Vision and Perception

Image in the frequency domain



References

Basic reading:

Szeliski textbook, Sections 3.4, 3.5

Additional reading:

The original Laplacian pyramid paper

• Burt and Adelson, "The Laplacian Pyramid as a Compact Image Code," IEEE ToC 1983.

Overview of today's lecture

- Fourier series
- Frequency domain
- Fourier transform
- Frequency-domain filtering

The frequency domain

Is this claim true?



Jean Baptiste Joseph Fourier (1768-1830)

The Fourier series claim (1807):

'<u>Any</u> univariate function can be rewritten as a weighted sum of sines and cosines of different frequencies.'

Well, almost.

- The theorem requires additional conditions.
- Close enough to be named after him.
- Very surprising result at the time.

Is this claim true?



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Malus



Lagrange



Legendre



Laplace

The committee
examining his paper
had expressed
skepticism, in part due
to not so rigorous
proofs

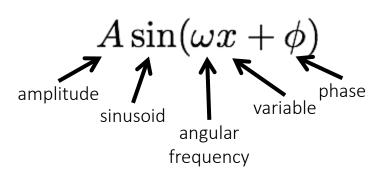
Fourier series

Basic building block

$$A\sin(\omega x + \phi)$$

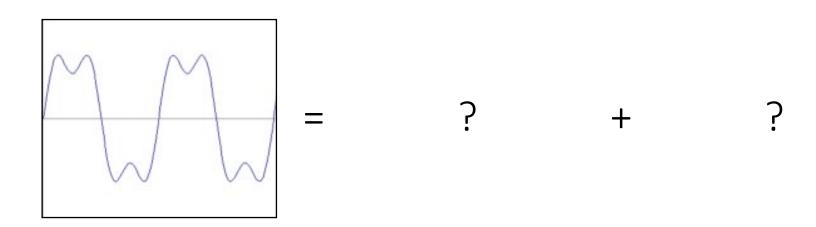
Fourier's claim: Add enough of these to get any periodic signal you want

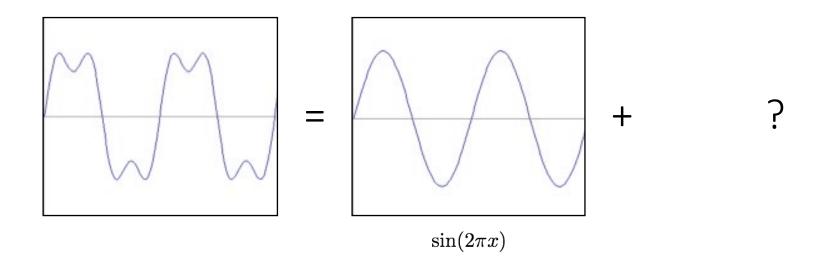
Basic building block

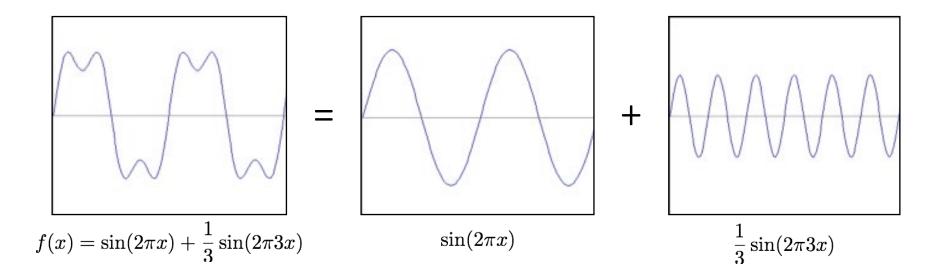


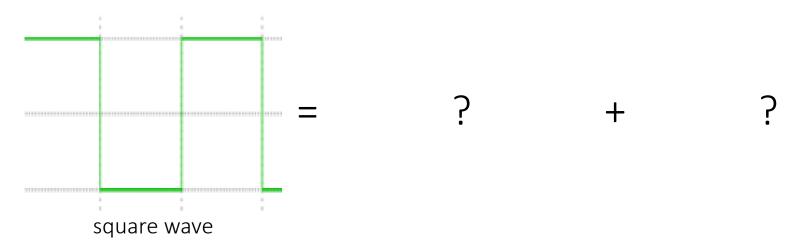
 $T = \frac{2\pi}{|\omega|}$

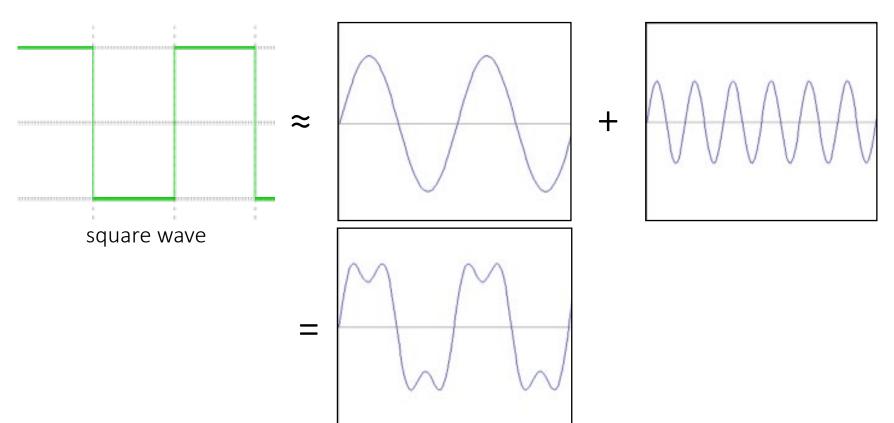
Fourier's claim: Add enough of these to get <u>any periodic</u> signal you want

