

FOURIER TRANSFORMATION AND ITS APPLICATIONS IN IMAGE PROCESSING

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Historical introduction

Jean-Baptiste Joseph Fourier 1768-1830

taught mathematics in Paris
eventually traveled to Egypt with
Napoleon to become the secretary of
the Institute of Egypt
after fall of Napoleon worked at Bureau
of Statistics
elected to National Academy of Sciences
in 1817



La Theorie Analytique de la Chaleur (The Analytic Theory of Heat), 1822

revolutionary ideas about how to solve a class of linear differential equations

Fourier: The Analytic Theory of Heat

- any periodic function can be represented by the sum of sinusoids and cosines: now called the Fourier Series;
- any curve, that eventually repeats itself, no matter how complex, can be expressed as the sum of smoothly oscillating functions;
- approach: multiply the sinusoids and cosines by coefficients to change their amplitude, shift them so that that either add or cancel one another (changing phase);
- non-periodic functions, those that have finite area, can also be represented in this way

Mathematics

Fourier transformation (FT)

$$f \xrightarrow{F} F$$

$$[Ff](X) = F(X) = \int_{-\infty}^{\infty} f(x) \cdot e^{-2\pi i x X} dx$$

inverse Fourier transformation (IFT)

$$f \xleftarrow{F^{-1}} F$$

$$[F^{-1}F](x) = f(x) = \int_{-\infty}^{\infty} F(X) \cdot e^{2\pi i x X} dX$$

$$f \xrightarrow{F} F$$

uniquely determined*

Mathematics

the FT of a function is usually complex:

$$\begin{aligned} F(X) &= \int_{-\infty}^{\infty} f(x) \cdot e^{-2\pi i x X} dx = \int_{-\infty}^{\infty} f(x) \cdot [\cos(2\pi x X) - i \cdot \sin(2\pi x X)] dx = \\ &= \underbrace{\int_{-\infty}^{\infty} f(x) \cdot \cos(2\pi x X) dx}_{\text{real part}} - i \cdot \underbrace{\int_{-\infty}^{\infty} f(x) \cdot \sin(2\pi x X) dx}_{\text{imaginary part}} \end{aligned}$$

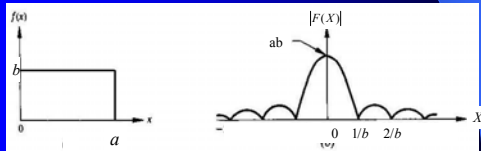
$$i = \sqrt{-1}$$

Mathematics

an example:

$$f(x) = \begin{cases} b, & \text{if } 0 \leq x \leq a \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} F(X) &= \int_0^a b \cdot e^{-2\pi i x X} dx = b \cdot \left. \frac{-1}{2\pi i X} \cdot e^{-2\pi i x X} \right|_0^a = \\ &= \frac{b}{2\pi i X} (1 - e^{-2\pi i a X}) = \frac{b \cdot e^{-\pi i a X}}{2\pi i X} (e^{\pi i a X} - e^{-\pi i a X}) = \\ &= \frac{b \cdot e^{-\pi i a X}}{\pi X} \cdot \sin(\pi a X) \end{aligned}$$

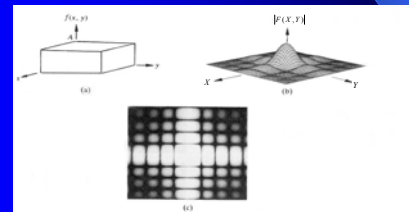


2-dimensional case

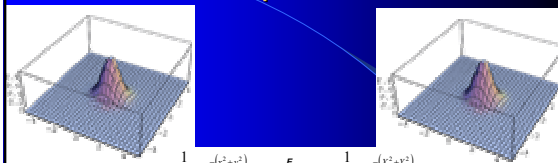
$$F(X, Y) = \iint_{-\infty}^{\infty} f(x, y) \cdot e^{-2\pi i (xX + yY)} dx dy$$

$$f(x, y) = \iint_{-\infty}^{\infty} F(X, Y) \cdot e^{2\pi i (xX + yY)} dX dY$$

an example



Properties



$$\frac{1}{\sqrt{2\pi}} e^{-(x^2+y^2)} \xrightarrow{F} \frac{1}{\sqrt{2\pi}} e^{-(X^2+Y^2)}$$

the FT of a Gaussian is another Gaussian, i.e., *eigenfunction*

Sums of sinusoids

inverse Fourier transformation (IFT)

