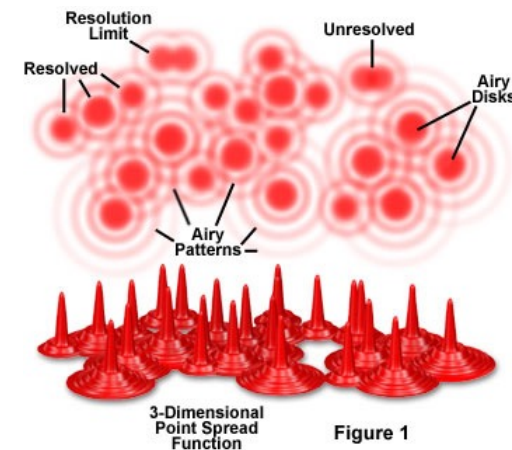
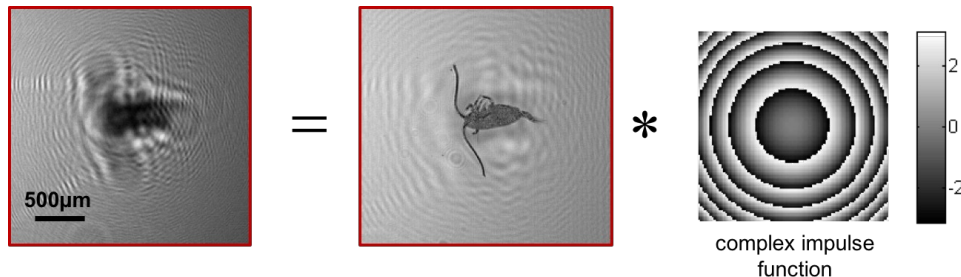


Introduction to Inverse Problem in Imaging

EC 522 Computational Optical Imaging

Lei Tian



Admins

- » HW 2 is posted
 - » Due 2/21 (Wednesday; after Presidents' day break)

Mathematical tools & road map

- » Vector space (IIP Appx A)
 - » Key idea: think about the imaging signals as a vector
- » Linear operator (IIP Appx B)
 - » Key idea: think about imaging process as a linear transformation, i.e. a linear operator
 - » Later, we will perform discretization and convert the operator into a matrix

Linear operator

Linear operator

- » Linear operator $A: \mathcal{X} \rightarrow \mathcal{Y}$ satisfies
 - » $A(\alpha_1 f_1 + \alpha_2 f_2) = \alpha_1 A(f_1) + \alpha_2 A(f_2)$, for any complex numbers α_1 and α_2
 - » Additivity: $A(f_1 + f_2) = A(f_1) + A(f_2)$
 - » Scalability: $A(\alpha f) = \alpha A(f)$

Range space*

- » The *Range space* of a linear operator A : $\mathcal{R}(A)$
 - » The set of all elements $g \in \mathcal{Y}$ from $Af = g$

$$\mathcal{R}(A) = \{g = Af \in \mathcal{Y}, f \in \mathcal{X}\}$$

Null space *

- » The **null space** of a linear operator A : $\mathcal{N}(A)$
 - » The set of all elements $f \in \mathcal{X}$ such that $Af = 0$

$$\mathcal{N}(A) = \{f \in \mathcal{X}, Af = 0\}$$

Implication of Null space

Adjoint operator *

- » The **adjoint** operator A^* (or A^H) of a linear and bounded operator A
 - » $A^*: \mathcal{Y} \rightarrow \mathcal{X}$ is the **adjoint** of $A: \mathcal{X} \rightarrow \mathcal{Y}$, when

$$\langle Ax, y \rangle_{\mathcal{Y}} = \langle x, A^* y \rangle_{\mathcal{X}} \text{ for every } x \in \mathcal{X}, y \in \mathcal{Y}$$

- » Generalization of the **Hermitian transpose** (complex conjugate transpose) of a matrix

Hermitian / adjoint – can be used interchangeably
https://en.wikipedia.org/wiki/Hermitian_adjoint

Example: DFT

Example: deconvolution

Adjoint of a convolution operator

» Adjoint of convolution operator A^*

$$\begin{aligned}\text{» } (A^*g)(x) &= K^*(-x) * g(x) \\ &= \int K^*(x' - x)g(x')dx'\end{aligned}$$

