# DIGITAL IMAGE PROCESSING

Lecture 4

Frequency domain

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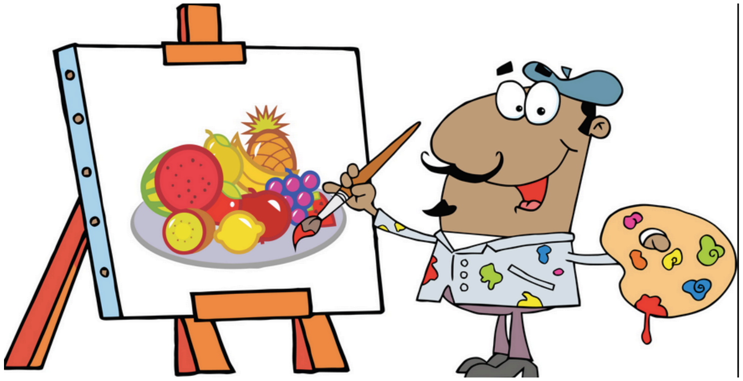
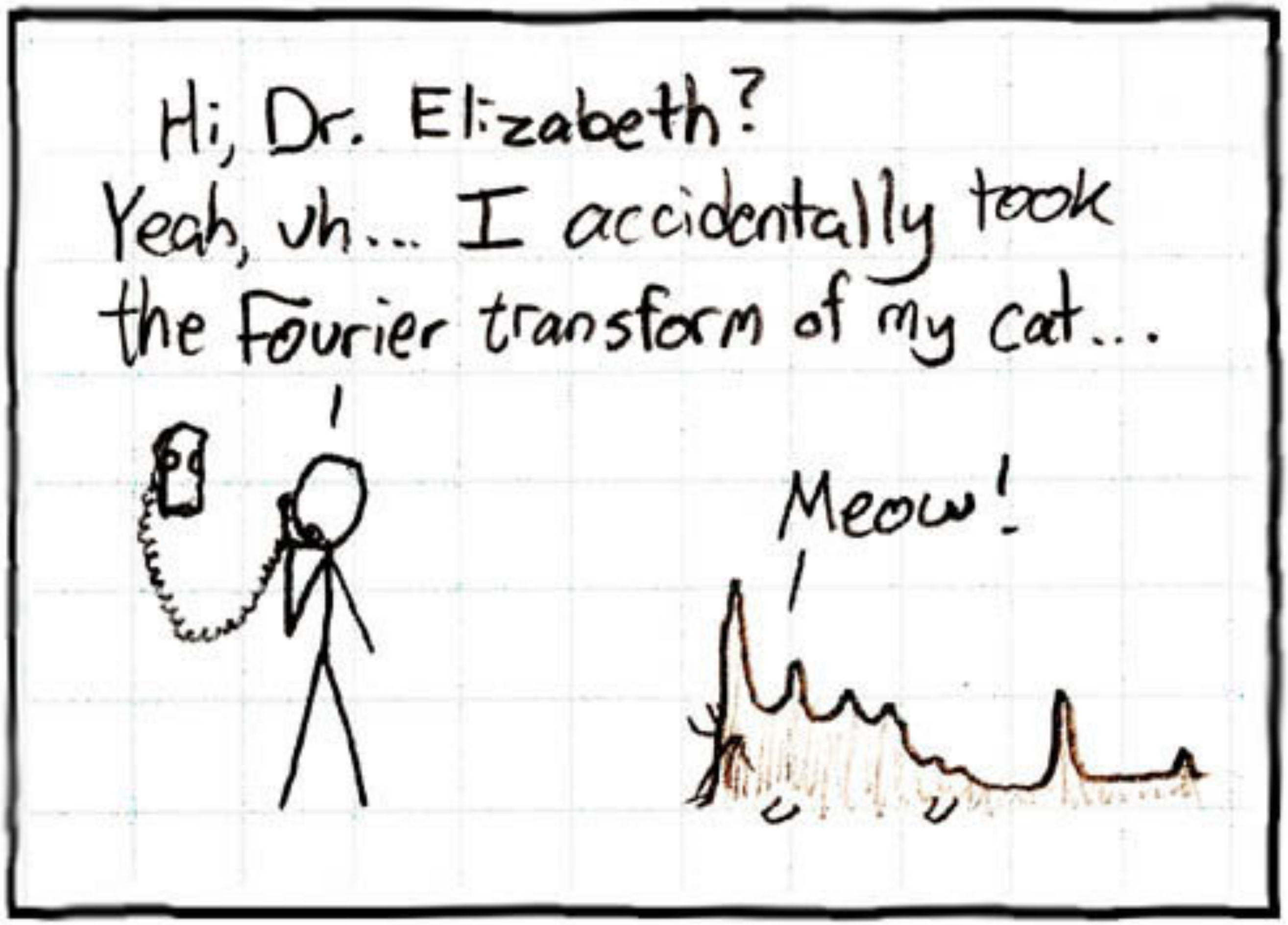


# Fourier Domain



# 2D Fourier transform and its applications

- Fourier transforms and spatial frequencies in 2D
  - Definition and meaning

- The Convolution Theorem
  - Applications to spatial filtering

- The Sampling Theorem and Aliasing

Much of this material is a straightforward generalization of the 1D Fourier analysis with which you are familiar.