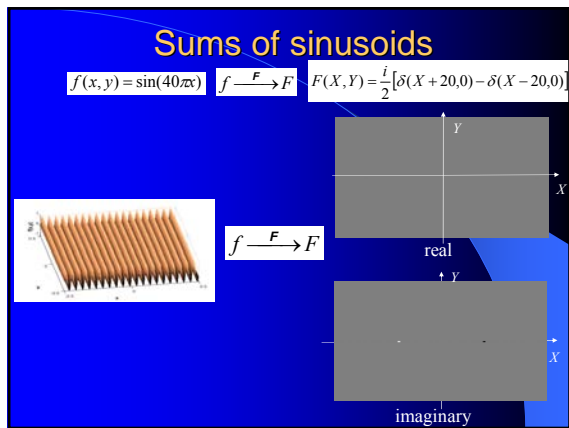
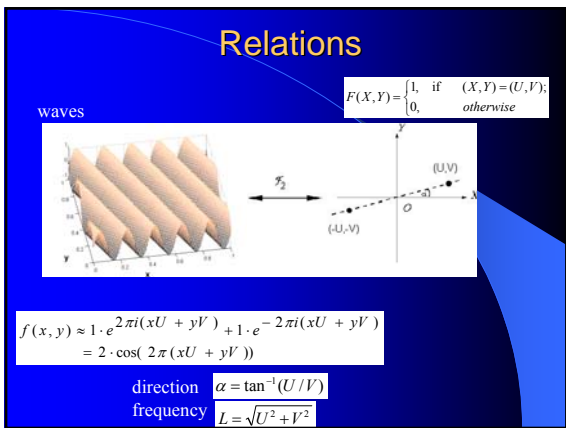
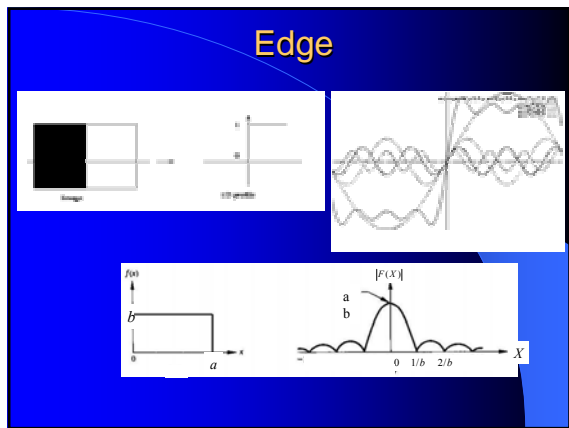
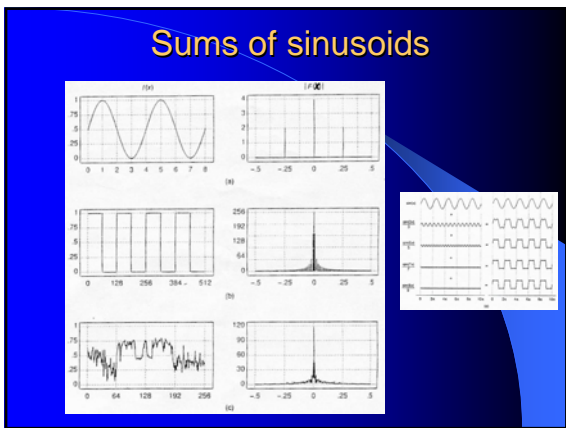
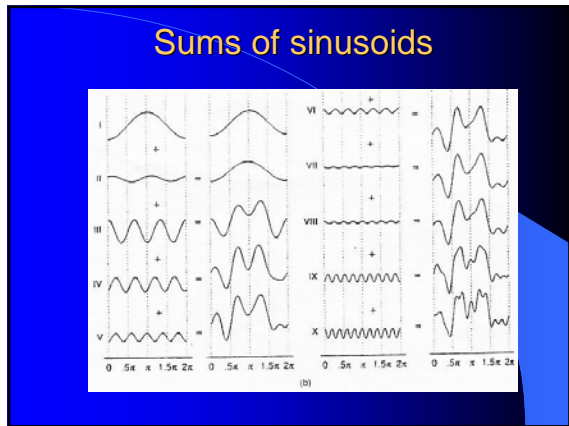
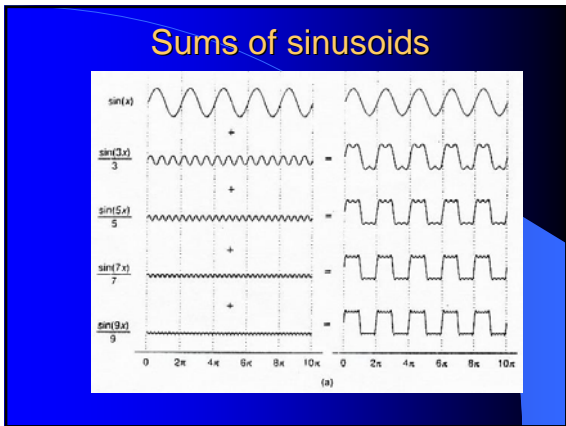
$$f \xleftarrow{F^{-1}} F$$

$$f(x) = \int_{-\infty}^{\infty} F(X) \cdot e^{2\pi i x X} dX$$

an interpretation:

