CS 4495 Computer Vision

Frequency and Fourier Transforms

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Administrivia

- Project 1 is (still) on line – you should really get started now!
- Readings for this week: FP Chapter 4 (which includes reviewing 4.1 and 4.2)

Questions about PS1?

- Where should I put the origin?
  - It's up to you – you get to define the geometry.

- Should θ go from $-\pi$ to π or $-\frac{\pi}{2}$ to $\frac{\pi}{2}$ or what?
  - It's up to you – you get to define the geometry.

- How do I draw the line?
  - I'm guessing that any line in your image crosses approximately two edges in the image. So given an equation of the line, you could try x=1 or x=256 or y=1 or y=256 and see what values you get. Just a thought…

Salvador Dali
"Gala Contemplating the Mediterranean Sea, which at 30 meters becomes the portrait of Abraham Lincoln", 1976

Decomposing an image

- A basis set is (edit from to Wikipedia):
  - A **basis** *B* of a vector space *V* is a linearly independent subset of *V* that spans *V*.
  - In more detail:suppose that $B = \{ v_1, \ldots, v_n \}$ is a finite subset of a vector space *V* over a field **F** (such as the real or complex numbers **R** or **C**). Then *B* is a basis if it satisfies the following conditions:
    - the *linear independence* property:
      - for all $a_1, \ldots, a_n \in \mathbf{F}$, if $a_1v_1 + \ldots + a_nv_n = 0$, then necessarily $a_1 = \ldots = a_n = 0$;
    - and the *spanning* property,
      - for every *x* in *V* it is possible to choose $a_1, \ldots, a_n \in \mathbf{F}$ such that $x = a_1v_1 + \ldots + a_nv_n$.
  - *Not necessarily orthogonal….*

- If we have a basis set for images, could perhaps be useful for analysis – especially for linear systems because we could consider each basis component independently. *(Why?)*

Images as points in a vector space

- Consider an image as a point in a NxN size space – can rasterize into a single vector $[x_{00} x_{10} x_{20} \dots x_{(n-1)0} x_{10} \dots x_{(n-1)(n-1)}]^T$

- The "normal" basis is just the vectors:

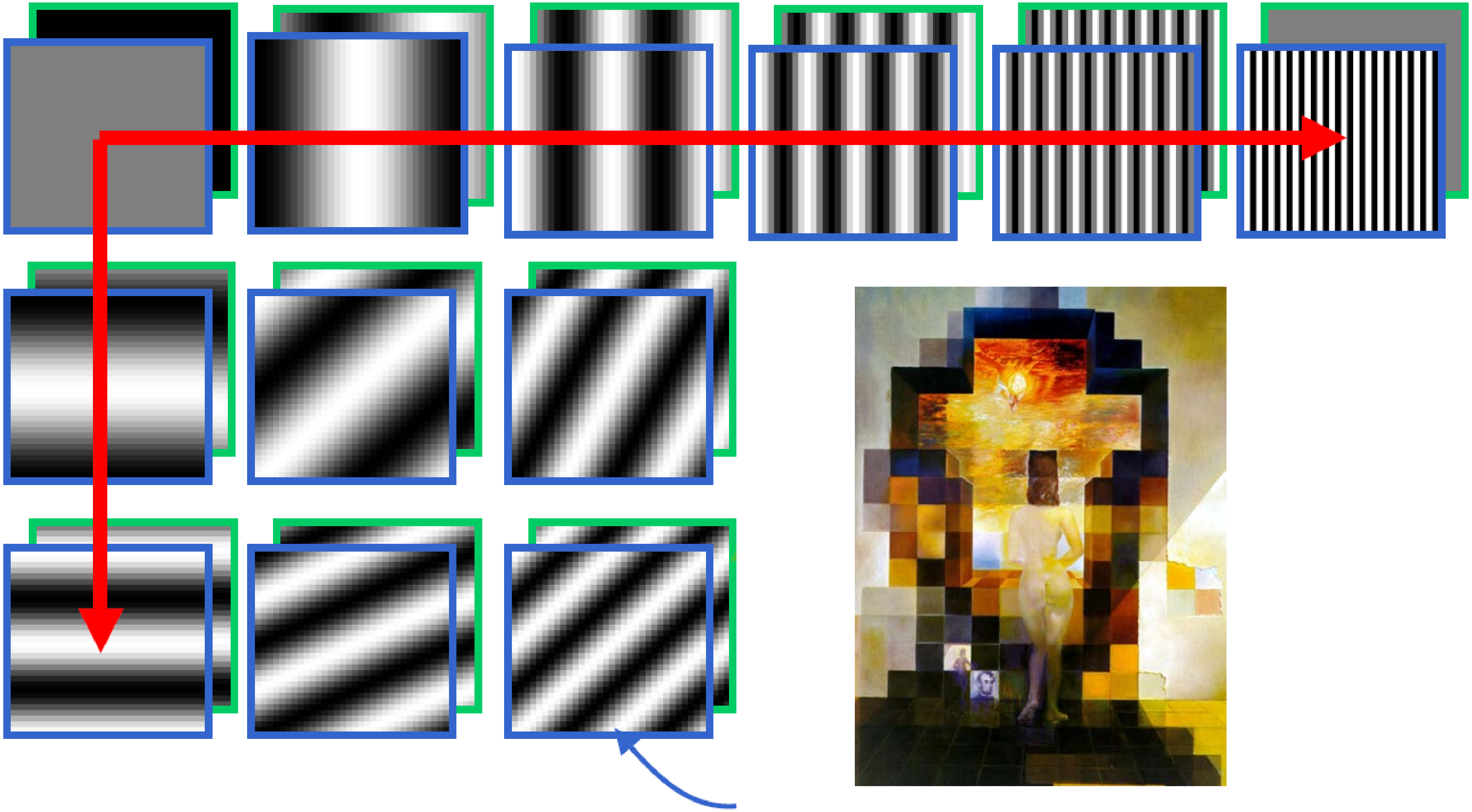
$$[0\ 0\ 0\ 0 \ldots 0 1\ 0\ 0\ 0 \ldots\ 0]^T$$

  - Independent
  - Can create any image

- But not very helpful to consider how each pixel contributes to computations.

A nice set of basis

Teases away fast vs. slow changes in the image.



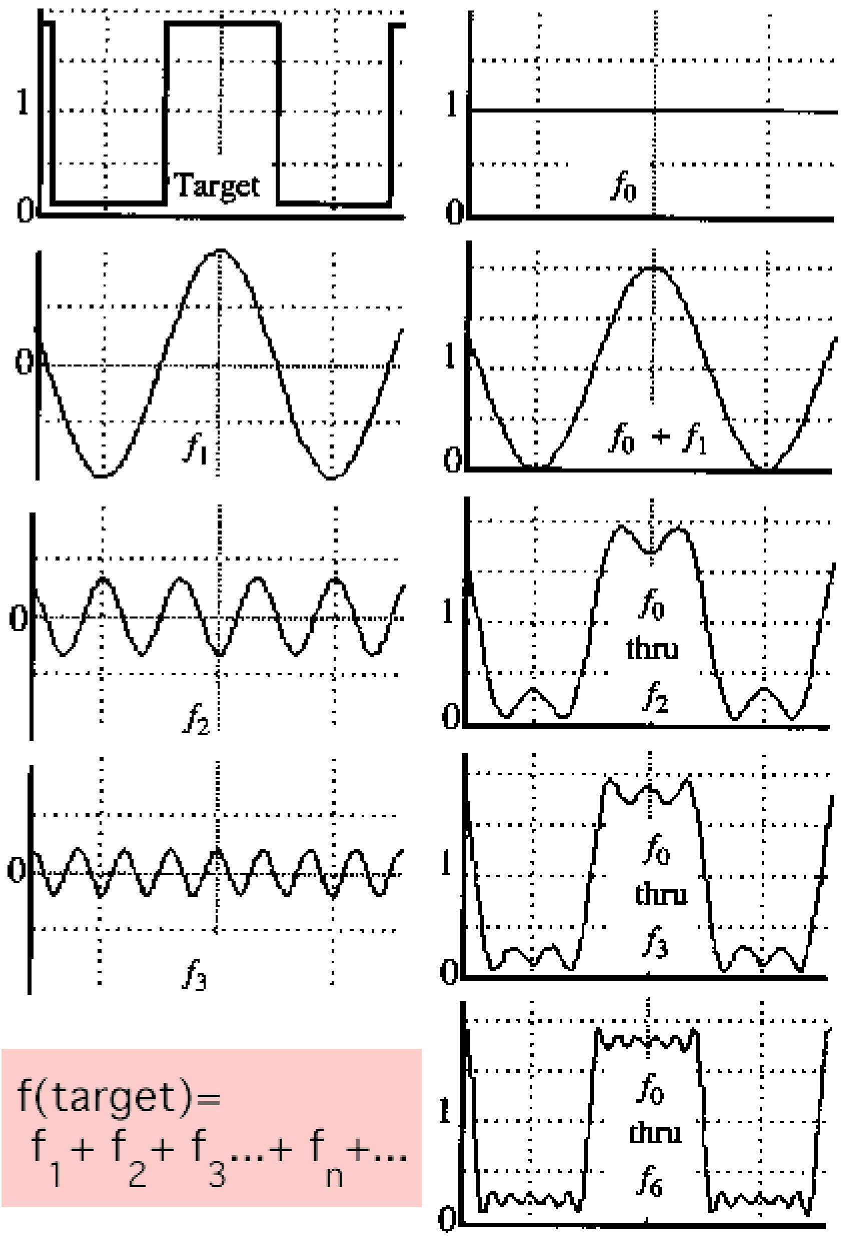
This change of basis has a special name…

Jean Baptiste Joseph Fourier (1768-1830)

- Had crazy idea (1807):
  - ***Any*** periodic function can be rewritten as a weighted sum of sines and cosines of different frequencies.
- Don’t believe it?
  - Neither did Lagrange, Laplace, Poisson and other big wigs
  - Not translated into English until 1878!
- But it’s true!
  - Called Fourier ***Series***

A sum of sines

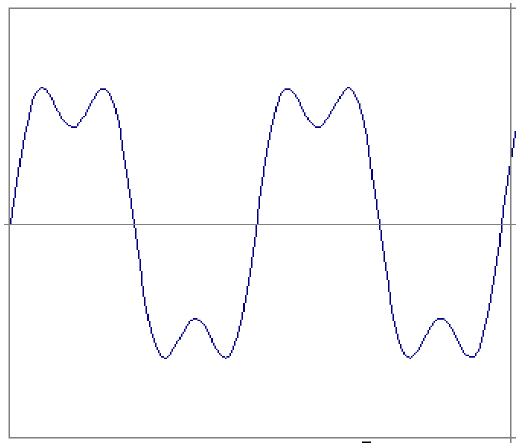
- Our building block:
- $$A\sin(\omega x + \phi)$$
- Add enough of them to get any signal *f(x)* you want!
- How many degrees of freedom?
- What does each control?
- Which one encodes the coarse vs. fine structure of the signal?



f(target)= $f_1 + f_2 + f_3 ... + f_n + ...$

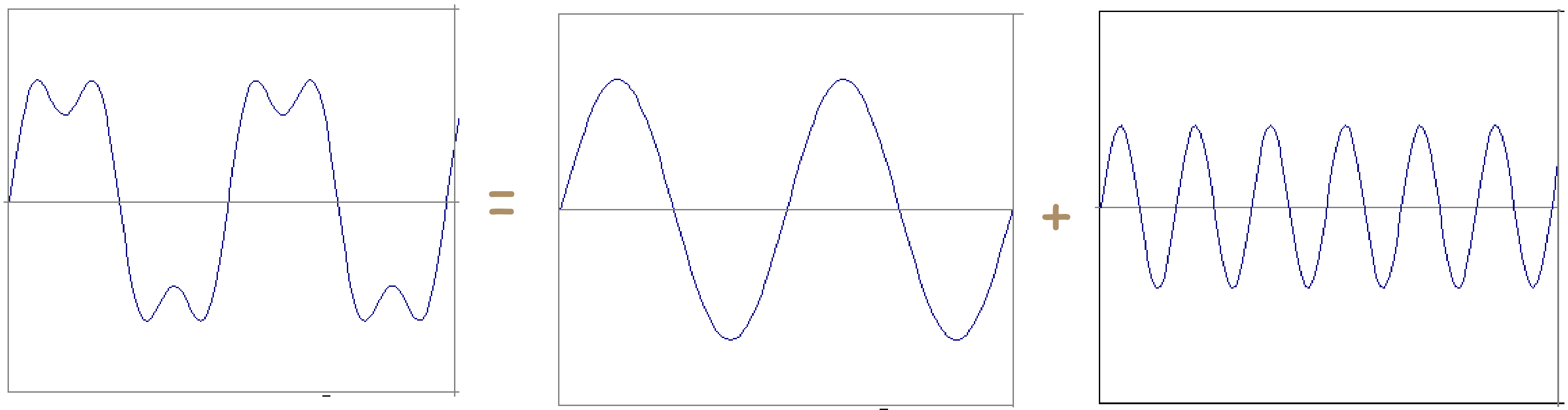
Time and Frequency

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



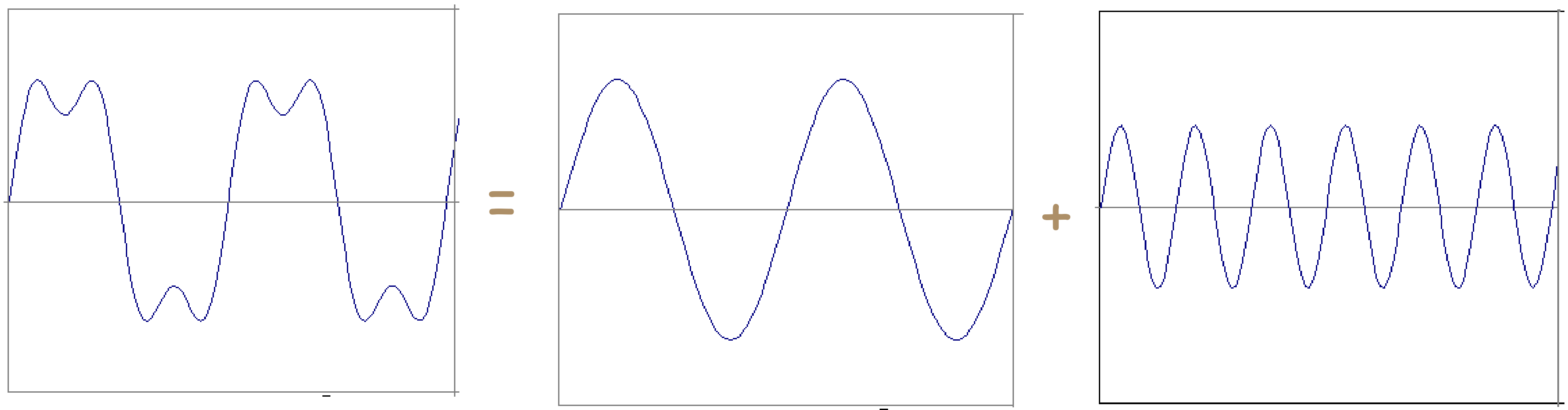
Time and Frequency

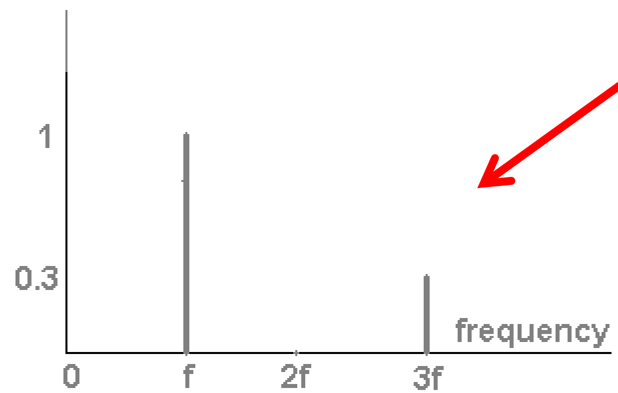
- example : $g(t) = \sin(2pf\ t) + (1/3)\sin(2p(3f)\ t)$



Frequency Spectra - Series

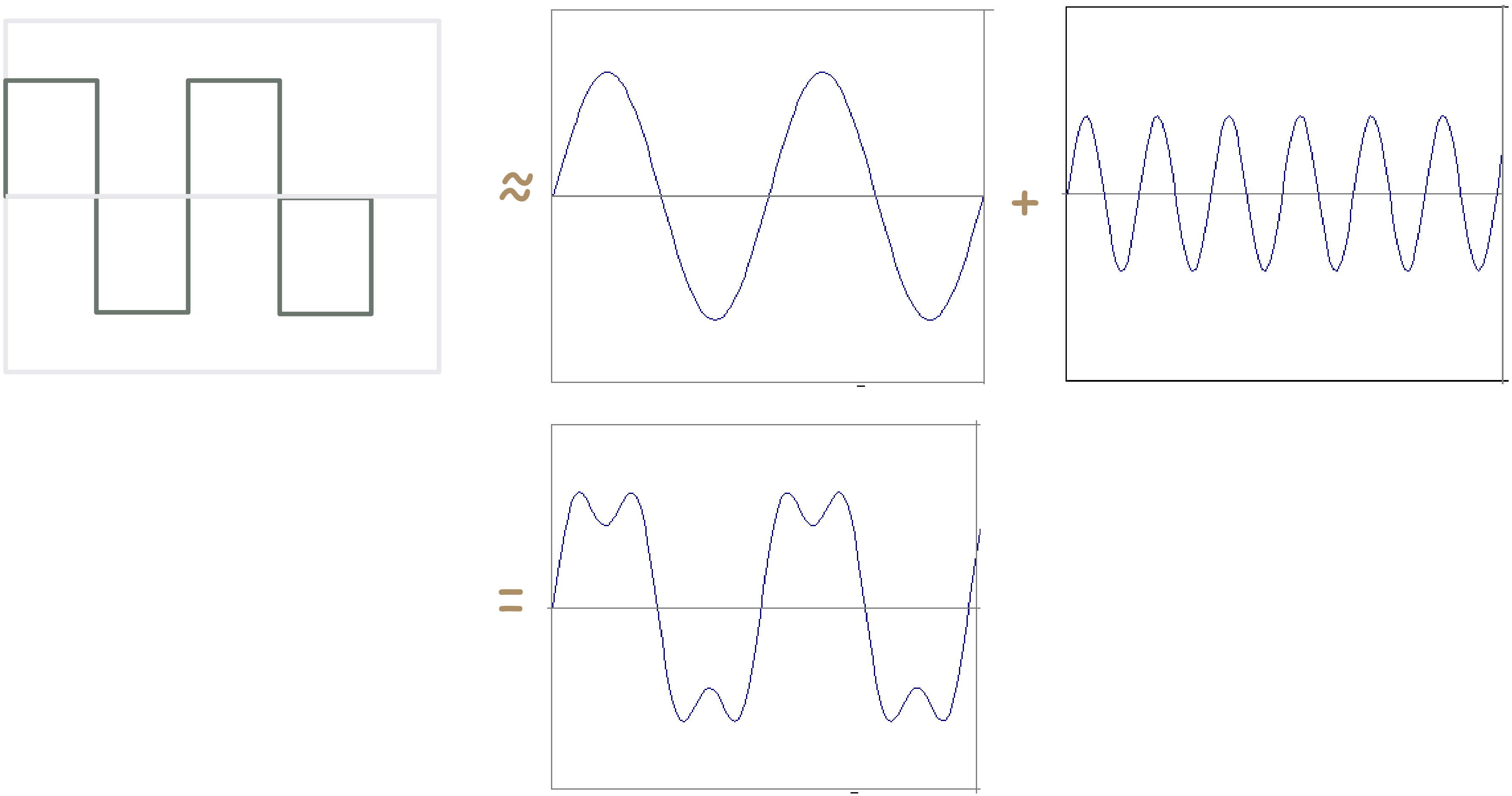
- example : $g(t) = \sin(2pf\, t) + (1/3)\sin(2p(3f)\, t)$