» Spectral representation

$$\text{» } (A^*g)(x) = \int \tilde{K}^*(u) \tilde{g}(u) e^{i2\pi xu} du$$

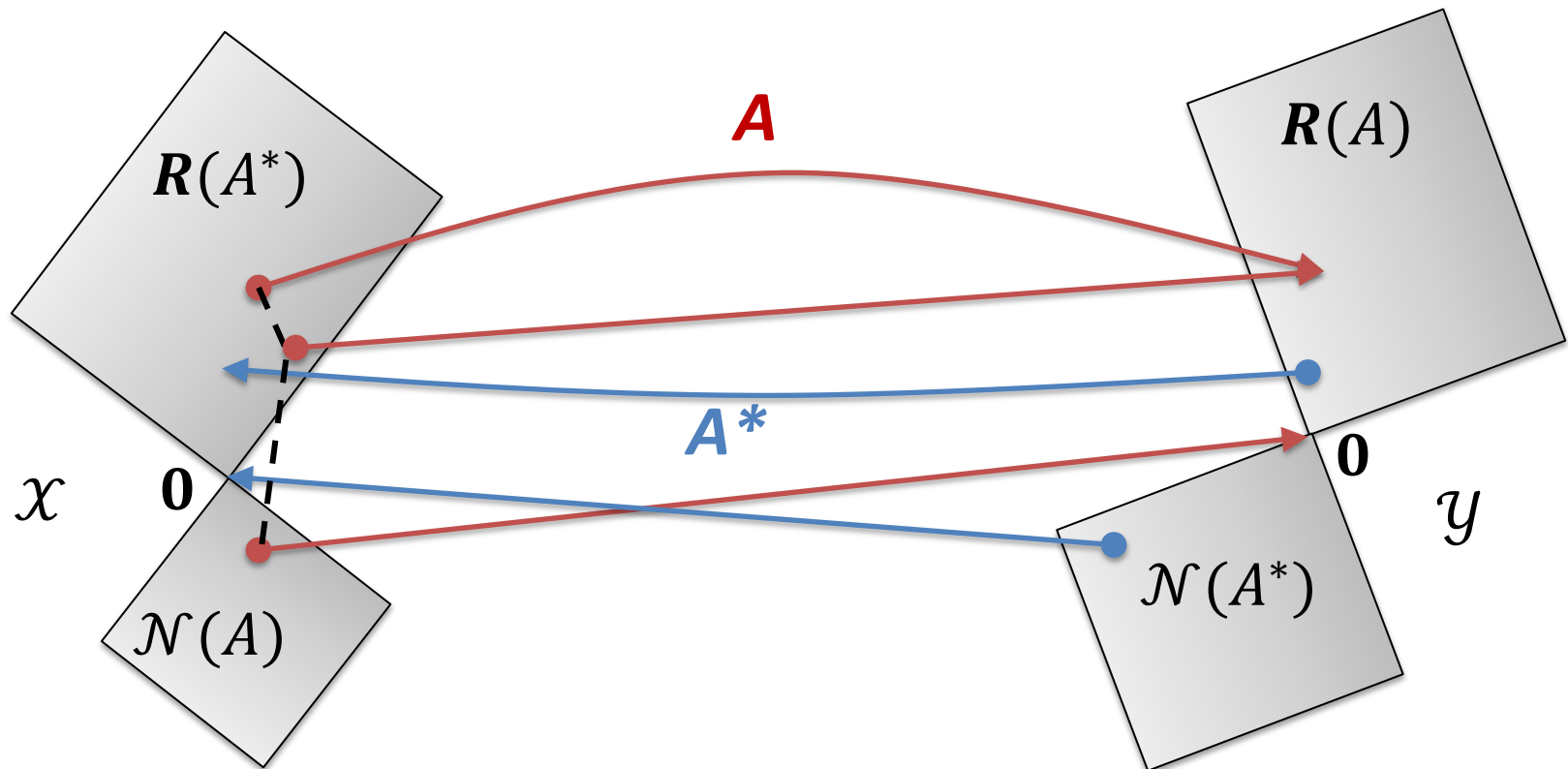
Proof?

Side note:

- I found it is easier to work with $u = \omega/2\pi$ in FT and IFT, the textbook uses ω .
- Throughout the lecture, we will use the definition in the u -space.

