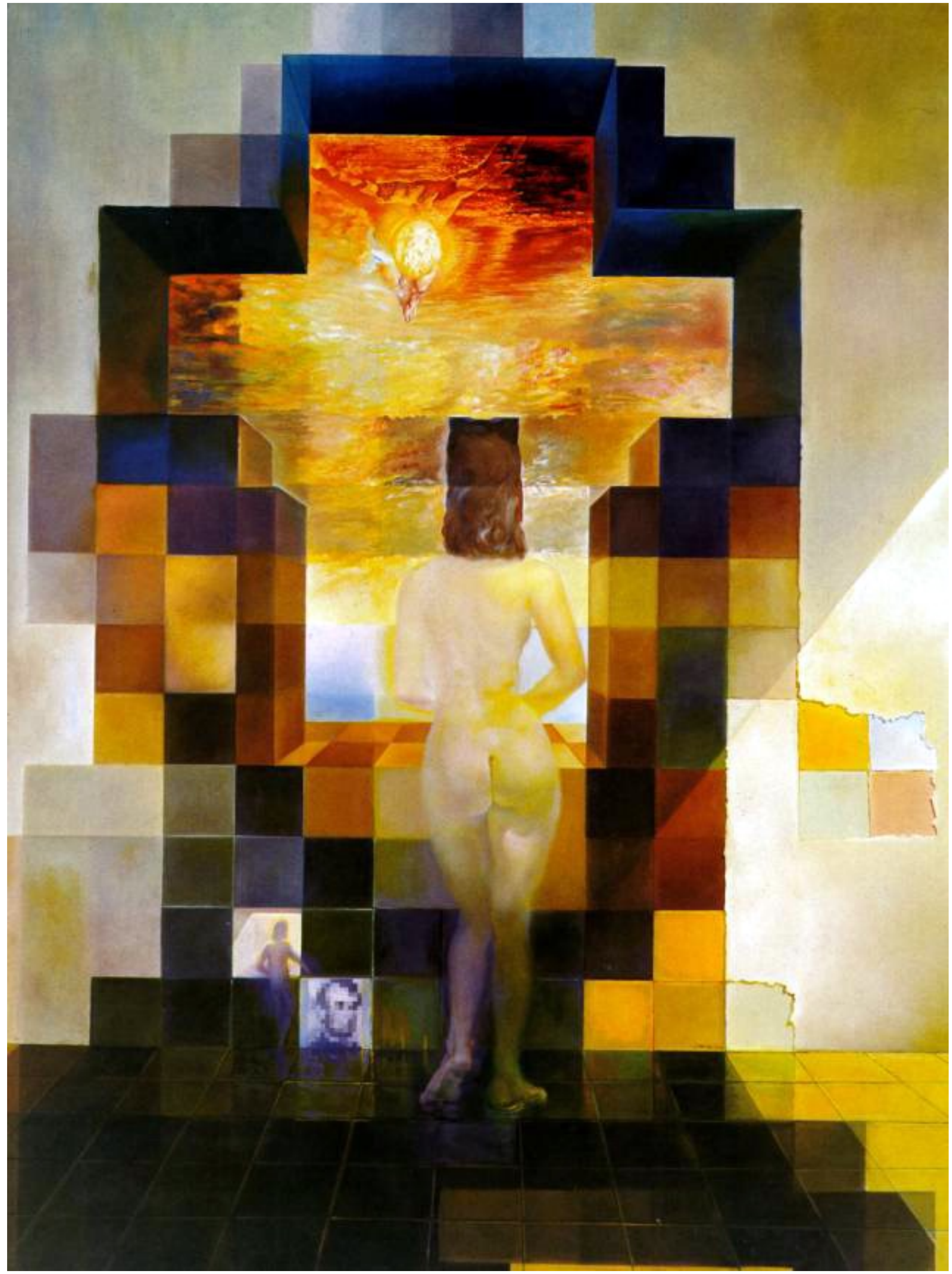
The Frequency Domain, without tears

Somewhere in Cinque Terre, May 2005

Many slides borrowed from Steve Seitz

CS194: Intro to Computer Vision and Comp. Photo

Angjoo Kanazawa & Alexei Efros, UC Berkeley, Fall 2022

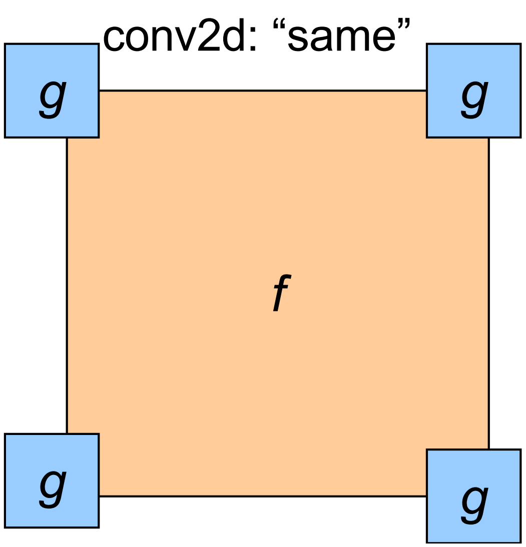


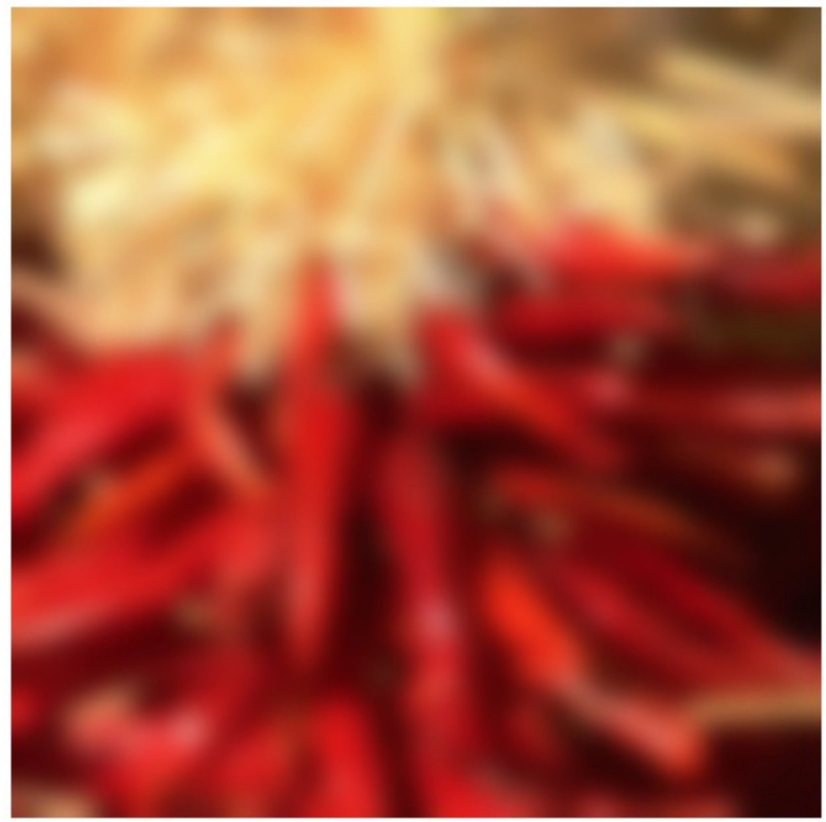
Salvador Dali
“Gala Contemplating the Mediterranean Sea, which at 30 meters becomes the portrait of Abraham Lincoln”, 1976

Conv/Filtering: Practical matters

What about near the edge?

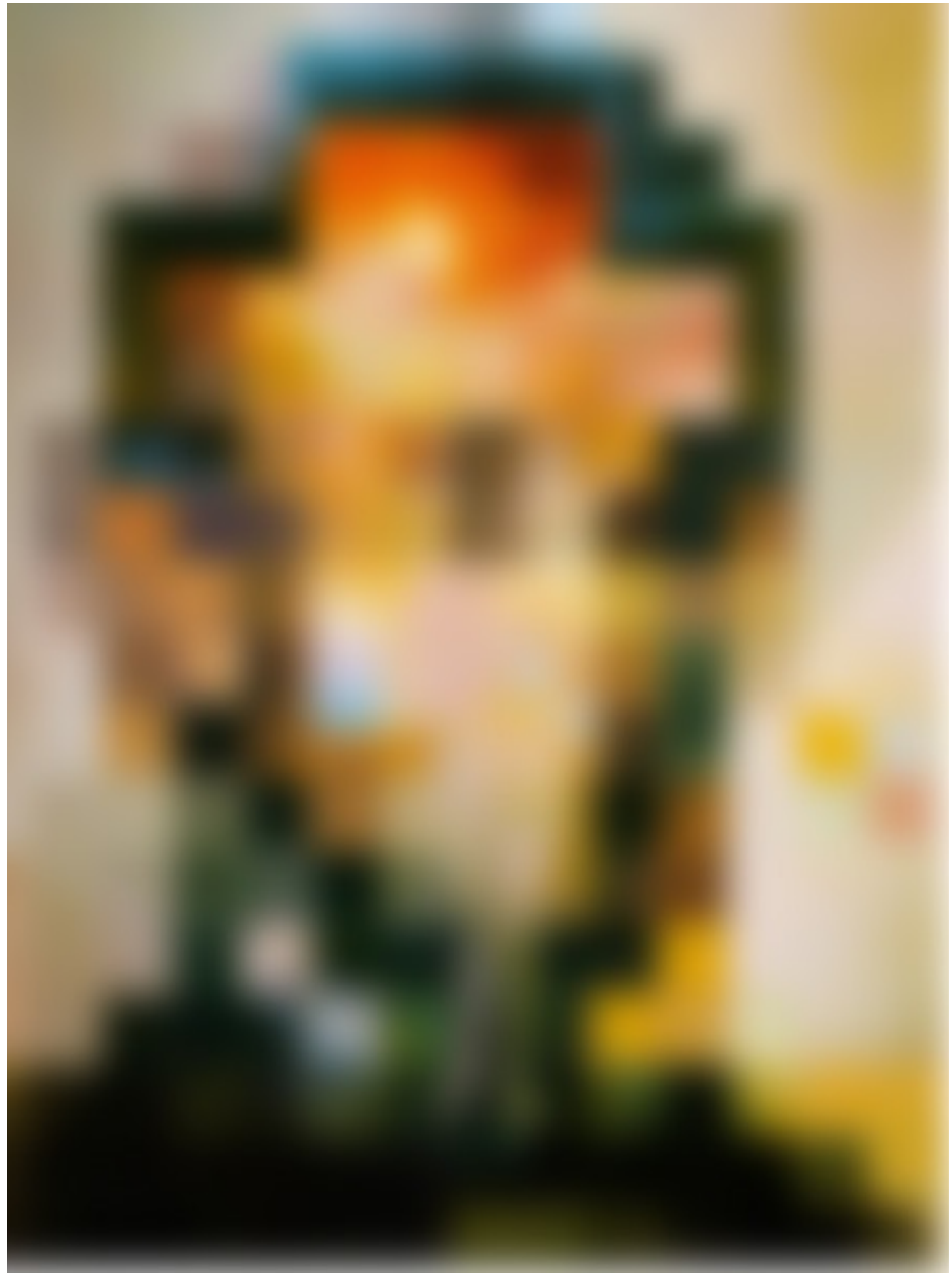
- the filter window falls off the edge of the image
- need to extrapolate
- methods:
  - clip filter (black)
  - wrap around (circular)
  - copy edge
  - reflect across edge