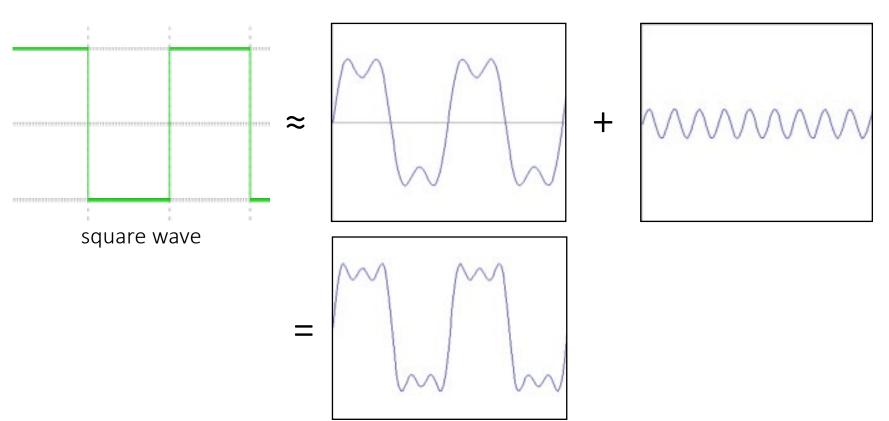


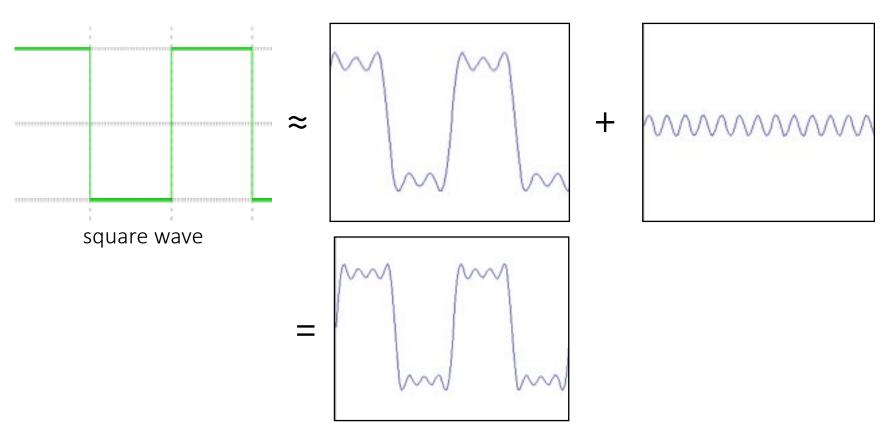


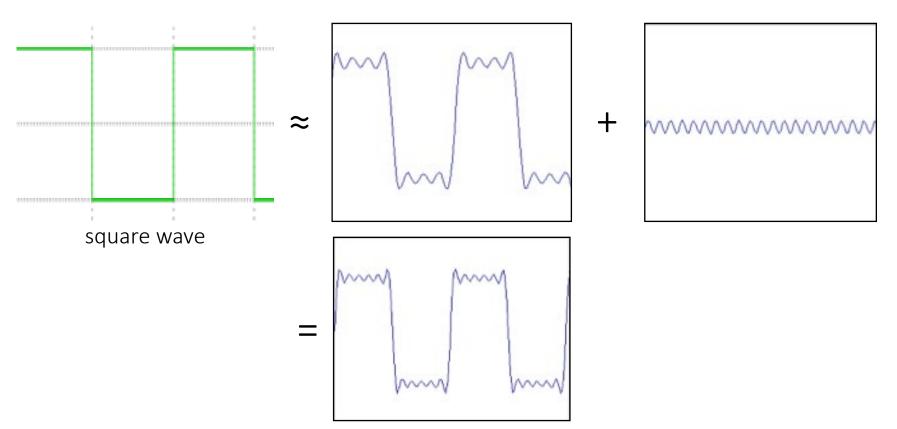


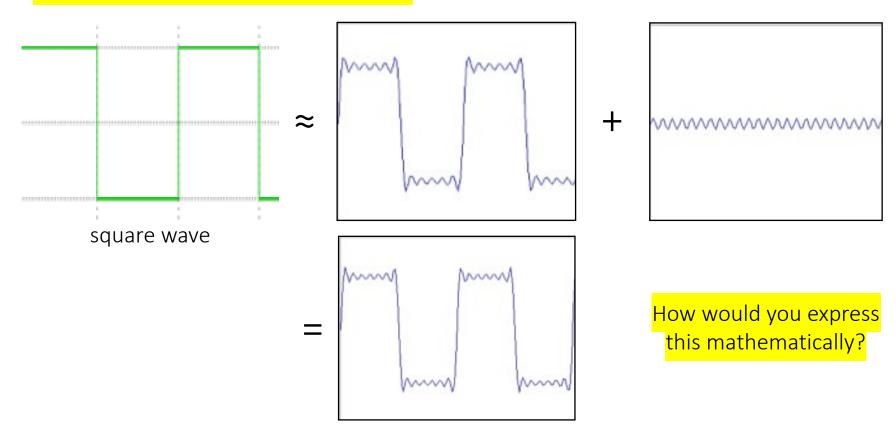


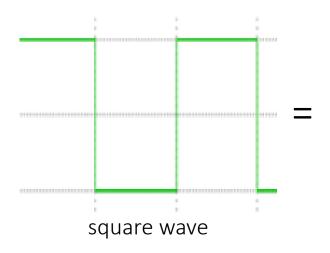








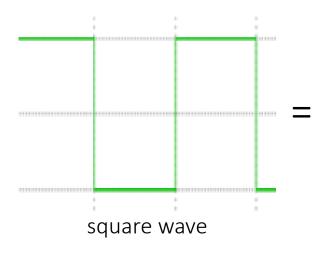




$$A\sum_{k=1}^{\infty} \frac{1}{k} \sin(2\pi kx)$$

infinite sum of sine waves

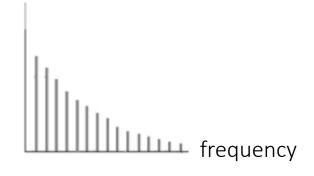
How would could you visualize this in the frequency domain?



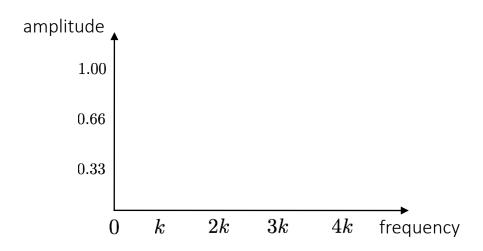
$$A\sum_{k=1}^{\infty} \frac{1}{k} \sin(2\pi kx)$$

infinite sum of sine waves

Magnitude (amplitude)

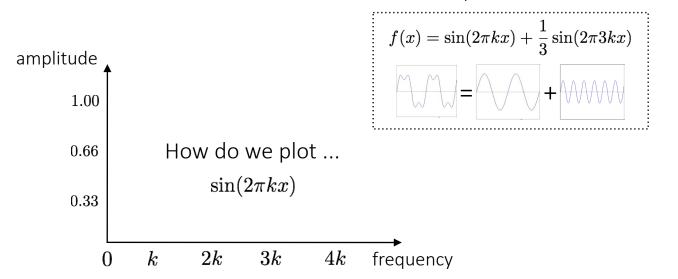


Frequency domain

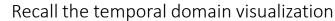


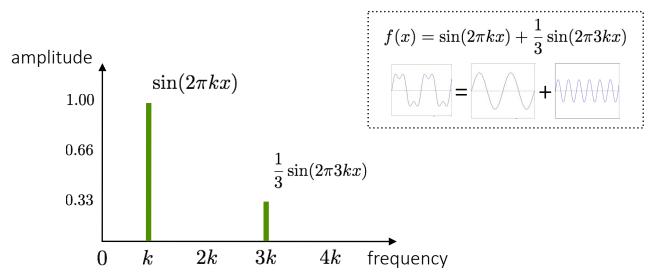
Recall the temporal domain visualization $f(x) = \sin(2\pi kx) + \frac{1}{3}\sin(2\pi 3kx)$ amplitude 1.00 0.660.333kk2k4k0 frequency