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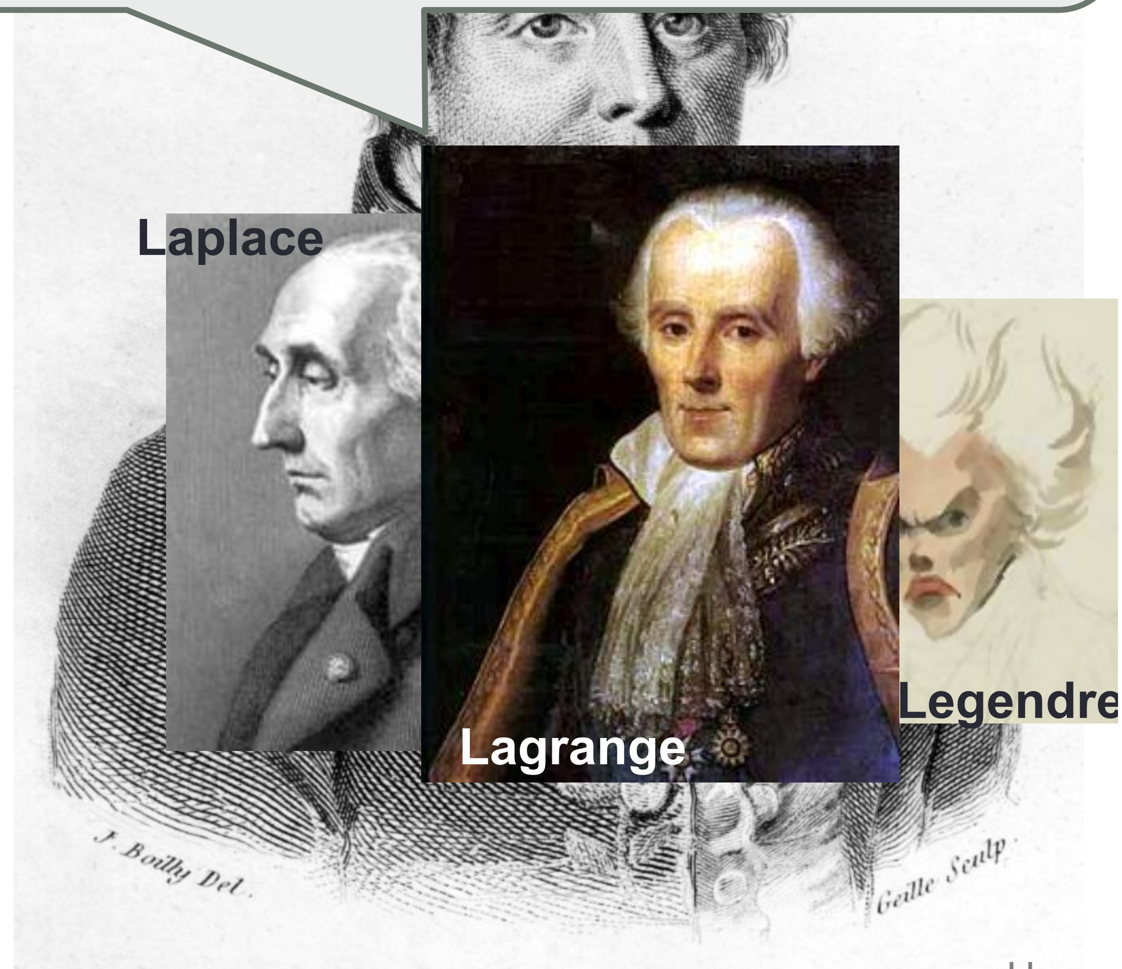
# Jean Baptiste Joseph Fourier (1768-1830)

*...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 bold idea (1807):

> ***Any*** *univariate 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 (mostly) true!
  - called Fourier Series
  - there are some subtle restrictions

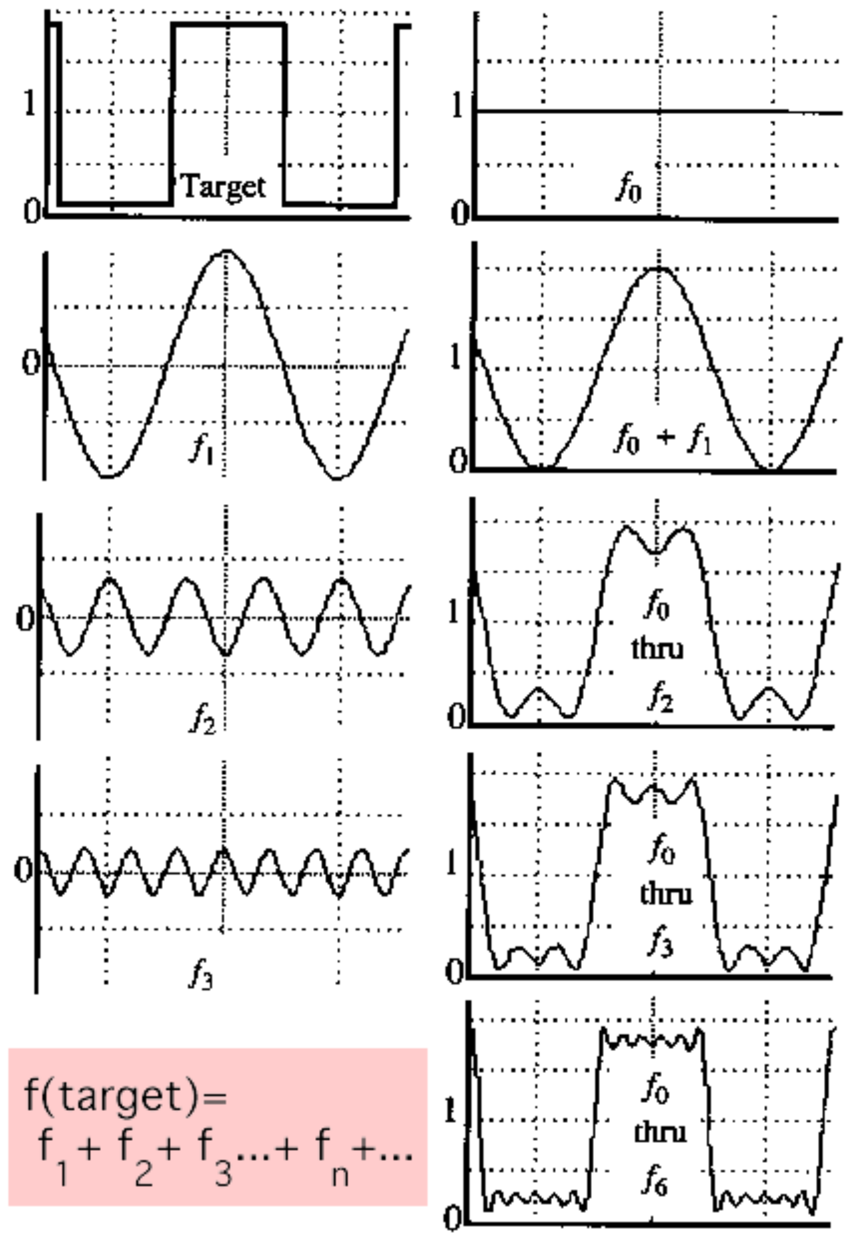


# A sum of sines and cosines

Our building block:

