

Lecture 3. Signal transformations and mathematical models of imaging systems.

1. Signal transformations

Generally, signal transformations are mappings in the signal space. In practice, a hierarchical description is adopted that regard arbitrary signal transformations as a combination of point-wise non-linear and linear transformations.

Point-wise transformations : $b(\mathbf{x} = \mathbf{x}) = \text{PWT} [a(\mathbf{x} = \mathbf{x})]$

Linear transformations satisfy the superposition principle: $\sum_{k=0}^{N-1} \hat{\mathbf{a}}_k a_k(x) \hat{\mathbf{b}}_k = \hat{\mathbf{a}}_k L(a_k(x))$

Linear signal transformations are defined only for linear signal space. Linearly transformed signals also form a linear signal space. Therefore for linear transforms, one may introduce the notion of the sum of transforms, i.e. $\hat{\mathbf{a}}_n L_n$, as well as the product of transforms, $\tilde{\mathbf{O}}_n L_n$. The physical equivalent of the product is a series (cascade) connection of units realizing the transform-factors. The physical equivalent of the sum of linear transforms is a parallel connection of units realizing the transform-items. Thanks to the linearity of the transforms, their multiplication is distributive with respect to addition:

$$L_1(L_2 + L_3) = L_1 L_2 + L_1 L_3; (L_1 + L_2)L_3 = L_1 L_3 + L_2 L_3.$$

If a linear transformation L performs a one-to-one mapping of a signal, then there exists an inverse transformation L^{-1} such that

$$L L^{-1} \mathbf{a} = L^{-1} L \mathbf{a} = \mathbf{a}$$

A linear transformation of discrete signals is fully characterized by a matrix $L = \{l_{k,n}\}$ linking the input $\mathbf{a} = \{a_k\}$ and output $\mathbf{b} = \{b_k\}$ pairs of the linear transformation $\mathbf{b} = L \mathbf{a}$, respectively:

$$\mathbf{b} = \sum_k \hat{\mathbf{a}}_k l_{k,n} \hat{\mathbf{b}}_k$$

Thus, in order to describe a linear transformation of a sequence of N numbers, it suffices to specify a matrix of N^2 numbers. In the general, linear transforms are not point-wise, and that they become so only if transformation matrix is a diagonal one ($\{l_{k,n} = l_k \delta_{k-n}\}$).

For continuous signals, integral transforms are the instruments by which one produces a meaningful description of linear transformations. Linear transformation

$$b(\mathbf{x}) = L a(x) = \int_F \hat{\mathbf{a}}(f) \mathbf{j}(x, f) df = \int_F \hat{\mathbf{a}}(f) [L \mathbf{j}(x, f)] df = \int_F \hat{\mathbf{a}}(f) h(\mathbf{x}, f) df$$

is fully specified by its response $h(\mathbf{x}, f) = L(\mathbf{j}(x, f))$ to the transform kernel. Spectra $\hat{\mathbf{b}}(f)$ and $\hat{\mathbf{a}}(f)$ of a signal and its linear transformation are also related with an integral transform

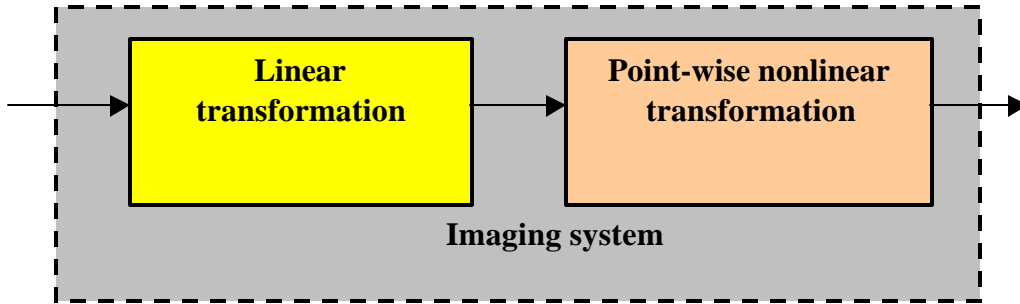
$$\hat{\mathbf{b}}(f) = \int_F \hat{\mathbf{a}}(p) H(f, p) dp, \text{ where } H(f, p) = \int \hat{\mathbf{h}}(\mathbf{x}, p) \mathbf{f}(f, \mathbf{x}) d\mathbf{x}$$

