Multidimensional Dirac impulse is separable:

$$\delta(x, y) = \delta(x) \cdot \delta(y) \quad \xleftrightarrow{\mathcal{F}} \quad 1$$

In d dimensions: $\delta(\mathbf{x}) = \prod_{i=1}^d \delta(x_i)$

■ Properties

- Normalized integral: $\langle \delta, 1 \rangle = \int_{\mathbb{R}^d} \delta(\mathbf{x}) \, dx_1 \cdots dx_d = 1$
- Fourier transform: $\delta(\mathbf{x}) \xleftrightarrow{\mathcal{F}} \int_{\mathbb{R}^d} \delta(\mathbf{x}) e^{-j\langle \boldsymbol{\omega}, \mathbf{x} \rangle} \, dx_1 \cdots dx_d = 1$
- Multiplication: $\forall f \in C^0, f(\mathbf{x}) \cdot \delta(\mathbf{x} - \mathbf{x}_0) = f(\mathbf{x}_0) \delta(\mathbf{x} - \mathbf{x}_0)$
- Sampling: $\forall f \in C^0, \langle f, \delta(\cdot - \mathbf{x}_0) \rangle = \int_{\mathbb{R}^d} f(\mathbf{x}) \delta(\mathbf{x} - \mathbf{x}_0) \, dx_1 \cdots dx_d = f(\mathbf{x}_0)$
- Convolution: $\forall f \in C^0, (f * \delta)(\mathbf{x}) = f(\mathbf{x})$
- Scaling: $\delta(\mathbf{x}/a) = |a|^d \cdot \delta(\mathbf{x})$

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1-23

Dirac-related Fourier transforms

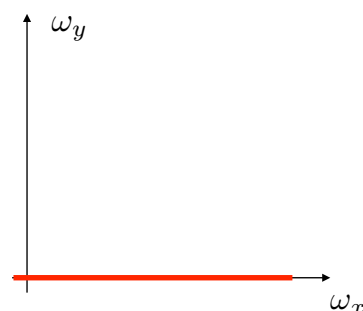
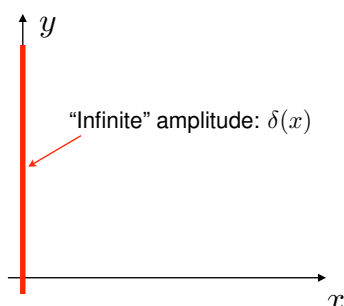
■ Constant

$$\begin{aligned} \text{One-dimensional:} \quad 1 & \xleftrightarrow{\mathcal{F}} \int_{-\infty}^{+\infty} e^{-j\omega x} \, dx = ? \\ & \lim_{A \rightarrow +\infty} \int_{-A}^{+A} e^{-j\omega x} \, dx = 2\pi \cdot \delta(\omega) \quad (\text{or by duality}) \end{aligned}$$

$$\text{Multidimensional:} \quad 1 \xleftrightarrow{\mathcal{F}} (2\pi)^d \delta(\boldsymbol{\omega})$$

■ Ideal line

$$f(x, y) = \delta(x) \cdot 1 = f_1(x) \cdot f_2(y) \xleftrightarrow{\mathcal{F}} \hat{f}_1(\omega_x) \cdot \hat{f}_2(\omega_y) = 1 \cdot 2\pi \delta(\omega_y)$$



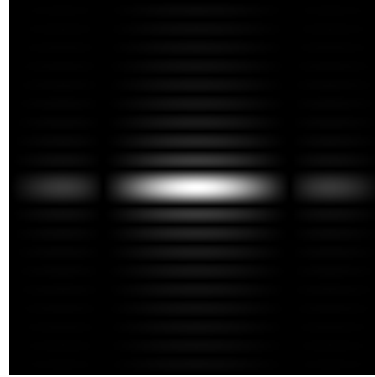
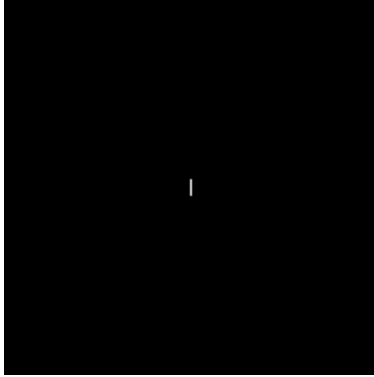
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1-24

