

# Computer Vision (10224)

## Lecture 4 – Sampling and Frequency

### Dr. Eyal Katz – Spring 2021

This presentation has been updated and reedited by  
Dr. Eyal Katz, Afeka College of Engineering

This Lecture is (mainly) based on  
Prof. James Hays  
Brown University's  
Lecture 5: Thinking in Frequency

See additional credits on the last page or on individual slides

# Administration – Spring 2021: Midterm Notes

- Since In-class learning is not expected to resume soon, the midterm is replaced by a separate work, per Afeka instructions.
- The midterm opening time and date will be published on AfekaNet (**currently published time is not final - 18-04-2021 07:59**).
- The work should be submitted no later than a week after the midterm opening time.
- Your submitted work should be individual, and original (No workgroups).
- Other details and instructions will be published.

# Review: Practice Questions Set 1: 1.4

## (reviewed based on last week)

1. Write down a  $3 \times 3$  filter that returns a positive value if the average value of the 4-adjacent neighbors is less than the center and a negative value otherwise
2. Write down a filter that will compute the gradient in the x-direction:

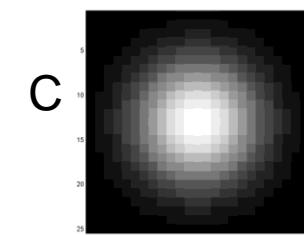
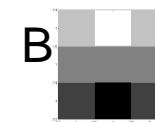
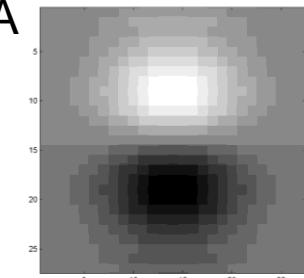
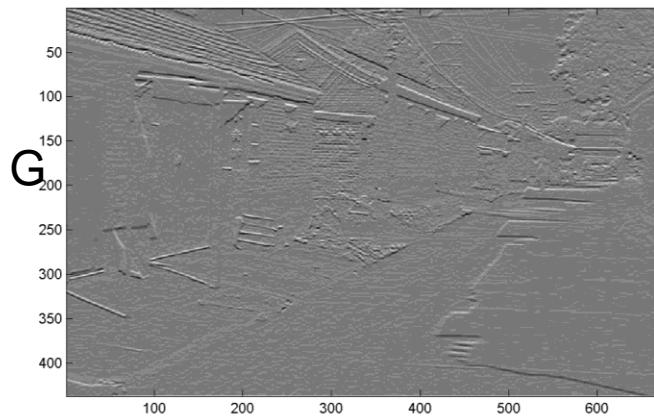
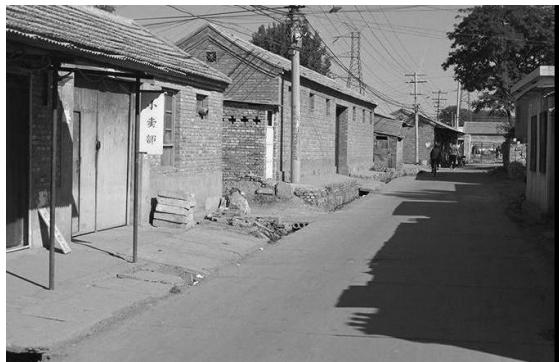
$$\text{grad}_x(y, x) = \text{im}(y, x+1) - \text{im}(y, x) \text{ for each } x, y$$

# Review: Practice Questions Set 1: 1.5

3. Fill in the blanks:

$$\begin{array}{l} \text{a) } \underline{\quad} = D * B \\ \text{b) } \overline{A} = \underline{\quad} * \underline{\quad} \\ \text{c) } F = \overline{D} * \underline{\quad} \\ \text{d) } \underline{\quad} = D * \overline{D} \end{array}$$

← Filtering Operator

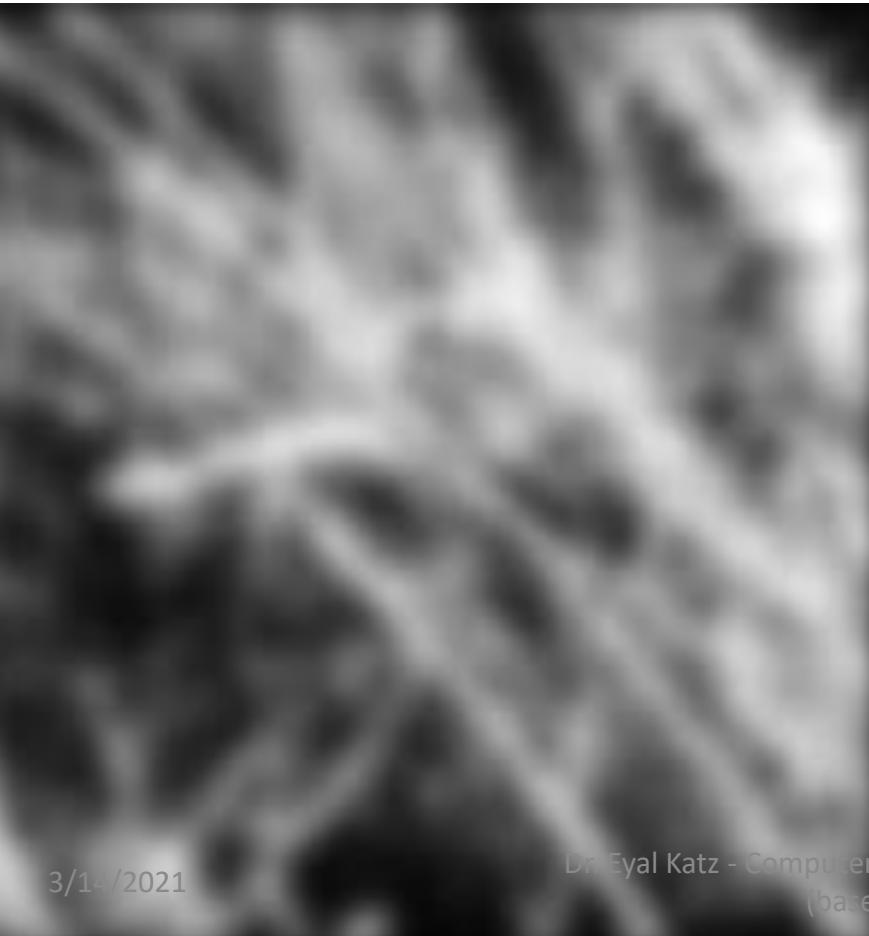


# Today's Class

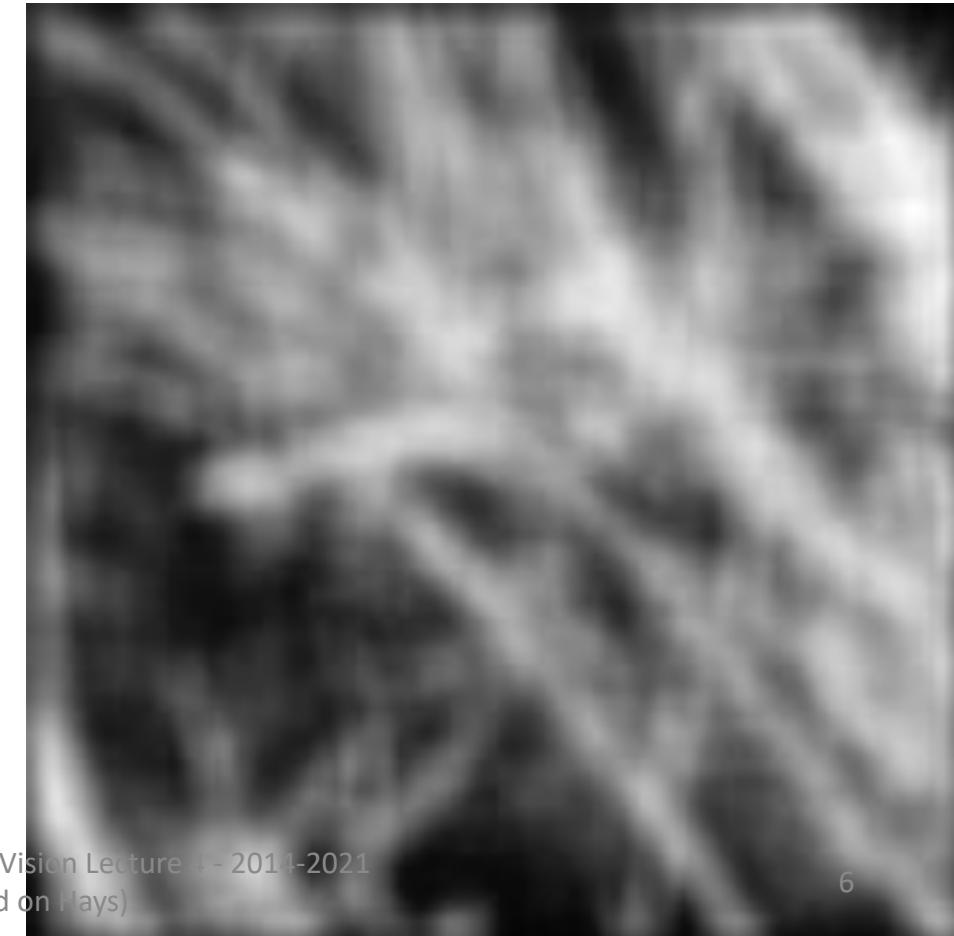
- Fourier transform and the frequency domain
  - Frequency-domain view of filtering (convolution)
  - Sampling
  - Hybrid images

# Motivation (I): Why does the Gaussian give a nice smooth image, but the square (box) filter give edgy artifacts?

Gaussian filter



Box filter

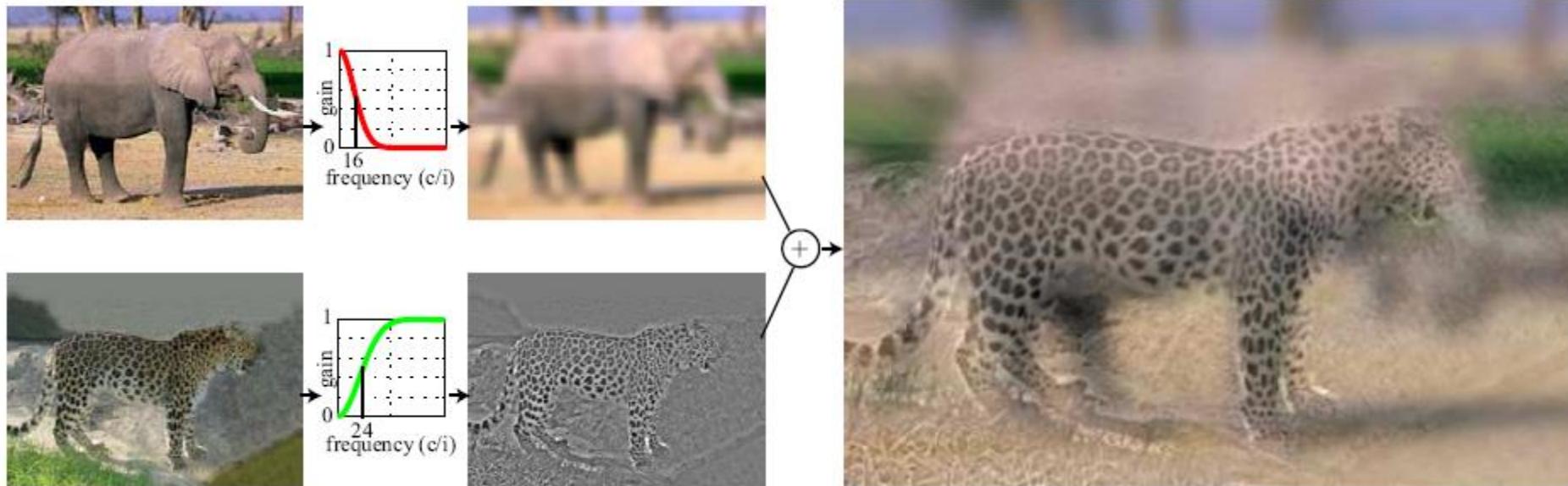


# Motivation (II)



# Motivation (II – cont.)

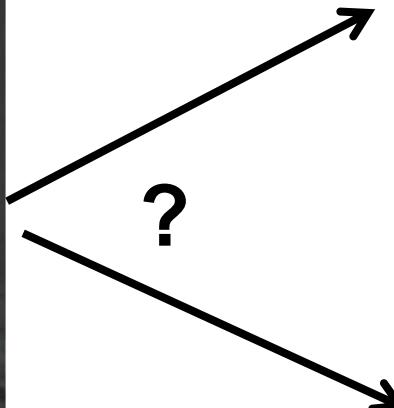
## Hybrid Images



- A. Oliva, A. Torralba, P.G. Schyns,  
“Hybrid Images,” SIGGRAPH 2006

## Motivation (II – cont.)

Why do we get different, distance-dependent interpretations of hybrid images?



# Motivation (III):

## Why does a lower resolution image still makes sense to us? What do we lose?

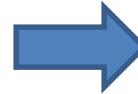
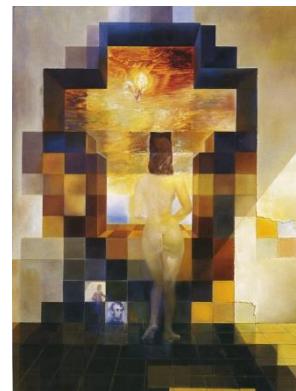


Image: <http://www.flickr.com/photos/igorms/136916757/>

## Motivation (IV)

# Thinking in terms of frequency



# Jean Baptiste Joseph Fourier (1768-1830)

had crazy idea (1807):

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

*...the manner in which the author arrives at these equations is not exempt of difficulties and...his analysis to integrate them still leaves something to be desired on the score of generality and even rigour.*

- Don't believe it?
  - Neither did Lagrange, Laplace, Poisson and other big wigs
  - Not translated into English until 1878!
- But it's (mostly) true!
  - called Fourier Series
  - there are some subtle restrictions



# A sum of sines

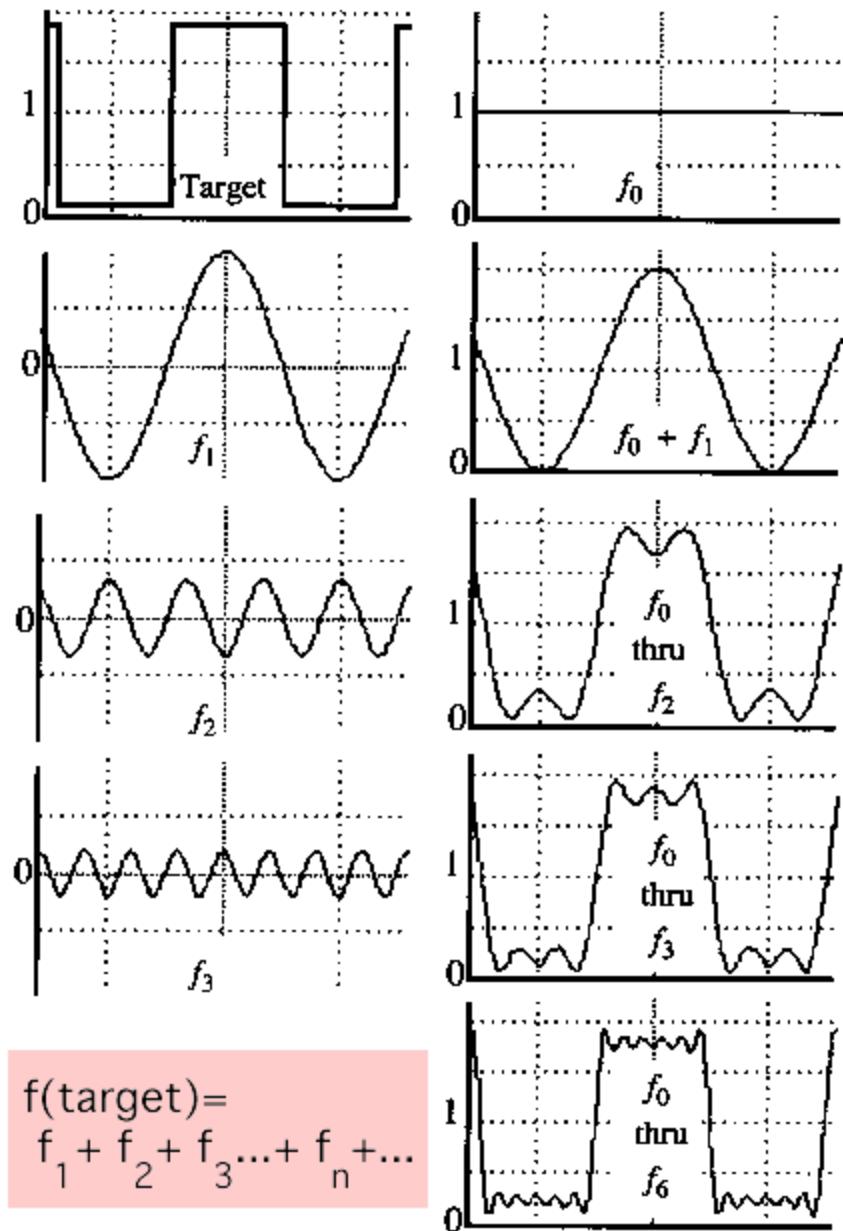
Our building block:

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

Add enough of them to get any signal  $f(x)$  you want!

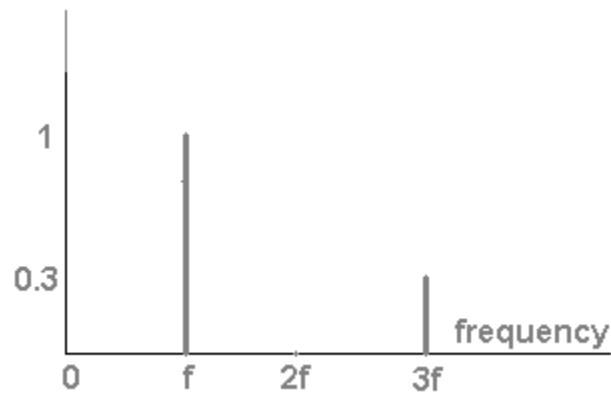
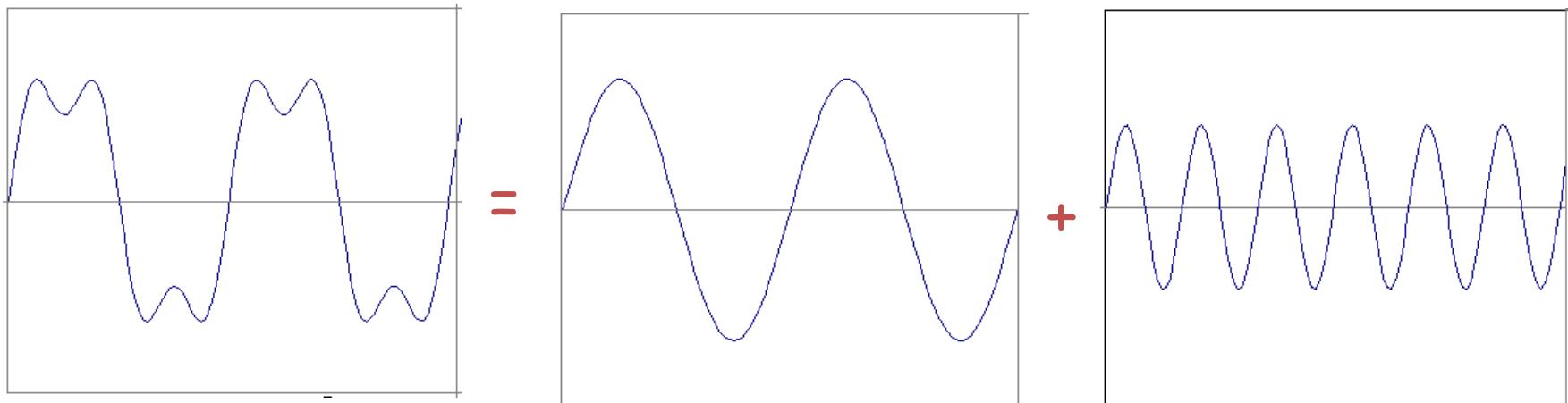
Note: we refer as

a **sinusoidal function**,  
or a **sinusoid**, to  
sine, cosine,  $e^{ix}$ ,  $e^{jx}$  etc.