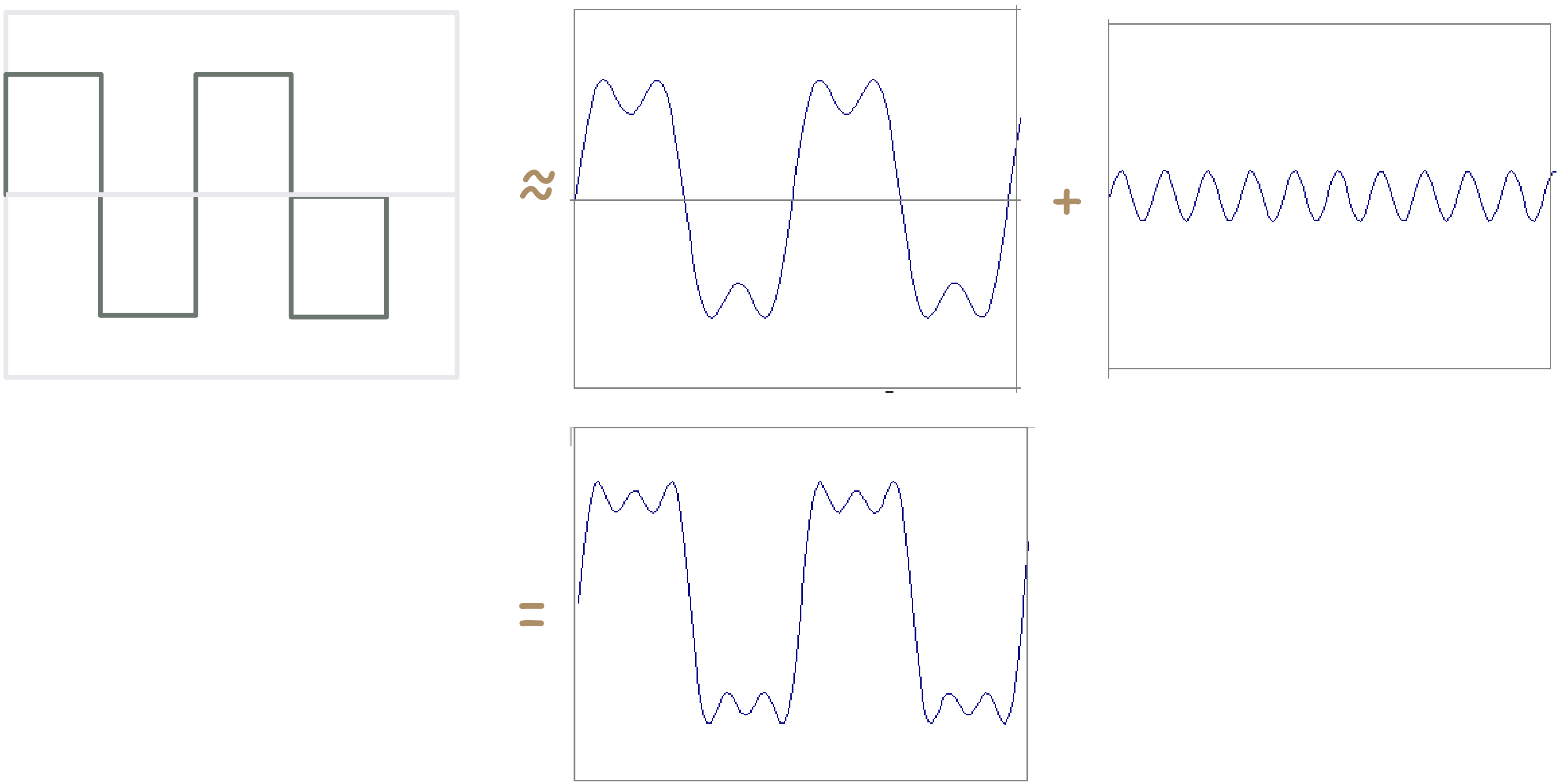


One form of *spectrum* – more in a bit

Frequency Spectra - Series



Frequency Spectra - Series



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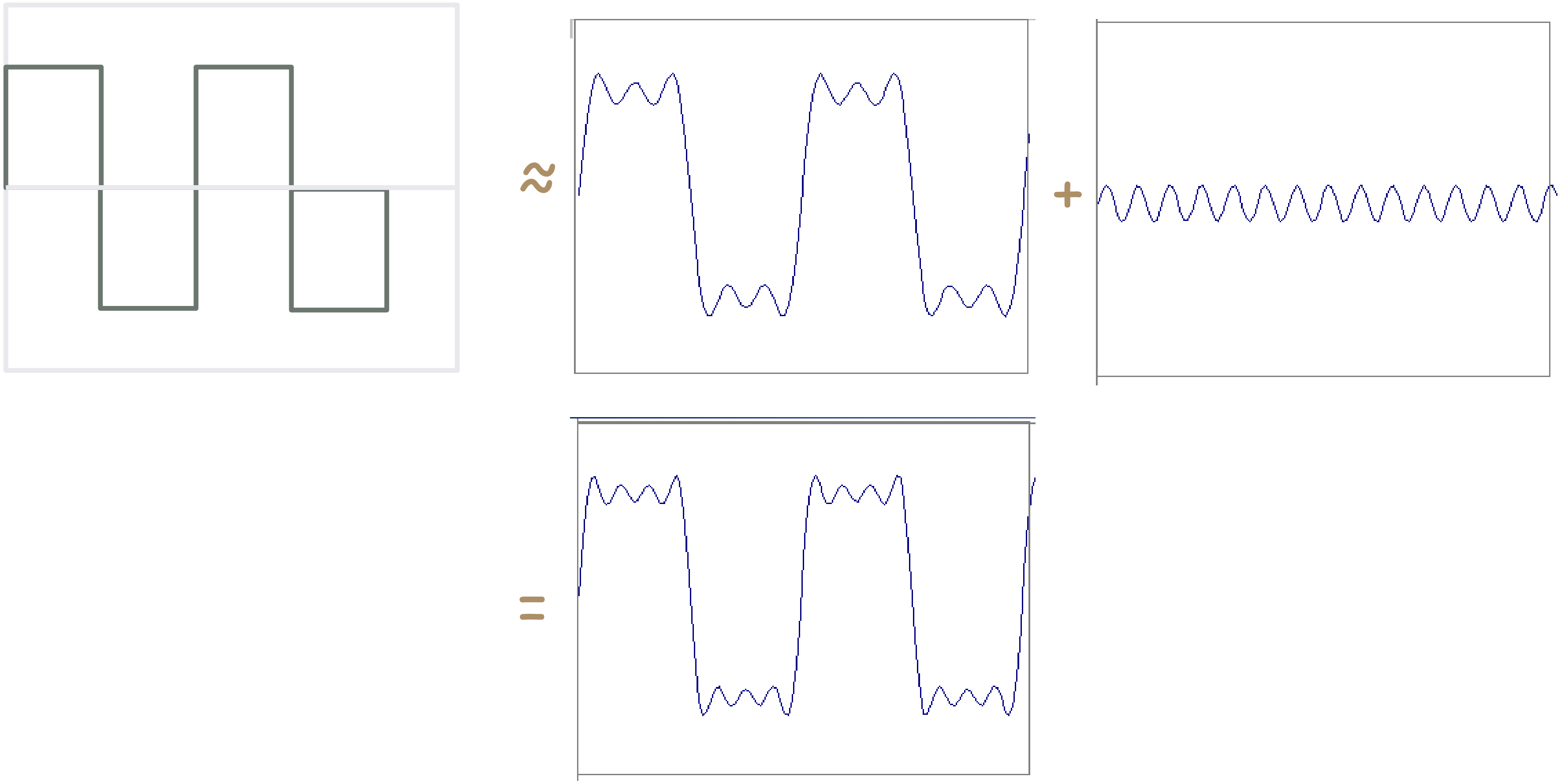
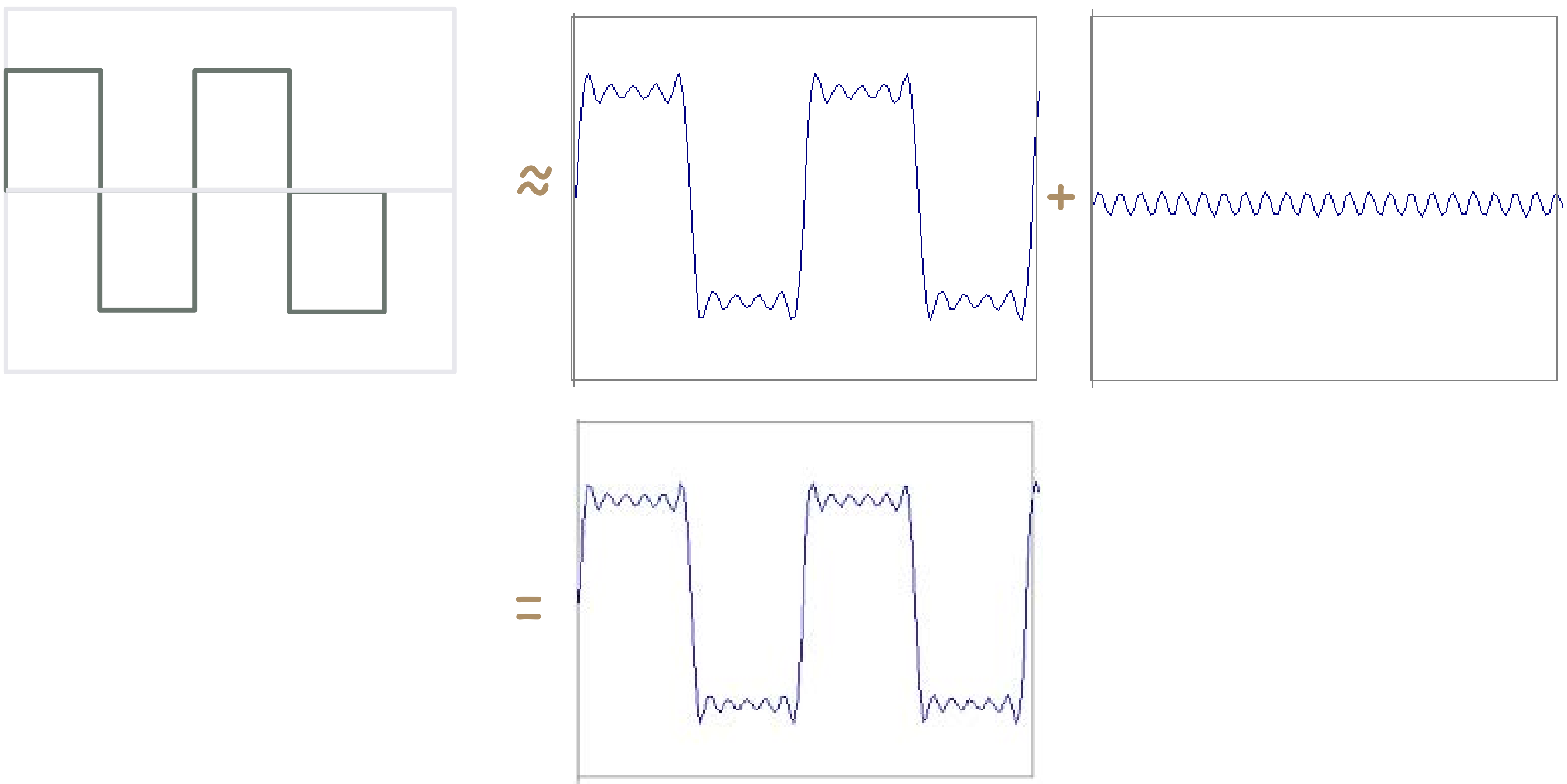
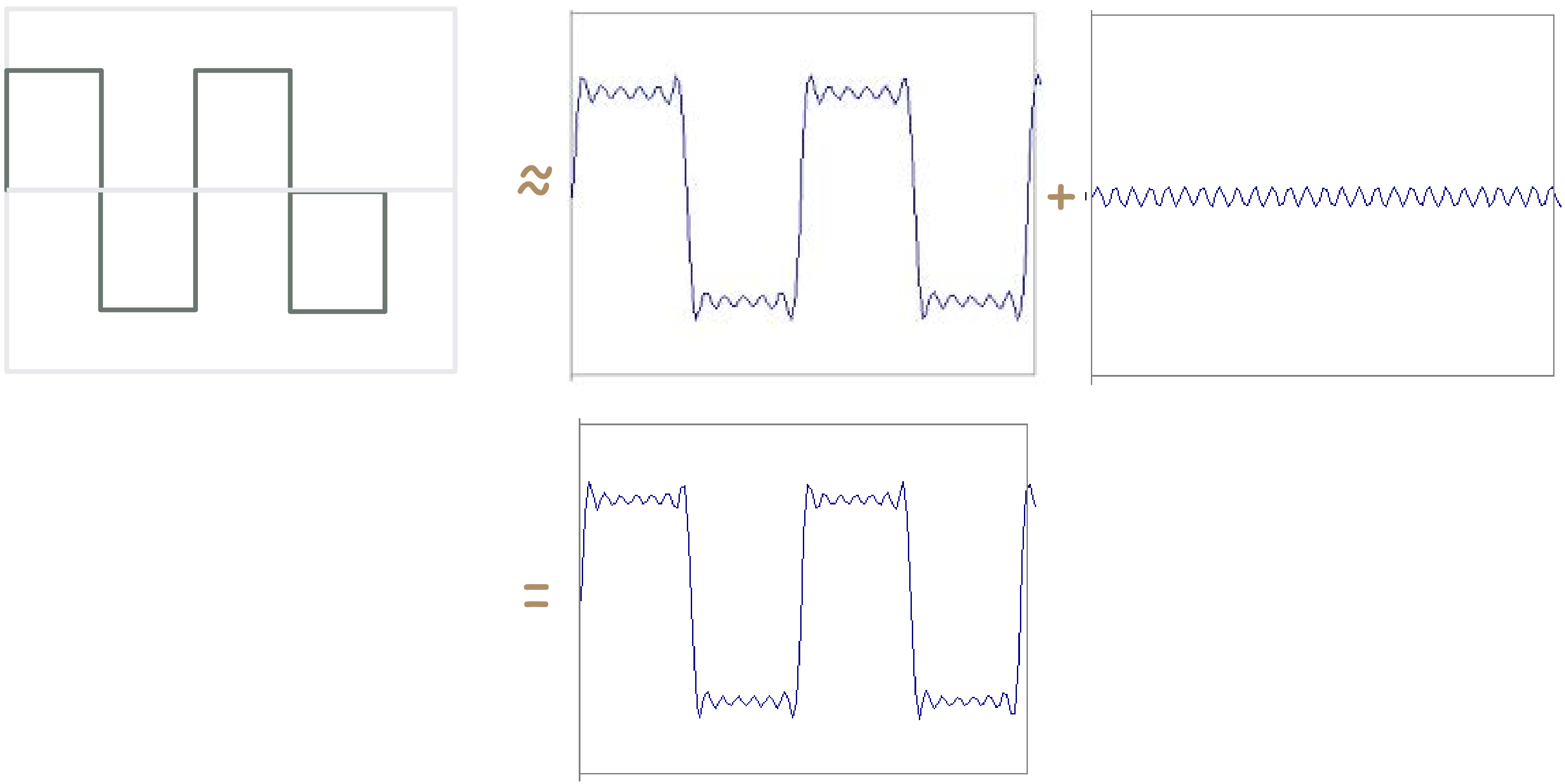


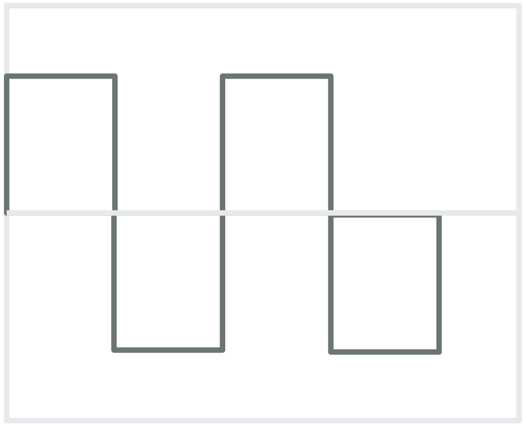
Frequency Spectra - Series



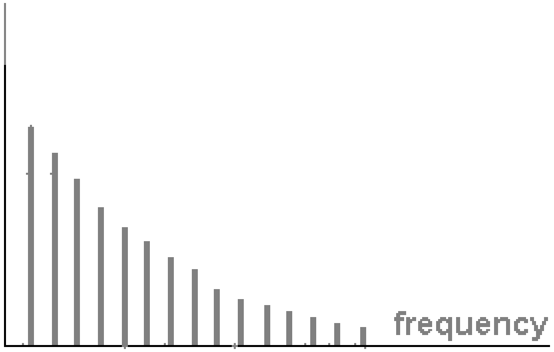
Frequency Spectra - Series



Frequency Spectra - Series



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



Usually, frequency is more interesting than the phase for CV because we're not reconstructing the image

Fourier *Transform*

We want to understand the frequency ω of our signal. So, let's reparametrize the signal by ω instead of *x*:

f(x) → **Fourier Transform** → ***F(ω)***

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

For every ω from 0 to inf (actually –inf to inf), ***F(ω)*** holds the amplitude *A* and phase ϕ of the corresponding sine

- How can *F* hold both? Complex number trick!

Recall : $e^{ik} = \cos k + i \sin k \qquad i = \sqrt{-1}$ (or j)

Even *Odd*

Matlab sinusoid demo…

Fourier Transform

We want to understand the frequency ω of our signal. So, let's reparametrize the signal by ω instead of *x*:

$$f(x) \longrightarrow \boxed{\text{Fourier Transform}} \xrightarrow{A\sin(\omega x + \phi)} F(\omega)$$

For every ω from 0 to inf, (actually –inf to inf), $F(\omega)$ holds the amplitude *A* and phase ϕ of the corresponding sine

- How can *F* hold both? Complex number trick!

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

$$F(\omega) = R(\omega) + iI(\omega)$$

Even *Odd*

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

And we can go back:

$$F(\omega) \longrightarrow \boxed{\textbf{\textit{Inverse}}\text{ Fourier Transform}} \longrightarrow f(x)$$

Computing FT: Just a basis

- The infinite integral of the product of two sinusoids of *different* frequency is zero. (Why?)

$$\int_{-\infty}^{\infty} \sin(ax+\phi)\sin(bx+\varphi)dx = 0, \text{ if } a \neq b$$

- And the integral is infinite if equal (unless exactly out of phase):

$$\int_{-\infty}^{\infty} \sin(ax+\phi)\sin(ax+\varphi)dx = \pm\infty$$

If ϕ and φ not exactly pi/2 out of phase (sin and cos).

Computing FT: Just a basis

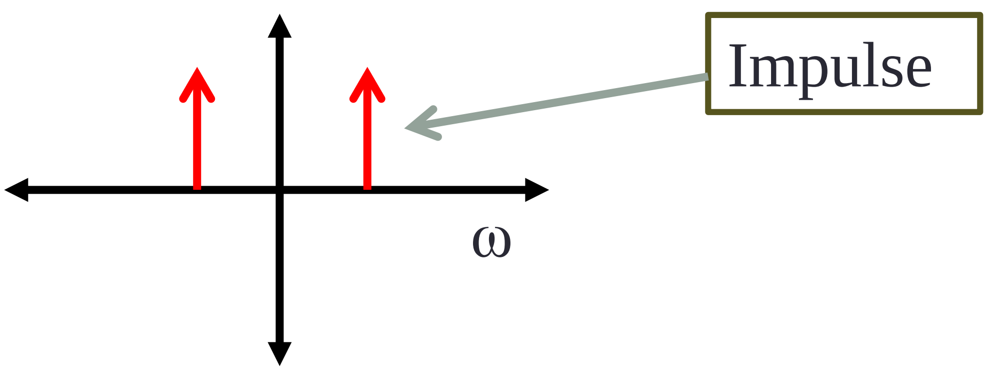
- So, suppose f(x) is a cosine wave of freq ω:

$$f(x) = \cos(2\pi\omega x)$$

- Then:

$$C(u) = \int_{-\infty}^{\infty} f(x)\cos(2\pi u x)dx$$

Is infinite if *u* is equal to ω (or - ω) and zero otherwise:



Computing FT: Just a basis

- We can do that for all frequencies *u.*
- But we'd have to do that for all *phases*, don't we???
- No! Any phase can be created by a weighted sum of cosine and sine. Only need each piece:

$$C(u) = \int_{-\infty}^{\infty} f(x)\cos(2\pi u x)dx$$

$$S(u) = \int_{-\infty}^{\infty} f(x)\sin(2\pi u x)dx$$

- Sinusoid demo?
- Or…

Fourier Transform – more formally

Represent the signal as an infinite weighted sum of an infinite number of sinusoids

$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-i 2\pi ux} dx$$

Again: $e^{ik} = \cos k + i \sin k \qquad i = \sqrt{-1}$

Spatial Domain (*x*) ⟶ Frequency Domain (*u or s*)

(Frequency Spectrum *F(u)*)

Inverse Fourier Transform (IFT) – add up all the sinusoids at x:

$$f(x) = \int_{-\infty}^{\infty} F(u) e^{i 2\pi ux} du$$

Fourier Transform - limitations

- The integral $\int_{-\infty}^{\infty} f(x)e^{-i2\pi ux}dx$ exists if the function f is integrable:

$$\int_{-\infty}^{\infty} | f(x) | dx < \infty$$

- If there is a bound of width *T* outside of which *f* is zero then obviously could integrate from just $-T/2$ to $T/2$

Fourier Transform ⇔ Fourier Series

- The bounded integral give some relation between the Fourier transform and the series and the Discrete Fourier transform.
- The ***Discrete FT***:

$$F(k) = \frac{1}{N} \sum_{x=0}^{x=N-1} f(x) e^{-i\frac{2\pi kx}{N}}$$

- *k* is the number "cycles per period of the signal" or "cycles per image.
- Only makes sense k = $-N/2$ to $N/2$. Why? What's the highest frequency you can unambiguously have in a discrete image?
- What is F(k) when *k* is zero?

2D Fourier Transforms

- The two dimensional version: .

$$F(u,v)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)e^{-i2\pi(ux+vy)}dx\,dy$$

- And the 2D ***Discrete FT***:

$$F(k_x,k_y)=\frac{1}{N}\sum_{x=0}^{x=N-1}\sum_{y=0}^{y=N-1} f(x,y)e^{-i\frac{2\pi(k_x x+k_y y)}{N}}$$

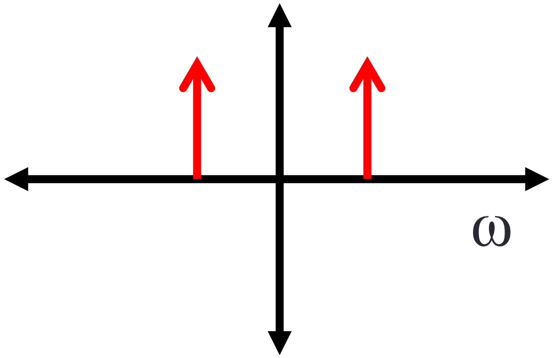
- Works best when you put the origin of *k* in the middle….

Frequency Spectra – Even/Odd

Frequency actually goes from –inf to inf.

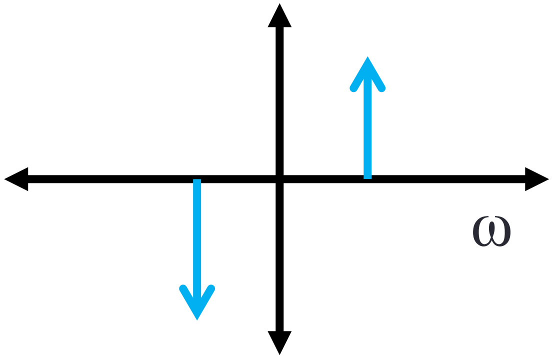
Sinusoid example:

Even (cos)



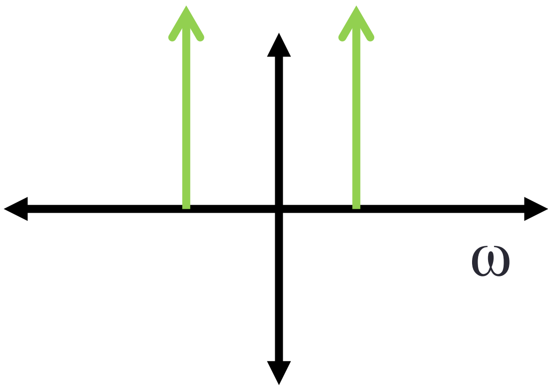
Real

Odd (sin)