Geometric relation between null space and range space

$$\begin{aligned}\mathcal{N}(A) &= \mathcal{R}(A^*)^\perp \\ \mathcal{N}(A^*) &= \mathcal{R}(A)^\perp\end{aligned}$$



Example: Relation between range and null space of a convolution operator

A is a convolution operator

$$\gg f_1 \in \mathcal{R}(A)$$

$$\gg f_2 \in \mathcal{N}(A)$$

$$\gg f_1 \perp f_2$$

and $\mathcal{N}(A) = \mathcal{R}(A)^\perp$

Why?

Relation between range and null space of a convolution operator

A is a convolution operator

» $f_1 \in \mathcal{R}(A)$ Only contain frequency component $u \in \mathcal{B}$

» $f_2 \in \mathcal{N}(A)$ Only contain frequency component $u \notin \mathcal{B}$

» $f_1 \perp f_2$

and $\mathcal{N}(A) = \mathcal{R}(A)^\perp$

Self-adjoint

» If $A = A^*$, A is self-adjoint or Hermitian

Example

Properties of Adjoint operator

- » The adjoint A^* is unique
- » $(A^*)^* = A$
- » The operators AA^* and A^*A are self-adjoint
- » If A is invertible, $(A^{-1})^* = (A^*)^{-1}$
- » $(A+B)^* = A^* + B^*$
- » $(BA)^* = A^*B^*$

Unitary operator

» A is unitary if and only if

$$A^{-1} = A^* \text{ or } A^* A = I$$

» If A is unitary, then $\|Ax\|^2 = \|x\|^2$

Unitary operator

- » Preserve geometry (lengths and angles) when mapping one vector space to another
- » A bounded linear operator $A: \mathcal{X} \rightarrow \mathcal{Y}$ is unitary, when
 - » A is invertible
 - » A preserves inner product

$$\langle f, h \rangle_{\mathcal{X}} = \langle Af, Ah \rangle_{\mathcal{Y}}, \text{ for every } f, h \in \mathcal{X}$$

Eigenvector and eigenvalue of a linear operator

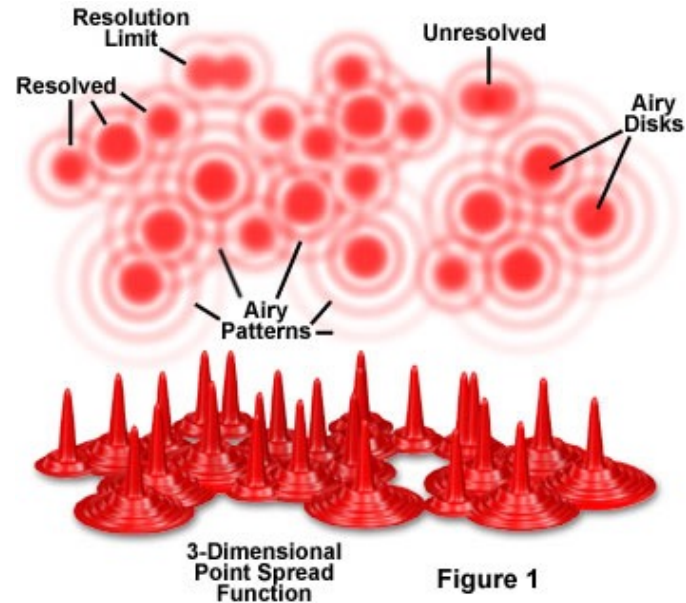
- » An **eigenvector** of a linear operator $A: H \rightarrow H$ is a nonzero vector $v \in H$, such that

$$Av = \lambda v$$

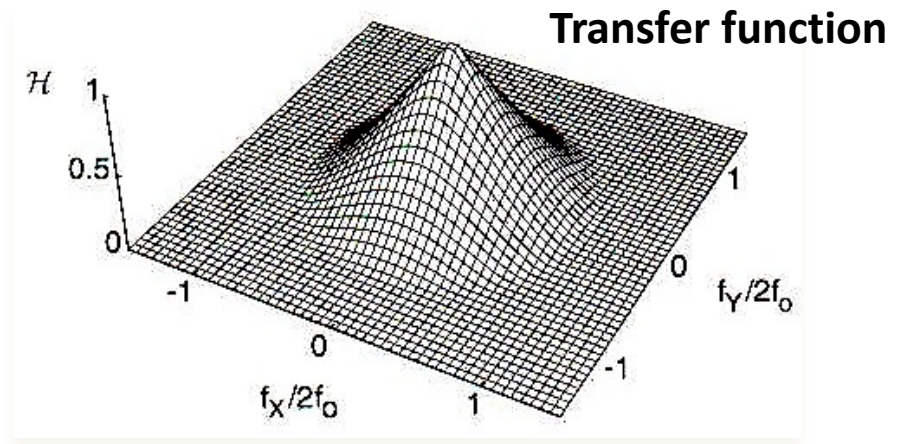
- » $\lambda \in \mathbb{C}$ is the **eigenvalue**.