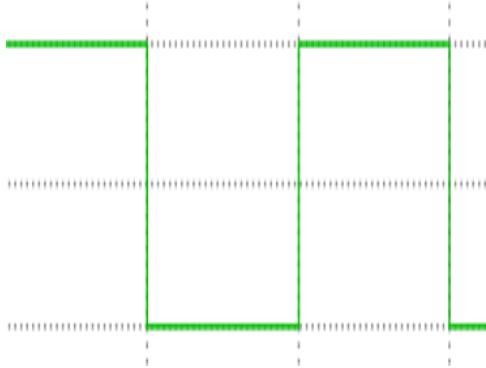


# Frequency Spectra

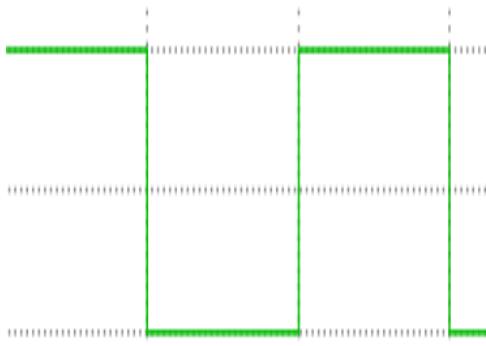
- example :  $g(t) = \sin(2\pi f t) + (1/3)\sin(2\pi(3f)t)$



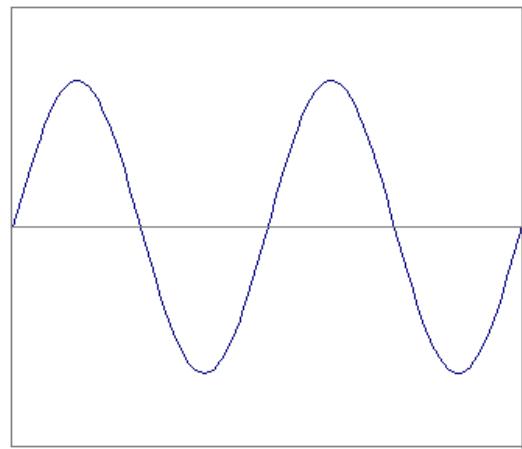
# Frequency Spectra



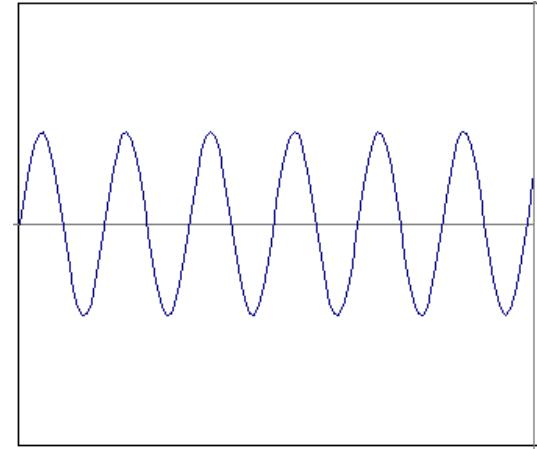
# Frequency Spectra



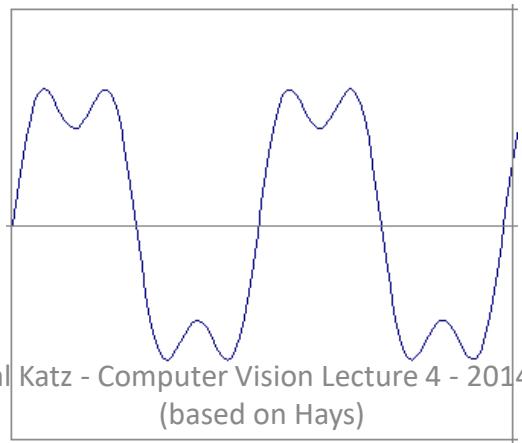
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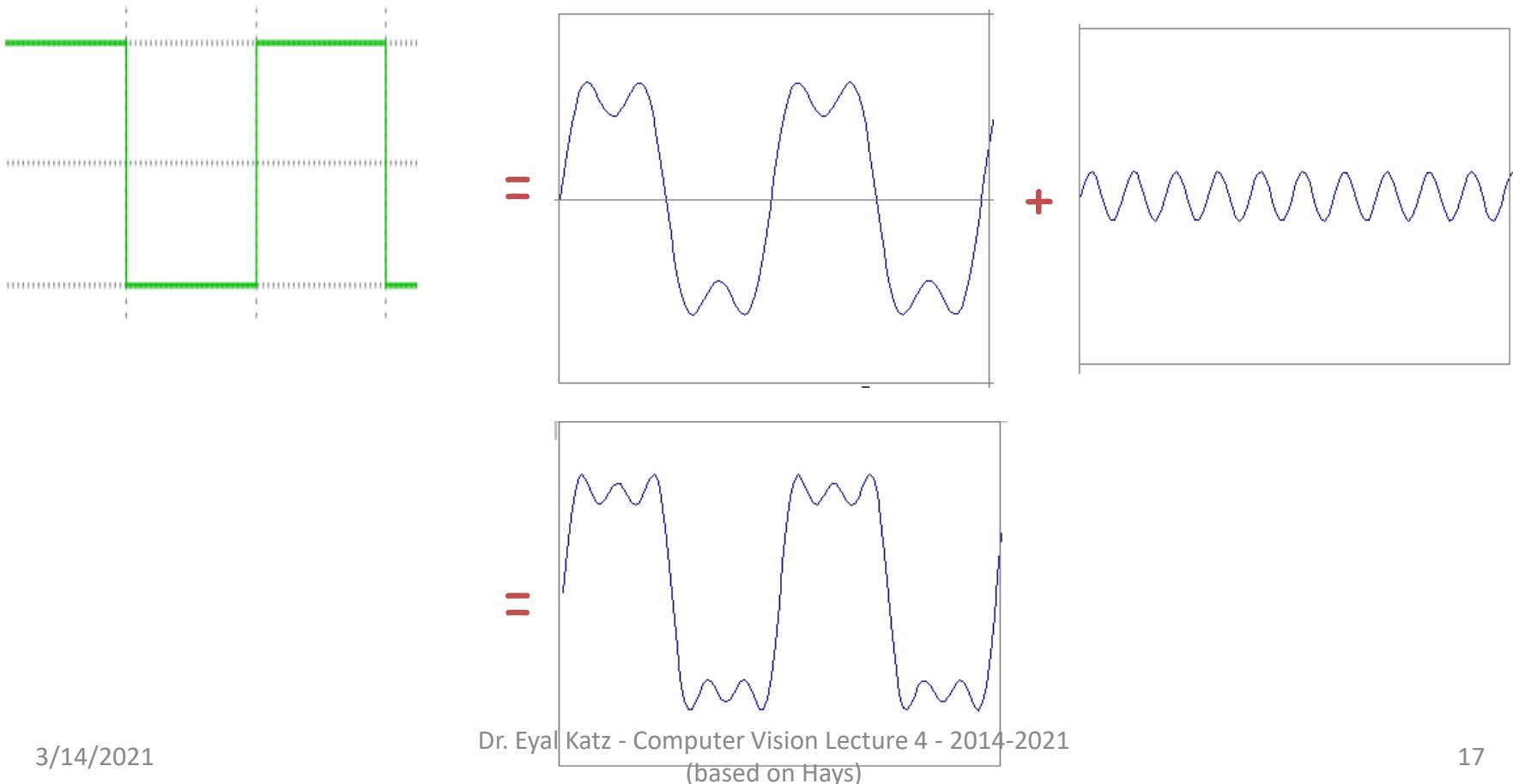
+