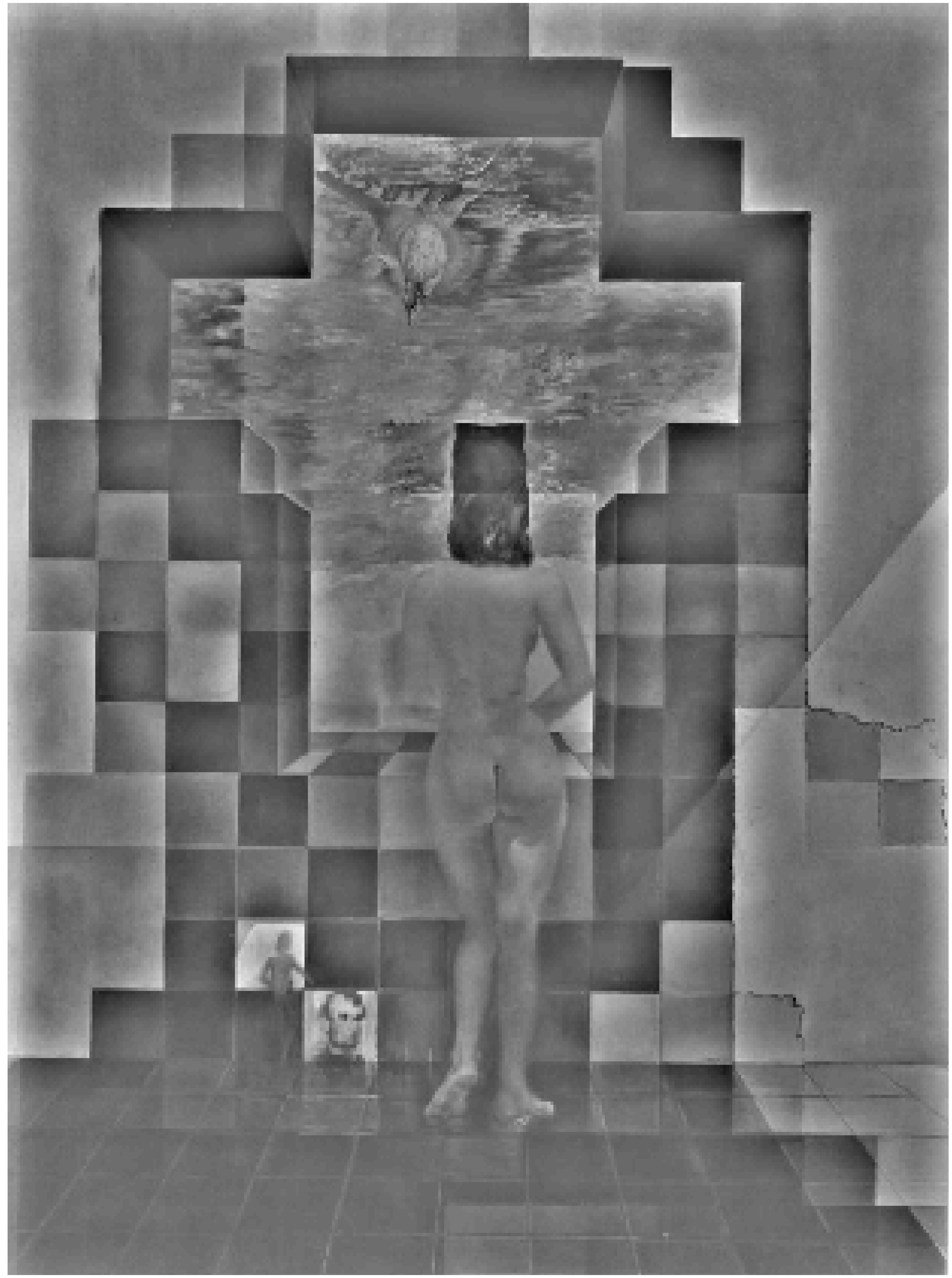




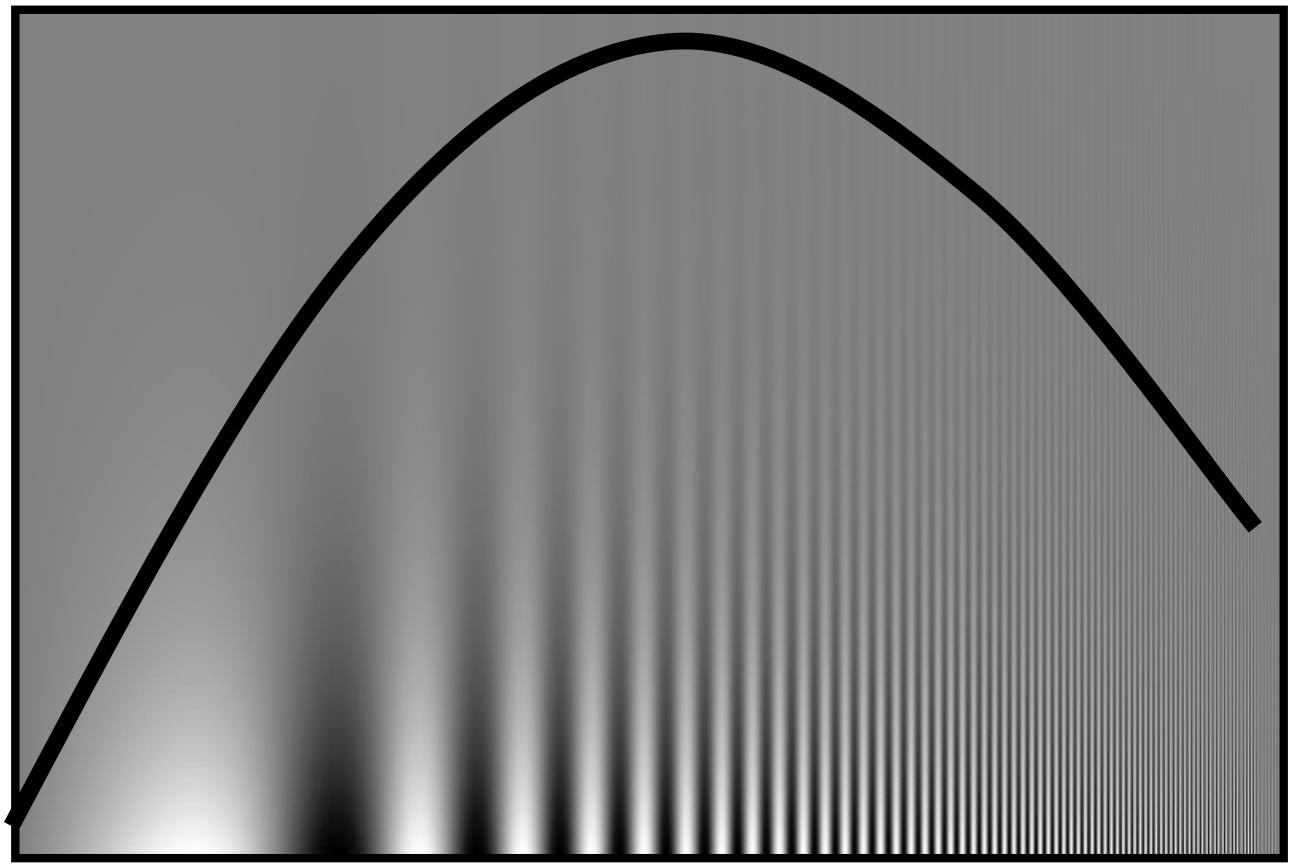
Source: S. Marschner

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





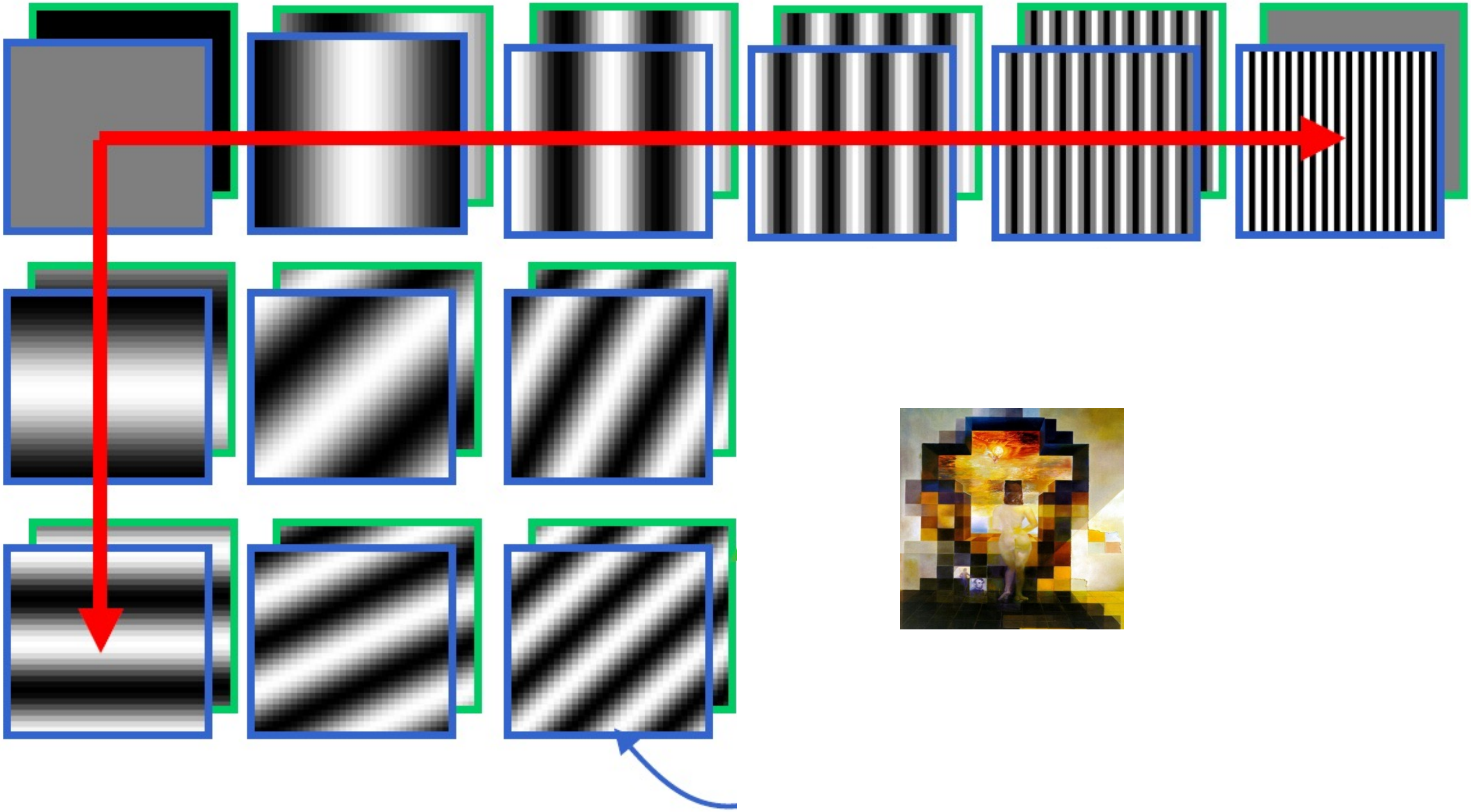
Spatial Frequencies and Perception



Campbell-Robson contrast sensitivity curve

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

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

...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.

A sum of sines

Our building block:

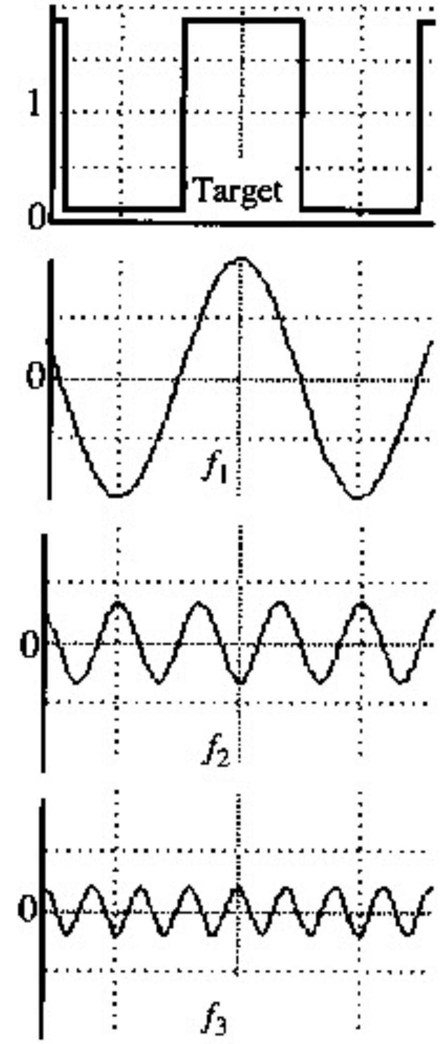
$$A\sin(\omega x + \phi)$$

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

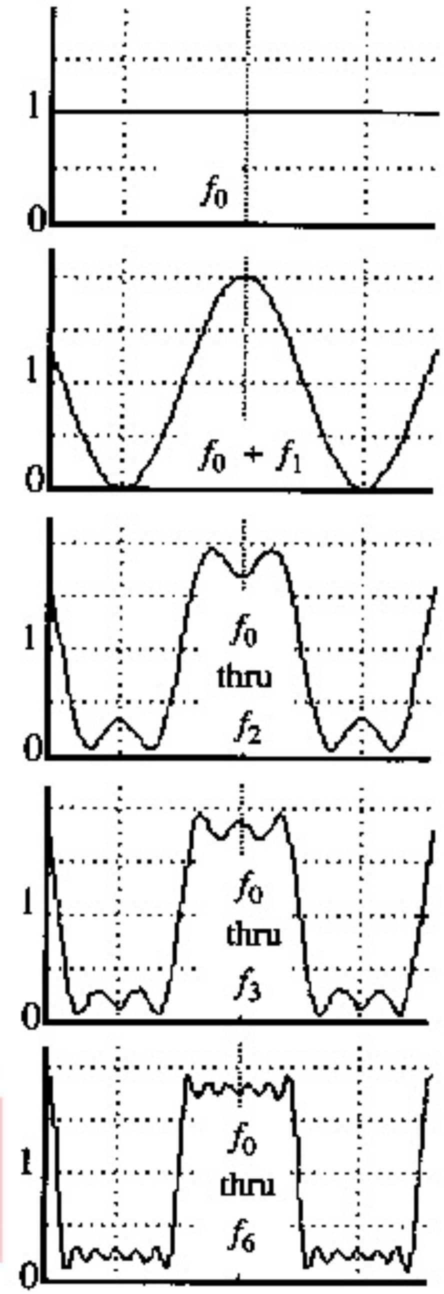
How many degrees of freedom?

What does each control?

Which one encodes the coarse vs. fine structure of the signal?



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



Fourier Transform

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

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

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

- How does *F* hold both?

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

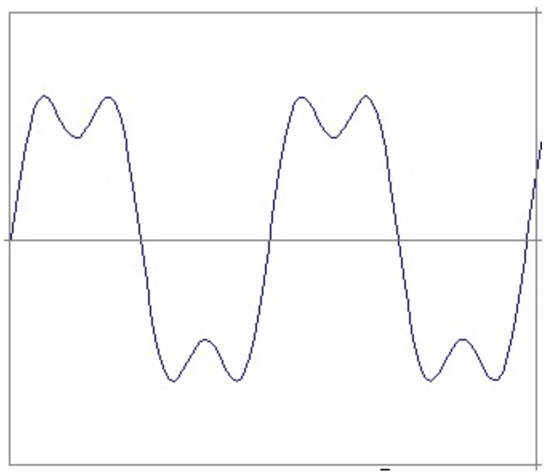
$$A = \pm\sqrt{R(\omega)^2 + I(\omega)^2} \qquad \phi = \tan^{-1}\frac{I(\omega)}{R(\omega)}$$

We can always go back:

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

Time and Frequency

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



Time and Frequency

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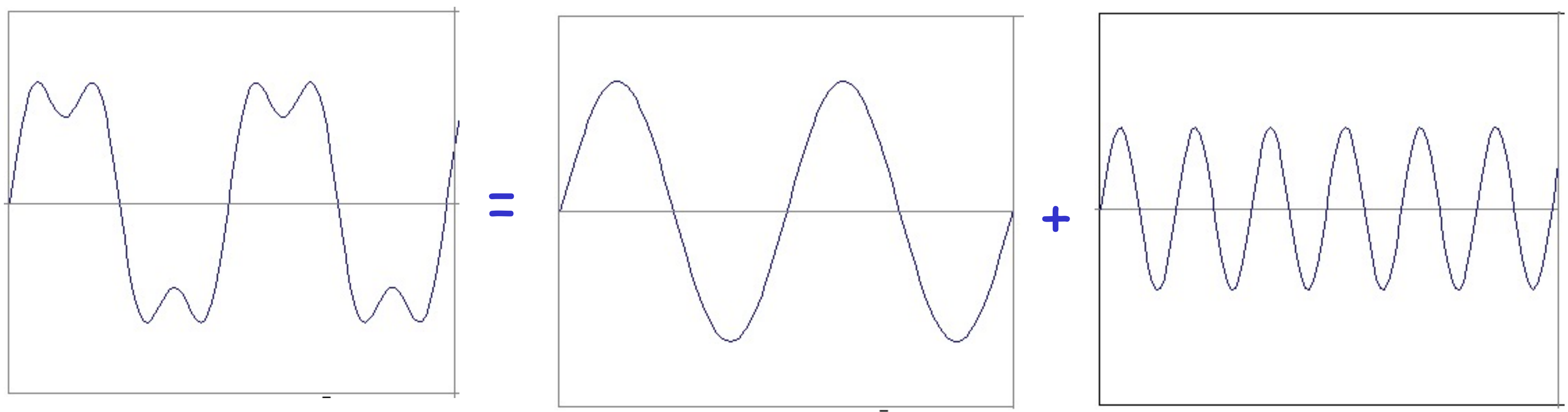
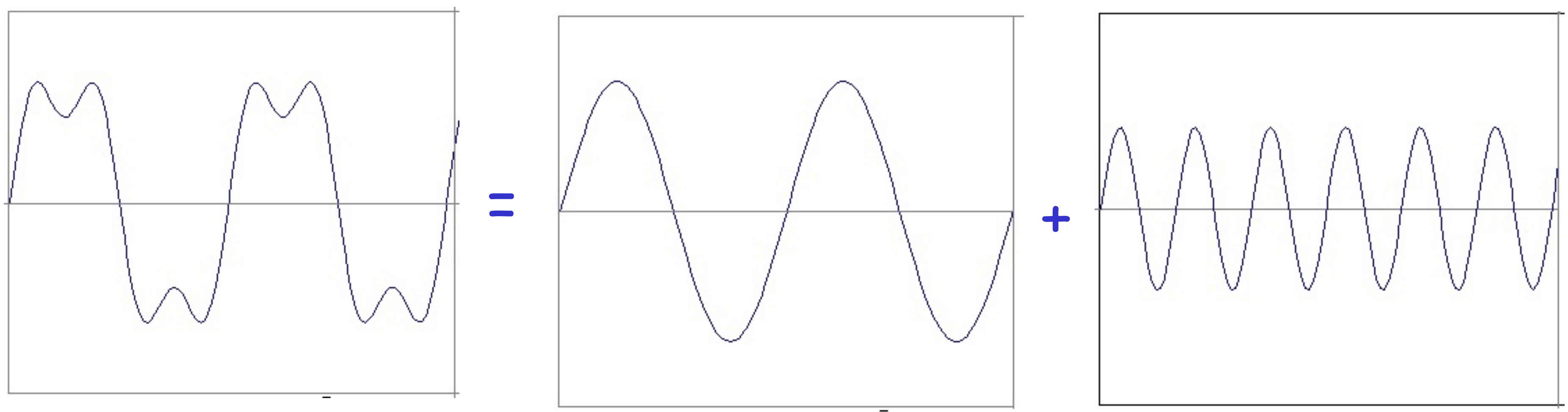
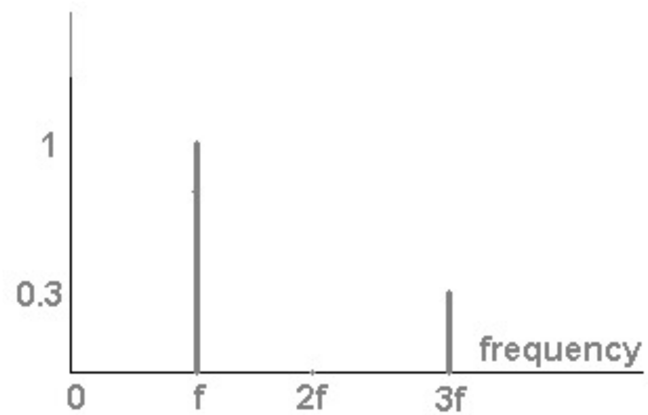


Frequency Spectra

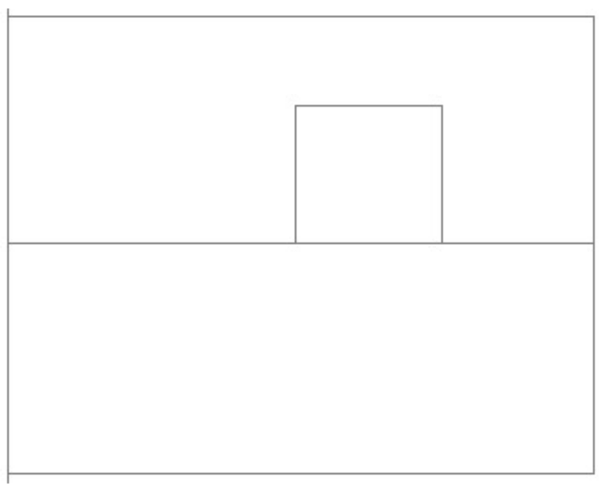
example : $g(t) = \sin(2pf\,t) + (1/3)\sin(2p(3f)\,t)$