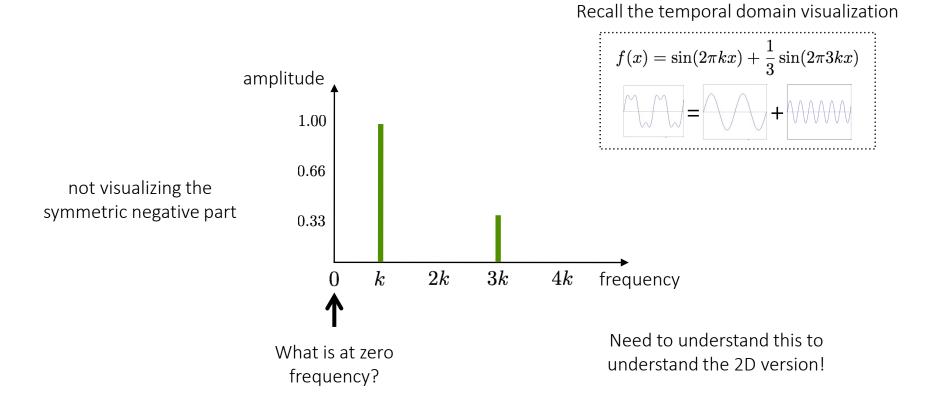
Recall the temporal domain visualization

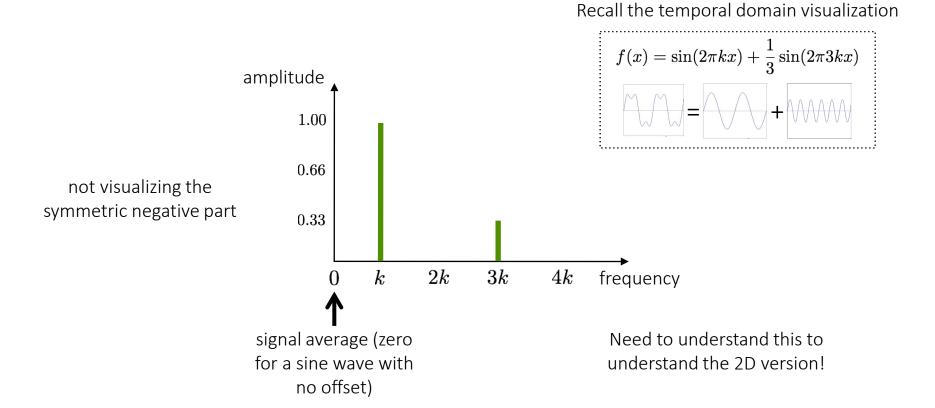


Recall the temporal domain visualization $f(x) = \sin(2\pi kx) + \frac{1}{3}\sin(2\pi 3kx)$ amplitude $\sin(2\pi kx)$ 1.00 0.660.33k2k3k4kfrequency 0

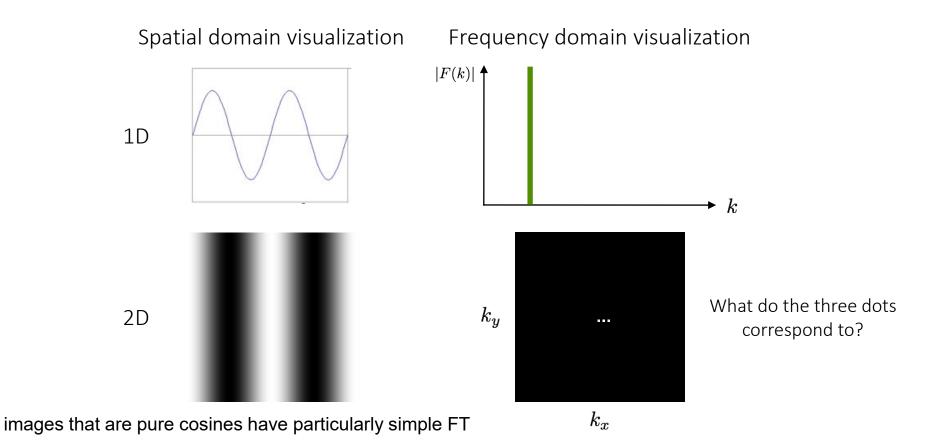




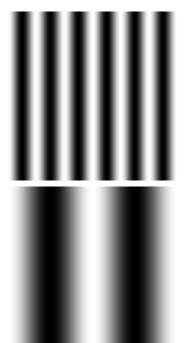




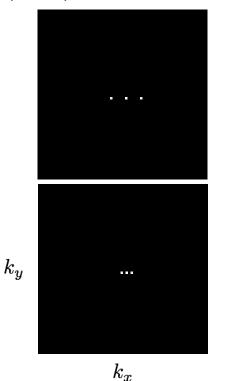
Spatial domain visualization Frequency domain visualization |F(k)|1D k2D



Spatial domain visualization

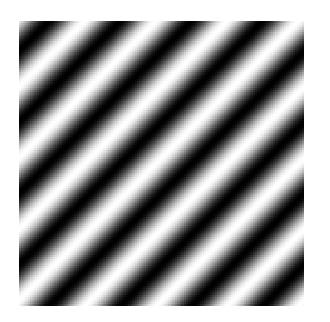


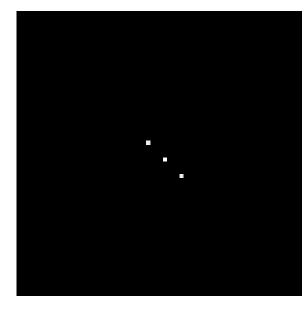
Frequency domain visualization



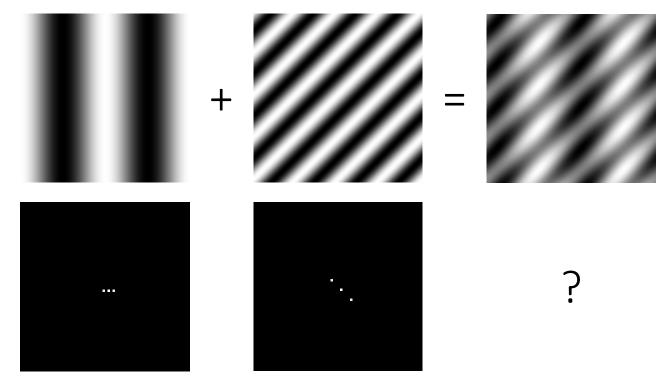
Scaling property of Fourier transform: if we stretch a function by a factor in the time domain then squeeze the Fourier transform by the same factor in the frequency domain

Rotation of the image results in equivalent rotation of its FT.