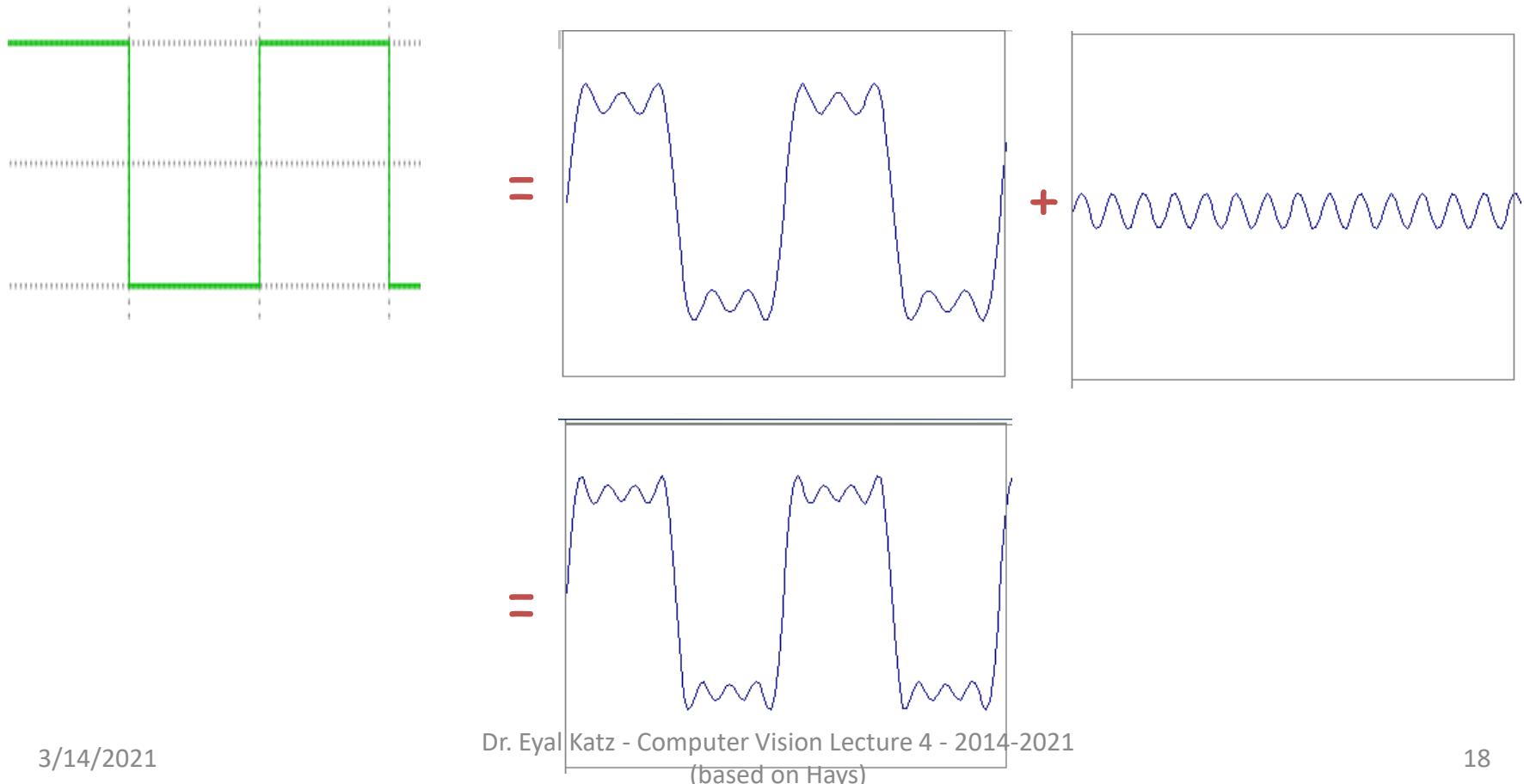
=



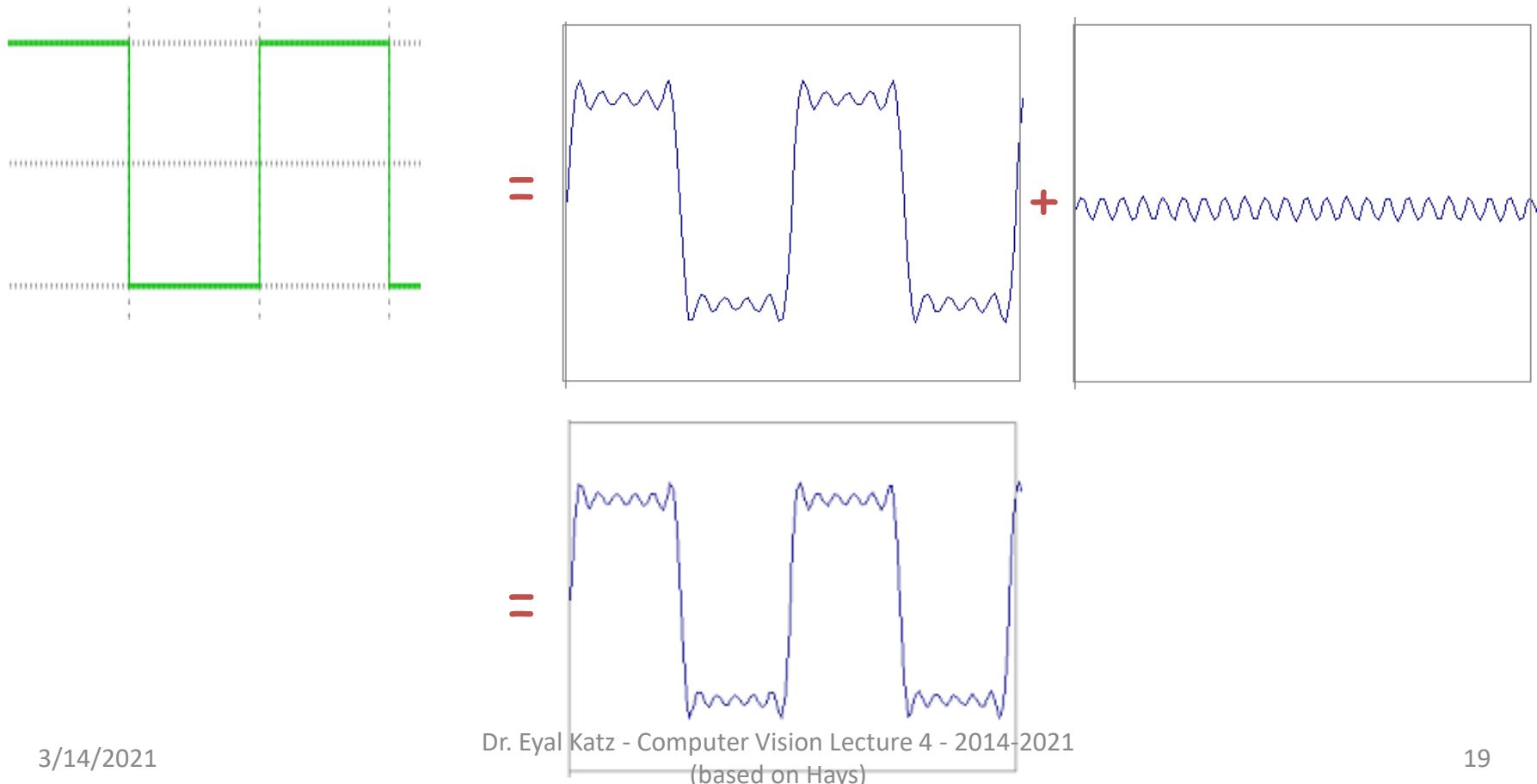
# Frequency Spectra



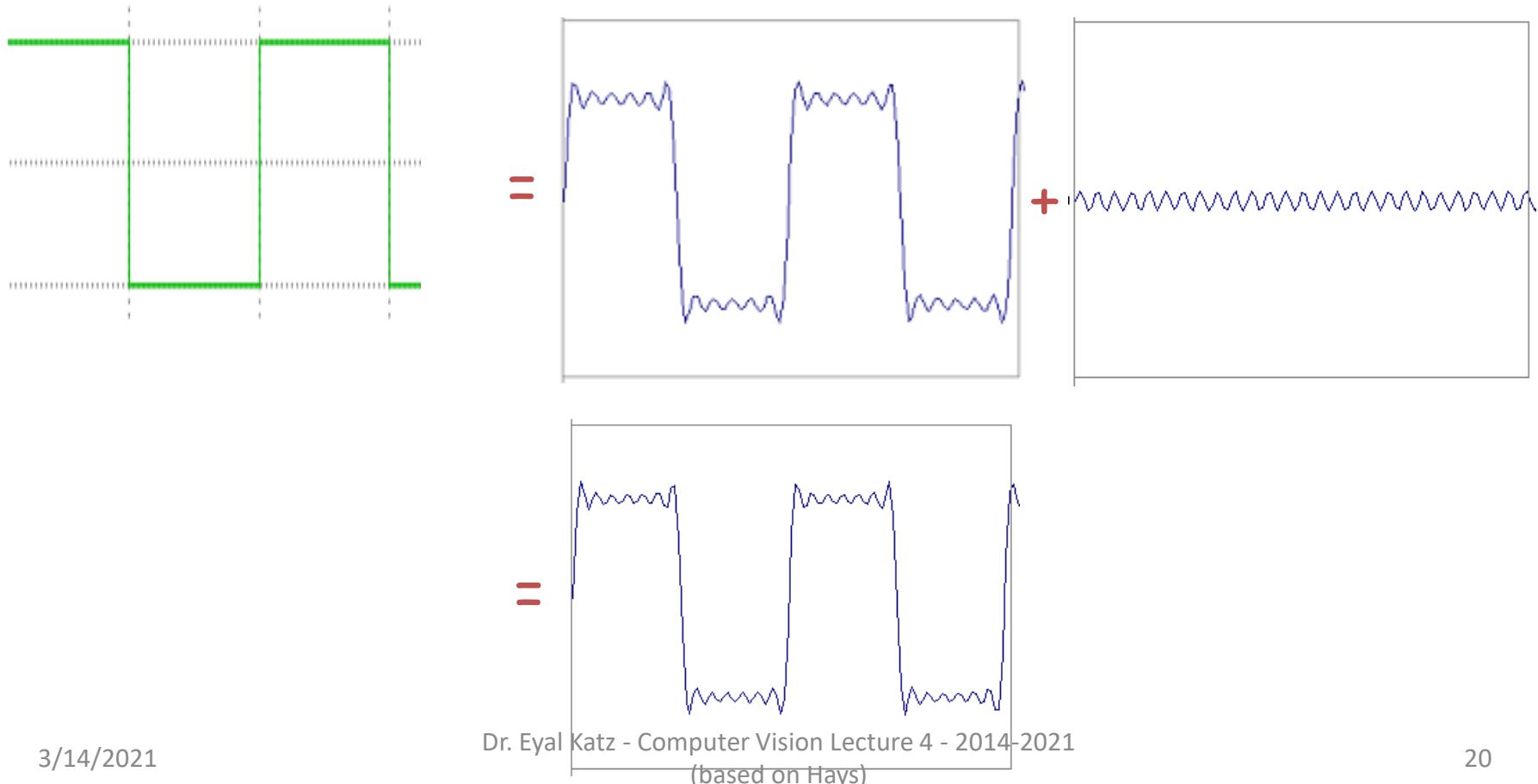
# Frequency Spectra



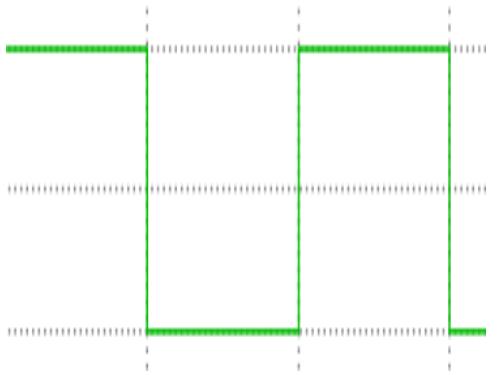
# Frequency Spectra



# Frequency Spectra

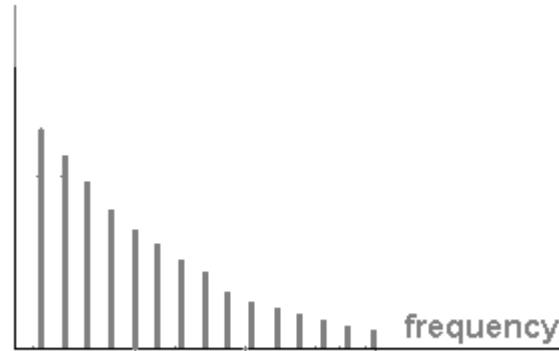


# Frequency Spectra



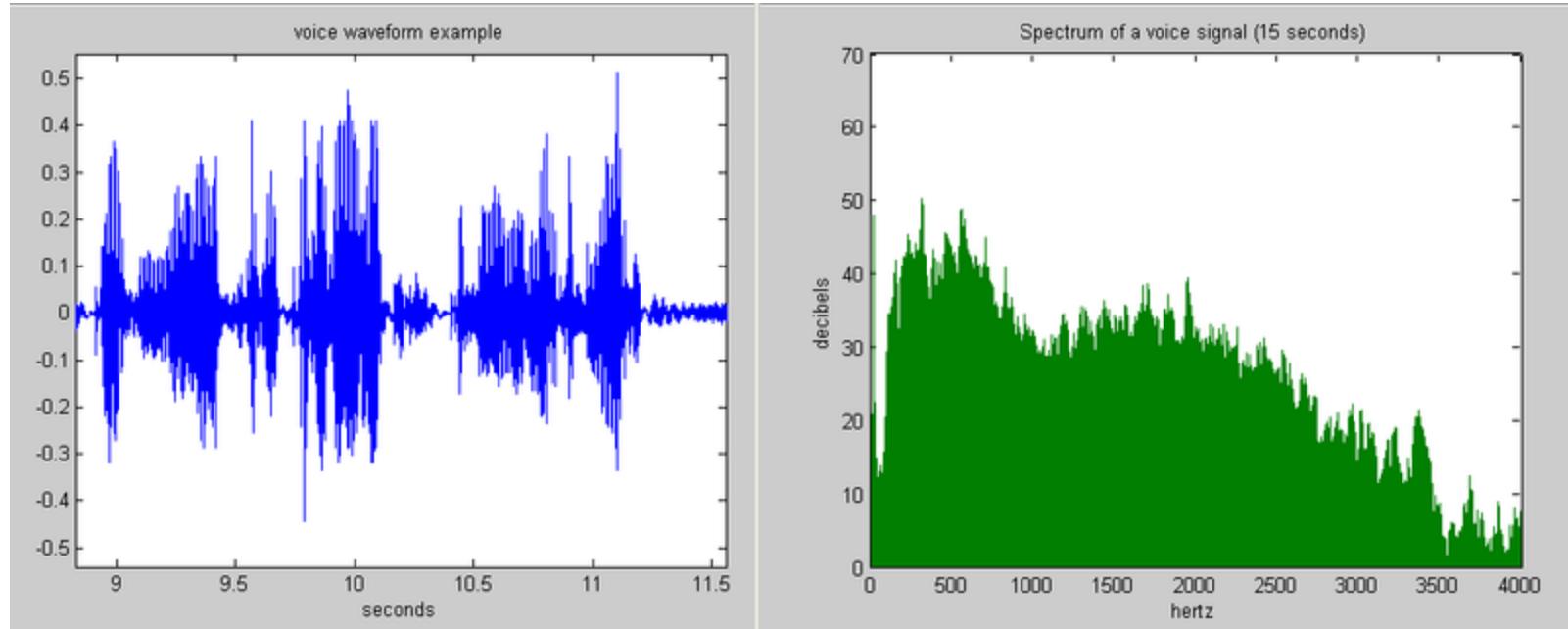
=

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



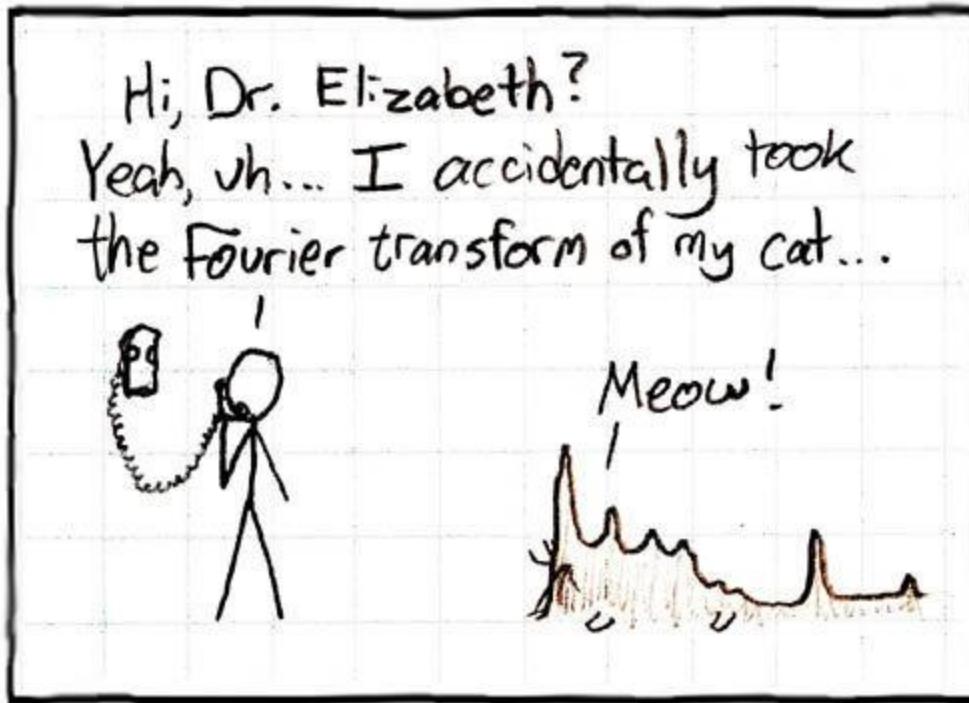
# Example: Music

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



# Other signals

- We can also think of all kinds of other signals the same way

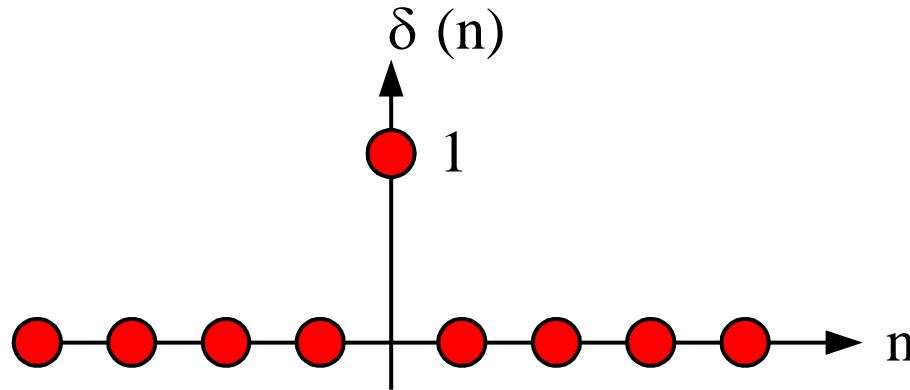


xkcd.com

# Recall: Some special functions

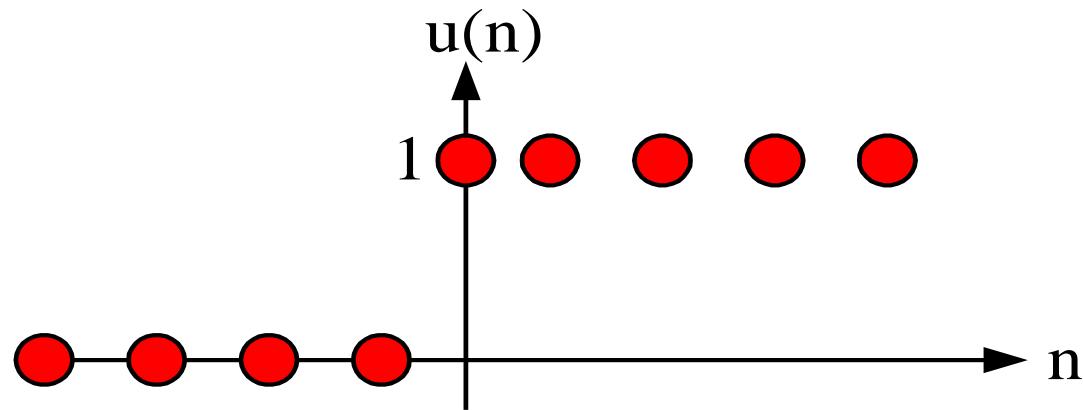
- Discrete **Impulse** Function  
(or **Kronecker Delta**):

$$\delta(n) = \begin{cases} 1 & n = 0 \\ 0 & otherwise \end{cases}$$



➤ Discrete **step** function:

$$u(n) = \begin{cases} 1 & n \geq 0 \\ 0 & \text{otherwise} \end{cases}$$



*These two are related:*  $\delta(n) = u(n) - u(n-1)$

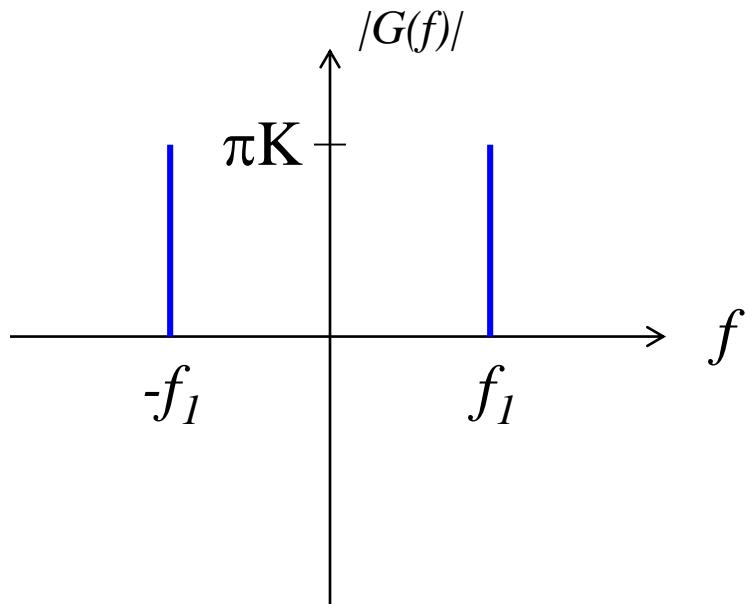
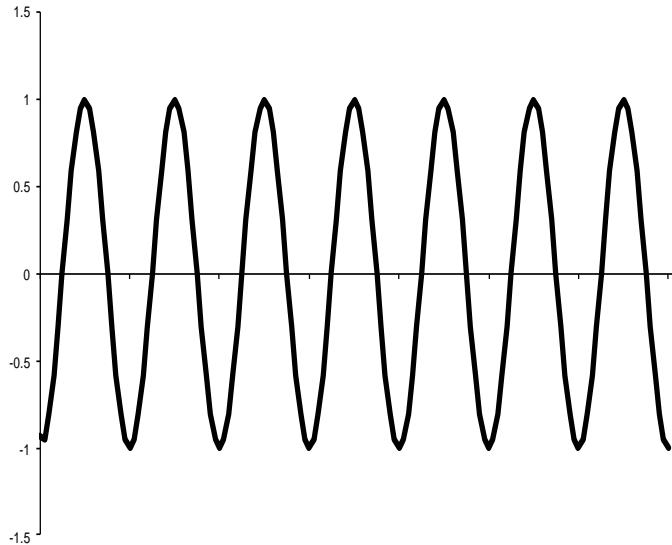
$$u(n) = \sum_{k=0}^{\infty} \delta(n-k)$$

# FT Example (a single 1D sinusoid): Cosine and Its Fourier Transform

$$g(x) = K \cos(2\pi f_1 x) \rightarrow \mathcal{F}\{g(x)\} = G(f)$$

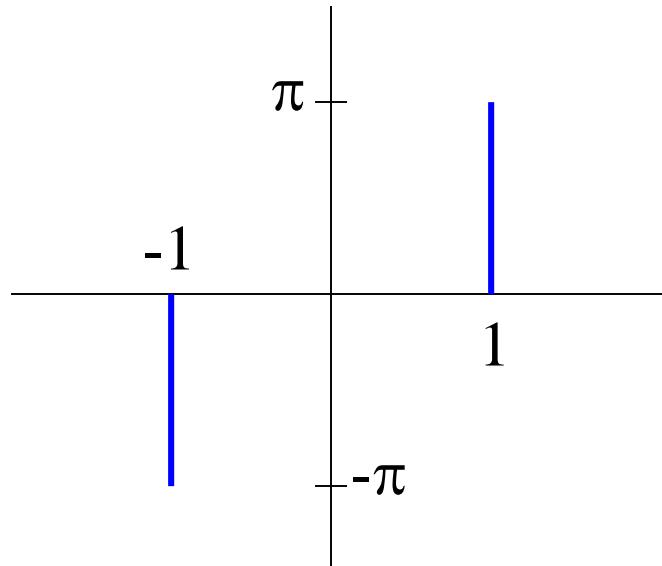
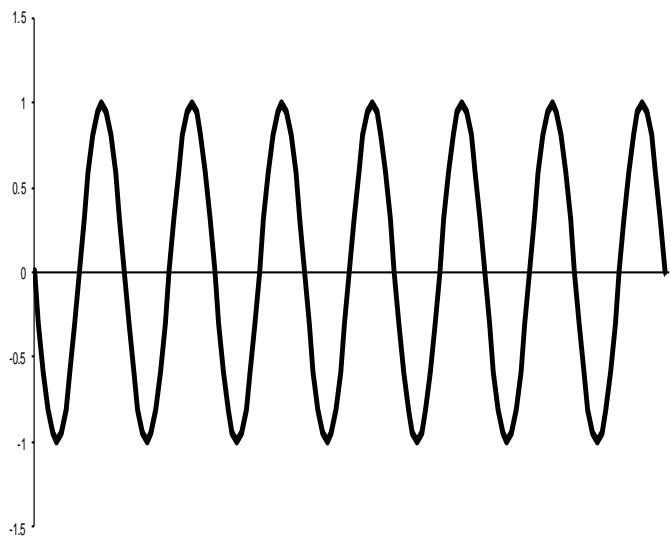
$f$  - frequency

$x$  - (“time”) index along the  $x$  axis



If  $g(2\pi f x)$  is even, so is  $G(\omega)$

# FT Example (a single 1D sinusoid): Sine and Its Transform



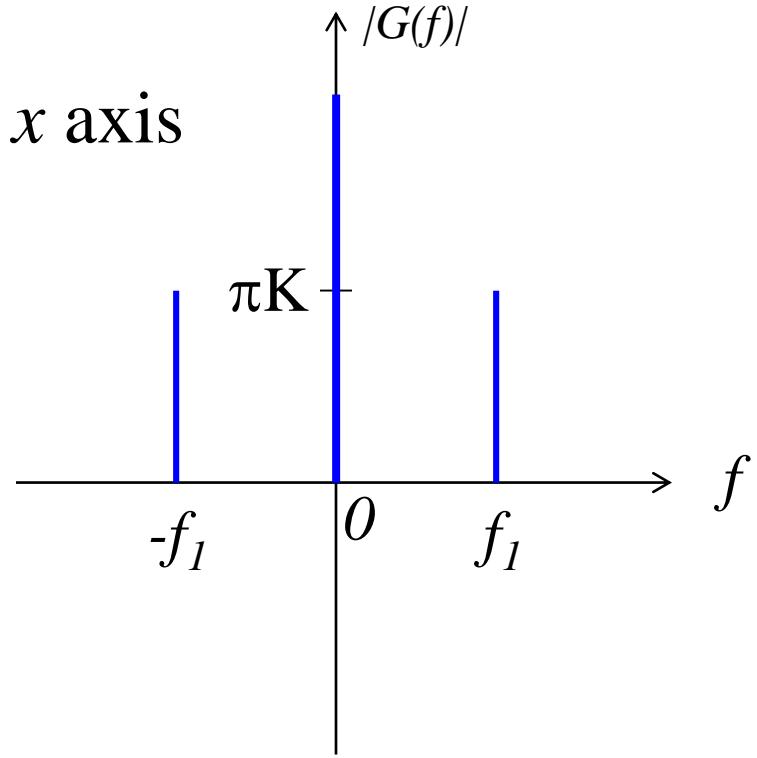
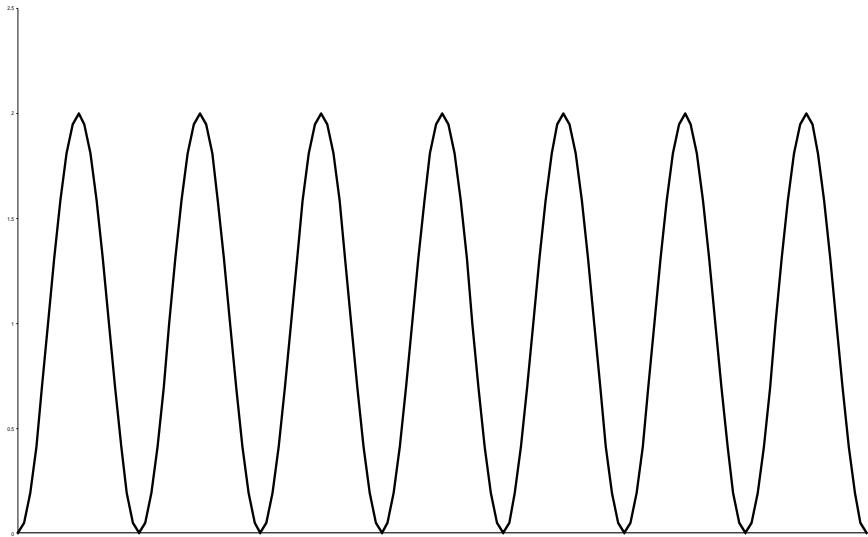
If  $f(x)$  is odd, so is  $F(\omega)$