Example: convolution operator

Example of convolution operator: microscopes



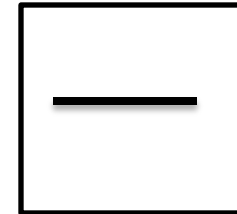
- » Range and null space?
- » Adjoint operator?
- » Inverse operator?



Example: motion blur

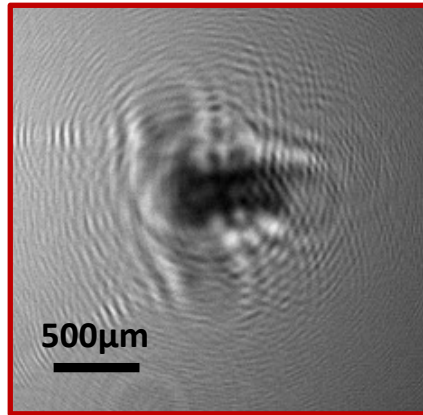


PSF



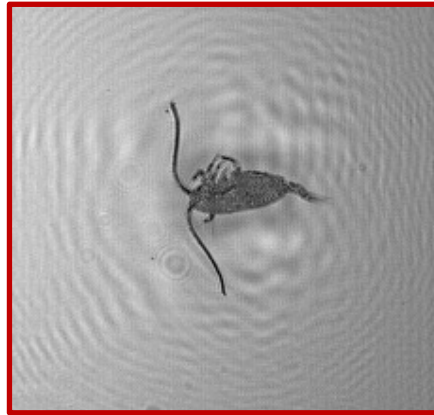
- » What are Object space \mathcal{X} and image space \mathcal{Y} ?
- » What is the operator \mathbf{A} ? linear?
- » Find an element in the null space?
 - » What's the implication of this?

Example of Shift-invariant system: holography



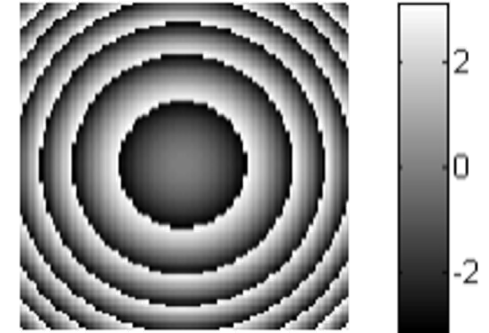
g_{out}

=



g_{in}

*



$$h(x, y) \approx \frac{e^{ikz}}{i\lambda z} e^{ik \frac{(x^2 + y^2)}{2z}}$$

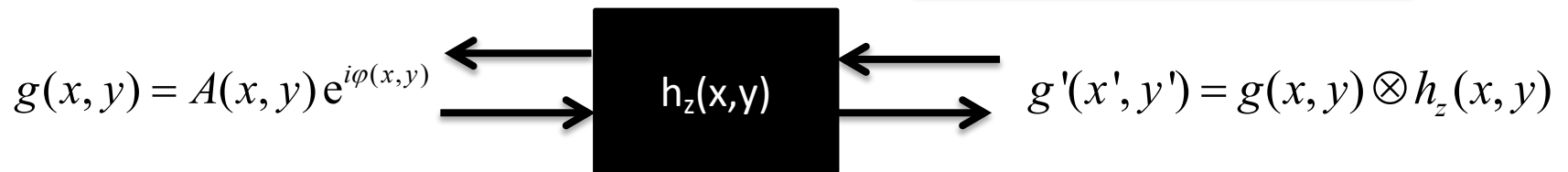
Transfer function $H(u, v) = e^{i2\pi z/\lambda} \exp \{-i\lambda z(u^2 + v^2)\}$