Signal integral representation via delta-function is of especial importance for the characterization of linear transformations. For such a representation, the relationship between output signal $b(\mathbf{x})$ and input signal $a(\mathbf{x})$ of a linear transformation is reduced to

$$b(\mathbf{x}) = \int_s \hat{\mathbf{a}}(\mathbf{x}) h(\mathbf{x}, \mathbf{x}) d\mathbf{x}, \text{ where } h(\mathbf{x}, \mathbf{x}) = L(\delta(\mathbf{x}, \mathbf{x}))$$

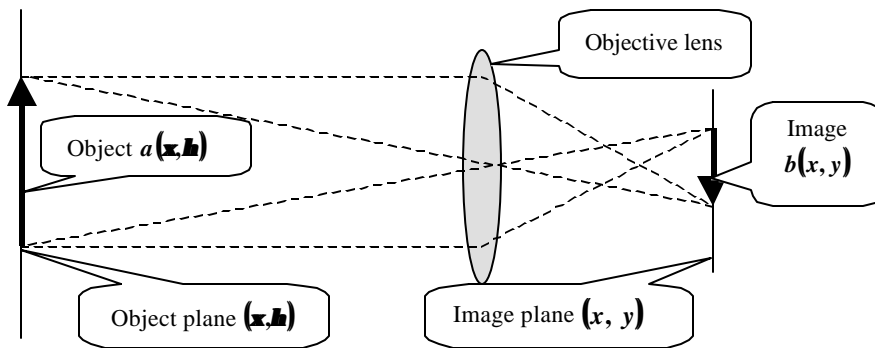
is linear transformation response to a delta-function called *impulse response* or *point spread function* of a linear system that implements this transformation.

Cascade combination of units performing linear and point-wise signal transformations is the basic model used to describe mathematically imaging and holographic systems.



Basic model of imaging and holographic systems

2. Direct image plane imaging

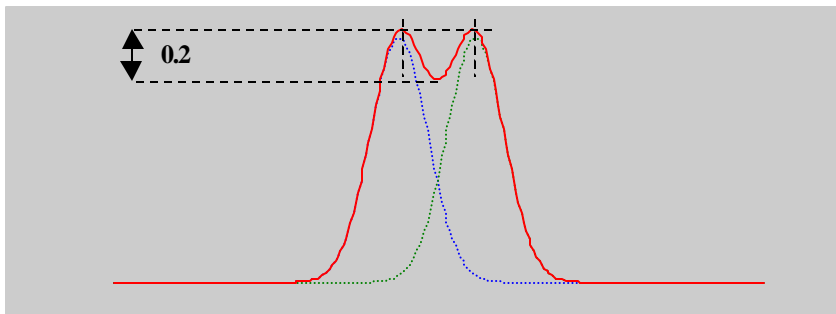


$$b(x, y) = \iint_{X, Y} a(\mathbf{x}, \mathbf{h}) h(x, y; \mathbf{x}, \mathbf{h}) d\mathbf{x} d\mathbf{h}$$

In space-invariant imaging: $h(x, y; \mathbf{x}, \mathbf{h}) = h(x - \mathbf{x}, y - \mathbf{h})$. It is modeled by the convolution integral

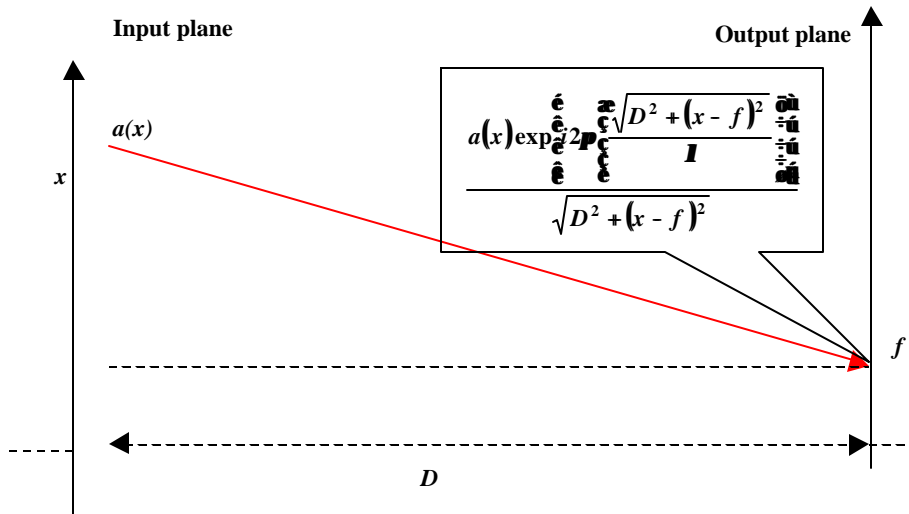
$$b(x, y) = \iint_{-\infty, -\infty}^{\infty, \infty} a(\mathbf{x}, \mathbf{h}) h(x - \mathbf{x}, y - \mathbf{h}) d\mathbf{x} d\mathbf{h}$$

Point spread function is the basic specification characteristic of imaging systems. It defines imaging system *resolving power*. On a qualitative level it is commonly accepted that resolving power of imaging systems is defined by the *Rayleigh's criterion*: two point sources are considered resolved if minimum between two corresponding PSF peaks does not exceed 80% or so of the peak maxima.