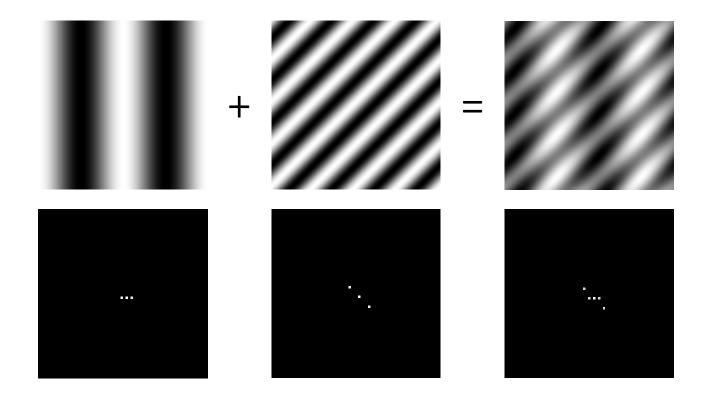




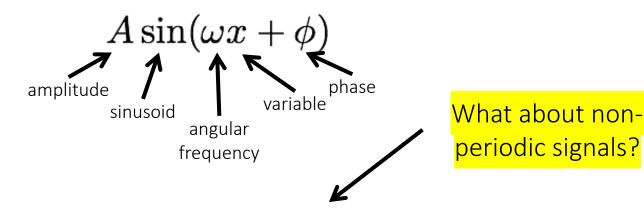
Has both an x and y components



Linearity Property



Basic building block



Fourier's claim: Add enough of these to get any periodic signal you want!

Background

- Any function that periodically repeats itself can be expressed as the sum of sines and/or cosines of different frequencies, each multiplied by a different coefficient (Fourier series).
- Even functions that are not periodic (but whose area under the curve is finite) can be expressed as the integral of sines and/or cosines multiplied by a weighting function (Fourier transform).

Fourier transform

inverse Fourier transform

continuous

$$F(k) = \int_{-\infty}^{-\infty} f(x)e^{-j2\pi kx}dx \qquad f(x) = \int_{-\infty}^{-\infty} F(k)e^{j2\pi kx}dk$$

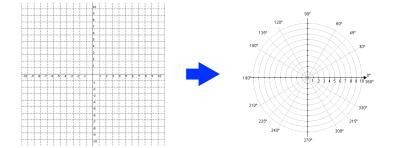
$$f(x) = \int_{-\infty}^{-\infty} F(k)e^{j2\pi kx}dk$$

$$F(k) = rac{1}{N} \sum_{x=0}^{N-1} f(x) e^{-j2\pi kx/N} \qquad \qquad f(x) = \sum_{k=0}^{N-1} F(k) e^{j2\pi kx/N} = \sum_{x=0,1,2,\ldots,N-1}^{N-1} F(x) e^{j2\pi kx/N}$$

Complex numbers have two parts:

rectangular coordinates

 $\underset{\text{real imaginary}}{R+jI}$



Complex numbers have two parts:

rectangular coordinates

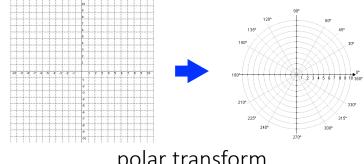
$$\underset{\text{real imaginary}}{R+jI}$$

Alternative reparameterization:

polar coordinates

$$r(\cos\theta + j\sin\theta)$$

how do we compute these?



polar transform

Complex numbers have two parts:

rectangular coordinates

$$\underset{\text{real imaginary}}{R+jI}$$

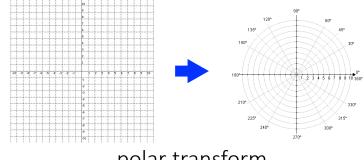
Alternative reparameterization:

polar coordinates

$$r(\cos\theta + j\sin\theta)$$

polar transform

$$\theta = \tan^{-1}(\frac{I}{R}) \quad r = \sqrt{R^2 + I^2}$$



polar transform

Complex numbers have two parts:

rectangular coordinates

$$R+jI$$
 real imaginary

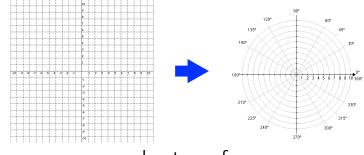
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$$\theta = \tan^{-1}(\frac{I}{R}) \quad r = \sqrt{R^2 + I^2}$$



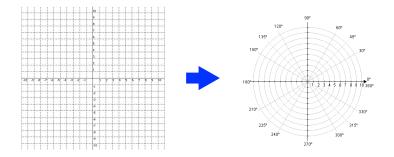
polar transform

How do you write these in exponential form?

Complex numbers have two parts:

rectangular coordinates

$$R+jI_{\text{real imaginary}}$$



Alternative reparameterization:

polar coordinates

$$r(\cos\theta+j\sin\theta)$$

polar transform

$$\tan^{-1}(\frac{I}{R}) \quad r = \sqrt{R^2 + I^2}$$

or equivalently

$$re^{j\theta}$$

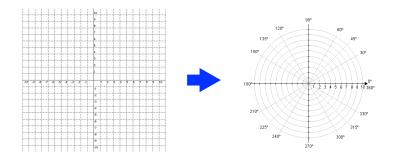
how did we get this?

exponential form

Complex numbers have two parts:

rectangular coordinates

$$R+jI$$
real imaginary



Alternative reparameterization:

polar coordinates

$$r(\cos\theta+j\sin\theta)$$

polar transform

$$\theta = \tan^{-1}(\frac{I}{R}) \quad r = \sqrt{R^2 + I^2}$$

or equivalently

$$re^{j(}$$

Euler's formula

$$e^{j\theta}=\cos\theta+j\sin\theta$$

exponential form

This will help us understand the Fourier transform equations

Fourier transform

inverse Fourier transform

continuous

$$F(k) = \int_{-\infty}^{-\infty} f(x)e^{-j2\pi kx}dx \qquad f(x) = \int_{-\infty}^{-\infty} F(k)e^{j2\pi kx}dk$$

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Fourier transform

inverse Fourier transform

continuous

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$$F(k) = rac{1}{N} \sum_{x=0}^{N-1} f(x) e^{-j2\pi kx/N} \qquad \qquad f(x) = \sum_{k=0}^{N-1} F(k) e^{j2\pi kx/N} \qquad \qquad f(x) = \sum_{x=0,1,2,\ldots,N-1}^{N-1} F(k) e^{j2\pi kx/N}$$

$$f(x) = \sum_{k=0}^{N-1} F(k) e^{j2\pi kx/N}$$

$$f(x) = \sum_{k=0}^{N-1} F(k) e^{j2\pi kx/N}$$
 Euler's formula
$$e^{j\theta} = \cos\theta + j\sin\theta$$
 sum over frequencies
$$f(x) = \sum_{k=0}^{N-1} F(k) \bigg\{ \cos(2\pi kx) + j\sin(2\pi kx) \bigg\}$$
 scaling parameter wave components