# FT Example: Cosine and Its Fourier Transform

$$g(x) = K(1 + \cos(2\pi f_1 x)) \rightarrow \mathcal{F}\{g(x)\} = G(f)$$

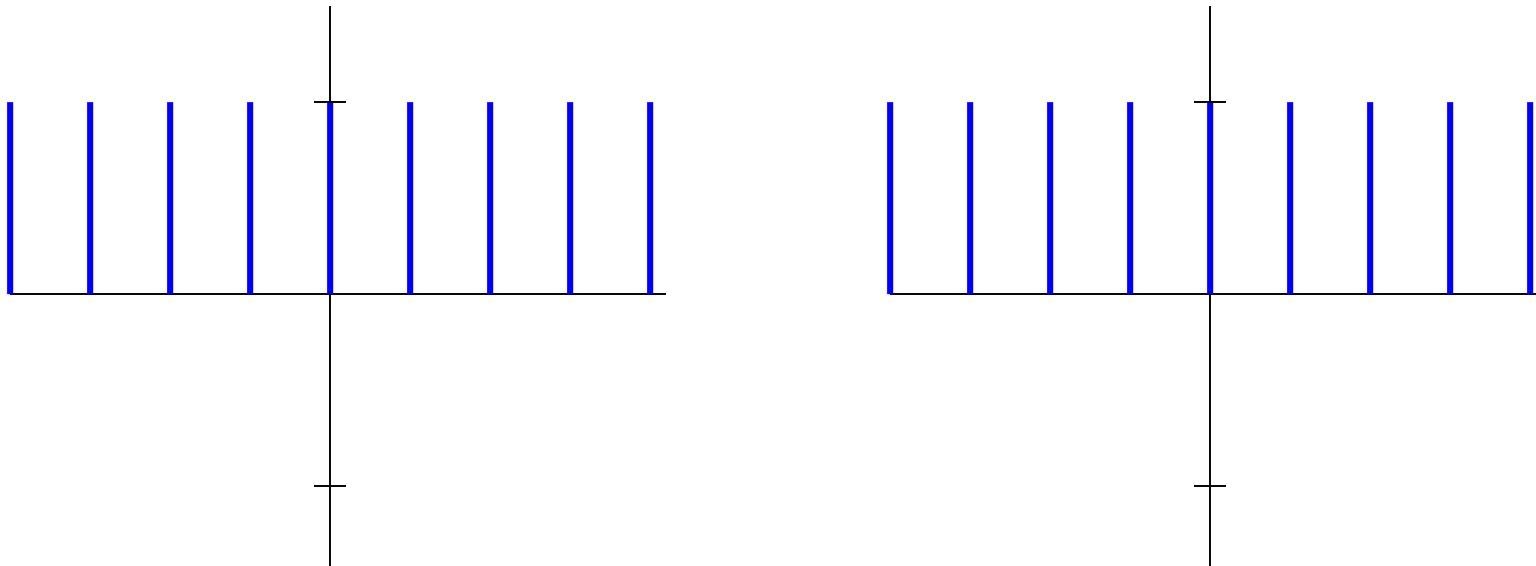
$f$  - frequency

$x$  - (“time”) index along the  $x$  axis

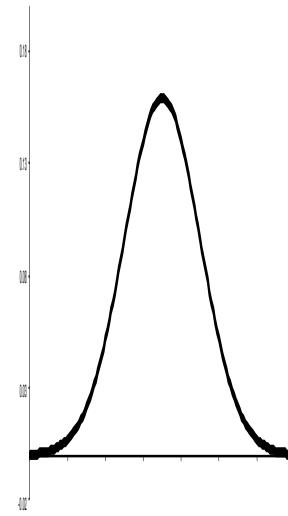
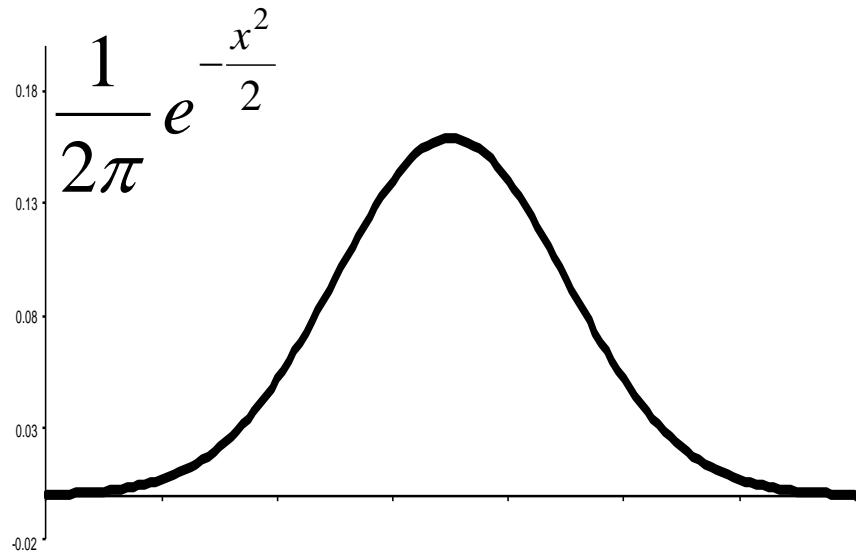


If  $g(2\pi fx)$  is even, so is  $G(\omega)$

# FT Example: Spikes and their Transform



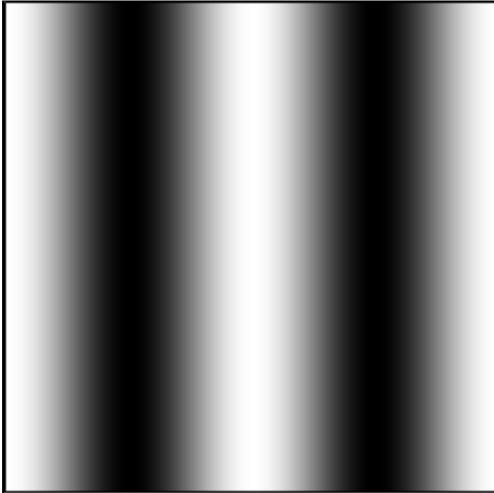
# FT Example: Gaussian and Its Transform



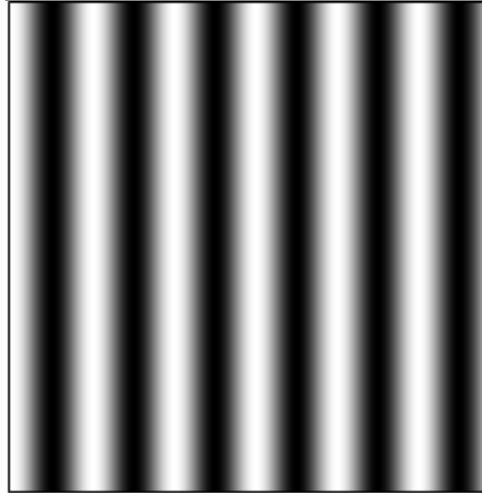
(Gaussian → Gaussian with different width / height)

# Fourier analysis in images (a single 2D sinusoid)

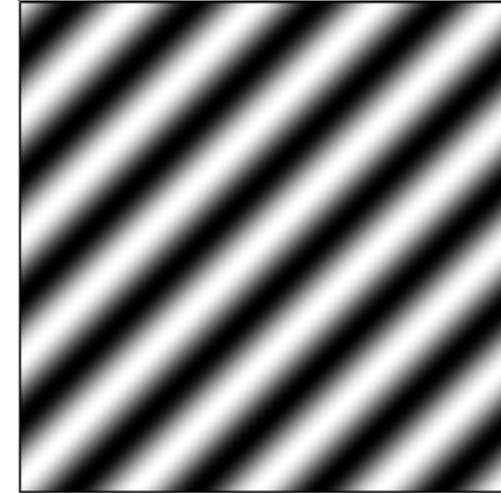
$f_x=2[\text{cyc/Img width}]$   
 $f_y=0[\text{cyc/Img height}]$



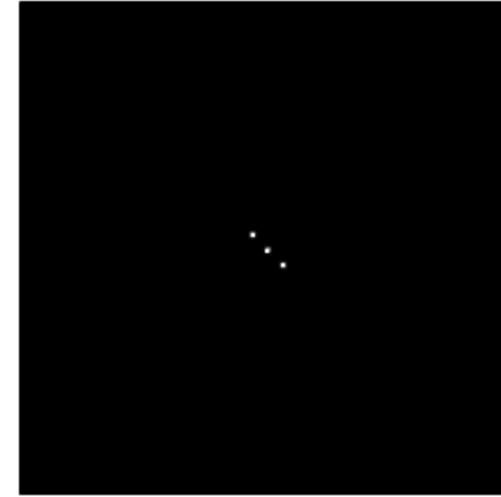
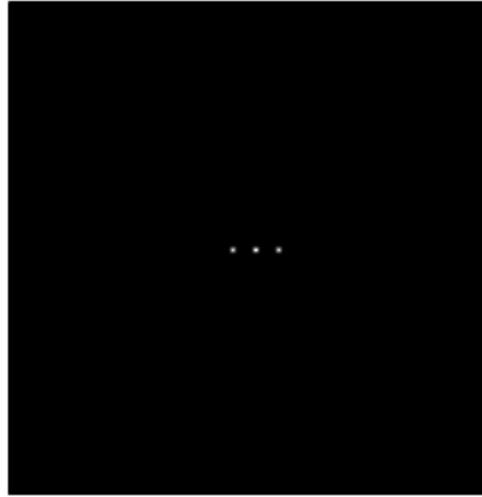
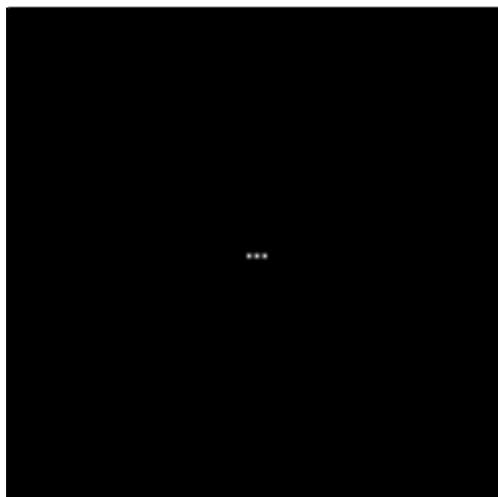
$f_x=6[\text{cyc/Img width}]$   
 $f_y=0[\text{cyc/Img height}]$



$f_x=4[\text{cyc/Img width}]$   
 $f_y=4[\text{cyc/Img height}]$



Intensity  
Image

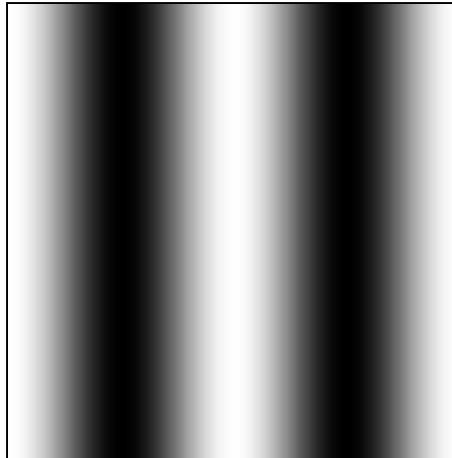


Fourier  
Image

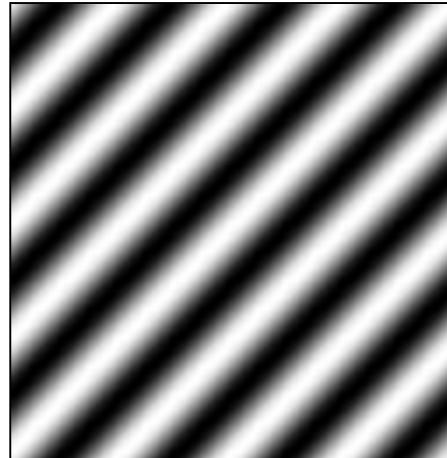
<http://sharp.bu.edu/~slehar/fourier/fourier.html#filtering>

# Signals can be composed

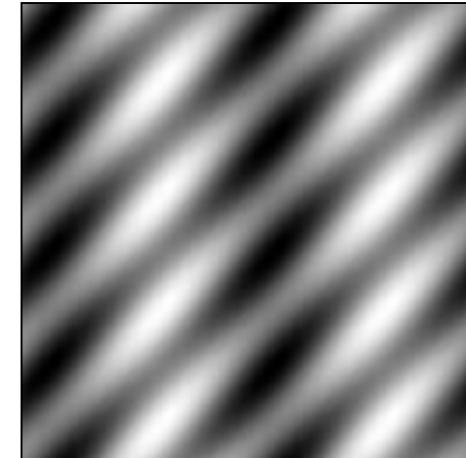
(a single 2D sinusoid)



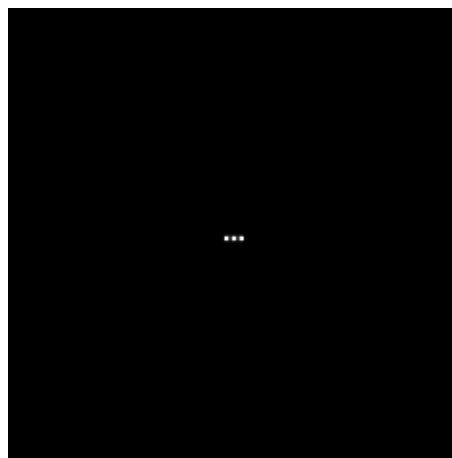
(a single 2D sinusoid)



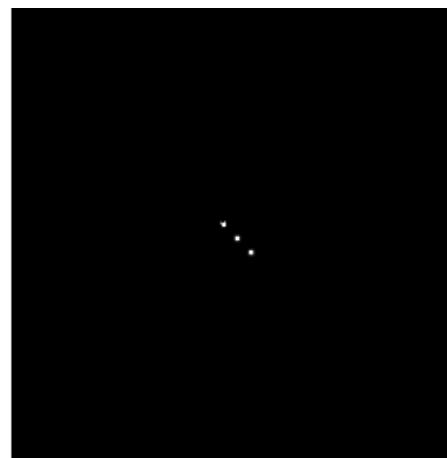
(a sum of 2 sinusoids)



+



=



Intensity  
Image

Fourier  
Image

<http://sharp.bu.edu/~slehar/fourier/fourier.html#filtering>

More: <http://www.cs.unm.edu/~brayer/vision/fourier.html>

Dr. Eyal Katz - Computer Vision Lecture 4 - 2014-2021  
(based on Hays)

# Fourier Transform

- Fourier transform stores the magnitude and phase at each frequency
  - Magnitude encodes how much signal there is at a particular frequency
  - Phase encodes spatial information (indirectly)
  - For mathematical convenience, this is often notated in terms of complex numbers

Magnitude:  $A = \pm \sqrt{R(\omega)^2 + I(\omega)^2}$

Phase:  $\phi = \tan^{-1} \frac{I(\omega)}{R(\omega)}$

# Computing the Fourier Transform (formal definition)

$$H(\omega) = \mathcal{F}\{h(x)\} = Ae^{j\phi}$$

Continuous

$$H(\omega) = \int_{-\infty}^{\infty} h(x)e^{-j\omega x}dx$$

Discrete

$$H(k) = \frac{1}{N} \sum_{x=0}^{N-1} h(x)e^{-j\frac{2\pi k x}{N}} \quad k = -N/2..N/2$$

Direct calculation of FT computational complexity:  $N^2$   
Fast Fourier Transform (FFT) computational complexity:  $N \log N$   
where  $N$  is the number of samples (image: number of pixels!)

# 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!

# Properties of Fourier Transforms

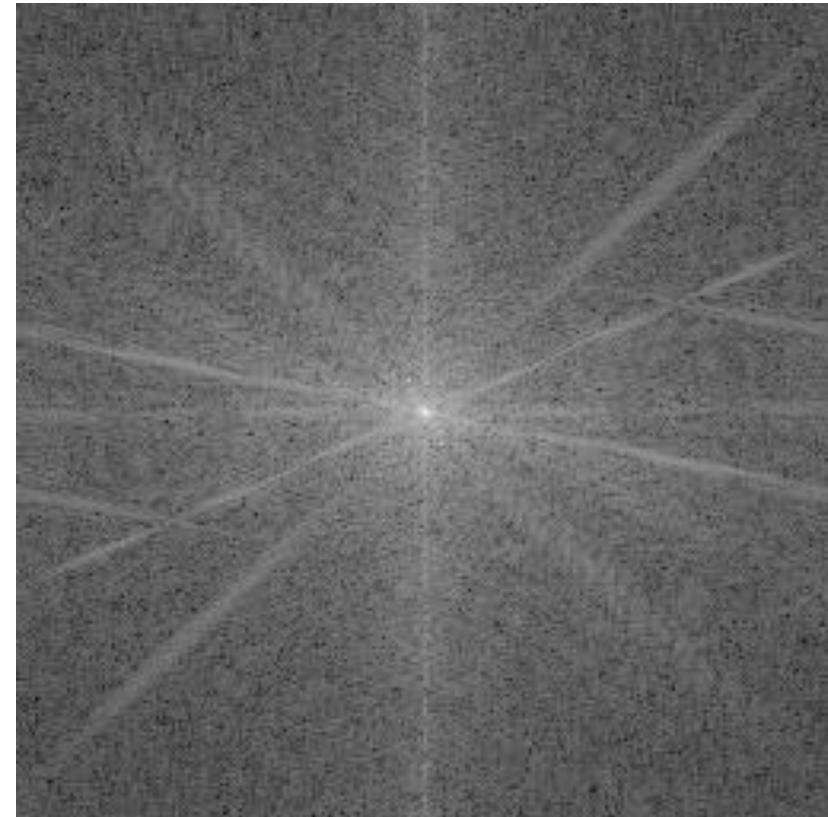
- Linearity  $\mathcal{F}[ax(t) + by(t)] = a\mathcal{F}[x(t)] + b\mathcal{F}[y(t)]$
- Fourier transform of a real signal is symmetric about the origin
- The energy of the signal is the same as the energy of its Fourier transform

# Fourier demo (I): sum of signals

cameraman.tif in //



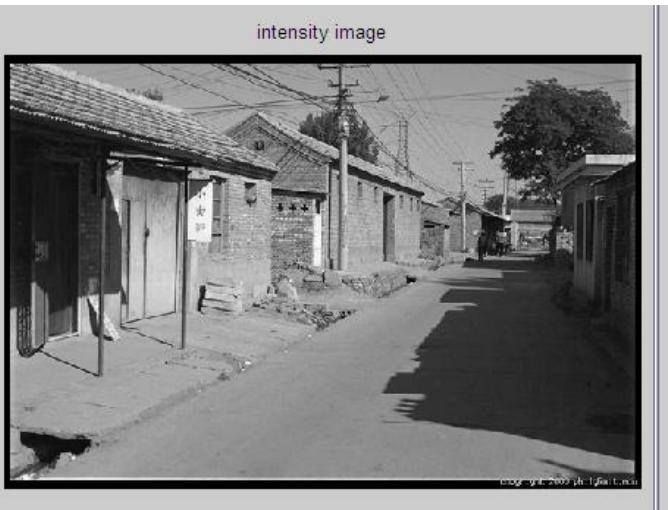
log (abs (fft (cameraman.tif in //)))