Any periodic function can be decomposed into a series of sinusoidal waveforms of various frequencies and amplitudes.

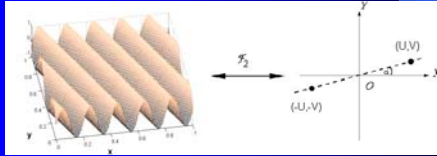
$$f(x) = \int_{-\infty}^{\infty} F(X) \cdot \cos(2\pi x X) dX + i \cdot \int_{-\infty}^{\infty} F(X) \cdot \sin(2\pi x X) dX$$



Waves, points, and frequencies

points in the image $F(X,Y)$ represent the contribution of frequency (X,Y) to the original image $f(x,y)$

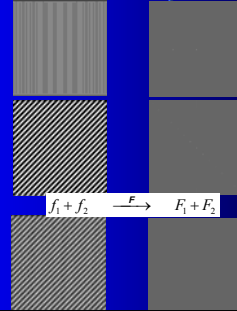
The Fourier transformation determines the magnitude (amplitude $= |F(X,Y)|$) of each possible frequency (X,Y) .



Linearity

$$a_1 \cdot f_1 + a_2 \cdot f_2 \xrightarrow{F} a_1 \cdot F_1 + a_2 \cdot F_2$$

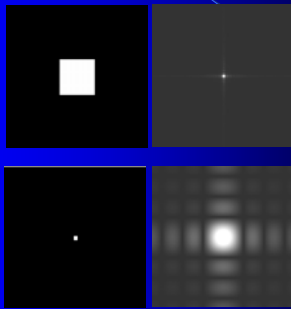
example



Scaling

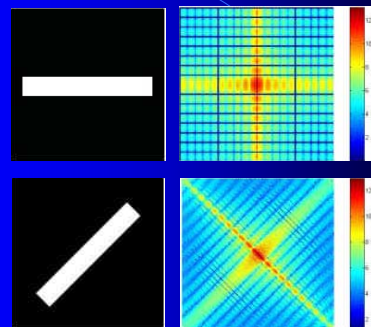
$$f(ax, by) \xrightarrow{F} \frac{1}{|ab|} F\left(\frac{X}{a}, \frac{Y}{b}\right)$$

example



Rotation

example



Discrete Fourier Transformation DFT

Discrete Fourier Transformation

DFT and IDFT:

$$f_0, f_1, \dots, f_{N-1} \xrightarrow{F} F_0, F_1, \dots, F_{N-1}$$

$$F_l = \sum_{k=0}^{N-1} f_k e^{-\frac{2\pi i k l}{N}}, \quad l = 0, 1, \dots, N-1$$

$$f_k = \frac{1}{N} \sum_{l=0}^{N-1} F_l e^{\frac{2\pi i k l}{N}}, \quad k = 0, 1, \dots, N-1$$

2D DFT and IDFT:

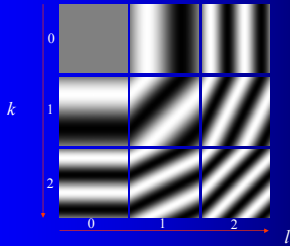
$$F_{k,l} = \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} f_{m,n} \cdot e^{-\frac{2\pi i}{N}(mk+nl)}, \quad k, l = 0, 1, \dots, N-1$$

$$f_{m,n} = \frac{1}{N^2} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} F_{k,l} \cdot e^{\frac{2\pi i}{N}(mk+nl)}, \quad m, n = 0, 1, \dots, N-1$$

2D Discrete Fourier Transformation

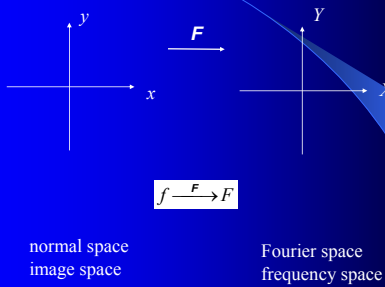
$$f_{m,n} = \frac{1}{N^2} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} F_{k,l} \cdot e^{j\frac{2\pi}{N}(mk+nl)}$$

f is the sum of so-called *base functions*:

