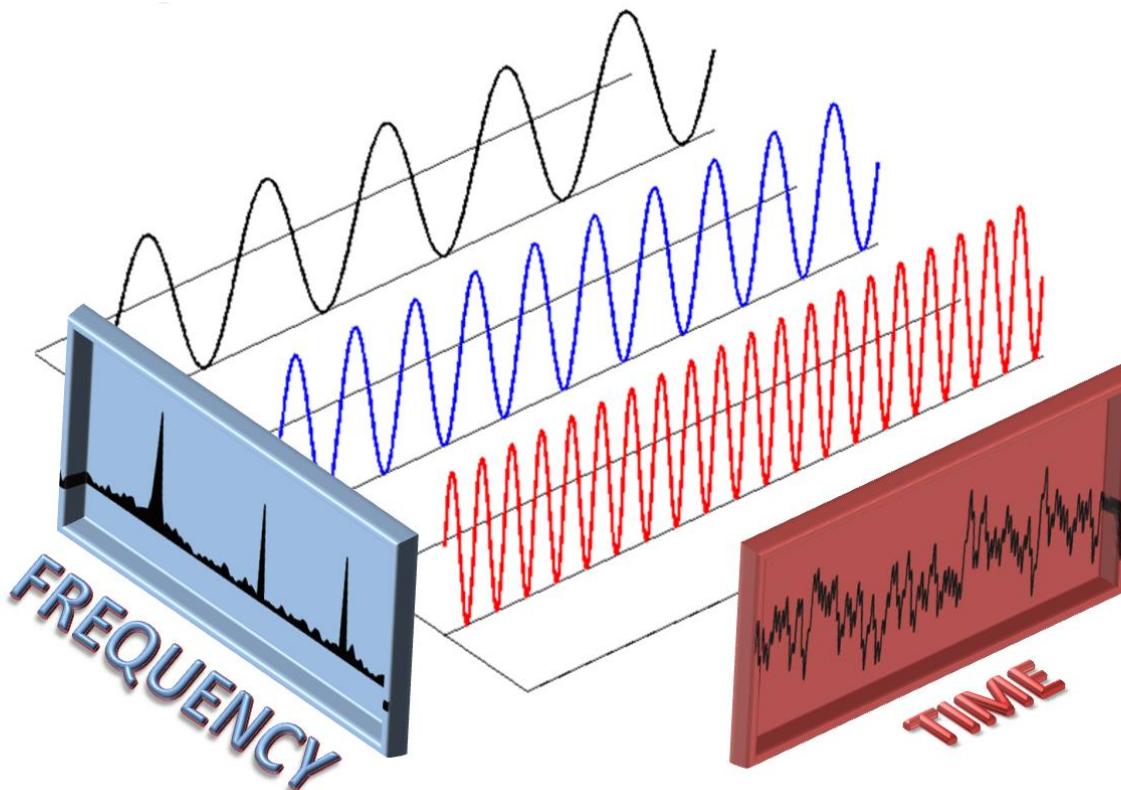
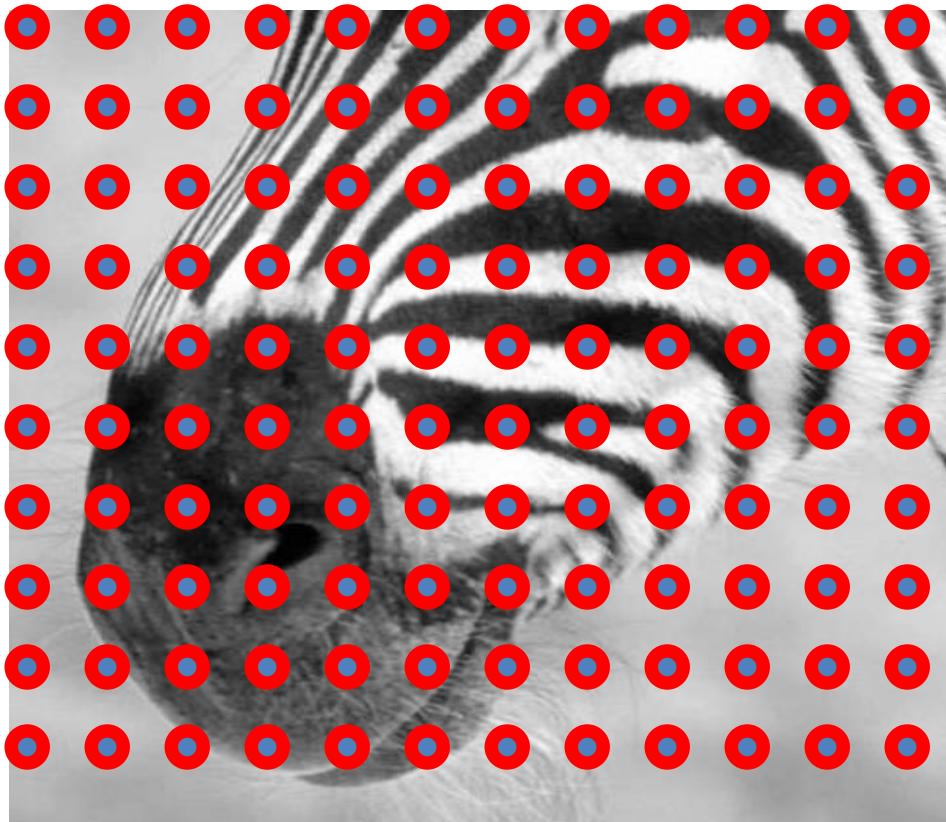


# Thinking in frequencies



# Subsampling by a factor of 2



Throw away every other row and column to create a 1/2 size image

# Sampling and aliasing

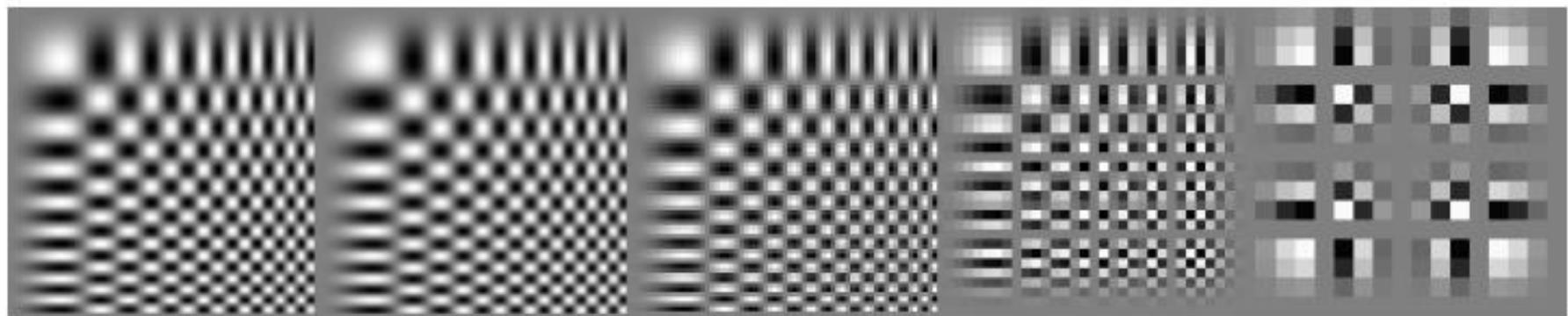
256x256

128x128

64x64

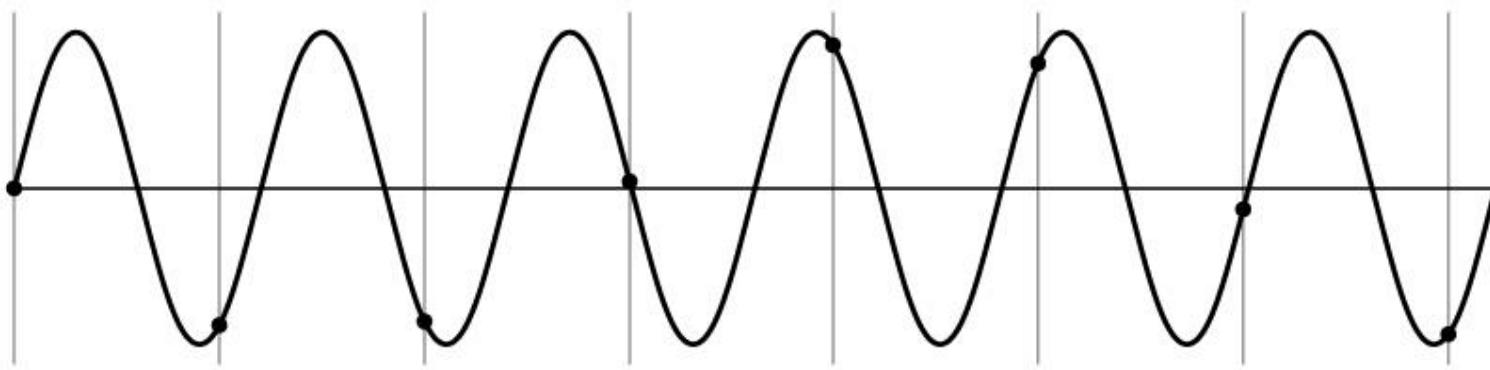
32x32

16x16



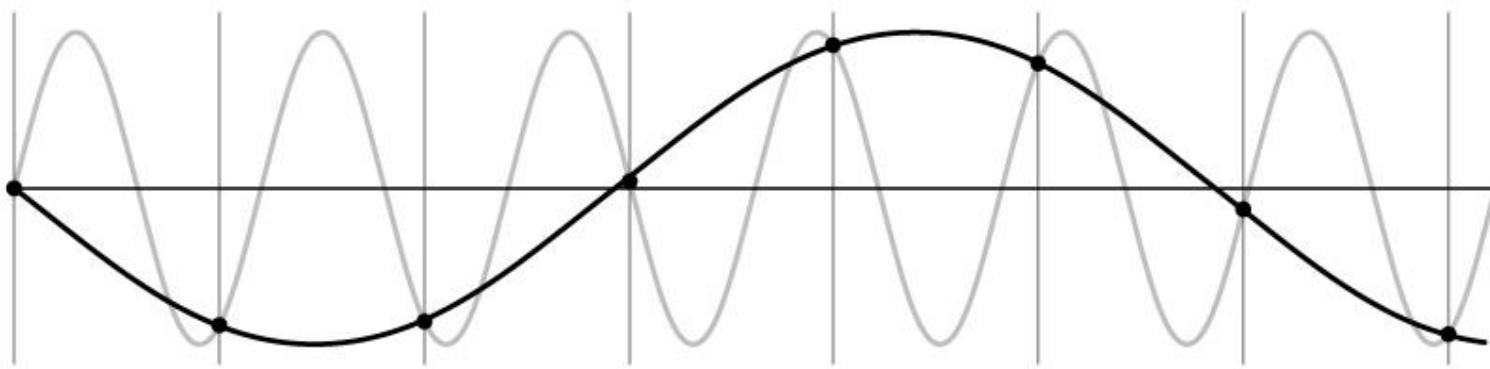
# Aliasing problem

- 1D example (sinewave):



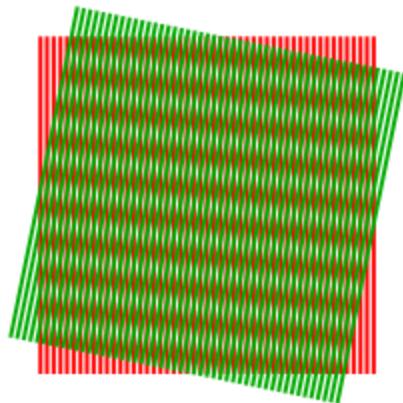
# Aliasing problem

- 1D example (sinewave):



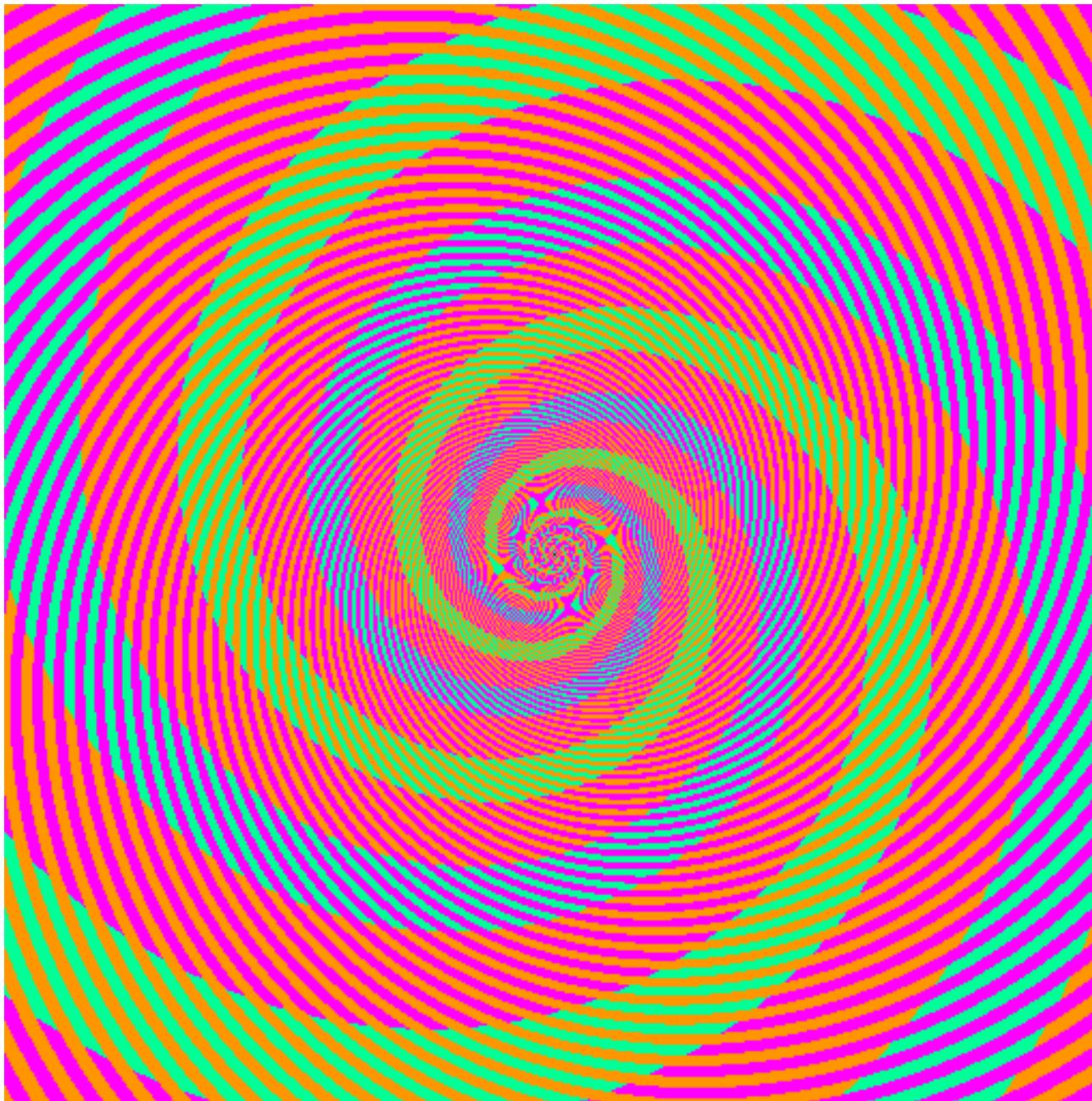
# Aliasing problem

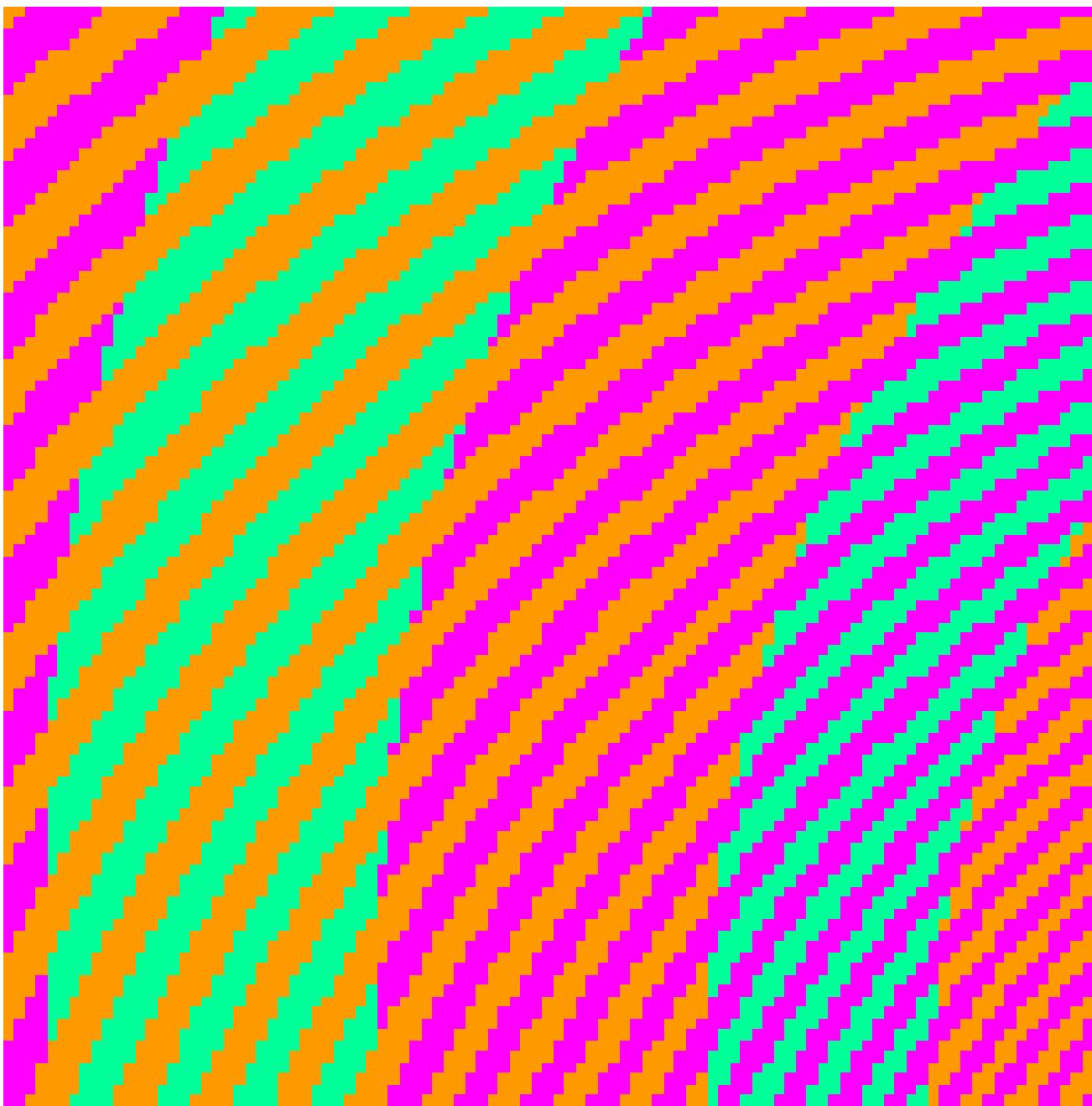
- Sub-sampling may be dangerous....
- Characteristic errors may appear:



# Aliasing in graphics







The blue and green colors are actually the same

<http://blogs.discovermagazine.com/badastronomy/2009/06/24/the-blue-and-the-green/>

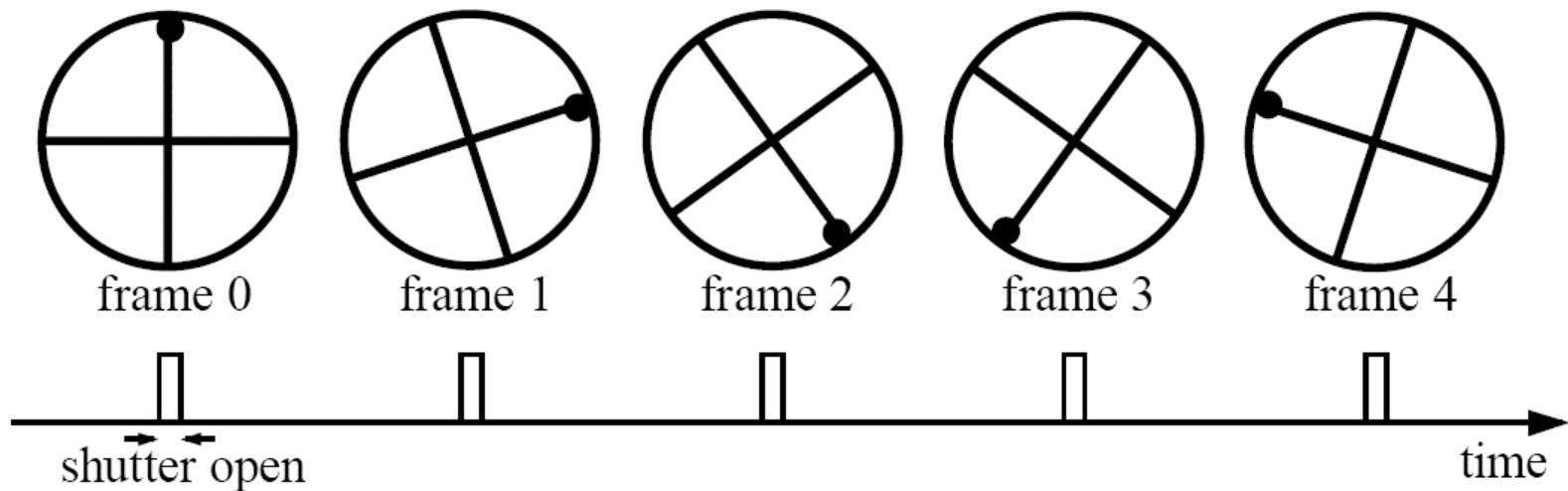
# Videos

# Aliasing in video

Imagine a spoked wheel moving to the right (rotating clockwise).