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

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

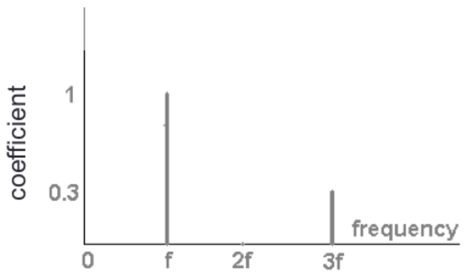


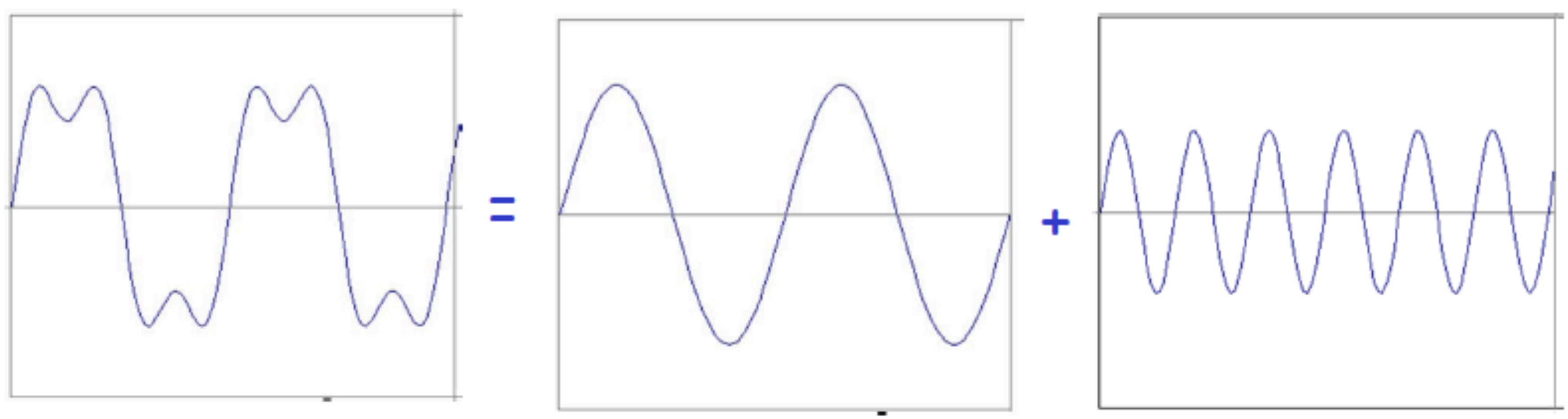

f(target)=
$f_1 + f_2 + f_3 ... + f_n + ...$

Hays

# Reminder: 1D Fourier Series

Example




$$f(x) = \sin x + \frac{1}{3} \sin 3x + \ldots$$

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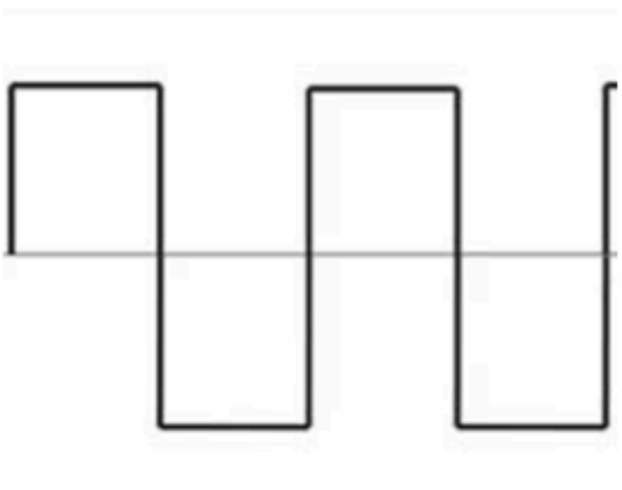
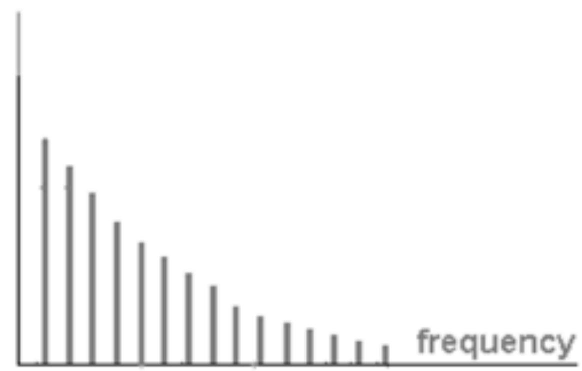
# Fourier Series of a Square Wave



