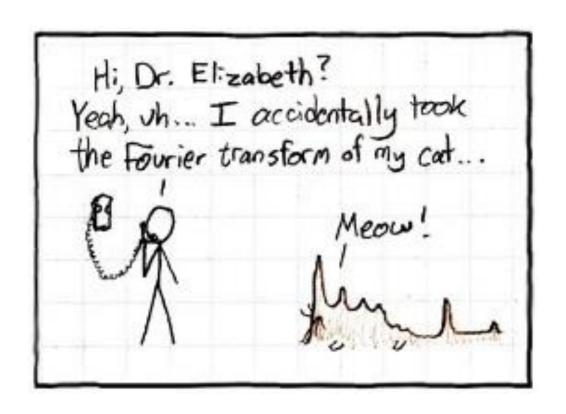
# Fourier Transform and Frequency Domain



# Overview of today's lecture

- Some history.
- Fourier series.
- Frequency domain.
- Fourier transform.
- Frequency-domain filtering.
- Revisiting sampling.

#### Slide credits

Most of these slides were adapted from:

Kris Kitani (15-463, Fall 2016).

Some slides were inspired or taken from:

- Fredo Durand (MIT).
- James Hays (Georgia Tech).

# Some history

# Who is this guy?



#### What is he famous for?



Jean Baptiste Joseph Fourier (1768-1830)

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Jean Baptiste Joseph Fourier (1768-1830)

The Fourier series claim (1807):

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

... and apparently also for the discovery of the greenhouse effect

#### Is this claim true?



Jean Baptiste Joseph Fourier (1768-1830)

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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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- Close enough to be named after him.
- Very surprising result at the time.



Malus



Lagrange



Legendre



Laplace

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

## Amusing aside



# Only known portrait of Adrien-Marie Legendre

1820 watercolor <u>caricatures</u> of French mathematicians <u>Adrien-Marie Legendre</u> (left) and Joseph Fourier (right) by French artist <u>Julien-Leopold Boilly</u>

For two hundred years, people were misidentifying this portrait as him



Louis Legendre (same last name, different person)

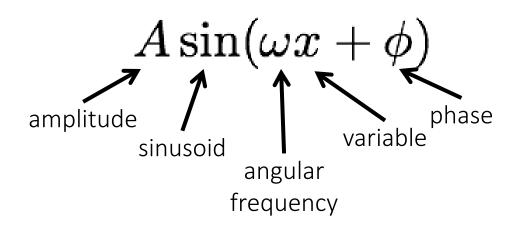
#### Fourier series

## Basic building block

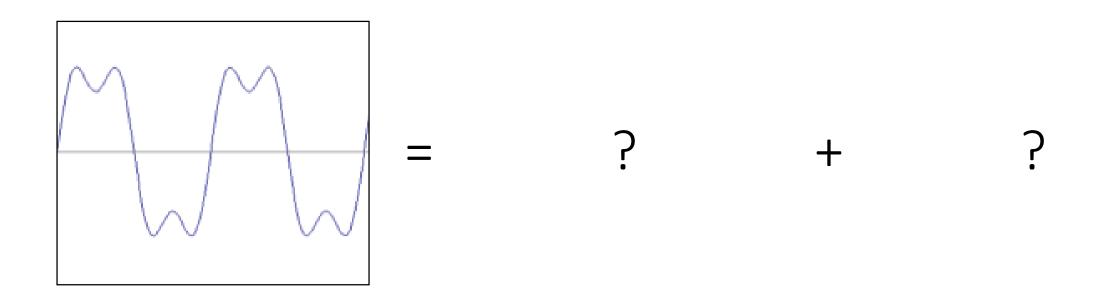
$$A\sin(\omega x + \phi)$$

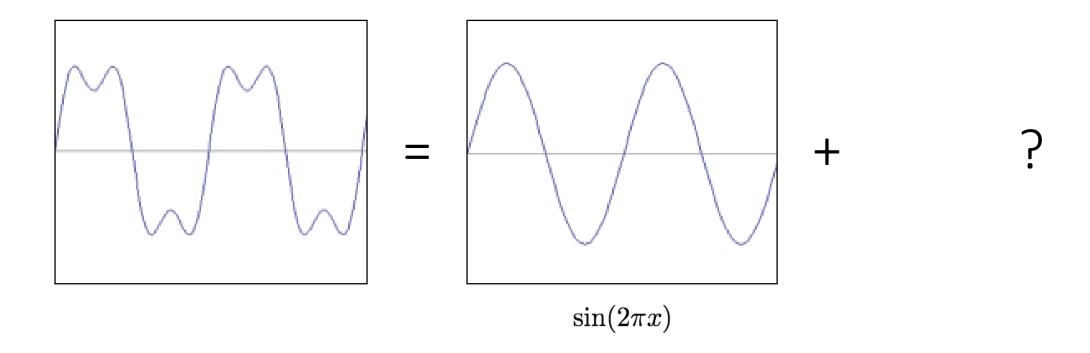
Fourier's claim: Add enough of these to get any periodic signal you want!