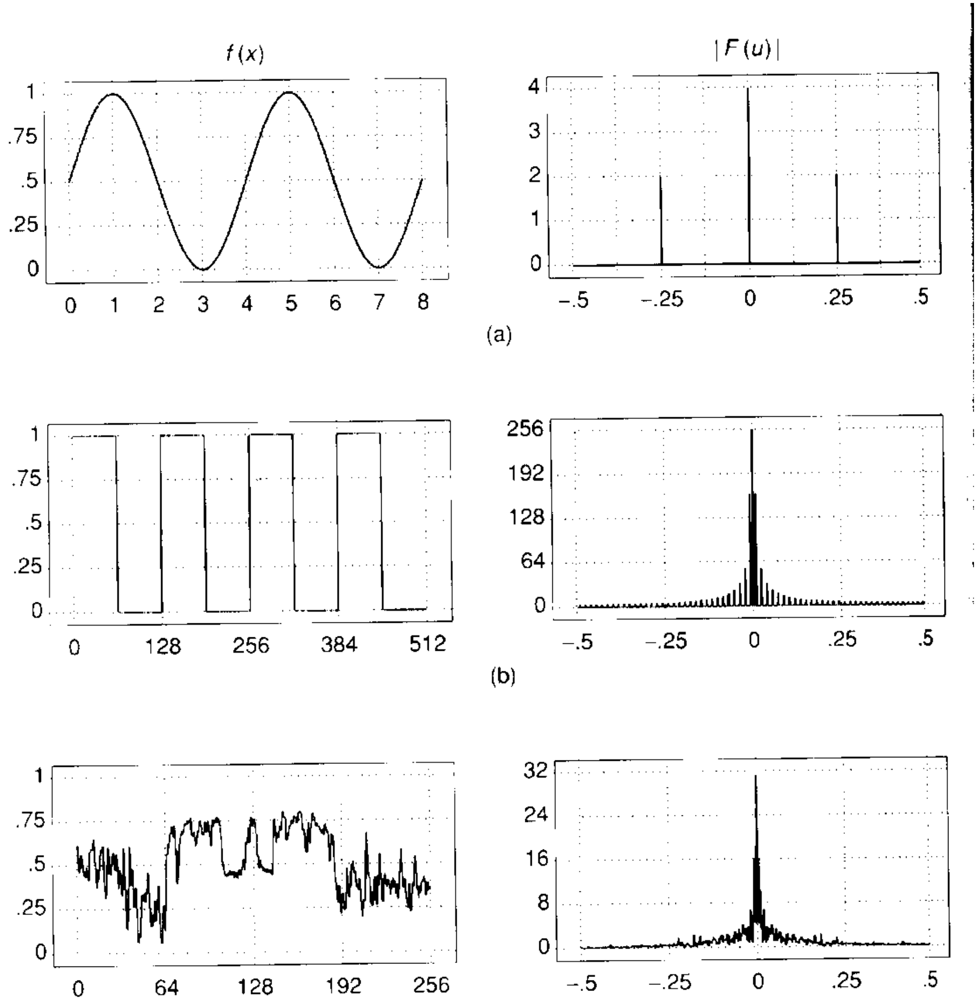
Imaginary

Magnitude



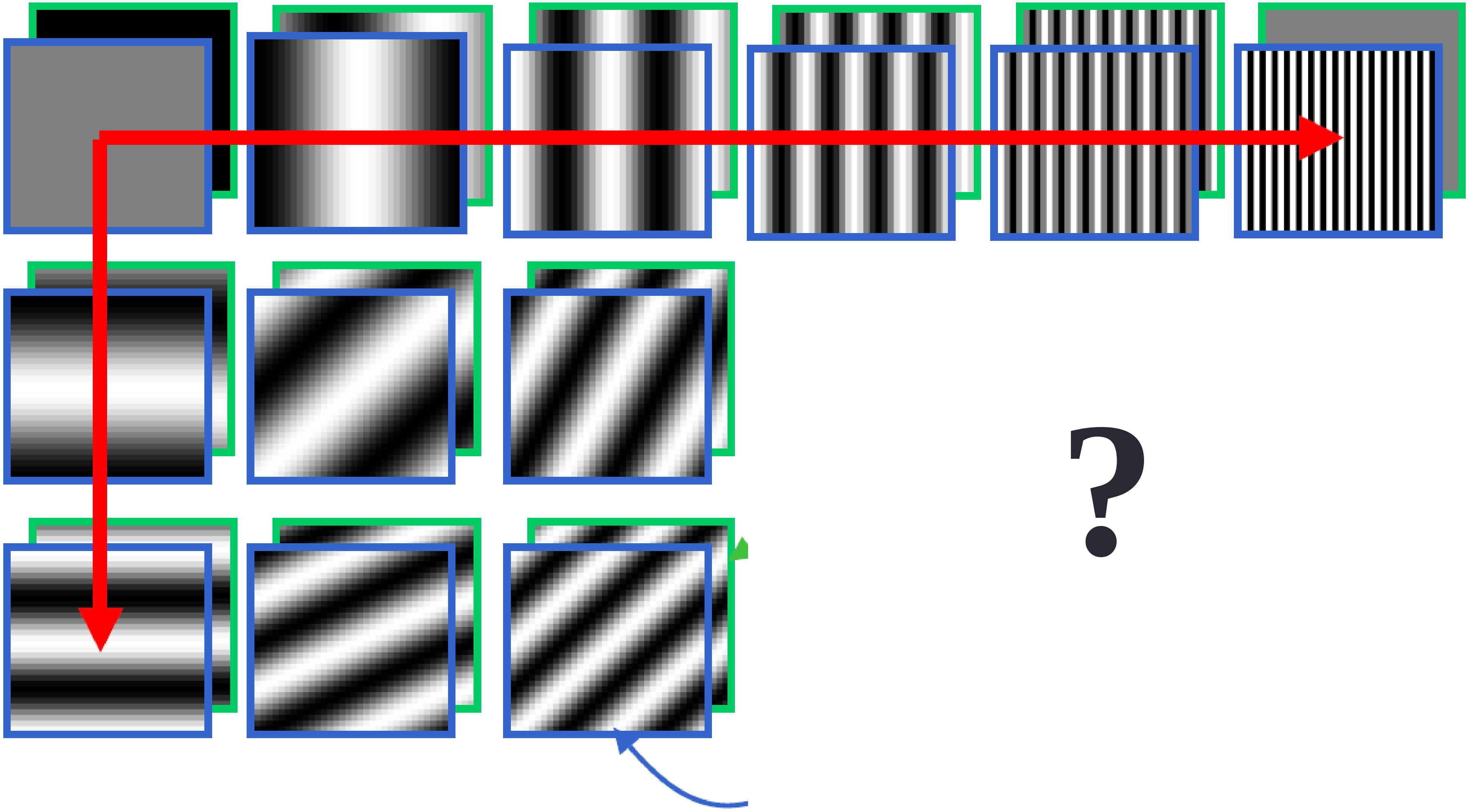
Power

Frequency Spectra

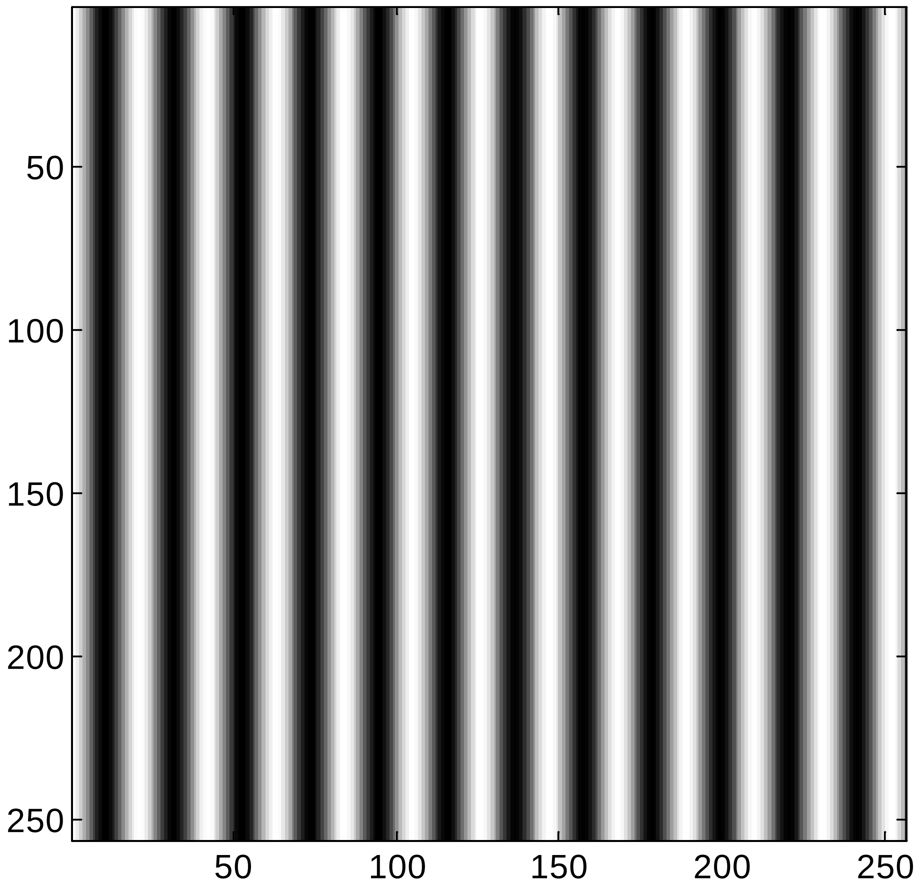


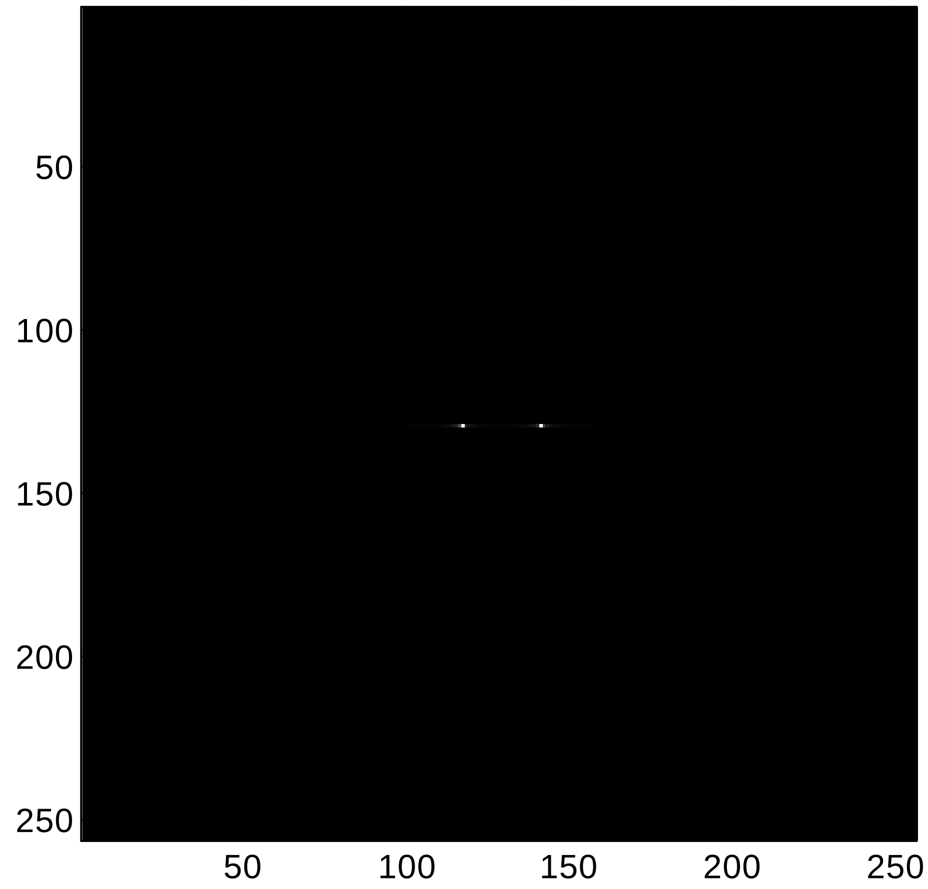
(a) (b) (c)

Extension to 2D

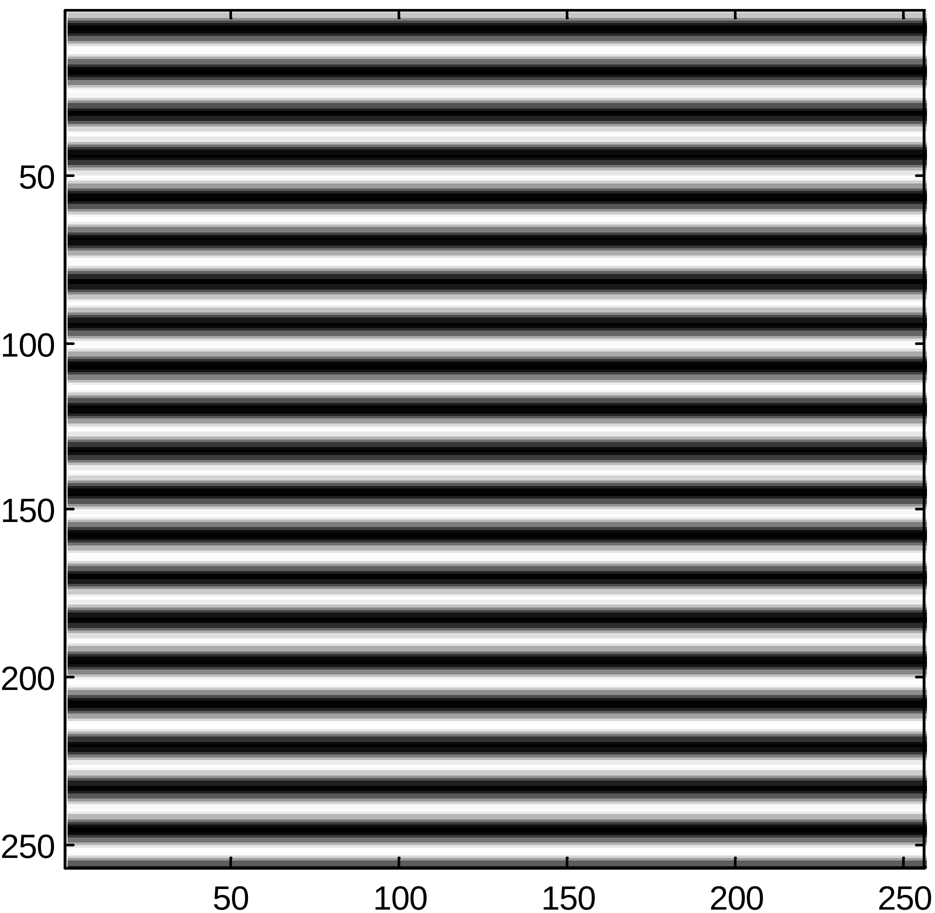


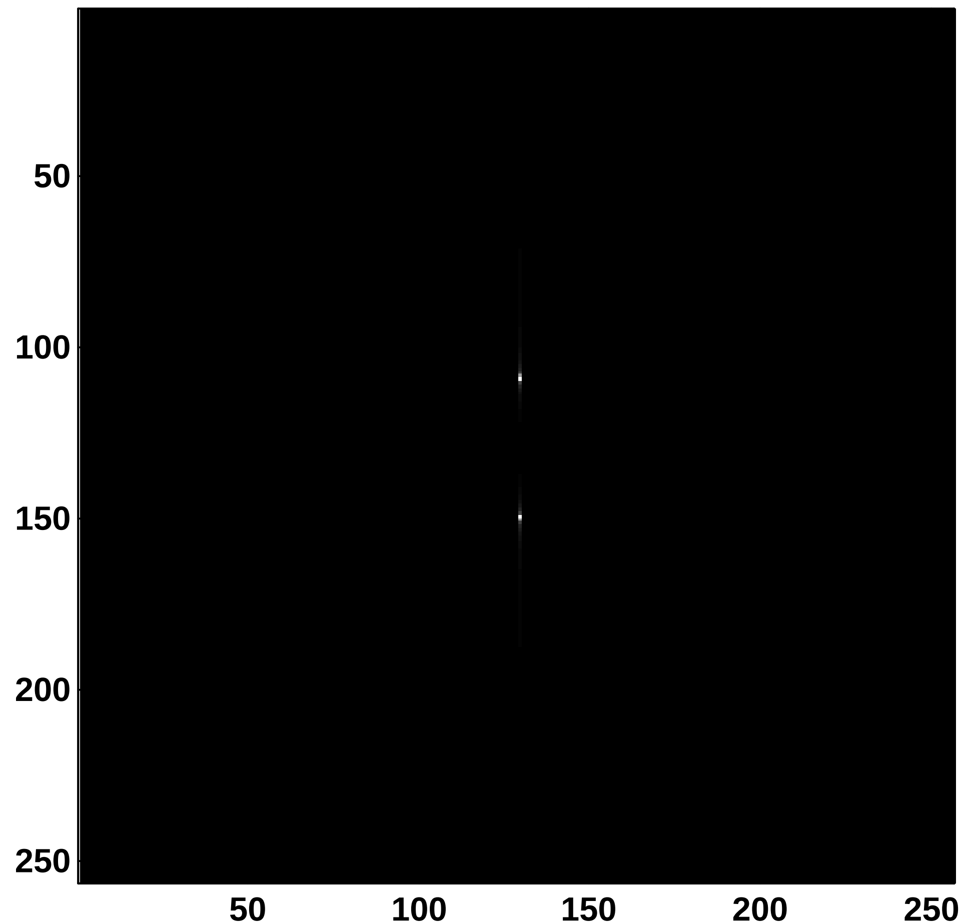
2D Examples – sinusoid magnitudes





2D Examples – sinusoid magnitudes





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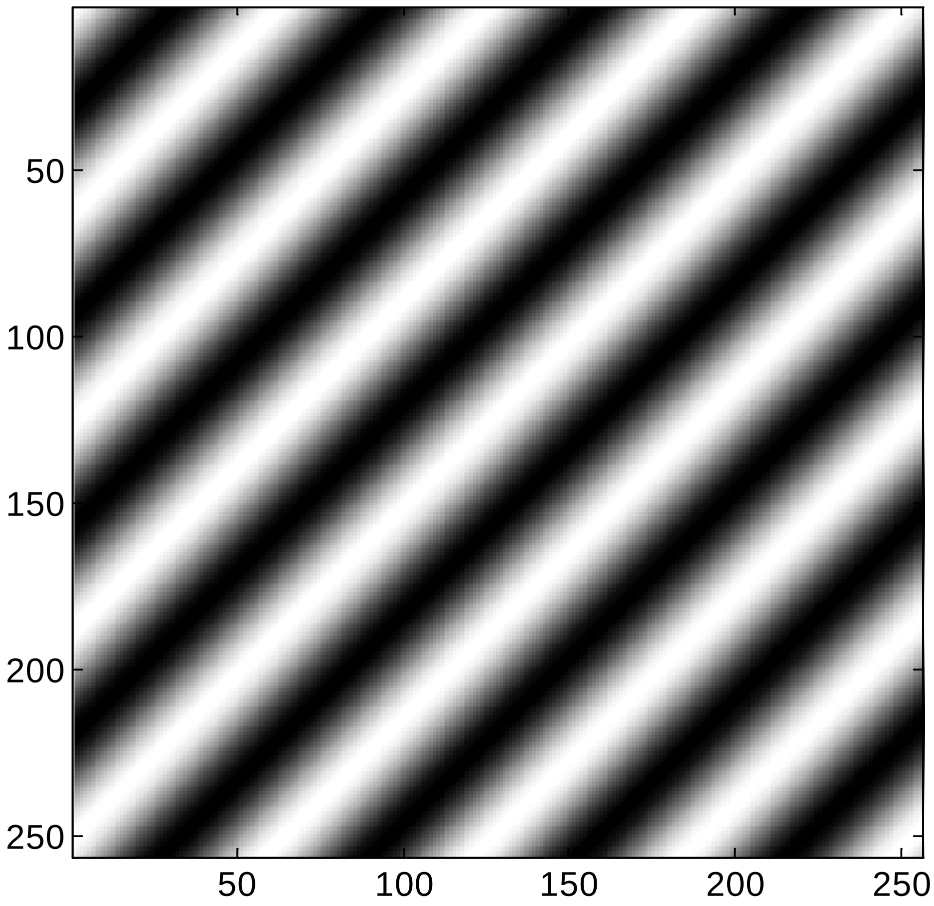
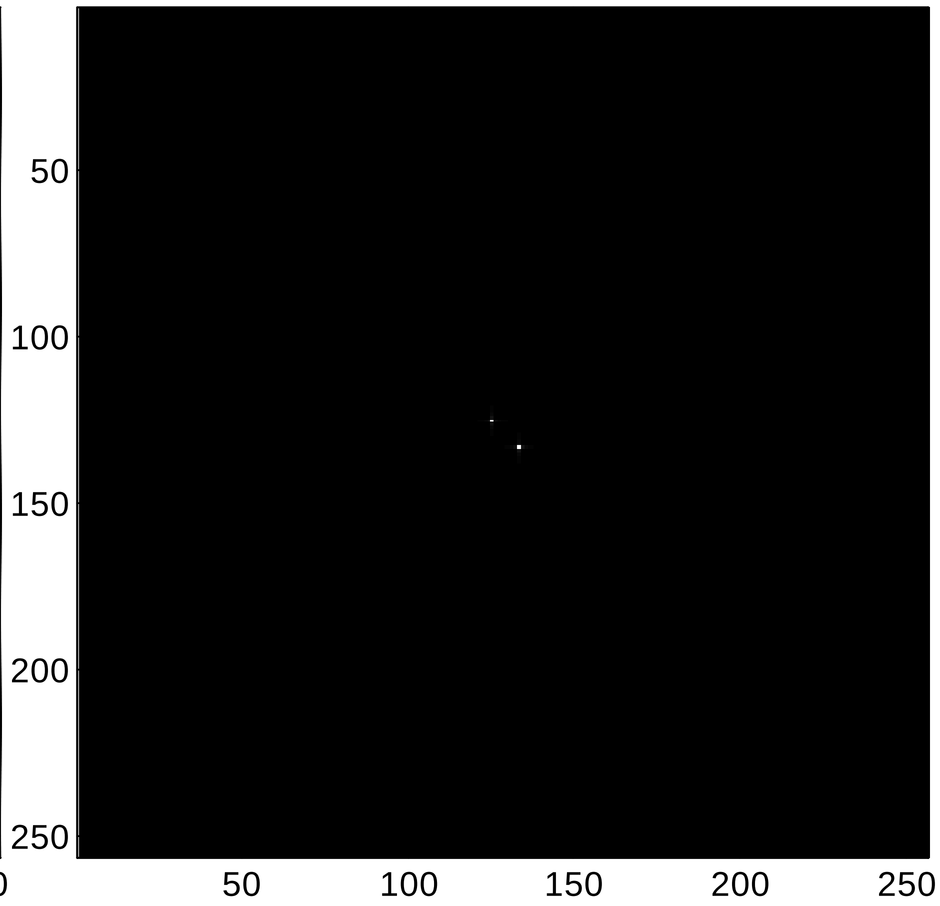
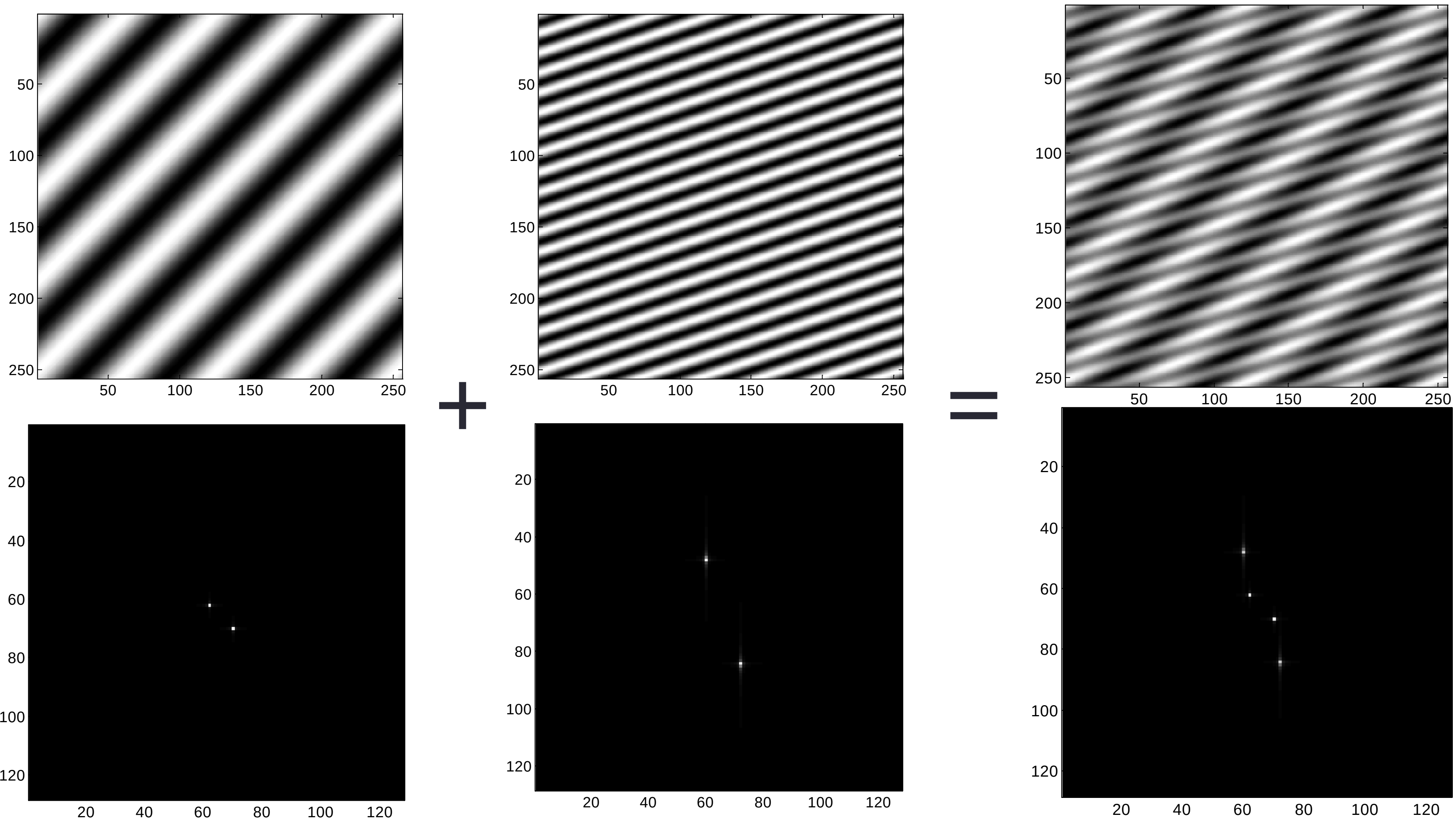
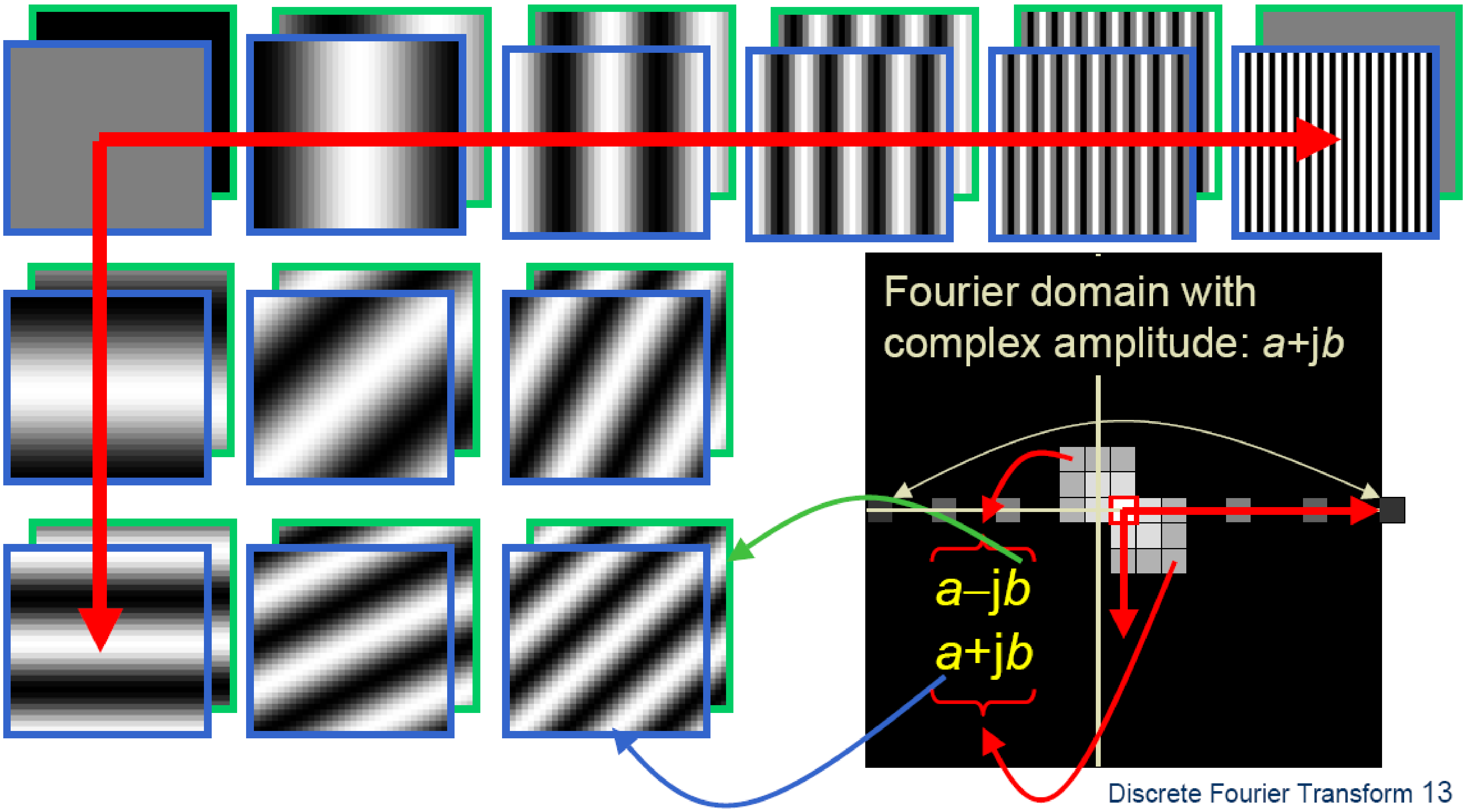