$$= \quad f(x) = \sum_{n=1,3,5,\ldots} \frac{1}{n} \sin nx$$

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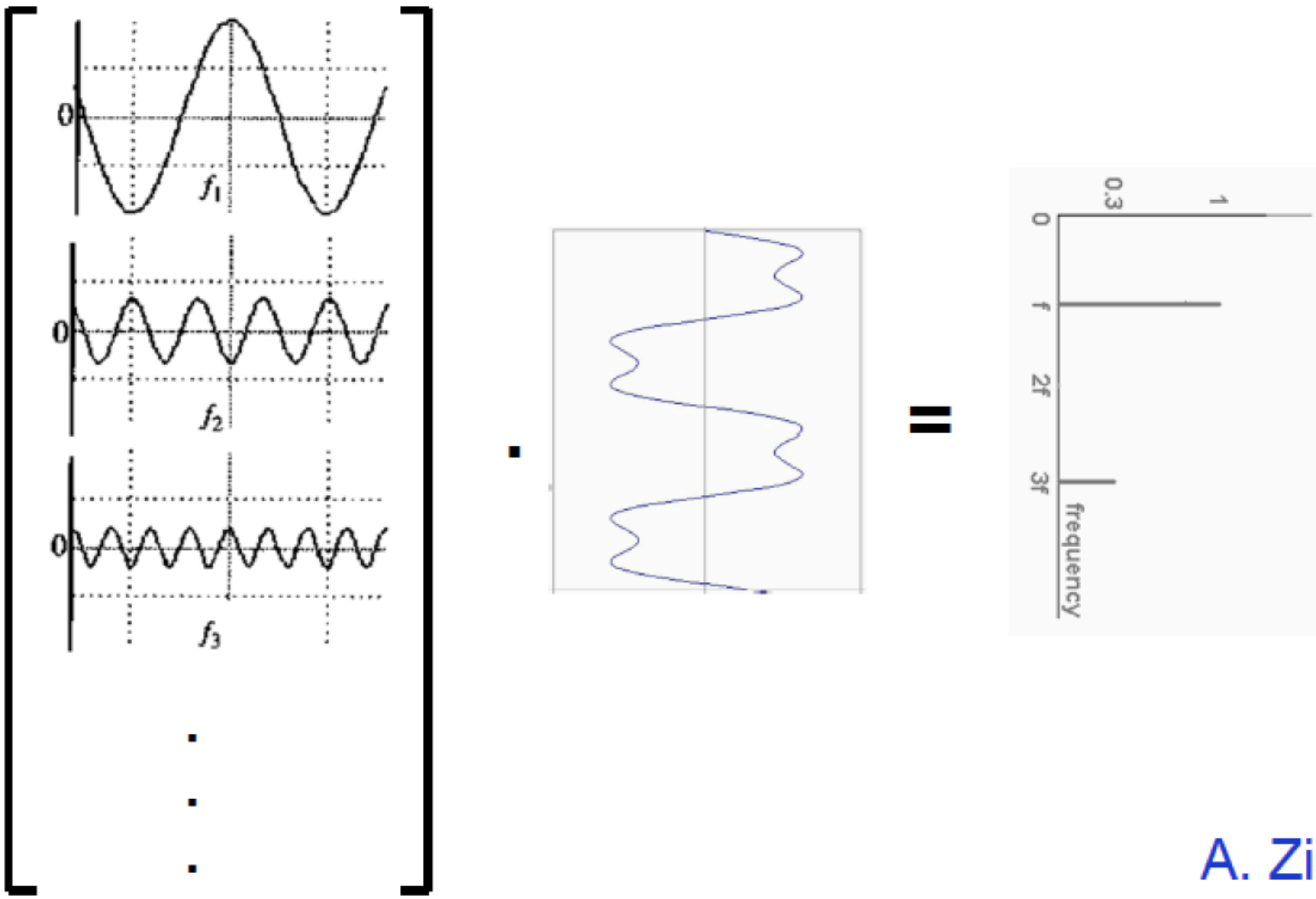
# Fourier Series: Just a change of basis

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

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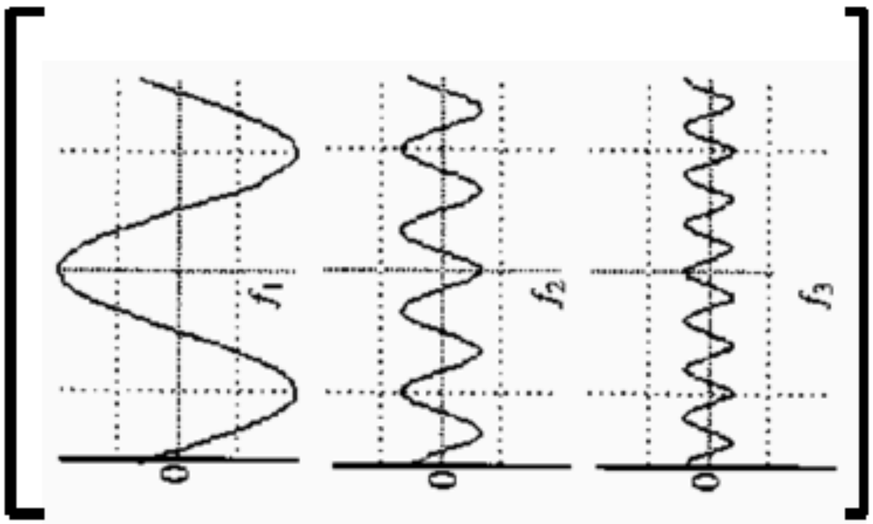
# Inverse FT: Just a change of basis

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

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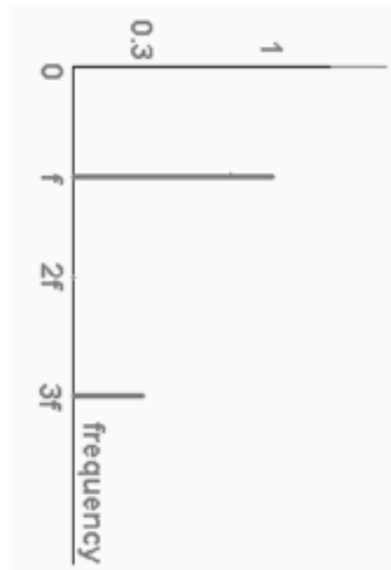


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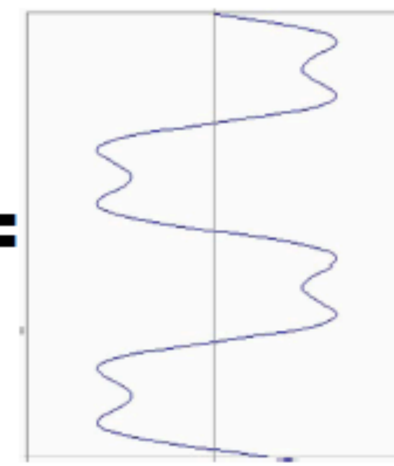

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# 1D Fourier Transform

$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-j2\pi ux}\, dx,$$
$$f(x) = \int_{-\infty}^{\infty} F(u) e^{j2\pi ux}\, du$$