More realistic line model

■ Rectangular shape

$$f(x, y) = \text{rect}(x/a) \cdot \text{rect}(y/A) \quad \xleftrightarrow{\mathcal{F}} \quad |a| \text{sinc}\left(\frac{a\omega_x}{2\pi}\right) \cdot |A| \text{sinc}\left(\frac{A\omega_y}{2\pi}\right)$$



Reminder:

$$\text{rect}(x) = \begin{cases} 1, & x \in [-\frac{1}{2}, +\frac{1}{2}] \\ 0, & \text{otherwise} \end{cases} \quad \xleftrightarrow{\mathcal{F}} \quad \text{sinc}\left(\frac{\omega}{2\pi}\right) = \frac{\sin(\omega/2)}{\omega/2}$$

Application: finding the orientation

Problem: Design a (real time?) system that can determine the orientation of a linear pattern placed at an arbitrary location in the image.

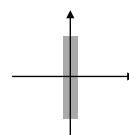
■ Reasons for working in the Fourier domain

■ Translation invariance

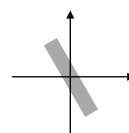
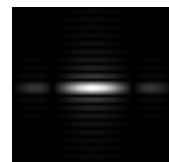
$$g(\mathbf{x}) = f(\mathbf{x} - \mathbf{x}_0) \quad \xleftrightarrow{\mathcal{F}} \quad \hat{f}(\boldsymbol{\omega}) \cdot e^{-j\langle \boldsymbol{\omega}, \mathbf{x}_0 \rangle} \quad \Rightarrow \quad |\hat{g}(\boldsymbol{\omega})| = |\hat{f}(\boldsymbol{\omega})|$$

■ Rotation property

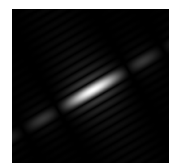
$$g_\theta(\mathbf{x}) = f(\mathbf{R}_\theta \mathbf{x}) \quad \xleftrightarrow{\mathcal{F}} \quad \hat{f}(\mathbf{R}_\theta \boldsymbol{\omega})$$



$\xleftrightarrow{\mathcal{F}}$



$\xleftrightarrow{\mathcal{F}}$



Problem solution

■ Compute Fourier inertia matrix

$$\mathbf{M} = \begin{bmatrix} \int \int \omega_x^2 |\hat{f}(\boldsymbol{\omega})|^2 d\omega_x d\omega_y & \int \int \omega_x \omega_y |\hat{f}(\boldsymbol{\omega})|^2 d\omega_x d\omega_y \\ \int \int \omega_y \omega_x |\hat{f}(\boldsymbol{\omega})|^2 d\omega_x d\omega_y & \int \int \omega_y^2 |\hat{f}(\boldsymbol{\omega})|^2 d\omega_x d\omega_y \end{bmatrix}$$

$$\mathbf{M} = \begin{bmatrix} \langle j\omega_x \hat{f}(\boldsymbol{\omega}), j\omega_x \hat{f}(\boldsymbol{\omega}) \rangle & \langle j\omega_x \hat{f}(\boldsymbol{\omega}), j\omega_y \hat{f}(\boldsymbol{\omega}) \rangle \\ \langle j\omega_y \hat{f}(\boldsymbol{\omega}), j\omega_x \hat{f}(\boldsymbol{\omega}) \rangle & \langle j\omega_y \hat{f}(\boldsymbol{\omega}), j\omega_y \hat{f}(\boldsymbol{\omega}) \rangle \end{bmatrix}$$

■ Determine axes of inertia

Eigen-decomposition: $\mathbf{M} = \begin{bmatrix} \mathbf{u}_1^T \\ \mathbf{u}_2^T \end{bmatrix} \cdot \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \cdot \begin{bmatrix} \mathbf{u}_1 & \mathbf{u}_2 \end{bmatrix}$

$\mathbf{u}_1$: eigenvector in the direction of the long axis

$\mathbf{u}_2$: eigenvector in the direction of the short axis

■ Fast algorithm:

$$\mathbf{M} = \begin{bmatrix} & \end{bmatrix}$$

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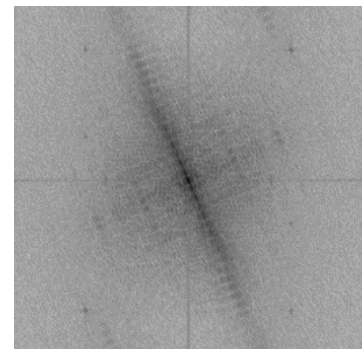
1-27