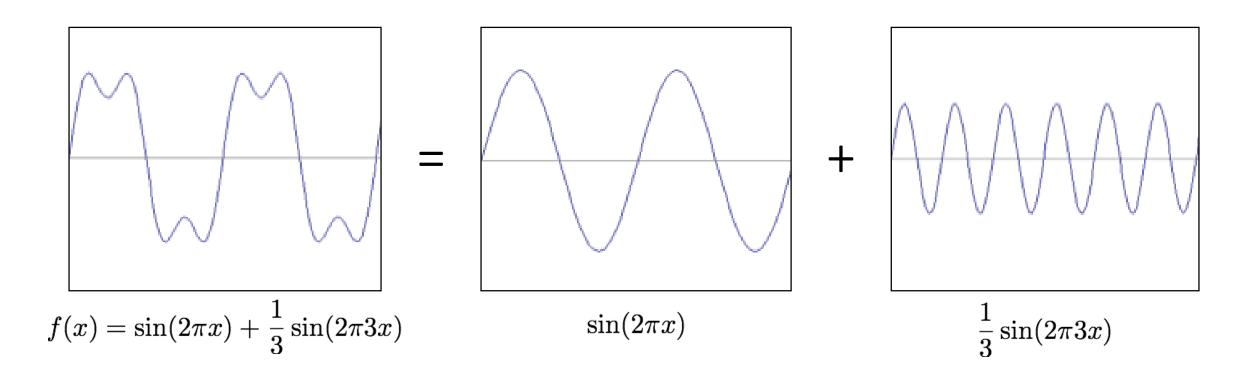
## Basic building block

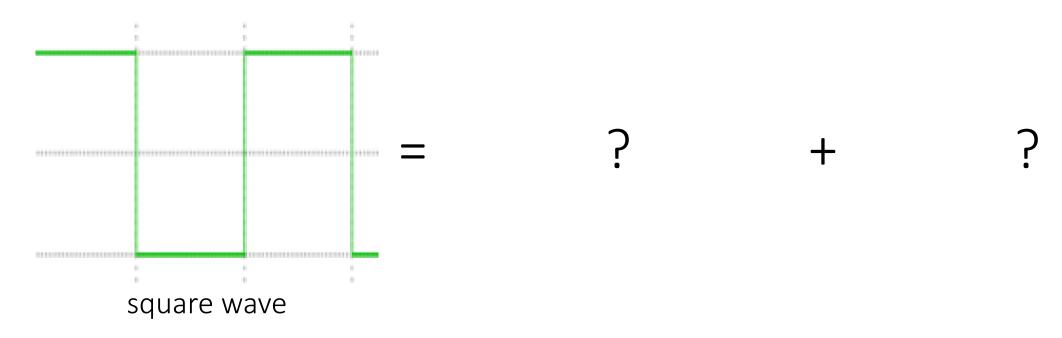


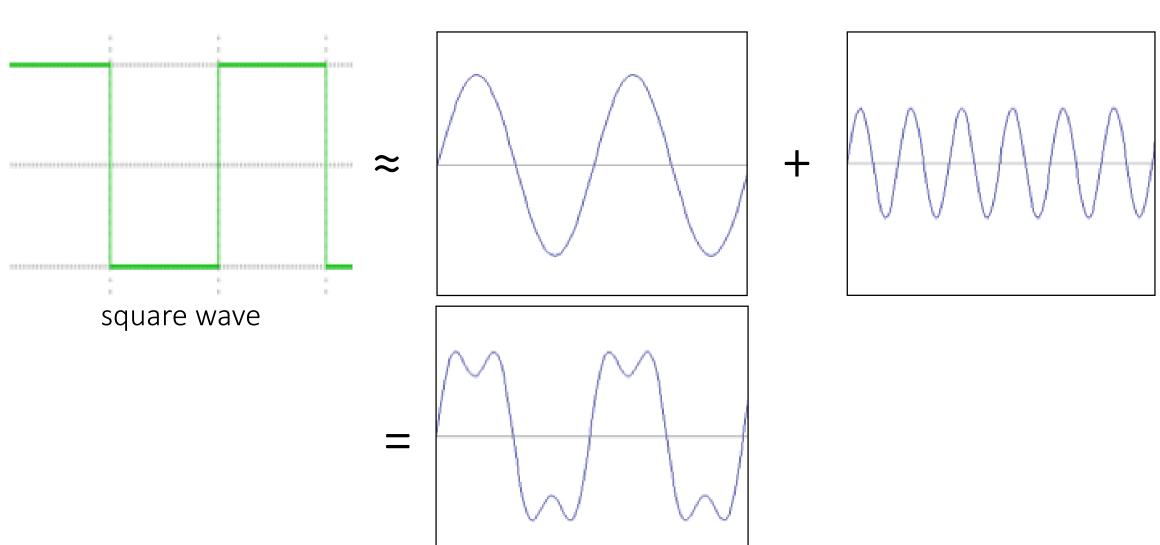
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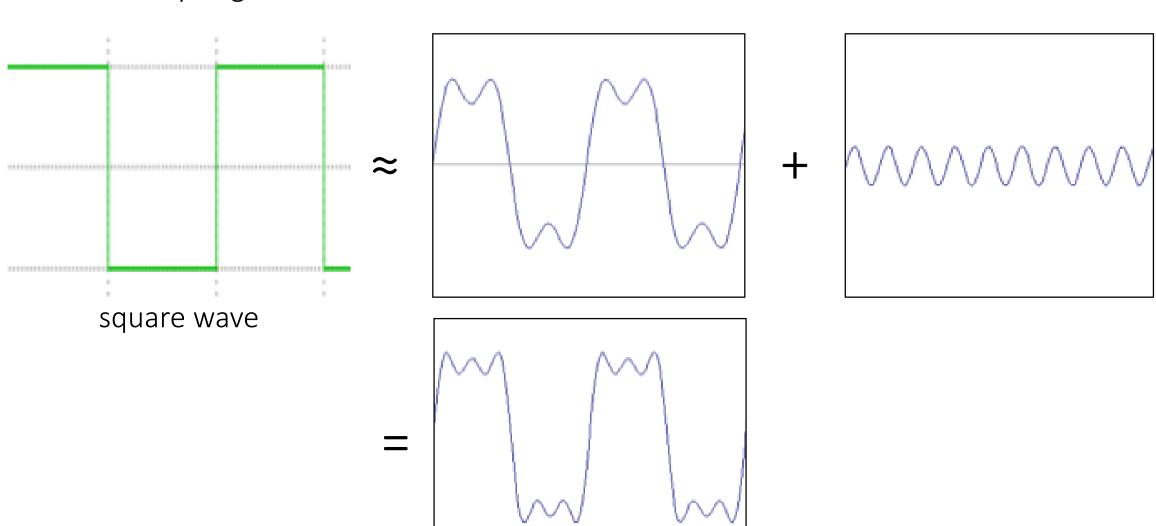


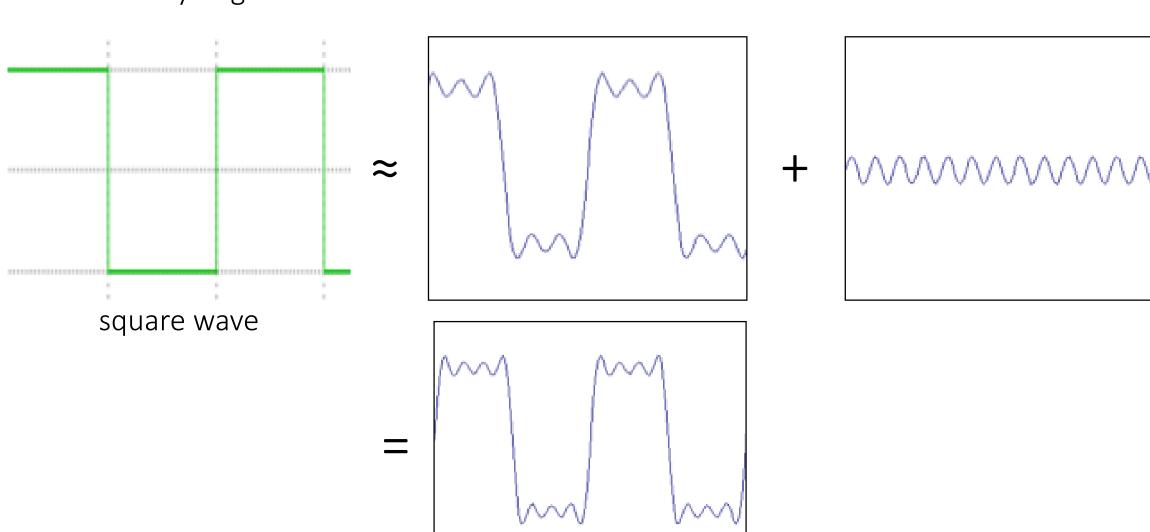


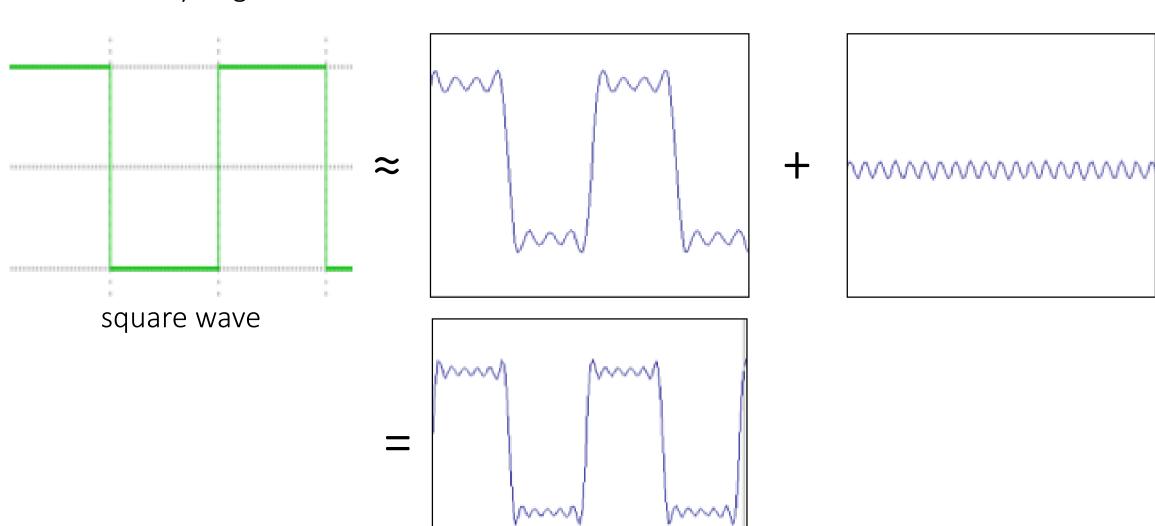


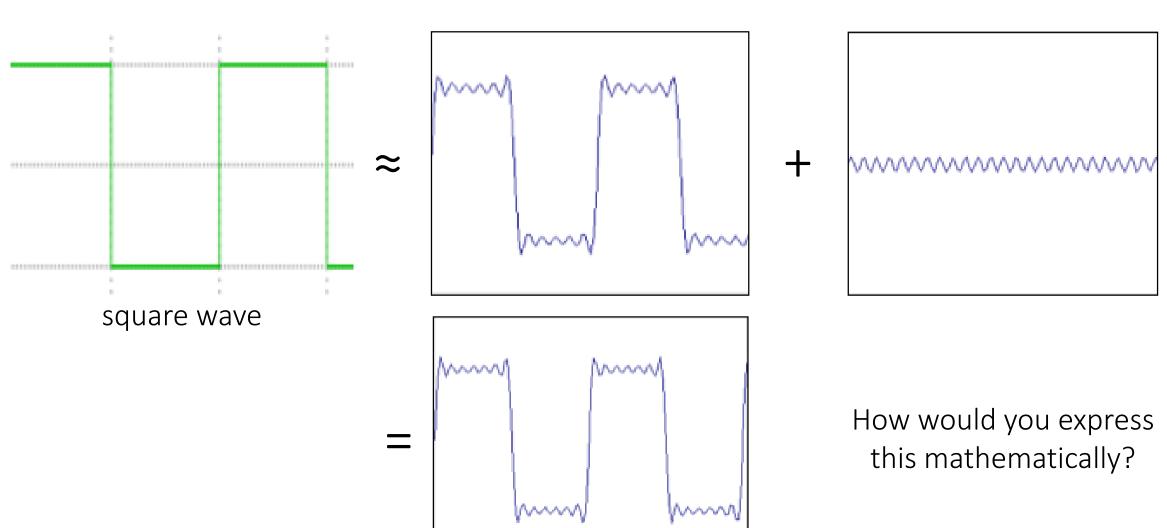


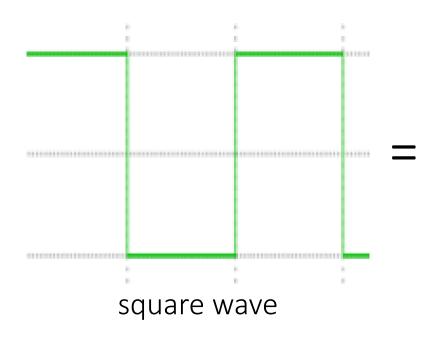








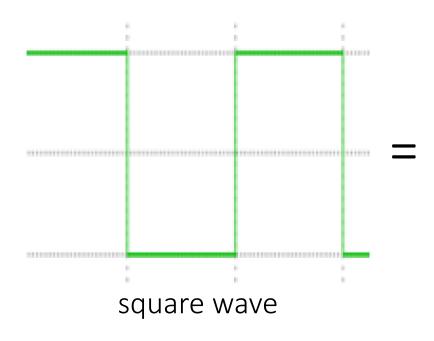




$$A\sum_{k=1}^{\infty} \frac{1}{k} \sin(2\pi kx)$$

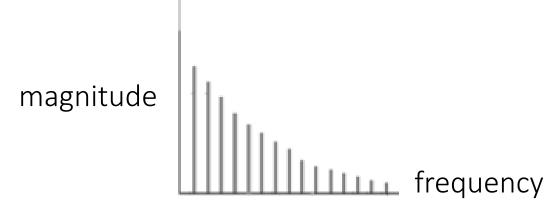
infinite sum of sine waves

How would could you visualize this in the frequency domain?