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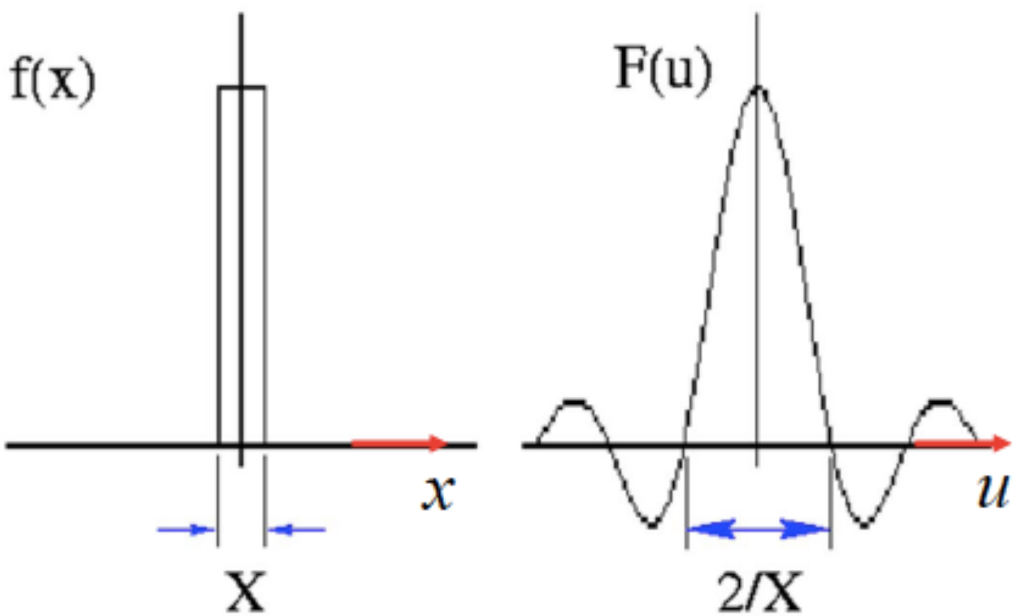
# 1D Fourier Transform

$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-j2\pi ux}\, dx,$$
$$f(x) = \int_{-\infty}^{\infty} F(u) e^{j2\pi ux}\, du$$

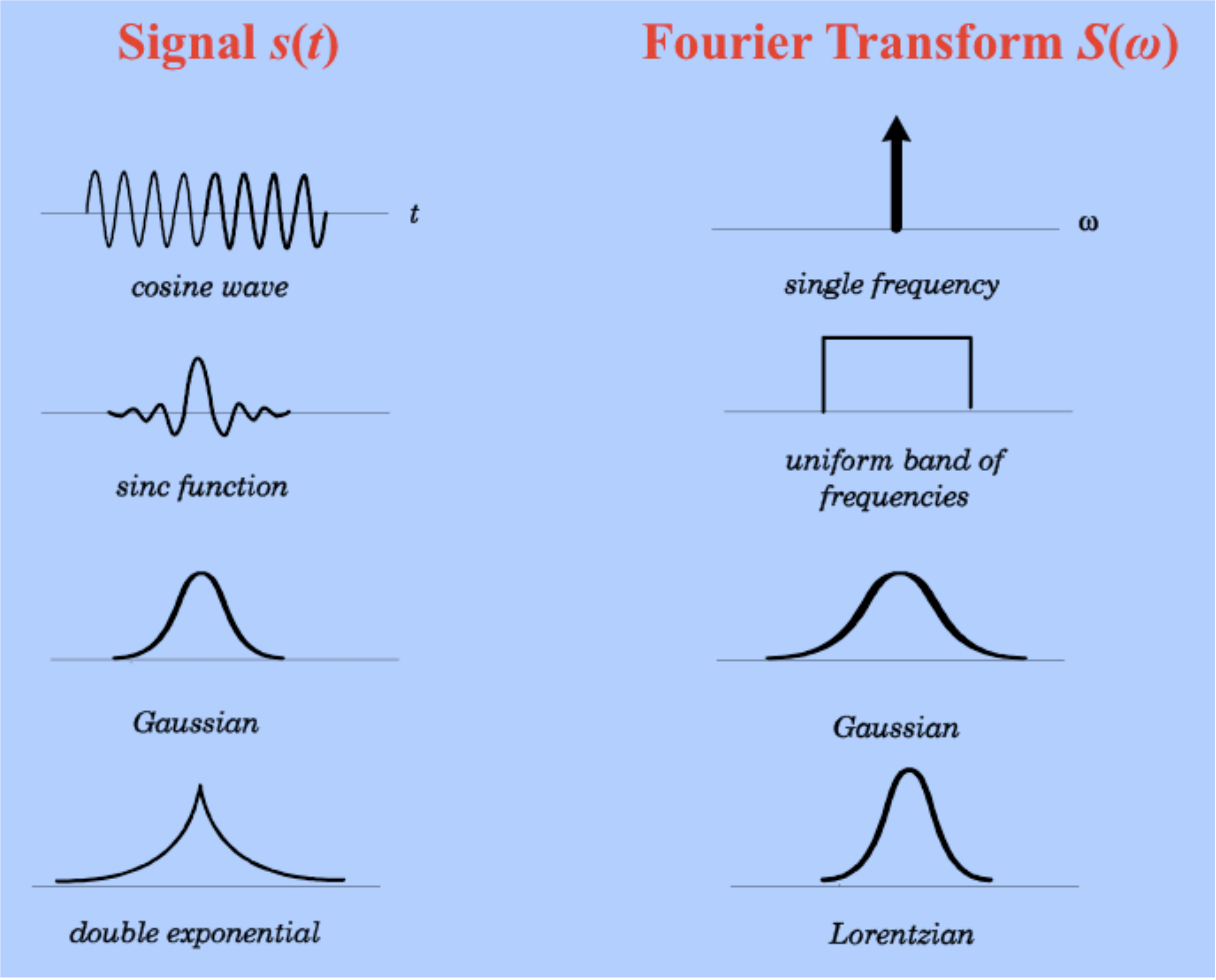



Example

$$f(x) = \begin{cases} 1, & |x| < \frac{X}{2}, \\ 0, & |x| \geq \frac{X}{2}. \end{cases}$$