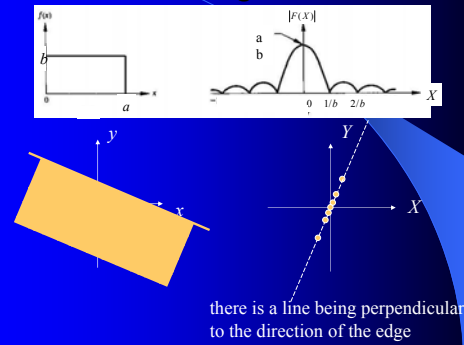


Fourier transformation of images

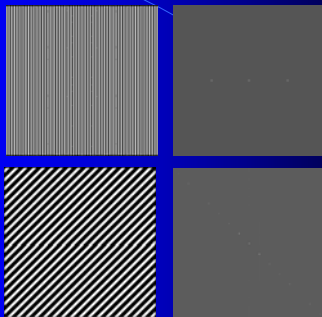
Image and frequency spaces



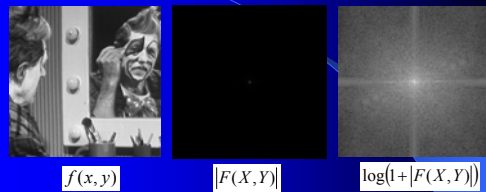
Edge



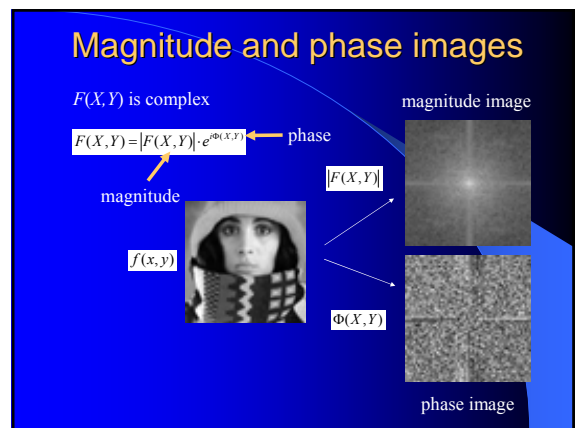
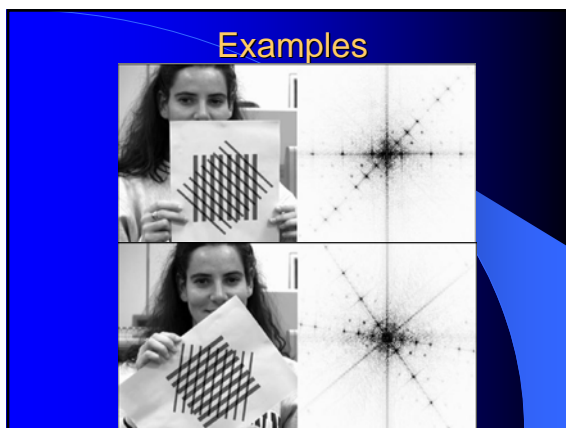
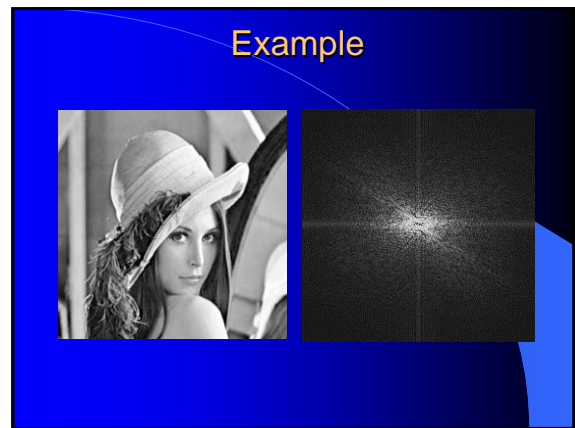
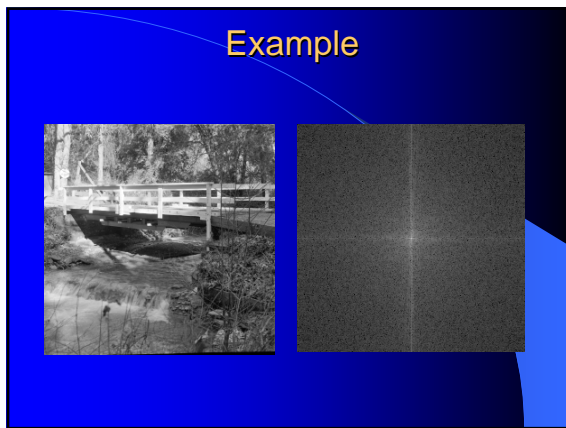
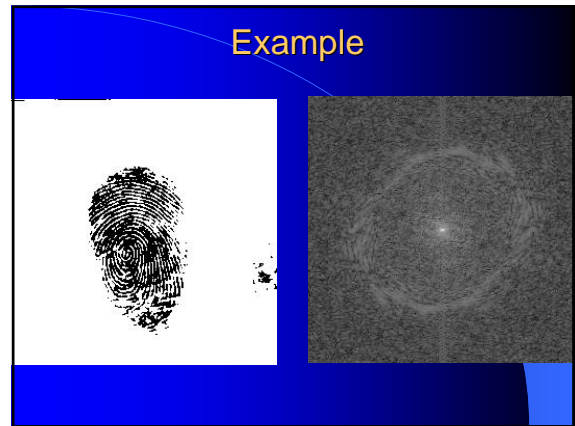
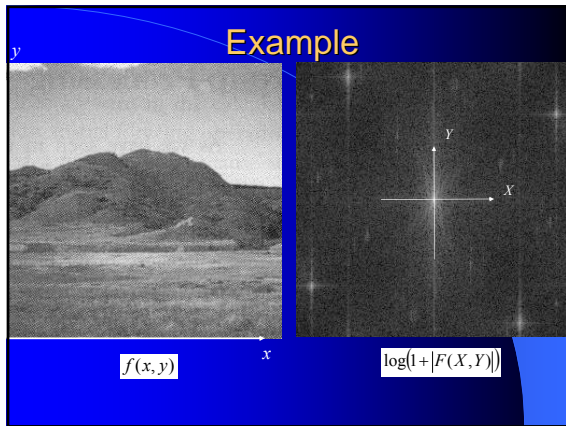
Example