Mark wheel with dot so we can see what's happening.

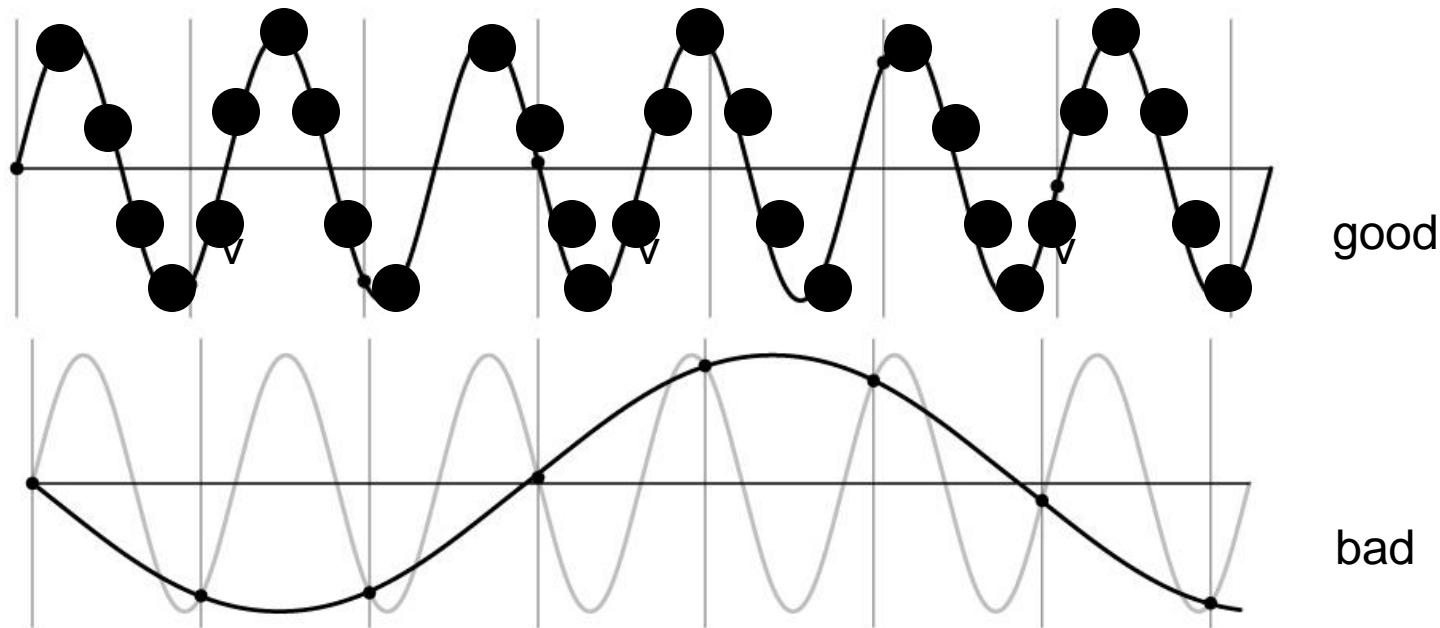
If camera shutter is only open for a fraction of a frame time (frame time =  $1/30$  sec. for video,  $1/24$  sec. for film):



Without dot, wheel appears to be rotating slowly backwards!  
(counterclockwise)

# Nyquist-Shannon Sampling Theorem

- When sampling a signal at discrete intervals, the sampling frequency must be  $\geq 2 \times f_{\max}$
- $f_{\max}$  = max frequency of the input signal
- This will allow to reconstruct the original perfectly from the sampled version



# How to fix aliasing?

## Solutions?

# Better sensors

Solutions:

- Sample more often

# Anti-aliasing

Solutions:

- Sample more often
- Get rid of all frequencies that are greater than half the new sampling frequency
  - Will lose information
  - But it's better than aliasing
  - Apply a smoothing (*low pass*) filter

# Anti-aliasing

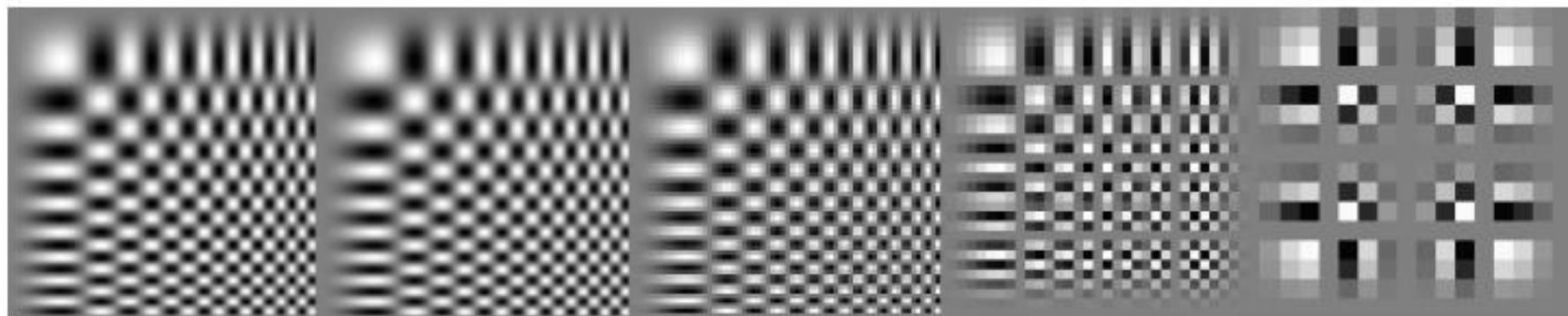
256x256

128x128

64x64

32x32

16x16



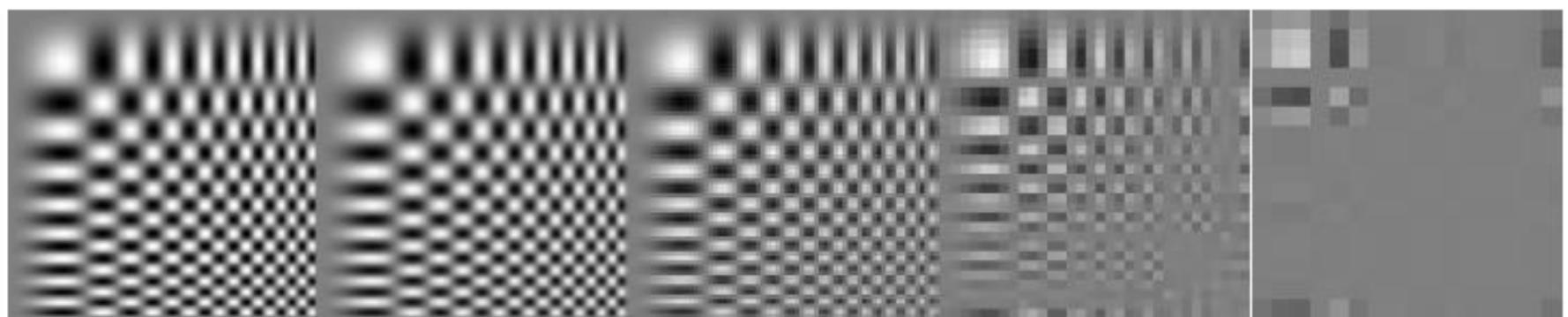
256x256

128x128

64x64

32x32

16x16



# Algorithm for downsampling by factor of 2

1. Start with image( $h, w$ )

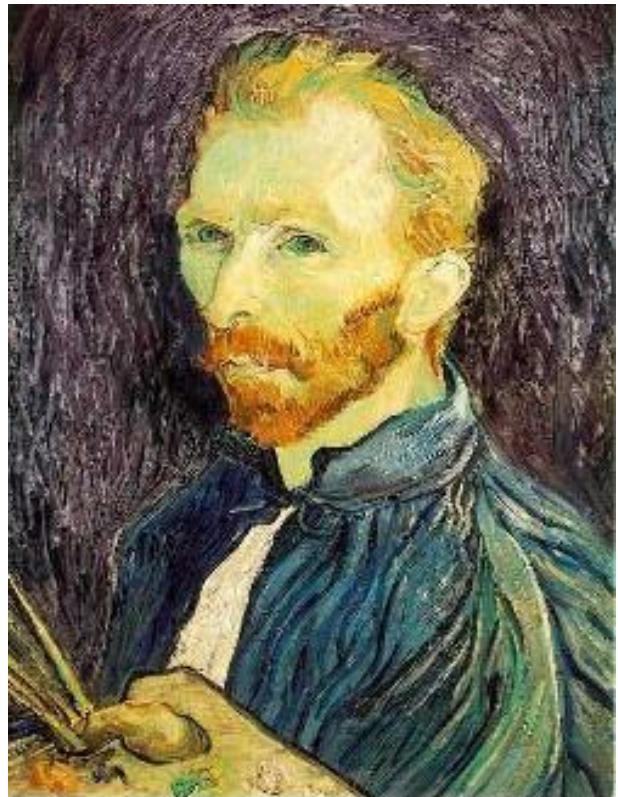
2. Apply low-pass filter

```
im.blur = imfilter( image, fspecial('gaussian', 7, 1) )
```

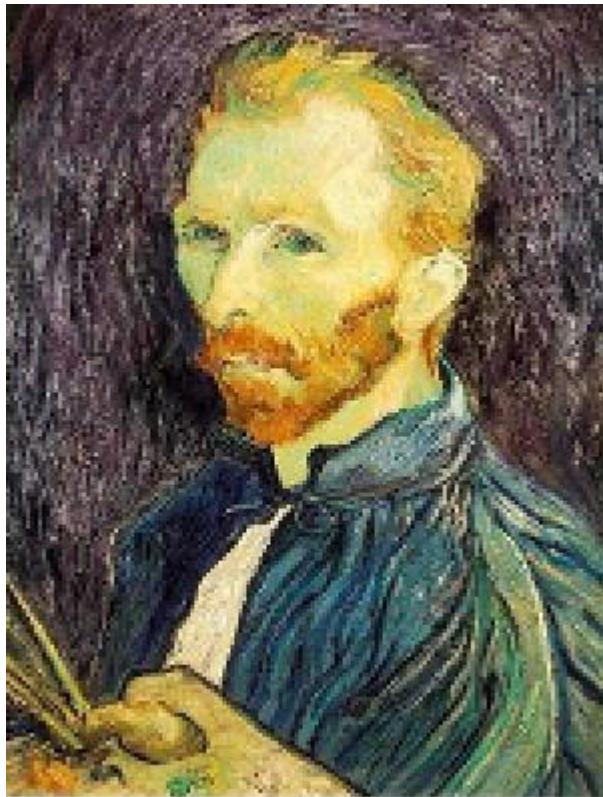
3. Sample every other pixel

```
im.small = im.blur( 1:2:end, 1:2:end );
```

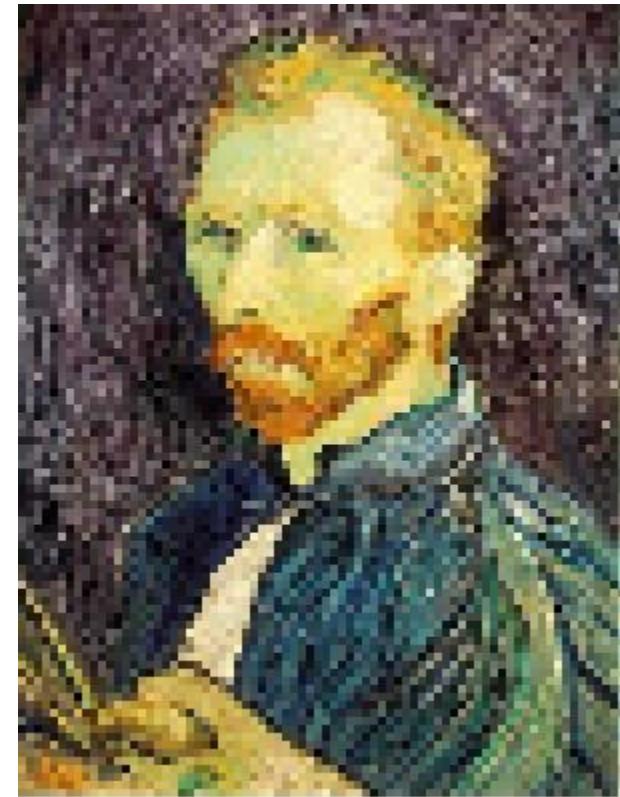
# Subsampling without pre-filtering



1/2

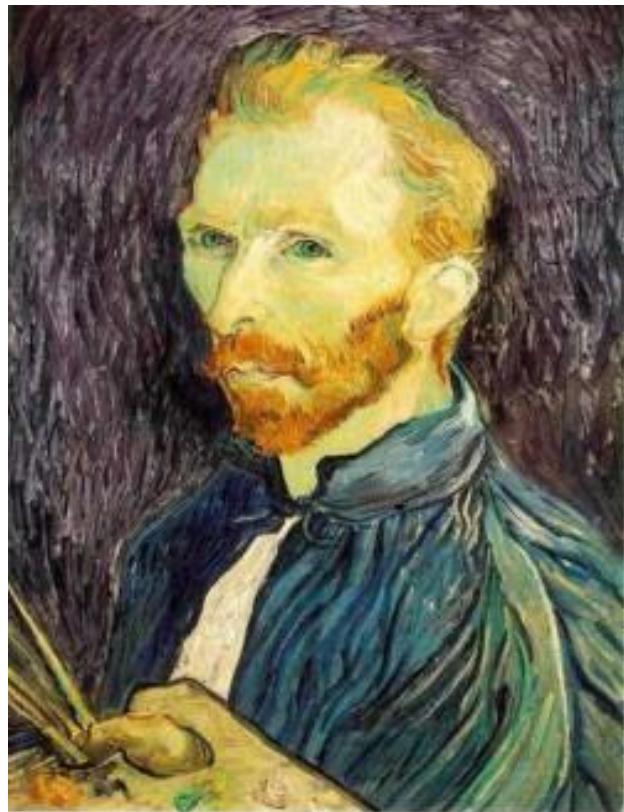


1/4 (2x zoom)



1/8 (4x zoom)

# Subsampling with Gaussian pre-filtering



Gaussian 1/2



G 1/4



G 1/8

Another way of thinking about frequency

# **FOURIER SERIES & FOURIER TRANSFORMS**

# Fourier series

A bold idea (1807):

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

Jean Baptiste Joseph Fourier (1768-1830)



# Fourier series

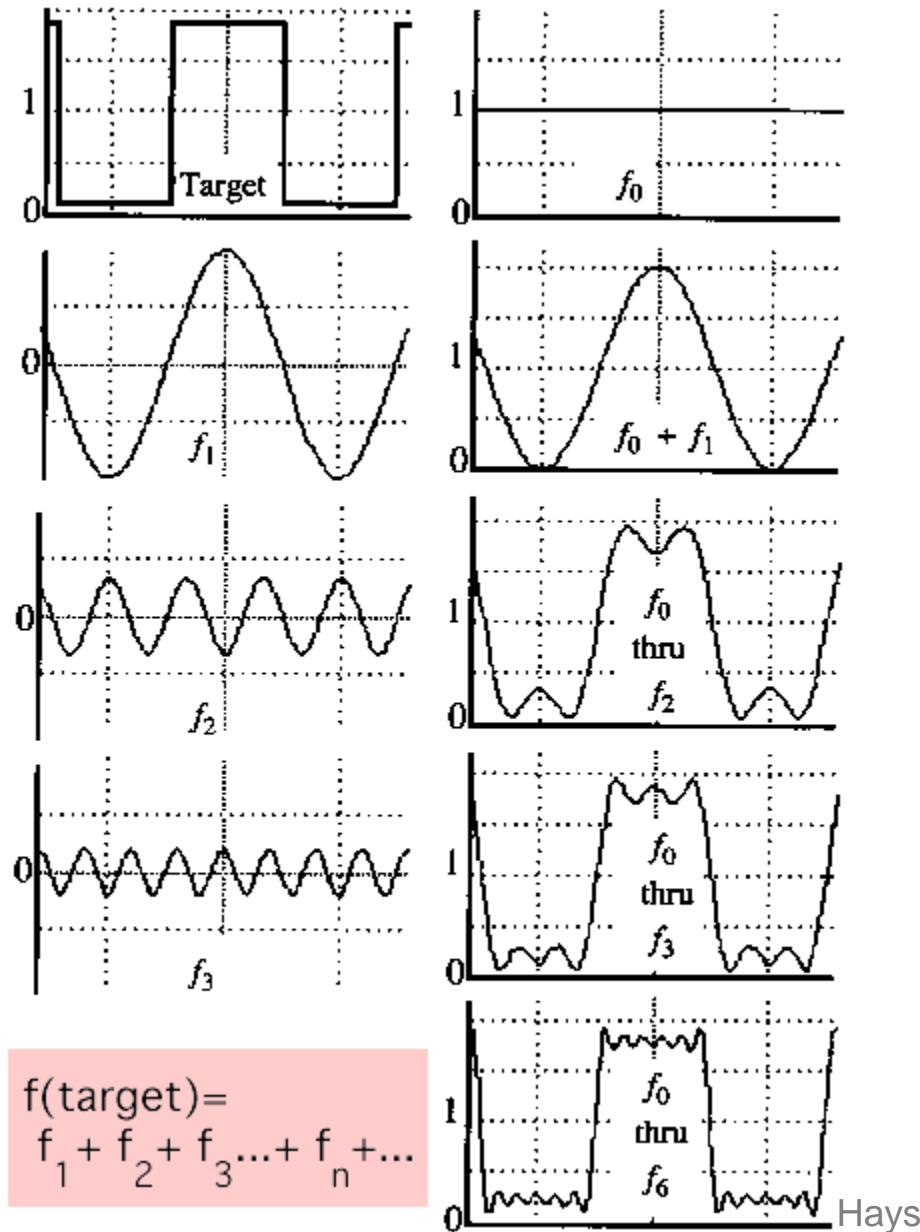
A bold idea (1807):