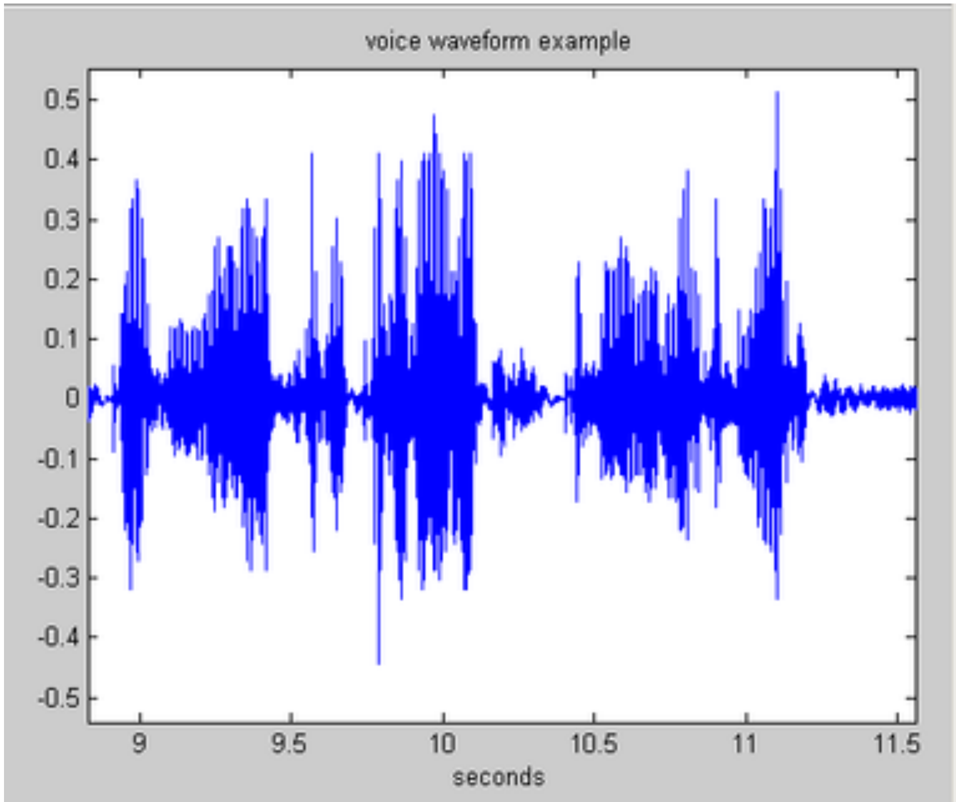
$$\begin{aligned} F(u) &= \int_{-\infty}^{\infty} f(x) e^{-j2\pi ux} dx \\ &= \int_{-X/2}^{X/2} e^{-j2\pi ux} dx \\ &= \frac{1}{-j2\pi u}[e^{-j2\pi uX/2} - e^{j2\pi uX/2}] \\ &= X \frac{\sin(\pi X u)}{(\pi X u)} = X \mathrm{sinc}(\pi \mathrm{X} \mathrm{u}). \end{aligned}$$