complex PSF

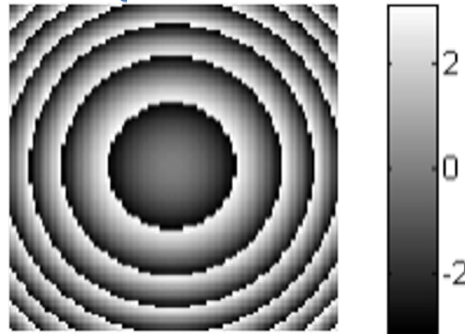
- » Range and null space?
- » Adjoint operator?
- » Inverse operator?

Application: back-propagation using adjoint operator = inverse operator!?

just make $z \rightarrow -z$? Why?



$H(x, y)$ has complex
point spread function
(PSF) and transfer
function



$$h_z(x, y) \approx \frac{e^{ikz}}{i\lambda z} e^{ik \frac{(x^2 + y^2)}{2z}}$$

Transfer function $H(u, v) = e^{i2\pi z/\lambda} \exp \{-i\lambda z(u^2 + v^2)\}$

Mathematical tools & road map

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- » Later, we will perform discretization and convert the operator into a matrix

From continuous to discrete model

Fully discrete LSI model

» Sampling & Discretization

- » Sampling of the image signal

- » Discretize the object signal

» What about the LSI system?

- » How to discretize the linear operator?

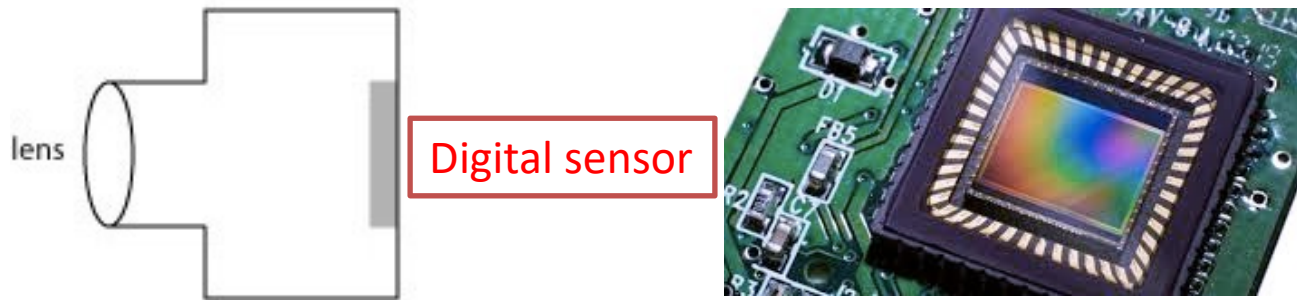
» “Transfer function” of discrete LSI system?

- » Eigenvalues of the imaging matrix

Sampling

Why do we need sampling

- » Lenses and filters are analog optical processors
- » Camera digitizes (samples) optical field