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

Our building block:

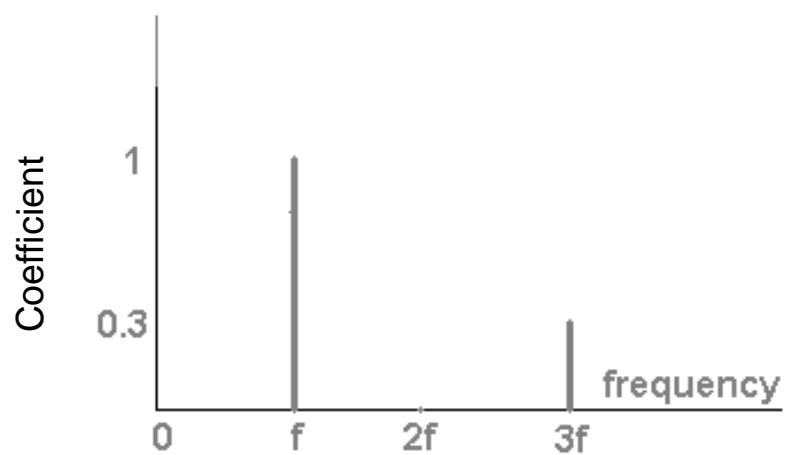
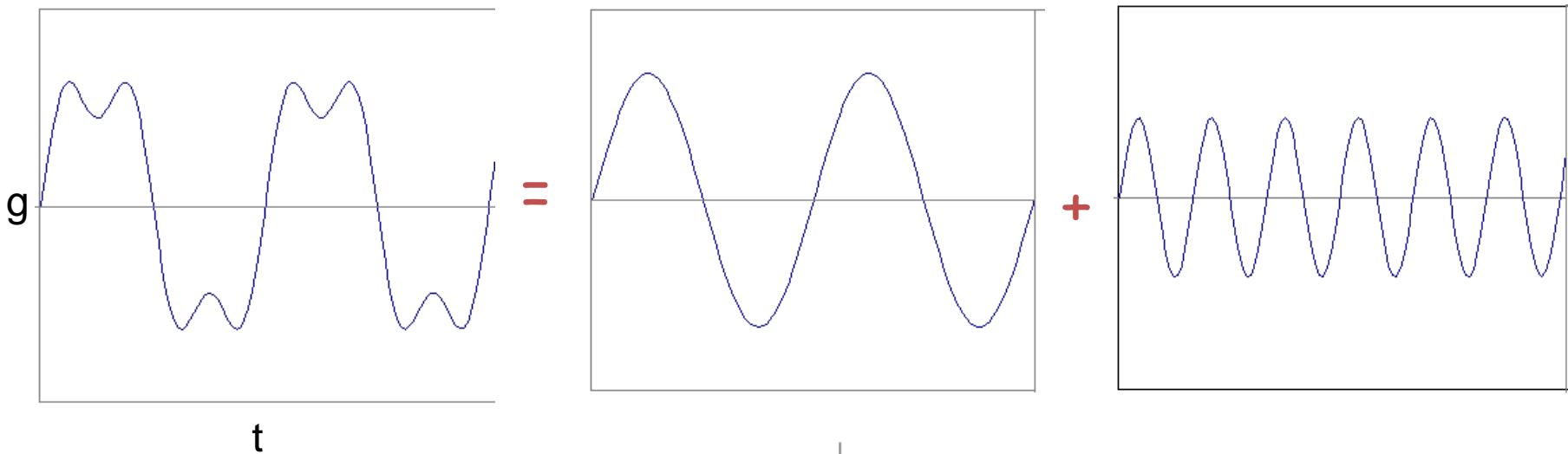
$$A \sin(\omega t) + B \cos(\omega t)$$

Add enough of them to get any signal  $g(t)$  you want!

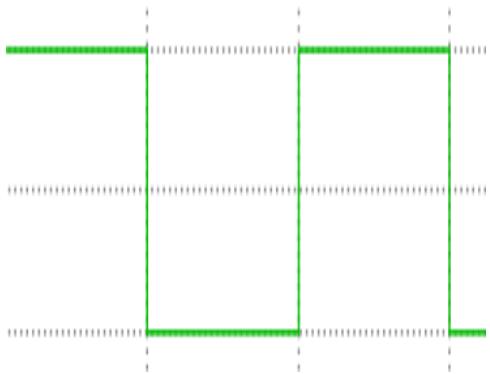


$$t = [0,2], f = 1$$

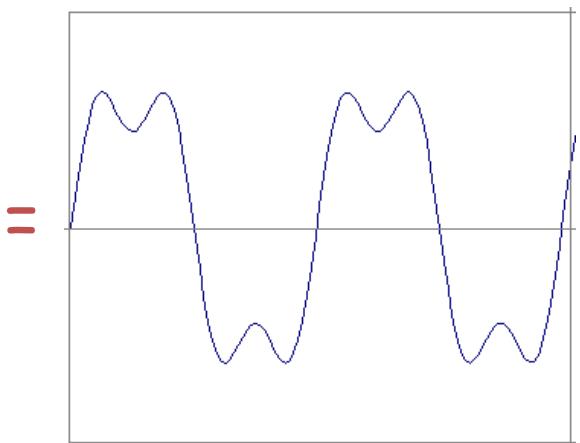
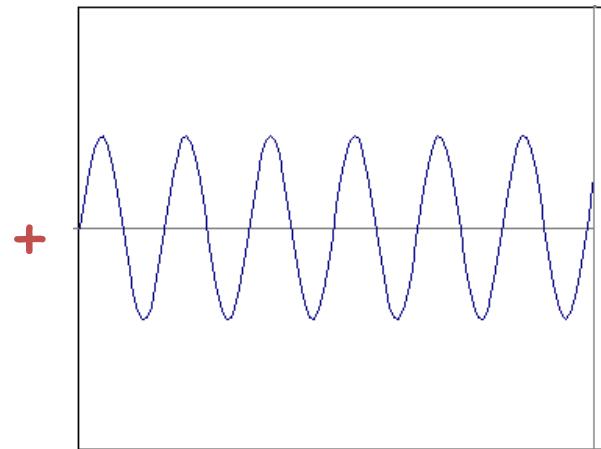
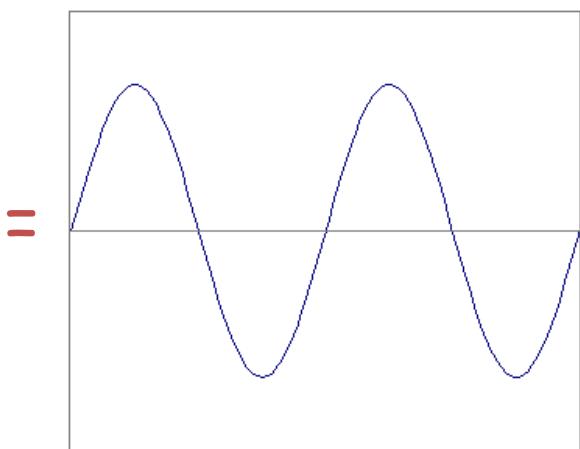
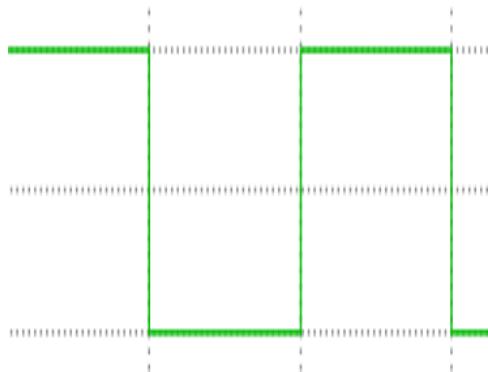
$$g(t) = \sin(2\pi f t) + (1/3)\sin(2\pi(3f)t)$$



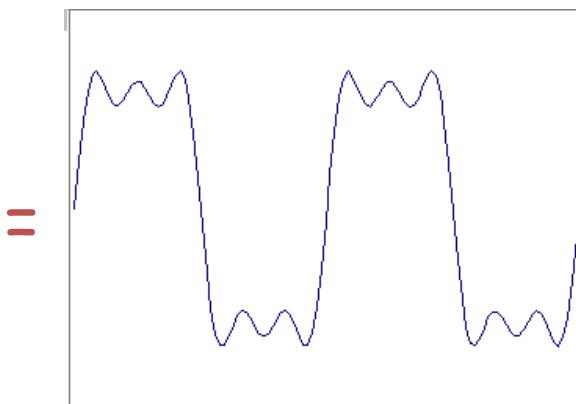
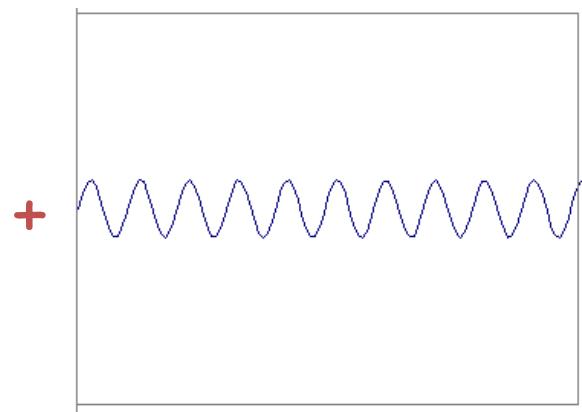
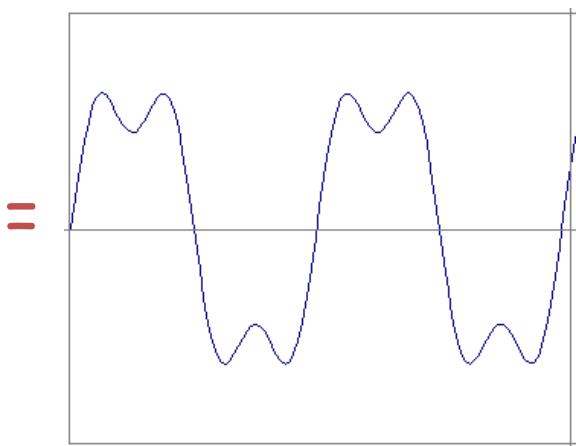
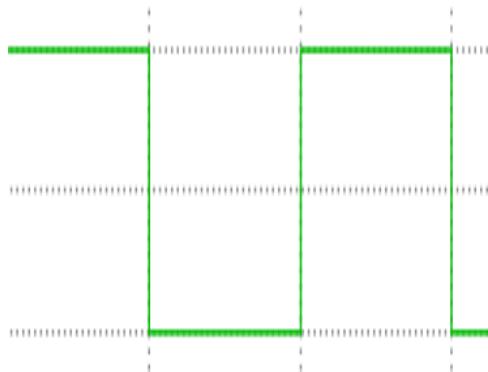
# Square wave spectra



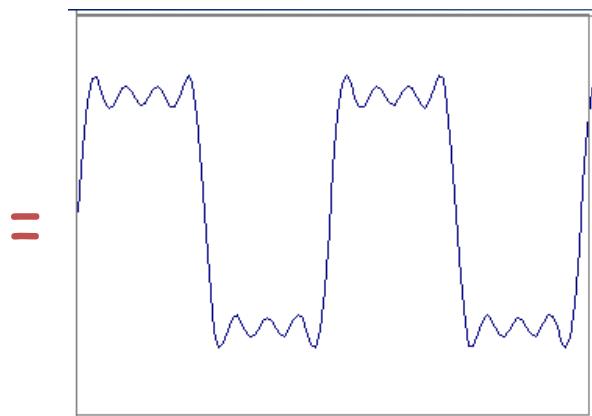
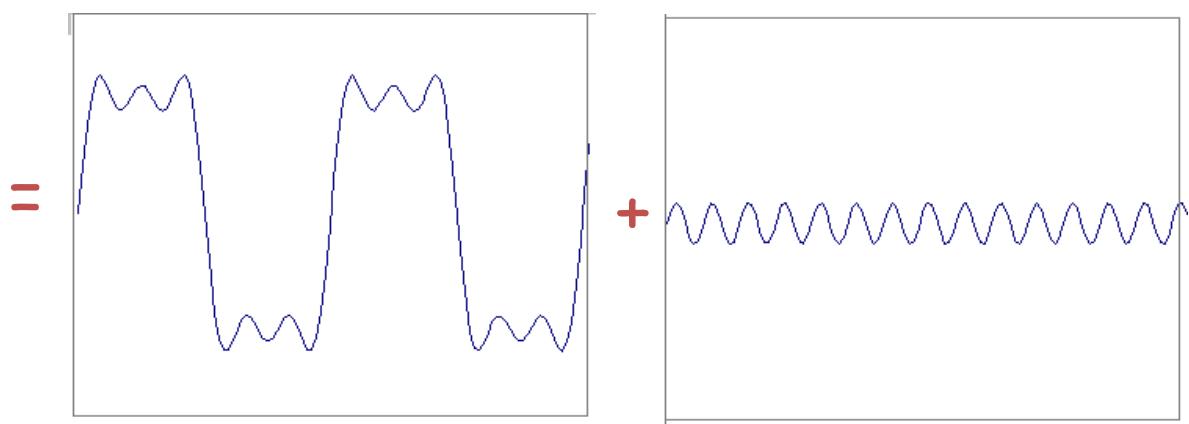
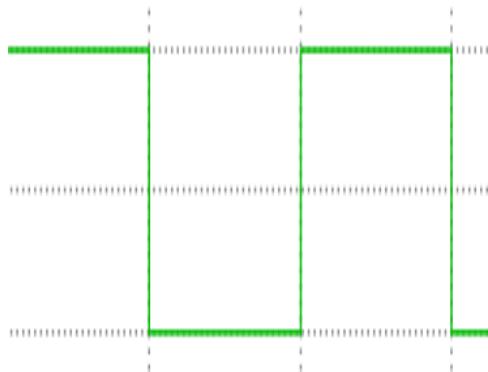
# Square wave spectra