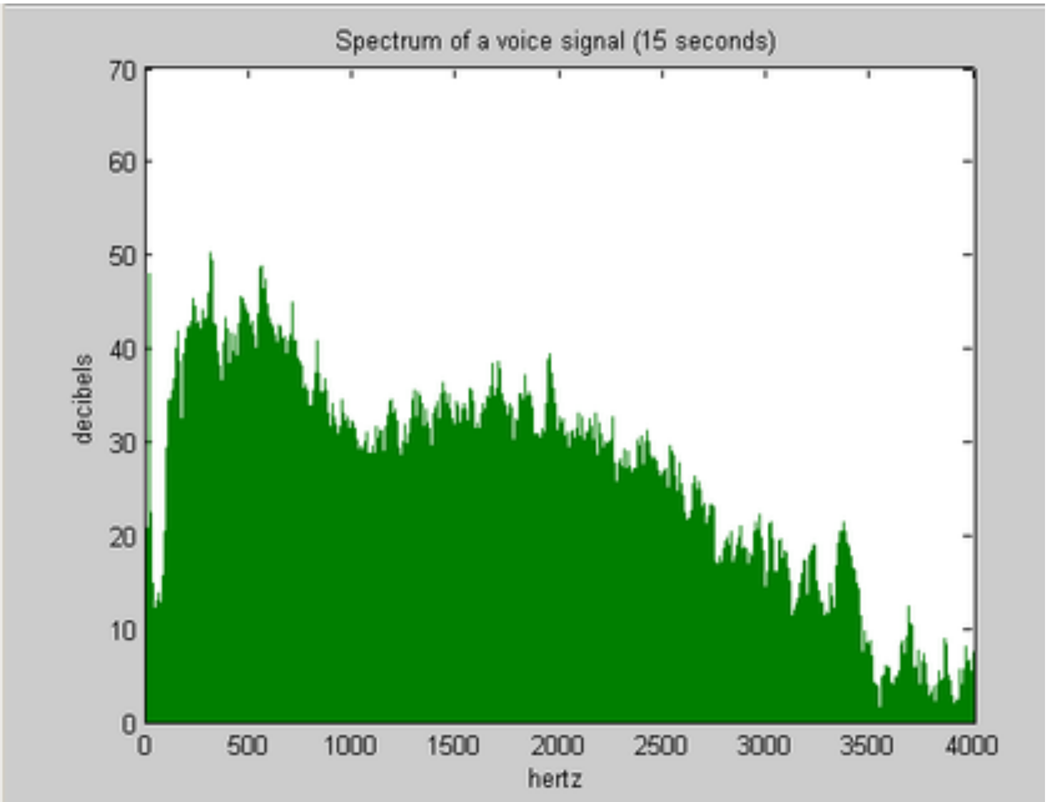
# Fourier Transform



# Example: Music

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



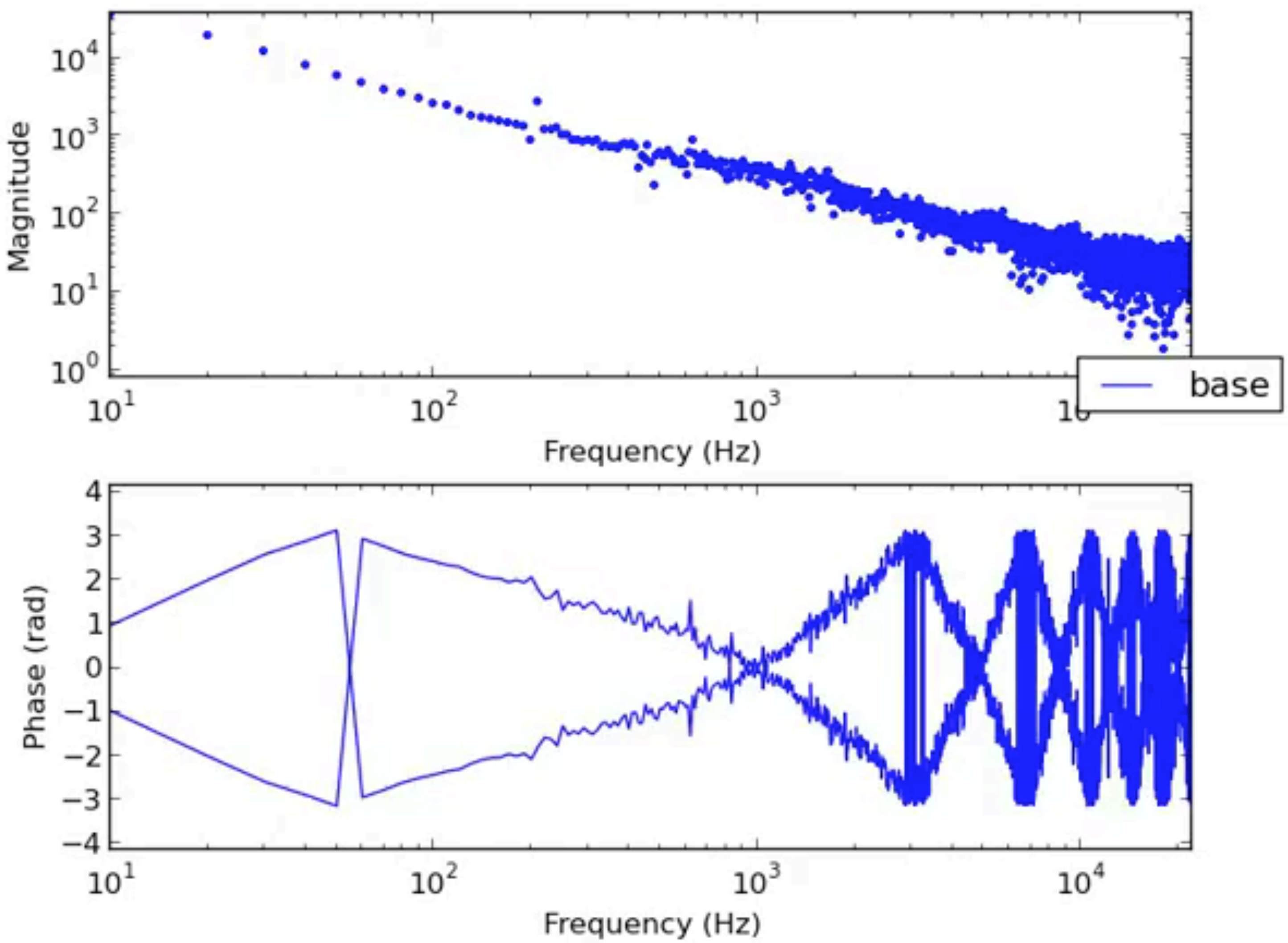




Slide: Hoiem

# Fourier Analysis of a Piano

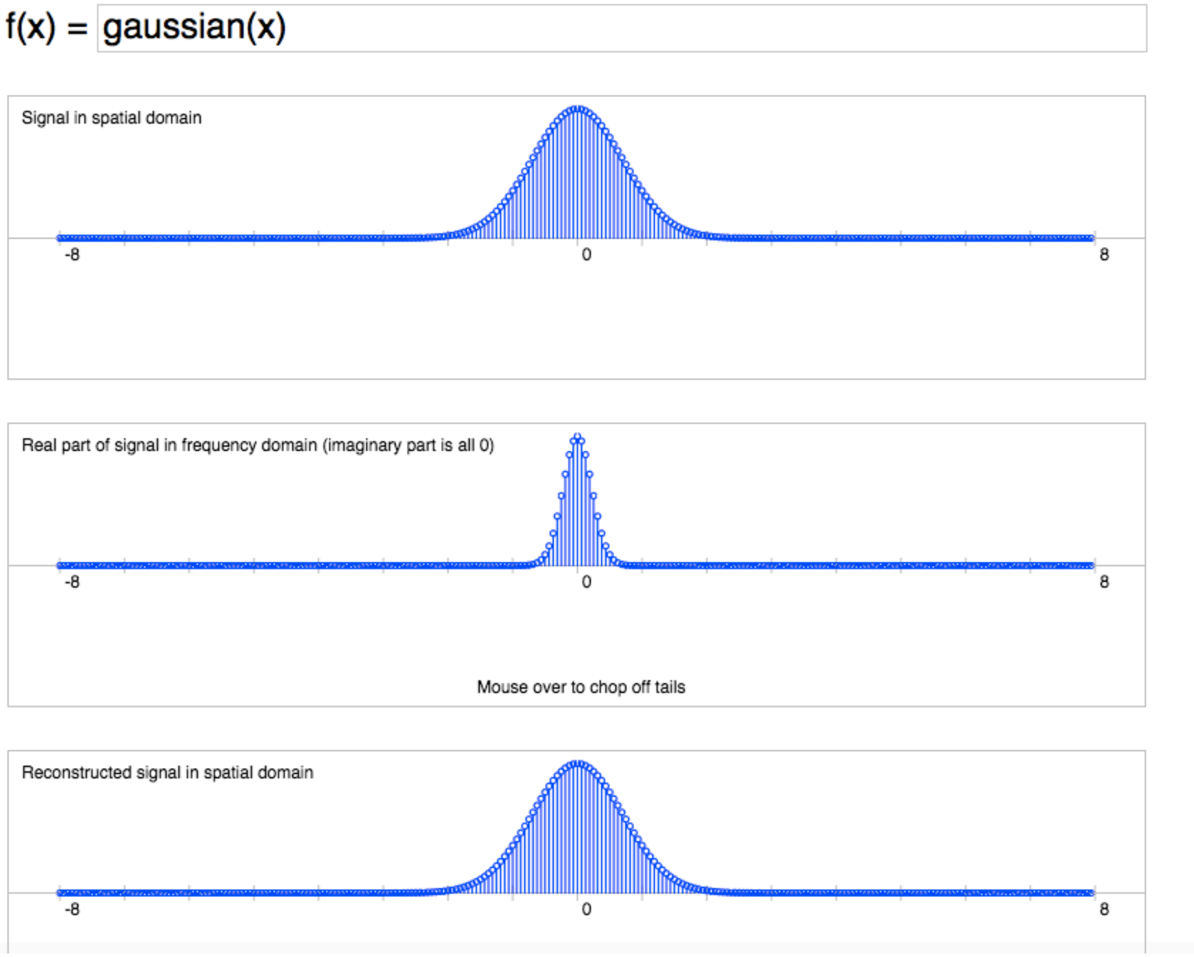
https://www.youtube.com/watch?v=6SR81Wh2cqU