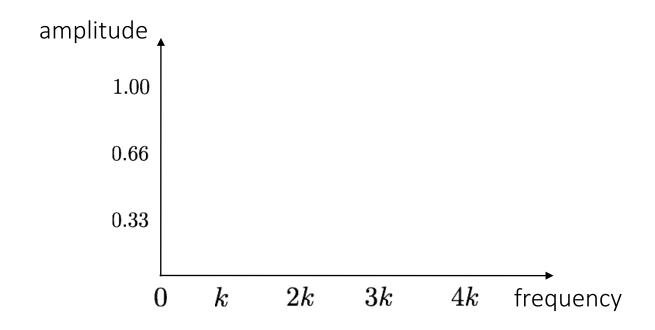


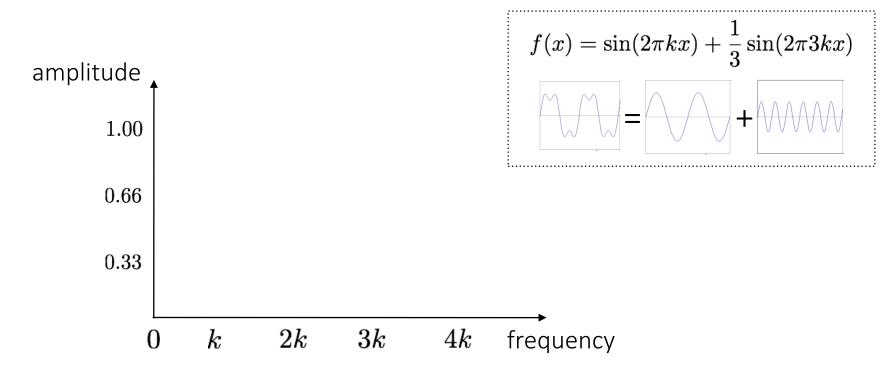
$$A\sum_{k=1}^{\infty} \frac{1}{k} \sin(2\pi kx)$$