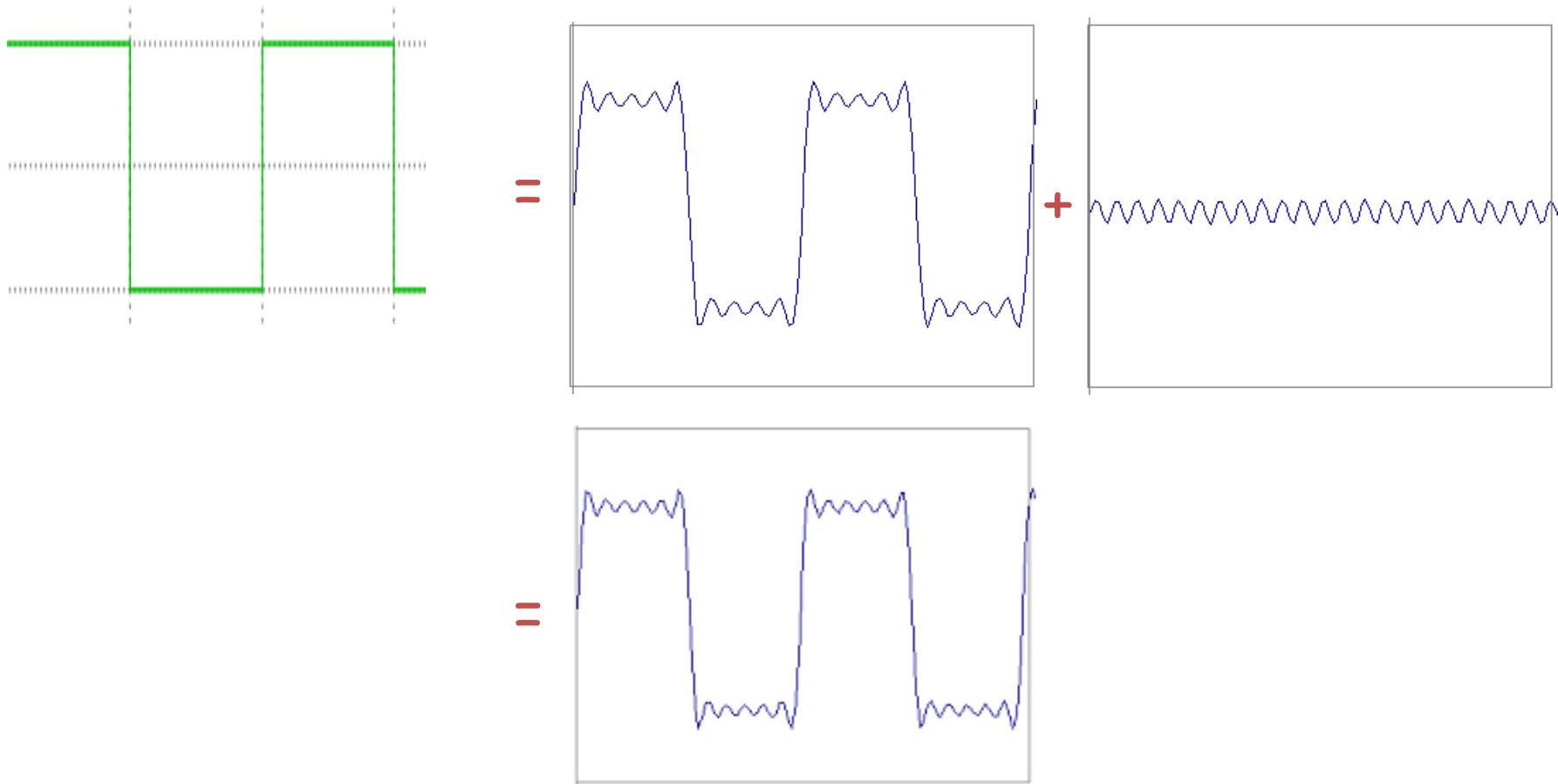
# Square wave spectra



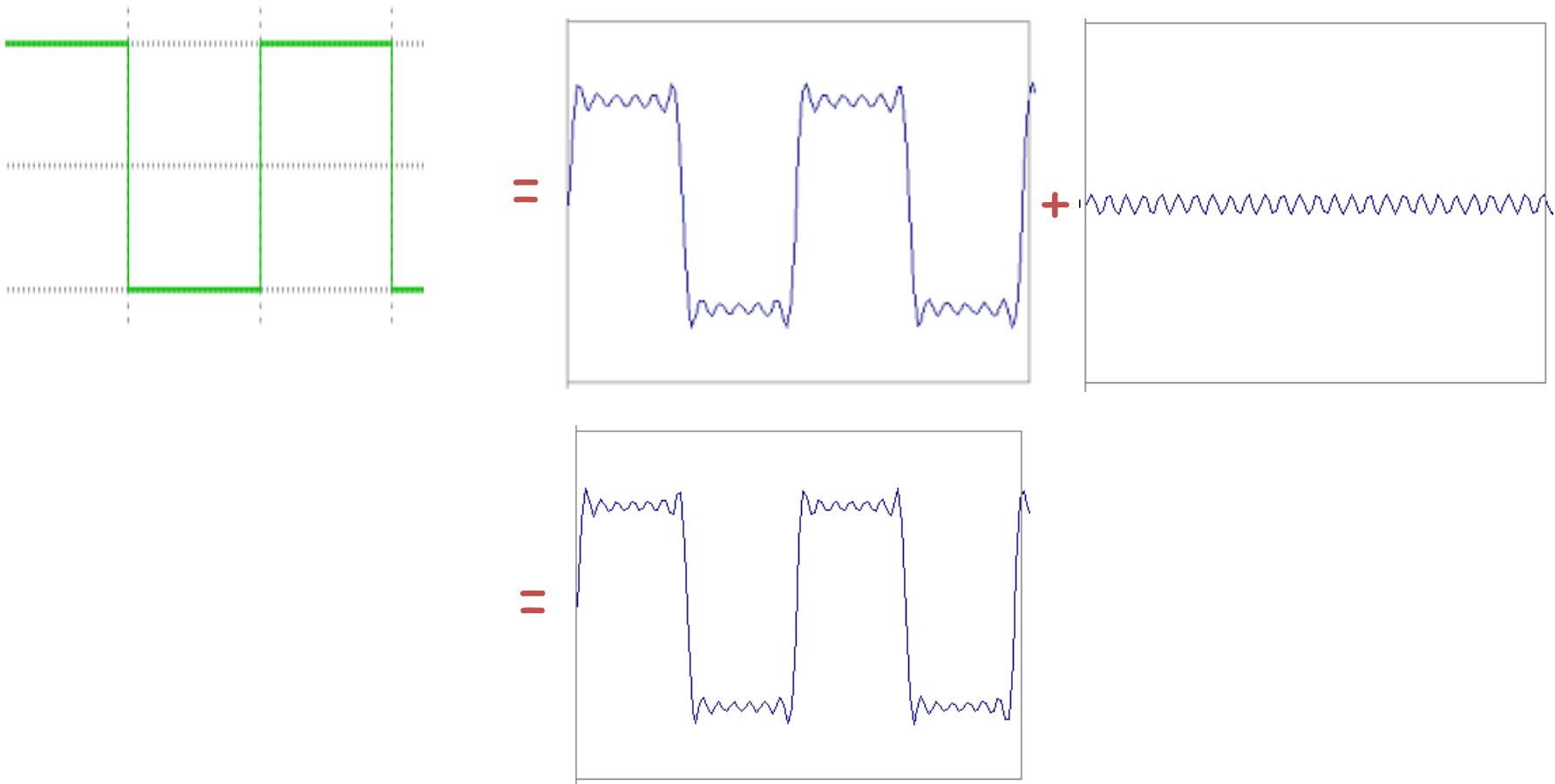
# Square wave spectra



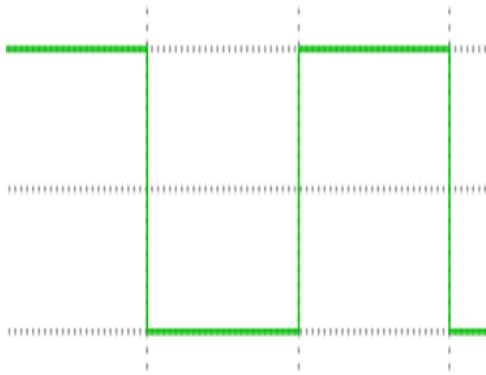
# Square wave spectra



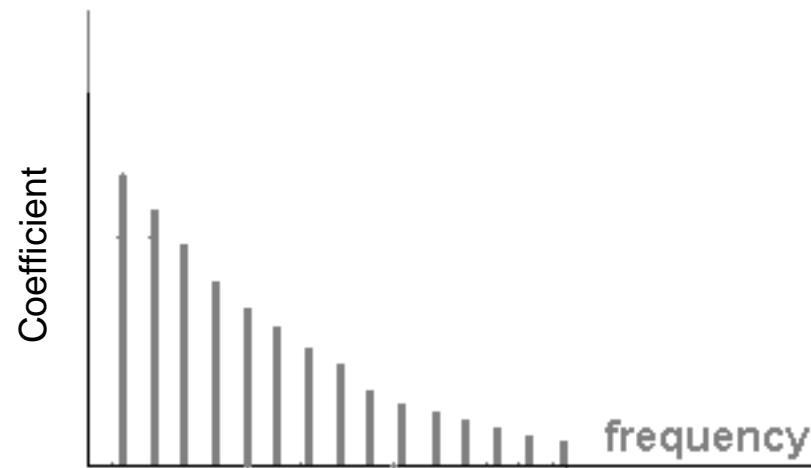
# Square wave spectra



# Square wave spectra

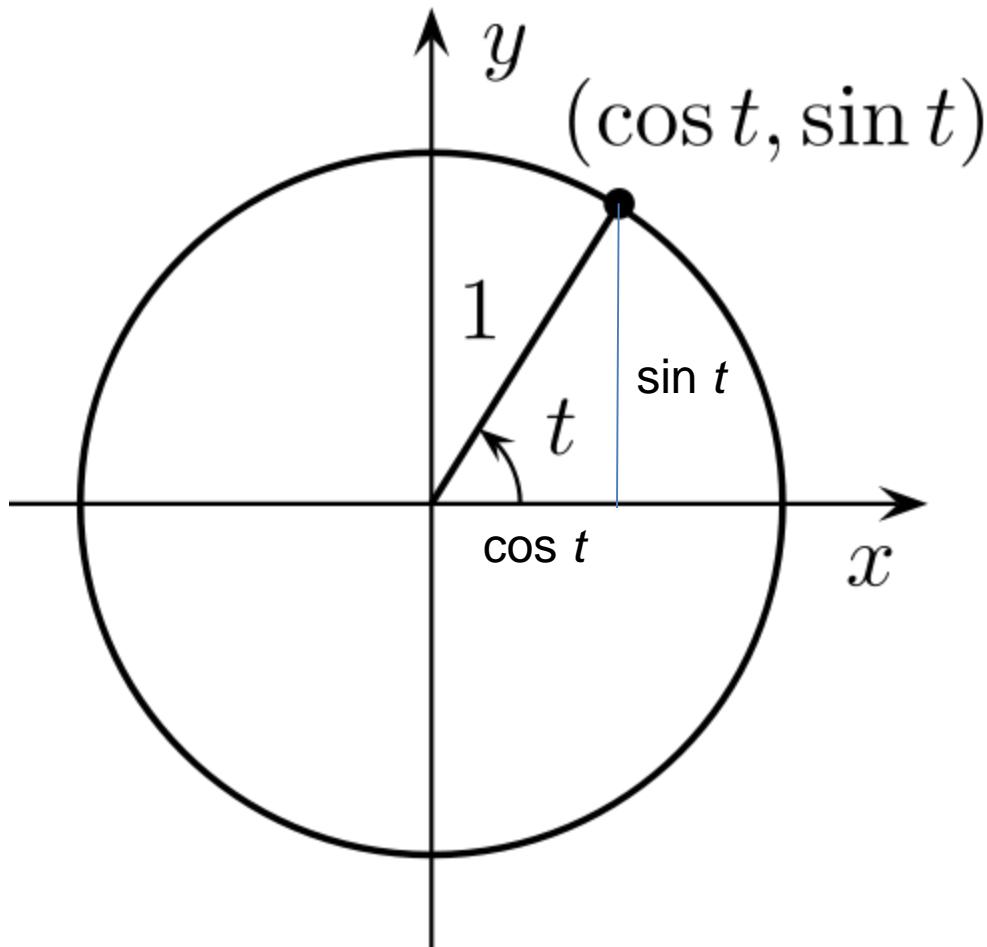


$$= A \sum_{f=1}^{\infty} \frac{1}{f} \sin(2\pi f t)$$

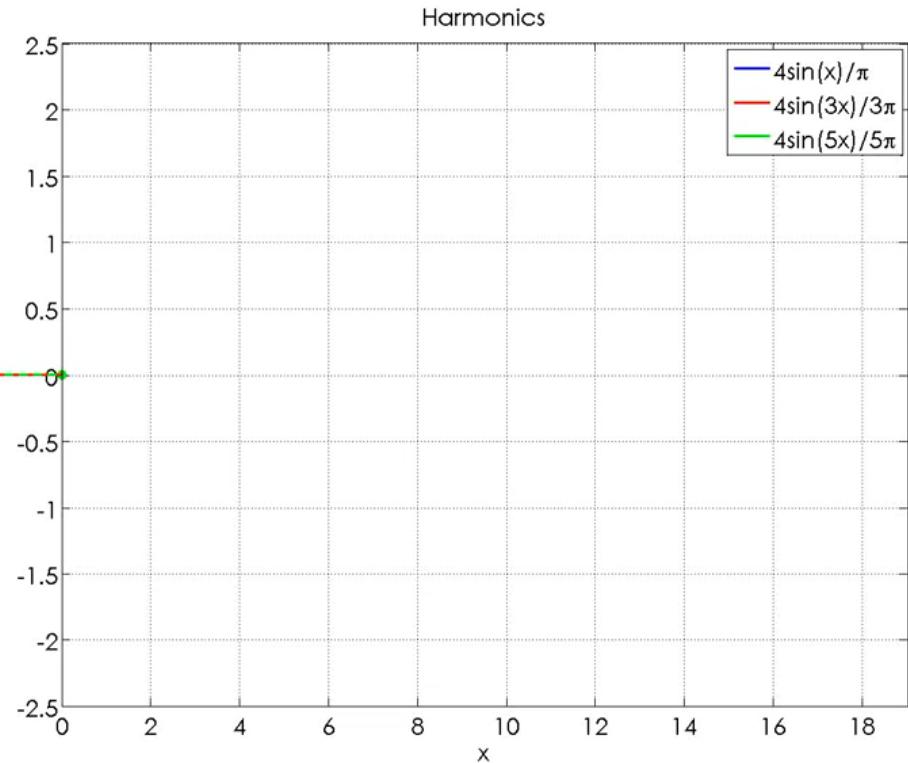
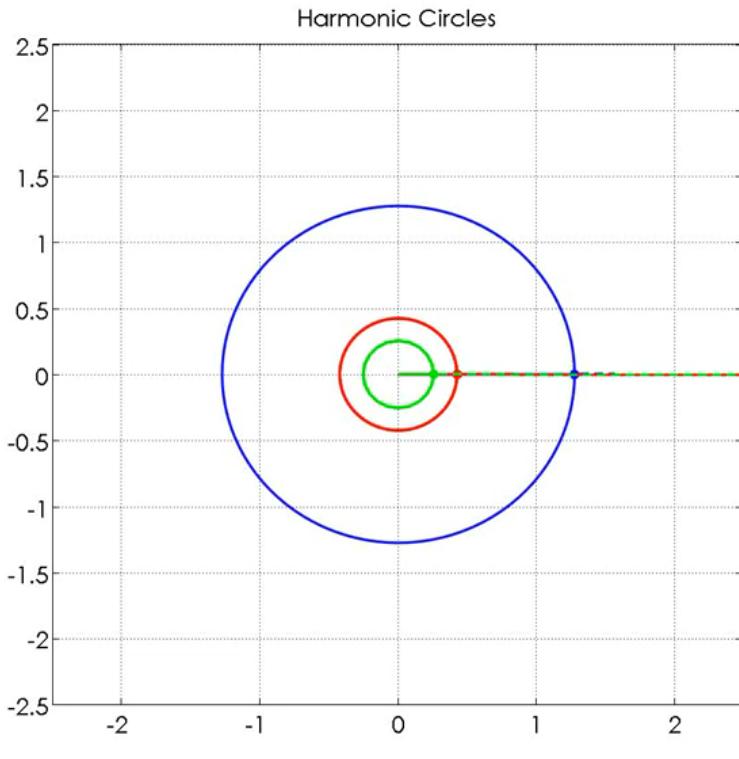




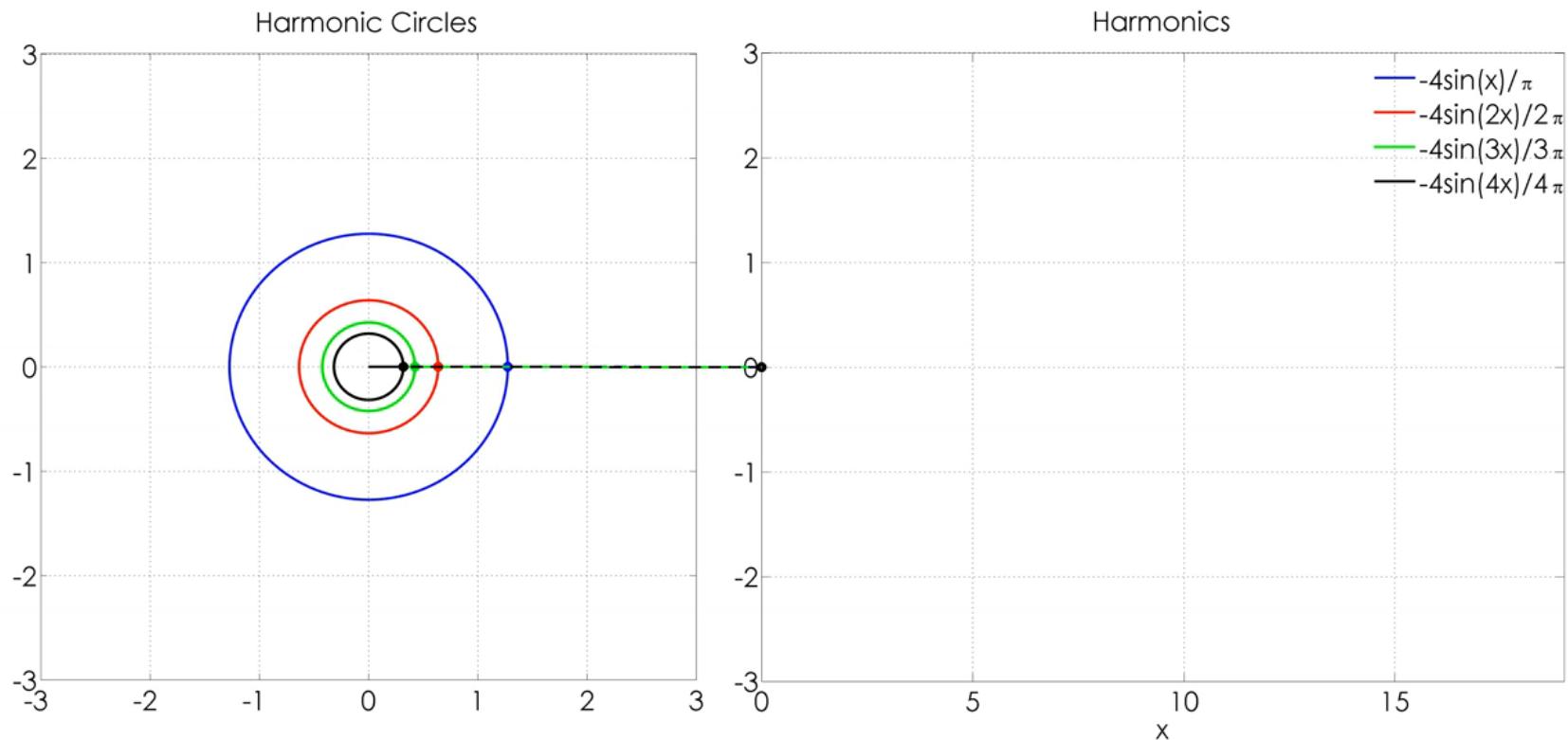
# Sine/cosine and circle



# Square wave (approx.)

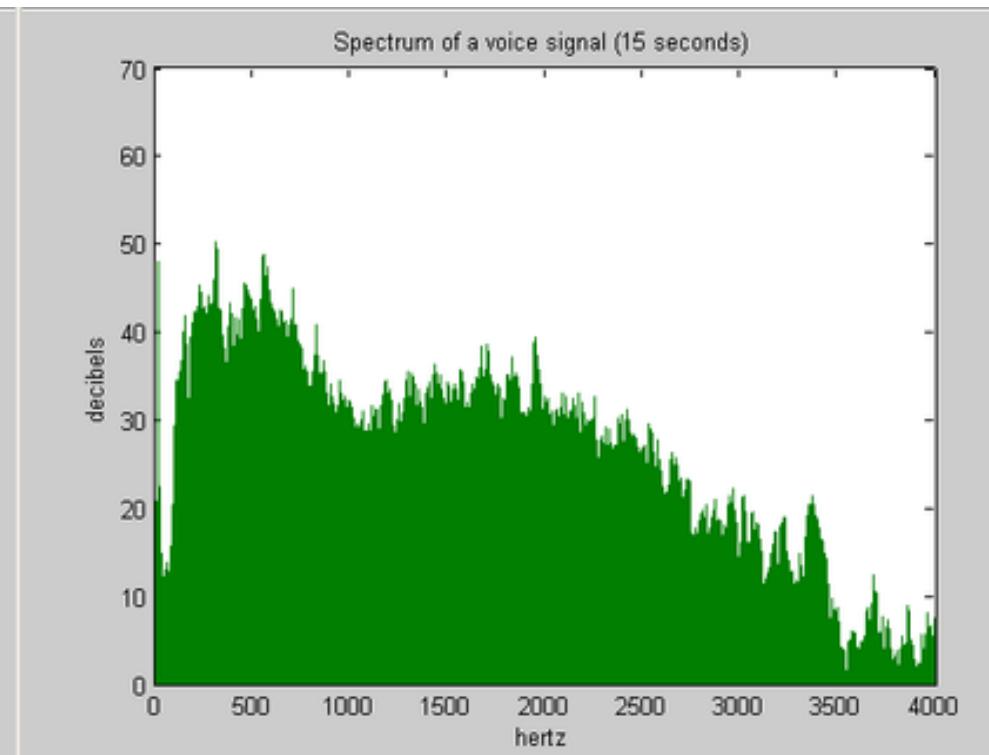
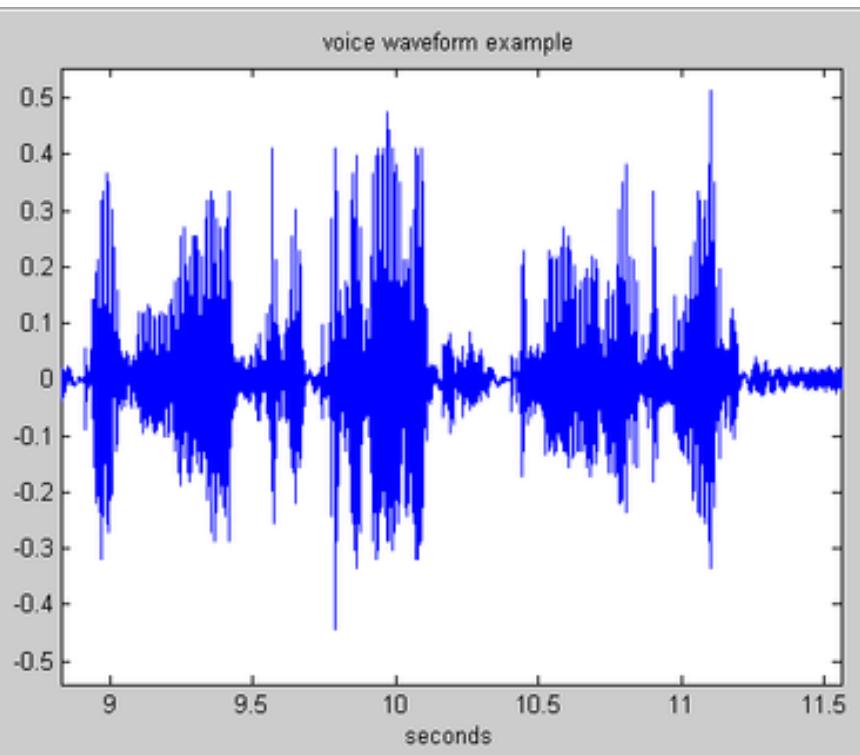