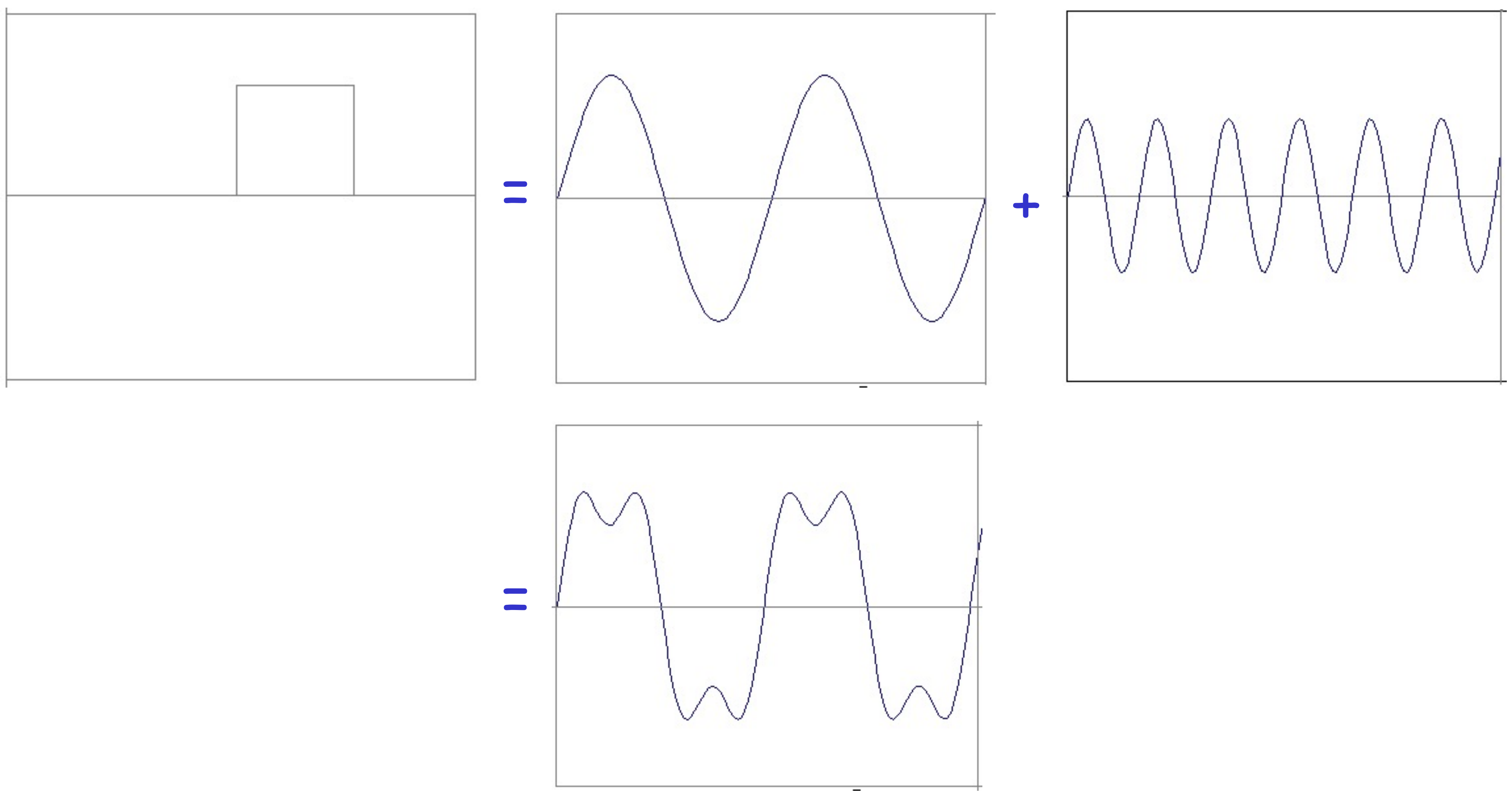


Frequency Spectra

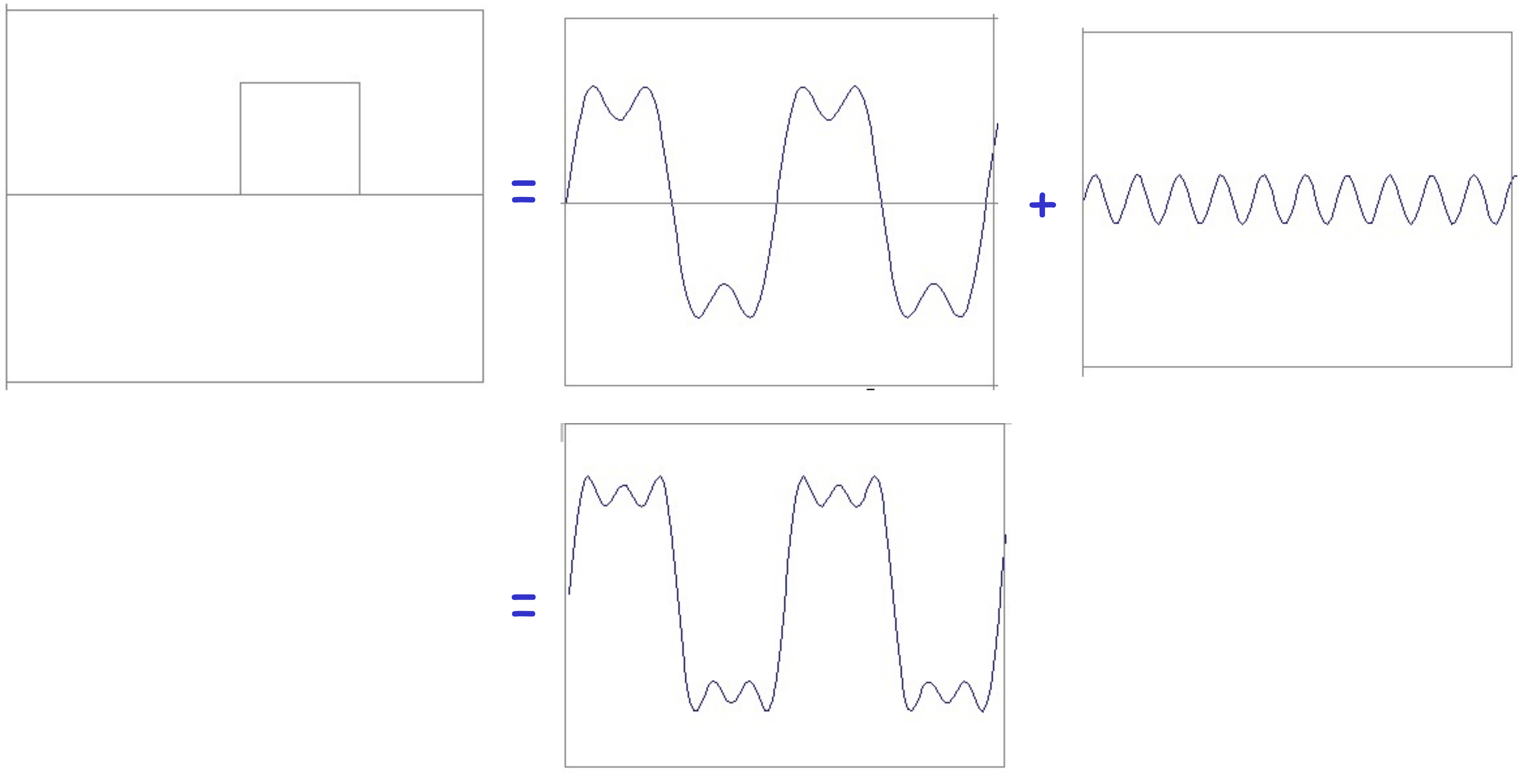
Usually, frequency is more interesting than the phase