2D Fourier Transform

DFT can be computed for any-dimensional input function. In particular, the 2D DFT is useful when working with images

2D Discrete Fourier transform:

$$F(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) e^{-j2\pi(ux/M + vy/N)}$$

Discrete Inverse Fourier transform:

$$f(x,y) = \frac{1}{MN} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u,v) e^{-j2\pi(ux/M + vy/N)}$$

Spectrum and phase angle

Because the 2-D DFT is complex in general, it can be expressed in polar form:

$$F(u,v) = |F(u,v)|e^{j\theta(u,v)}$$

Where the magnitude

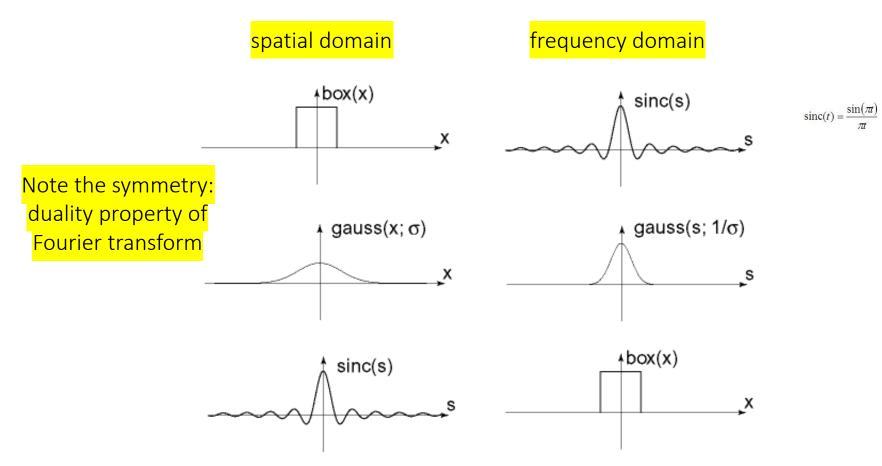
$$|F(u,v)| = \sqrt{R^2(u,v) + I^2(u,v)}$$

Is called the Fourier spectrum and

$$\theta(u, v) = \arctan\left(\frac{I(u, v)}{R(u, v)}\right)$$

Is called the phase angle

Fourier transform pairs



Computing the discrete Fourier transform (DFT)

Computing the discrete Fourier transform (DFT)

$$F(k) = \frac{1}{N} \sum_{x=0}^{N-1} f(x) e^{-j2\pi kx/N}$$
 is just a matrix multiplication:

$$F = Wf$$

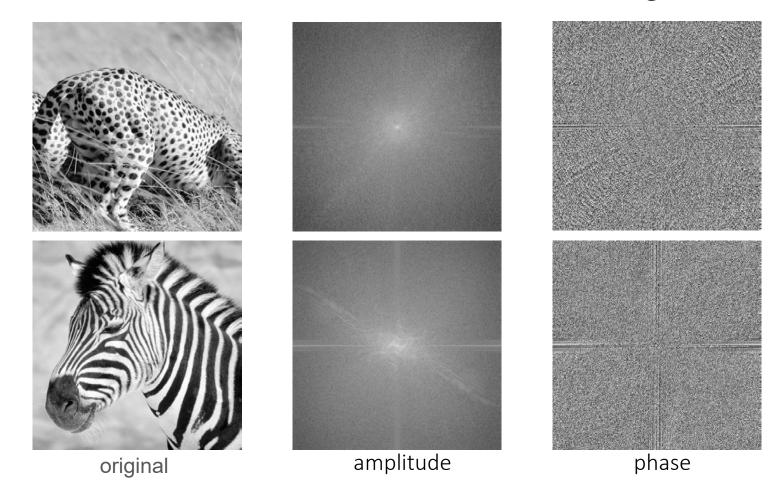
• Basically a matrix-vector product:

$$\begin{bmatrix} X_0 \\ X_1 \\ X_2 \\ \vdots \\ X_{N-1} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 & \cdots & 1 \\ 1 & W_N & W_N^2 & W_N^3 & \cdots & W_N^{N-1} \\ 1 & W_N^2 & W_N^4 & W_{N6} & \cdots & W_N^{2(N-1)} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & W_N^{N-1} & W_N^{2(N-1)} & \cdots & \cdots & W_N^{(N-1)(N-1)} \end{bmatrix} \times \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_{N-1} \end{bmatrix}$$

$$(W_N = e^{-j2\pi/N})$$

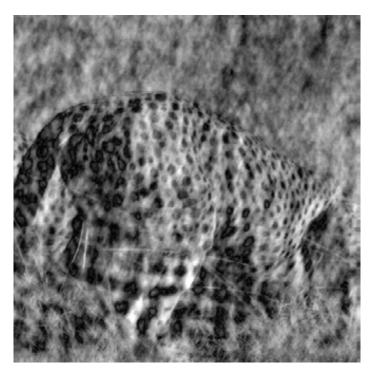
In practice this is implemented using the fast Fourier transform (FFT) algorithm.

Fourier transforms of natural images

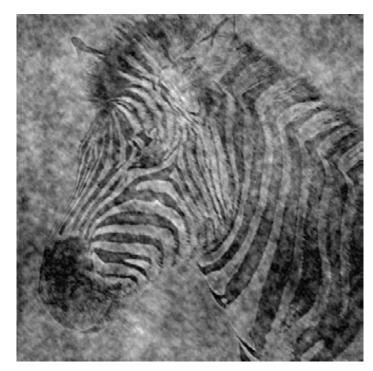


Fourier transforms of natural images

Image phase matters!

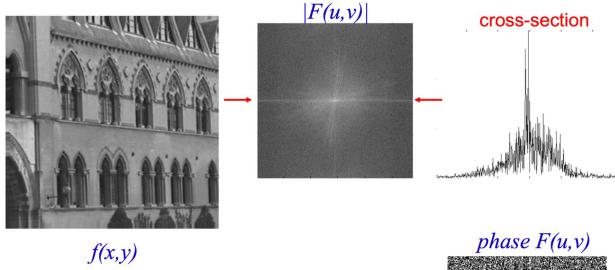


cheetah phase with zebra amplitude

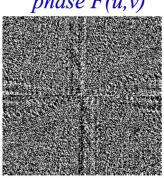


zebra phase with cheetah amplitude

Discrete Fourier Transform - Visualization



- |f(u,v)| generally decreases with higher spatial frequencies
- phase appears less informative



Frequency-domain filtering

Why do we care about all this?