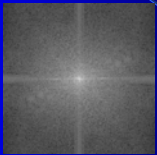
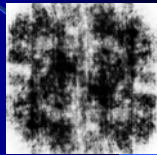
Example



$F(0,0)$ -value is by far the largest component of the image, other frequency components are usually much smaller, the magnitude of $F(X,Y)$ decreases quickly



Phase image

$f(x,y)$
 $\log(1+|F(X,Y)|)$
 $F^{-1}(|F(X,Y)|)$

the phase information is also important

Fisher, Perkins, Walker, Wolfart, 1994


Filtering


Convolution


$$[f * g](x) = \int_{-\infty}^{\infty} f(\xi) \cdot g(x-\xi) d\xi \quad \text{1D}$$

$$[f * g](x,y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\xi,\eta) \cdot g(x-\xi, y-\eta) d\xi d\eta \quad \text{2D}$$

example: smoothing

$f(x)$


$g(x) = \begin{cases} 1, & \text{if } |x| < 1/2, \\ 0, & \text{otherwise} \end{cases}$


$[f * g](x) = \int_{x-1/2}^{x+1/2} f(\xi) d\xi$


Convolution theorem

$f * h \xrightarrow{F} F \cdot H$

$f \cdot h \xrightarrow{F} F * H$

Filtering

(in the Fourier space) multiplication of F with a filter function H :
 $F \cdot H$

Convolution theorem:

$$f * h \xrightarrow{F} F \cdot H$$

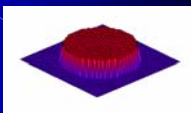
$$h = \frac{1}{l^2} \begin{pmatrix} 1 & \dots & 1 \\ \vdots & & \vdots \\ 1 & \dots & 1 \end{pmatrix}_{|s|}$$



$$\xrightarrow{F} H(j,k) = \frac{1}{N} \sum_{m=0}^{l-1} \sum_{n=0}^{l-1} 1 \cdot e^{-\frac{2\pi}{N}(mj+nk)} = \frac{1}{N} \left(\sum_{m=0}^{l-1} e^{-\frac{2\pi}{N}mj} \right) \cdot \left(\sum_{n=0}^{l-1} e^{-\frac{2\pi}{N}nk} \right) = \frac{1}{N} \frac{e^{j\pi(l-1)(j+k)}}{\sin(\pi j)} \cdot \frac{\sin(\pi k l)}{\sin(\pi k)}$$