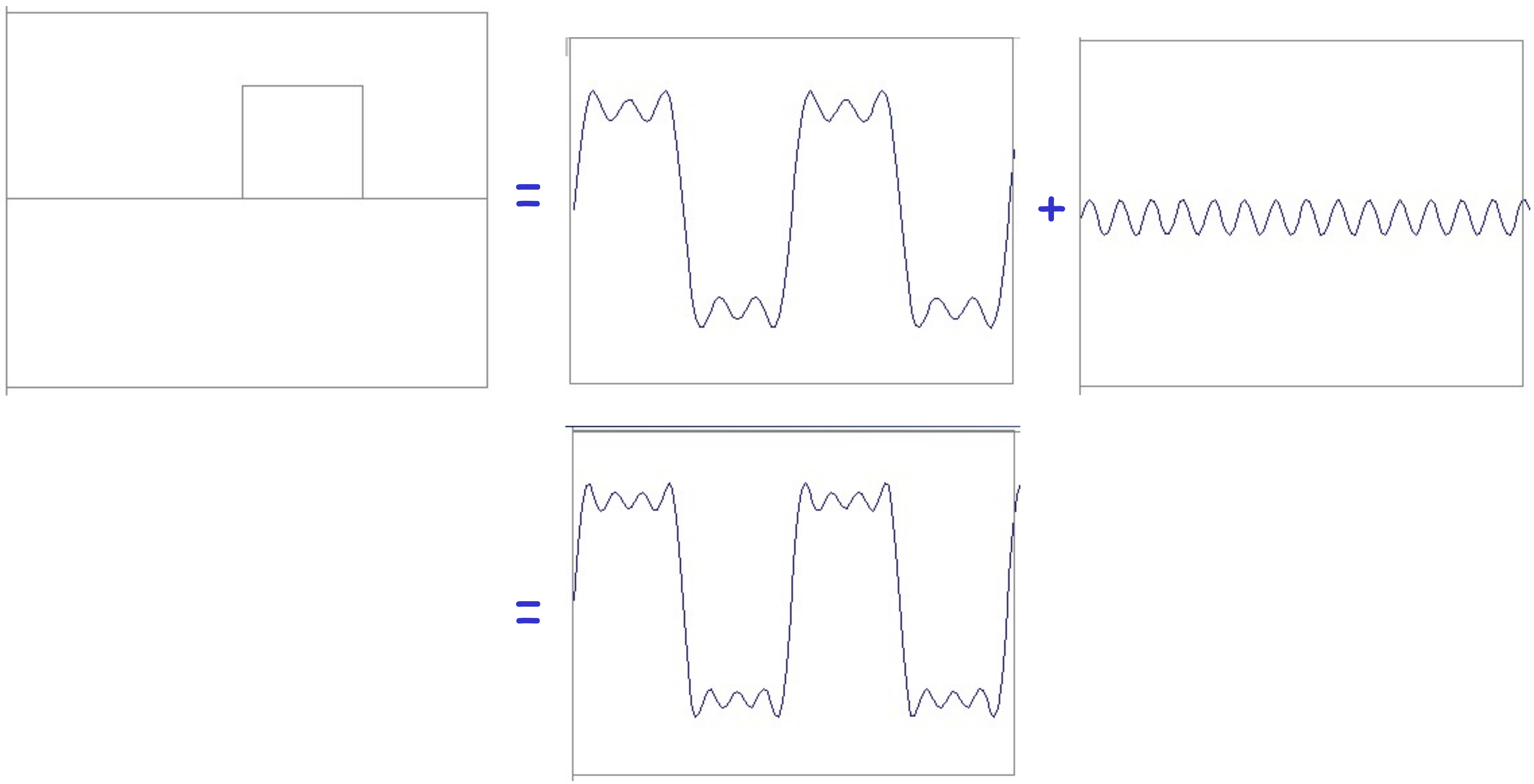
Frequency Spectra



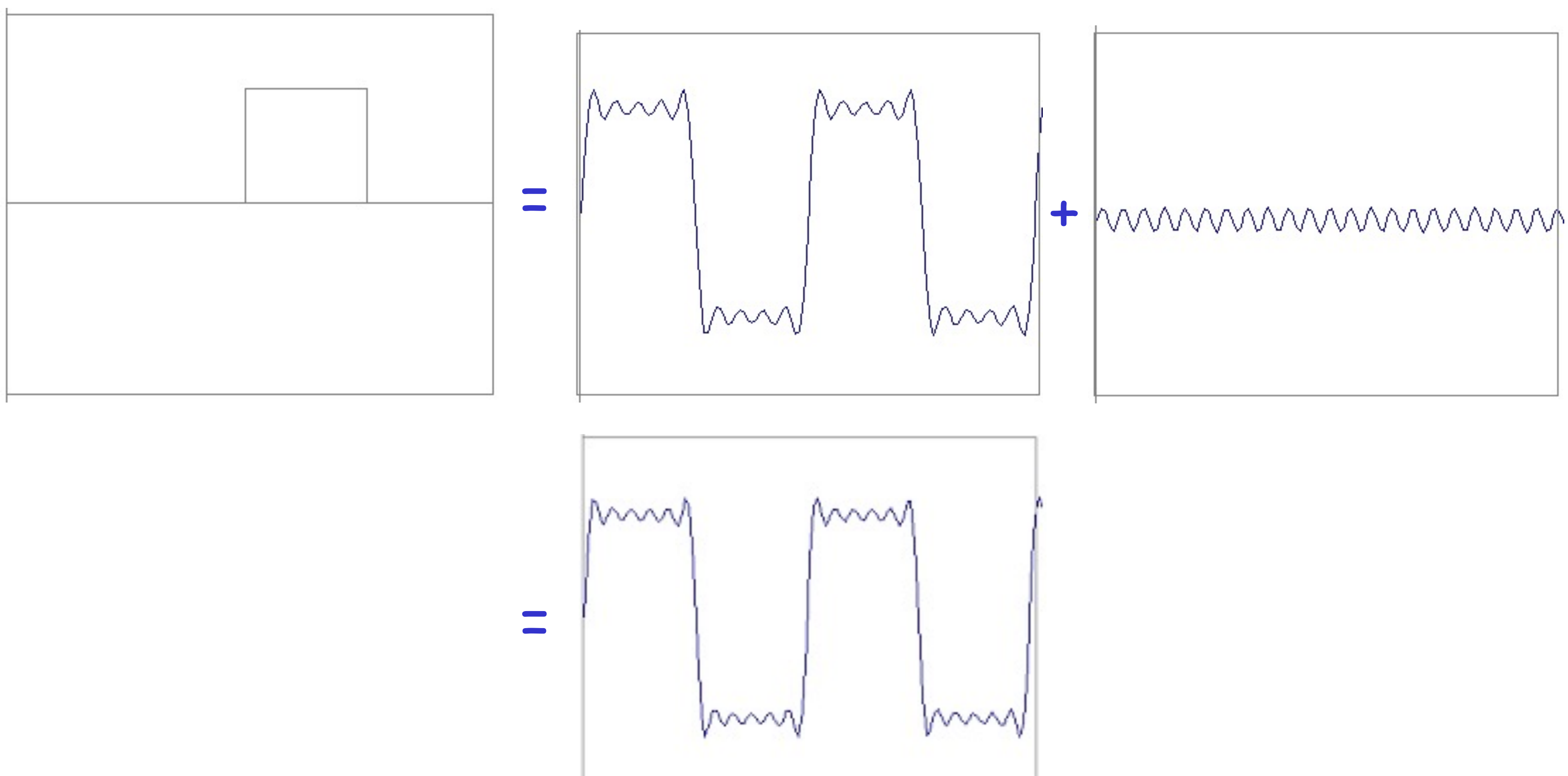
Frequency Spectra



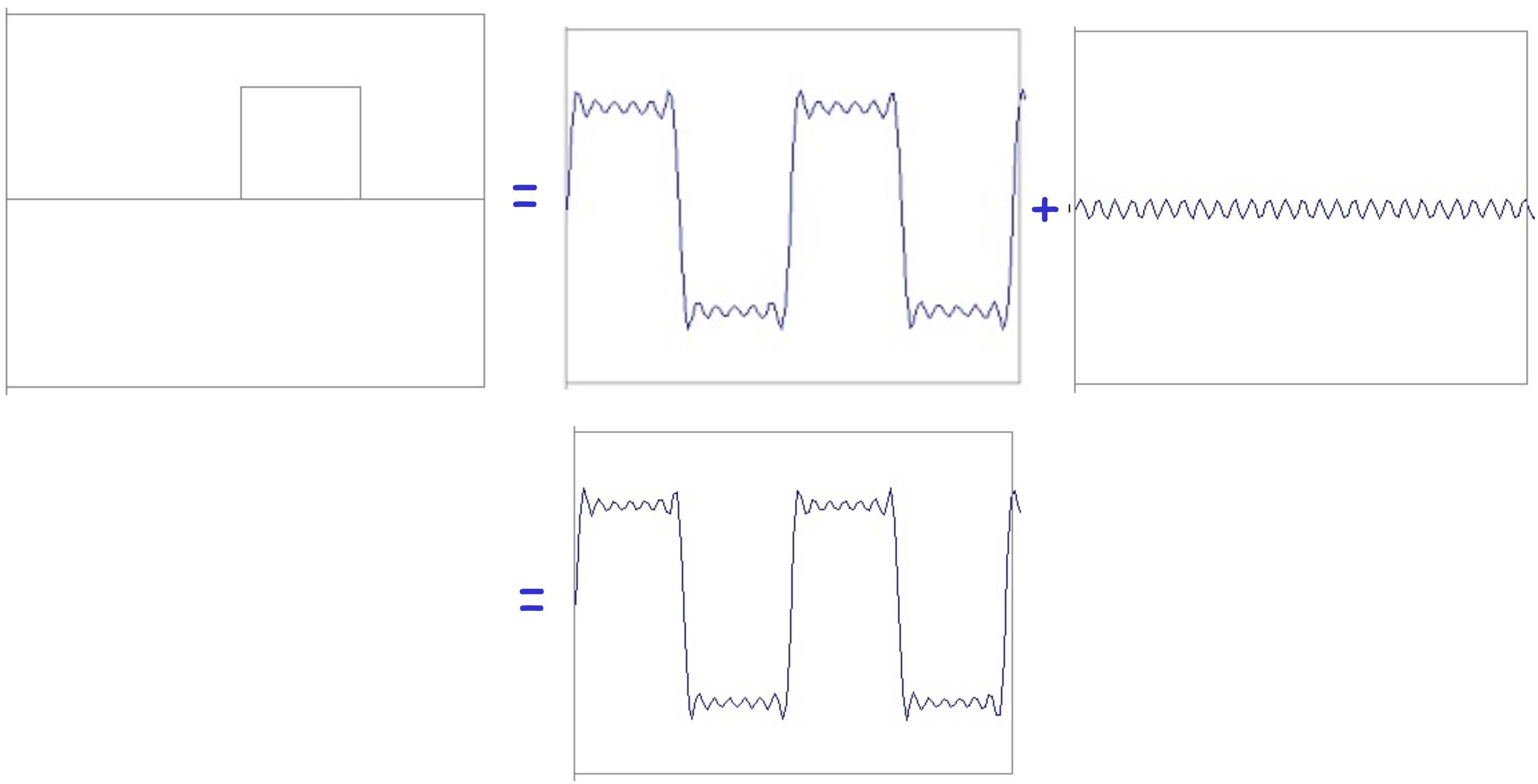
Frequency Spectra



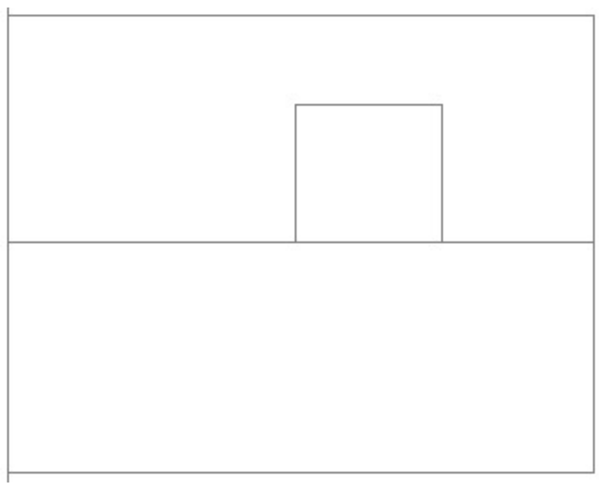
Frequency Spectra



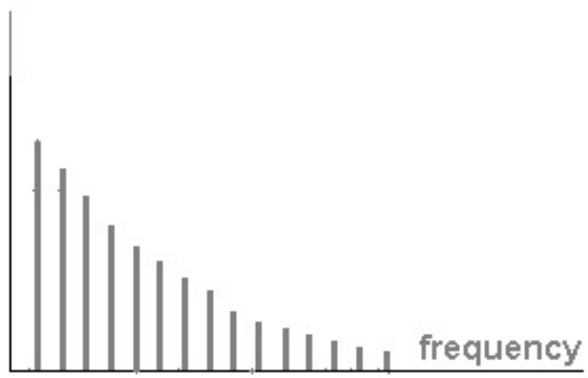
Frequency Spectra



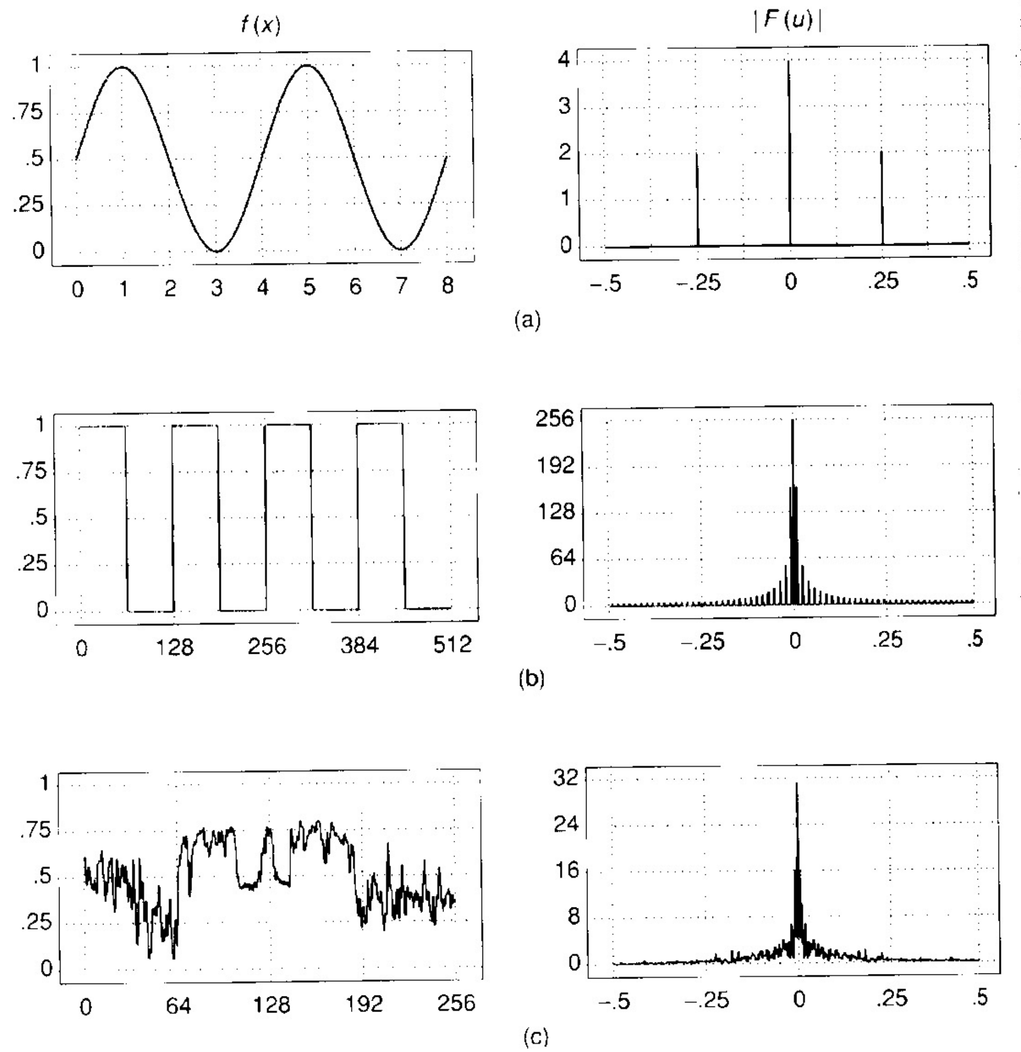
Frequency Spectra



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

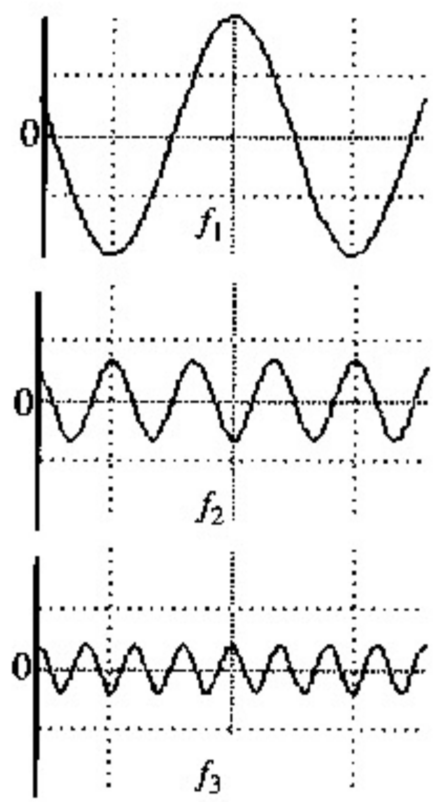


Frequency Spectra



FT: Just a change of basis

$$M * f(x) = F(\omega)$$



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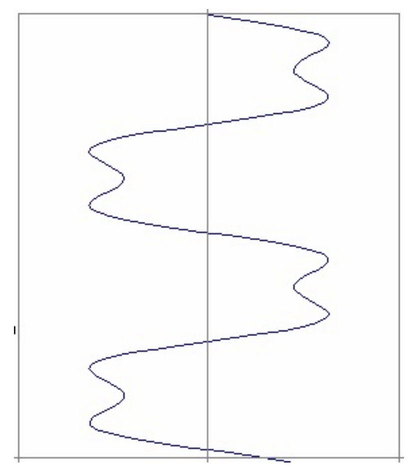

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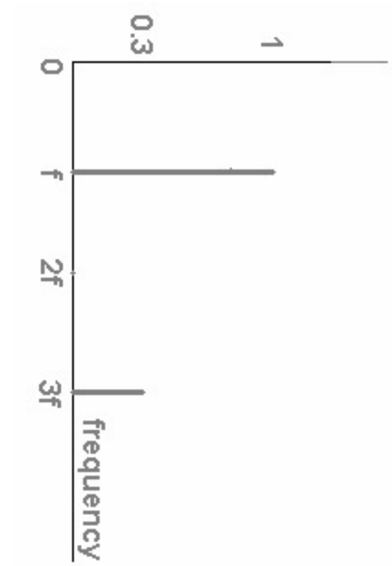


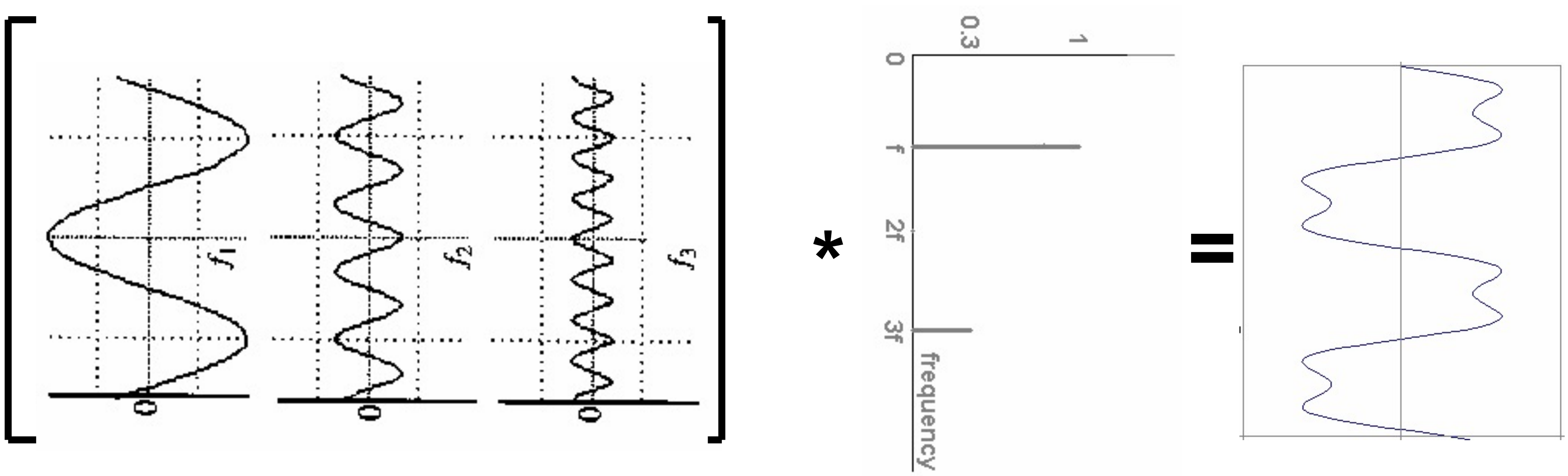
F x N

N x 1

F x 1

IFT: Just a change of basis

$$M^{-1} * F(\omega) = f(x)$$



.

.

. N x F   F x 1   N x 1

Finally: Scary Math

$$\text{Fourier Transform}: \quad F(\omega) = \int_{-\infty}^{+\infty} f(x) e^{-i\omega x} dx$$

$$\text{Inverse Fourier Transform}: \quad f(x) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} F(\omega) e^{i\omega x} d\omega$$

Finally: Scary Math

$$\text{Fourier Transform}: \quad F(\omega) = \int_{-\infty}^{+\infty} f(x) e^{-i\omega x} dx$$

$$\text{Inverse Fourier Transform}: \quad f(x) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} F(\omega) e^{i\omega x} d\omega$$