The convolution theorem

The Fourier transform of the convolution of two functions is the product of their Fourier transforms:

$$\mathcal{F}\{g * h\} = \mathcal{F}\{g\}\mathcal{F}\{h\}$$

The inverse Fourier transform of the product of two Fourier transforms is the convolution of the two inverse Fourier transforms:

$$\mathcal{F}^{-1}{gh} = \mathcal{F}^{-1}{g} * \mathcal{F}^{-1}{h}$$

Convolution in spatial domain is equivalent to multiplication in frequency domain!

What do we use convolution for?

Convolution for 1D continuous signals

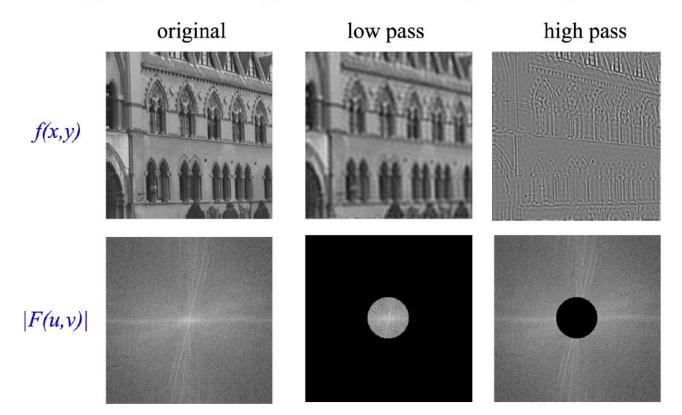
Definition of linear shift-invariant filtering as convolution:

$$(f*g)(x) = \int_{-\infty}^{\infty} f(y)g(x-y)dy$$
 filter signal input signal

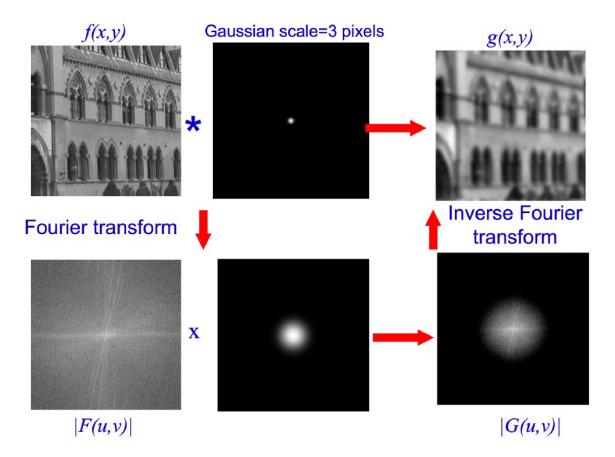
Why implement convolution in frequency domain?

Using the convolution theorem, we can interpret and implement all types of linear shift-invariant filtering as multiplication in frequency domain.

Image Filtering in the Frequency Domain

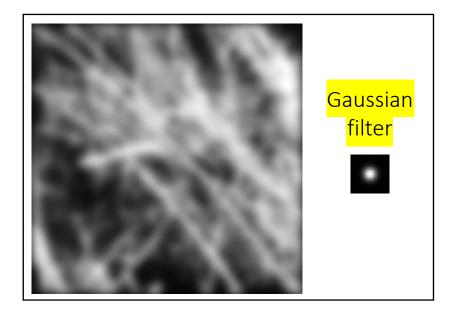


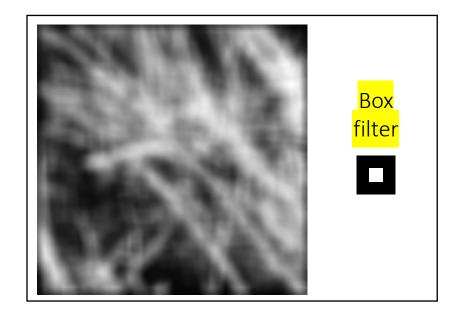
Blurring in the Time vs Frequency Domain



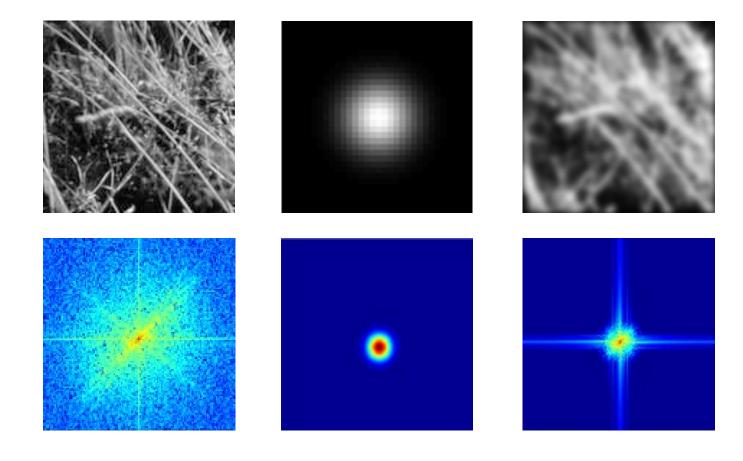
Revisiting blurring

Why does the Gaussian give a nice smooth image, but the square filter give edgy artifacts?

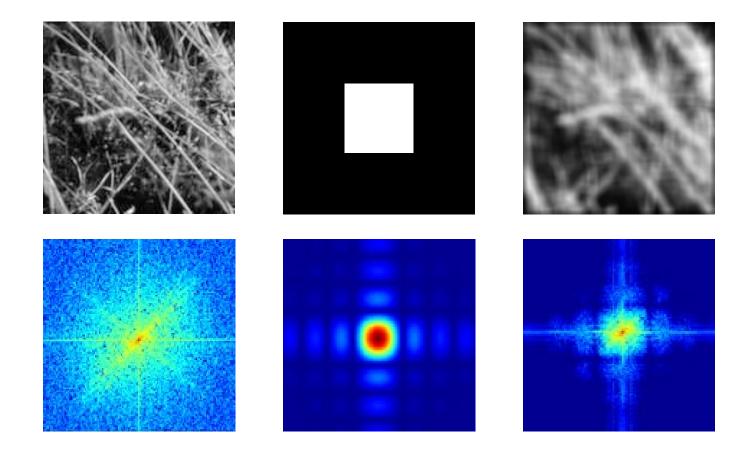




Gaussian blur



Box blur

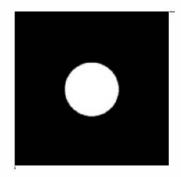


Ideal Low-pass filter

An ideal low-pass filter ILPF is defined by:

$$H(u, v) = \begin{cases} 1 & \text{if } D(u, v) \leq D_0 \\ 0 & \text{if } D(u, v) > D_0 \end{cases}$$

The point of transition between H(u, v) = 1 and H(u, v) = 0 is called the **cutoff frequency**