Linearity of Sum

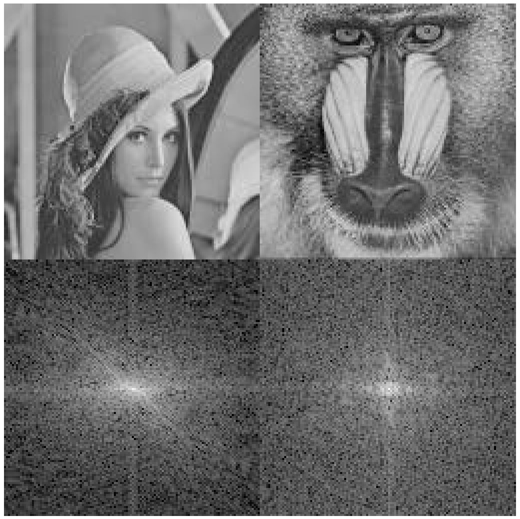
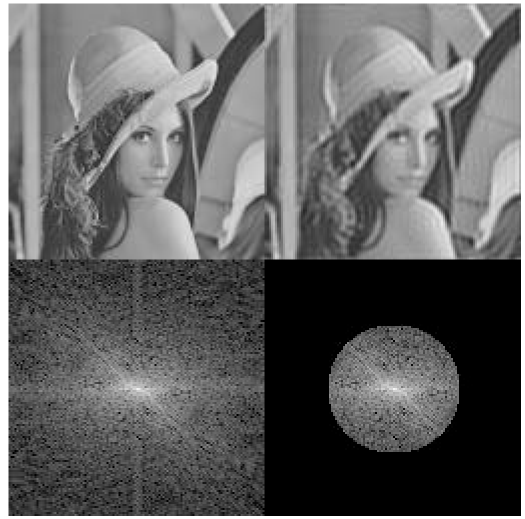
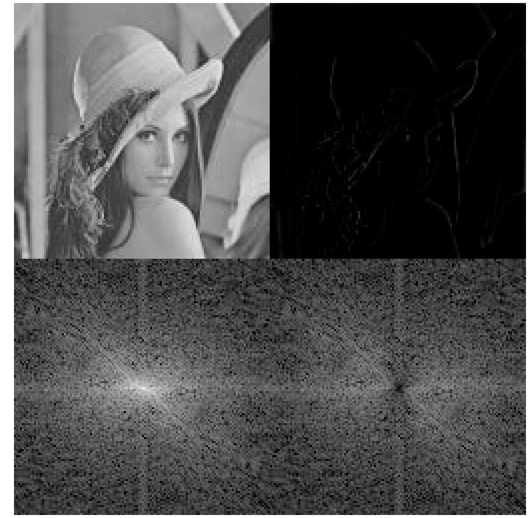


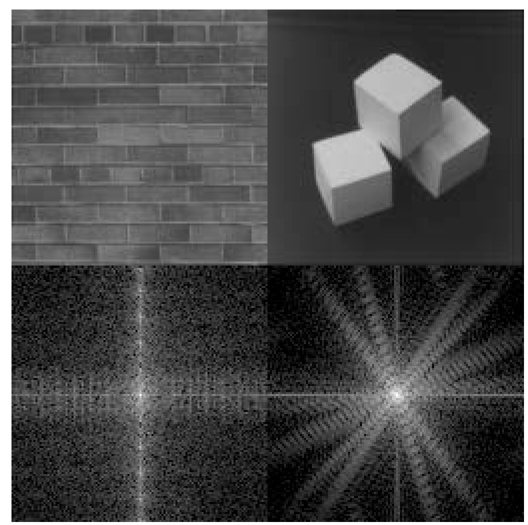
Extension to 2D – Complex plane



Both a Real and Im version

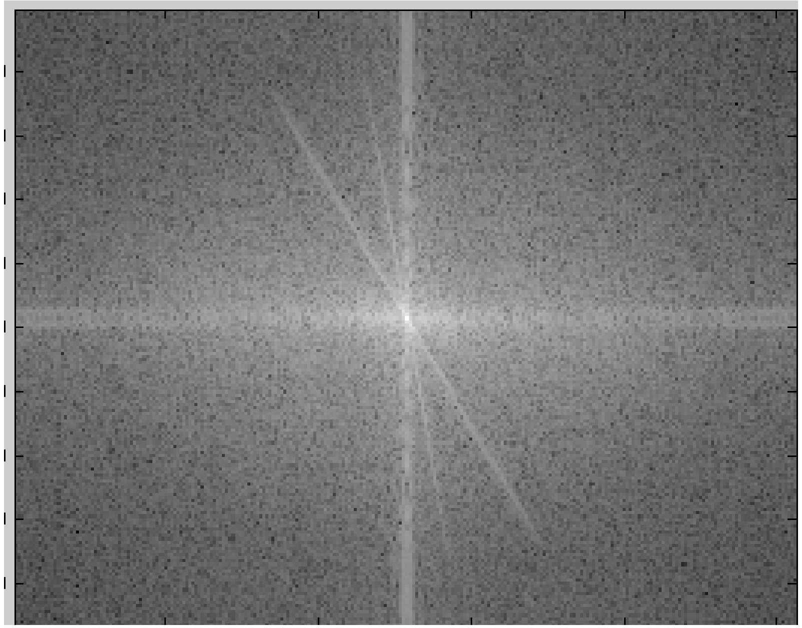
Examples



B.K. Gunturk

Man-made Scene



Where is this strong horizontal suggested by vertical center line?

Fourier Transform and Convolution

Let $g = f * h$

Then $$G(u) = \int_{-\infty}^{\infty} g(x) e^{-i2\pi ux} dx$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\tau) h(x-\tau) e^{-i2\pi ux} d\tau dx$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[f(\tau) e^{-i2\pi u\tau} d\tau \right] \left[h(x-\tau) e^{-i2\pi u(x-\tau)} dx \right]$$

$$= \int_{-\infty}^{\infty} \left[f(\tau) e^{-i2\pi u\tau} d\tau \right] \int_{-\infty}^{\infty} \left[h(x') e^{-i2\pi ux'} dx' \right]$$

$$= F(u) H(u)$$

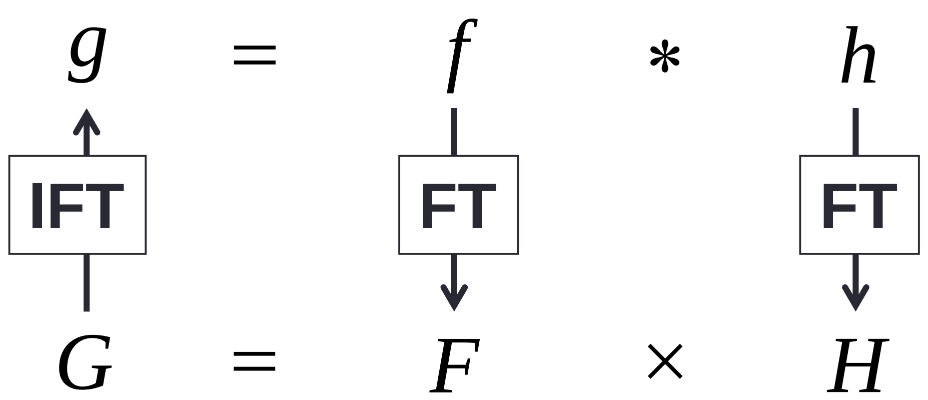
Convolution in spatial domain

$\Leftrightarrow$ *Multiplication in frequency domain*

Fourier Transform and Convolution

Spatial Domain *(x)*		Frequency Domain *(u)*
$g = f * h$	$\longleftrightarrow$	$G = FH$
$g = fh$	$\longleftrightarrow$	$G = F * H$

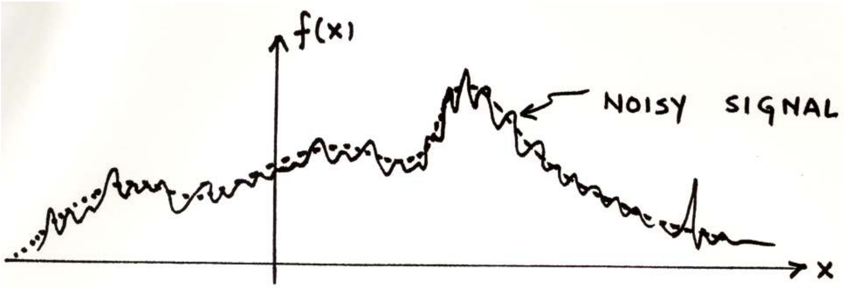
So, we can find *g(x)* by Fourier transform



Example use: Smoothing/Blurring

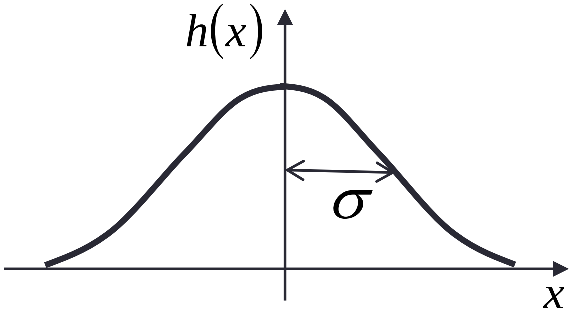
- We want a smoothed function of *f(x)*

$$g(x) = f(x) * h(x)$$



- Let us use a Gaussian kernel

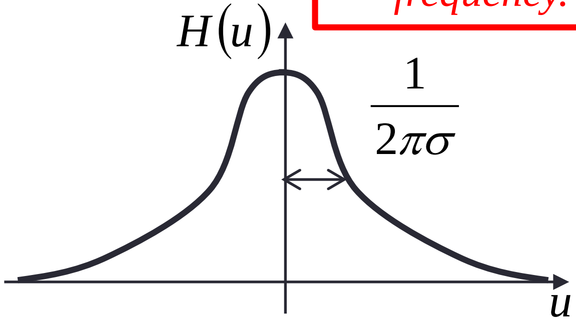
$$h(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{1}{2} \frac{x^2}{\sigma^2} \right]$$



Fat Gaussian in space is skinny Gaussian in frequency. Why?

- The Fourier transform of a Gaussian is a Gaussian

$$H(u) = \exp\left[-\frac{1}{2} (2\pi u)^2 \sigma^2 \right]$$



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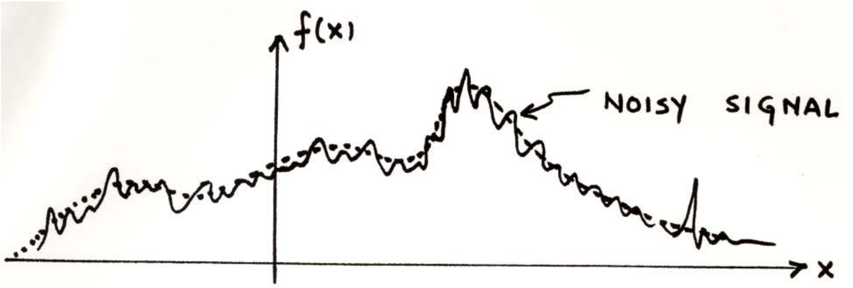

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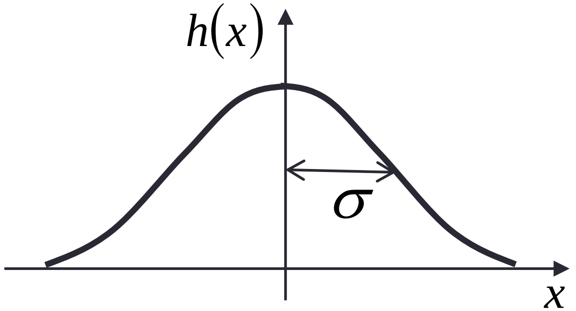
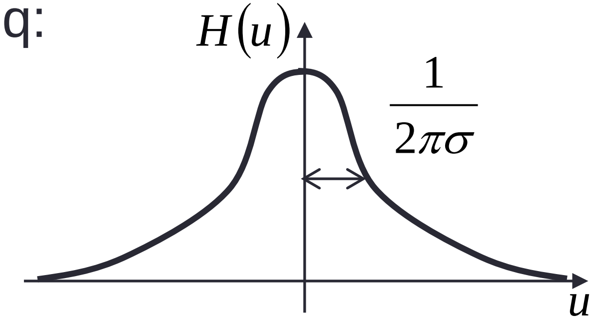


- Convolution in space is multiplication in freq:

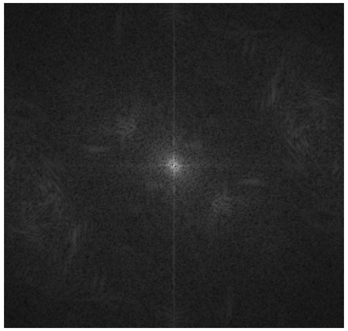
$$G(u) = F(u)H(u)$$



H(u) ***attenuates*** high frequencies in *F(u)* (Low-pass Filter)!

2D convolution theorem example

$f(x,y)$

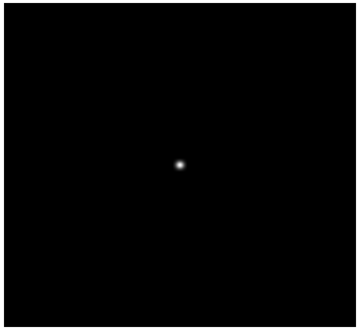


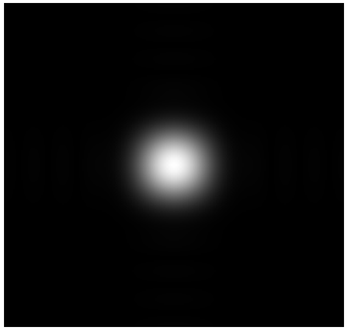
$|F(s_x,s_y)|$

(or $|F(u,v)|$)

$*$ $\times$

$h(x,y)$

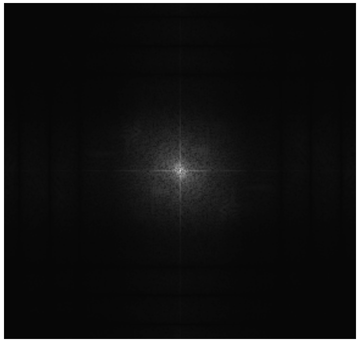




$|H(s_x,s_y)|$

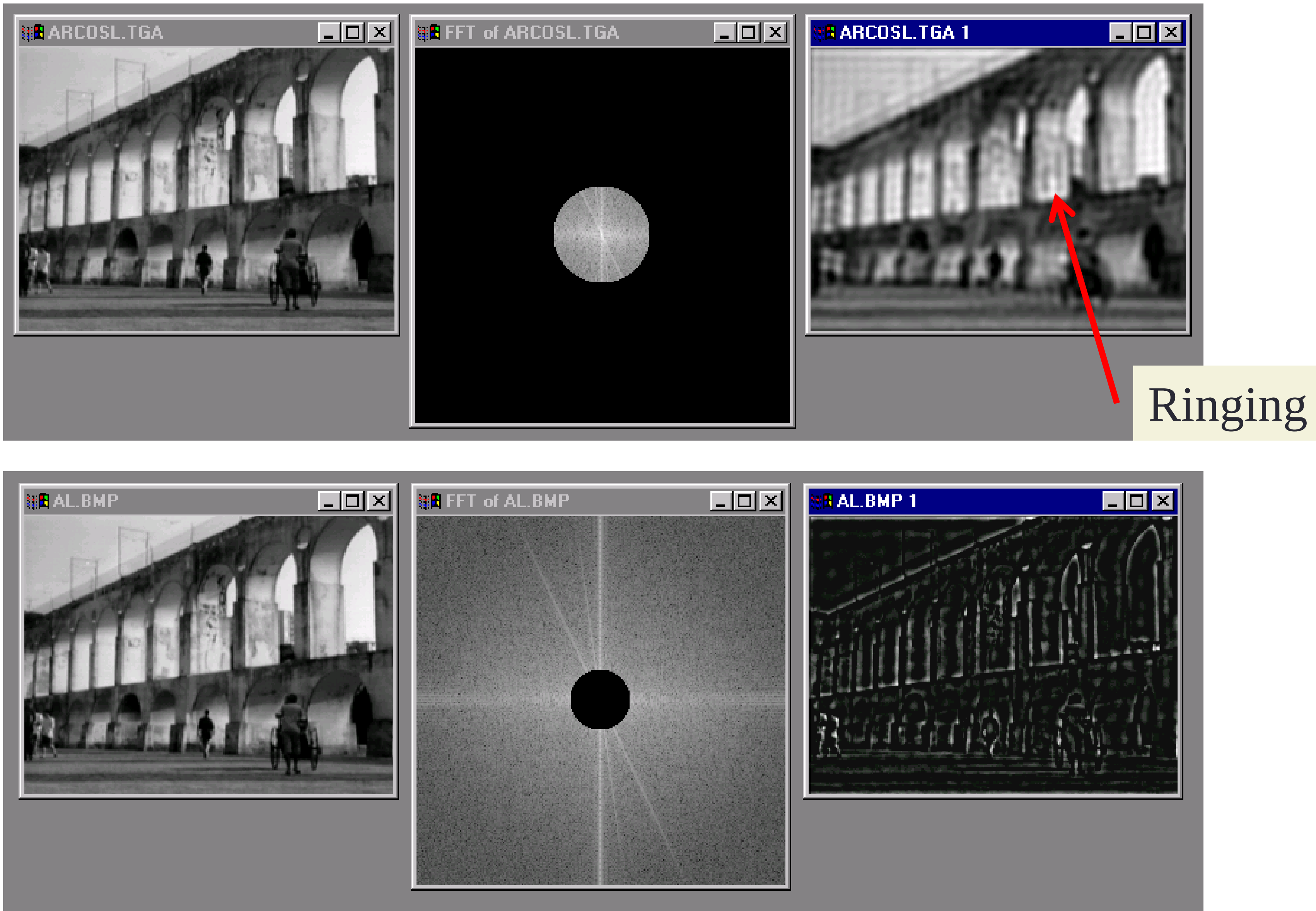
$\Downarrow$ $\Downarrow$

$g(x,y)$



$|G(s_x,s_y)|$

Low and High Pass filtering



Properties of Fourier Transform

	Spatial Domain *(x)*	Frequency Domain *(u)*
Linearity	$c_1 f(x) + c_2 g(x)$	$c_1 F(u) + c_2 G(u)$
Scaling	$f(ax)$	$\frac{1}{\lvert a \rvert} F\left(\frac{u}{a}\right)$
Shifting	$f(x - x_0)$	$e^{-i2\pi u x_0} F(u)$
Symmetry	$F(x)$	$f(-u)$
Conjugation	$f^*(x)$	$F^*(-u)$
Convolution	$f(x) * g(x)$	$F(u)G(u)$
Differentiation	$\frac{d^n f(x)}{dx^n}$	$(i2\pi u)^n F(u)$

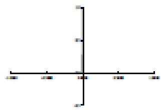
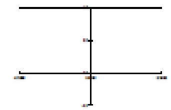
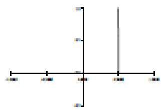
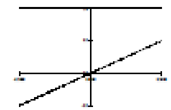
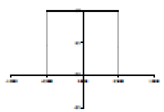
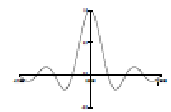
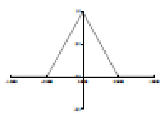
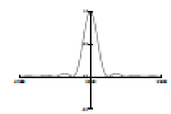
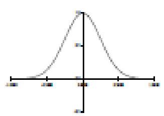
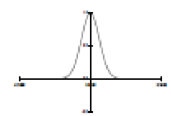
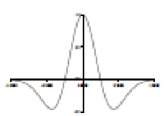
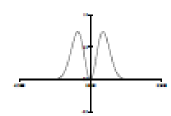
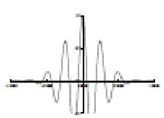
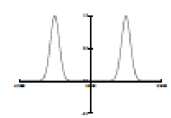
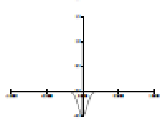
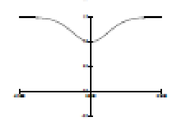
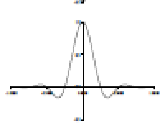
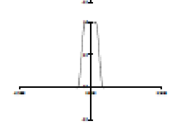
Shrink

Stretch

Differentiate

Multiply by u

Fourier Pairs (from Szeliski)

Name		Signal		Transform	
impulse		$\delta(x)$	$\Leftrightarrow$	1	
shifted impulse		$\delta(x-u)$	$\Leftrightarrow$	$e^{-j\omega u}$	
box filter		$\text{box}(x/a)$	$\Leftrightarrow$	$a\text{sinc}(a\omega)$	
tent		$\text{tent}(x/a)$	$\Leftrightarrow$	$a\text{sinc}^2(a\omega)$	
Gaussian		$G(x;\sigma)$	$\Leftrightarrow$	$\frac{\sqrt{2\pi}}{\sigma}G(\omega;\sigma^{-1})$	
Laplacian of Gaussian		$(\frac{x^2}{\sigma^4}-\frac{1}{\sigma^2})G(x;\sigma)$	$\Leftrightarrow$	$-\frac{\sqrt{2\pi}}{\sigma}\omega^2 G(\omega;\sigma^{-1})$	
Gabor		$\cos(\omega_0 x)G(x;\sigma)$	$\Leftrightarrow$	$\frac{\sqrt{2\pi}}{\sigma}G(\omega\pm\omega_0;\sigma^{-1})$	
unsharp mask		$(1+\gamma)\delta(x)$ $-\gamma G(x;\sigma)$	$\Leftrightarrow$	$(1+\gamma)-$ $\frac{\sqrt{2\pi}\gamma}{\sigma}G(\omega;\sigma^{-1})$	
windowed sinc		$\text{rcos}(x/(aW))$ $\text{sinc}(x/a)$	$\Leftrightarrow$	(see Figure 3.29)	