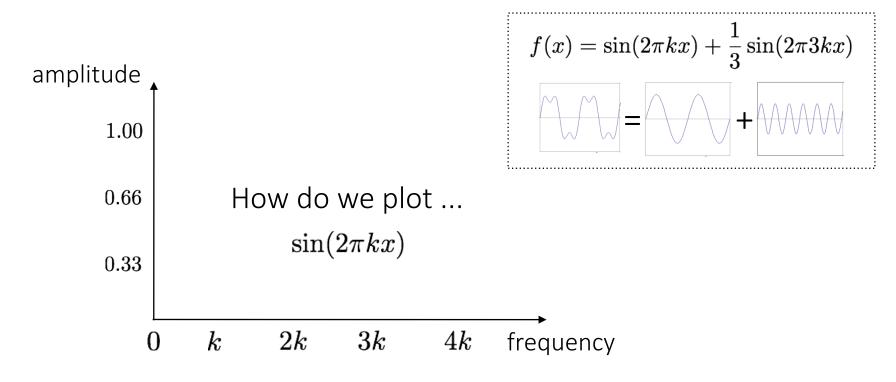
infinite sum of sine waves

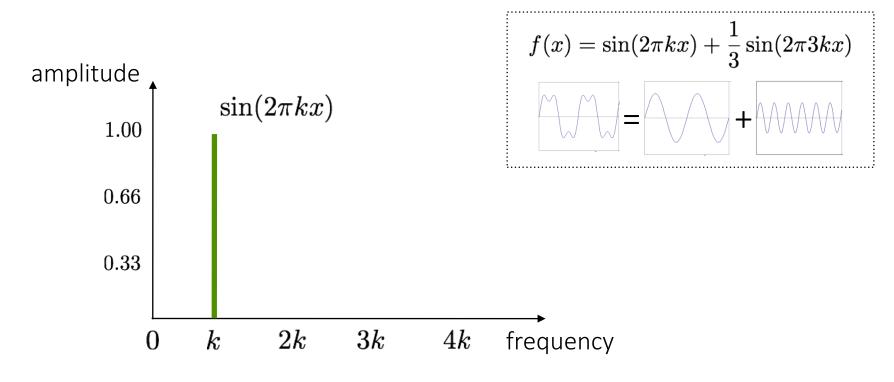


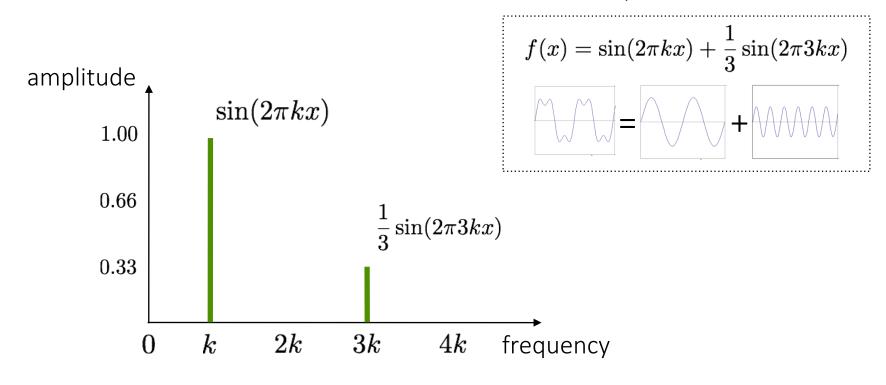
# Frequency domain



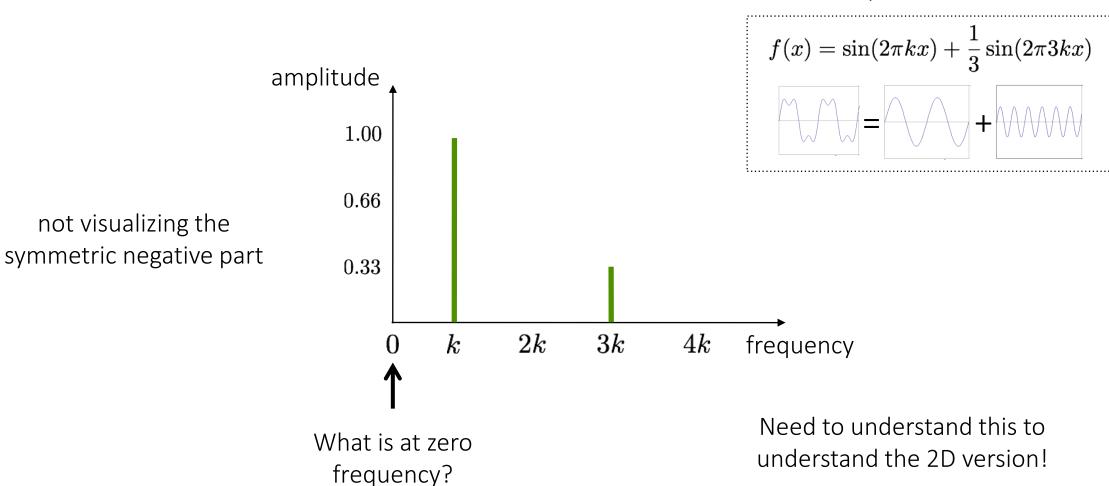




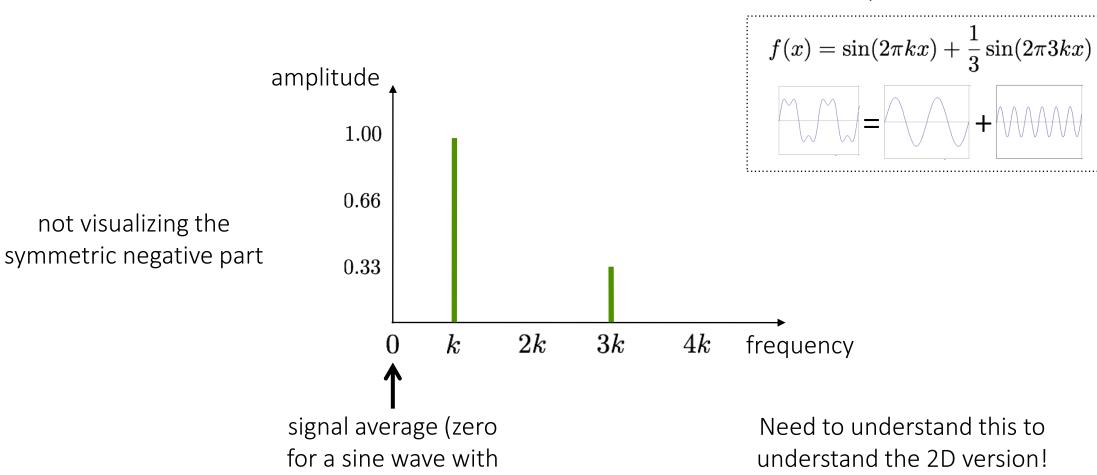




not visualizing the

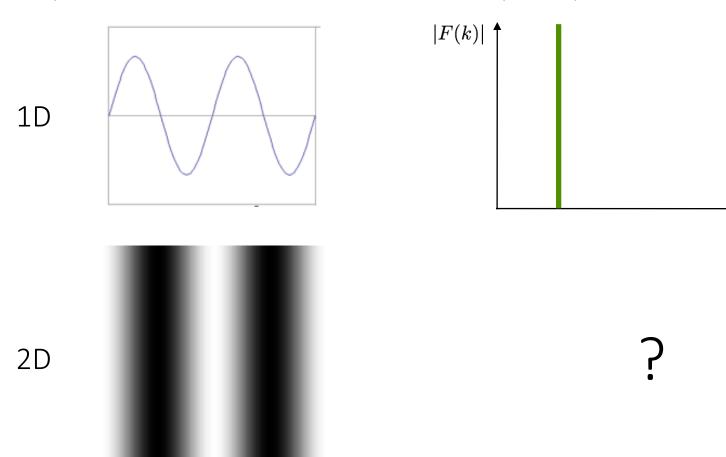


no offset)



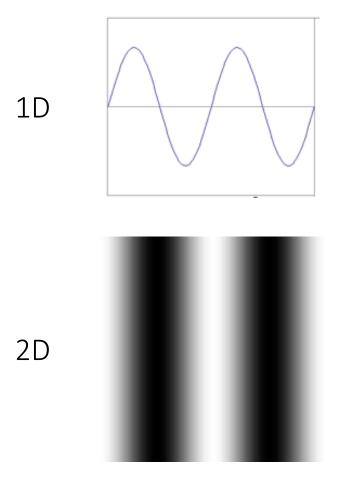
Spatial domain visualization

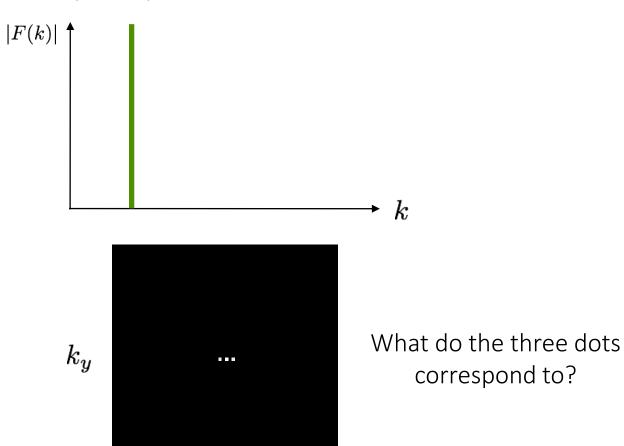
Frequency domain visualization



Spatial domain visualization

Frequency domain visualization

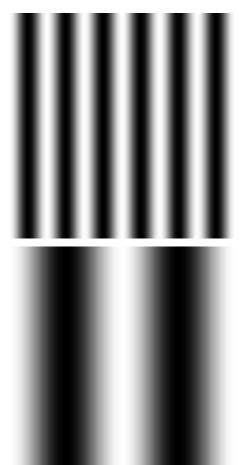




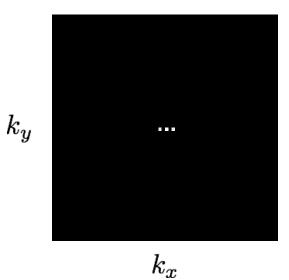
 $k_x$ 

Spatial domain visualization

Frequency domain visualization



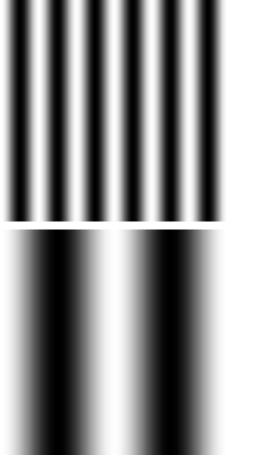
?

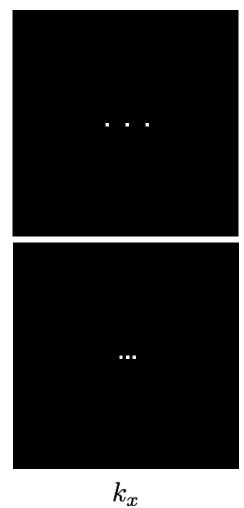


Spatial domain visualization

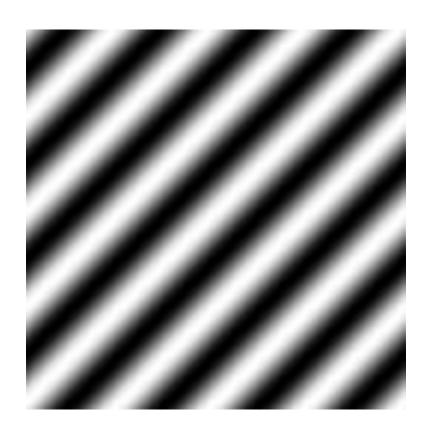
Frequency domain visualization

 $k_y$ 

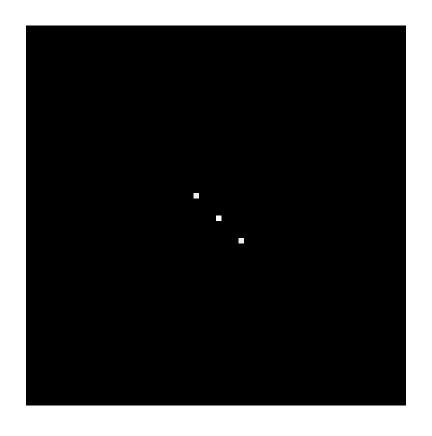




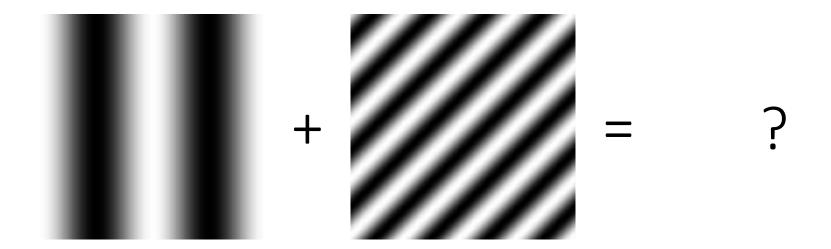
How would you generate this image with sine waves?

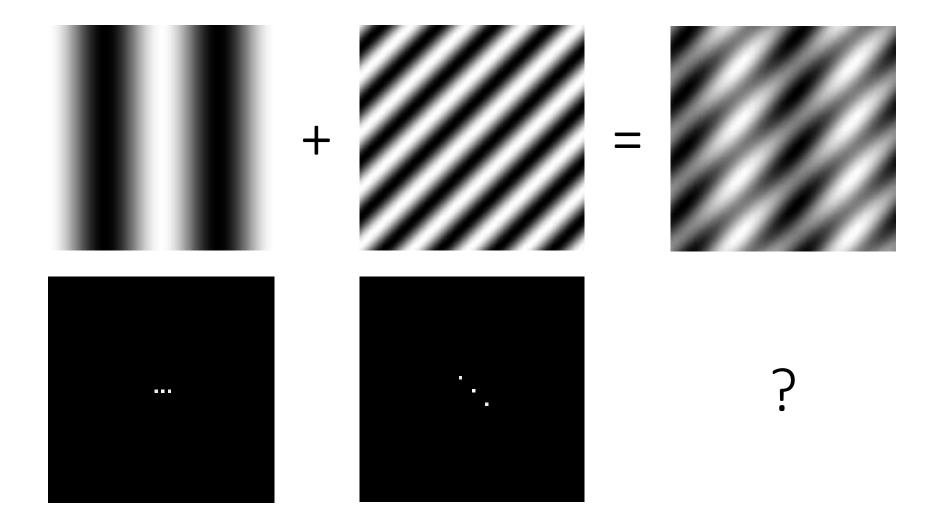


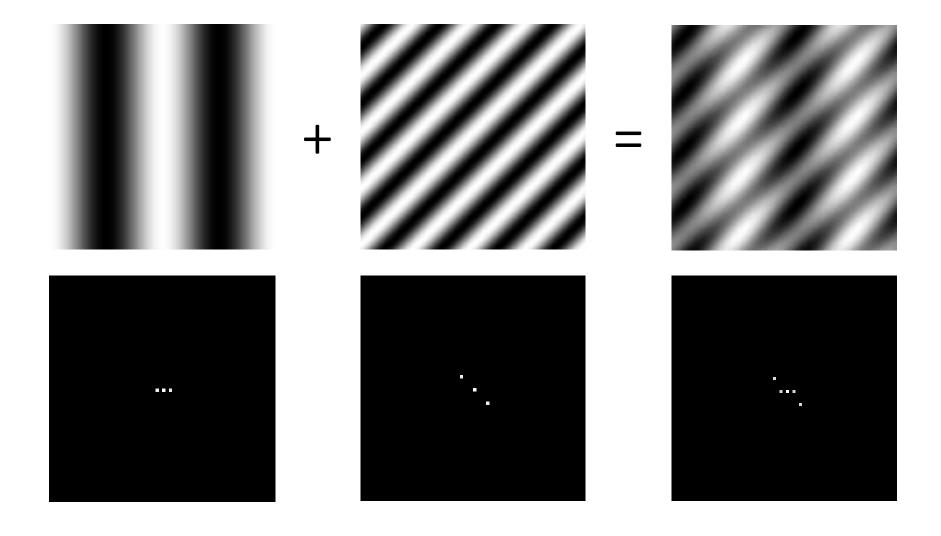
How would you generate this image with sine waves?