…not really scary: $e^{i\omega x} = \cos(\omega x) + i\sin(\omega x)$

is hiding our old friend: $\sin(\omega x + \phi)$

phase can be encoded by sin/cos pair $\longrightarrow$

$$P\cos(x) + Q\sin(x) = A\sin(x + \phi)$$

$$A = \pm\sqrt{P^2 + Q^2} \qquad \phi = \tan^{-1}\left(\frac{P}{Q}\right)$$

So it's just our signal *f(x)* times sine at frequency ω

Extension to 2D

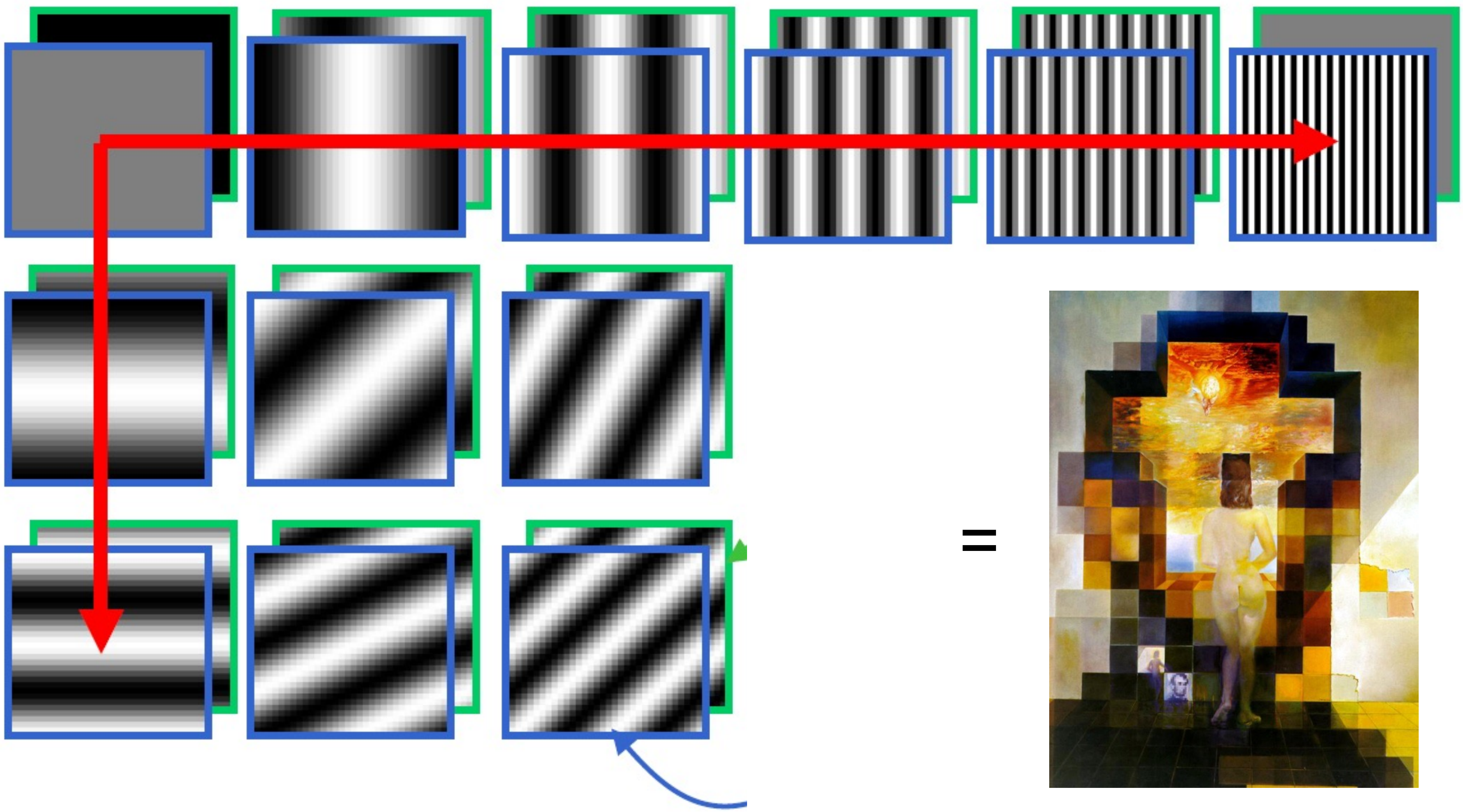
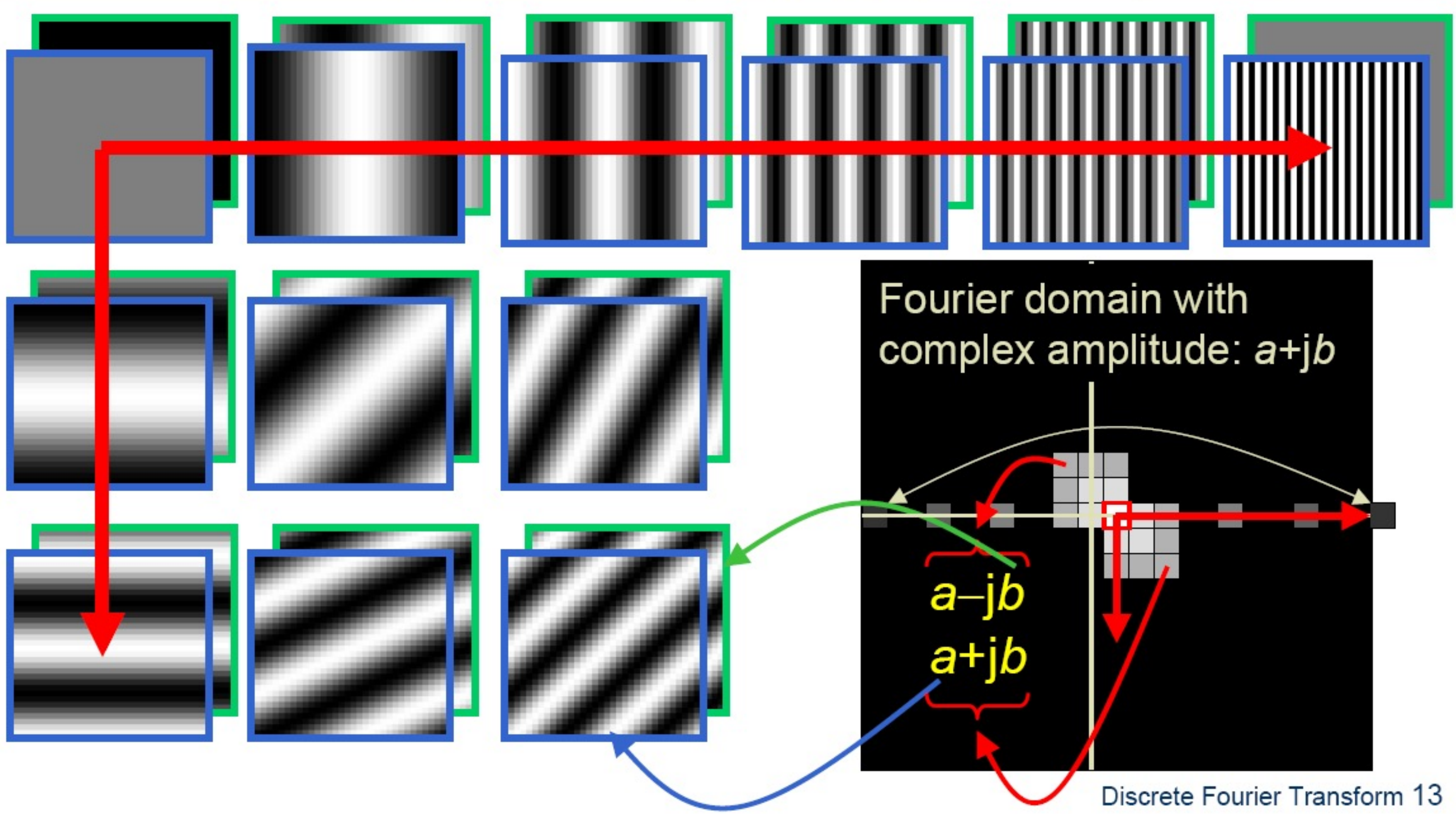


Image as a sum of basis images

Extension to 2D

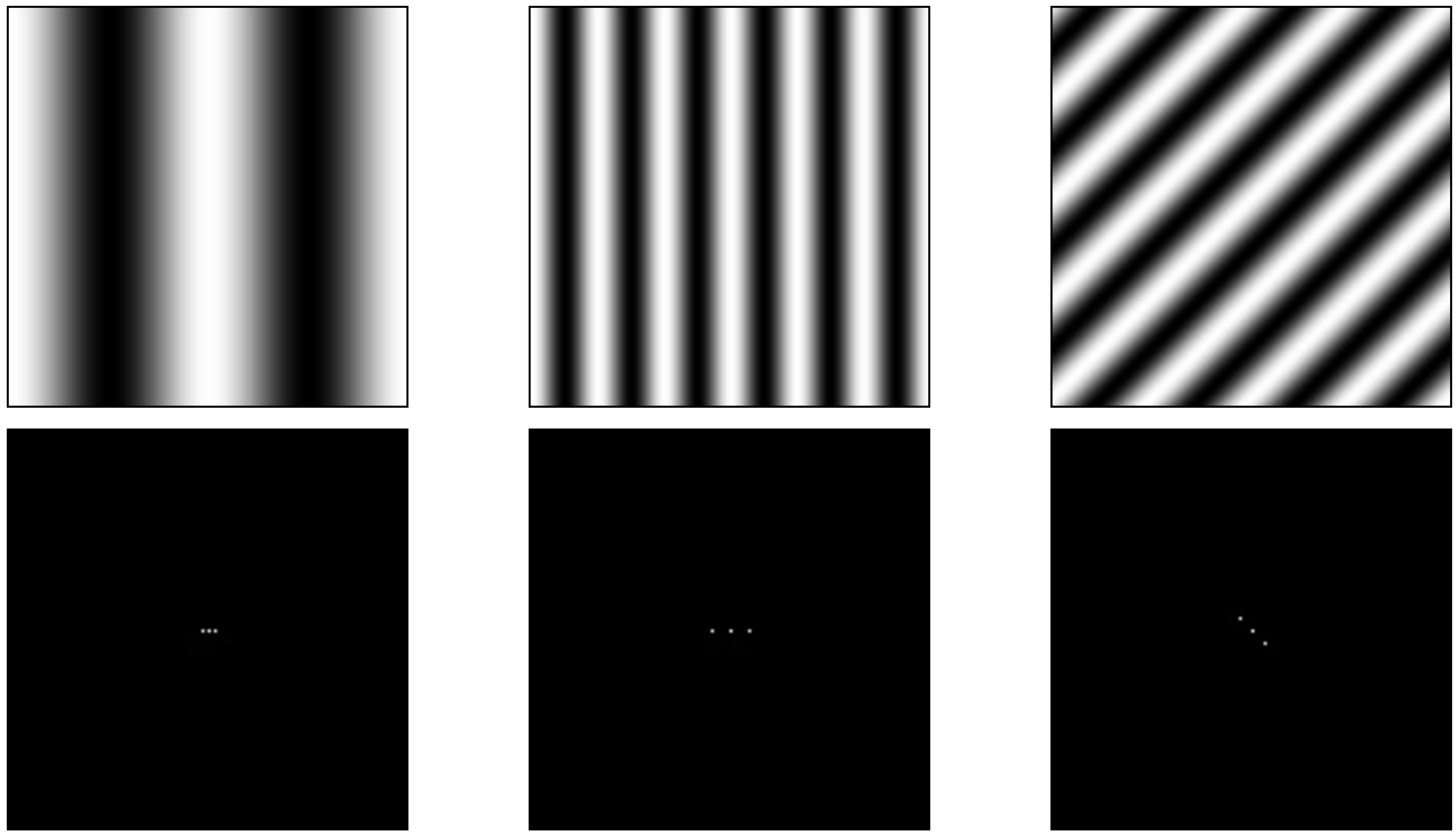


in Matlab, check out: imagesc(log(abs(fftshift(fft2(im)))));

Fourier analysis in images

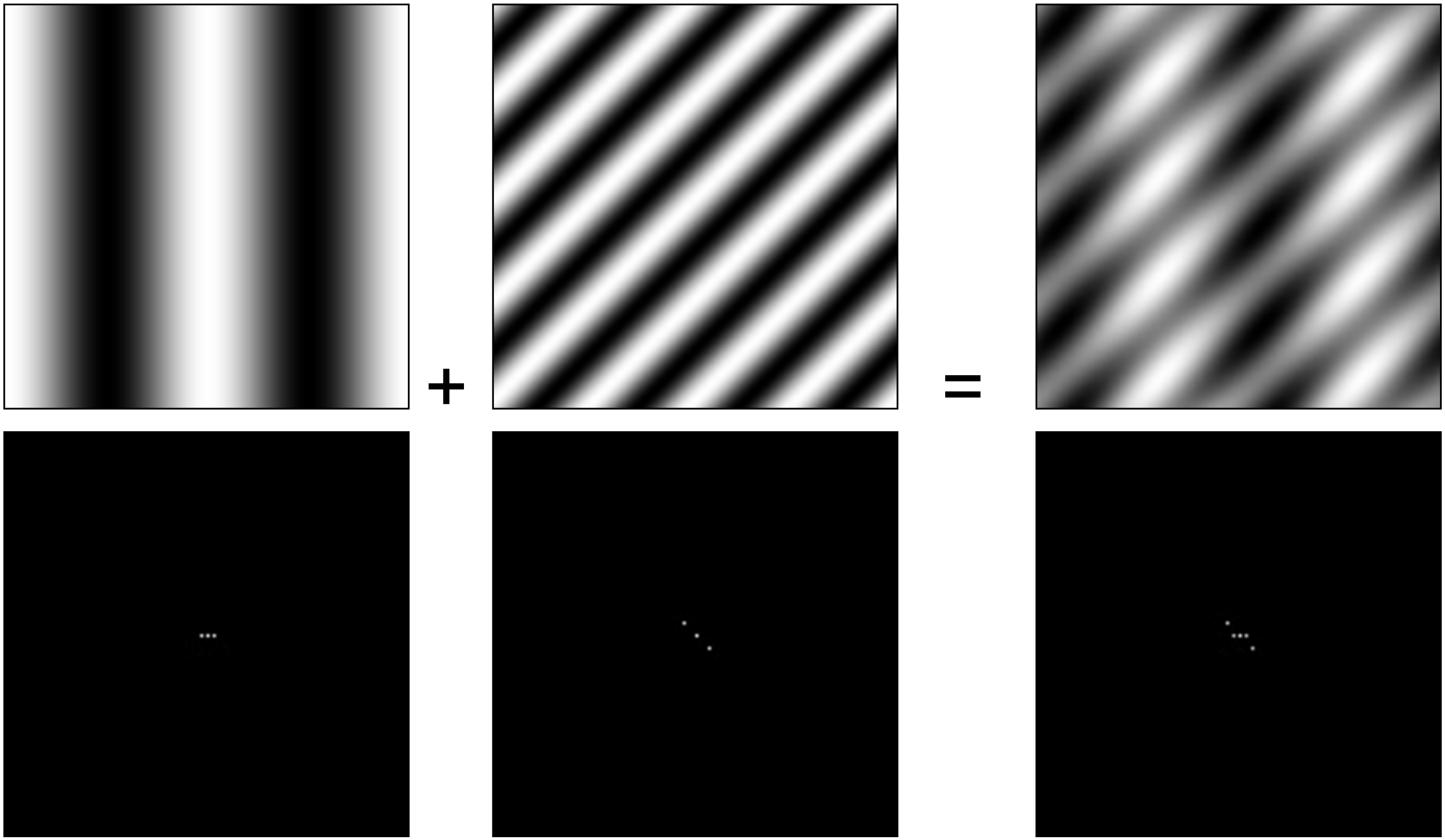
Intensity Image

Fourier Image



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

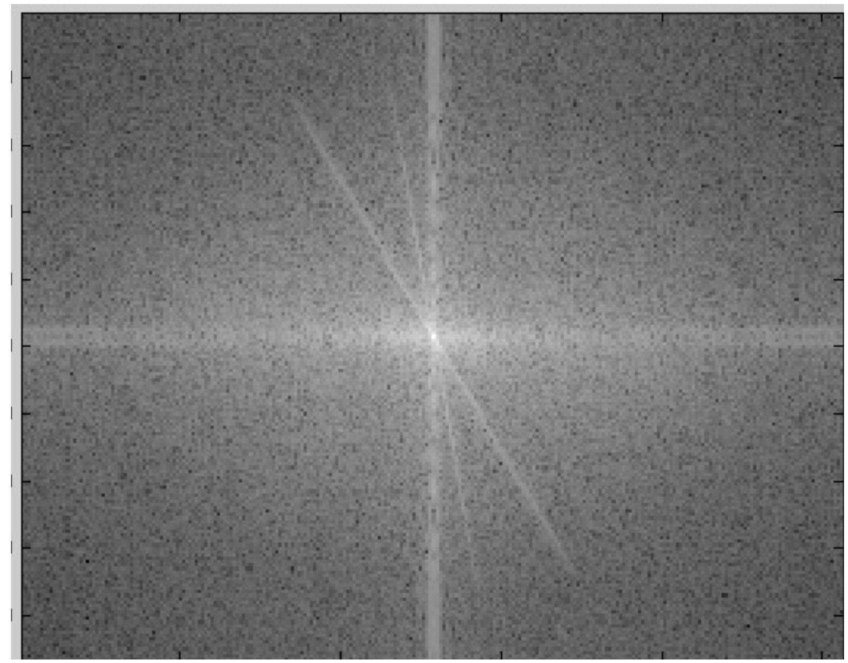
Signals can be composed

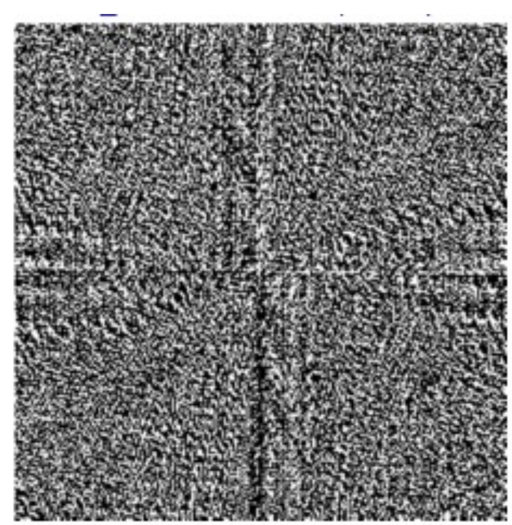


http://sharp.bu.edu/~slehar/fourier/fourier.html#filtering
More: http://www.cs.unm.edu/~brayer/vision/fourier.html

Man-made Scene

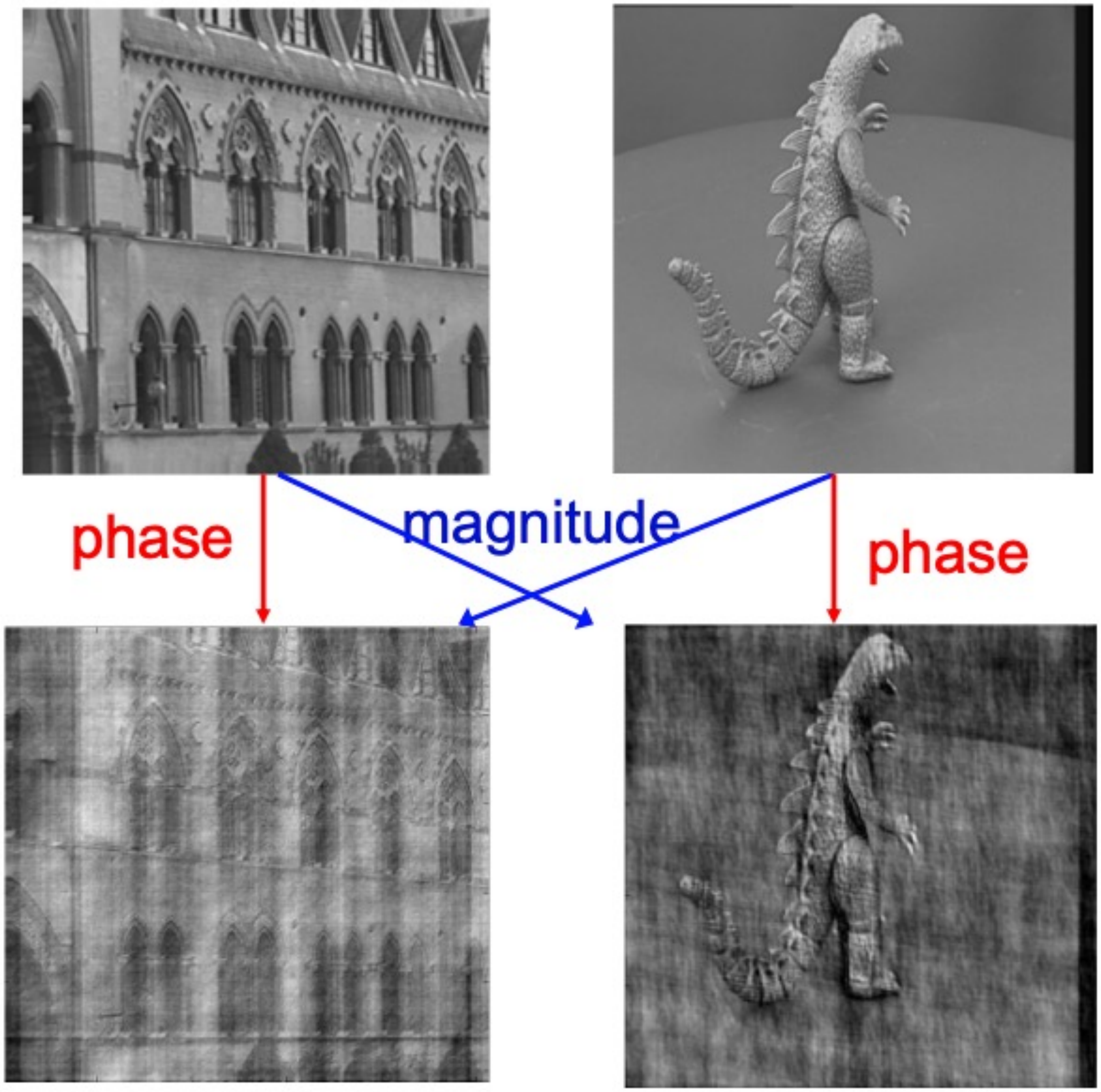
Amplitude Spectrum





what does phase look like, you ask?
(less visually informative)