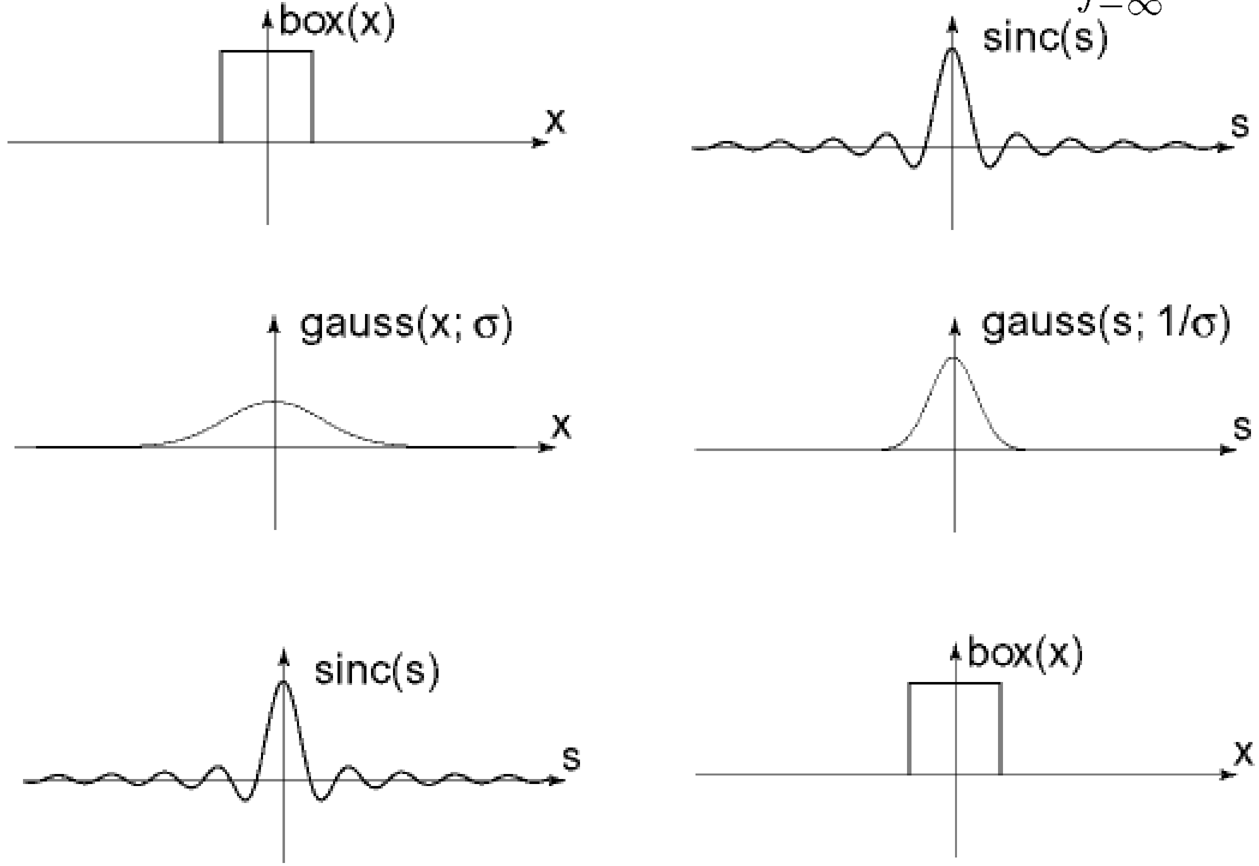
Fourier Transform smoothing pairs

Spatial domain

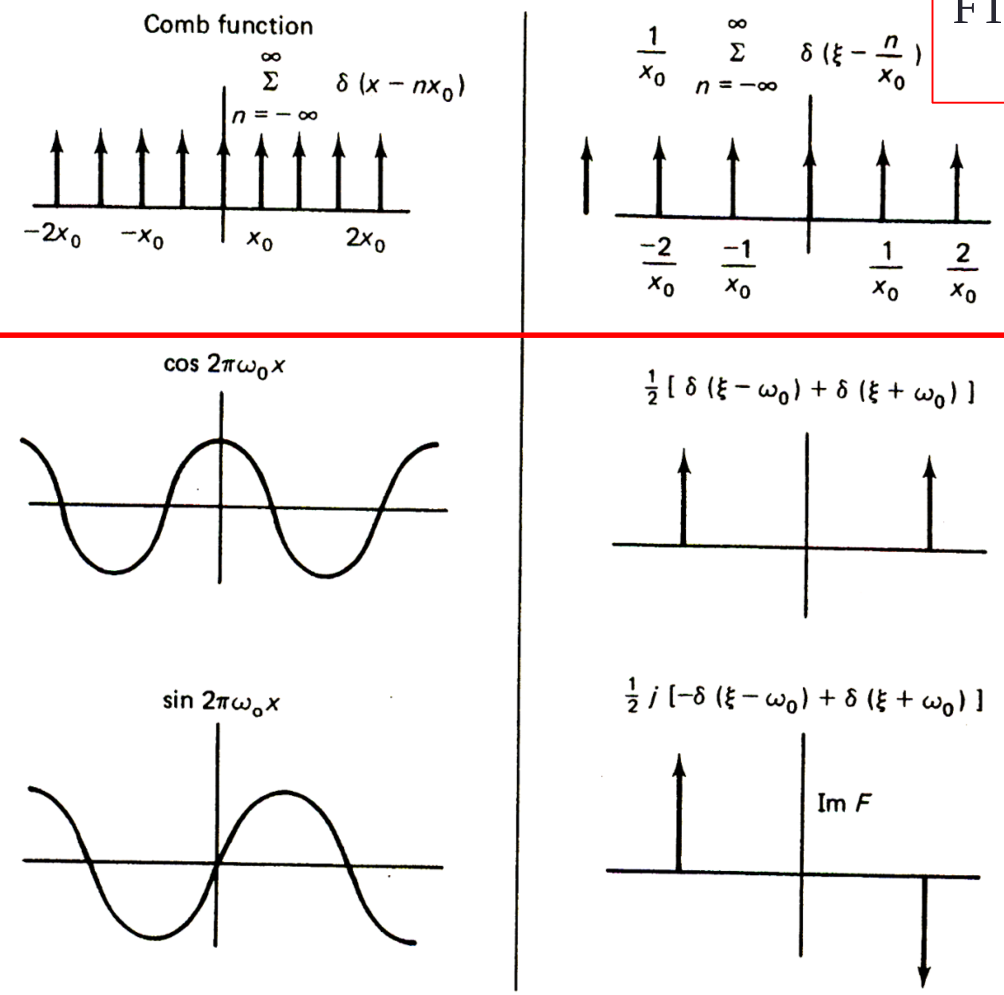
$f(x)$

Frequency domain

$$F(s) = \int_{-\infty}^{\infty} f(x) e^{-i2\pi sx} dx$$



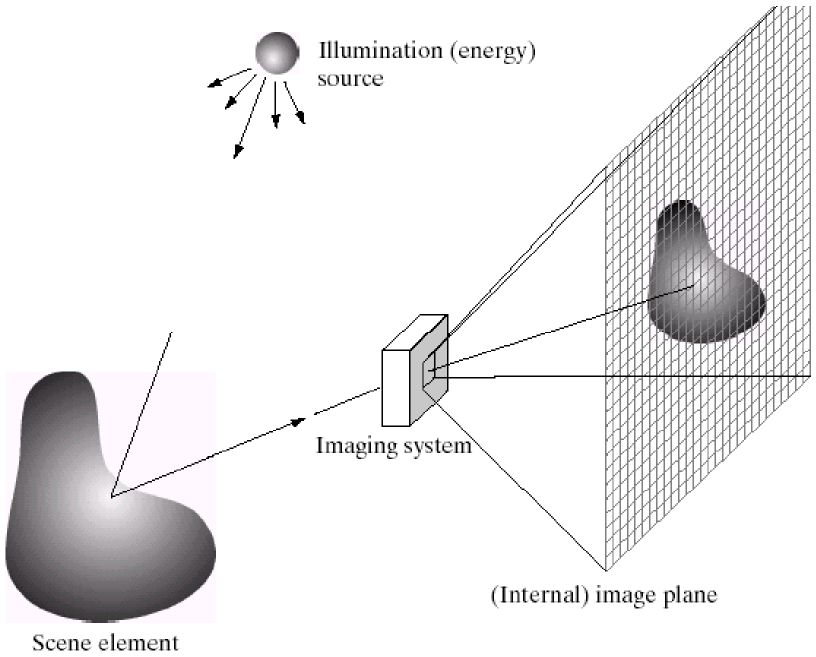
Fourier Transform Sampling Pairs

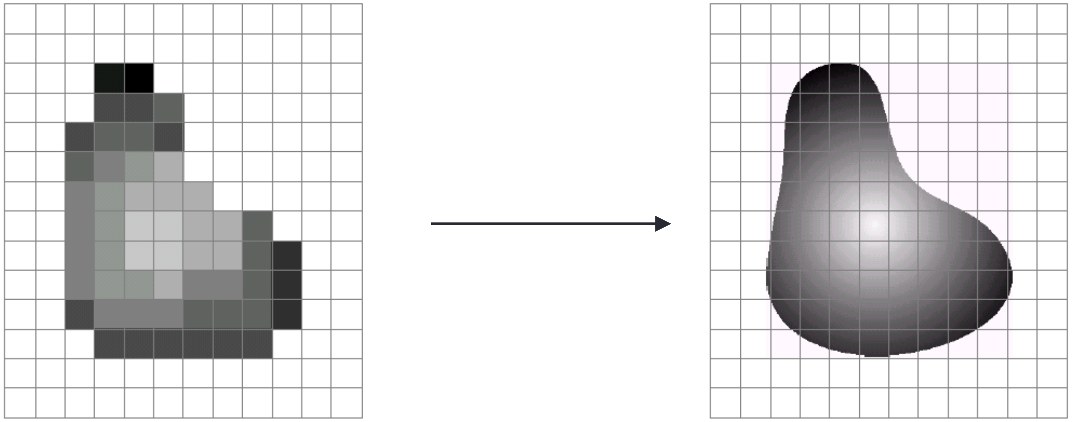


FT of an "impulse train" is an impulse train

Sampling and Aliasing

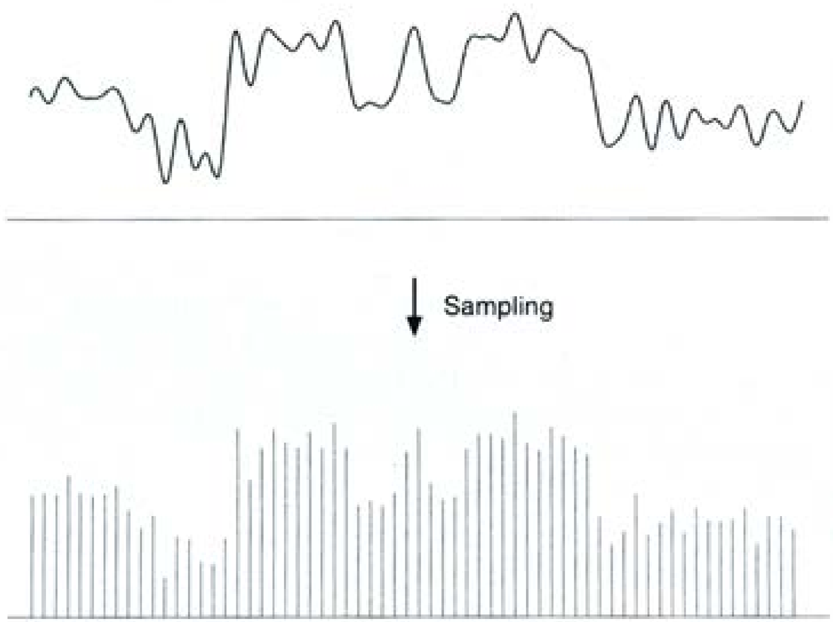
Sampling and Reconstruction





Sampled representations

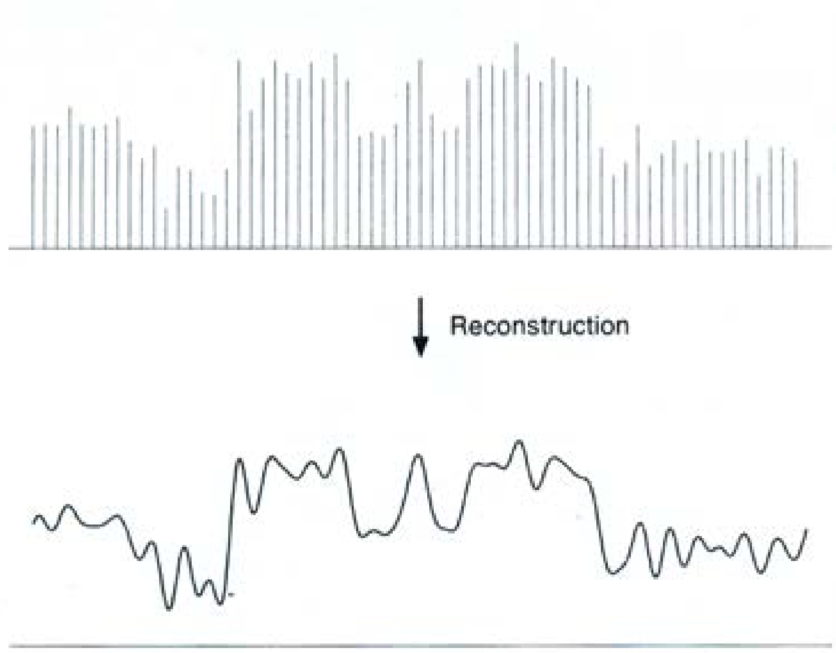
- How to store and compute with continuous functions?
- Common scheme for representation: samples
  - write down the function's values at many points



S. Marschner

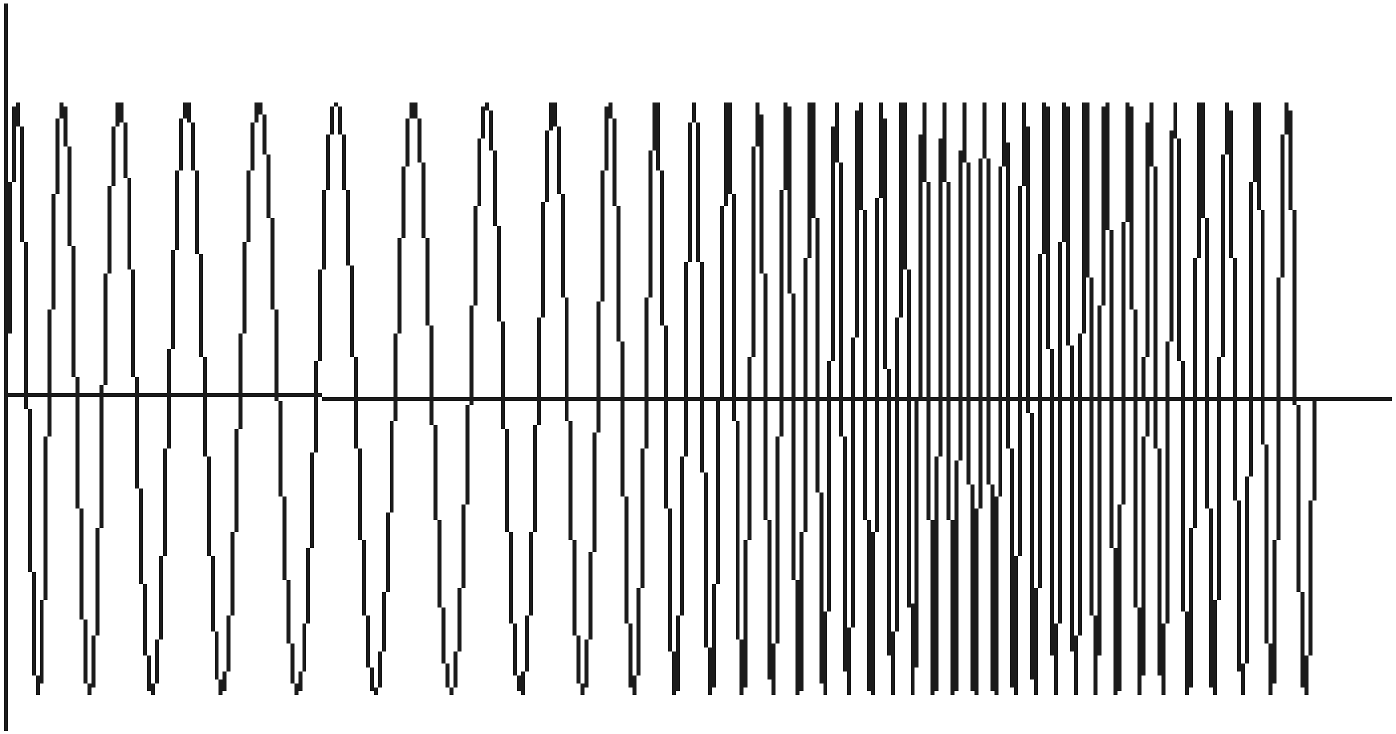
Reconstruction

- Making samples back into a continuous function
  - for output (need realizable method)
  - for analysis or processing (need mathematical method)
  - amounts to “guessing” what the function did in between



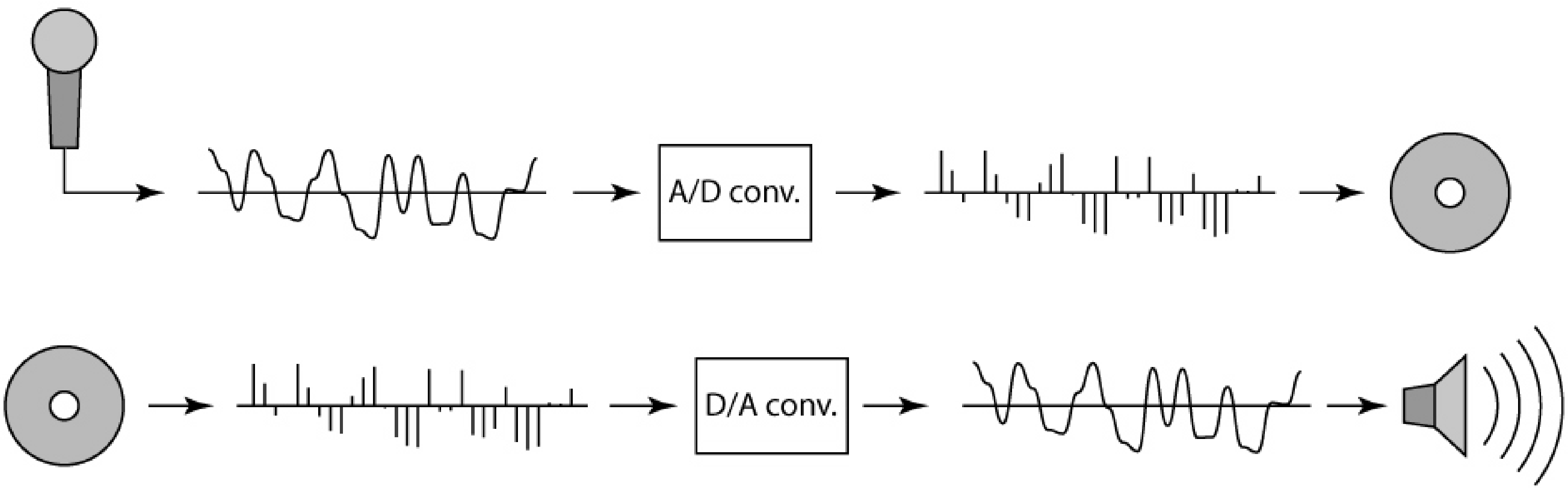
S. Marschner

1D Example: Audio



Sampling in digital audio

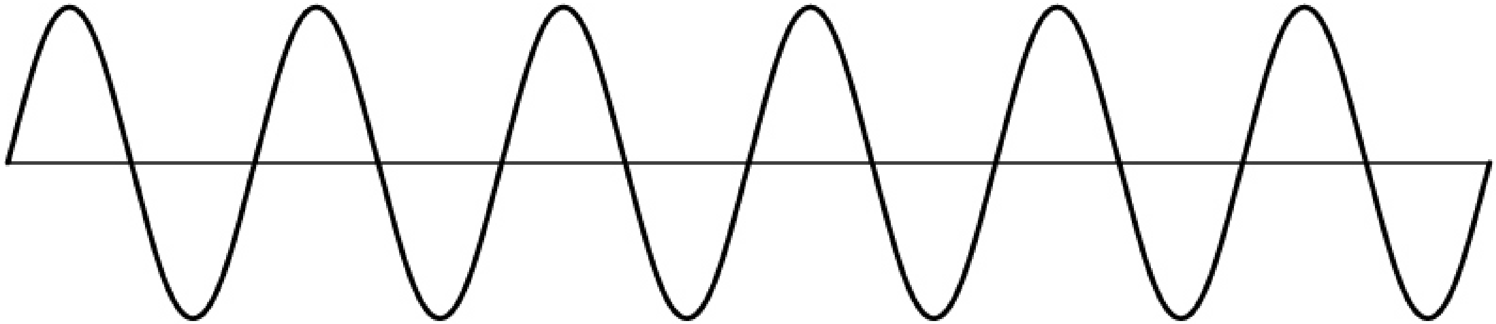
- Recording: sound to analog to samples to disc
- Playback: disc to samples to analog to sound again
  - how can we be sure we are filling in the gaps correctly?



S. Marschner

Sampling and Reconstruction

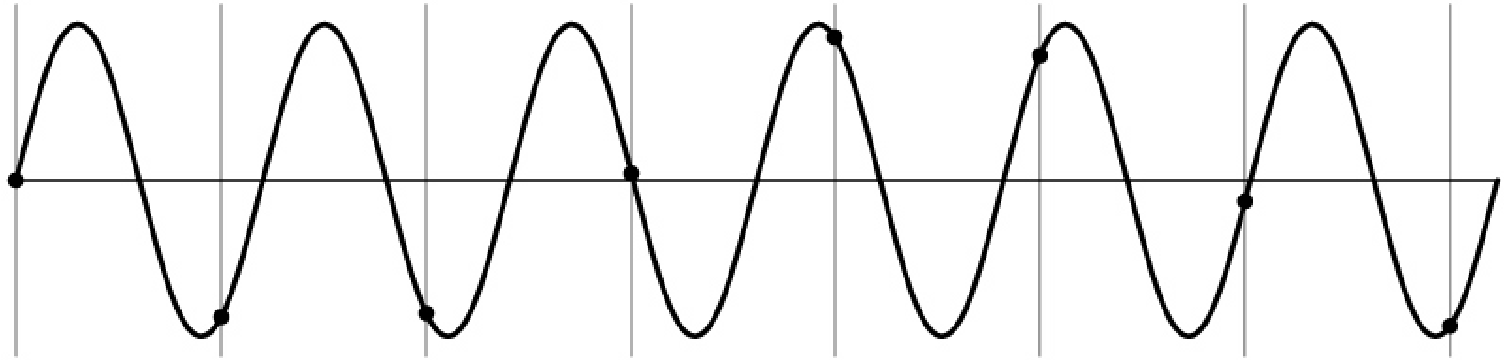
- Simple example: a sign wave



S. Marschner

Undersampling

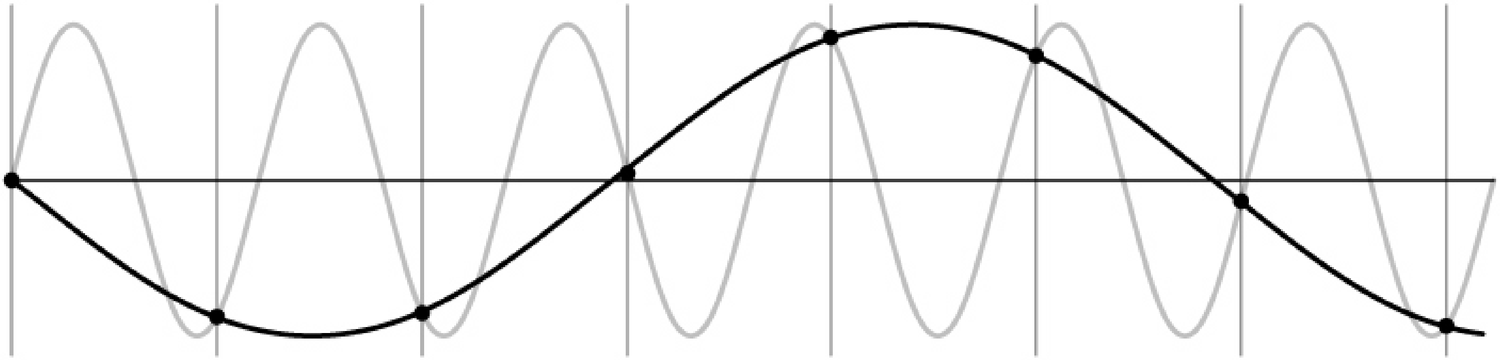
- What if we “missed” things between the samples?
- Simple example: undersampling a sine wave
  - unsurprising result: information is lost



S. Marschner

Undersampling

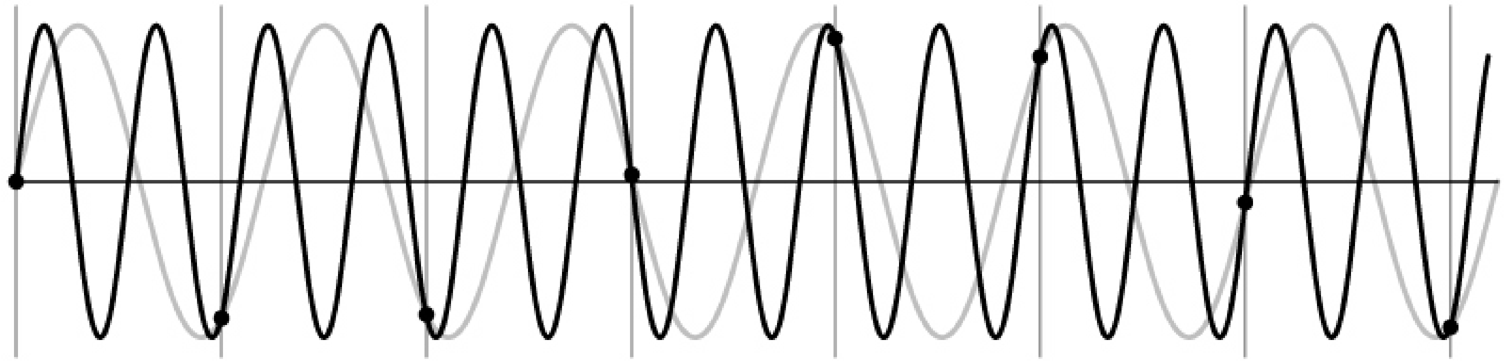
- What if we "missed" things between the samples?
- Simple example: undersampling a sine wave
  - unsurprising result: information is lost
  - surprising result: indistinguishable from lower frequency



S. Marschner

Undersampling

- What if we “missed” things between the samples?
- Simple example: undersampling a sine wave
  - unsurprising result: information is lost
  - surprising result: indistinguishable from lower frequency
  - also was always indistinguishable from higher frequencies
  - *aliasing*: signals “traveling in disguise” as other frequencies