Ideal low pass filter

a b c

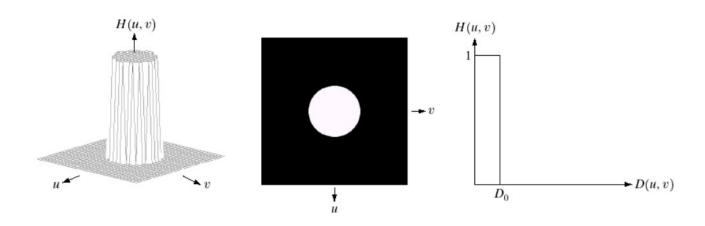
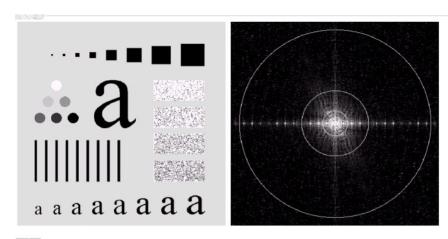


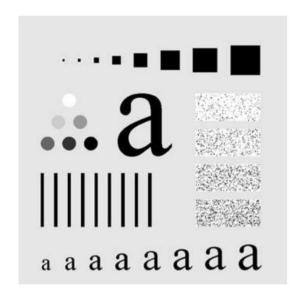
FIGURE 4.10 (a) Perspective plot of an ideal lowpass filter transfer function. (b) Filter displayed as an image. (c) Filter radial cross section.

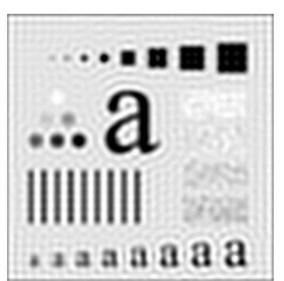
Idel low pass filter



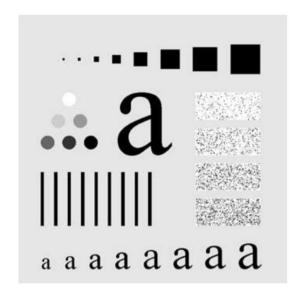
a b

FIGURE 4.11 (a) An image of size 500×500 pixels and (b) its Fourier spectrum. The superimposed circles have radii values of 5, 15, 30, 80, and 230, which enclose 92.0, 94.6, 96.4, 98.0, and 99.5% of the image power, respectively.





ILPF with cutoff frequency =60





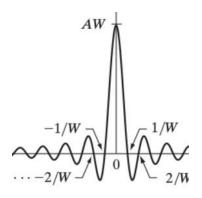
ILPF with cutoff frequency =30

ILPF

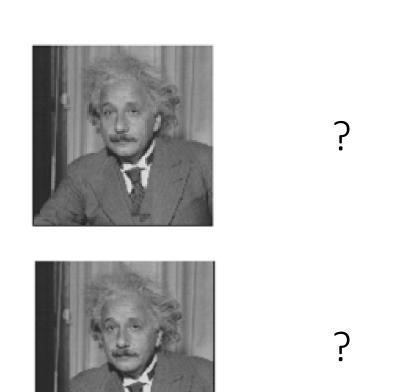
The blurring and ringing properties of ILPFs can be explained using the convolution theorem:

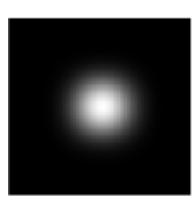
Because a cross section of the ILPF in the frequency domain looks like a box filter, a cross section of the corresponding spatial filter has the shape of a sinc.

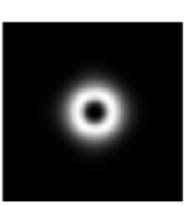
Convolving a sinc with an impulse copies the sinc at the location of the impulse. The sinc center lobe causes the blurring, while the outer lobes are responsible for ringing.

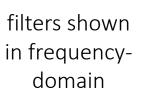


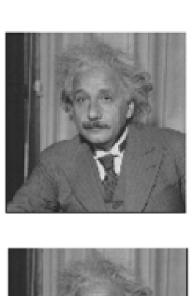
More filtering examples

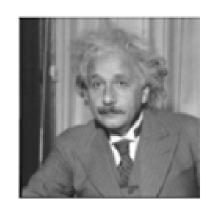


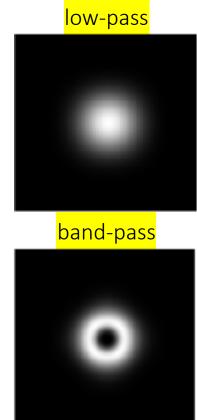


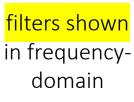


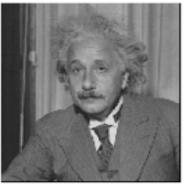




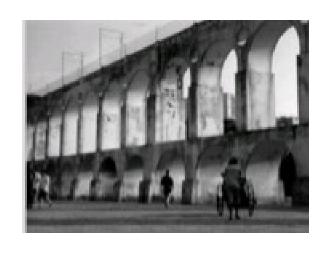






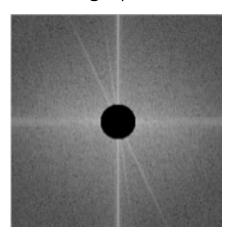


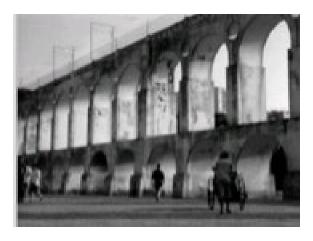


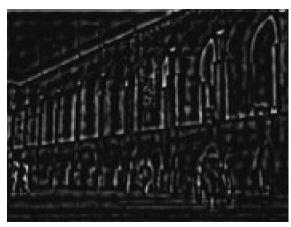


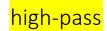
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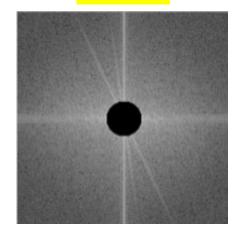
high-pass



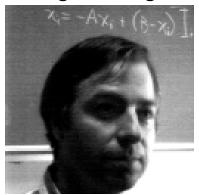




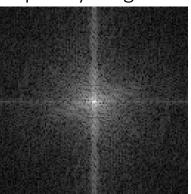




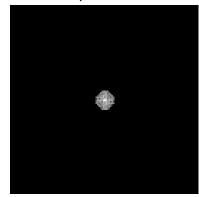
original image



frequency magnitude



low-pass filter

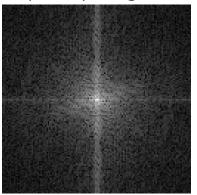


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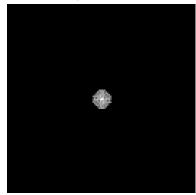
original image