The importance of Phase

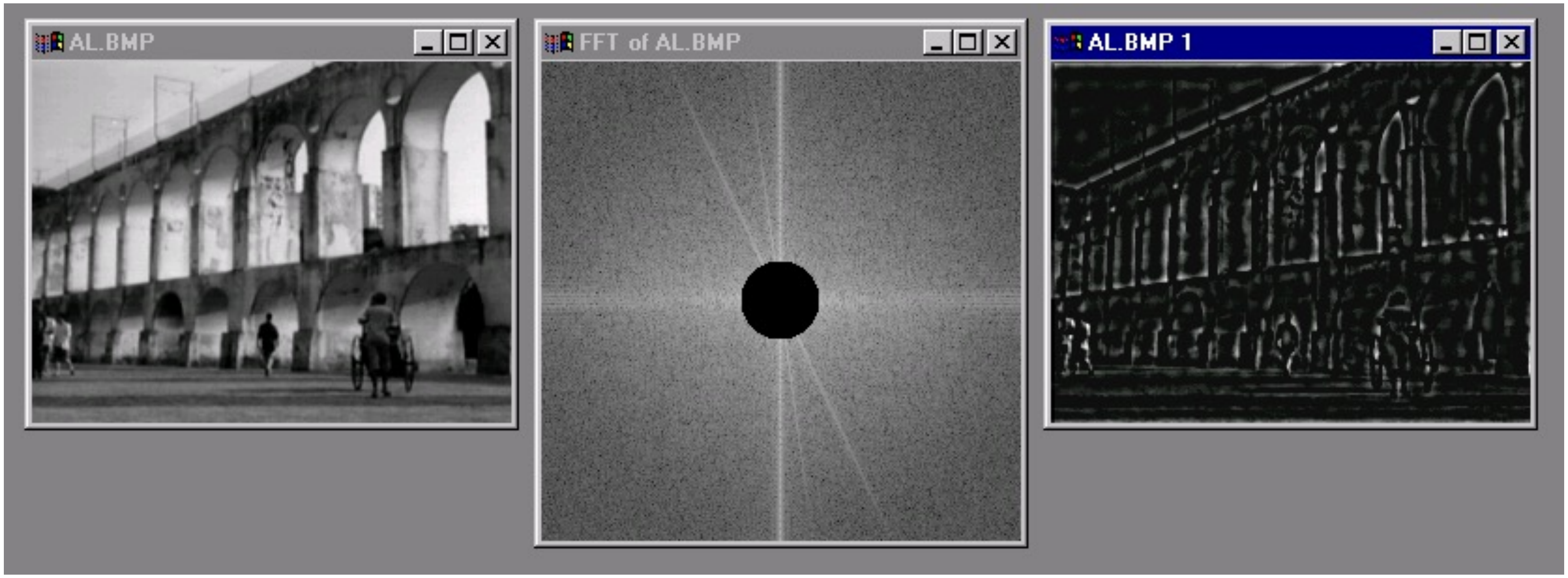


Slide: Andrew Zisserman

Can change spectrum, then reconstruct

Local change in one domain, courses global change in the other

Low and High Pass filtering



The Convolution Theorem

The greatest thing since sliced (banana) bread!

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

$$\mathrm{F}[g * h] = \mathrm{F}[g]\mathrm{F}[h]$$

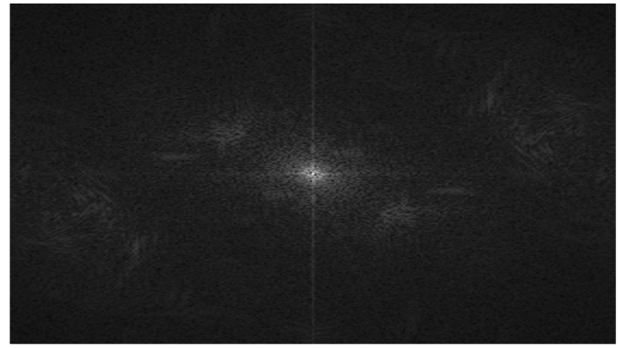
- The inverse Fourier transform of the product of two Fourier transforms is the convolution of the two inverse Fourier transforms

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

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

2D convolution theorem example

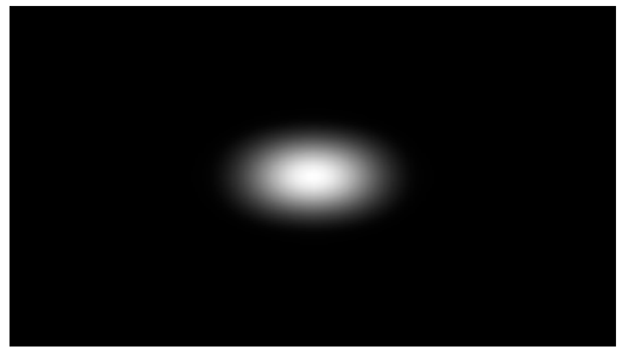
$f(x,y)$



$|F(s_x,s_y)|$

$*$ $\times$

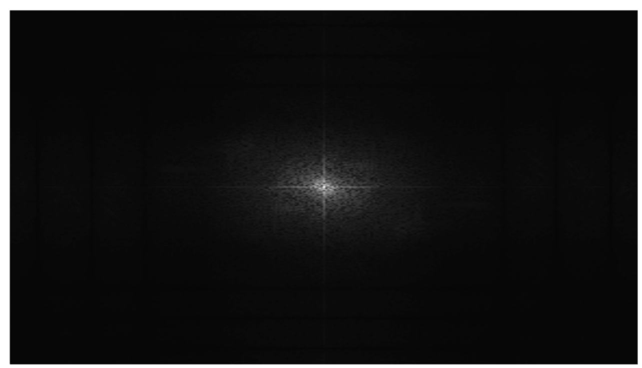
$h(x,y)$



$|H(s_x,s_y)|$

$\Downarrow$ $\Downarrow$

$g(x,y)$



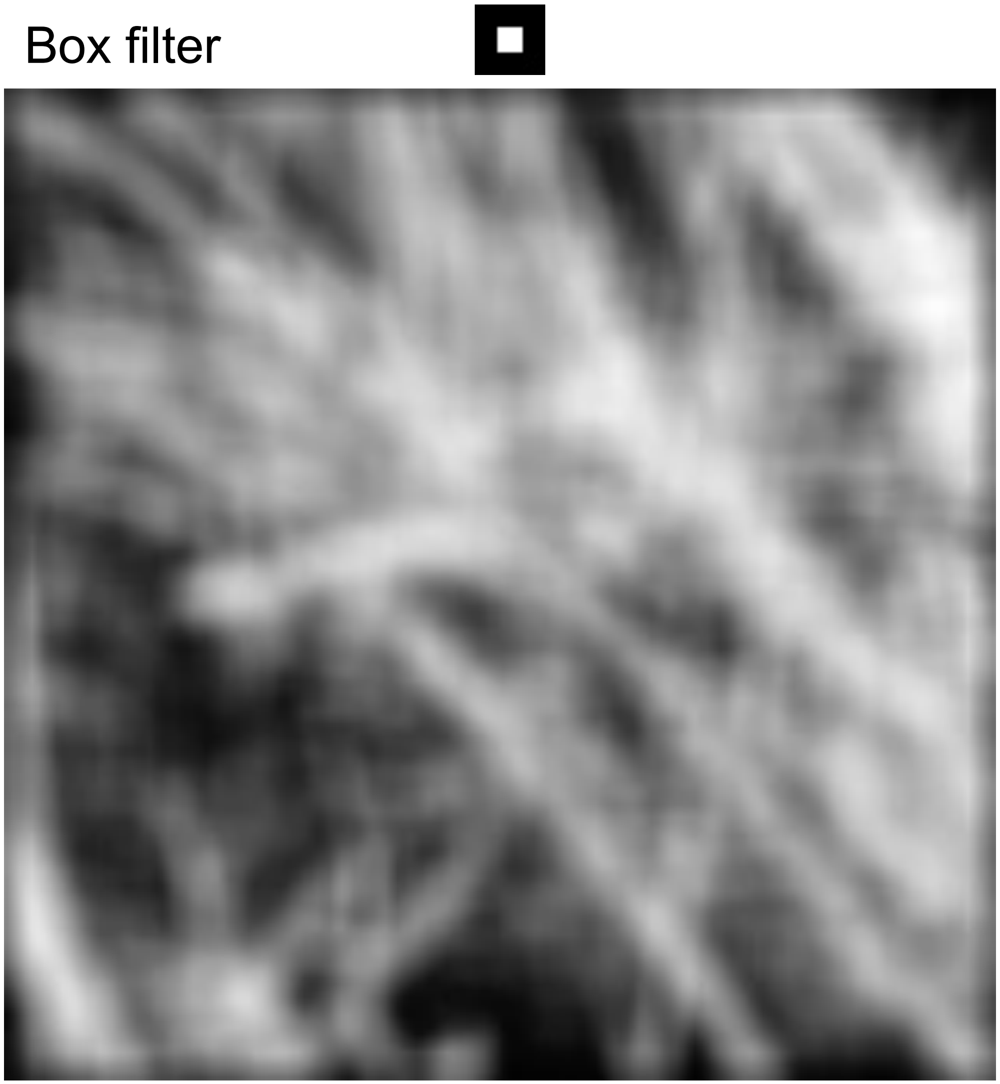
$|G(s_x,s_y)|$

Filtering

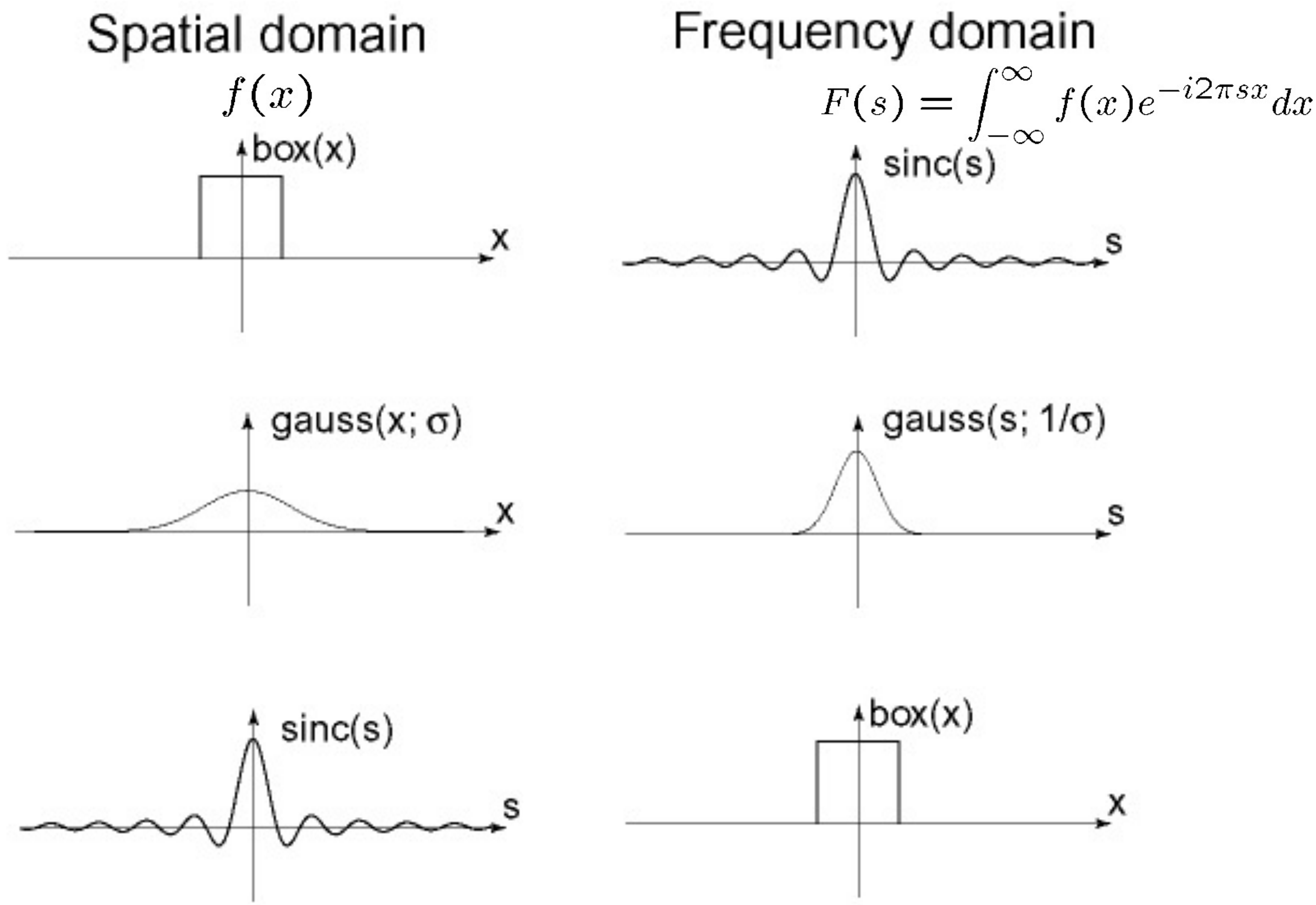
Why does the Gaussian give a nice smooth image, but the square filter give edgy artifacts?