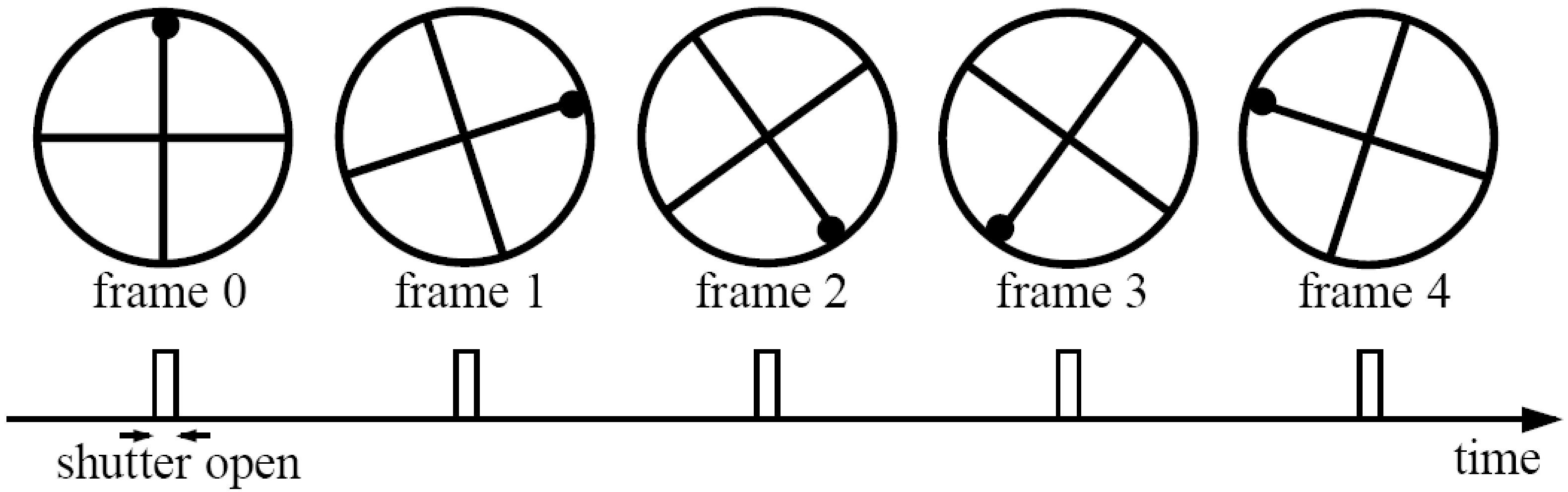


S. Marschner

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):



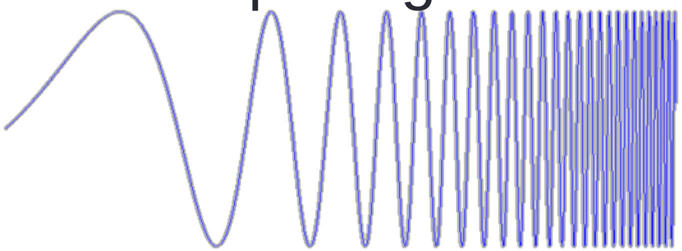
Without dot, wheel appears to be rotating slowly backwards! (counterclockwise)

S. Seitz

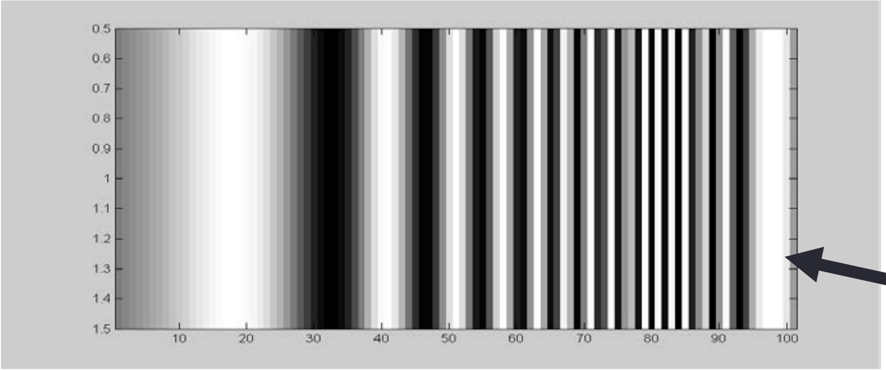
Aliasing in images

What's happening?

Input signal:

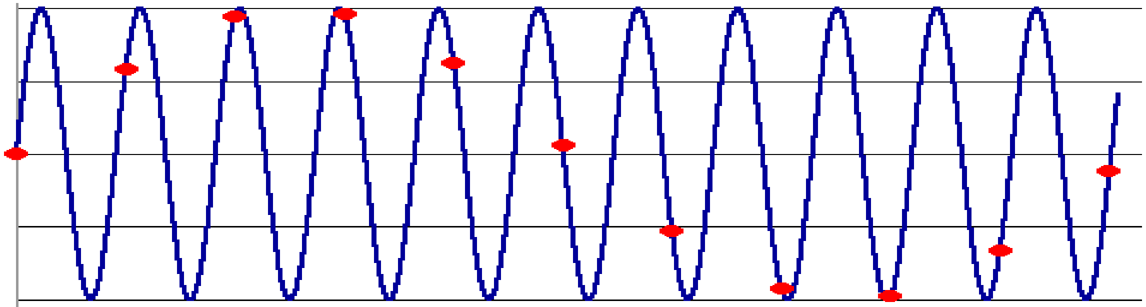


Plot as image:



Alias!
Not enough samples

x = 0:.05:5; imagesc(sin((2.^x).*x))



Antialiasing

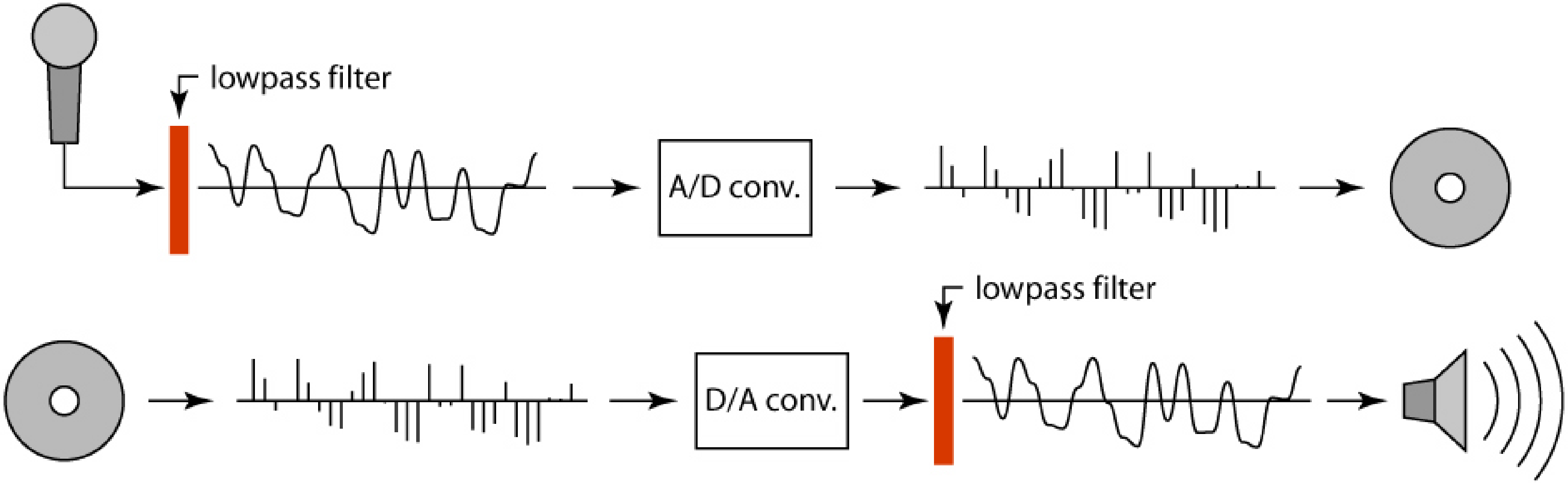
- What can we do about aliasing?

- Sample more often
  - Join the Mega-Pixel craze of the photo industry
  - But this can't go on forever

- Make the signal less "wiggly"
  - Get rid of some high frequencies
  - Will loose information
  - But it's better than aliasing

Preventing aliasing

- Introduce lowpass filters:
  - remove high frequencies leaving only safe, low frequencies
  - choose lowest frequency in reconstruction (disambiguate)



S. Marschner

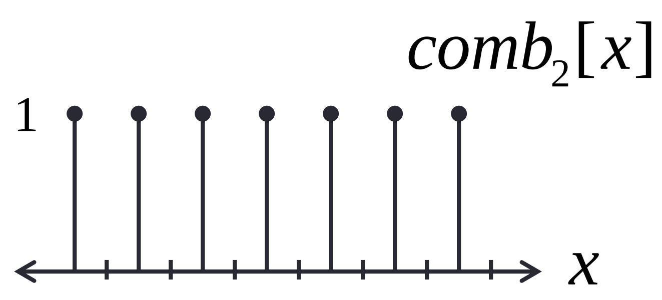
(Anti)Aliasing in the Frequency Domain

Impulse Train

- Define a *comb* function (impulse train) in 1D as follows

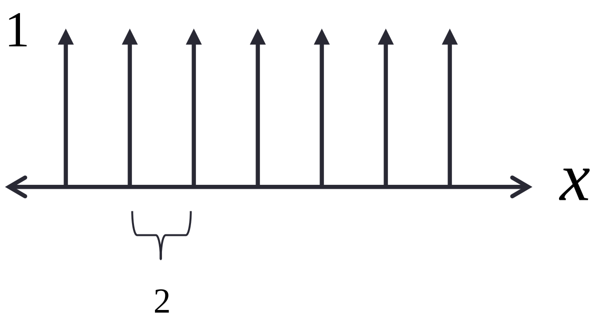
$$comb_M[x] = \sum_{k=-\infty}^{\infty} \delta[x - kM]$$

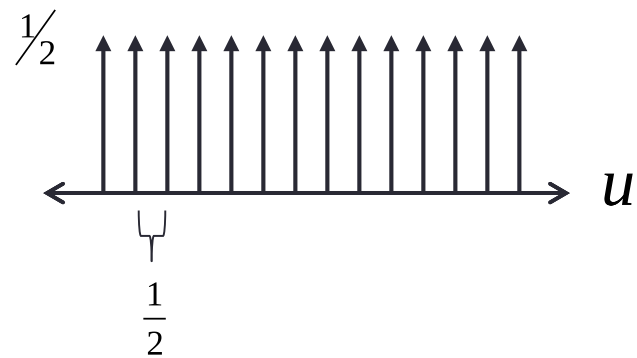
where *M* is an integer



Impulse Train in 1D

$$comb_2(x) \Longleftrightarrow \frac{1}{2} comb_{\frac{1}{2}}(u)$$





Remember:

Scaling $f(ax)$ $\frac{1}{|a|} F\left(\frac{u}{a}\right)$

B.K. Gunturk

Impulse Train in 2D *(bed of nails)*

$$comb_{M,N}(x,y) \equiv \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} \delta\left(x-kM, y-lN\right)$$

- Fourier Transform of an impulse train is also an impulse train:

$$\underbrace{\sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} \delta\left(x-kM, y-lN\right)}_{comb_{M,N}(x,y)} \Leftrightarrow \underbrace{\frac{1}{MN} \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} \delta\left(u-\frac{k}{M}, v-\frac{l}{N}\right)}_{comb_{\frac{1}{M},\frac{1}{N}}(u,v)}$$

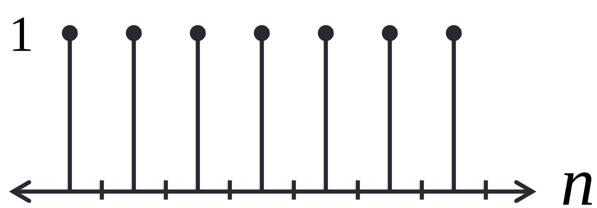
As the comb samples get further apart, the spectrum samples get closer together!

B.K. Gunturk

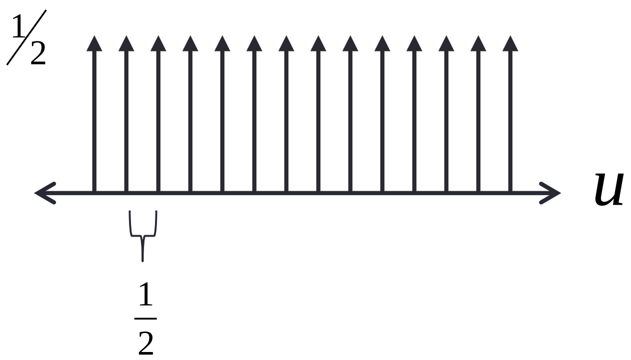
Impulse Train

$comb_2[n]$

$\frac{1}{2} comb_{\frac{1}{2}}(u)$



$\Leftrightarrow$

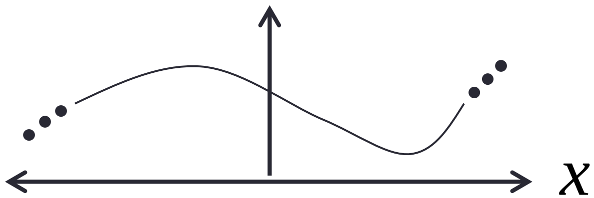


Remember:

Scaling $f(ax)$ $\frac{1}{|a|} F\left(\frac{u}{a}\right)$

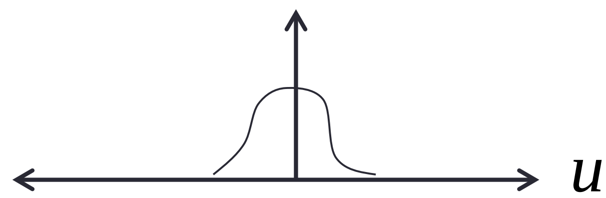
Sampling low frequency signal

$f(x)$

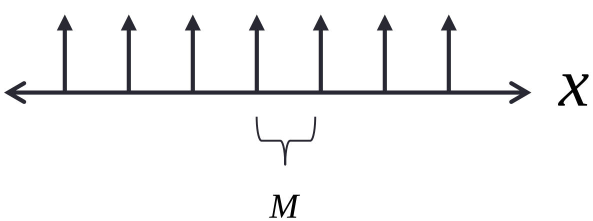


$\Leftrightarrow$

$F(u)$

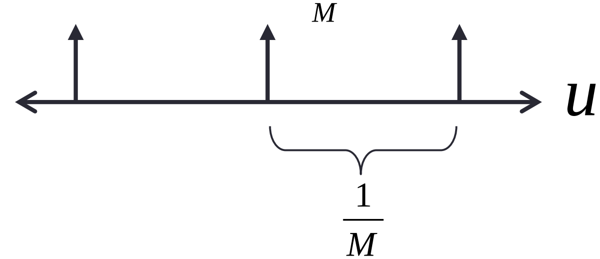


$comb_M(x)$



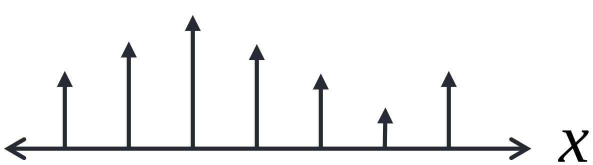
$\Leftrightarrow$

$comb_{\frac{1}{M}}(u)$



Multiply:

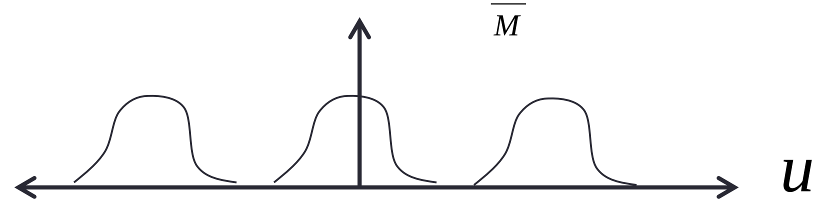
$f(x)comb_M(x)$



$\Leftrightarrow$

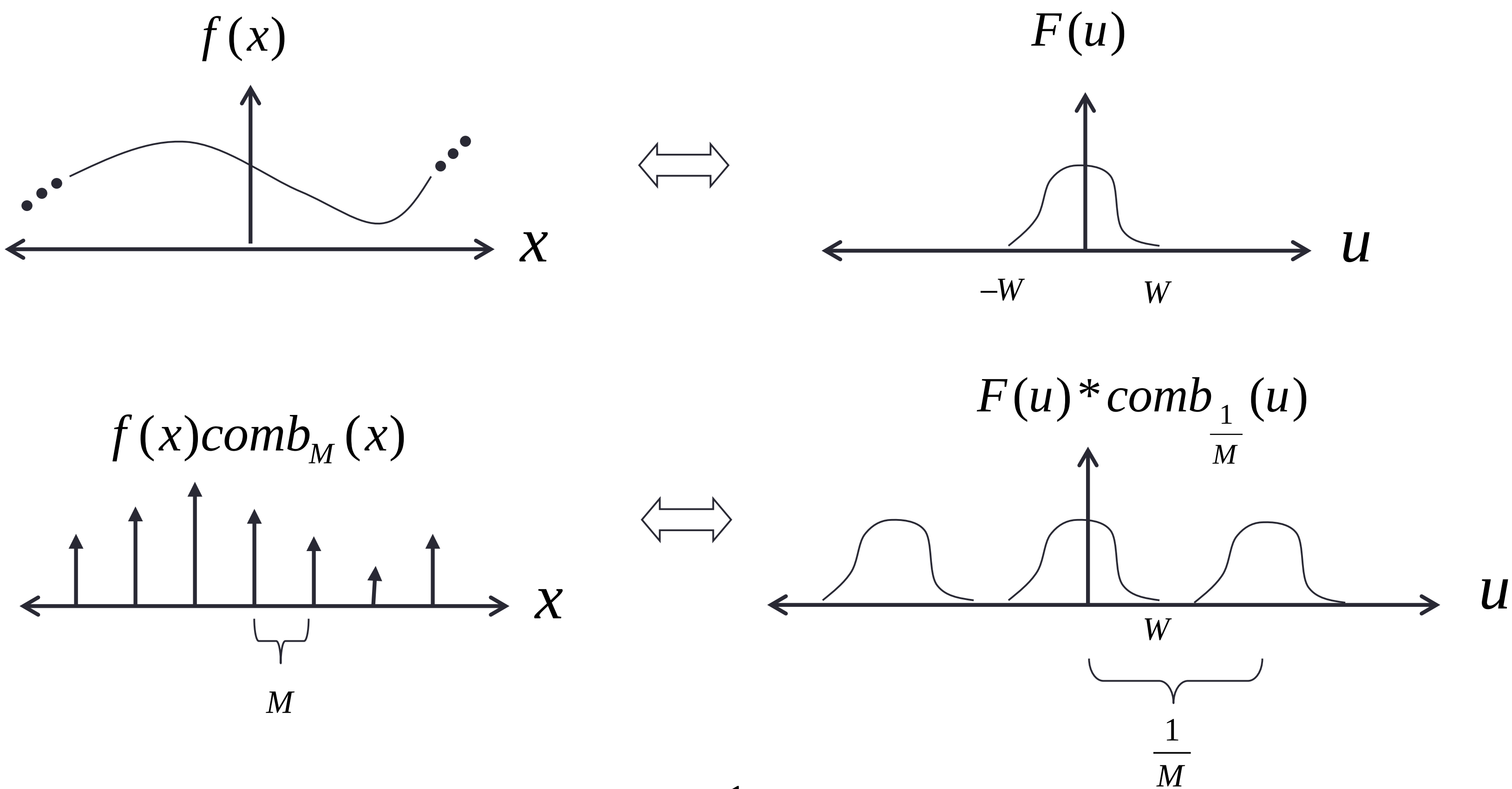
Convolve:

$F(u) * comb_{\frac{1}{M}}(u)$



B.K. Gunturk

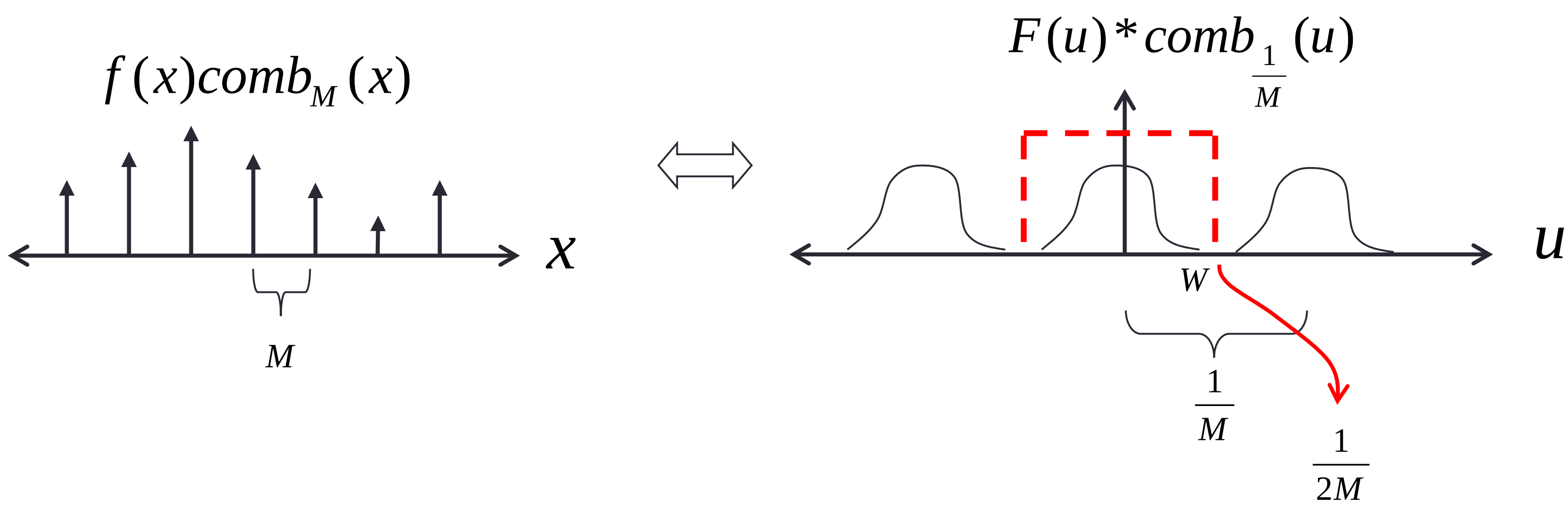
Sampling low frequency signal



No "problem" if $\frac{1}{M} > 2W$

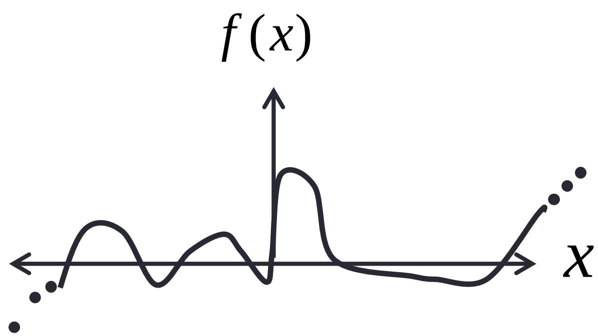
B.K. Gunturk

Sampling low frequency signal

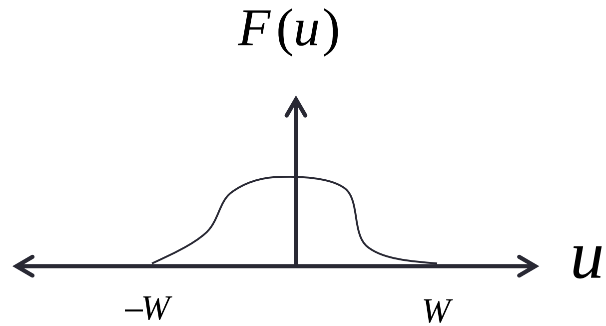


If there is no overlap, the original signal can be recovered from its samples by low-pass filtering.