# Sawtooth wave (approx.)



# Example: Music

- We think of music in terms of frequencies at different magnitudes



# Computing Fourier transform

The Fourier transform of a discrete function of one variable,  $f(x)$ ,  $x = 0, 1, 2, \dots, M - 1$ , is given by the equation

$$F(u) = \frac{1}{M} \sum_{x=0}^{M-1} f(x) e^{-j2\pi ux/M} \quad \text{for } u = 0, 1, 2, \dots, M - 1. \quad (4.2-5)$$

This *discrete Fourier transform* (DFT) is the foundation for most of the work in this chapter. Similarly, given  $F(u)$ , we can obtain the original function back using the inverse DFT:

$$f(x) = \sum_{u=0}^{M-1} F(u) e^{j2\pi ux/M} \quad \text{for } x = 0, 1, 2, \dots, M - 1. \quad (4.2-6)$$

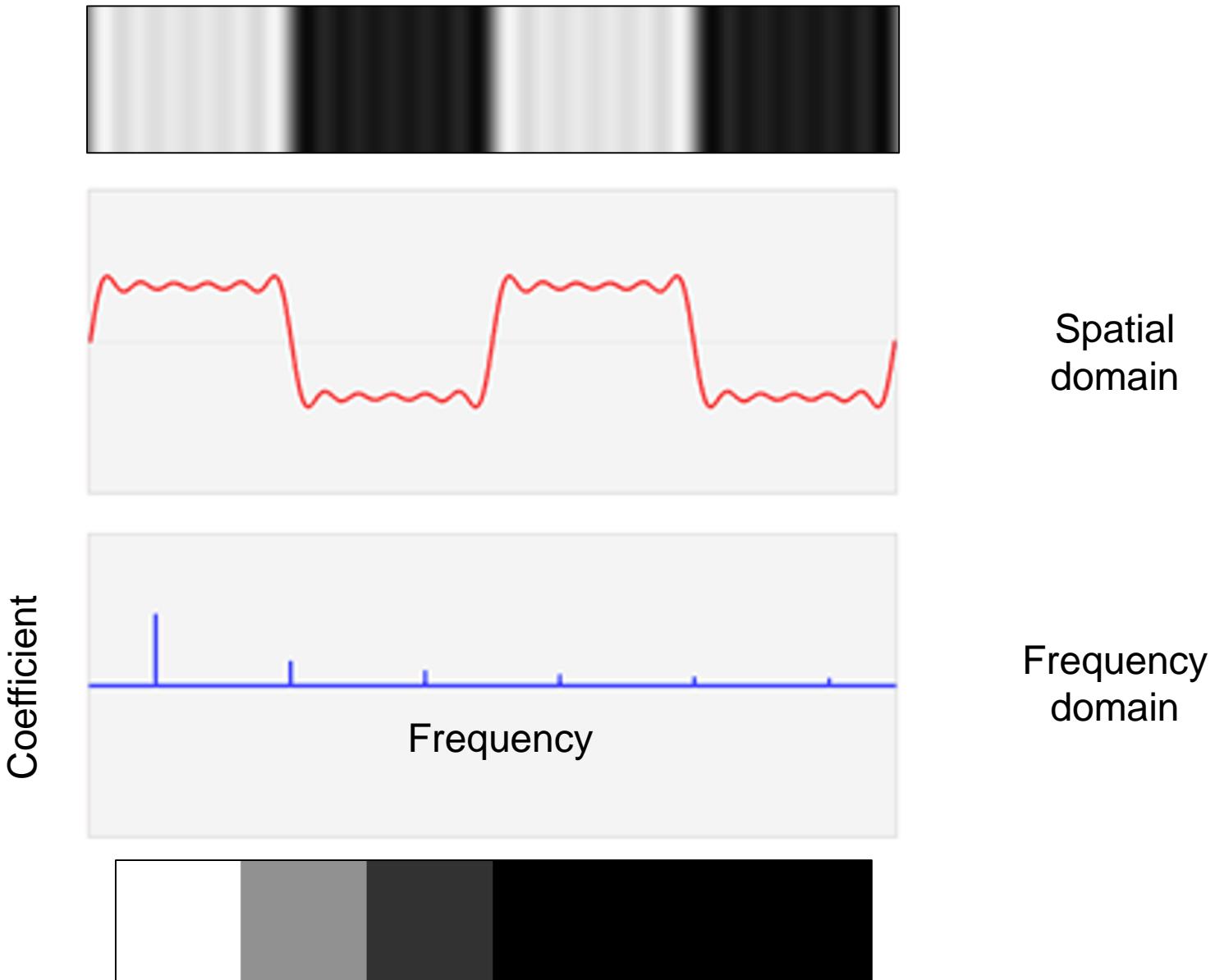
# Computing Fourier transform

The concept of the frequency domain, mentioned numerous times in this chapter and in Chapter 3, follows directly from Euler's formula:

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

Substituting this expression into Eq. (4.2-5), and using the fact that  $\cos(-\theta) = \cos \theta$ , gives us

$$F(u) = \frac{1}{M} \sum_{x=0}^{M-1} f(x) [\cos 2\pi u x / M - j \sin 2\pi u x / M]$$



# 2D FFT

Direct transform

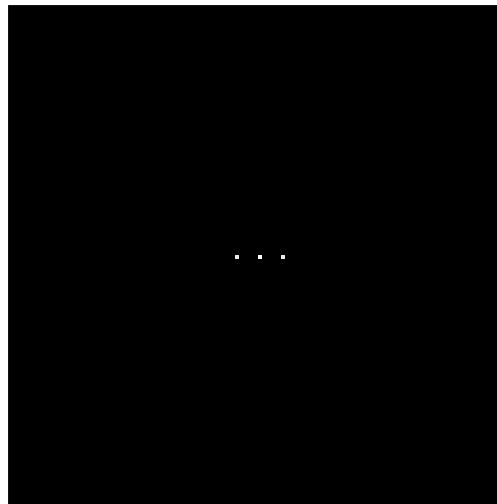
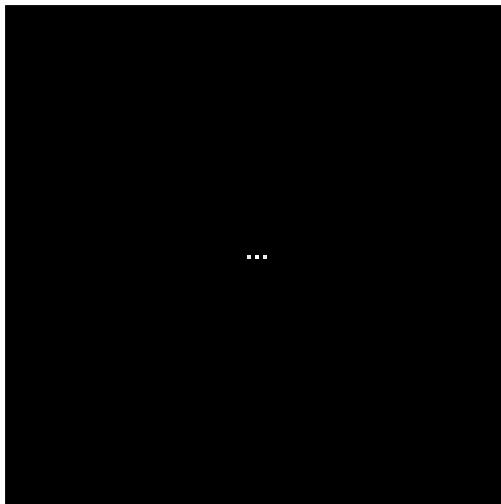
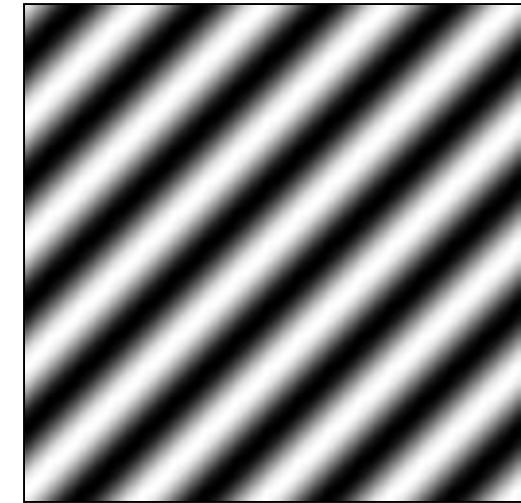
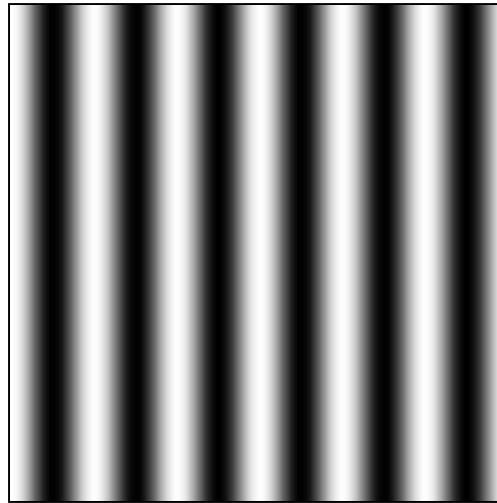
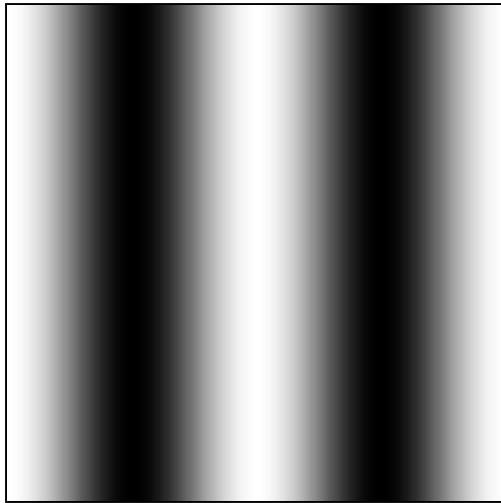
$$F(u, v) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m, n) \exp \left[ -2\pi i \left( \frac{mu}{M} + \frac{nv}{N} \right) \right],$$
$$u = 0, 1, \dots, M-1, \quad v = 0, 1, \dots, N-1,$$

Inverse transform

$$f(m, n) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u, v) \exp \left[ 2\pi i \left( \frac{mu}{M} + \frac{nv}{N} \right) \right],$$
$$m = 0, 1, \dots, M-1, \quad n = 0, 1, \dots, N-1.$$

# Fourier analysis in images

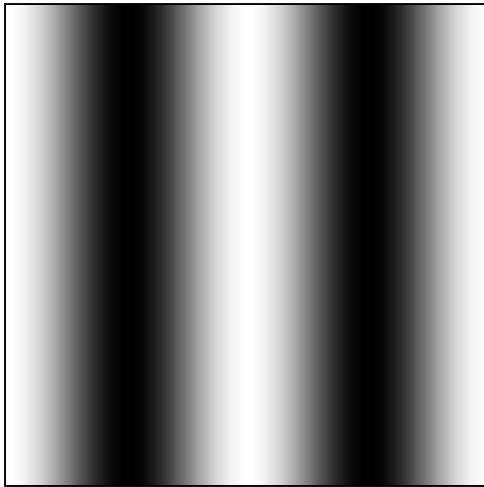
Spatial domain images



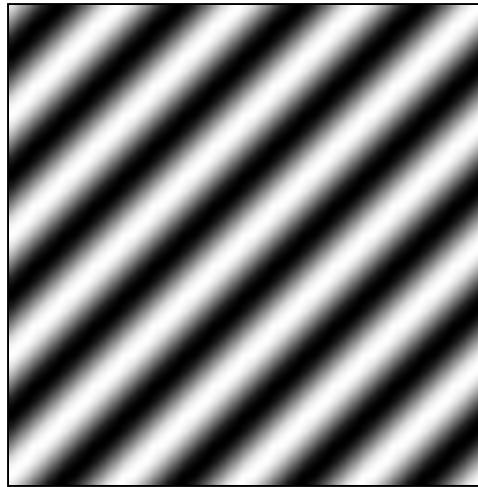
Fourier decomposition frequency amplitude images

# Signals can be composed

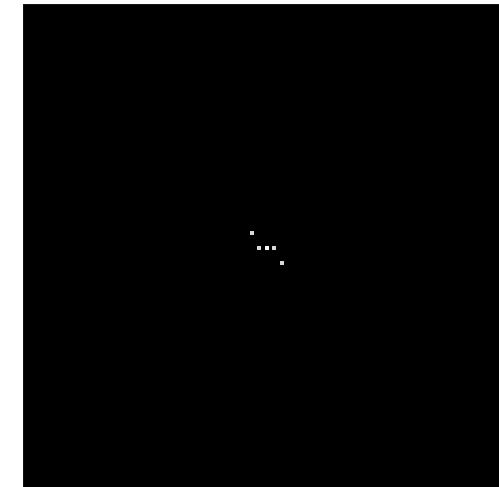
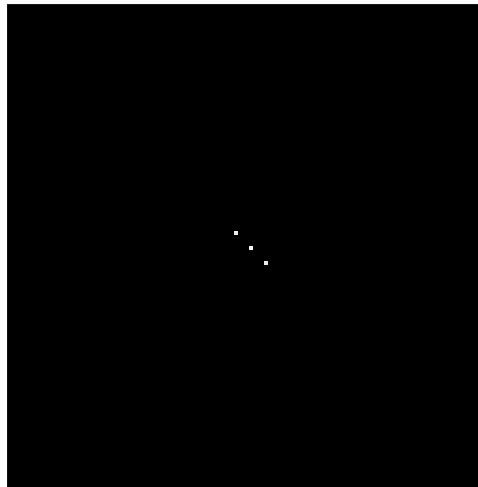
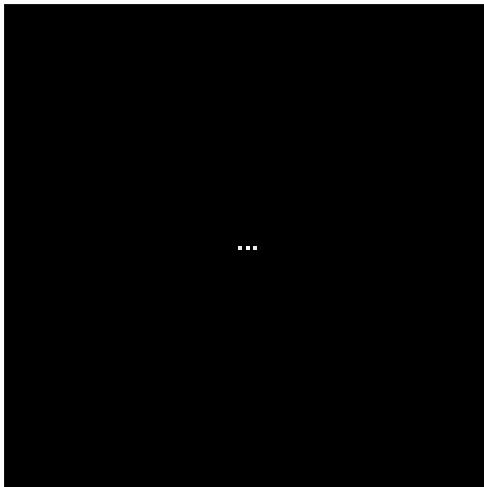
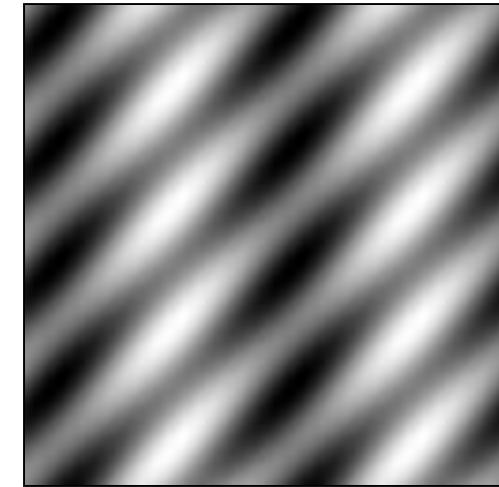
Spatial domain images



+



=



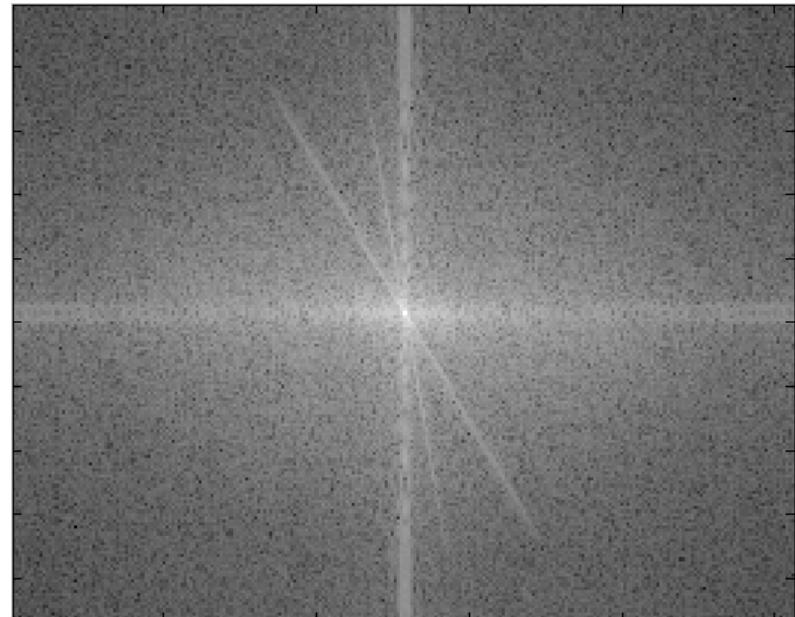
Fourier decomposition frequency amplitude images

# Natural image

Natural image



Fourier decomposition  
Frequency coefficients (amplitude)

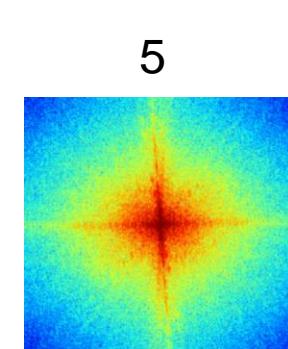
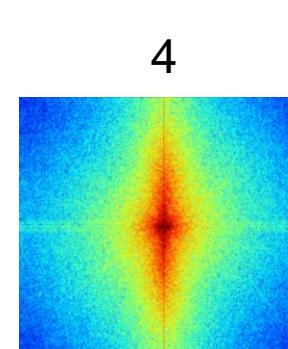
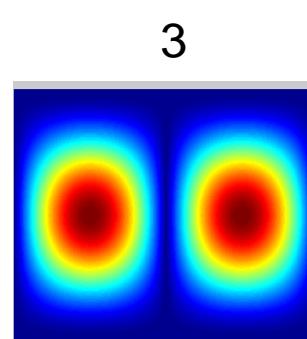
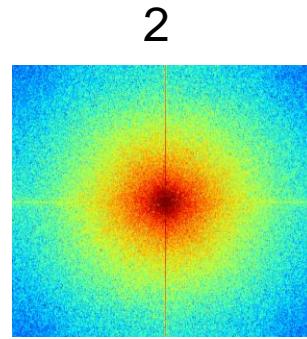
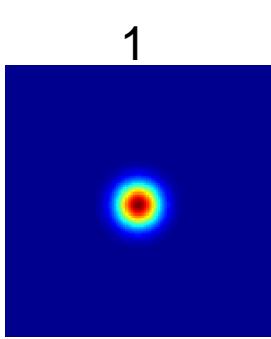


What does it mean to be at pixel  $x,y$ ?