Ideal low-pass filter (ILPF)

$$H_l(X,Y) = \begin{cases} 1, & \text{if } X^2 + Y^2 \leq D_0^2 \\ 0, & \text{otherwise} \end{cases}$$

frequencies greater than D_0 are deleted



smoothing

Low pass filtering

S. Karmienko

Ideal high-pass filter (IHPF)

$$H_2(X,Y) = \begin{cases} 0, & \text{if } X^2 + Y^2 \leq D_0^2 \\ 1, & \text{otherwise} \end{cases}$$

$$H_2 = 1 - H_1$$

$$FH_2 = F(1 - H_1) = F - FH_1$$

frequencies less than D_0 are deleted

edge (and noise) enhancement

High pass filtering

S. Karmienko

Filtering frequencies

??

A. Hanbury

Band filtering

Frequency filtering

Frequency filtering

This slide illustrates the concept of frequency filtering. It shows a grayscale image of a man's face on the left. To its right is a grid of diamond-shaped patterns. Below the grid are two rows of diamond-shaped patterns, one with a higher frequency than the other. Arrows indicate the relationship between the original image and the filtered versions.

Texture analysis

This slide is a solid blue background with the text "Texture analysis" centered in a yellow font.

Textures

an electron microscope view of the fibers in a metal specimen

cell structures

This slide shows two examples of texture analysis. The top example shows a grayscale image of fibers in a metal specimen, a white vertical bar, and a corresponding frequency spectrum plot. The bottom example shows a grayscale image of cell structures, a white vertical bar, and a corresponding frequency spectrum plot.

Textures

forest

mud

This slide shows two examples of texture analysis for natural scenes. The top example shows a grayscale image of a forest, a color-coded frequency spectrum plot, and the label "forest". The bottom example shows a grayscale image of mud, a color-coded frequency spectrum plot, and the label "mud".

Textures

field

pond

This slide shows two examples of texture analysis for natural scenes. The top example shows a grayscale image of a field, a color-coded frequency spectrum plot, and the label "field". The bottom example shows a grayscale image of a pond, a color-coded frequency spectrum plot, and the label "pond".

Textures

village

water

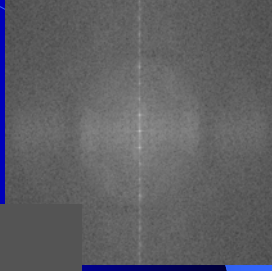
This slide shows two examples of texture analysis for natural scenes. The top example shows a grayscale image of a village, a color-coded frequency spectrum plot, and the label "village". The bottom example shows a grayscale image of water, a color-coded frequency spectrum plot, and the label "water".

To find text orientation

Sonnet for Lena

O dear Lena, your beauty is no vast
 It is hard sometimes to describe it best
 I thought the entire world I could surpass
 If only your portrait I could compass.
 Alas! Fate when I tried to see 'NQ
 I found that your cheeks belong to only you.
 Your silky hair contains a thousand lines
 Hard to count with some of discrete cosine
 And for your lips, around and tucked
 Thirteen Greek found not the proper tuck.
 And while those methods are all quite severe
 I might have found them with luck here or there.
 But when filters took sparkle from your eyes
 I said, "Damn all this. I'll just digitize."

Thomas Cobblepot




Fisher, Perkins, Walker, Wolfart, 1994

To find text orientation

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Fisher, Perkins, Walker, Wolfart, 1994

Measurements on the power spectrum

$E(X,Y) = |F(X,Y)|^2$ Fourier power spectrum

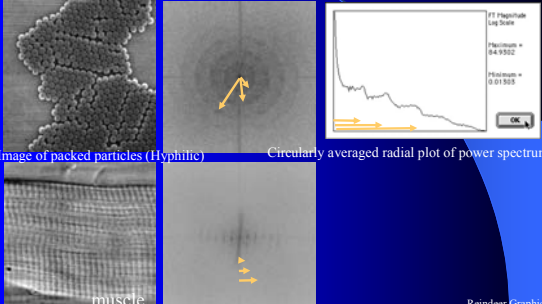


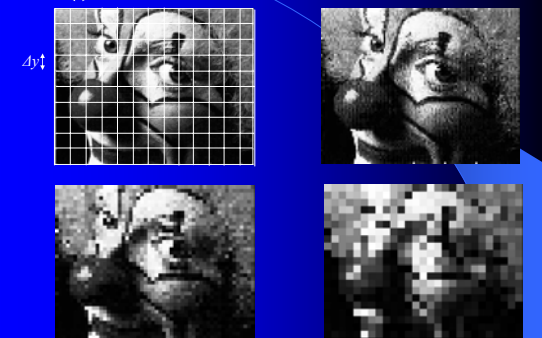
Image of packed particles (Hyphic) Circularly averaged radial plot of power spectrum