Sampling high frequency signal

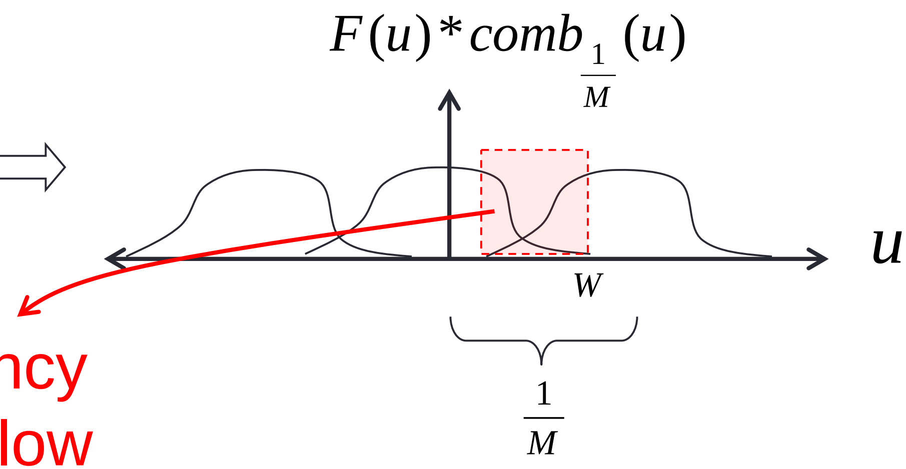


$\Leftrightarrow$



$$f(x)comb_M(x)$$

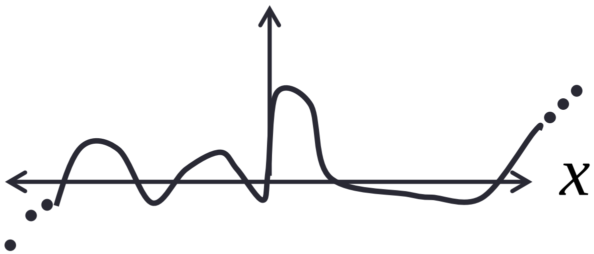
$\Leftrightarrow$



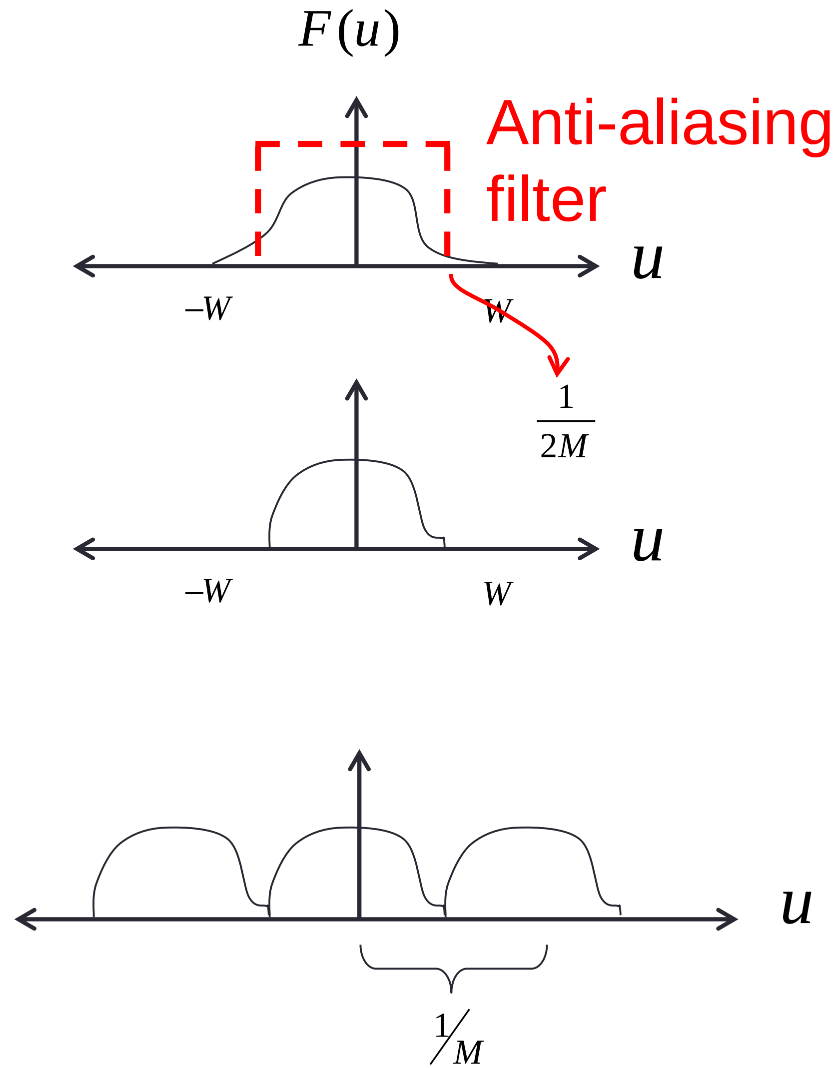
Overlap: The high frequency energy is folded over into low frequency. It is "aliasing" as lower frequency energy. And you cannot fix it once it has happened.

Sampling high frequency signal

$f(x)$



$\Leftrightarrow$



$f(x) * h(x) \Leftrightarrow$

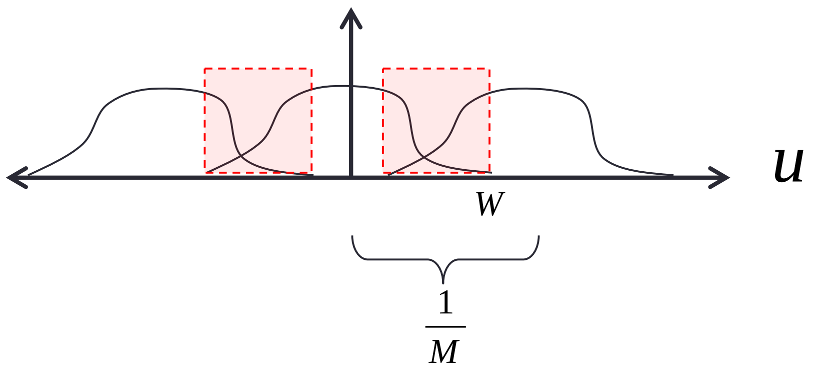
$[f(x) * h(x)]\, comb_M(x) \Leftrightarrow$

B.K. Gunturk

Sampling high frequency signal

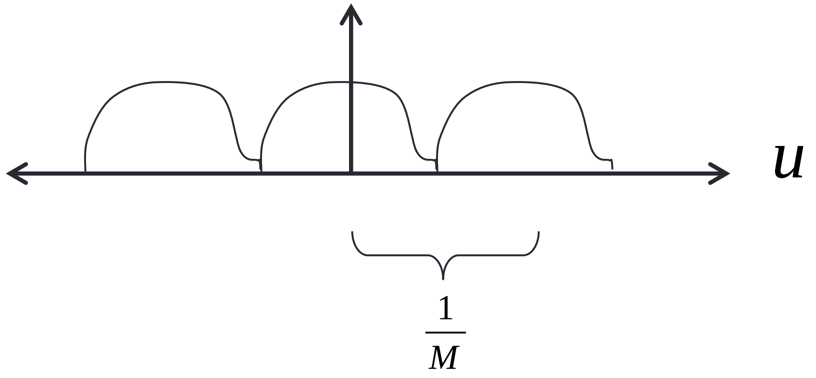
- Without anti-aliasing filter:

$$f(x)comb_M(x) \Longleftrightarrow$$



- With anti-aliasing filter:

$$[f(x) * h(x)]comb_M(x) \Longleftrightarrow$$



B.K. Gunturk

Aliasing in Images

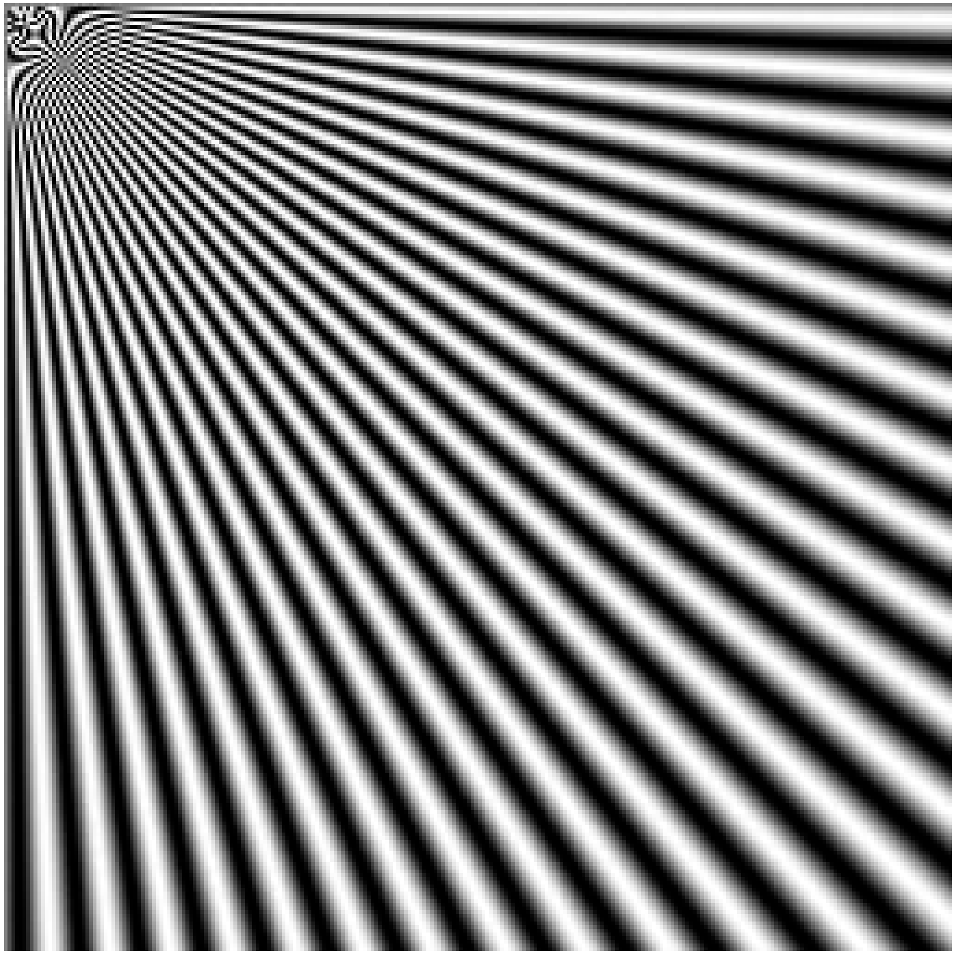
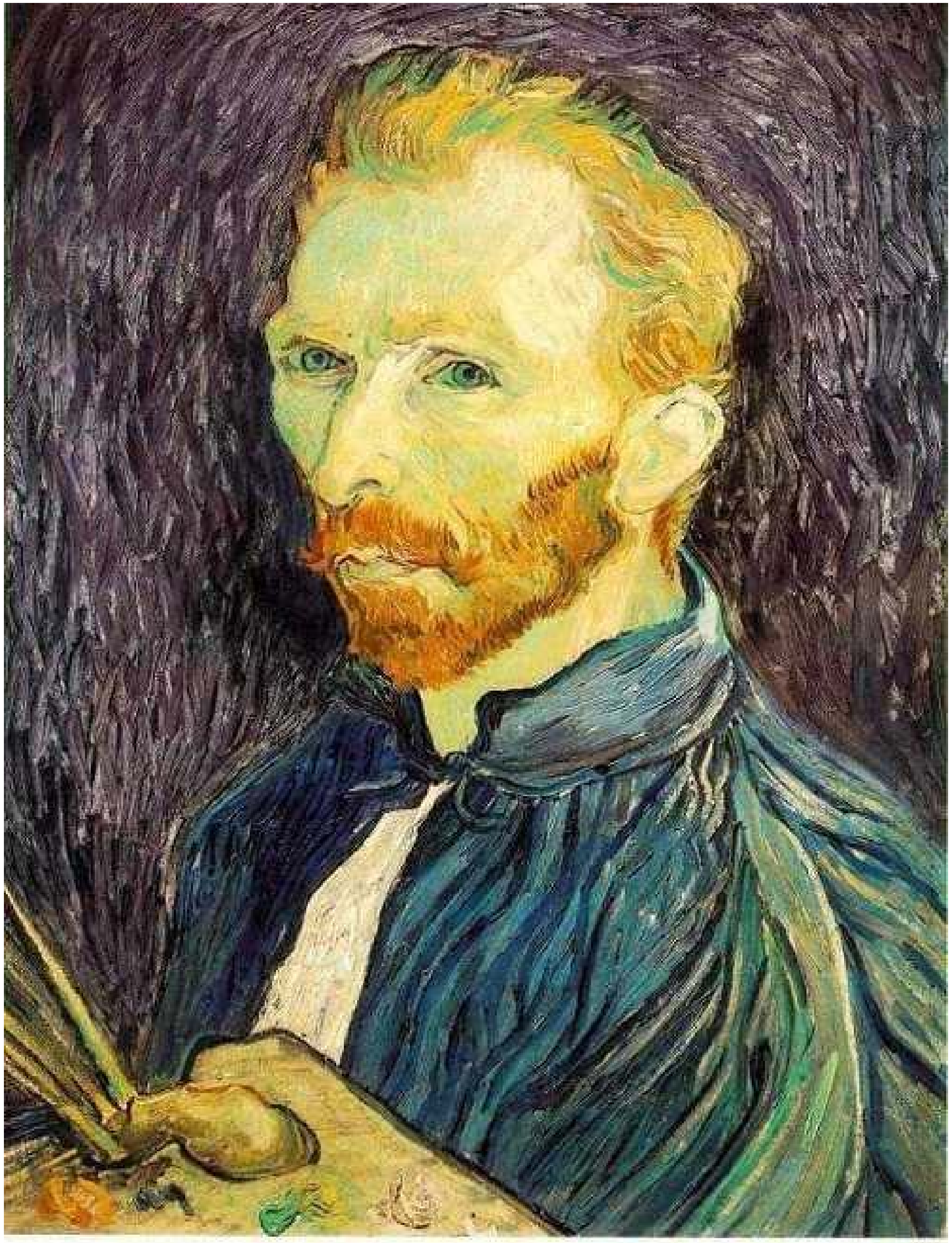


Image half-sizing

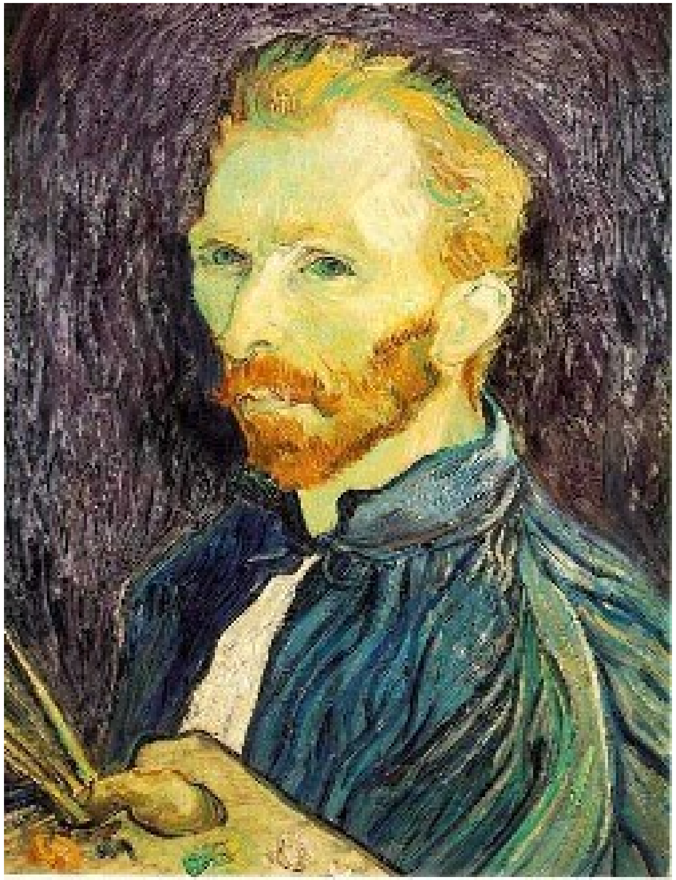
This image is too big to fit on the screen. How can we reduce it?

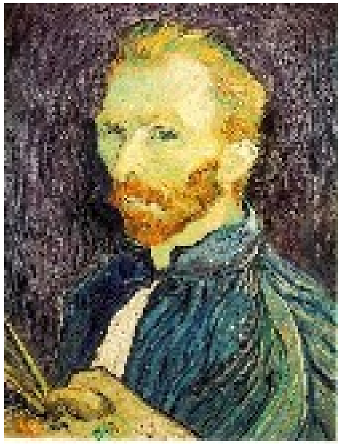
How to generate a half-sized version?



S. Seitz

Image sub-sampling





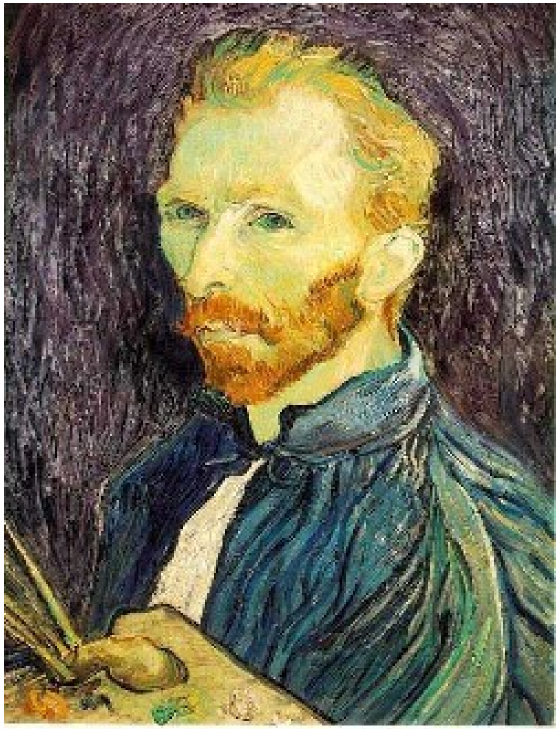
1/4

1/8

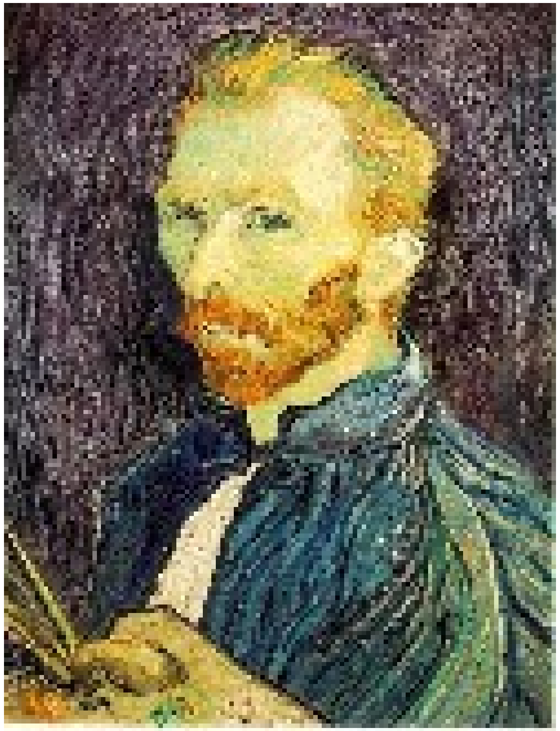
Throw away every other row and column to create a 1/2 size image
- called *image sub-sampling*

S. Seitz

Image sub-sampling



1/2



1/4 (2x zoom)

1/8 (4x zoom)

Aliasing! What do we do?

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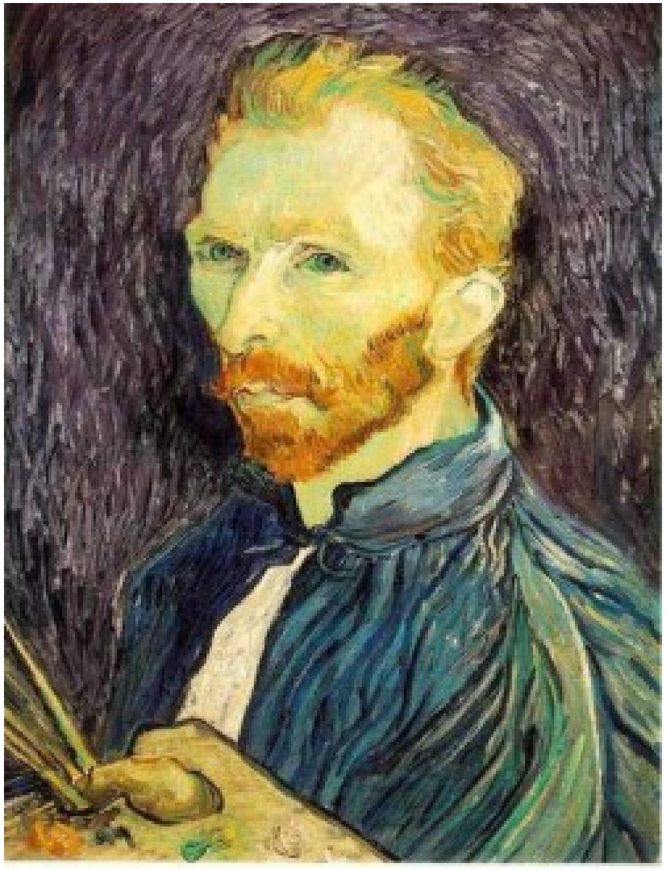
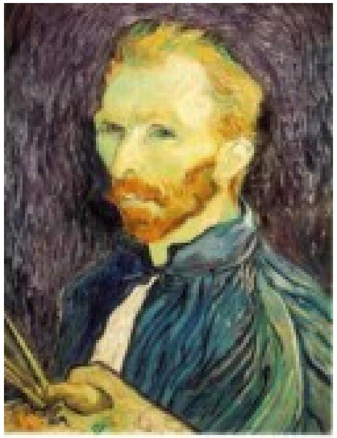
Gaussian (lowpass) pre-filtering



Gaussian 1/2



G 1/4

G 1/8

Solution: filter the image, *then* subsample

- Filter size should double for each ½ size reduction. Why?

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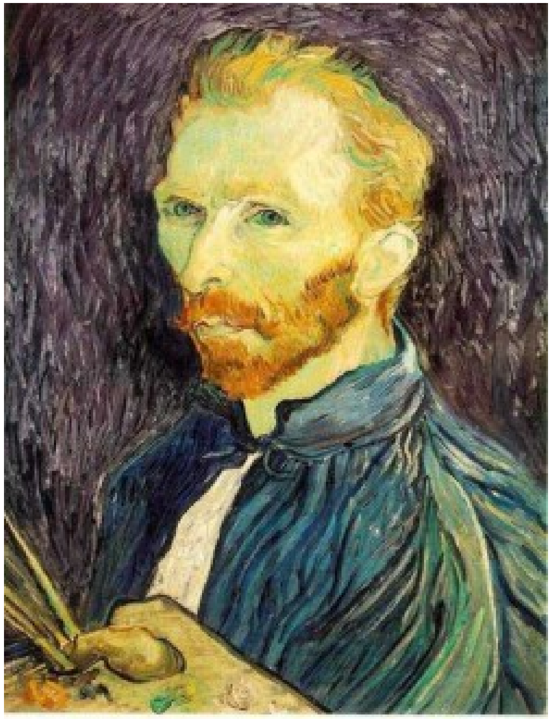
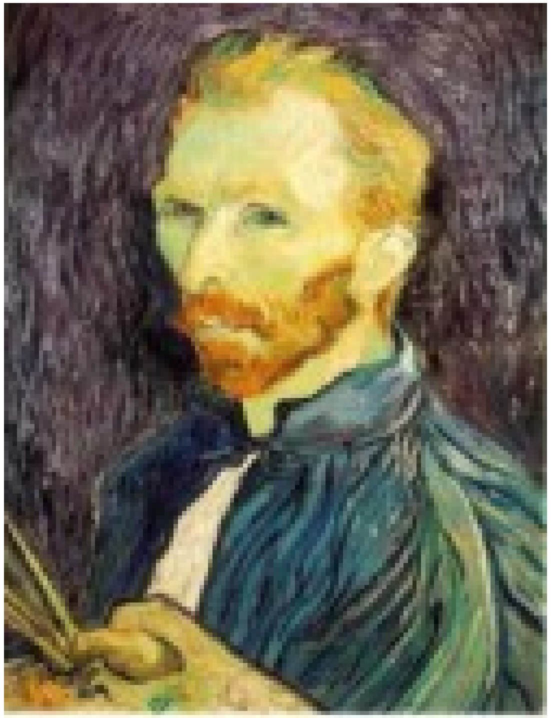
Subsampling with Gaussian pre-filtering



Gaussian 1/2



G 1/4

G 1/8

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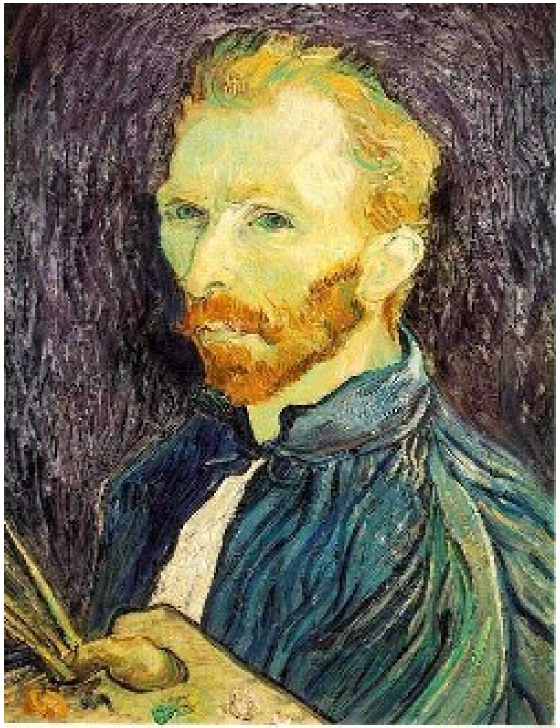
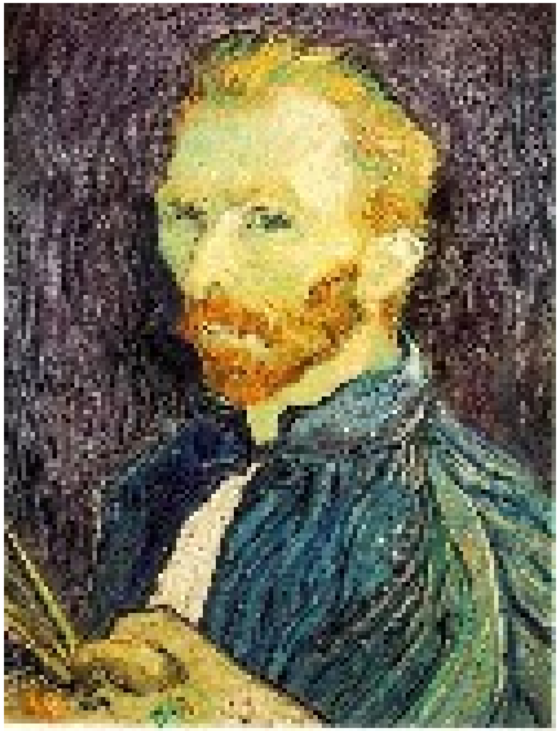
Compare with...