Orientation estimation: examples

■ Image 1:

Measured angle: $25^\circ \pm 2^\circ$

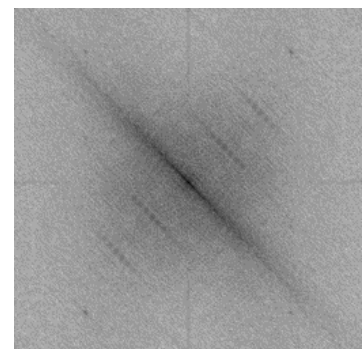
Computed angle: 27°



■ Image 2

Measured angle: $44^\circ \pm 2^\circ$

Computed angle: 45.6°



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1-28

Importance of the phase

- Fourier transform

$$\hat{f}(\omega) = \int_{\mathbb{R}^d} f(x) e^{-j\langle \omega, x \rangle} dx_1 \cdots dx_d = |\hat{f}(\omega)| \cdot \exp(j\Phi_{\hat{f}}(\omega))$$

- Fourier modulus:

$$|\hat{f}(\omega)| = \left(\hat{f}(\omega) \cdot \hat{f}^*(\omega) \right)^{1/2} = \sqrt{\operatorname{Re} [\hat{f}(\omega)]^2 + \operatorname{Im} [\hat{f}(\omega)]^2}$$

- Fourier phase:

$$\Phi_{\hat{f}}(\omega) = \arg(\hat{f}(\omega)) = \arctan \left(\frac{\operatorname{Im} [\hat{f}(\omega)]}{\operatorname{Re} [\hat{f}(\omega)]} \right)$$

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1-29

Module or phase ?

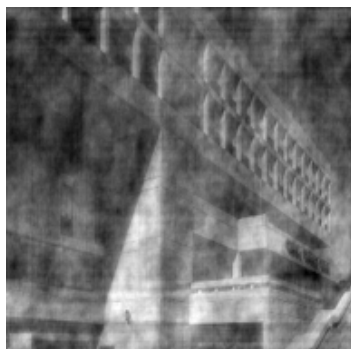
Image 1



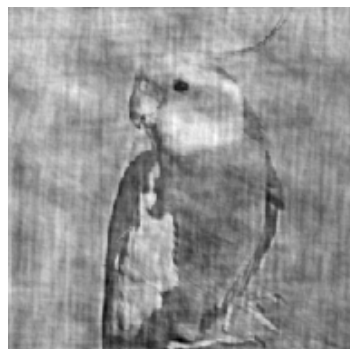
Image 2



Module(Image2), Phase(Image1)



Module(Image1), Phase(Image2)



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1-30

2D Convolution theorem

■ 2D convolution integral

$$\begin{aligned}(f * h)(x, y) &= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(u, v) h(x - u, y - v) du dv \\ &= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} h(u, v) f(x - u, y - v) du dv = (h * f)(x, y)\end{aligned}$$

■ Convolution theorem: $(f * h)(\mathbf{x}) \xleftrightarrow{\mathcal{F}} \hat{f}(\boldsymbol{\omega}) \hat{h}(\boldsymbol{\omega})$

Proof: (in d dimensions) $g(\mathbf{x}) = (f * h)(\mathbf{x}) = \int_{\mathbb{R}^d} f(\mathbf{u}) h(\mathbf{x} - \mathbf{u}) d\mathbf{u}_1 \cdots d\mathbf{u}_d$

$\updownarrow \mathcal{F}$

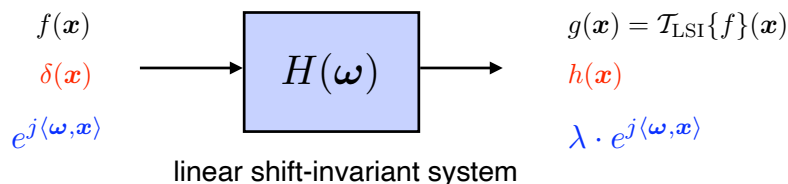
$$\begin{aligned}\hat{g}(\boldsymbol{\omega}) &= \int_{\mathbb{R}^d} \left(\int_{\mathbb{R}^d} f(\mathbf{u}) h(\mathbf{x} - \mathbf{u}) d\mathbf{u}_1 \cdots d\mathbf{u}_d \right) e^{-j\langle \boldsymbol{\omega}, \mathbf{x} \rangle} d\mathbf{x}_1 \cdots d\mathbf{x}_d \\ &= \int_{\mathbb{R}^d} \left(\int_{\mathbb{R}^d} f(\mathbf{u}) h(\mathbf{v}) e^{-j\langle \boldsymbol{\omega}, \mathbf{u} + \mathbf{v} \rangle} d\mathbf{u}_1 \cdots d\mathbf{u}_d \right) d\mathbf{v}_1 \cdots d\mathbf{v}_d \quad (\text{change of variable } \mathbf{v} = \mathbf{x} - \mathbf{u}) \\ &= \int_{\mathbb{R}^d} f(\mathbf{u}) e^{-j\langle \boldsymbol{\omega}, \mathbf{u} \rangle} d\mathbf{u}_1 \cdots d\mathbf{u}_d \int_{\mathbb{R}^d} h(\mathbf{v}) e^{-j\langle \boldsymbol{\omega}, \mathbf{v} \rangle} d\mathbf{v}_1 \cdots d\mathbf{v}_d\end{aligned}$$