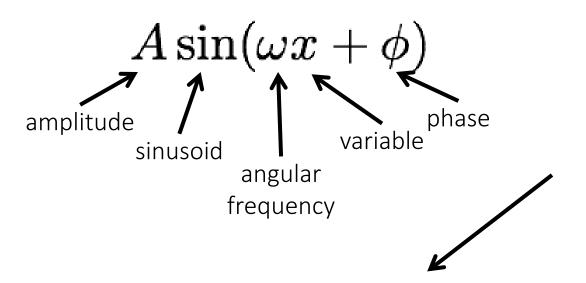
Has both an x and y components







#### Basic building block



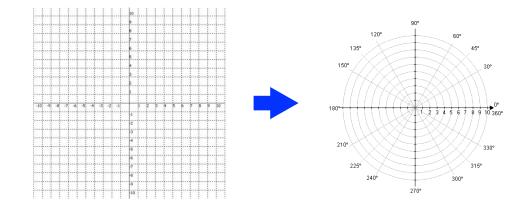
What about non-periodic signals?

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

Complex numbers have two parts:

rectangular coordinates

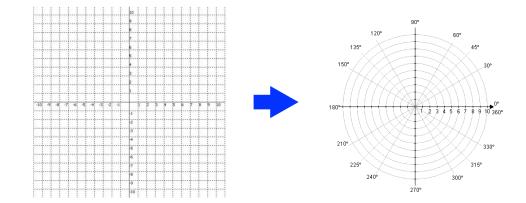
$$R+jI$$
 what's this?



Complex numbers have two parts:

rectangular coordinates

$$R+jI$$
 real imaginary



Complex numbers have two parts:

rectangular coordinates

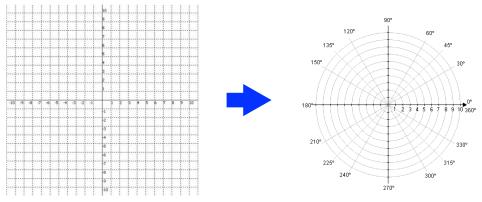
$$R+jI$$
real imaginary

Alternative reparameterization:

polar coordinates

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

how do we compute these?



polar transform

Complex numbers have two parts:

rectangular coordinates

$$R+jI$$
real imaginary

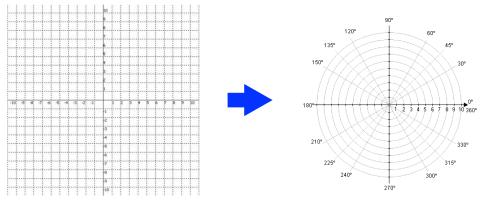
Alternative reparameterization:

polar coordinates

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

polar transform

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



polar transform

Complex numbers have two parts:

rectangular coordinates

$$R+jI$$
real imaginary

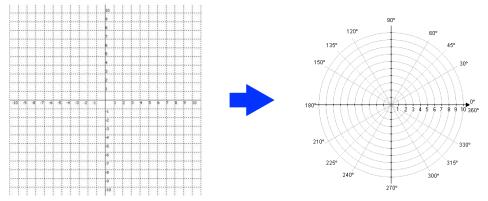
Alternative reparameterization:

polar coordinates

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polar transform

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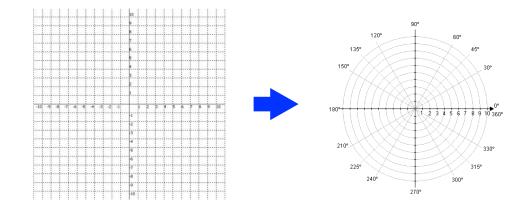
polar transform

How do you write these in 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

$$re^{j\theta}$$

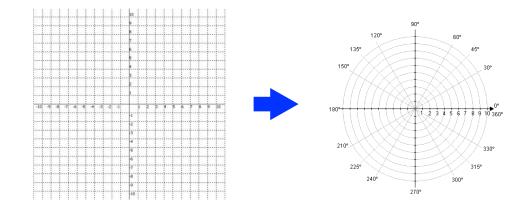
how did we get this?

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

$$re^{j\theta}$$

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

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

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

liscrete

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

Where is the connection to the 'summation of sine waves' idea?

Fourier transform

inverse Fourier transform

continuous

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

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

liscrete

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

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

Where is the connection to the 'summation of sine waves' idea?

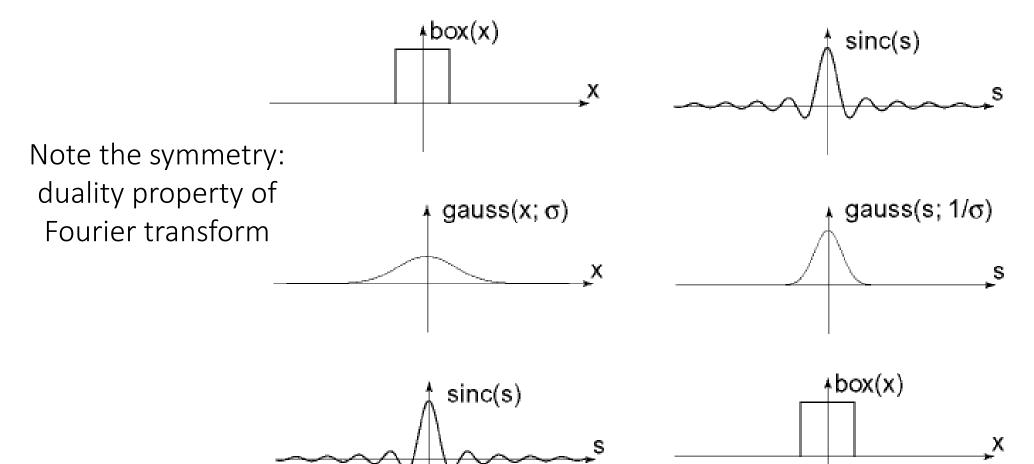
Where is the connection to the 'summation of sine waves' idea?

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

## Fourier transform pairs

spatial domain

frequency domain



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:

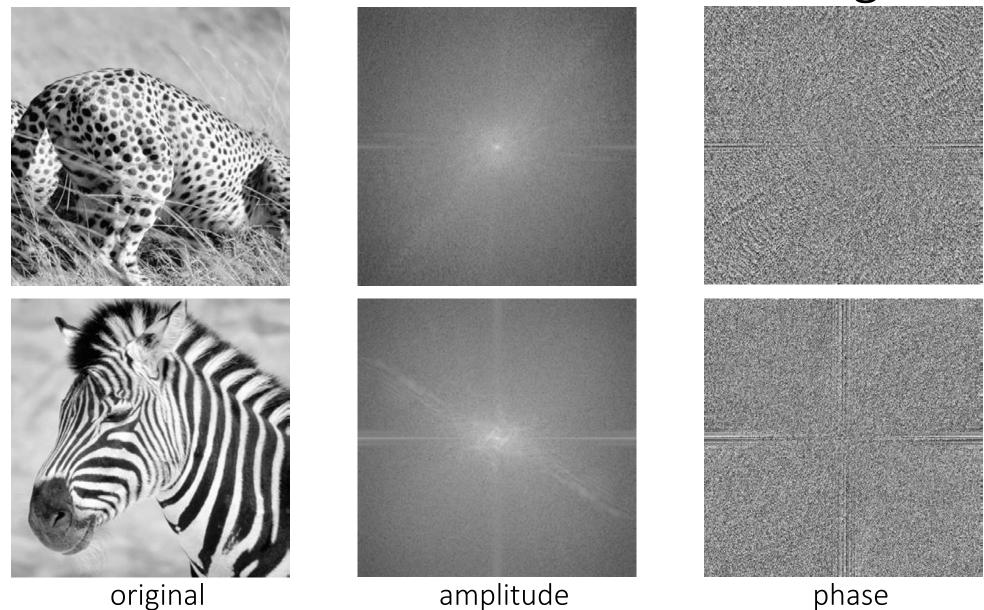
$$F = Wf$$

$$\begin{bmatrix} F(0) \\ F(1) \\ F(2) \\ F(3) \\ \vdots \\ F(N-1) \end{bmatrix} = \begin{bmatrix} W^0 & W^0 & W^0 & W^0 & \cdots & W^0 \\ W^0 & W^1 & W^2 & W^3 & \cdots & W^{N-1} \\ W^0 & W^2 & W^4 & W^6 & \cdots & W^{N-2} \\ W^0 & W^3 & W^6 & W^9 & \cdots & W^{N-3} \\ \vdots & & & & \ddots & \vdots \\ W^0 & W^{N-1} & W^{N-2} & W^{N-3} & \cdots & W^1 \end{bmatrix} \begin{bmatrix} f(0) \\ f(1) \\ f(2) \\ f(3) \\ \vdots \\ f(N-1) \end{bmatrix}$$