1/2



1/4 (2x zoom)

1/8 (4x zoom)

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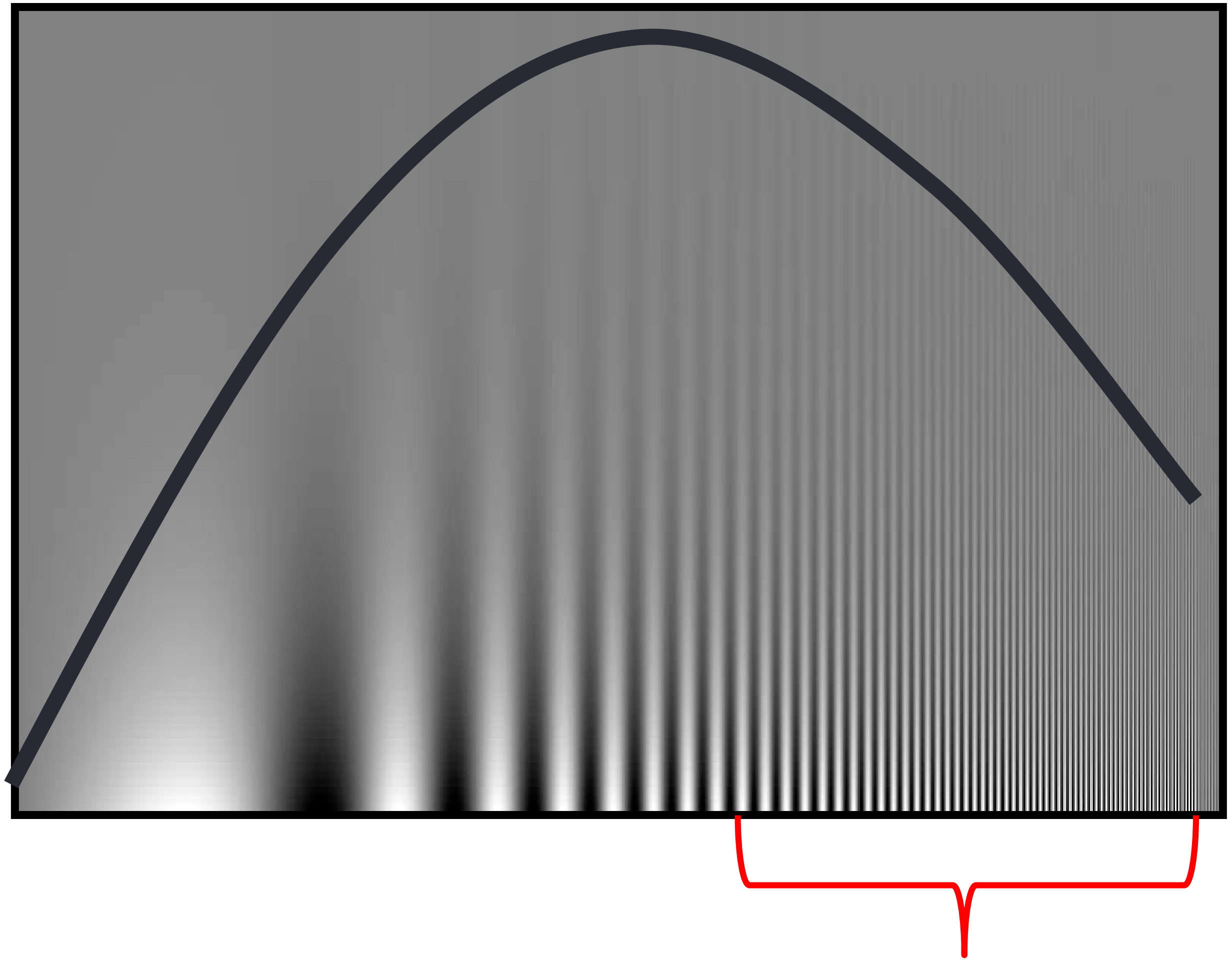
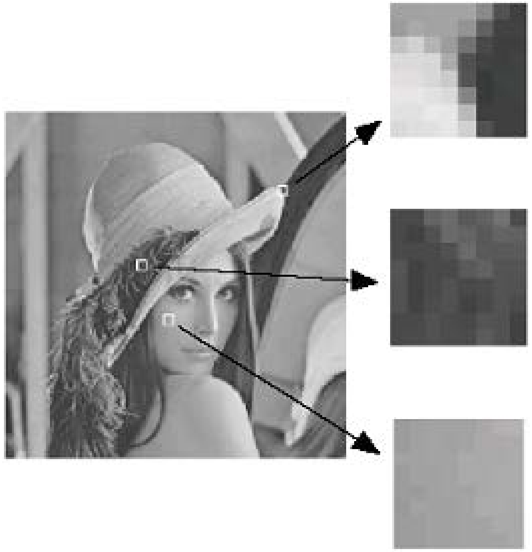
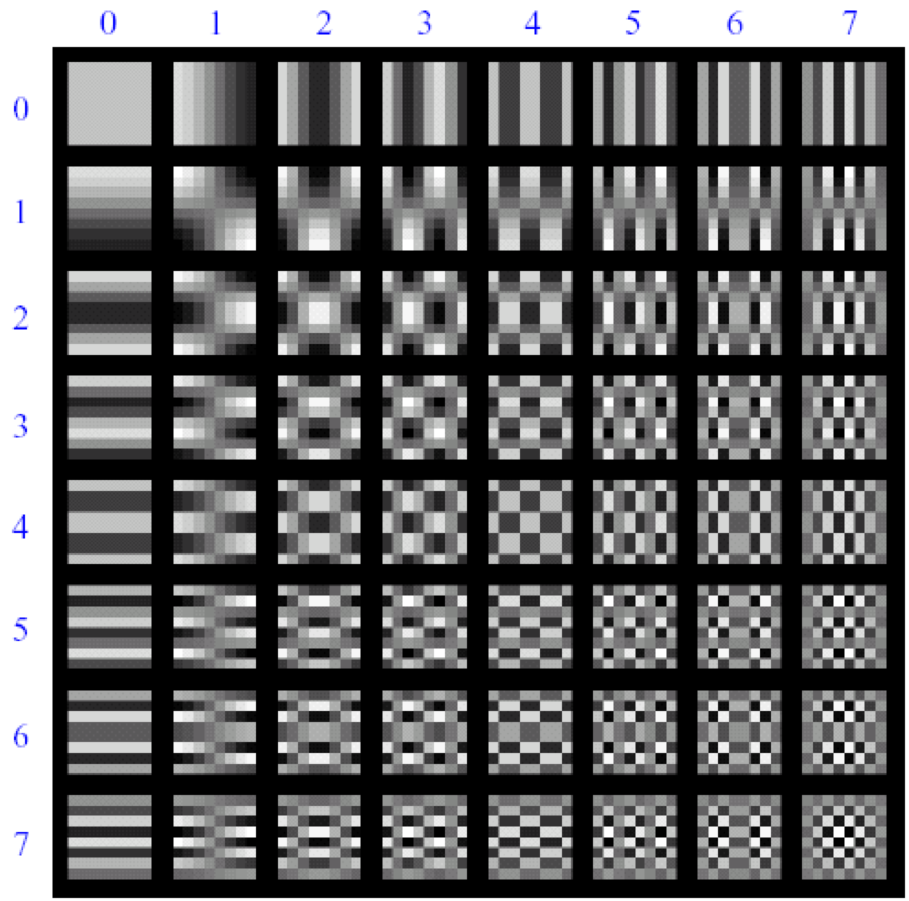
Campbell-Robson contrast sensitivity curve



The higher the frequency the less sensitive human visual system is…

Lossy Image Compression (JPEG)





Block-based Discrete Cosine Transform (DCT) on 8x8

Using DCT in JPEG

- The first coefficient $B(0,0)$ is the DC component, the average intensity
- The top-left coeffs represent low frequencies, the bottom right – high frequencies

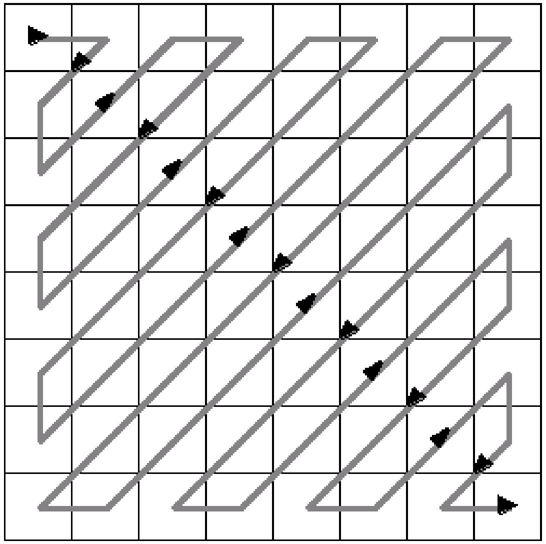


Image compression using DCT

- DCT enables image compression by concentrating most image information in the low frequencies
- Lose unimportant image info (high frequencies) by cutting $B(u,v)$ at bottom right
- The decoder computes the inverse DCT – IDCT

•Quantization Table

3	5	7	9	11	13	15	17
5	7	9	11	13	15	17	19
7	9	11	13	15	17	19	21
9	11	13	15	17	19	21	23
11	13	15	17	19	21	23	25
13	15	17	19	21	23	25	27
15	17	19	21	23	25	27	29
17	19	21	23	25	27	29	31

JPEG compression comparison

89k

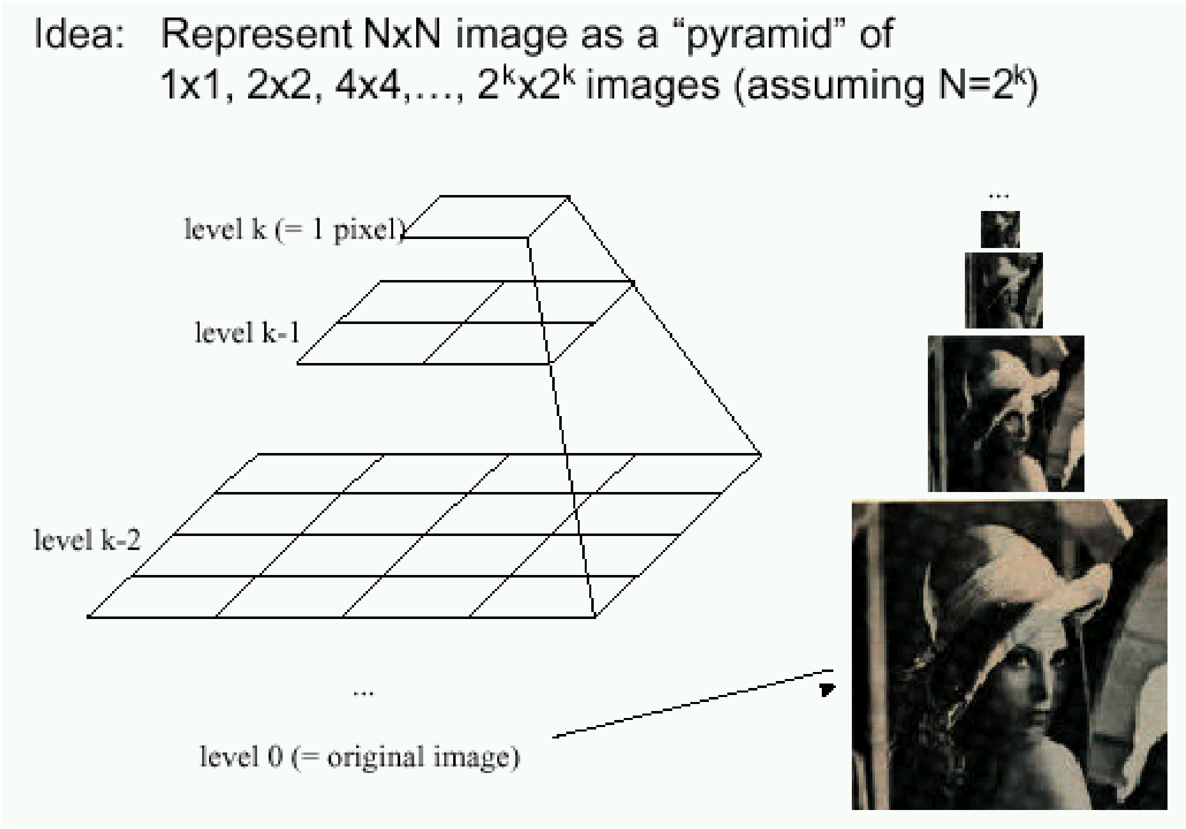
12k

Maybe the end?

Or not!!!

- *A teaser on pyramids…*

Image Pyramids



Known as a **Gaussian Pyramid** [Burt and Adelson, 1983]

- In computer graphics, a *mip map* [Williams, 1983]
- A precursor to *wavelet transform*

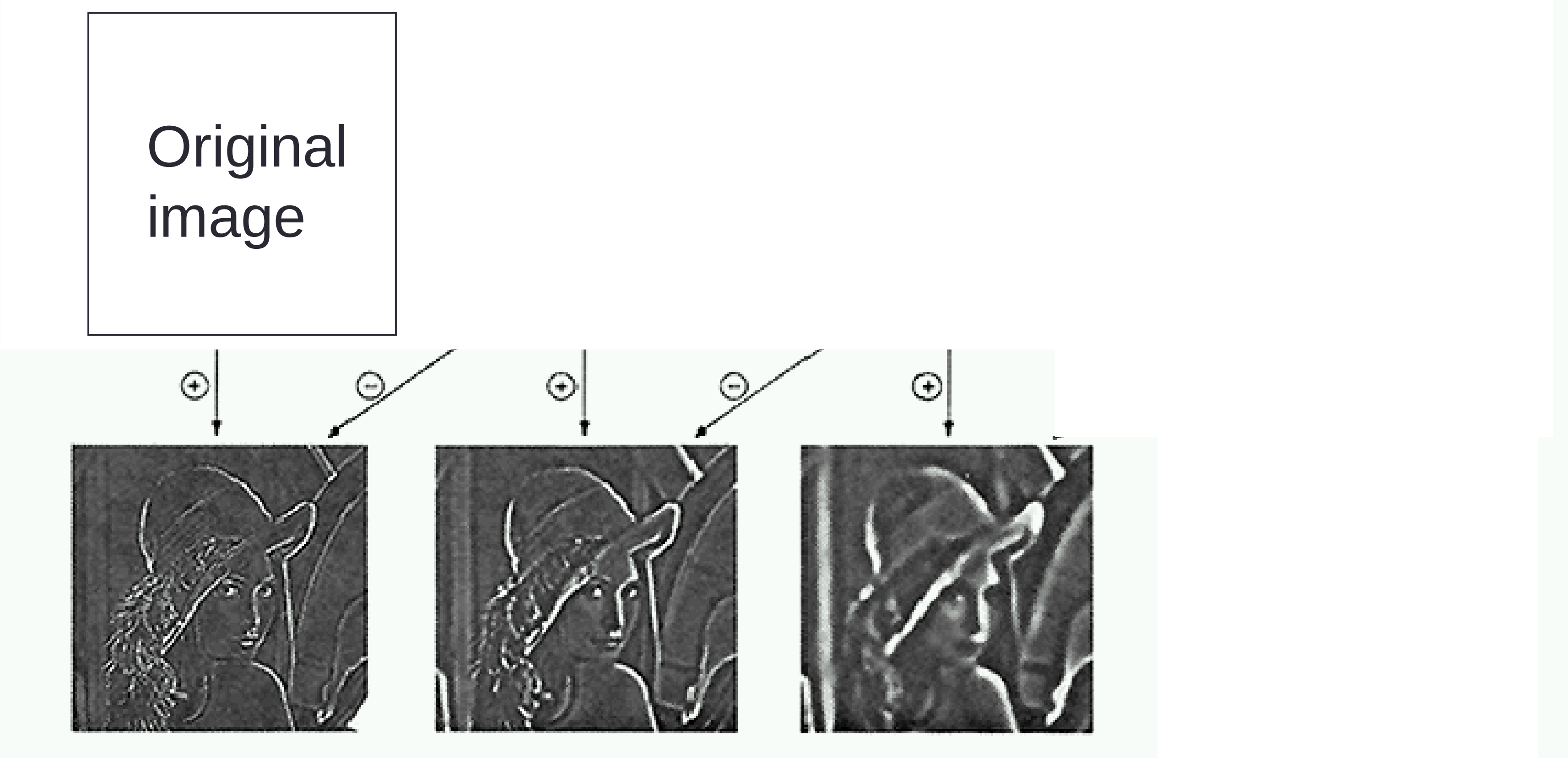
S. Seitz

Band-pass filtering

Gaussian Pyramid (low-pass images)

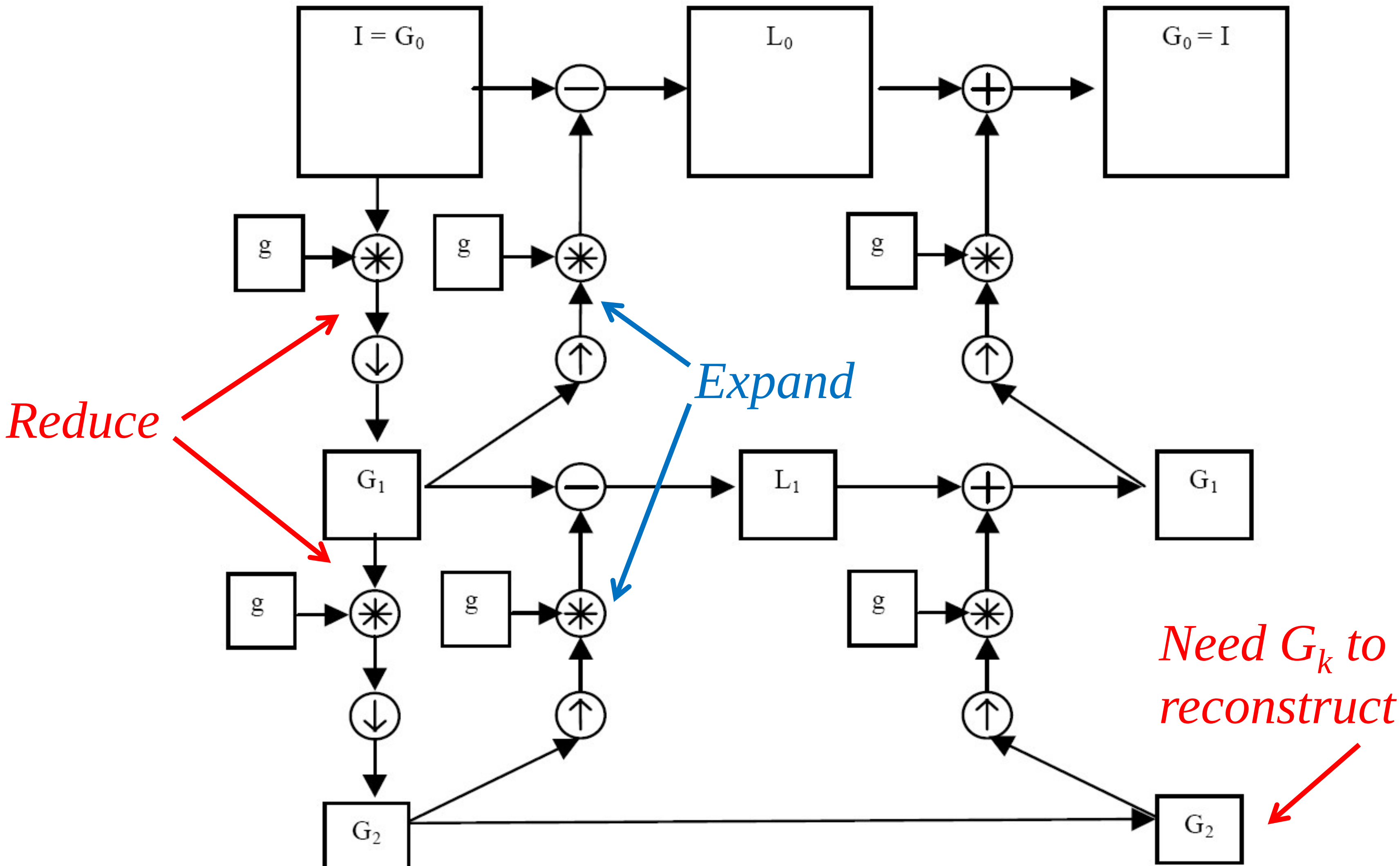
These are "bandpass" images (almost).

Laplacian Pyramid



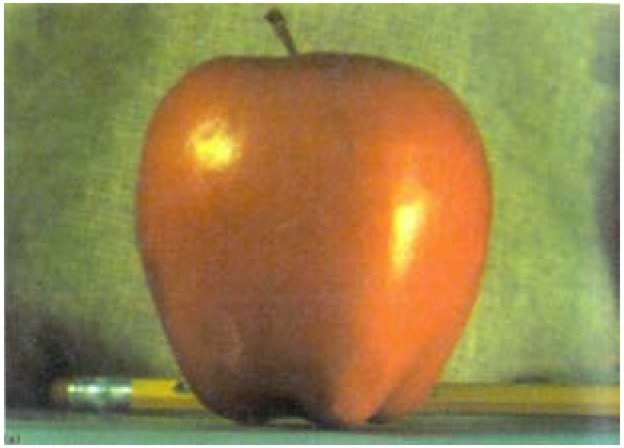
- How can we reconstruct (collapse) this pyramid into the original image?

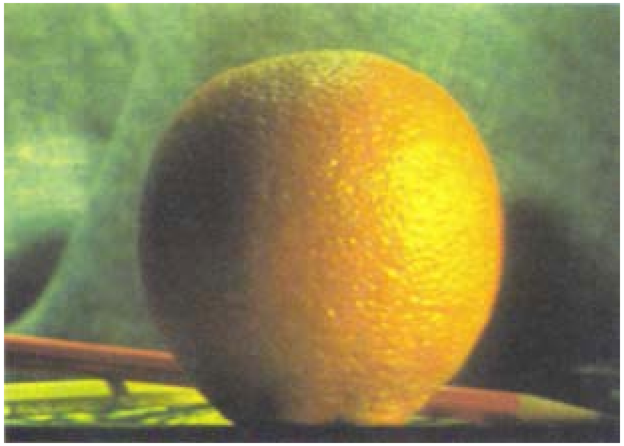
Computing the Laplacian Pyramid



Don't worry about these details – YET! (PS4?)

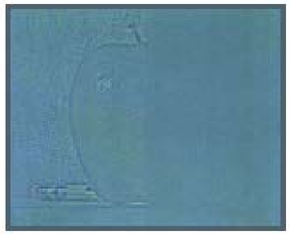
What can you do with band limited imaged?





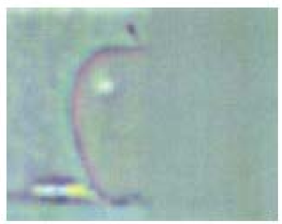
Apples and Oranges in bandpass

Fine L_0



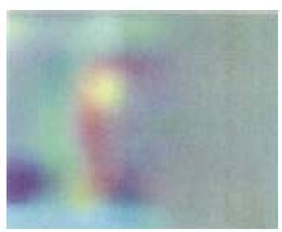
(a)

L_2



(d)

Coarse L_4



(g)

Reconstructed

(j)

What can you do with band limited imaged?