Technical hypothesis: $h, f \in L_1(\mathbb{R}^d) \Rightarrow g \in L_1(\mathbb{R}^d)$

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1-33

Transfer function



■ Method 1: identify the impulse response $H(\boldsymbol{\omega})$: Engineer notation for $\hat{h}(\boldsymbol{\omega})$

$$g(\mathbf{x}) = \int_{\mathbb{R}^d} f(\mathbf{y}) h(\mathbf{x} - \mathbf{y}) d\mathbf{y}_1 \cdots d\mathbf{y}_d = (h * f)(\mathbf{x})$$

$$\text{Transfer function: } \mathcal{F}\{h\} \Rightarrow H(\boldsymbol{\omega}) = \int_{\mathbb{R}^d} h(\mathbf{x}) e^{-j\langle \boldsymbol{\omega}, \mathbf{x} \rangle} d\mathbf{x}_1 \cdots d\mathbf{x}_d$$

■ Method 2: Fourier-domain formulation

$$\text{Input/output relation: } \hat{g}(\boldsymbol{\omega}) = H(\boldsymbol{\omega}) \cdot \hat{f}(\boldsymbol{\omega}) \Rightarrow \text{Transfer function: } H(\boldsymbol{\omega}) = \frac{\hat{g}(\boldsymbol{\omega})}{\hat{f}(\boldsymbol{\omega})}$$

■ Method 3: use eigenfunction property of complex sinusoids

$$\text{Compute: } \mathcal{T}_{\text{LSI}}\{e^{j\langle \boldsymbol{\omega}, \mathbf{x} \rangle}\} = \lambda \cdot e^{j\langle \boldsymbol{\omega}, \mathbf{x} \rangle} \Rightarrow H(\boldsymbol{\omega}) = \lambda = \frac{\mathcal{T}_{\text{LSI}}\{e^{j\langle \boldsymbol{\omega}, \mathbf{x} \rangle}\}}{e^{j\langle \boldsymbol{\omega}, \mathbf{x} \rangle}}$$

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1-34

Modeling of optical systems

$$f(x, y) \rightarrow \text{Optical System} \rightarrow g(x, y) = (h * f)(x, y)$$

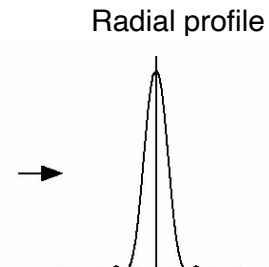
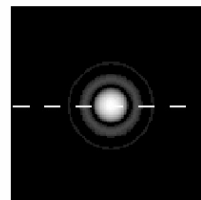
$h(x, y)$: Point Spread Function (PSF)

Diffraction-limited optics = LSI system

■ Aberration-free point spread function (in focal plane)

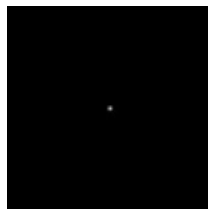
$$h(x, y) = h(r) = C \cdot \left[\frac{2J_1(\pi r)}{\pi r} \right]^2$$

where $r = \sqrt{x^2 + y^2}$ (radial distance)

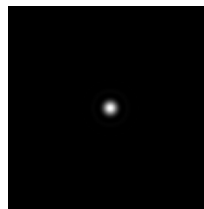


■ Effect of misfocus

Point source



output



(in focus)

(defocus)