Note that the log is used for display purposes only, of FFT Magnitude  
(due to the limited dynamic range of an image (0-255))

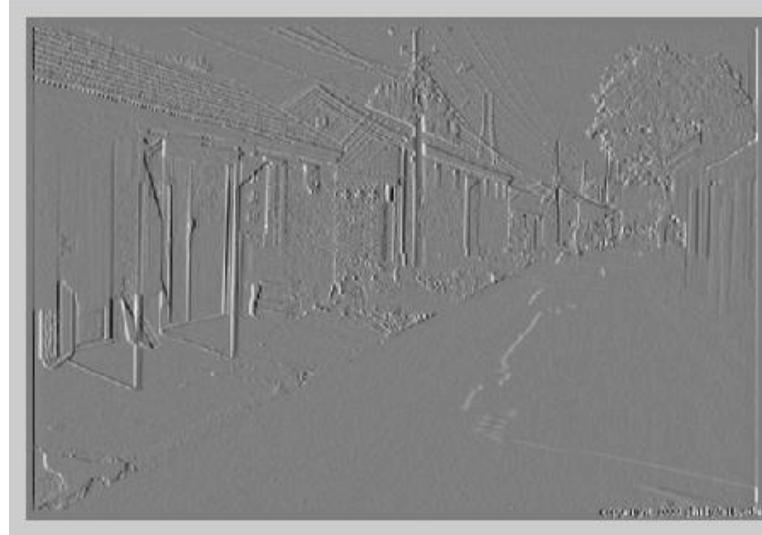
# Filtering in spatial domain

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

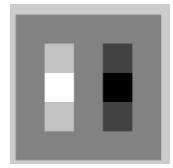


$$\begin{matrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{matrix}$$

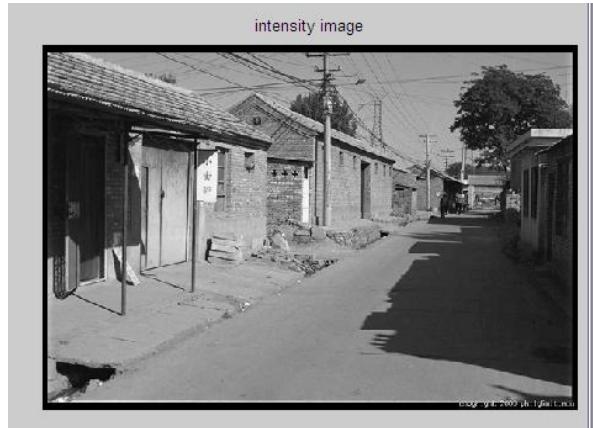
$$\ast =$$



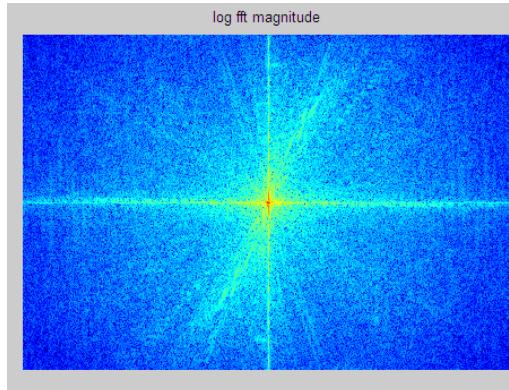
# Filtering in frequency domain (Convolution Theorem Implementation)



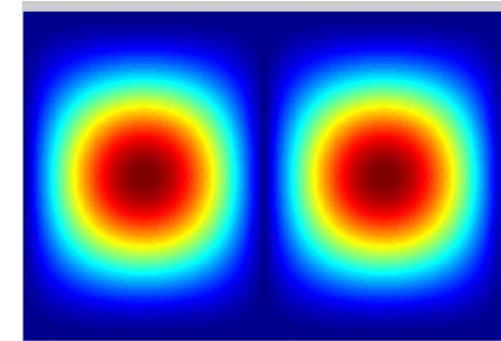
FFT



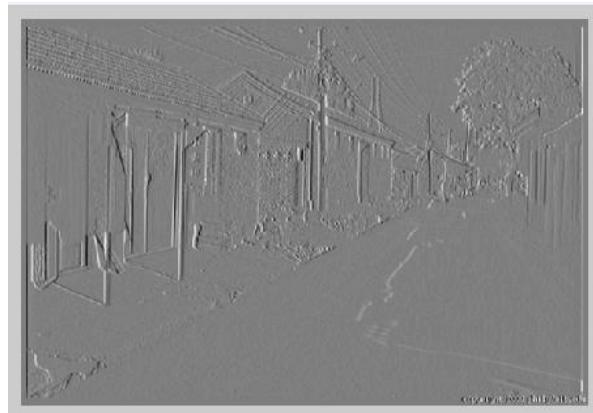
FFT



X

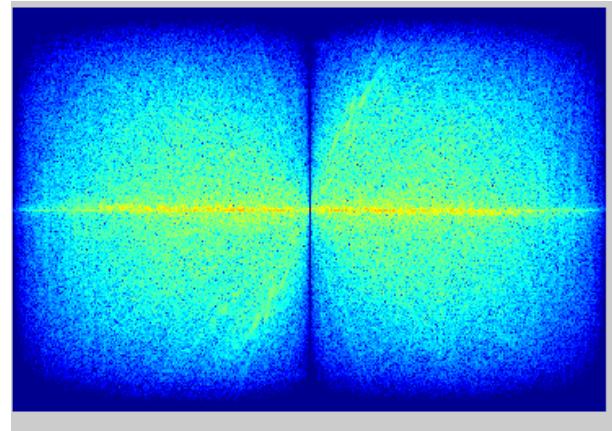


||



Inverse FFT

←

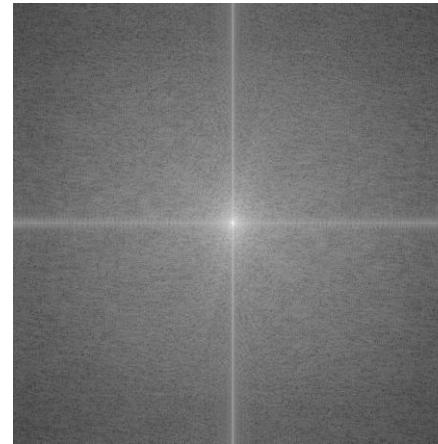


# Fourier demo (II): Convolution Theorem = Filtering in Frequency Domain

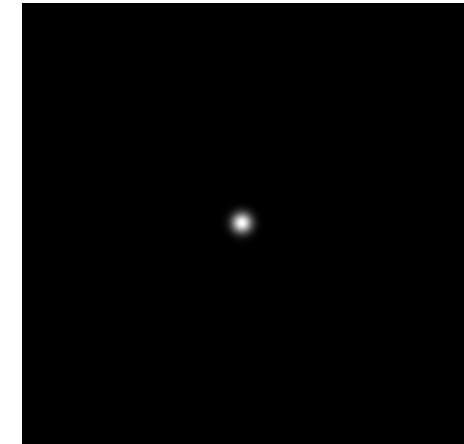
orig img



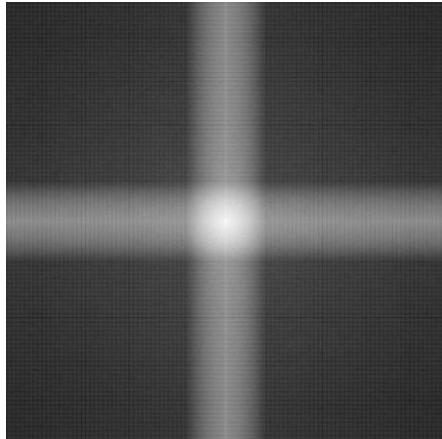
log mag fft2 of img (fftshift)



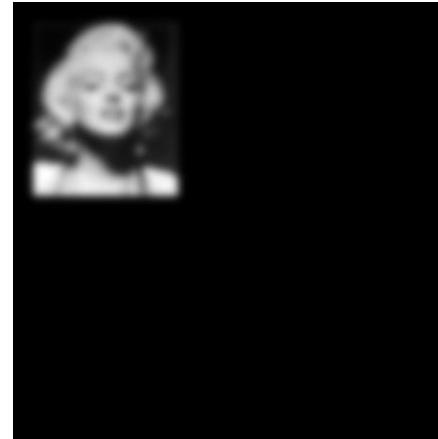
fft2 of filter (fftshift)



fft2 of img (fftshift)



filtered img



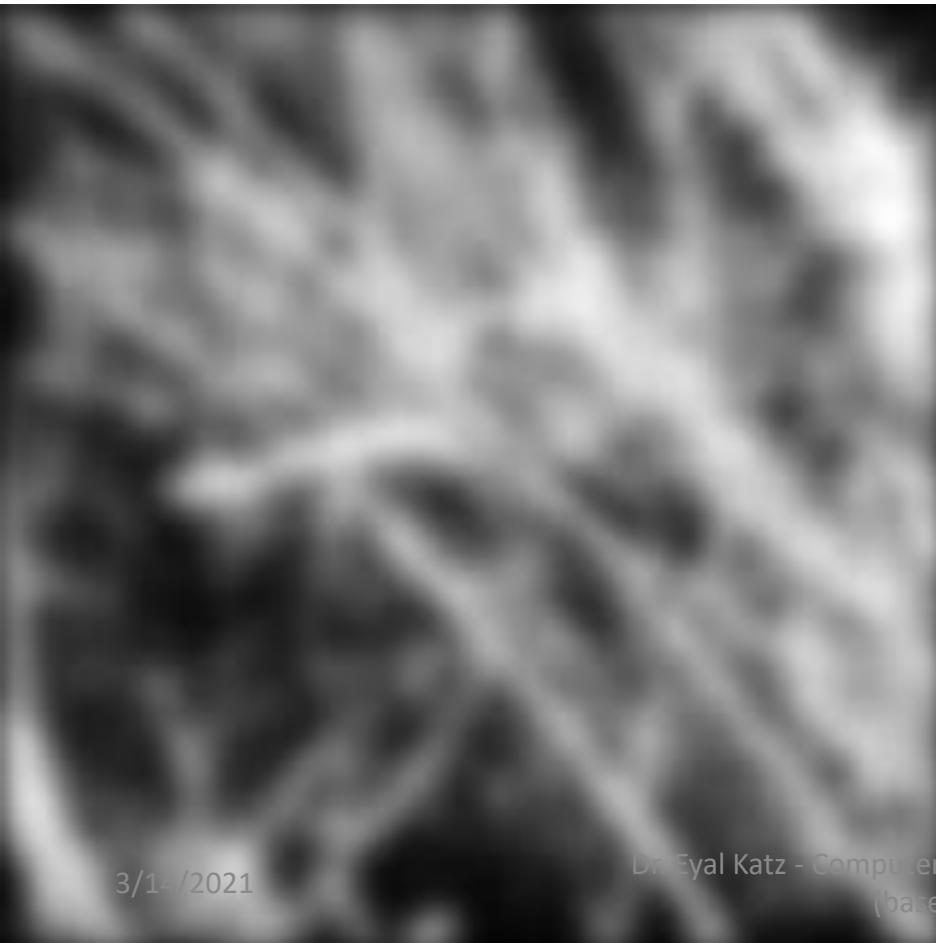
filtered img



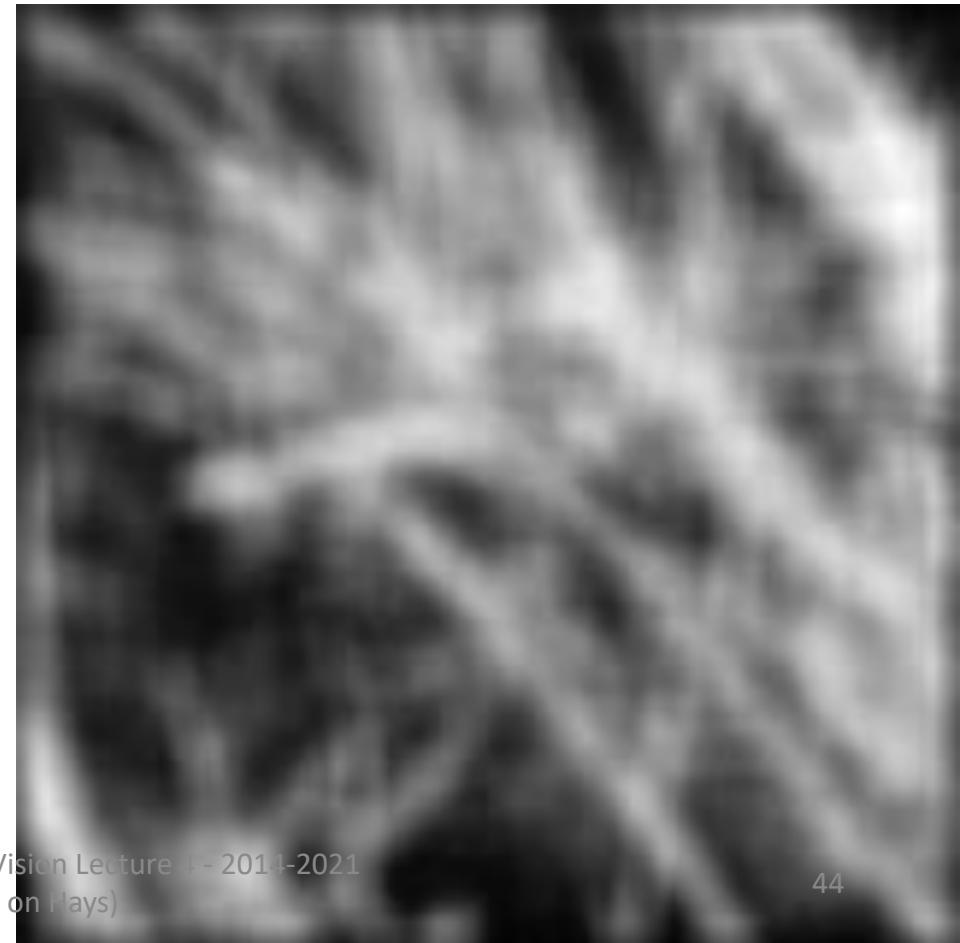
# Filtering - Revisited

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

Gaussian



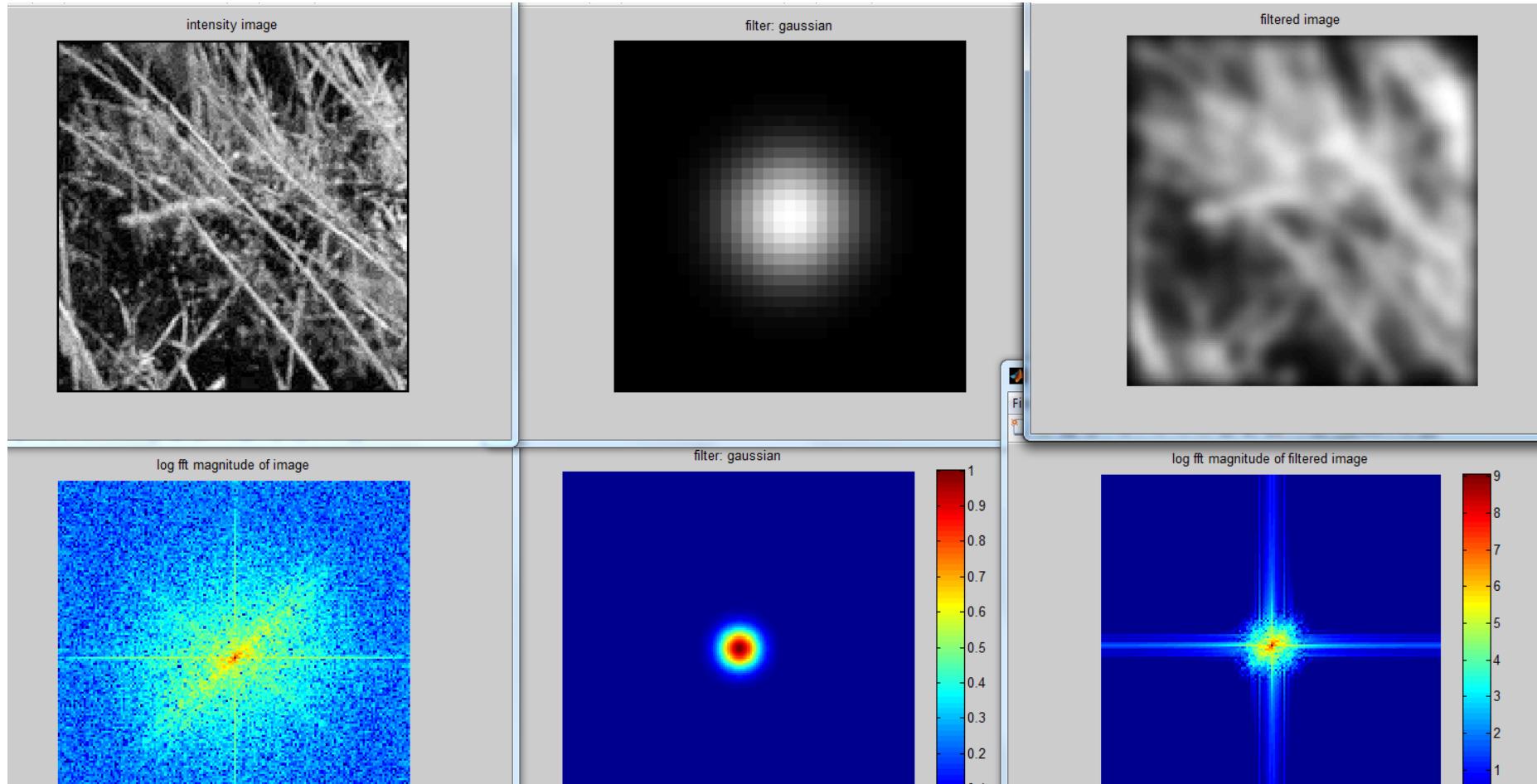
Box filter



# Filtering: Gaussian Filter (Low Pass)

Original Image    Gaussian Filter    Blurred Image

(convolution in space =  
Multiplication in Frequency)