$$W = e^{-j2\pi/N}$$

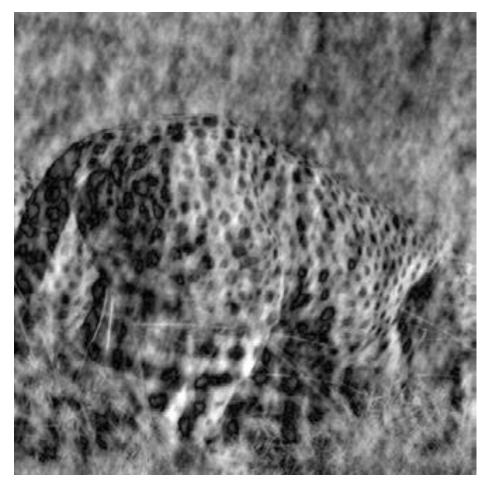
In practice this is implemented using the fast Fourier transform (FFT) algorithm.

## Fourier transforms of natural images

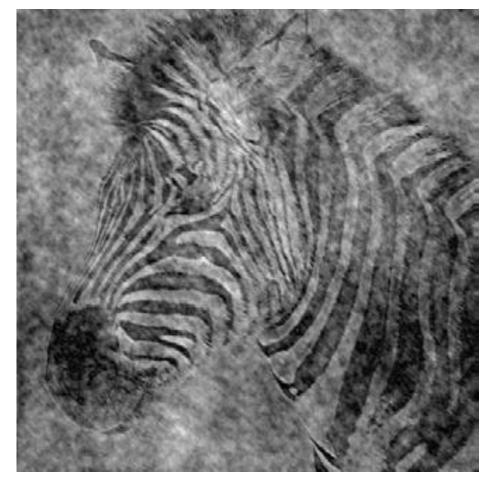


#### Fourier transforms of natural images

Image phase matters!



cheetah phase with zebra amplitude



zebra phase with cheetah amplitude

## 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

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

Why implement convolution in frequency domain?

#### Frequency-domain filtering in Matlab

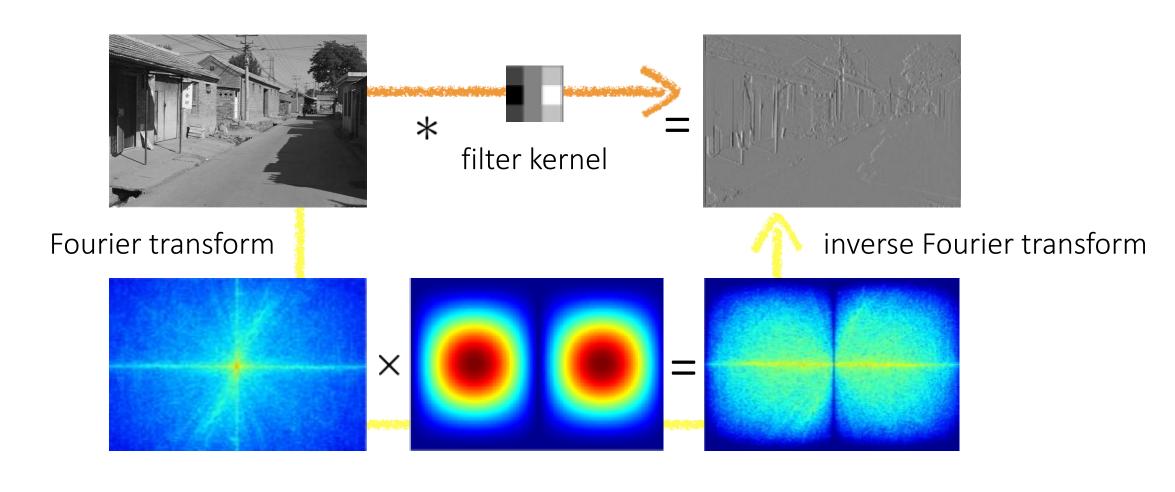
#### Filtering with fft:

```
im = double(imread('...'))/255;
im = rgb2gray(im); % "im" should be a gray-scale floating point image
[imh, imw] = size(im);
hs = 50; % filter half-size
fil = fspecial('gaussian', hs*2+1, 10);
fftsize = 1024; % should be order of 2 (for speed) and include padding
im fft = fft2(im, fftsize, fftsize);
                                                          % 1) fft im with
padding
fil fft = fft2(fil, fftsize, fftsize);
                                                          % 2) fft fil, pad to
same size as image
im fil fft = im fft .* fil fft;
                                                           % 3) multiply fft
images
im fil = ifft2(im fil fft);
                                                          % 4) inverse fft2
im fil = im fil(1+hs:size(im,1)+hs, 1+hs:size(im, 2)+hs); % 5) remove padding
```