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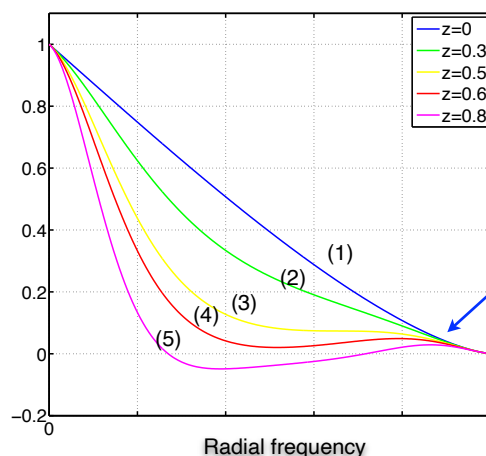
1-35

Optical transfer function

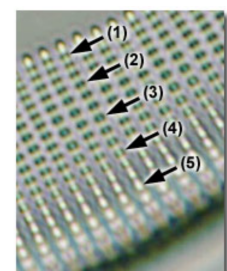
■ $H(\omega_x, \omega_y) = \mathcal{F}\{h\}$: Optical transfer function (OTF)

■ $|H(\omega_x, \omega_y)|$: Modulation transfer function (MTF)

■ Isotropic: $H(\omega_x, \omega_y) = H(\omega)$ where $\omega = \sqrt{\omega_x^2 + \omega_y^2}$ (radial frequency)



$$\omega_c = \frac{\text{NA}}{\pi \cdot \lambda_{\text{light}}}$$



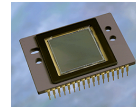
Transfer function of a lens for various degrees of misfocus

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1-36

Examples of transfer functions

- CCD camera



Sampling aperture (photosite or “pixel” integration area):



$$h(x, y) = \frac{1}{L^2} \text{rect}\left(\frac{x}{L}\right) \cdot \text{rect}\left(\frac{y}{L}\right) \quad \xleftrightarrow{\mathcal{F}} \quad H(\omega_x, \omega_y) = \text{sinc}\left(\frac{L\omega_x}{2\pi}\right) \cdot \text{sinc}\left(\frac{L\omega_y}{2\pi}\right)$$

- Motion blur

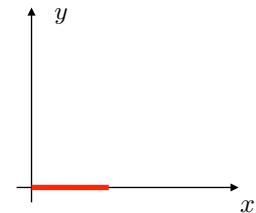
Hypothesis: translational motion of the camera: $\mathbf{x}_0(t)$

$$g(\mathbf{x}) = \frac{1}{T} \int_0^T f(\mathbf{x} - \mathbf{x}_0(t)) dt \quad \Rightarrow \quad H(\omega) = \frac{1}{T} \int_0^T e^{-j\langle \omega, \mathbf{x}_0(t) \rangle} dt$$

Example:

uniform motion in x : $\mathbf{x}_0(t) = (at/T, 0)$

$$H(\omega) = e^{-j\omega\omega_x/2} \text{sinc}\left(\frac{a\omega_x}{2\pi}\right) \xleftrightarrow{\mathcal{F}} h(x, y) = \frac{1}{|a|} \text{rect}\left(\frac{x-a/2}{a}\right) \cdot \delta(y)$$



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1-37

1.4 SUMMARY

- Continuous-space images are modeled as functions $f(x, y)$ of the spatial variables x and y .
- These functions have finite energy: $f \in L_2$. It is convenient to view them as points in a Hilbert space.
- A continuous-domain image-processing operator is a mapping $\mathcal{T} : L_2 \rightarrow L_2$.
- The complex sinusoids $e^{j\langle \omega, x \rangle}$ are the eigenfunctions of linear shift-invariant (LSI) systems. They are $(2\pi/\|\omega\|)$ -periodic plane waves that propagate in the direction ω .
- The 2D Fourier transform of an image reveals its spatial frequency content. The Fourier phase contains the information most relevant perceptually (contours).
- The 2D Fourier transform is very similar to the 1D one; one simply replaces the scalar variables x and ω by vectors. Thus, it has essentially the same properties.
- The 2D Fourier transform of a separable signal $f(x, y) = f_1(x)f_2(y)$ should be determined using 1D transforms only.
- A LSI system performs a convolution.
- Continuous-space LSI systems are entirely characterized by their impulse response (point-spread function or sampling aperture), $h(x, y) = \mathcal{T}_{\text{LSI}}\{\delta\}(x, y)$, or, equivalently, by their transfer function $H(\omega_x, \omega_y) = \mathcal{F}\{h\}(\omega_x, \omega_y)$.

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1-38