What does it mean to be more or less bright in the Fourier decomposition image?

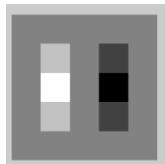
# Think-Pair-Share

Match the spatial domain image to the Fourier magnitude image



B

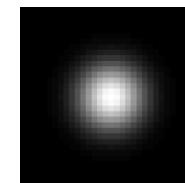
A



C



D

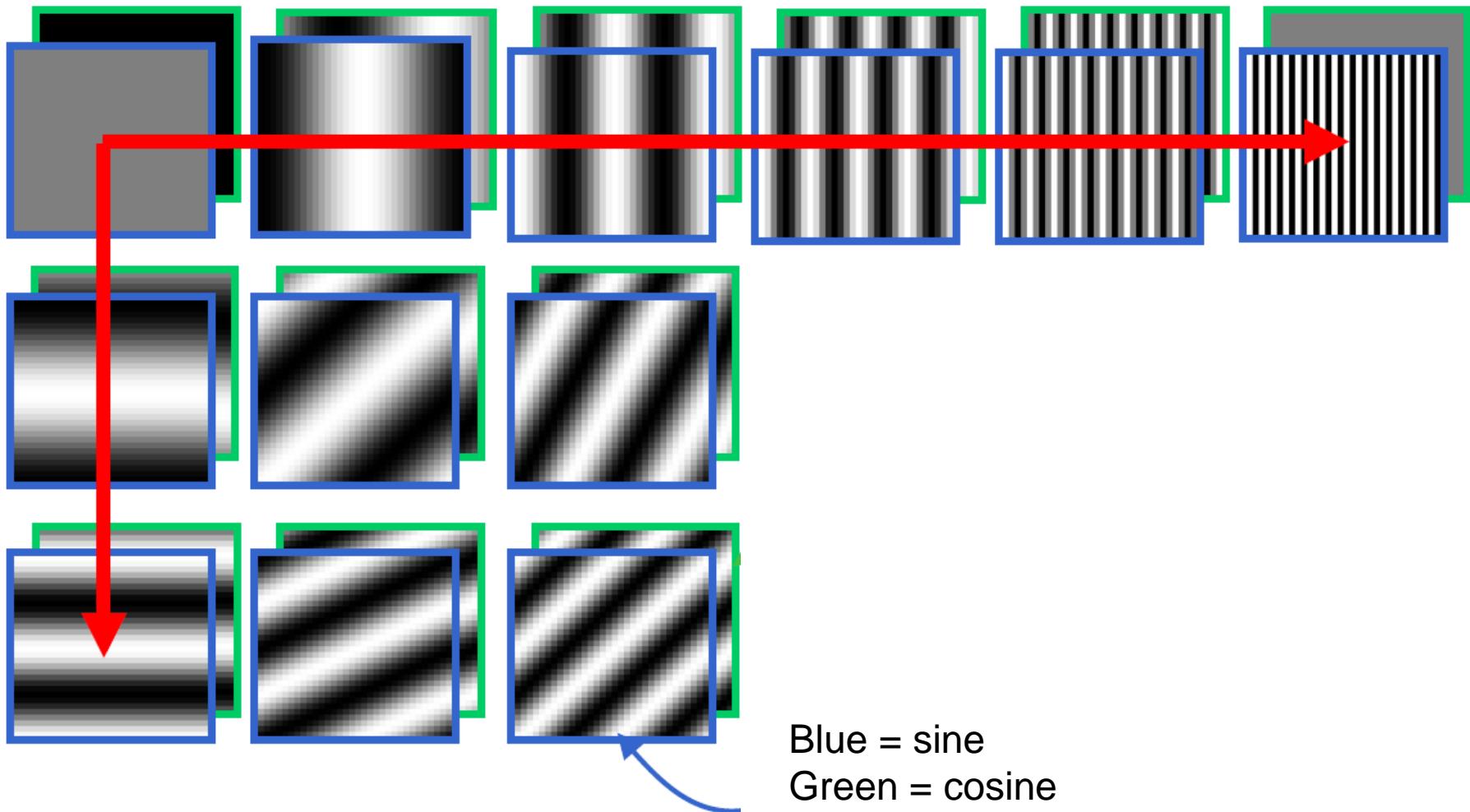


E



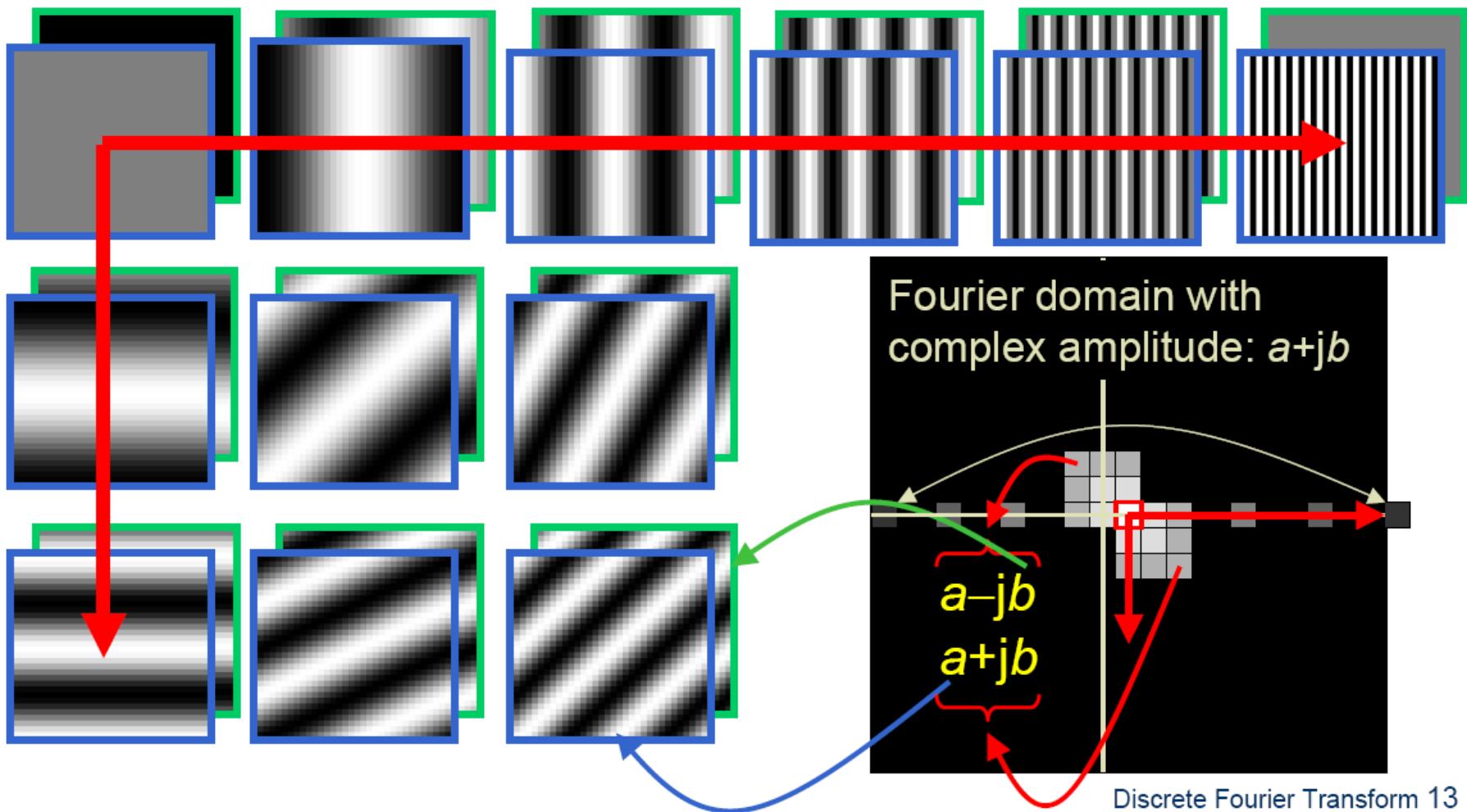
# Fourier Bases

Teases away ‘fast vs. slow’ changes in the image.



This change of basis is the Fourier Transform

# Fourier Bases



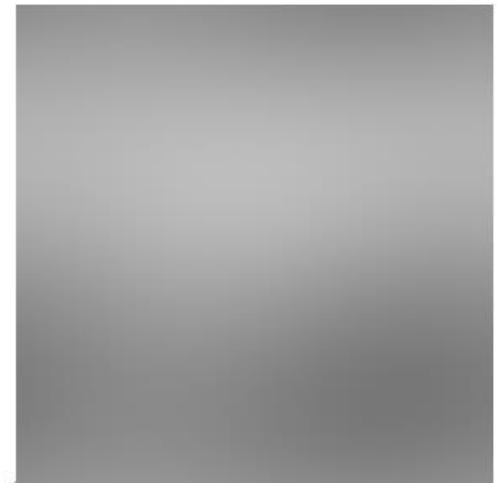
# Basis reconstruction



Full image



First 1 basis fn



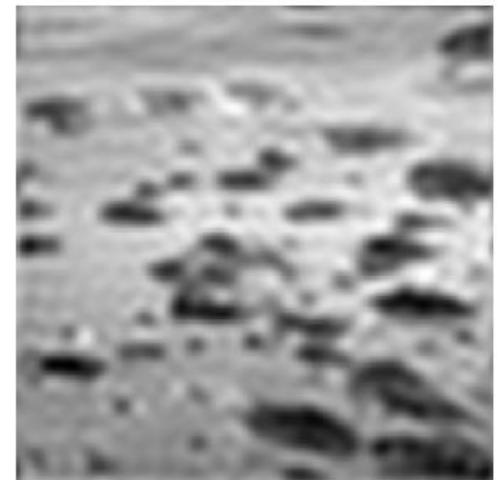
First 4 basis fns



First 9 basis fns



First 16 basis fns



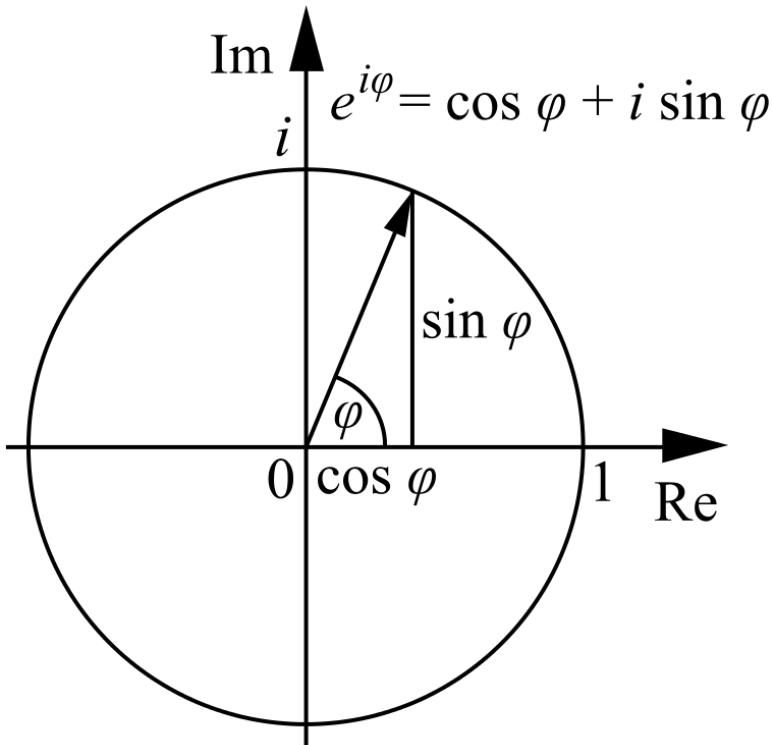
First 400 basis fns

# Fourier Transform

- Stores the amplitude and phase at each frequency:
  - For mathematical convenience, this is often notated in terms of real and complex numbers
  - Related by Euler's formula

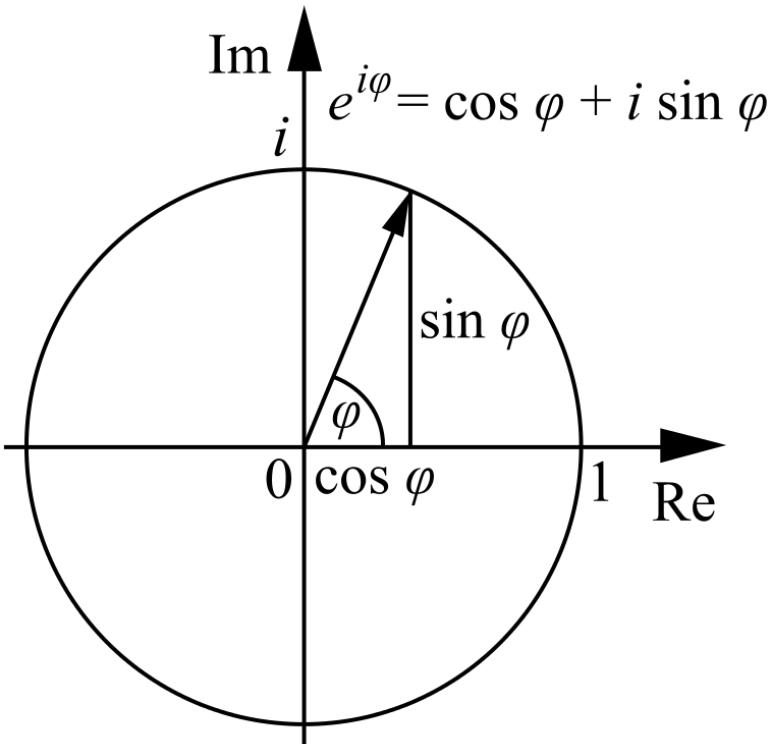
# Fourier Transform

- Stores the amplitude and phase at each frequency:
  - For mathematical convenience, this is often notated in terms of real and complex numbers
  - Related by Euler's formula



# Fourier Transform

- Stores the amplitude and phase at each frequency:
  - For mathematical convenience, this is often notated in terms of real and complex numbers
  - Related by Euler's formula



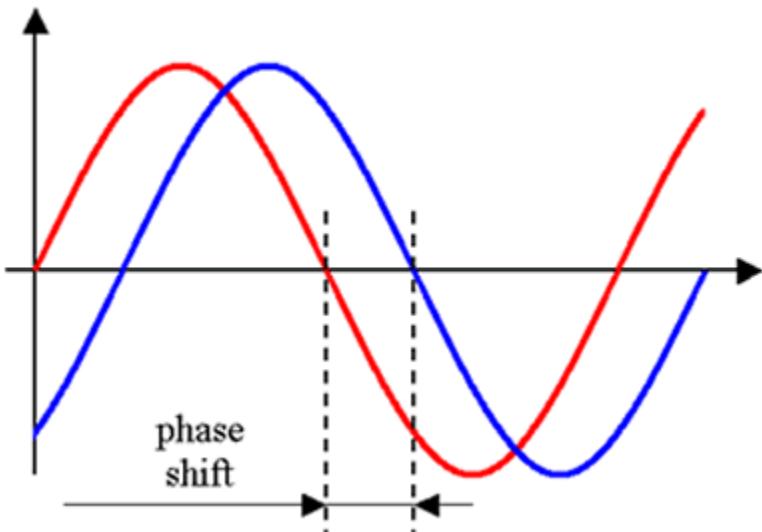
Amplitude encodes how much signal there is at a particular frequency:

$$A = \pm \sqrt{\operatorname{Re}(\varphi)^2 + \operatorname{Im}(\varphi)^2}$$

Phase encodes spatial information (indirectly):

$$\phi = \tan^{-1} \frac{\operatorname{Im}(\varphi)}{\operatorname{Re}(\varphi)}$$

# Amplitude / Phase



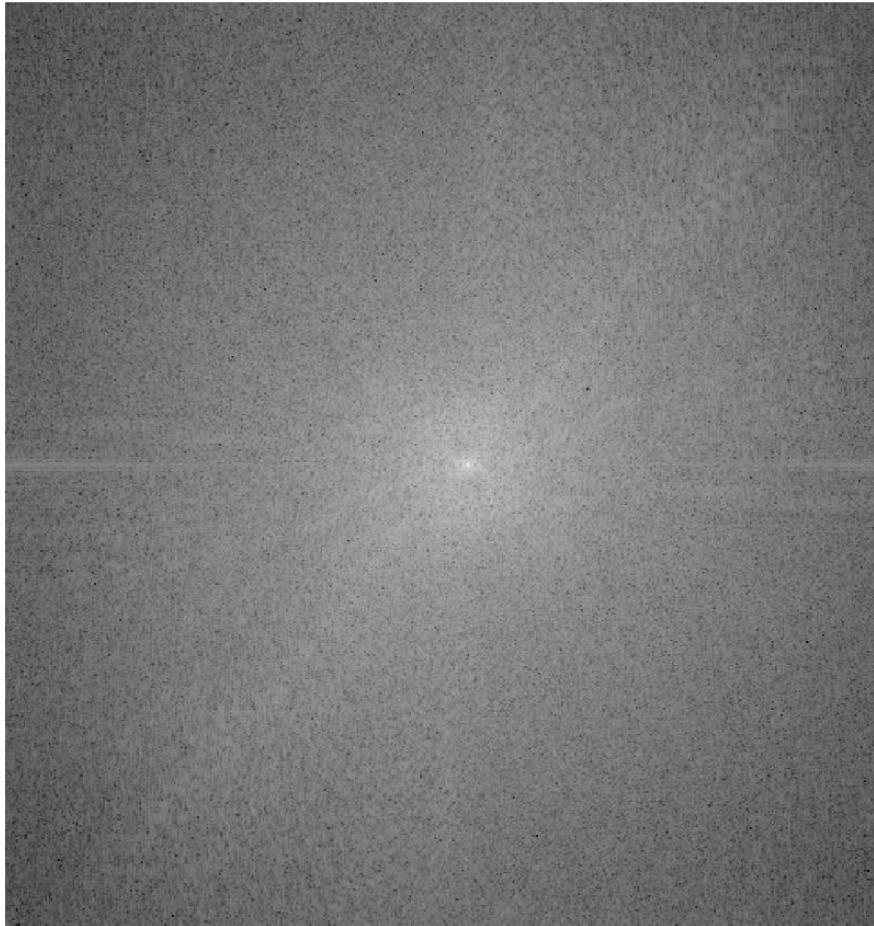
- Amplitude tells you “how much”
- Phase tells you “where”
- Translate the image?
  - Amplitude unchanged
  - Adds a constant to the phase.