muscle

Reindeer Graphics

Sampling

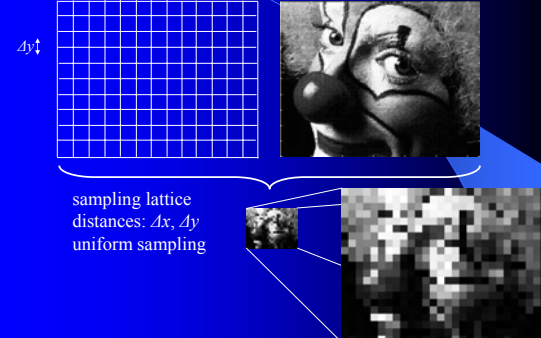
What is sampling?



Δx

Δy

2D sampling



Δx

Δy

sampling lattice
 distances: Δx , Δy
 uniform sampling

If the sampling is not suitable...

original
4th points
8th points

Impulse function

$$\delta(x) \approx \begin{cases} \infty, & \text{if } x=0 \\ 0, & \text{otherwise} \end{cases} \quad \delta(x) = \lim_{a \rightarrow 0} a^2 e^{-a^2 x^2}$$

$$\delta(x, y) = \delta(x) \cdot \delta(y) \quad \text{2D}$$

properties:

$$\int_{-\infty}^{\infty} \delta(x) dx = 1,$$

$$\int_{-\infty}^{\infty} f(x) \cdot \delta(x) dx = f(0),$$

$$[f * \delta](x) = \int_{-\infty}^{\infty} f(\xi) \cdot \delta(x - \xi) d\xi = f(x),$$

$$[F\delta](\lambda) = \int_{-\infty}^{\infty} \delta(x) \cdot e^{-2\pi i \lambda x} dx = e^{-2\pi i \lambda \cdot 0} = 1$$

Sampling function

$$s(x) = \sum_{j=-\infty}^{\infty} \delta(x - j \cdot \Delta x)$$

properties:

An important property

$$f(ax) \xrightarrow{F} \frac{1}{|a|} F\left(\frac{X}{a}\right) \quad \text{scaling}$$

more dense sampling higher frequencies

Sampling

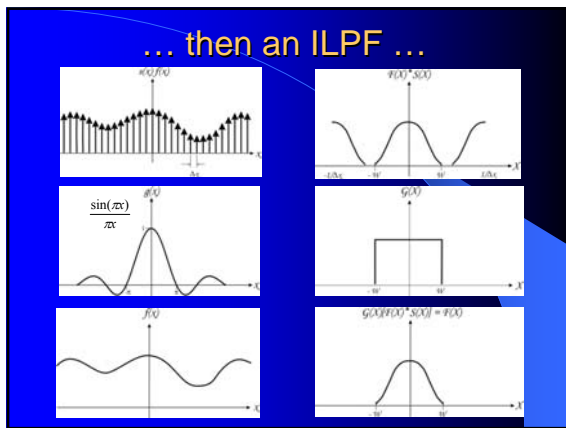
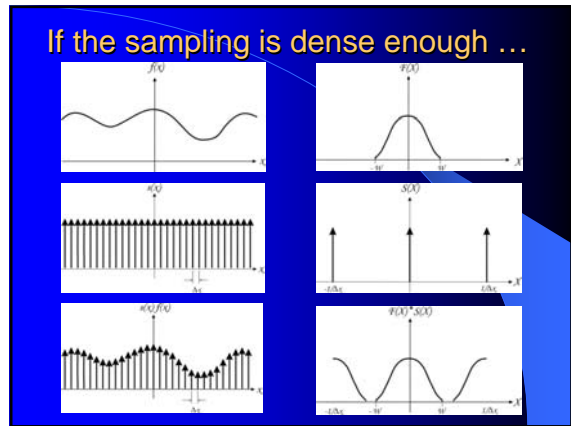
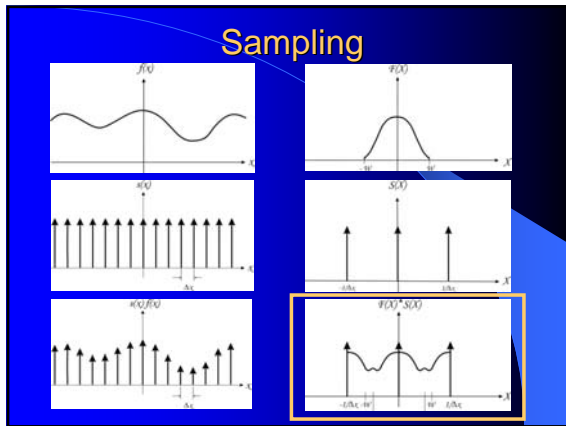
$F * S = ??$