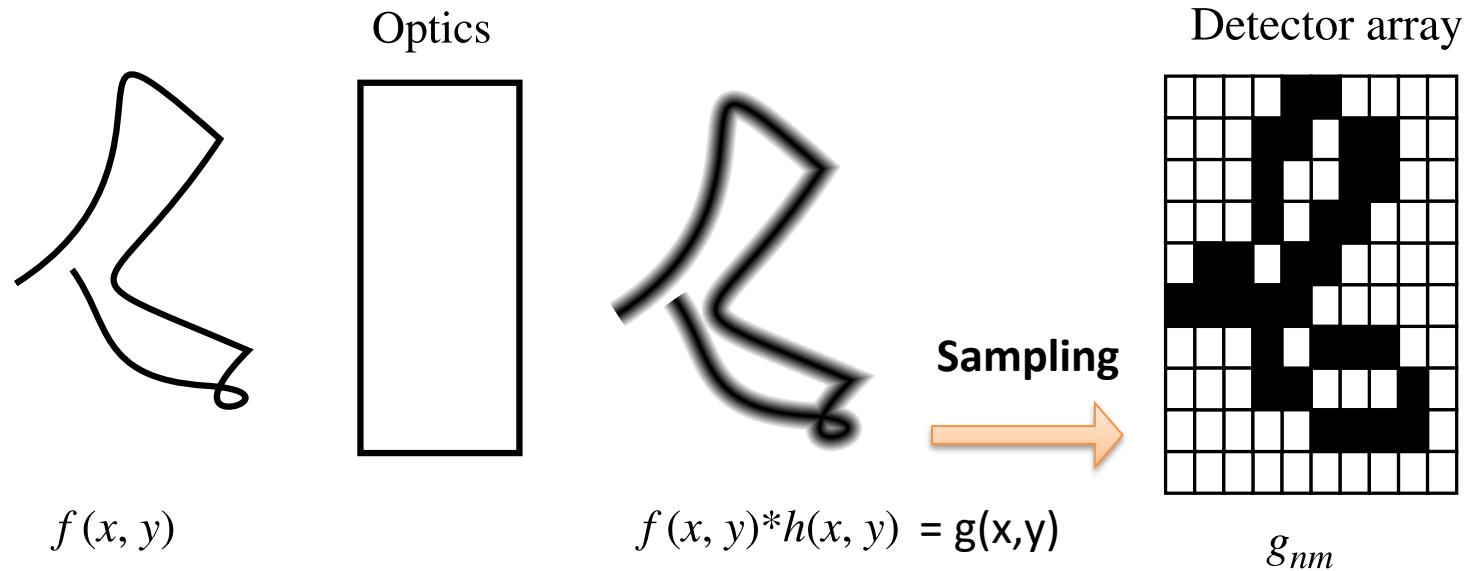


Optical pre-
processing is
analog(continuous)

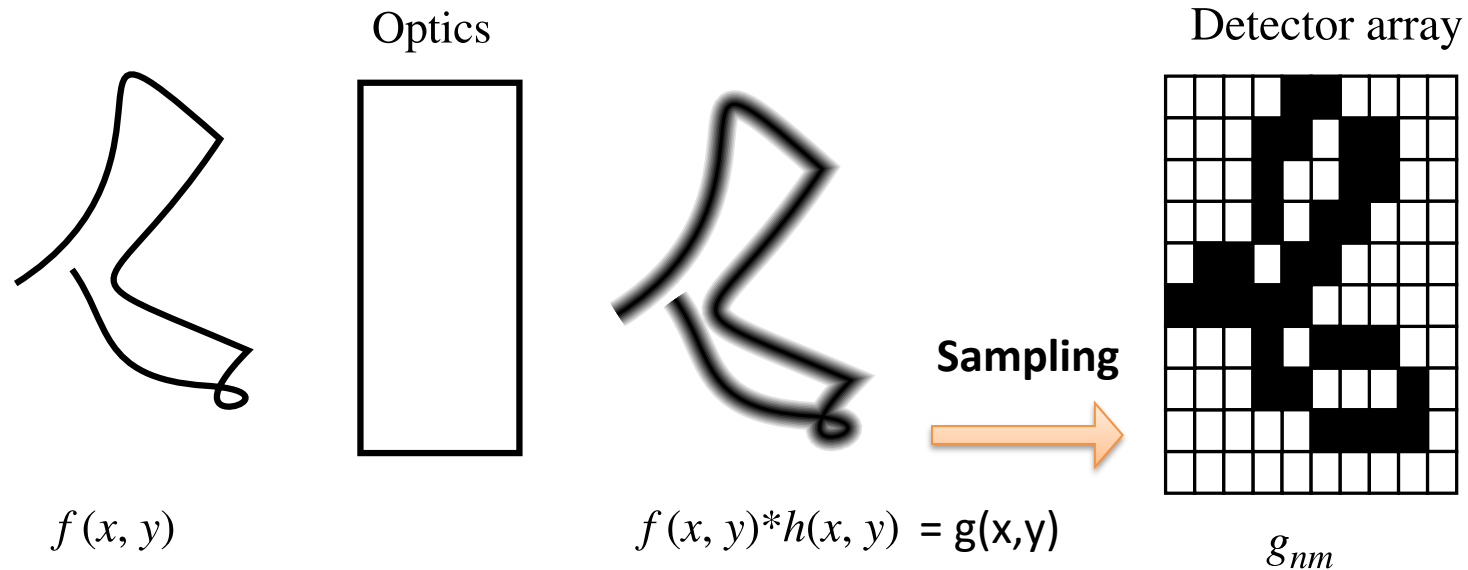
Digital post-
processing is
digital(discrete)