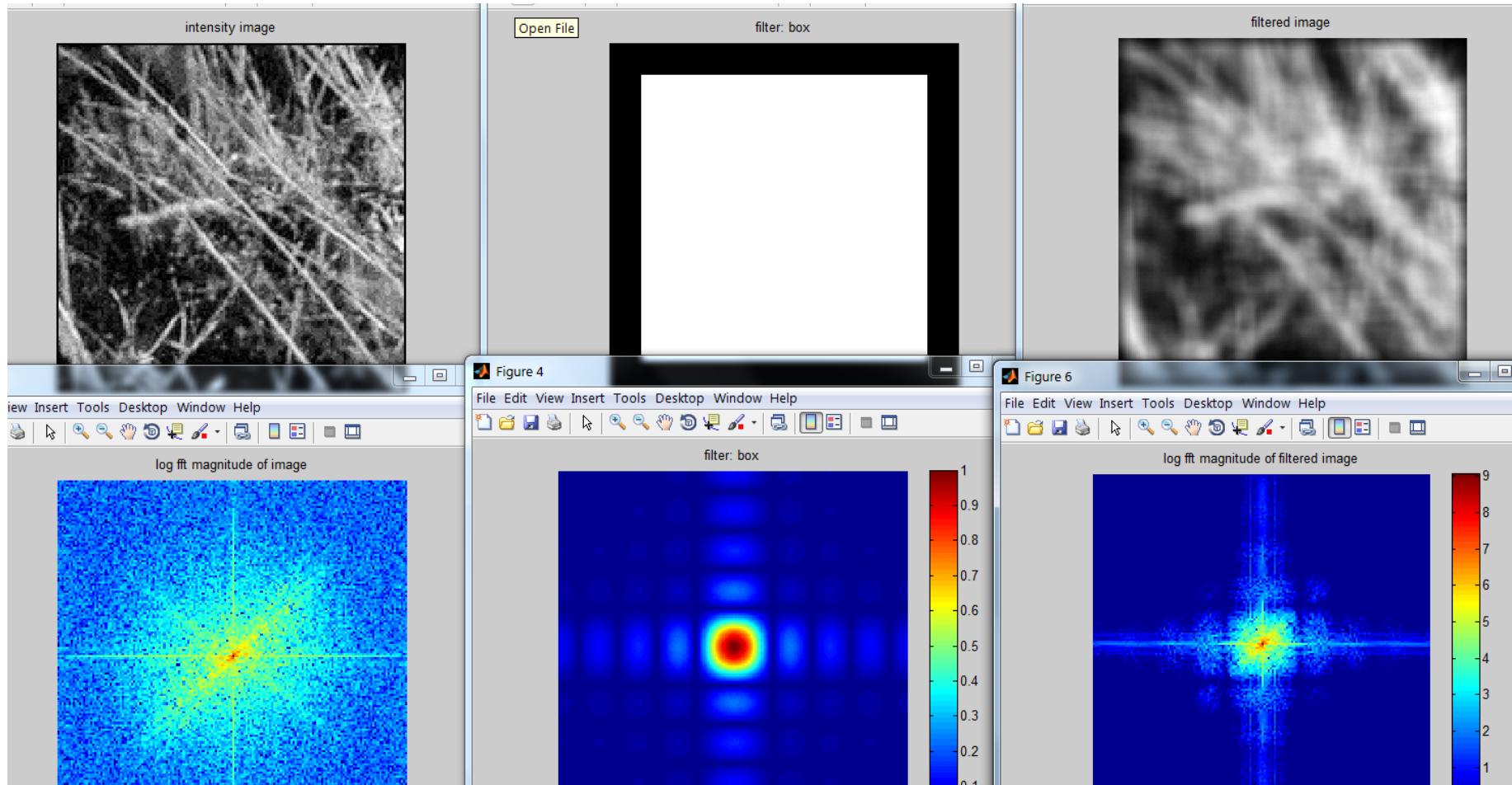
# Filtering: Box Filter (Low Pass Filter)

Original Image

Box Filter

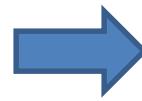
Blurred Image

(convolution in space =  
Multiplication in Frequency)

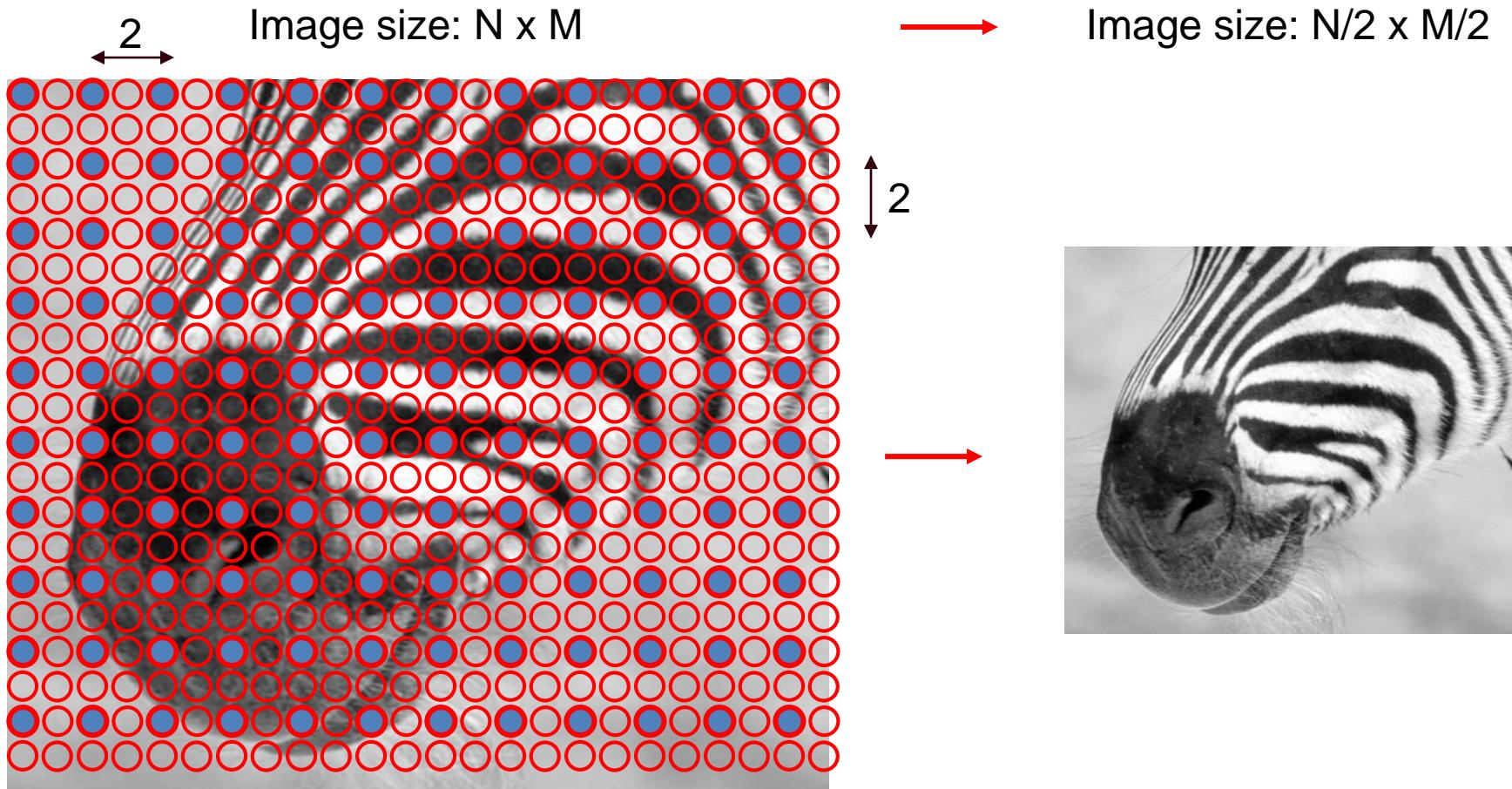


# Sampling

Why does a lower resolution image still make sense to us? What do we lose?



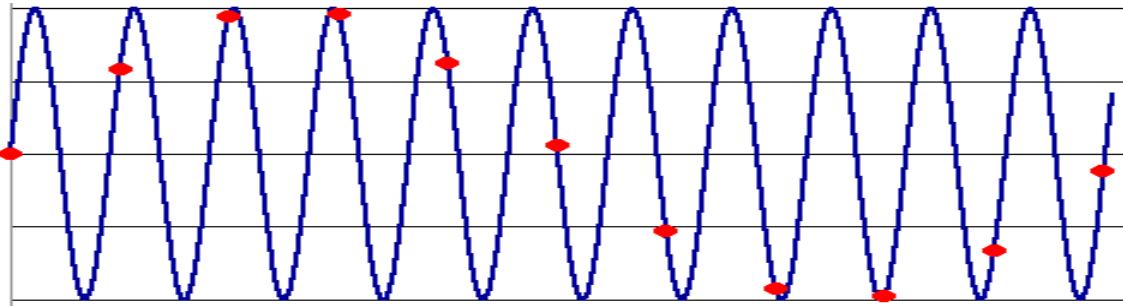
# Subsampling (Down-Sampling) by a factor of 2



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

# Down-sampling

---



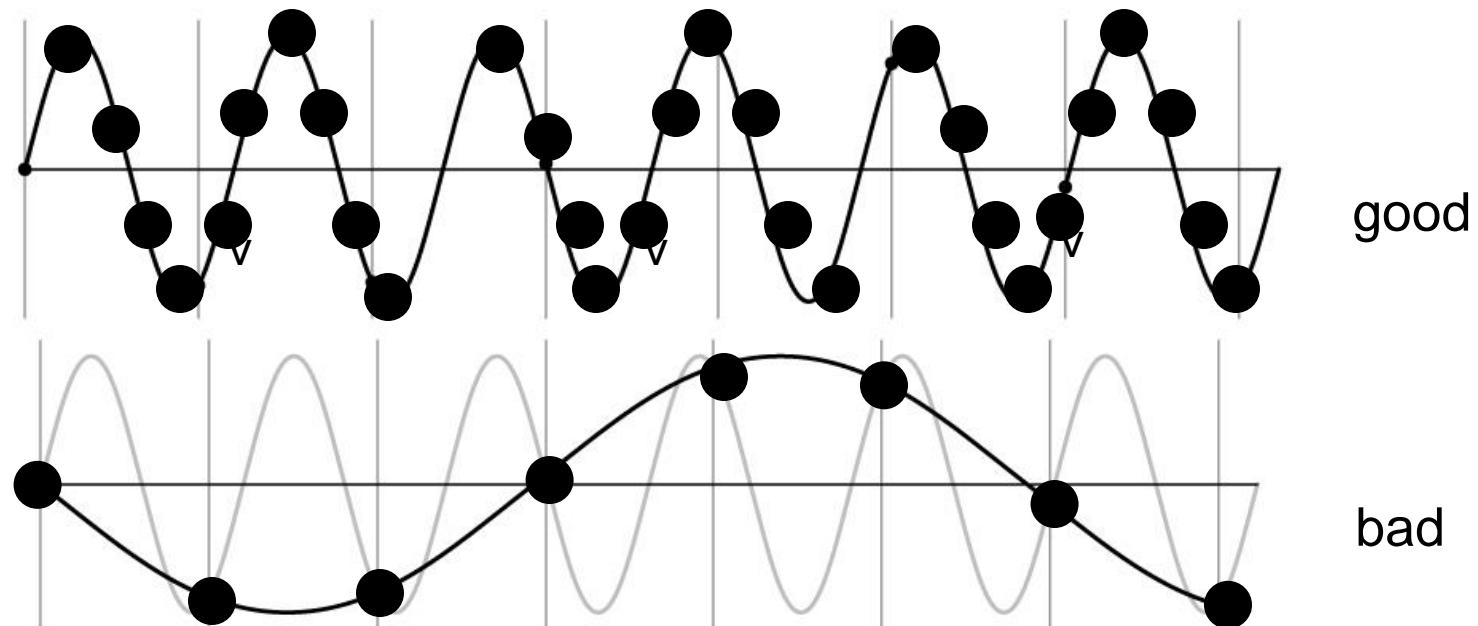
- **Aliasing** can arise when you sample a continuous signal or image
  - occurs when your sampling rate is not high enough to capture the amount of detail in your image
  - Can give you the wrong signal/image—an *alias*
  - formally, the image contains structure at different scales
    - called “frequencies” in the Fourier domain
  - the sampling rate must be high enough to capture the highest frequency in the image

# Aliasing problem

- Sub-sampling may be dangerous....
- Characteristic errors may appear:
  - “Wagon wheels rolling the wrong way in movies”
  - “Checkerboards disintegrate in ray tracing”
  - “Striped shirts look funny on color television”

# Nyquist-Shannon Sampling Theorem

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



# Anti-aliasing

Possible Solutions:

- Increase sampling rate (sample more often)
- **Anti-aliasing Filtering (pre-filtering):**  
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 filter

# 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

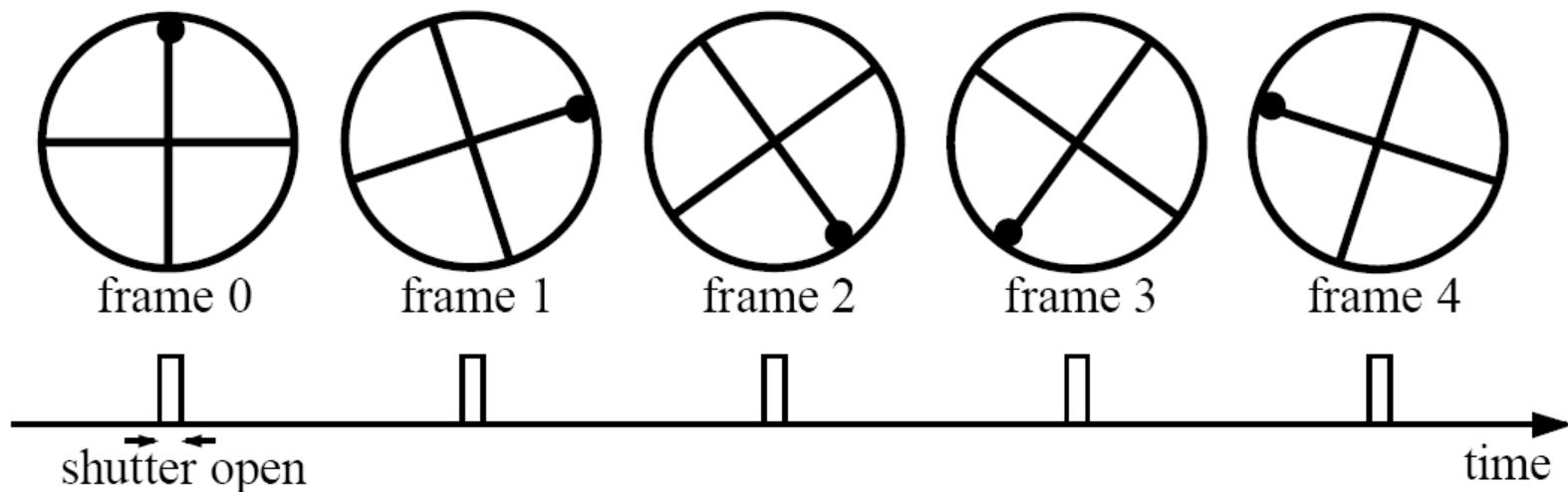
```
im.small = im.blur(1:2:end, 1:2:end);
```

# Aliasing in video (Temporal Aliasing)

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

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

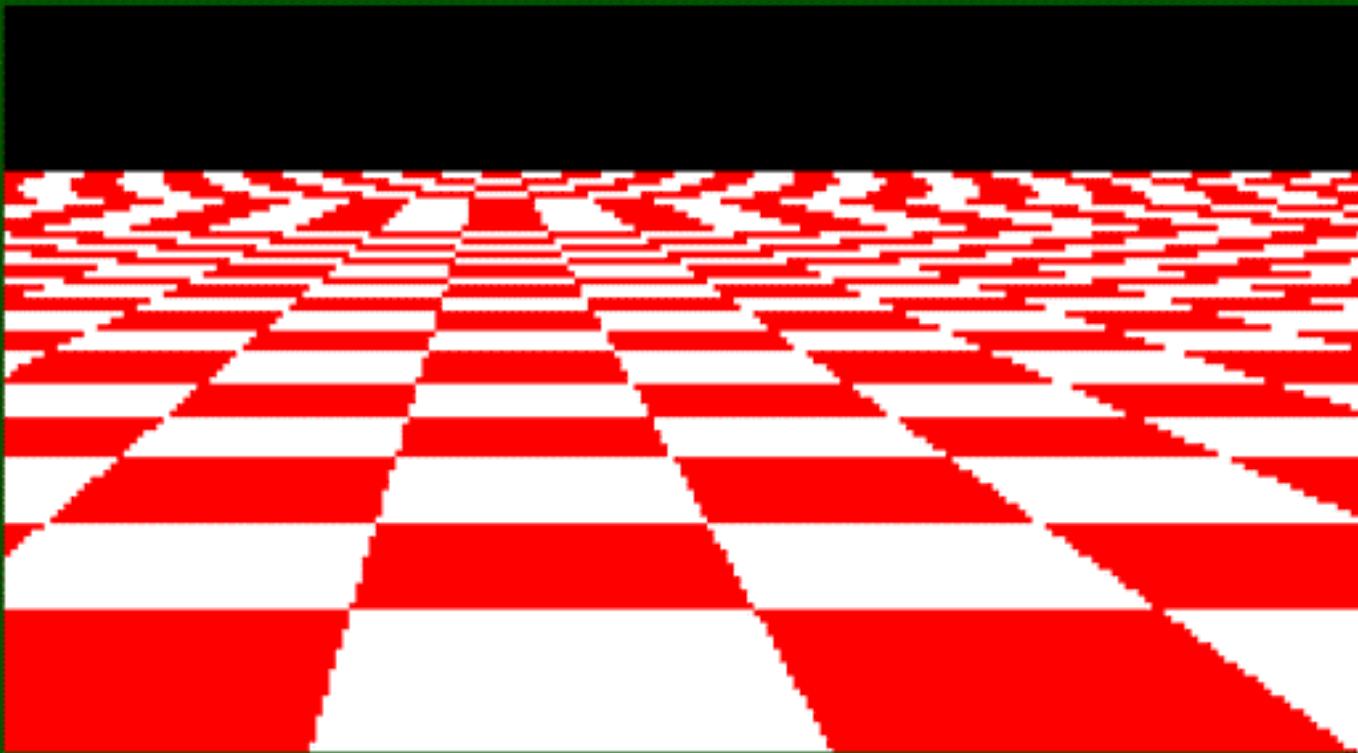
If camera shutter is only open for a fraction of a frame time (frame time = 1/30 sec. for video, 1/24 sec. for film):



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

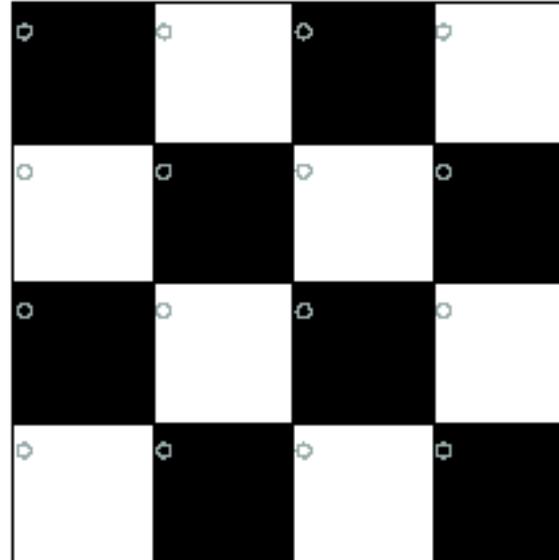
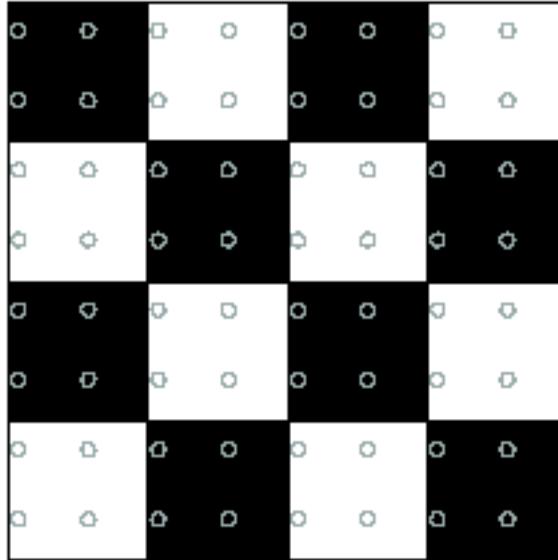
Some links: <https://vimeo.com/4041788>, [www.youtube.com/watch?v=2pbYKDW0myU](http://www.youtube.com/watch?v=2pbYKDW0myU)  
<https://www.youtube.com/watch?v=HqKfCUW17QM>