Sampling

overlapping

let us use

$$F * \delta = F$$



Result

If the function f has no arbitrary big frequencies
 (i.e., its Fourier transformation F has bounded support, say, there is a W such that $F(X) = 0$ if $|X| > W$)
and
the sampling of f is dense enough
 (i.e., $\Delta x \leq 1/(2W)$ or, equivalently, $W \leq 1/(2\Delta x)$)
then
 f can be reconstructed from its discrete samples.

Band limited functions

$f(x)$ is *band limited* if there is a W such that $F(X) = 0$ if $|X| > W$
 that is, f has no bigger frequency than W

examples: counterexamples:

<p>sin, cos</p>	<p>step f.</p>
<p>ILPF</p>	<p>Gaussian</p>

Whittaker-Shannon theorem

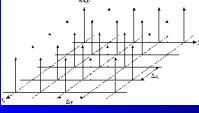
Let $f(x)$ be a band-limited signal with $F(X) = 0$ for $|X| > W$. Then $f(x)$ is uniquely determined by its samples $f(n/(2W))$, $n = 0, \pm 1, \pm 2, \dots$,

$$f(x) = \sum_{n=-\infty}^{\infty} f\left(\frac{n}{2W}\right) \cdot \frac{\sin[\pi(2Wx - n)]}{\pi(2Wx - n)}$$


Nyquist frequency: $1/(2\Delta x)$

2D sampling

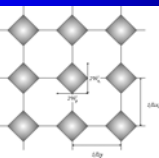
2D sampling function:



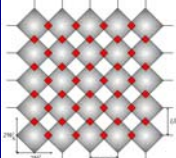
support of the 2D Fourier transformation:



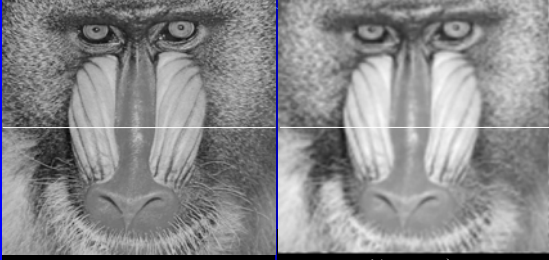
if the sampling is dense enough:



if not:



Aliasing




4th points

Shape description and representation

Planar shape representation

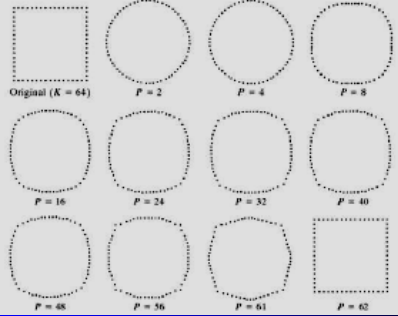
$f_k = x_k + iy_k$, $k=0,1,\dots,N-1$, points on the complex plane

$$f_0, f_1, \dots, f_{N-1} \xrightarrow{F} F_0, F_1, \dots, F_{N-1}$$

$$f_k = \frac{1}{N} \sum_{l=0}^{N-1} F_l e^{i \frac{2\pi}{N} kl}, k = 0, 1, \dots, N-1$$


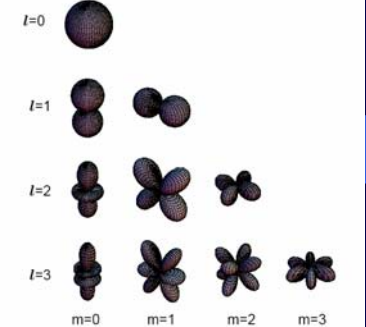
original 1 2 3 10 20
number of harmonics
(i.e., Fourier coefficients/descriptors)

Planar shape representation



Original ($K = 64$) $P = 2$ $P = 4$ $P = 8$
 $P = 16$ $P = 24$ $P = 32$ $P = 40$
 $P = 48$ $P = 56$ $P = 61$ $P = 62$

Fourier descriptors in 3D



$l=0$ $l=1$ $l=2$ $l=3$
 $m=0$ $m=1$ $m=2$ $m=3$

basis functions: spherical harmonics

M. de Bruijne