# What about phase?

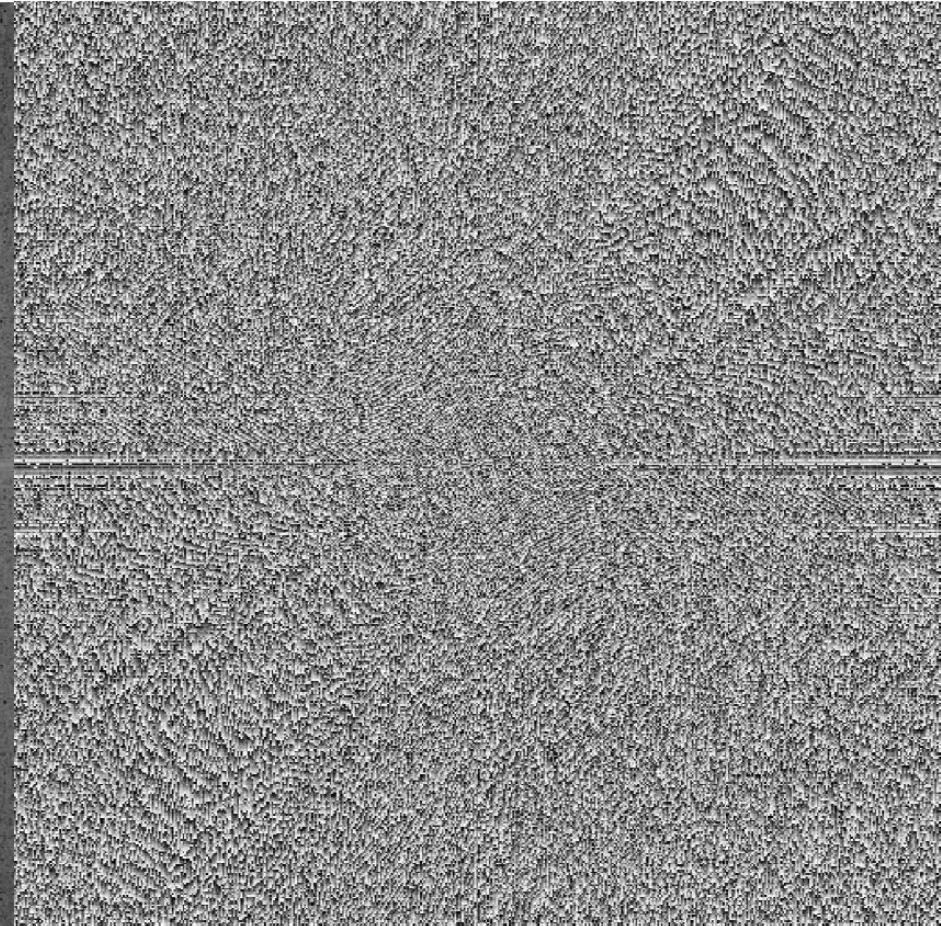


# What about phase?

Amplitude



Phase

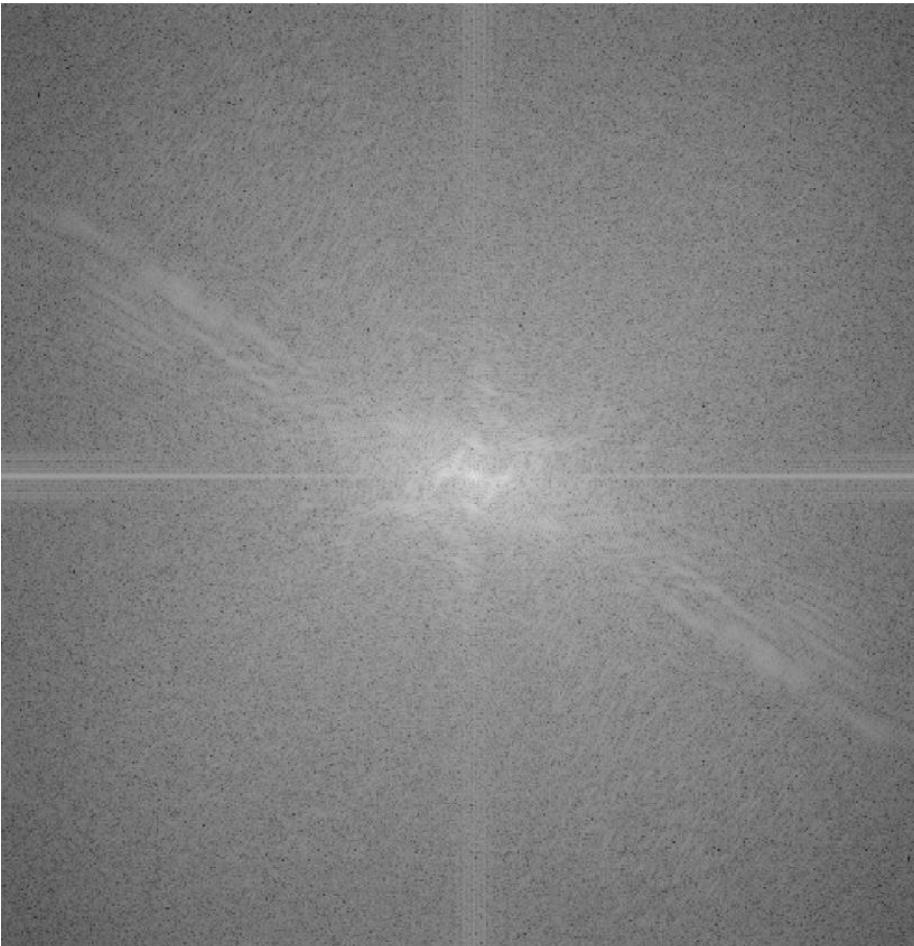


# What about phase?

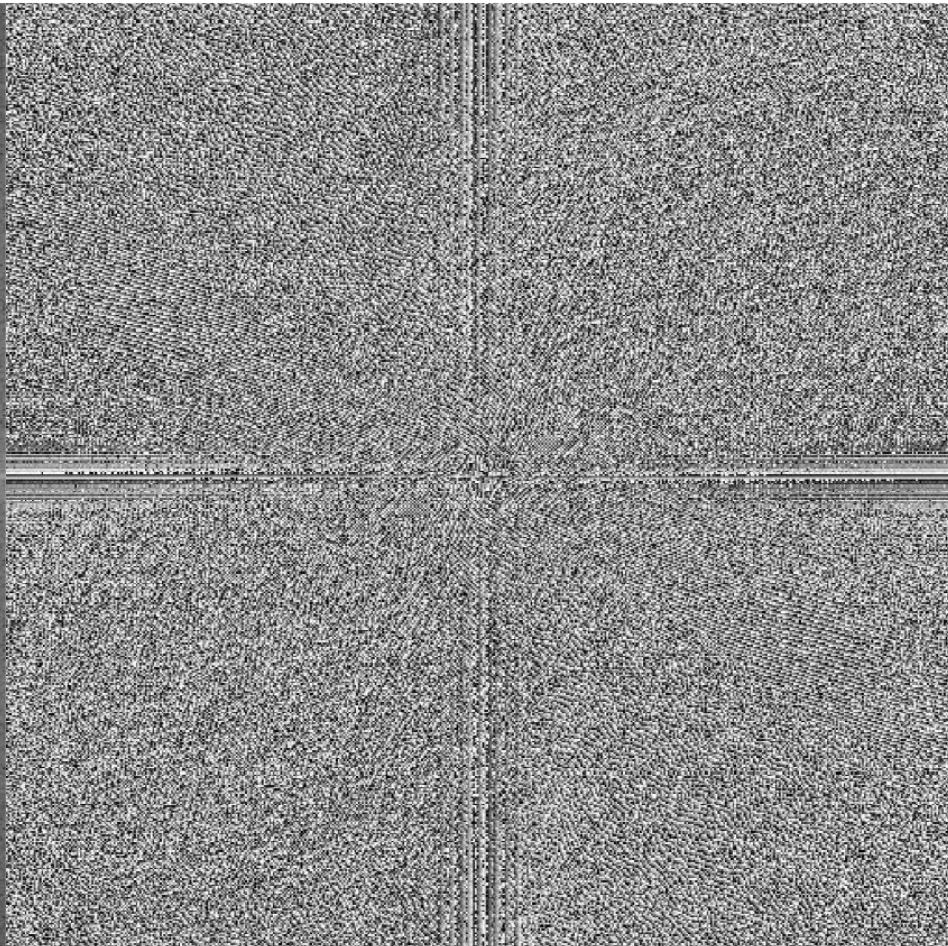


# What about phase?

Amplitude



Phase

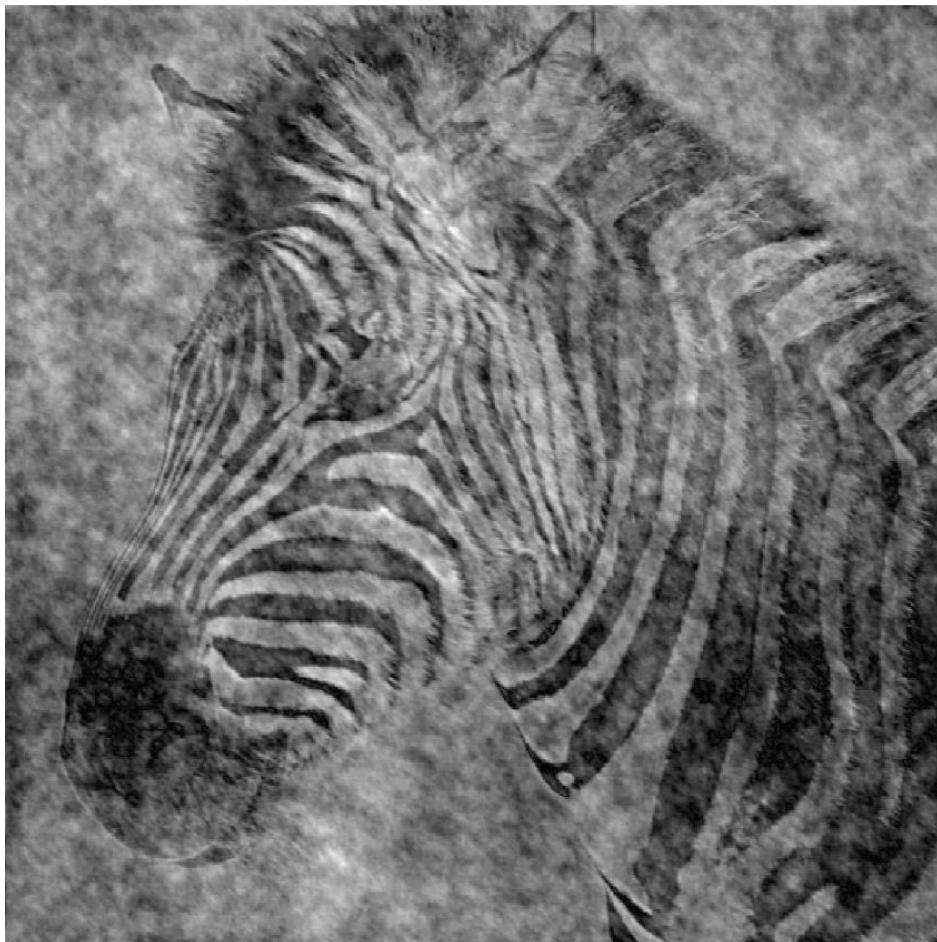


# Think-Pair-Share

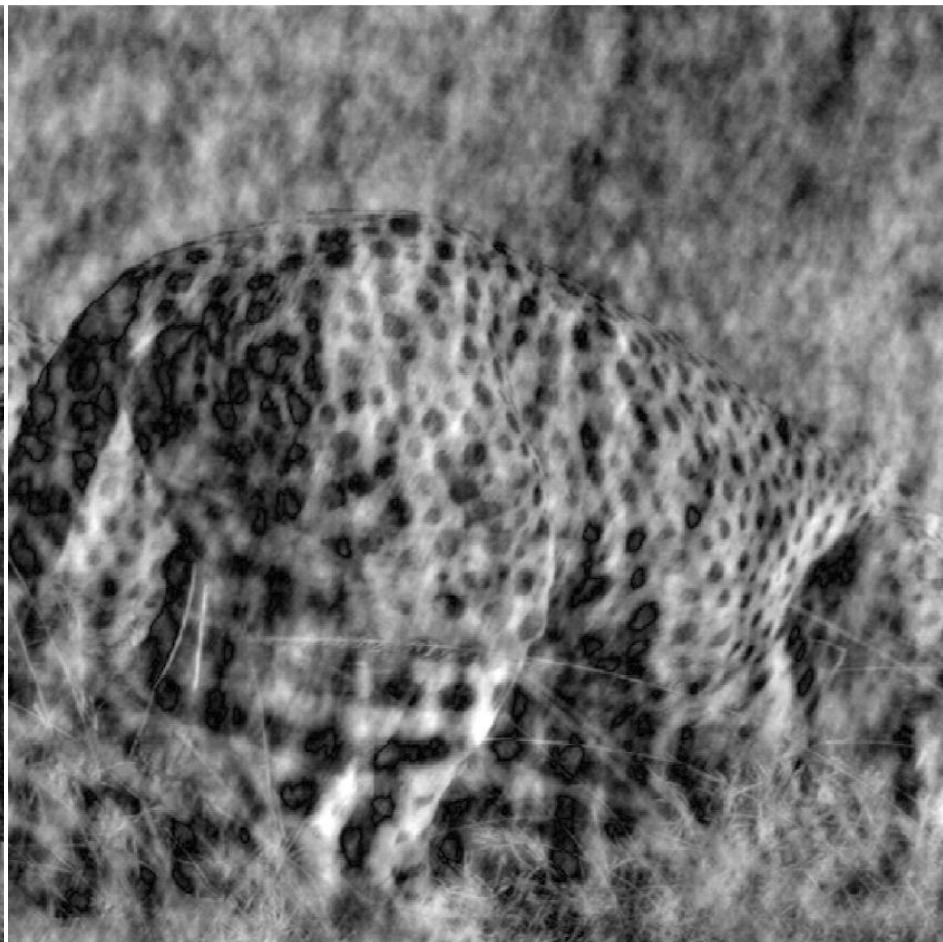
- In Fourier space, where is more of the information that we see in the visual world?
  - Amplitude
  - Phase

# Cheebra

Zebra phase, cheetah amplitude



Cheetah phase, zebra amplitude



- The frequency amplitude of natural images are quite similar
  - Heavy in low frequencies, falling off in high frequencies
  - Will *any* image be like that, or is it a property of the world we live in?
- Most information in the image is carried in the phase, not the amplitude
  - Not quite clear why

# Some properties of Fourier Transforms

- Linearity  $\mathcal{F}[ax(t) + by(t)] = a \mathcal{F}[x(t)] + b \mathcal{F}[y(t)]$
- Fourier transform of a real signal is symmetric about the origin
- The energy of the signal is the same as the energy of its Fourier transform

# The Convolution Theorem

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

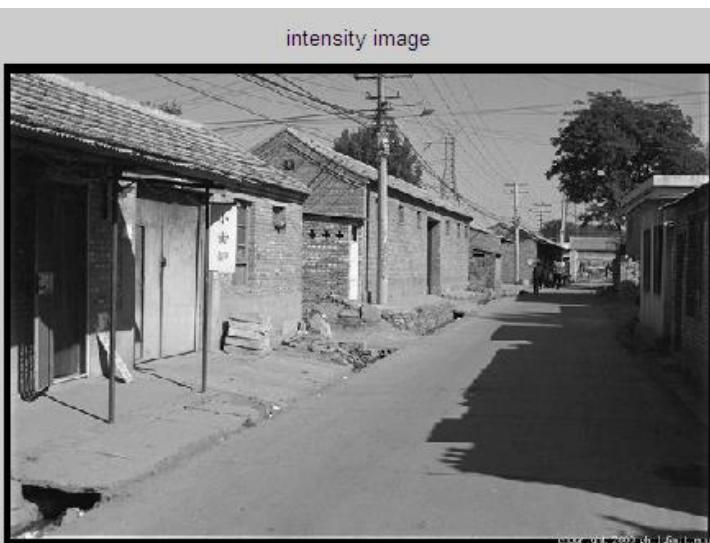
$$F[g * h] = F[g]F[h]$$

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

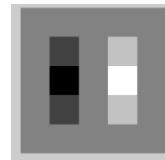
$$g * h = F^{-1}[F[g]F[h]]$$

# Filtering in spatial domain

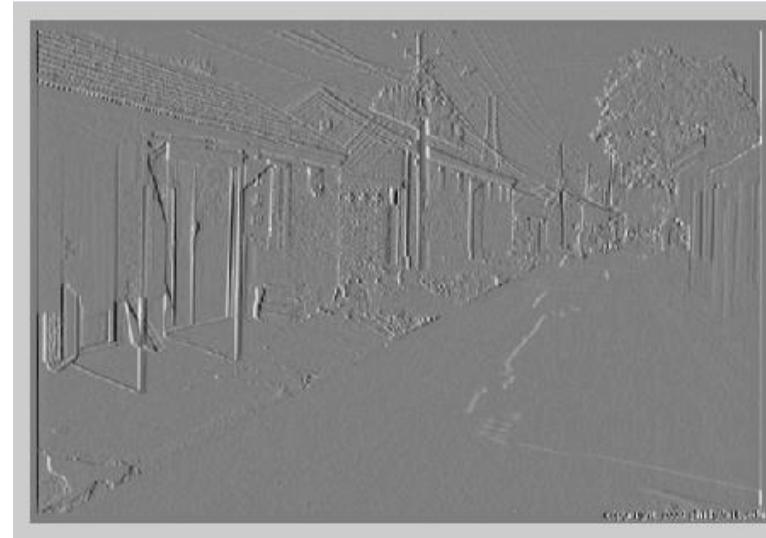
1	0	-1
2	0	-2
1	0	-1



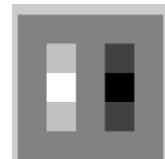
\*



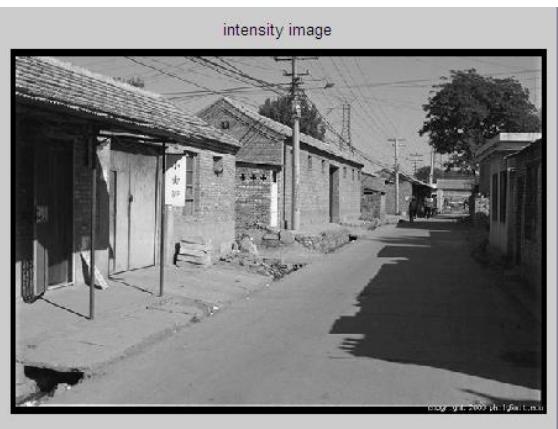
=



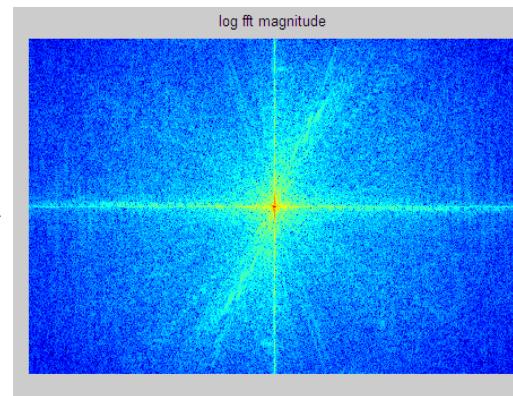
# Filtering in frequency domain



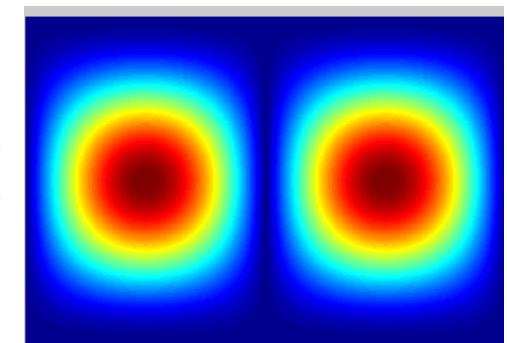
FFT



FFT



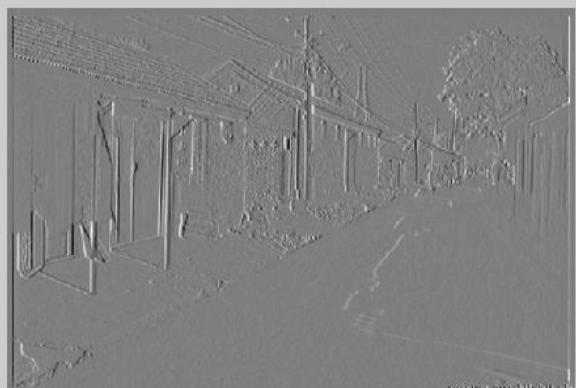
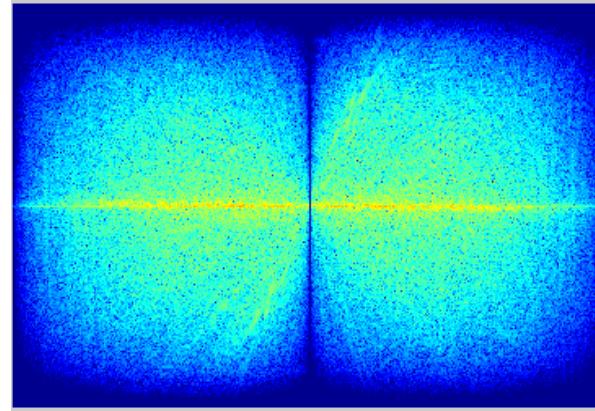
X