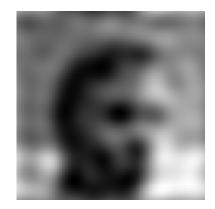


frequency magnitude

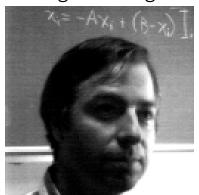


low-pass filter

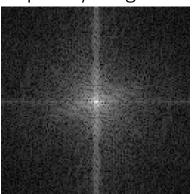




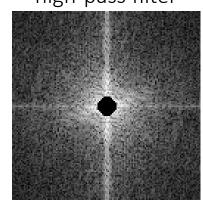
original image



frequency magnitude

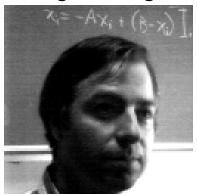


high-pass filter

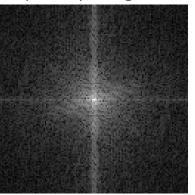


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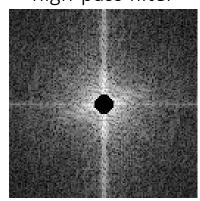
original image



frequency magnitude



high-pass filter

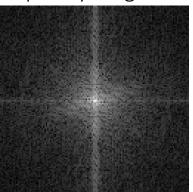




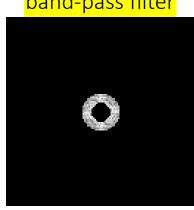
original image



frequency magnitude



band-pass filter

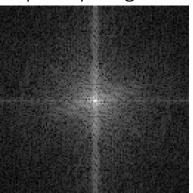




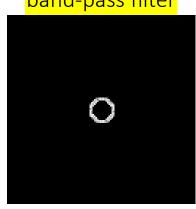
original image

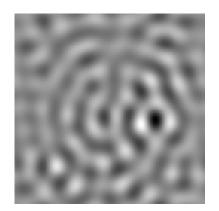


frequency magnitude



band-pass filter

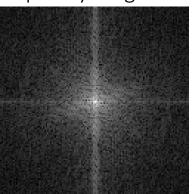




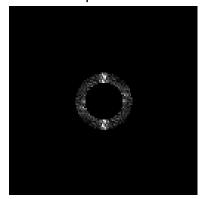
original image



frequency magnitude

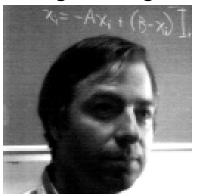


band-pass filter

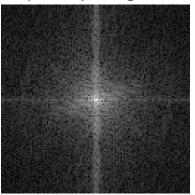




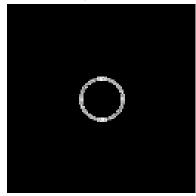
original image

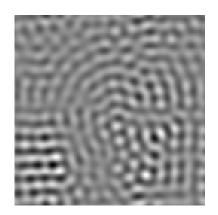


frequency magnitude



band-pass filter





Recognizing character



Revisiting sampling

The Nyquist-Shannon sampling theorem

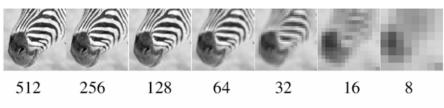
A continuous signal can be perfectly reconstructed from its discrete version using linear interpolation, if sampling occurred with frequency:

$$f_{s} \ge 2f_{\max}$$

This is called the Nyquist frequency

Equivalent reformulation: When downsampling, aliasing does not occur if samples are taken at the Nyquist frequency or higher.

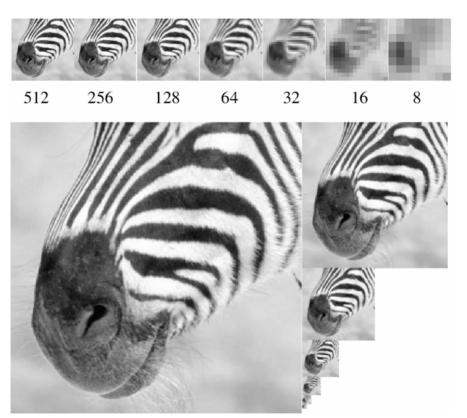
Gaussian pyramid



How does the Nyquist-Shannon theorem relate to the Gaussian pyramid?



Gaussian pyramid



How does the Nyquist-Shannon theorem relate to the Gaussian pyramid?

- Gaussian blurring is low-pass filtering.
- By blurring we try to sufficiently decrease the Nyquist frequency to avoid aliasing.

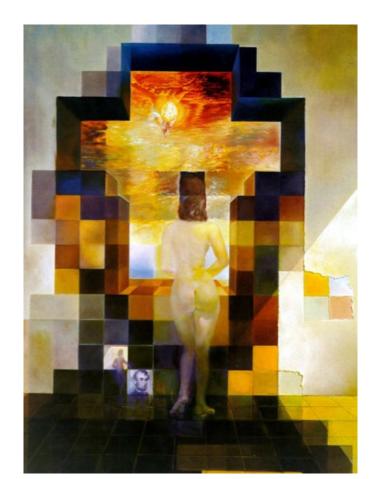
How large should the Gaussian blur we use be?

- The cut-off frequency of the Gaussian filter is proportional to the standard deviation of the filter in the frequency domain
- The range is equal to double the standard deviation. In general we use a mask three times the standard deviation



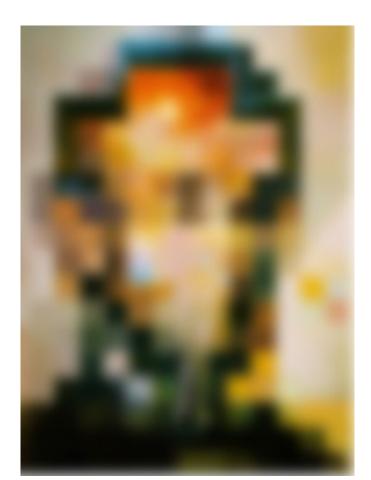
"Hybrid image"

Aude Oliva and Philippe Schyns

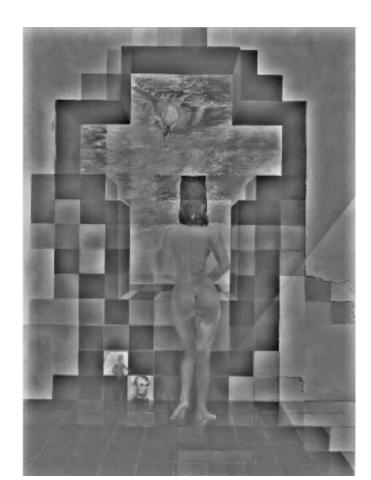


Gala Contemplating the
Mediterranean Sea Which at Twenty
Meters Becomes the Portrait of
Abraham Lincoln
(Homage to Rothko)

Salvador Dali, 1976



Low-pass filtered version



High-pass filtered version

Acknowledgement: some slides and material from Bernt Schiele, Mario Fritz, Michael Black, Bill Freeman, Fei-Fei, Justin Johnson, Serena Yeung, R. Szelisky, Fabio Galasso, Ioannis Gkioulekas