**How sampling works on a typical
optical detector?**

Sampling by optical detectors



Sampling by optical detectors



Pixel size: $X * Y$, spacing $\Delta * \Delta$

Pixel sampling function

$$g_{nm} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-X/2}^{X/2} \int_{-Y/2}^{Y/2} f(x, y) h(x' - x, y' - y) \times p(x' - n\Delta, y' - m\Delta) dx' dy' dx dy$$

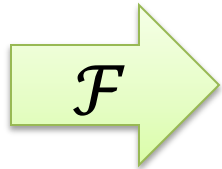
How to describe square pixels?

Similar to zero-order hold sampling!

Effect of pixel sampling: pixel transfer function

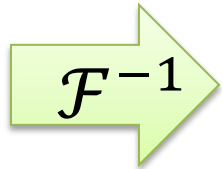
$$g_{nm} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-X/2}^{X/2} \int_{-Y/2}^{Y/2} f(x, y) h(x' - x, y' - y) \\ \times p(x' - n\Delta, y' - m\Delta) dx' dy' dx dy$$

Pixel sampling function



$$\hat{g}(u, v) = \hat{f}(u, v) \underbrace{\hat{h}(u, v) \hat{p}(u, v)}_{\text{Pixel transfer function (PTF)}}$$

System transfer function (STF) combines optical TF and pixel TF!



$$g_{nm} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{2\pi i u n \Delta} e^{2\pi i v m \Delta} \hat{f}(u, v) \hat{h}(u, v) \hat{p}(u, v) du dv$$

How different is the “rect-sampling” as compared to the “impulse sampling”?

Sampling

- » Practically

- » Sampling relates the continuous world to discrete world

- » Mathematically

- » Sampling can also be treated by linear decomposition!

Linear decomposition and sampling

- » Denote the (real-valued) m^{th} pixel sampling function: $p_m(x)$
 - » In practice, can assume the pixel sampling function forms an orthonormal basis: $\{p_m, m = 0, \dots, N - 1\}$, satisfying
$$\langle p_m, p_n \rangle = \delta_{m,n}$$
- » The pixel reading from the m^{th} pixel is
 - » $g_m = \int g(x)p_m(x)dx = (g, p_m)$
 - » which can be treated as the inner product between g and m th basis p_m
- » The optical detector takes N discrete samples from a continuous object $g(x)$ to produce a vector (an image)

$$\begin{aligned}\mathbf{g} &= [g_0, g_1, \dots, g_{N-1}]^T \\ &= [(g, p_0), (g, p_1), \dots, (g, p_{N-1})]^T\end{aligned}$$

- » In other words, the object is linearly decomposed as

$$g(x) = \sum_{m=0}^{N-1} g_m p_m$$

Semi-Discrete mapping

» Mapping from continuous object to discrete measurement

» Recall the continuous linear forward model

$$g = Af = \int h(x, x')f(x')dx'$$

» $g_m = (Af, p_m) = (f, A^*p_m)$

Definition of Adjoint operator

Physical meaning?