#### Displaying with fft:

```
figure(1), imagesc(log(abs(fftshift(im_fft)))), axis image, colormap jet
```

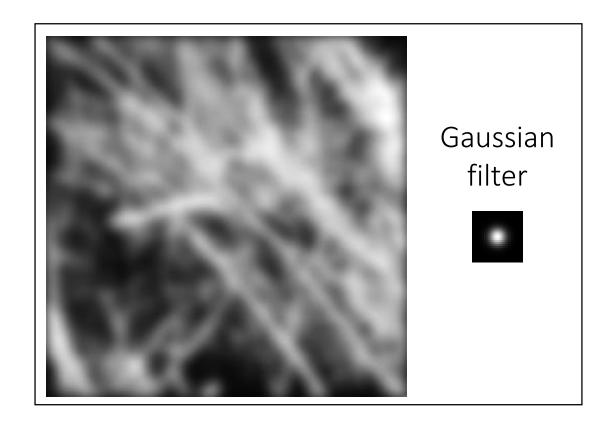
## Spatial domain filtering

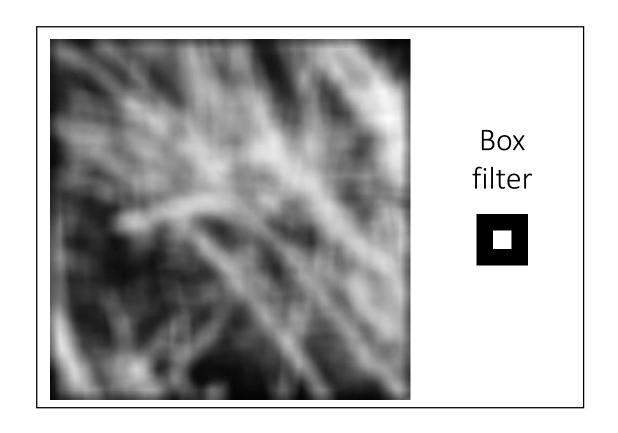


Frequency domain filtering

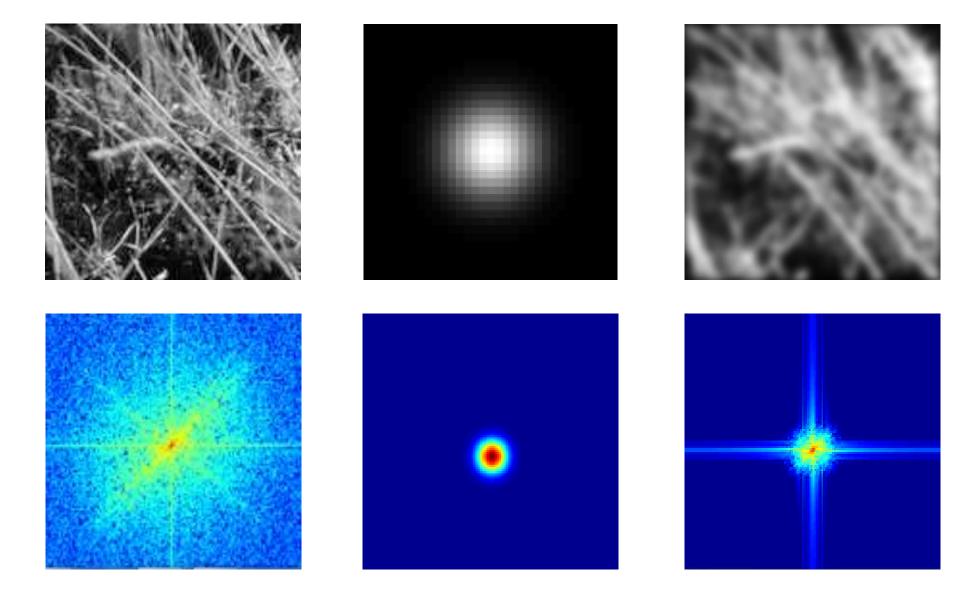
#### Revisiting blurring

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

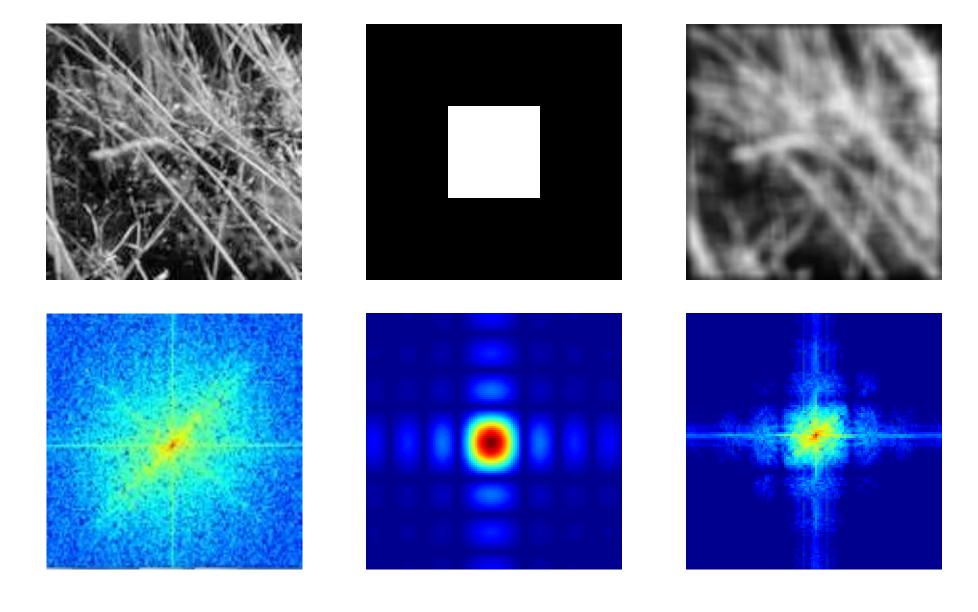




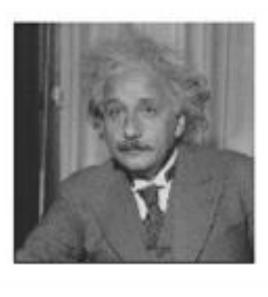
#### Gaussian blur



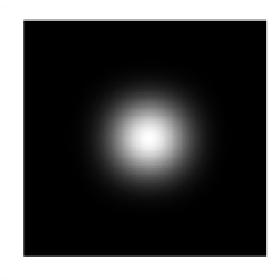
# Box blur



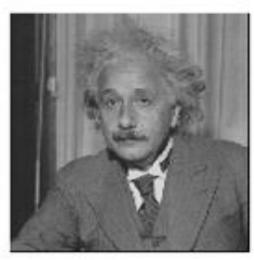
# More filtering examples



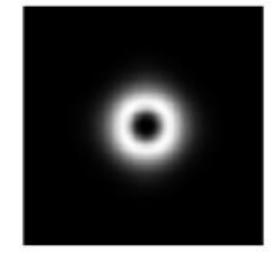
?



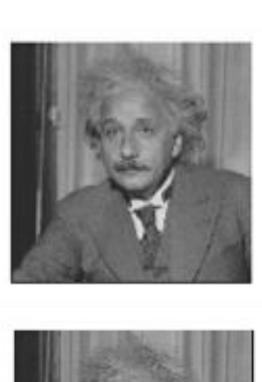
filters shown in frequency-domain

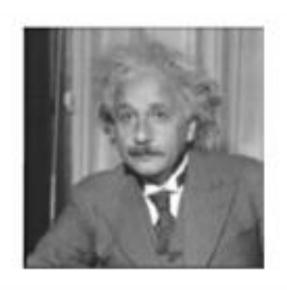


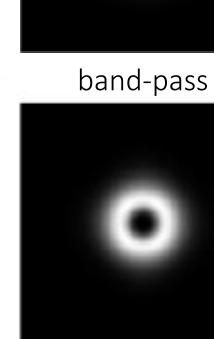
?