Gaussian

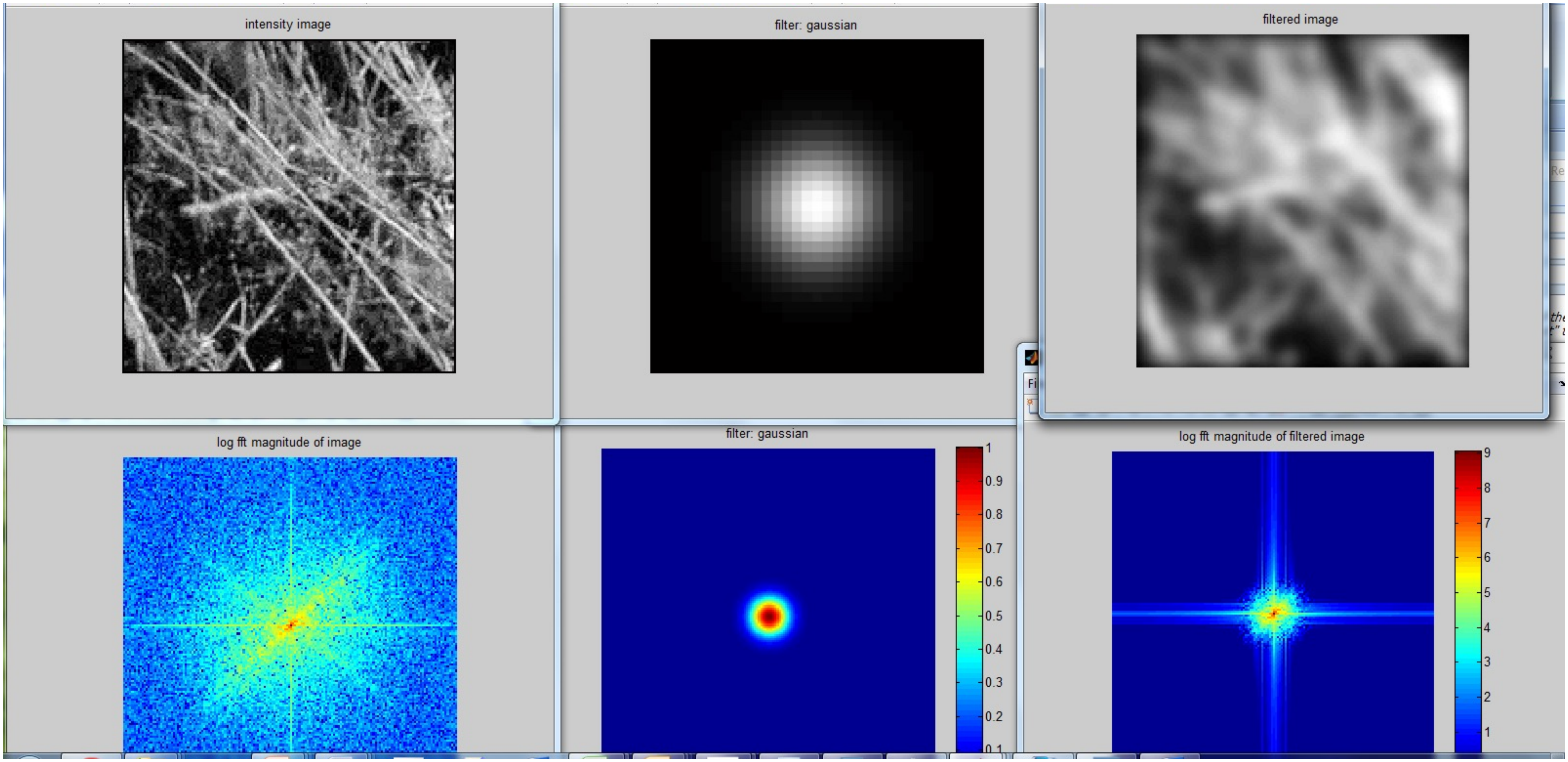
Box filter



Fourier Transform pairs

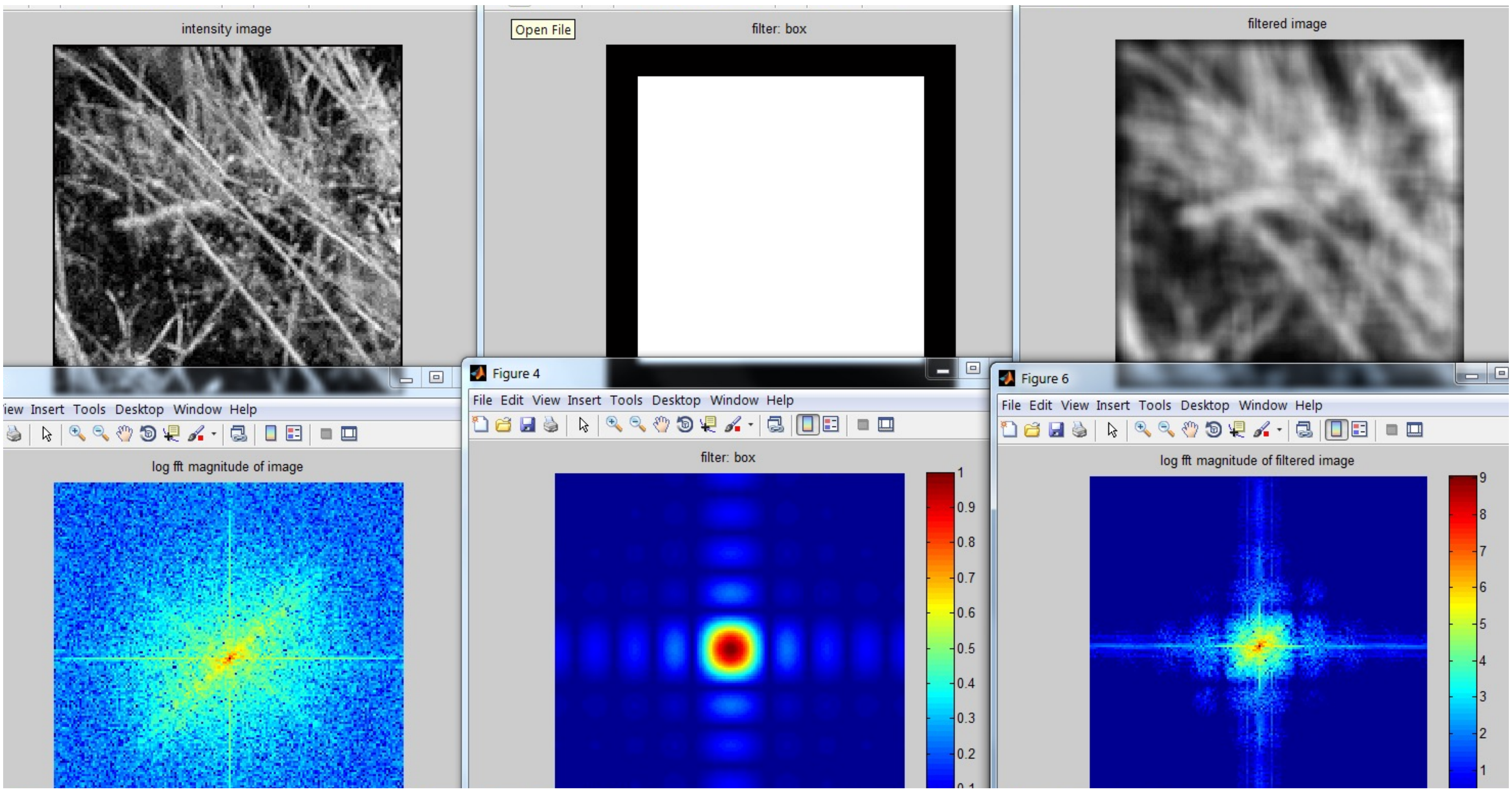


Gaussian



intensity image
filter: gaussian
filtered image
log fft magnitude of image
filter: gaussian
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
log fft magnitude of filtered image
9
8
7
6
5
4
3
2
1

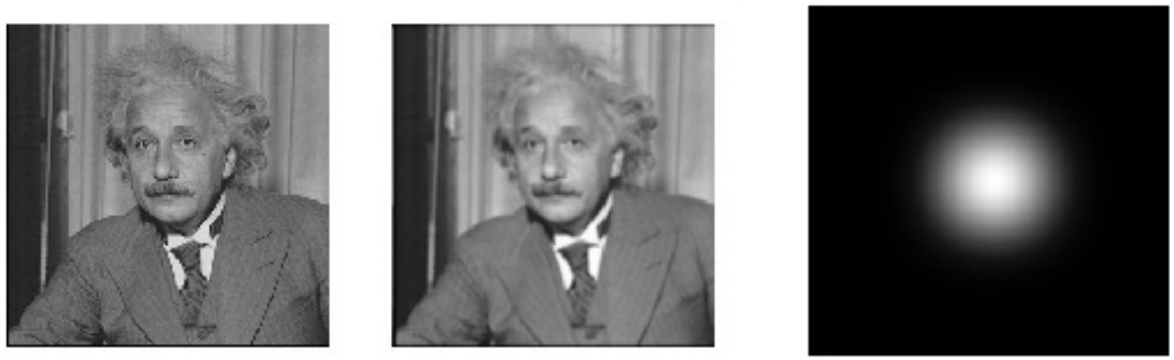
Box Filter



intensity image
Open File
filter: box
filtered image
Figure 4
Figure 6
File Edit View Insert Tools Desktop Window Help
log fft magnitude of image
filter: box
log fft magnitude of filtered image

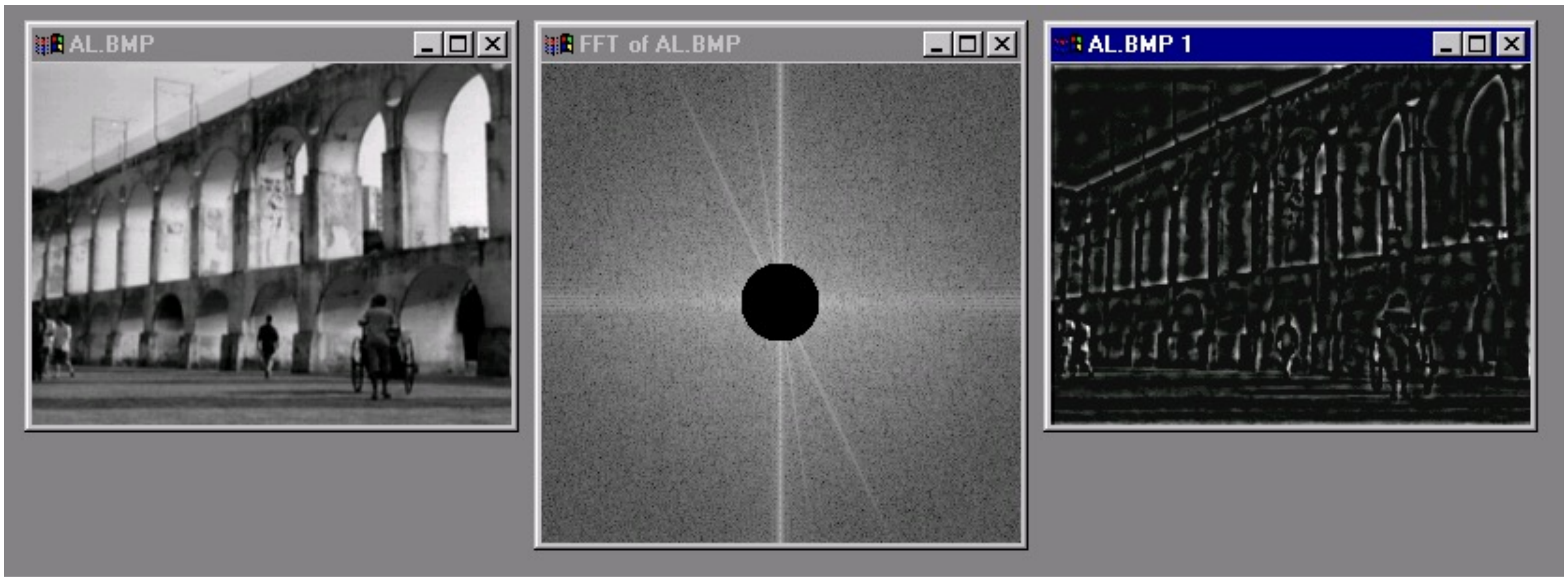
Low-pass, Band-pass, High-pass filters

low-pass:



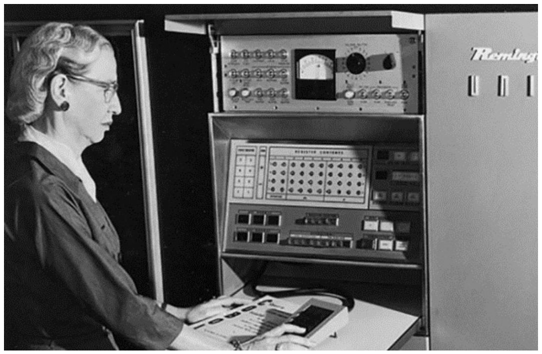
High-pass / band-pass:

Edges in images



Low Pass vs. High Pass filtering

Image



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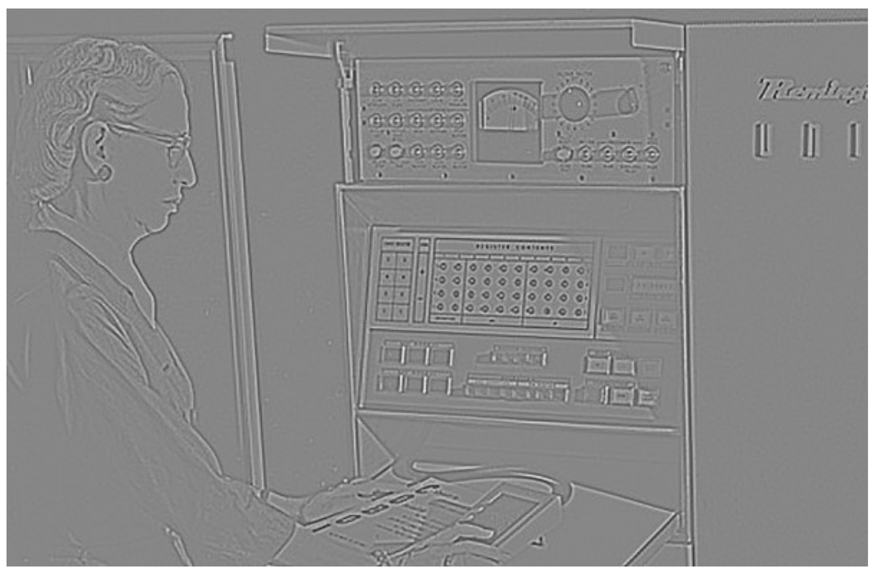
Smoothed