“impulse response” from the detector point of view & reciprocity

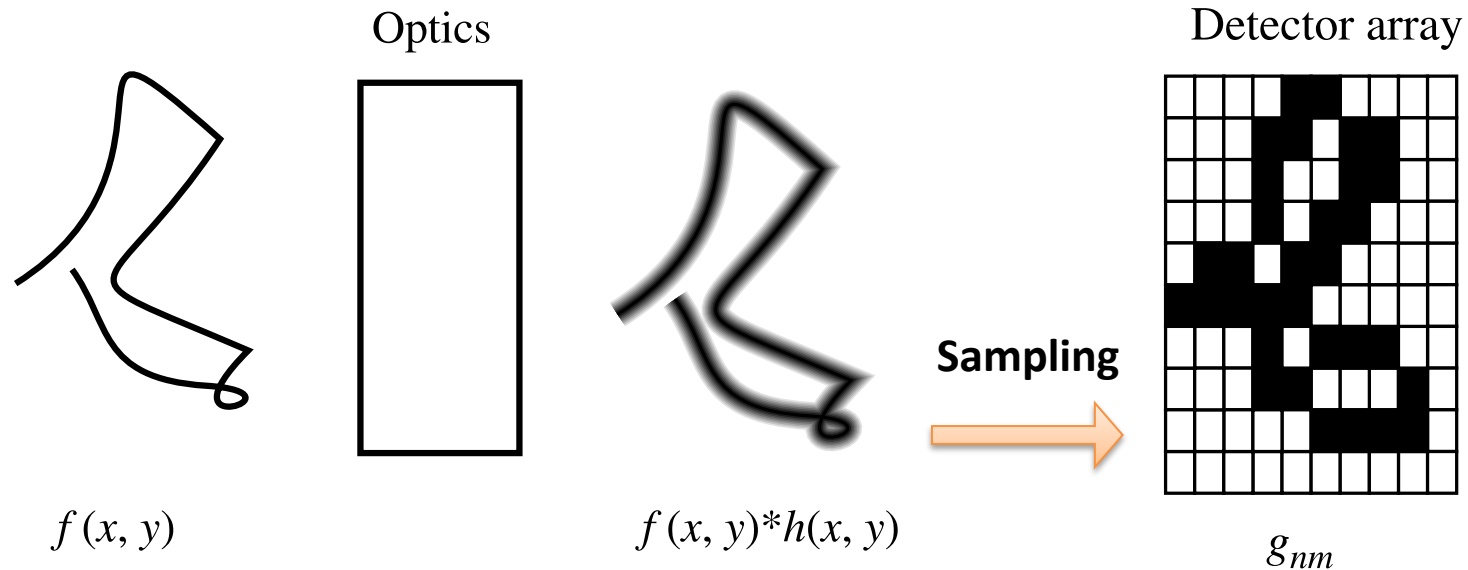
» Define $\phi_m(x') = (A^*p_m)(x') = \int h^*(x', x)p_m(x)dx$

Proof?

» Semi-discrete mapping A_M :

$$g_m = (A_M f)_m = (f, \phi_m)$$

Semi-discrete mapping



- » Measurement g_{nm} is discrete
- » Description of object $f(x, y)$ is continuous
- » Not convenient for computation
- » Mostly useful for theoretical purpose
- » Next, fully discretized model
 - » most widely used approach for both computation and analysis!

Fully discrete LSI model

» **Sampling & Discretization**

- » Sampling of the image signal

- » **Discretize the object signal**

» What about the LSI system?

- » How to discretize the linear operator?

» “Transfer function” of discrete LSI system?

- » Eigenvalues of the imaging matrix

Discretization/decomposition of object function

» Represent continuous function $f(x)$ by a vector

$$\mathbf{f} = [f_0, f_1, \dots, f_{N-1}]^T$$

» Assume a set of orthonormal basis functions $\{\psi_0, \psi_1, \dots, \psi_{N-1}\}$

$$f(x) = \sum_{n=0}^{N-1} f_n \psi_n(x)$$

Idea is similar to sampling! → sampling requirement needs to be satisfied

Fully discrete LSI model

» **Sampling & Discretization**

- » Sampling of the image signal
- » Discretize the object signal

» **What about the LSI system?**

- » **How to discretize the linear operator?**
- » “Transfer function” of discrete LSI system?
 - » Eigenvalues of the imaging matrix

Fully discrete linear forward model

$$\begin{aligned}\gg g_m = (f, \phi_m) &= (\sum_{n=0}^{N-1} f_n \psi_n, \phi_m) \\ &= \sum_{n=0}^{N-1} (\psi_n, \phi_m) f_n\end{aligned}$$

» Discrete forward model

$$\mathbf{g} = \mathbf{A}\mathbf{f}$$

$$\gg \mathbf{A}_{mn} = (\psi_n, \phi_m) = (\psi_n, A^* p_m) = (A\psi_n, p_m)$$

Proof?

Physical interpretation?

The result of a point measurement is
Impulse response of \mathbf{A} and the then
“blurred” by the pixel

Most widely used: fully discrete LSI model with ideal (impulse) sampling

- » Assume ideal impulse sampling on both object and detector

$$p_m = \delta(x - x_m)$$

- » Standard basis

$$\psi_n(x) = \delta(x - x_n)$$

- » LSI model

$$h(x, x') = h(x - x')$$

- » What is \mathbf{A} ?

$$\mathbf{A}_{mn} = h(x_m - x_n)$$

What does A matrix look like?