# Aliasing in graphics

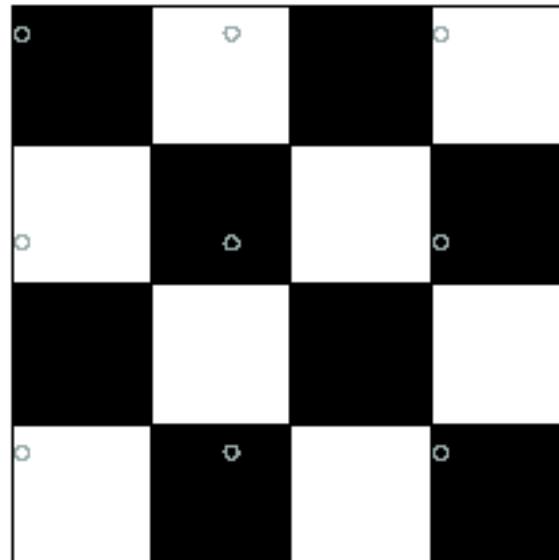
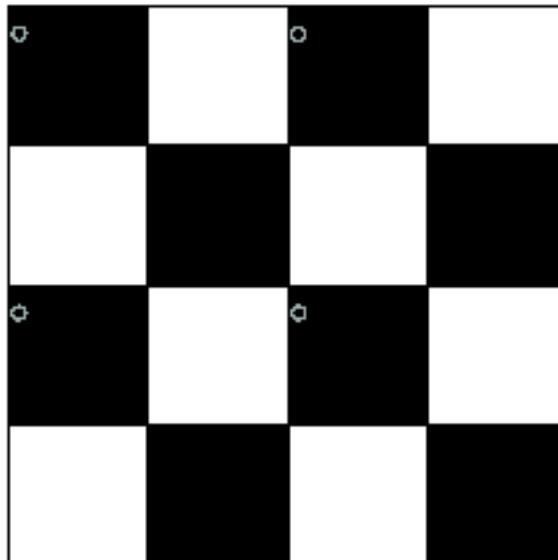


**Disintegrating textures**

# 2D example



Good sampling



Bad sampling

# Sampling and aliasing: no pre-filter

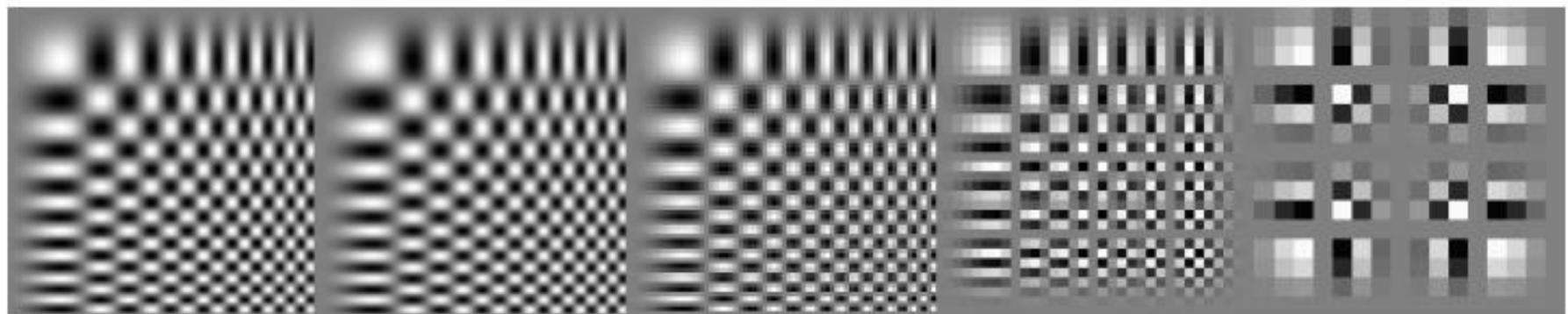
256x256

128x128

64x64

32x32

16x16



# Anti-aliasing

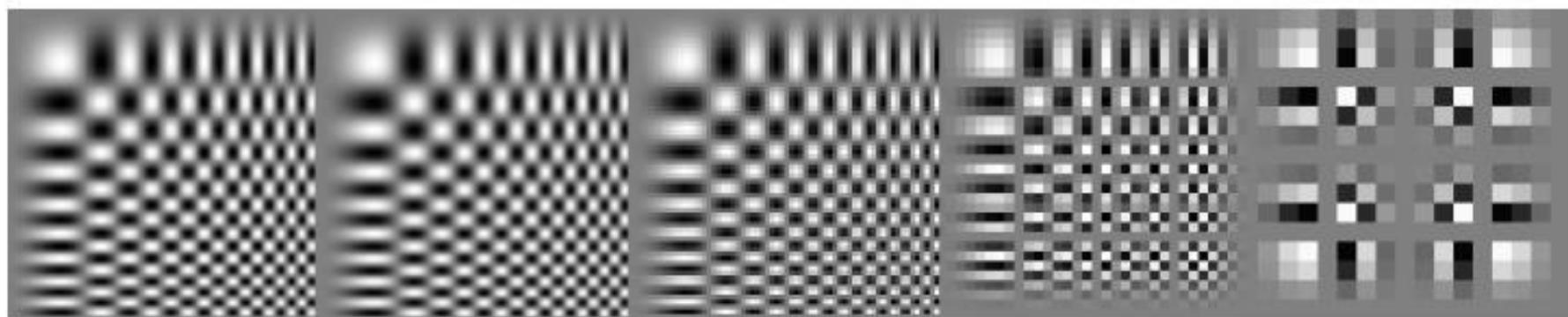
256x256

128x128

64x64

32x32

16x16



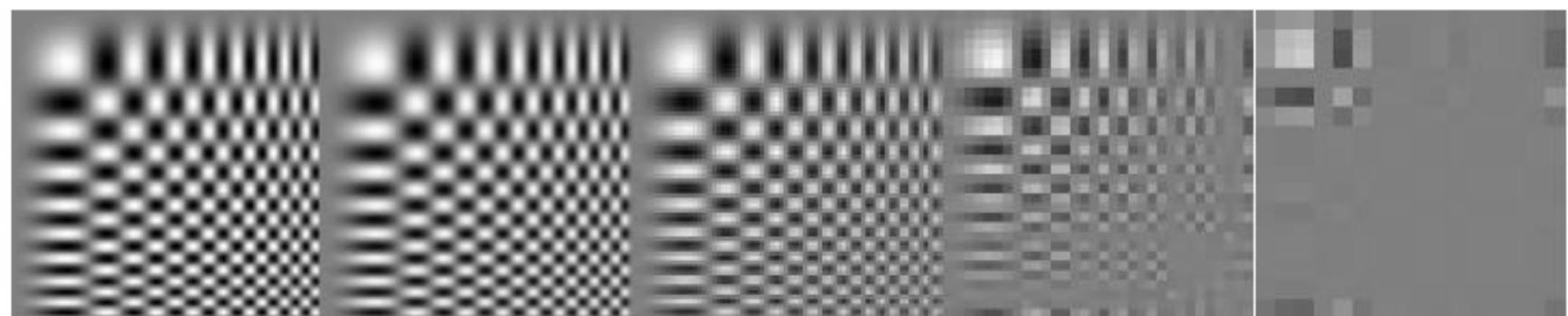
256x256

128x128

64x64

32x32

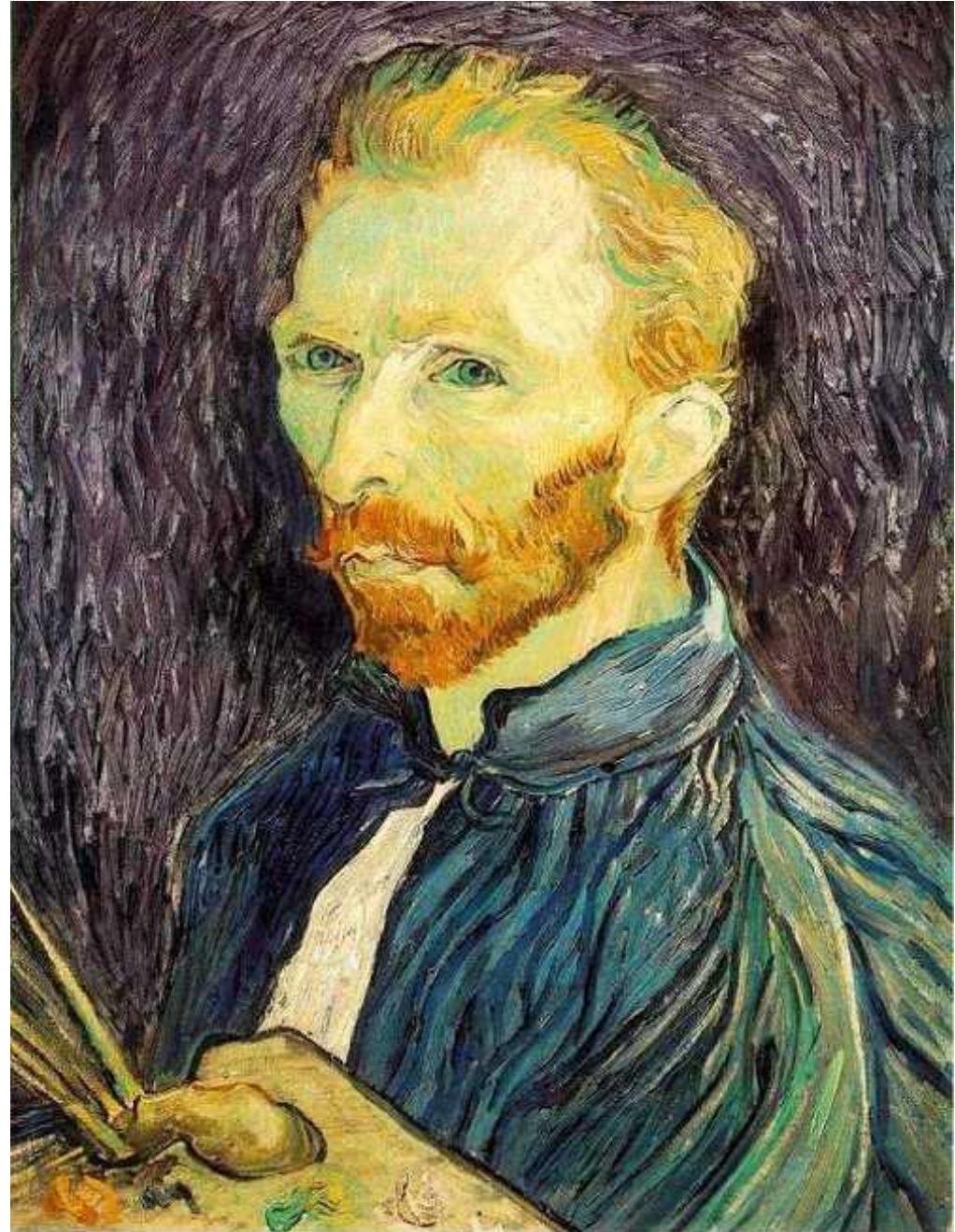
16x16



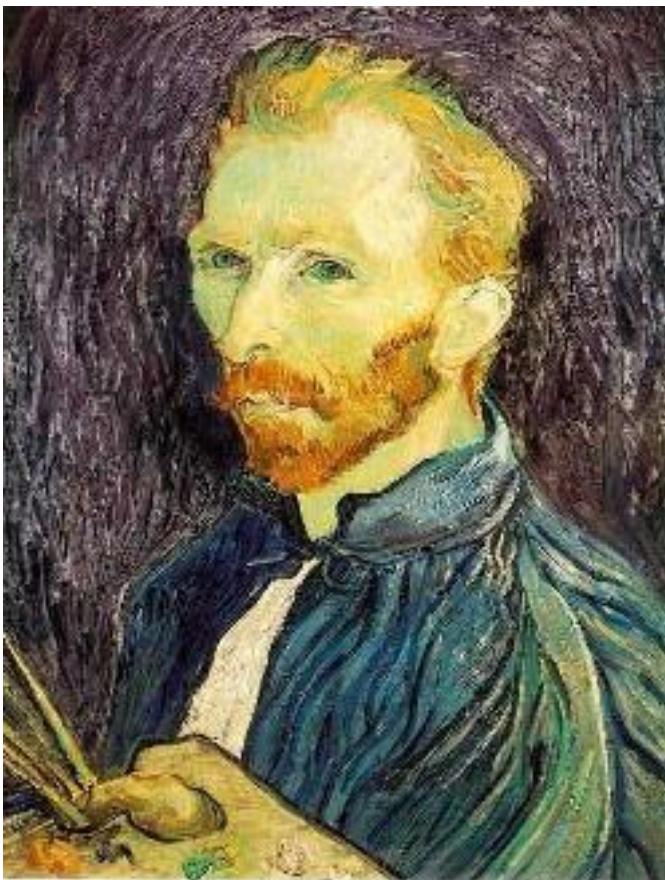
# Image Scaling

This image is too big to fit on the screen.  
How can we reduce it?

How to generate a half-sized version?



# Image sub-sampling: resizing: 1:2, 1:4, 1:8 of original image



1/4



1/8

Throw away every other row and column to create a **1/2** size image  
- called *image sub-sampling*

# Image sub-sampling (up-sampled for display)



1/2

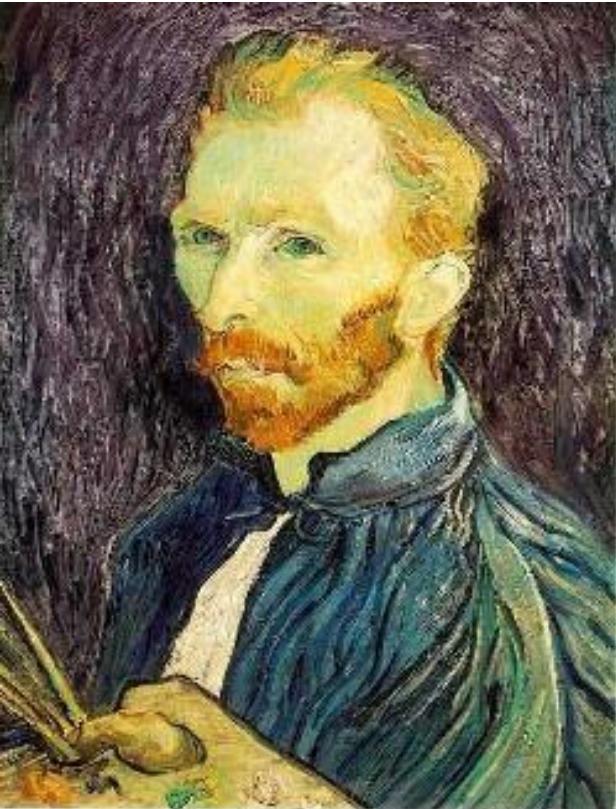
1/4 (2x zoom)

1/8 (4x zoom)

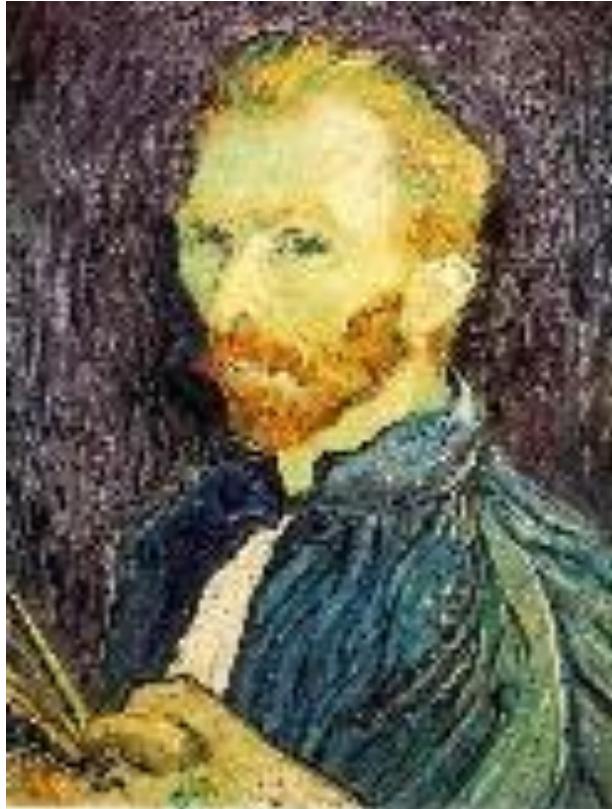
Why does this look so crulty?

... Aliasing!

# Subsampling without pre-filtering



1/2

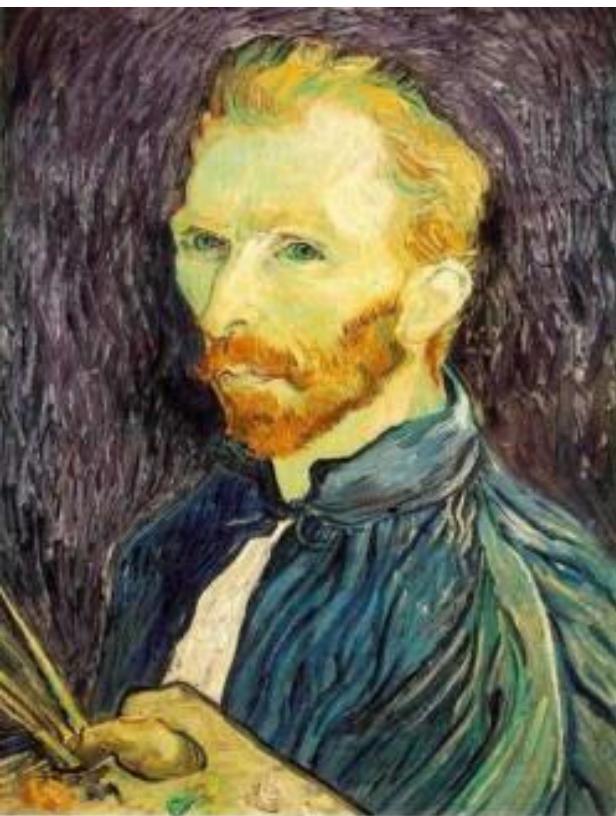


1/4 (2x zoom)



1/8 (4x zoom)

# Subsampling with Gaussian pre-filtering



Gaussian 1/2



G 1/4



G 1/8



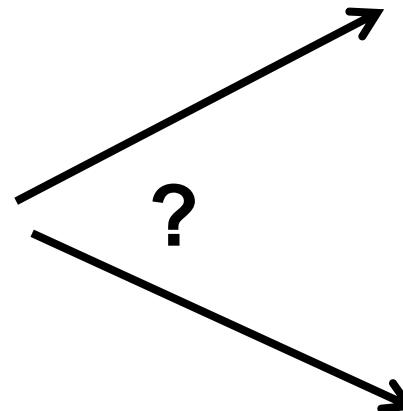
Moiré patterns in real-world images. Here are comparison images by Dave Etchells of [Imaging Resource](#) using the Canon D60 (with an antialias filter) and the Sigma SD-9 (which has no antialias filter). The bands below the fur in the image at right are the kinds of artifacts that appear in images when no antialias filter is used. Sigma chose to eliminate the filter to get more sharpness, but the resulting apparent detail may or may not reflect features in the image.