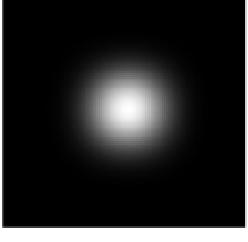


### More filtering examples



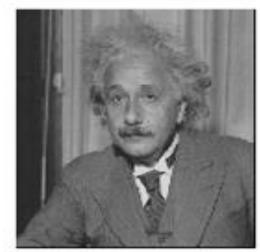






low-pass

filters shown in frequency-domain



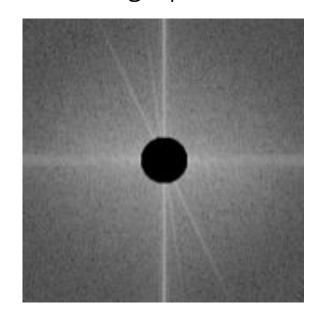


# More filtering examples



 $\dot{7}$ 

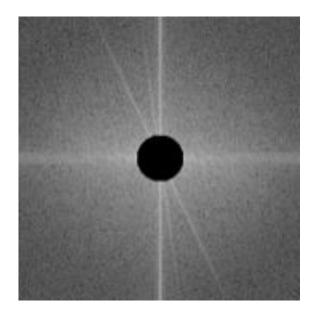
high-pass







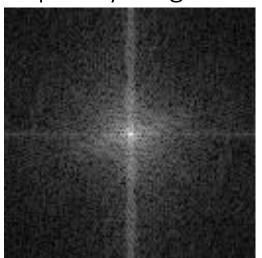
high-pass



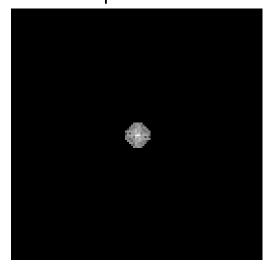
original image



frequency magnitude

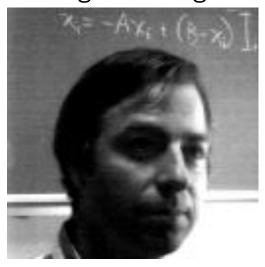


low-pass filter

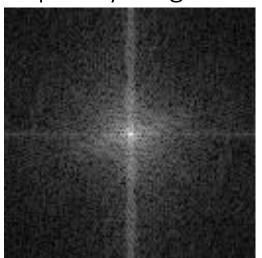




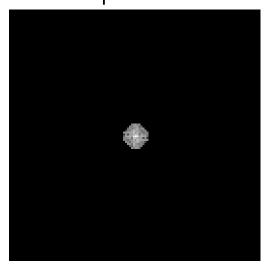
original image

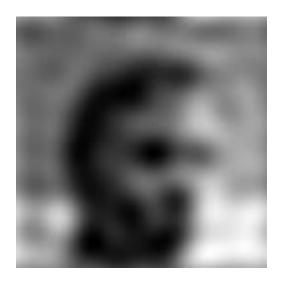


frequency magnitude



low-pass filter

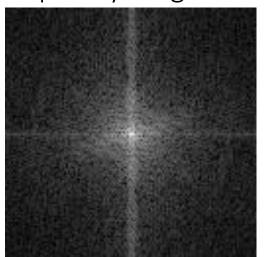




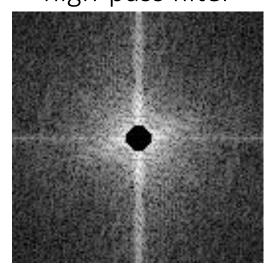
original image



frequency magnitude



high-pass filter

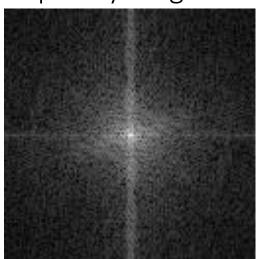




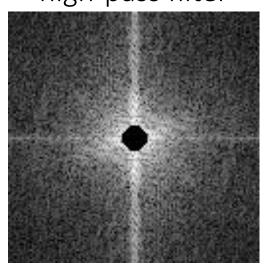
original image



frequency magnitude



high-pass filter

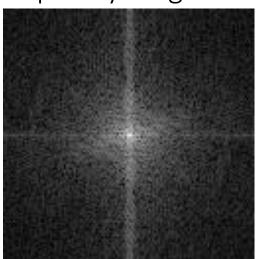




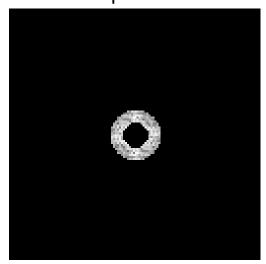
original image



frequency magnitude



band-pass filter

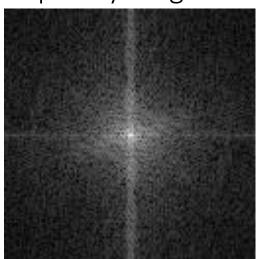




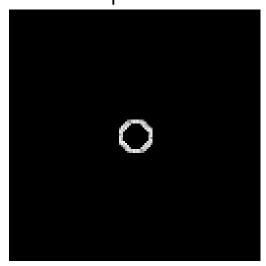
original image

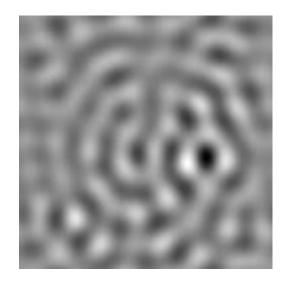


frequency magnitude



band-pass filter

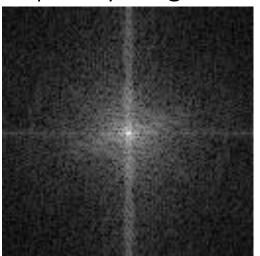




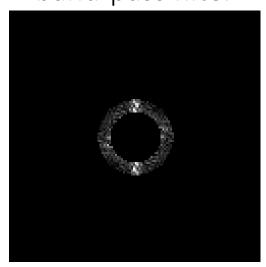
original image



frequency magnitude



band-pass filter

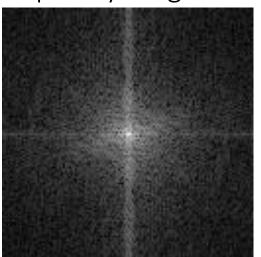




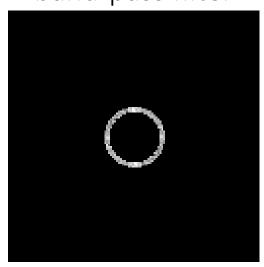
original image

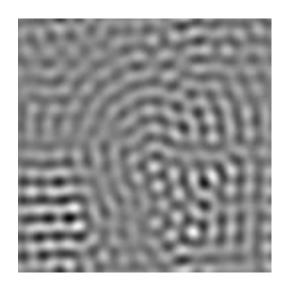


frequency magnitude



band-pass filter





Revisiting sampling

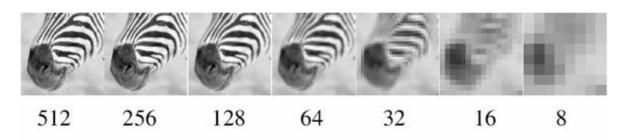
#### The Nyquist-Shannon sampling theorem

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

$$f_{s} \geq 2f_{\max}$$
 — This is called the Nyquist frequency

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

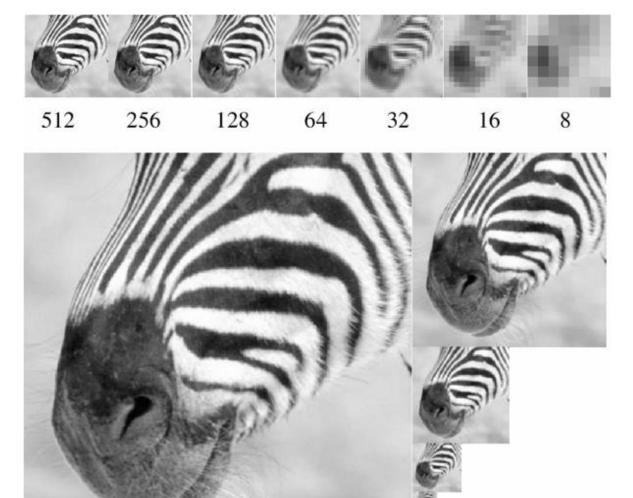
#### Gaussian pyramid



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 Gauss blur we use be?

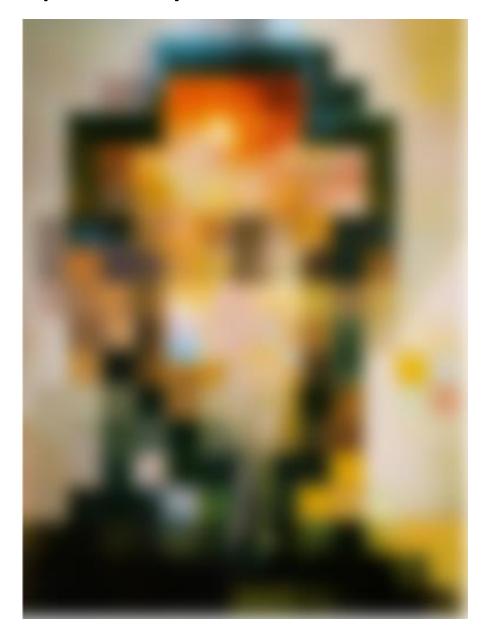
#### Frequency-domain filtering in human vision



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

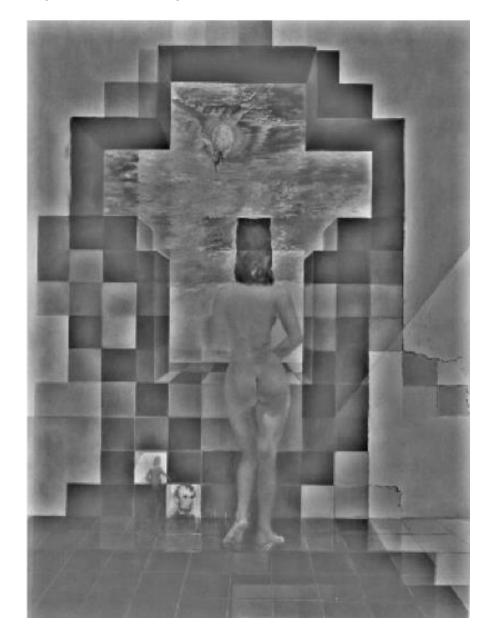
Salvador Dali, 1976

## Frequency-domain filtering in human vision



Low-pass filtered version

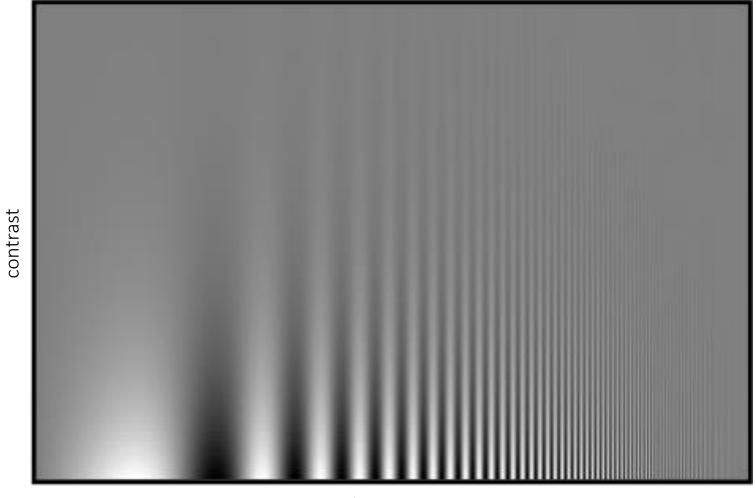
# Frequency-domain filtering in human vision



High-pass filtered version

# Variable frequency sensitivity

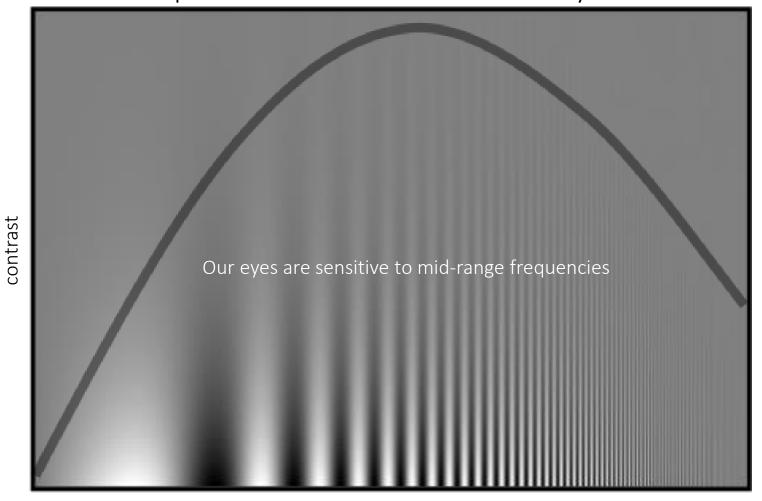
Experiment: Where do you see the stripes?



frequency

#### Variable frequency sensitivity

Campbell-Robson contrast sensitivity curve



- Early processing in humans filters for various orientations and scales of frequency
- Perceptual cues in the mid frequencies dominate perception

frequency

#### References

#### Basic reading:

Szeliski textbook, Sections 3.4.

#### Additional reading:

- Hubel and Wiesel, "Receptive fields, binocular interaction and functional architecture in the cat's visual cortex," The Journal of Physiology 1962
  - a foundational paper describing information processing in the visual system, including the different types of filtering it performs; Hubel and Wiesel won the Nobel Prize in Medicine in 1981 for the discoveries described in this paper