Rayleigh's criterion of the resolving power

3. Transform domain imaging



Free space wave propagation point spread function

$$h(x, y; f_x, f_y) = \frac{\exp(i 2\pi \sqrt{D^2 + (x - f_x)^2 + (y - f_y)^2} / \lambda)}{\sqrt{D^2 + (x - f_x)^2 + (y - f_y)^2}}$$

Kirchhoff's integral: the relationship between complex amplitudes $a(x, y)$ and $a(f_x, f_y)$, respectively of the wave front in the input and output planes

$$a(f_x, f_y) = \iint_{-x-x}^{x-x} a(x, y) \frac{\exp(i 2\pi \sqrt{D^2 + (x - f_x)^2 + (y - f_y)^2} / \lambda)}{\sqrt{D^2 + (x - f_x)^2 + (y - f_y)^2}} dx dy$$

In "near zone" approximation: $\sqrt{D^2 + (x - f_x)^2 + (y - f_y)^2} \approx D$;

$$\exp(i 2\pi \sqrt{D^2 + (x - f_x)^2 + (y - f_y)^2} / \lambda) \approx \exp(i 2\pi D / \lambda) \exp(i \pi \frac{(x - f_x)^2 + (y - f_y)^2}{\lambda D})$$

Kirchhoff's integral is reduced to its Fresnel approximation:

$$a(f_x, f_y) = \iint_{-x-x}^{x-x} a(x, y) \exp(i \pi \frac{(x - f_x)^2 + (y - f_y)^2}{\lambda D}) dx dy$$

Far zone approximation: $\lambda(f_x^2 + f_y^2) / D \gg 0$ and $\lambda(x^2 + y^2) / D \gg 0$, Fourier integral can be used:

$$a(f_x, f_y) = \iint_{-x-x}^{x-x} a(x, y) \exp(i 2\pi \frac{x f_x + y f_y}{\lambda D}) dx dy$$