# More examples – Moire Patterns



Check out Moire patterns on the web.

# Why do we get different, distance-dependent interpretations of hybrid images?



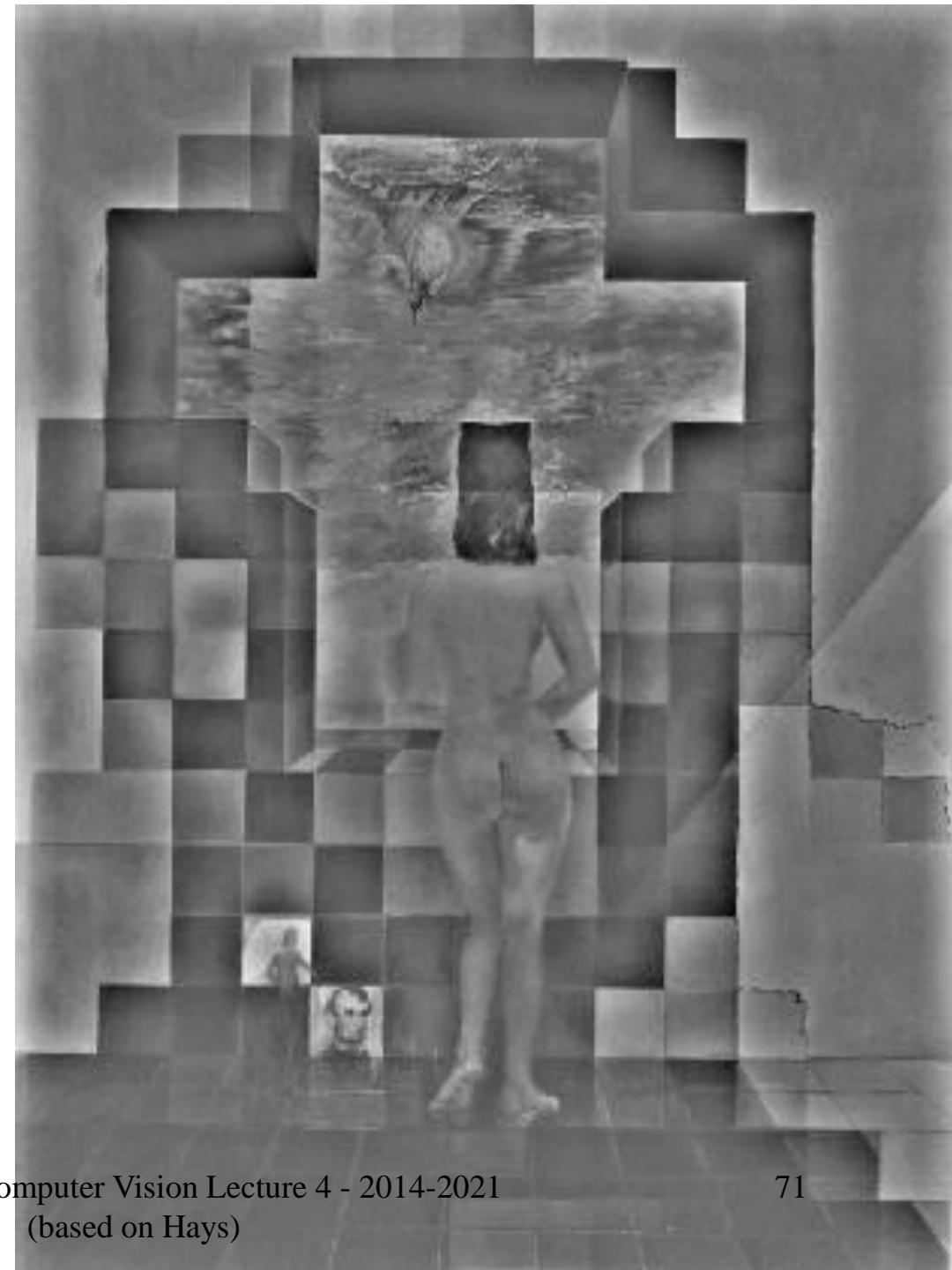
**Salvador Dali invented Hybrid Images?**

## Salvador Dali

*“Gala Contemplating the Mediterranean Sea,  
which at 30 meters becomes the portrait  
of Abraham Lincoln”, 1976*

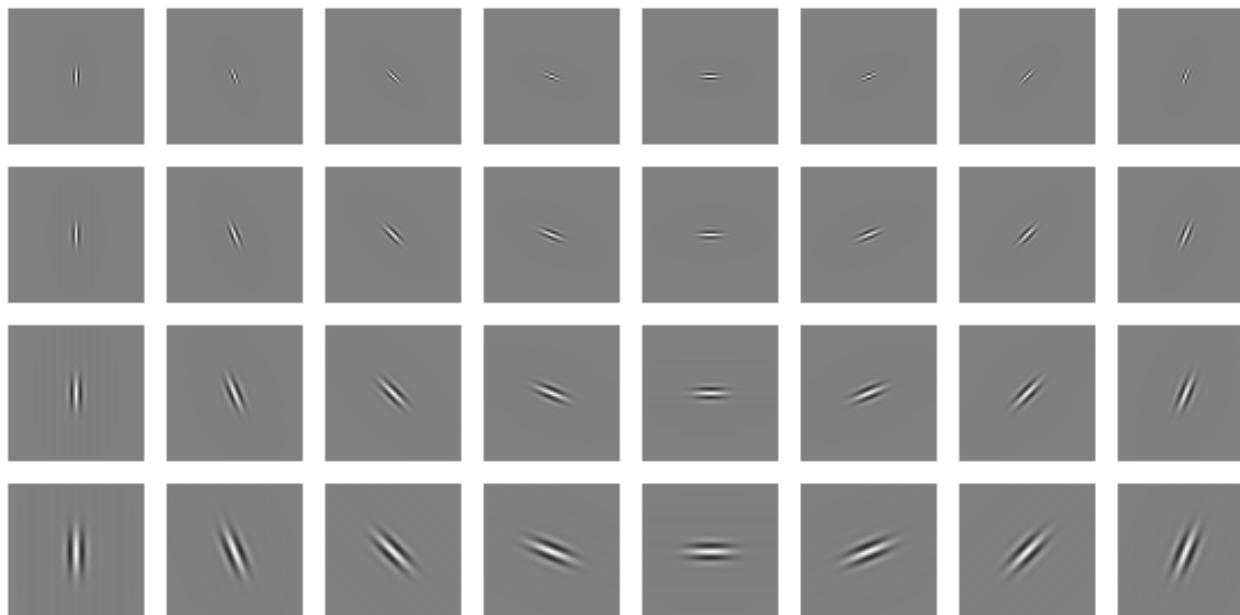






# Clues from Human Perception

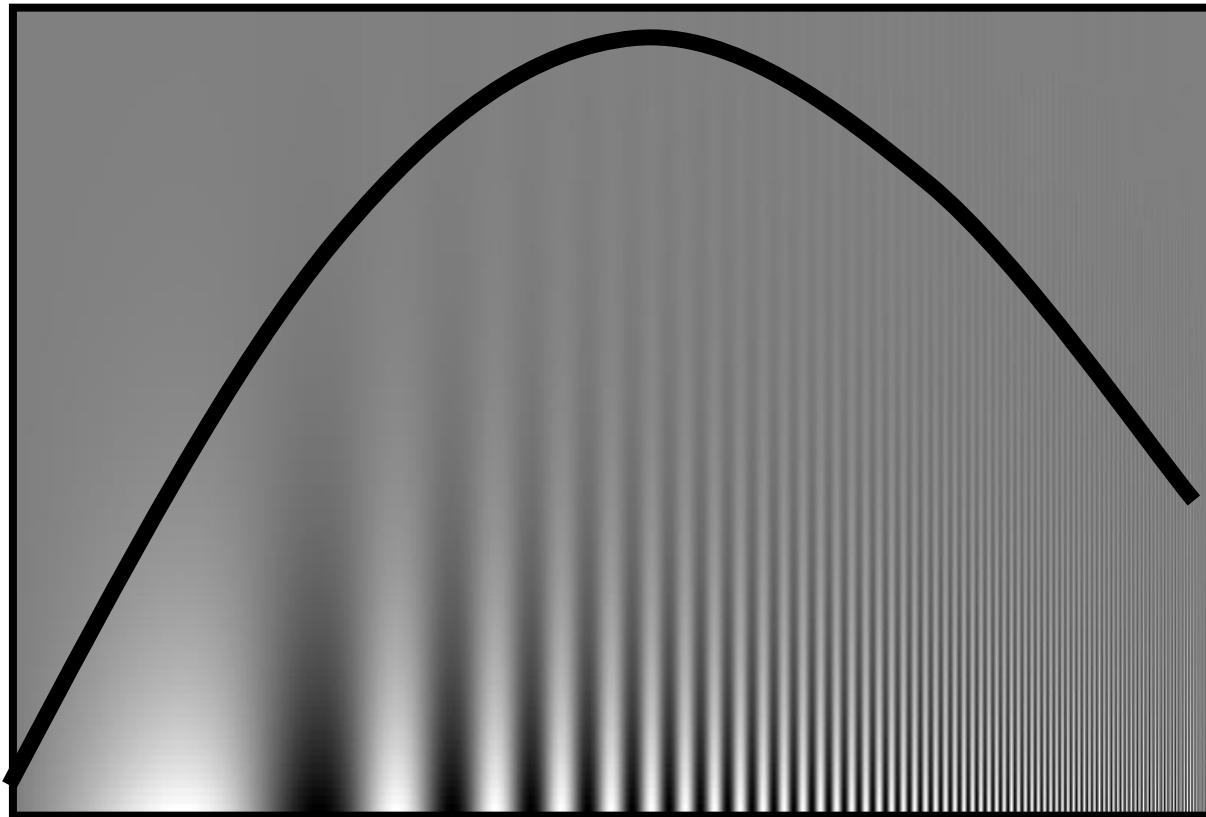
- Early processing in humans filters for various orientations and scales of frequency
- Perceptual cues in the mid-high frequencies dominate perception
- When we see an image from far away, we are effectively subsampling it



Early Visual Processing: Multi-scale edge and blob filters

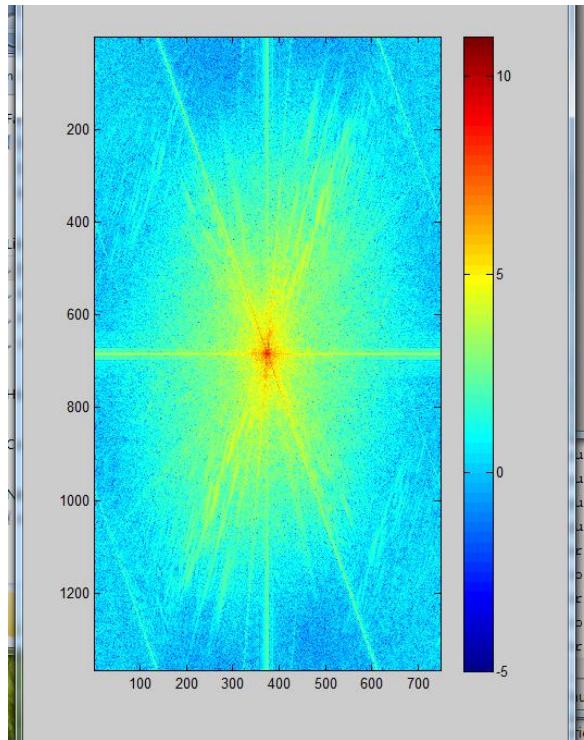
# Campbell-Robson contrast sensitivity curve

---

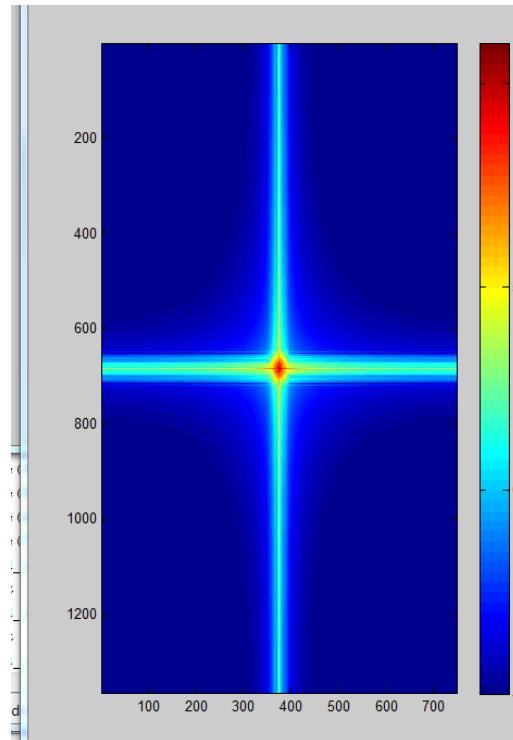


# Hybrid Image in FFT

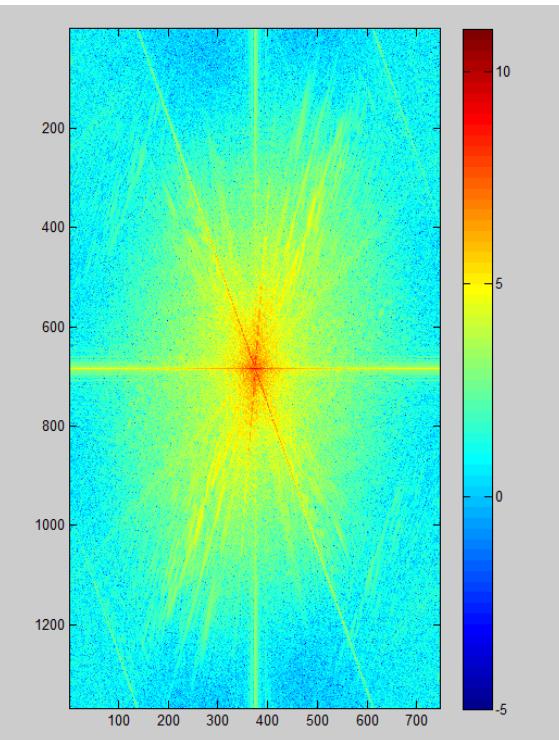
Hybrid Image



Low-passed Image

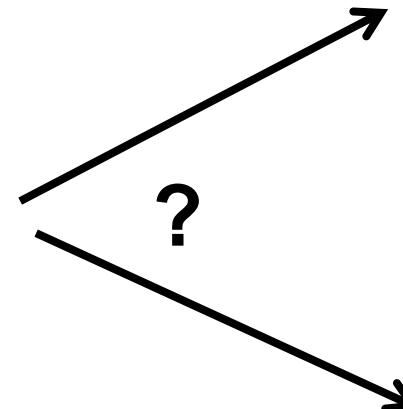


High-passed Image



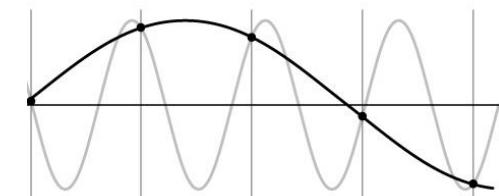
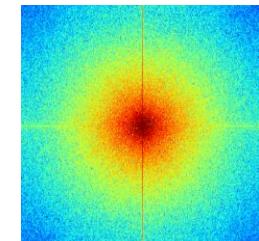
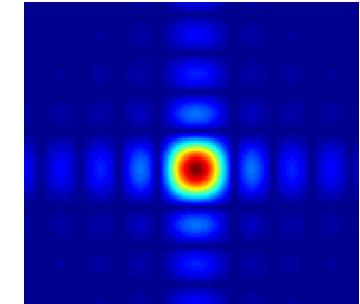
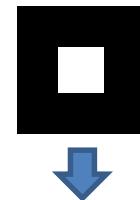
# Perception

**Why do we get different, distance-dependent interpretations of hybrid images?**



# Things to Remember

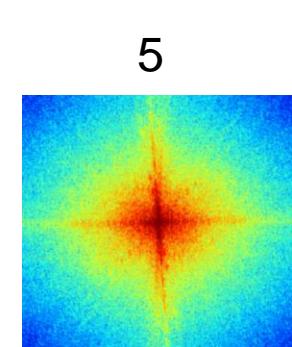
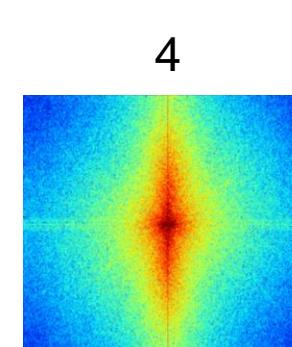
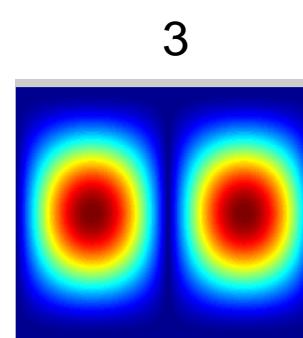
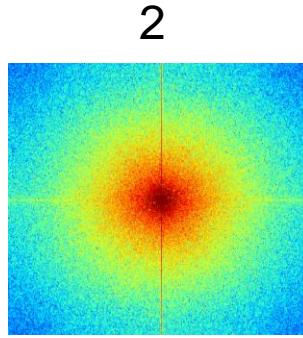
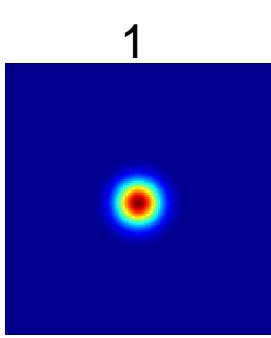
- Sometimes it makes sense to think of images and filtering in the frequency domain
  - Fourier analysis
- Can be faster to filter using FFT for large images ( $N \log N$  vs.  $N^2$  for auto-correlation)
- Images are mostly smooth
  - Basis for compression
- Remember to low-pass (apply anti-aliasing filter), before down-sampling



# Practice Question

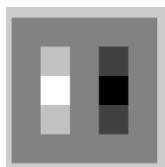
(check at home, discuss next lecture)

1. Match the spatial domain image to the Fourier magnitude image



B

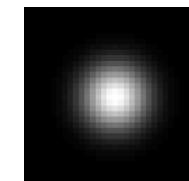
A



C



D



E



# Additional Slide Credits

- James Hays
- Derek Hoiem
- Steve Seitz
- Larry Zitnick
- Ali Farhadi