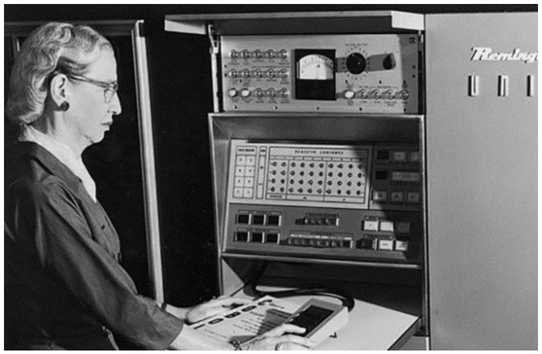
Details

=



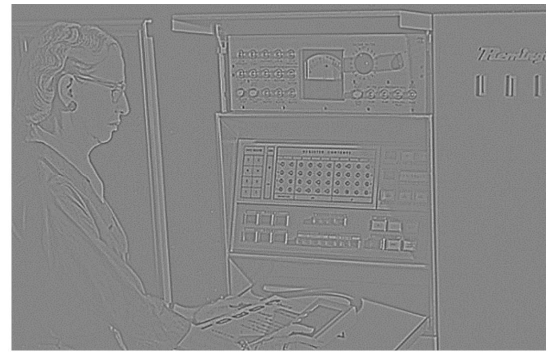
Filtering – Sharpening

Image



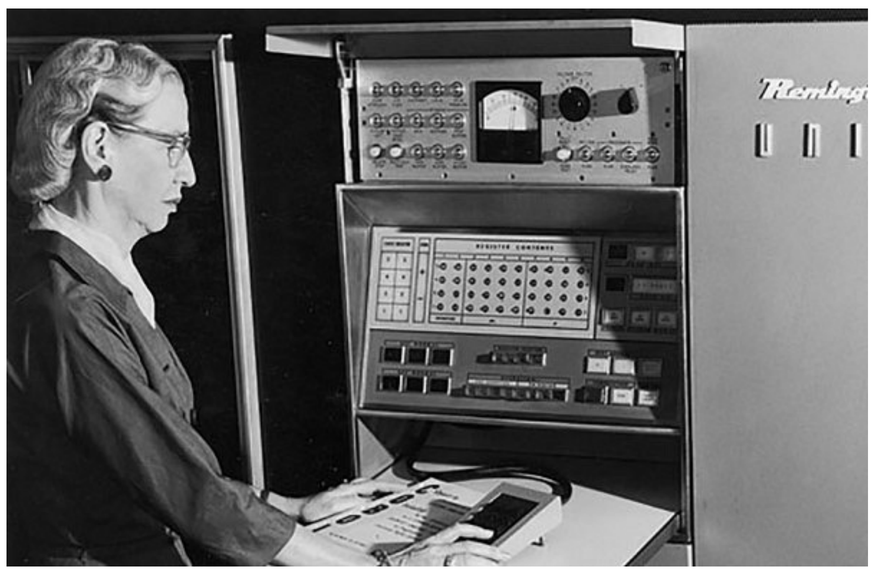
+α

Details



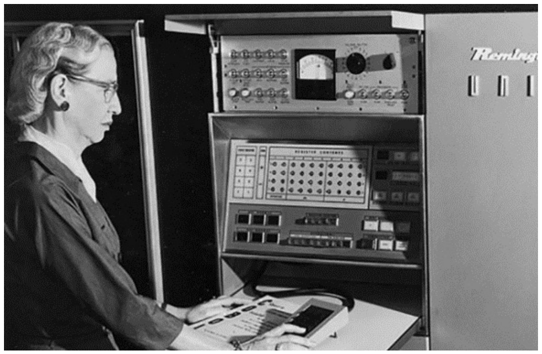
“Sharpened” α=1

=



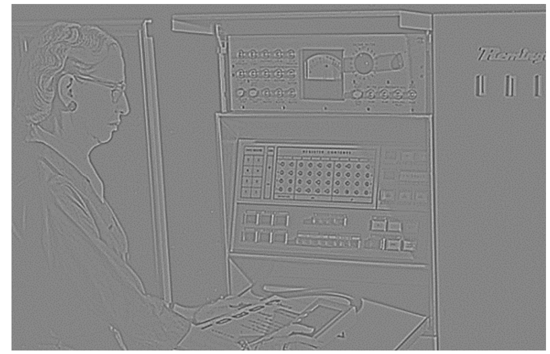
Filtering – Sharpening

Image



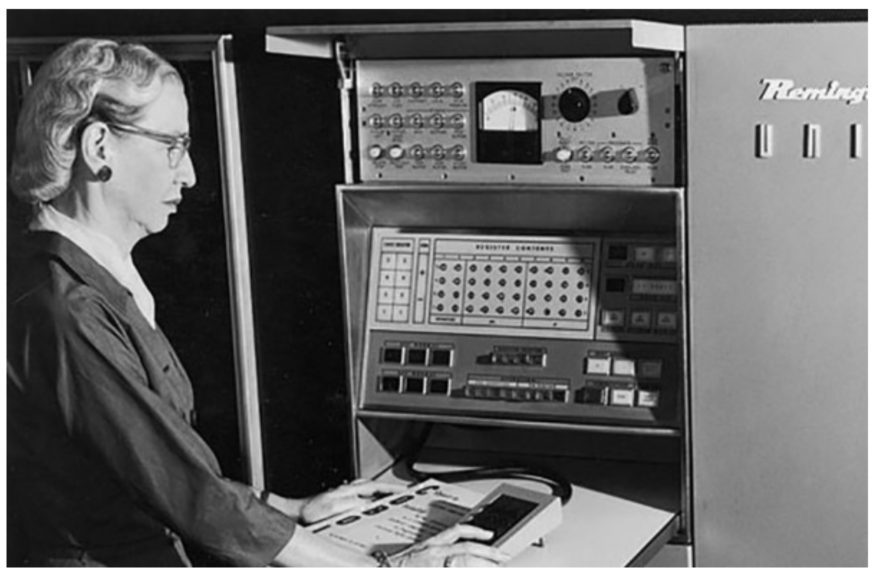
+α

Details



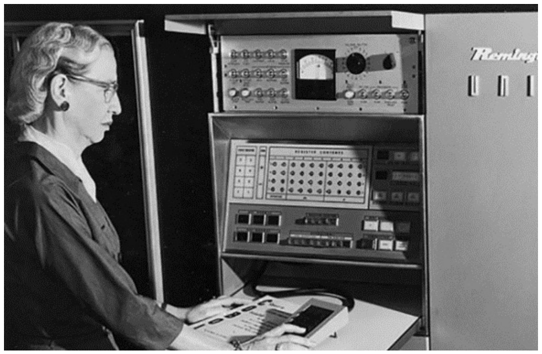
“Sharpened” α=0

=



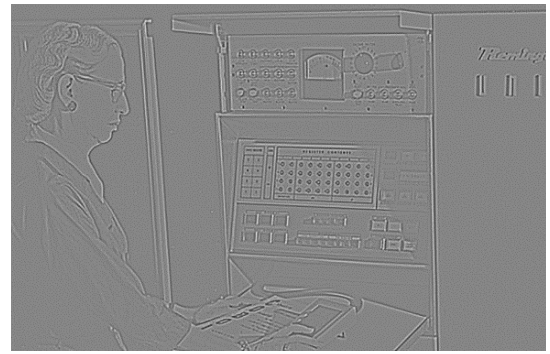
Filtering – Sharpening

Image



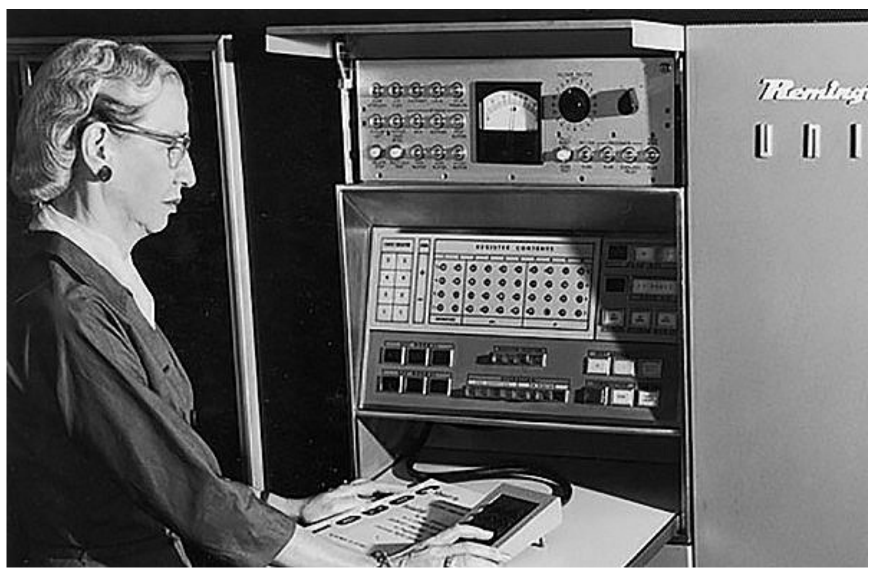
+α

Details



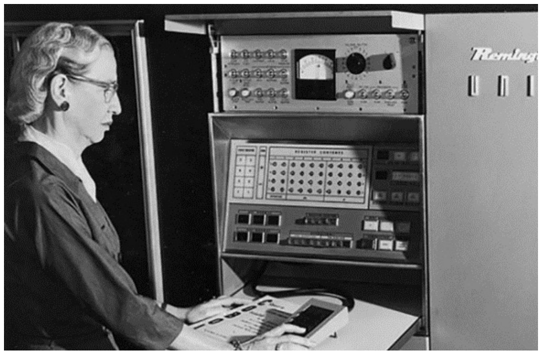
"Sharpened" α=2

=



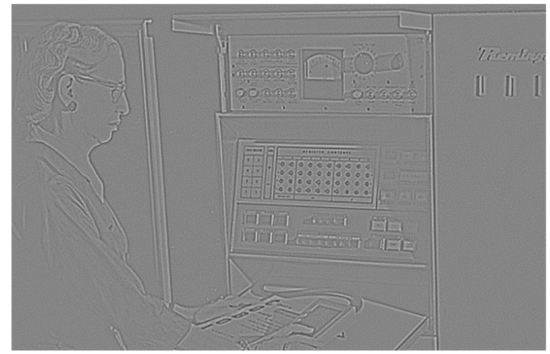
Filtering – Sharpening

Image



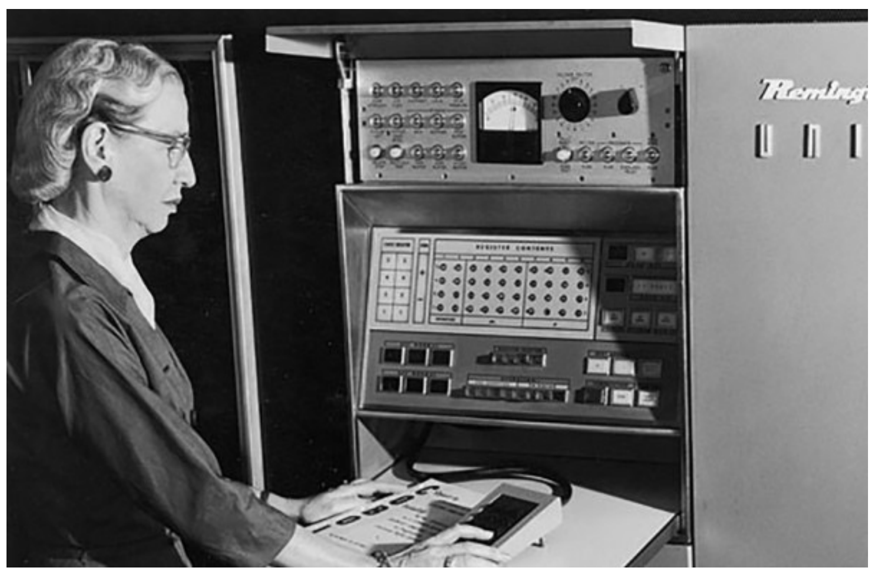
+α

Details



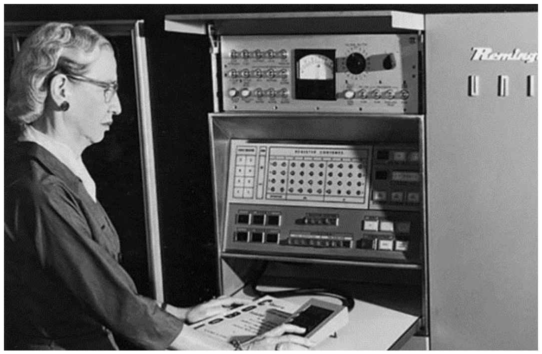
“Sharpened” α=0

=



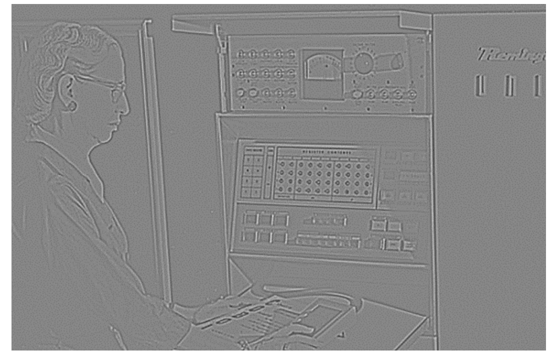
Filtering – Extreme Sharpening

Image



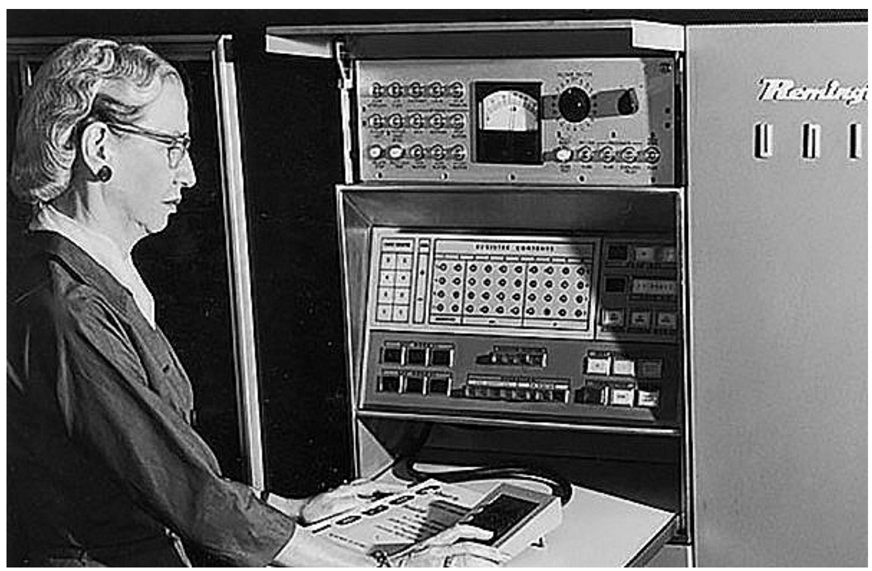
+α

Details



“Sharpened” α=10

=



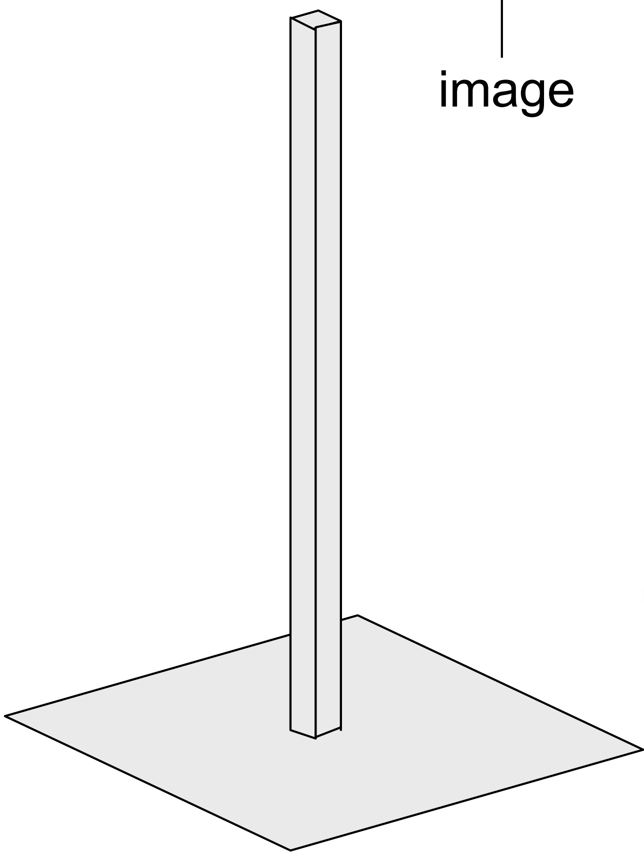
Unsharp mask filter

$$f + \alpha(f - f * g) = (1+\alpha)f - \alpha\, f * g = f * ((1+\alpha)e - \alpha g)$$

image

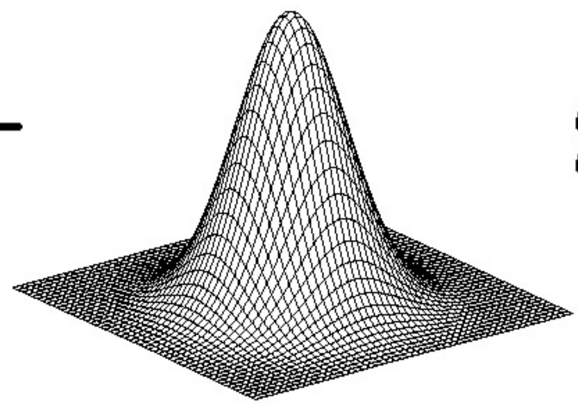
blurred image

unit impulse (identity)



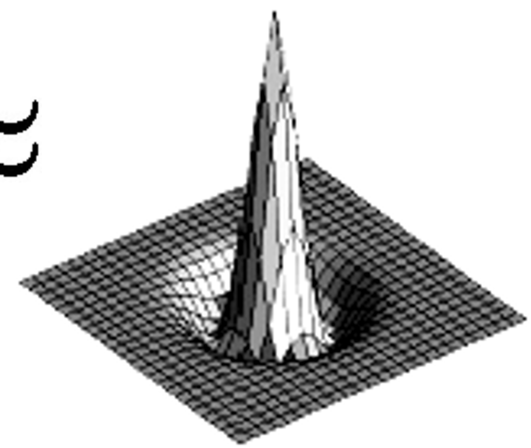
unit impulse

$-$



Gaussian

$\approx$

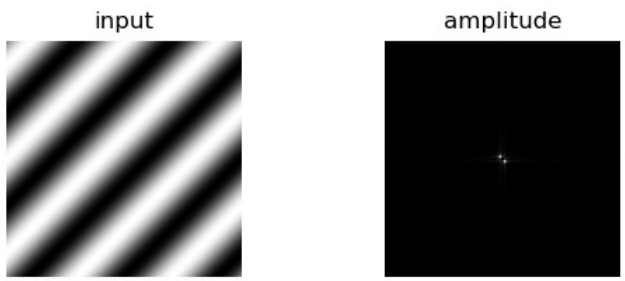


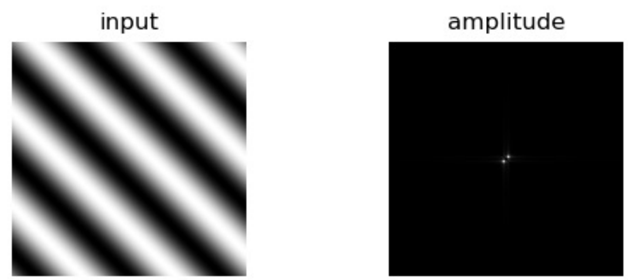
Laplacian of Gaussian

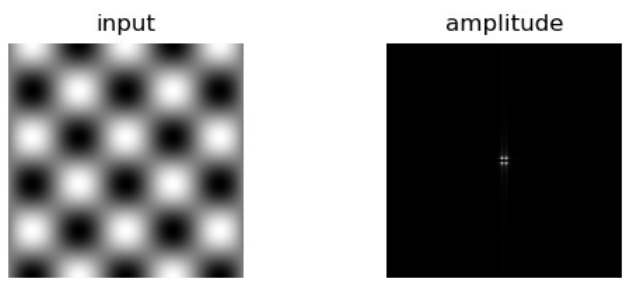
5 min recap

Fourier Transform in 5 minutes: The Case of the Splotched Van Gogh, Part 3

https://www.youtube.com/watch?v=JciZYrh36LY


input
amplitude


input
amplitude


input
amplitude