Properties of Fourier transform

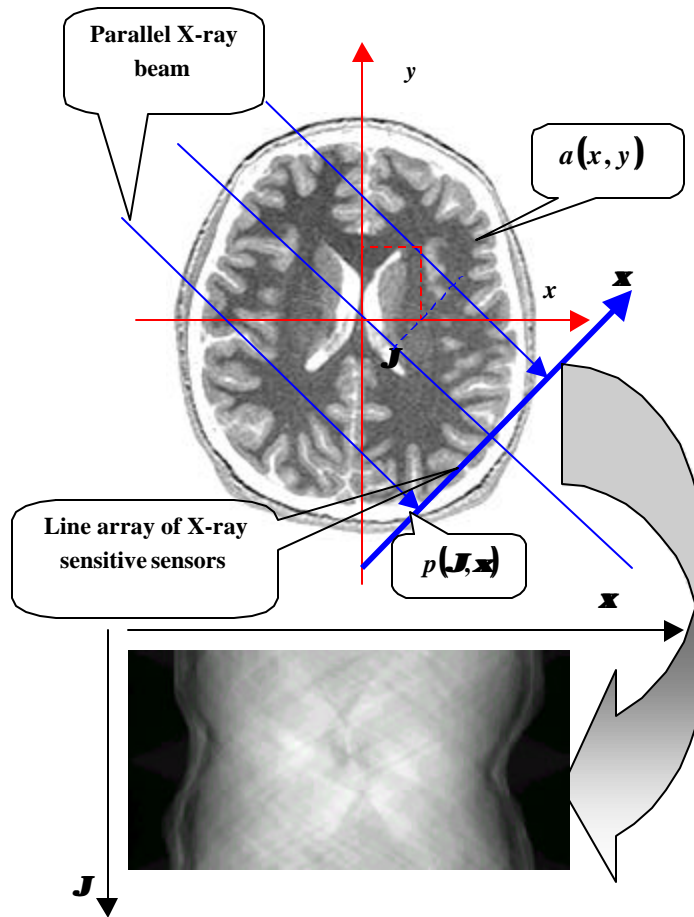
Signal	Fourier Transform
$a(x) = \lim_{F \rightarrow \infty} \int_{-F}^F a(f) \exp(-i2\pi fx) df = \int_{-\infty}^{\infty} a(f) \exp(-i2\pi fx) df$	$a(f) = \int_{-\infty}^{\infty} a(x) \exp(i2\pi fx) dx$
$a(0) = \int_{-\infty}^{\infty} a(x) dx$	$a(0) = \int_{-\infty}^{\infty} a(x) dx$
$a(-x)$	$a(-f)$
$a(x) = \pm a(-x)$	$a(f) = \pm a(-f)$
$a^*(x)$	$a^*(-f)$
$a(x) = \pm a^*(x)$	$a(f) = \pm a^*(-f)$
$a(x) = \pm a(-x) = a^*(x)$	$a(f) = \pm a(-f) = a^*(-f)$
$\frac{d^n}{(dx)^n} a(x)$	$(i2\pi f)^n a(f)$
$\frac{1}{D_x} \text{rect}\left(\frac{x + D_x/2}{D_x}\right)$	$\frac{1}{D_x} \int_{-D_x/2}^{D_x/2} \exp(i2\pi fx) dx = \frac{\sin(\pi D_x f)}{\pi D_x f}$
$\int_{-F}^F \exp(-i2\pi fx) df = 2F \frac{\sin(2\pi Fx)}{2\pi Fx} = 2F \text{sinc}(2\pi Fx)$	$\text{rect}\left(\frac{x + F}{2F}\right)$
$\exp(-i2\pi f_0 x)$	$a(f) = \lim_{F \rightarrow \infty} \int_{-F}^F \exp[i2\pi(f - f_0)x] dx = \lim_{X \rightarrow \infty} 2X \text{sinc}[2\pi X(f - f_0)] = \delta(f - f_0)$
$\int_{-\infty}^x a(x) dx$	$\frac{i}{2\pi f} a(f) + a(0) \delta(f)$
$\cos(2\pi f_0 x)$	$[a(f + f_0) + a(f - f_0)]/2$
$\sin(2\pi f_0 x)$	$[a(f + f_0) - a(f - f_0)]/2i$
Shift theorem: $a(x - x_0)$	$a(f) \exp(-i2\pi f x_0)$
Convolution theorem $b(x) = \int_{-\infty}^{\infty} a(x) h(x - x') dx'$	$B(f) = a(f) H(f)$, where $a(f)$ and $H(f)$ are Fourier Transforms of $a(x)$ and $h(x)$
Parseval's identities: $\int_{-\infty}^{\infty} a(x) h^*(x) dx = \int_{-\infty}^{\infty} a(f) H^*(f) df$; $\int_{-\infty}^{\infty} a(x) ^2 dx = \int_{-\infty}^{\infty} a(f) ^2 df$	
$a(x) \cos(2\pi f_0 x)$	$[a(f + f_0) + a(f - f_0)]/2$
$\sum_{k=-\infty}^{\infty} a(kD_x) \delta(x - kD_x)$	$\frac{1}{D_x} \sum_{r=-\infty}^{\infty} a(r/D_x) \delta(f - r/D_x)$

2-D Fourier Transform:

$a(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} a(f_x, f_y) \exp[-i2\pi(f_x x + f_y y)] df_x df_y$	$a(f_x, f_y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} a(x, y) \exp[i2\pi(f_x x + f_y y)] dx dy$
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For shift-invariant imaging systems, Fourier Transform of impulse response is called *frequency response* or *modulation transfer function* (MTF).

4. Imaging from projections



Radon transform:

$$p(\theta, x) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} a(x, y) \delta(x \cos \theta - y \sin \theta - x) dx dy$$

Projection theorem:

$$P(\theta, f_x) = \int_{-\infty}^{\infty} p(\theta, x) \exp(i 2 \pi f_x x) dx = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} a(x, y) \exp[i 2 \pi f_x (x \cos \theta + y \sin \theta)] dx dy = A(f_x \cos \theta, f_x \sin \theta)$$

5. Stochastic transforms and noise models

Additive signal independent noise model (ASIN-model) :

$$b(x) = a(x) + n(x),$$

Multiplicative noise (MN-) model assumes signal transformation defined as

$$b(x) = m(x) * a(x),$$

Impulse noise model (ImpN-) model

$$b(x) = [1 - e(x)] * a(x) + e(x) n(x)$$

Home work HW-1: Derive, following the table of properties of 1-D Fourier Transform, as many properties of 2-D Fourier Transform as you can