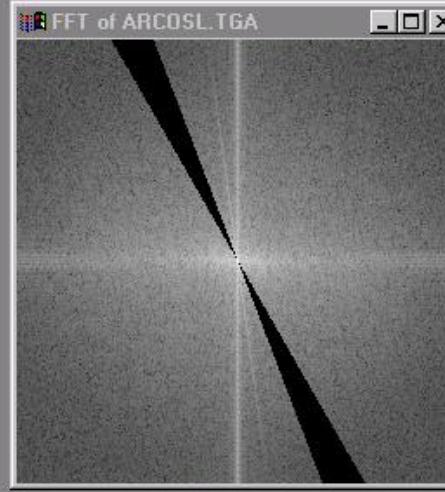
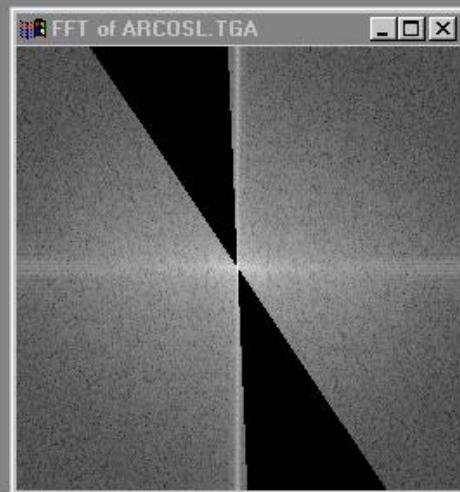
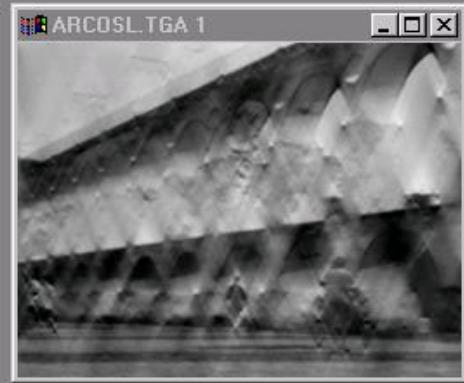
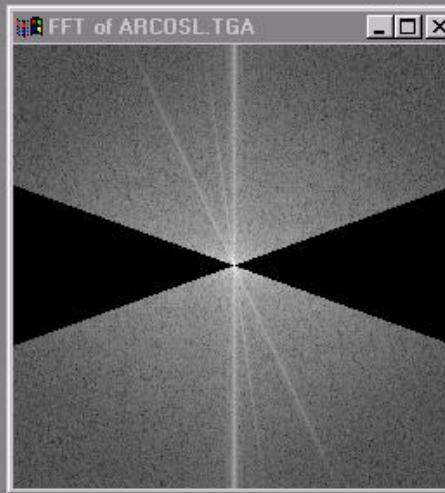
||

Inverse FFT

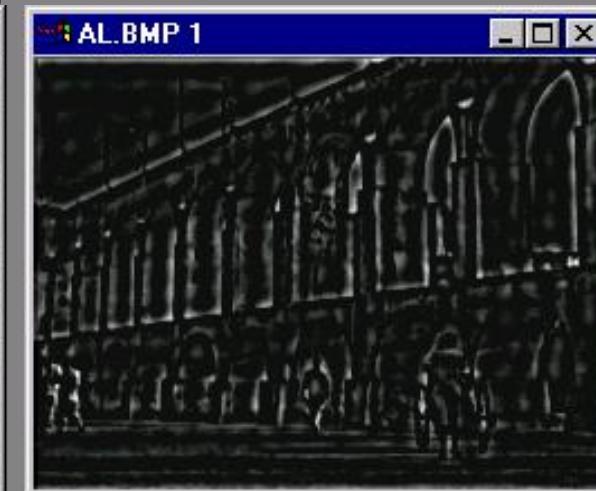
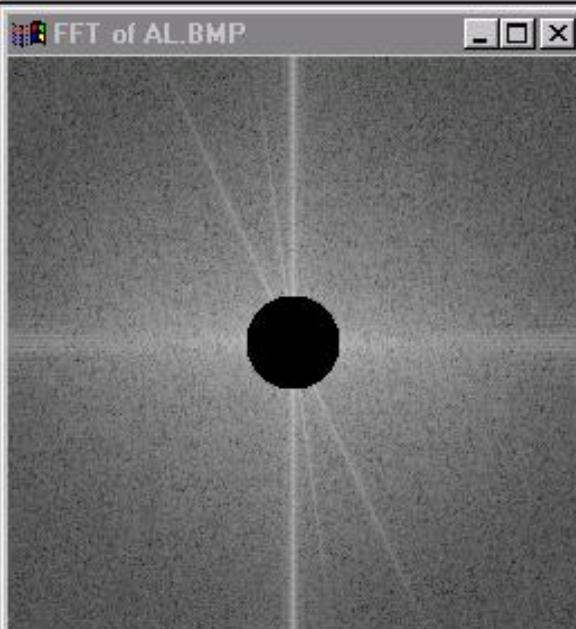
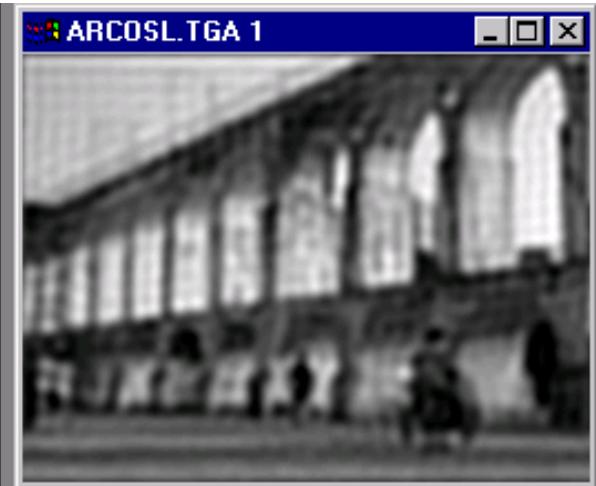
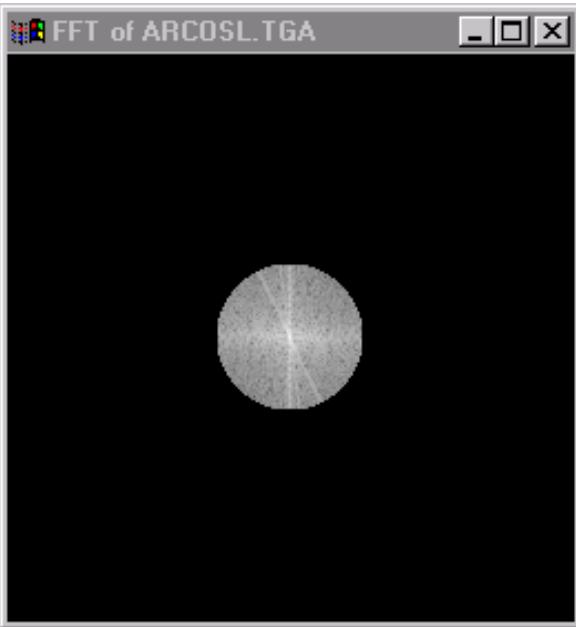
←



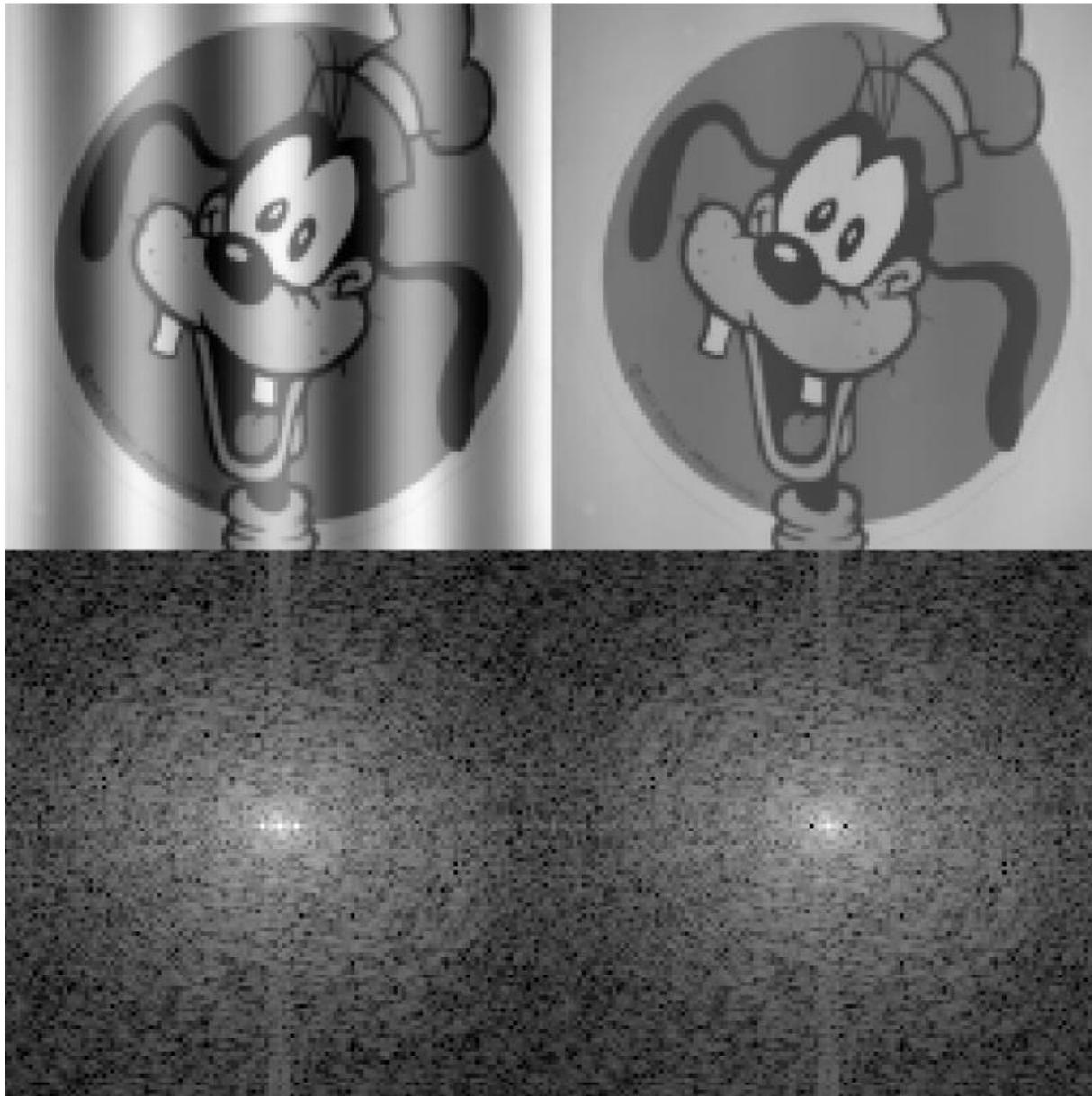
# Now we can edit frequencies!



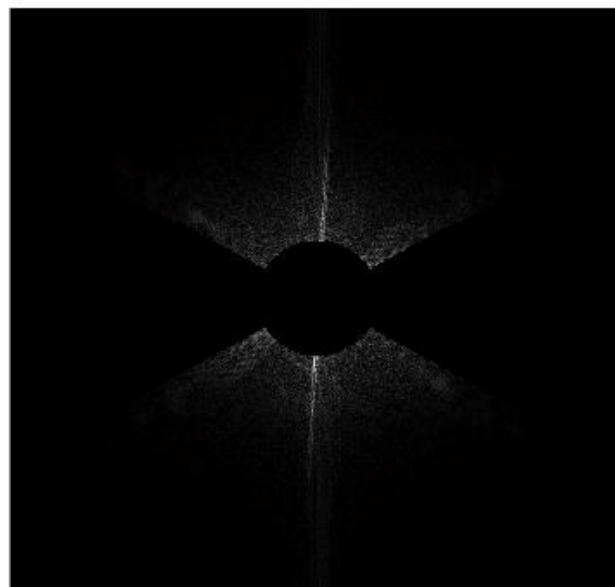
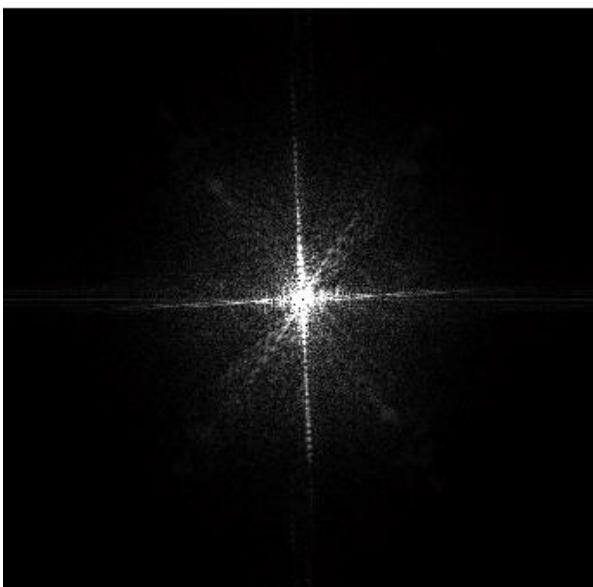
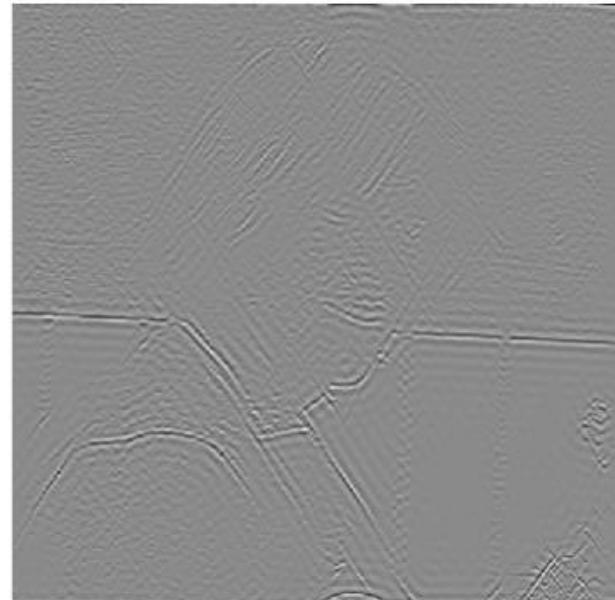
# Low and High Pass filtering



# Removing frequency bands



# High pass filtering + orientation



# Application: Hybrid Images

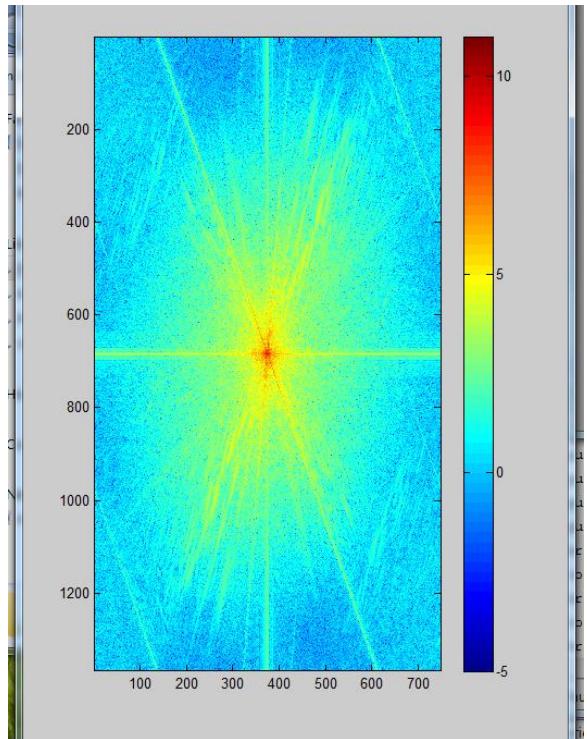
When we see an image from far away, we are effectively subsampling it!



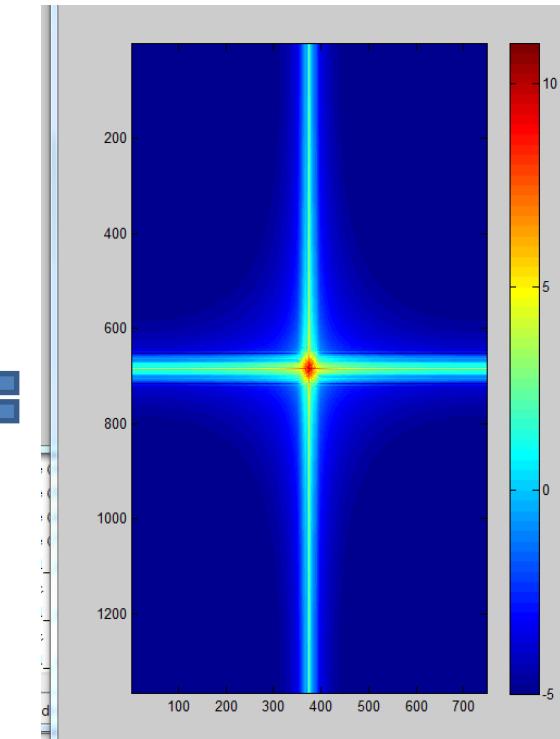
A. Oliva, A. Torralba, P.G. Schyns, SIGGRAPH 2006

# Hybrid Image in FFT

Hybrid Image



Low-passed Image



High-passed Image