# Fourier Analysis of a Piano



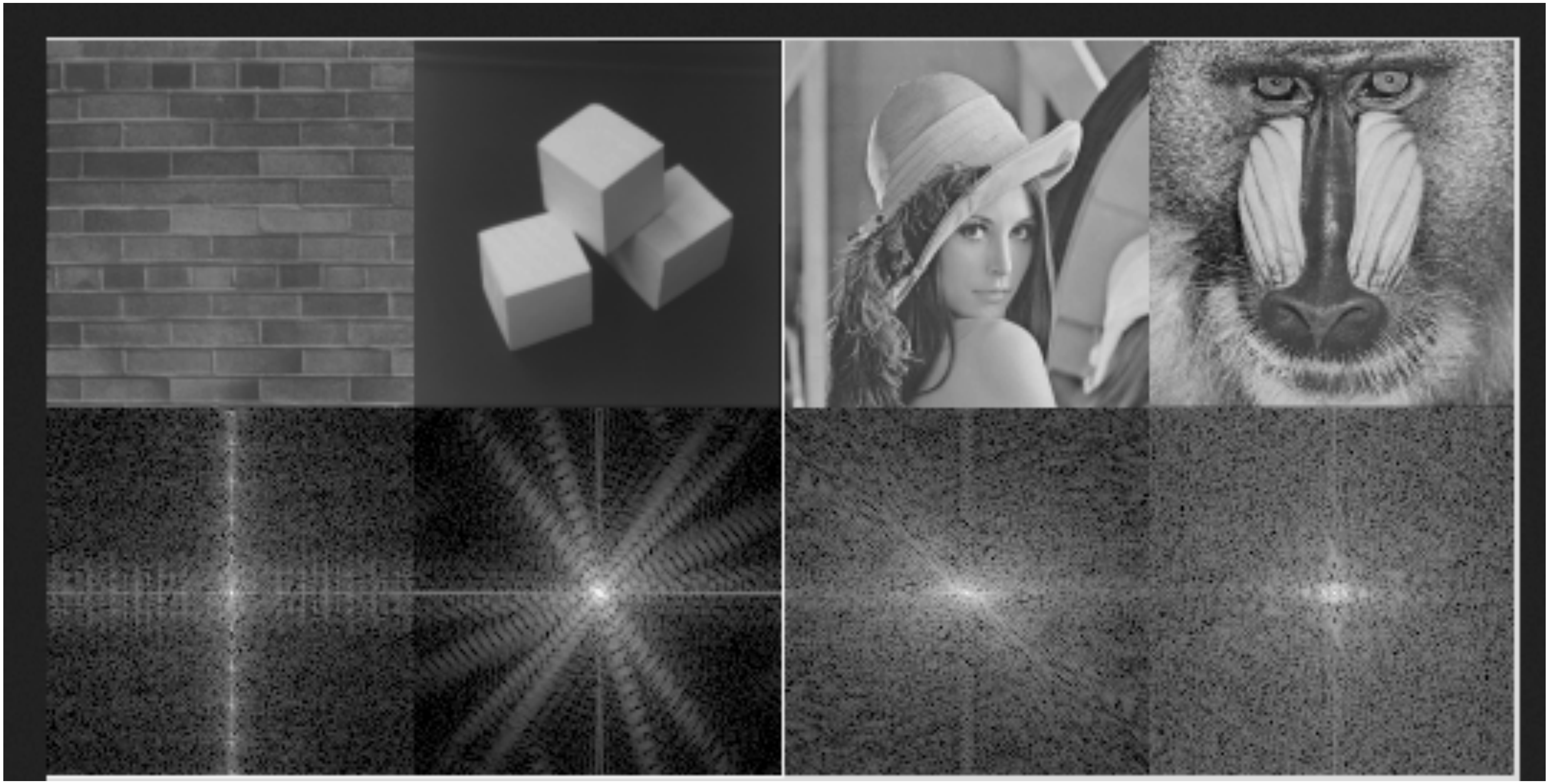
# Discrete Fourier Transform Demo

http://madebyevan.com/dft/




Evan Wallace

# 2D Fourier Transform



# 2D Fourier Transform

## Definition

$$F(u,v) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)e^{-j2\pi(ux+vy)}\,dx\,dy,$$

$$f(x,y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} F(u,v)e^{j2\pi(ux+vy)}\,du\,dv$$

where $u$ and $v$ are spatial frequencies.

Also will write FT pairs as $f(x,y) \Leftrightarrow F(u,v)$.

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# 2D Fourier Transform

- $F(u, v)$ is complex in general,

$$F(u, v) = F_{\mathrm{R}}(u, v) + jF_{\mathrm{I}}(u, v)$$

- $|F(u, v)|$ is the magnitude spectrum
- $\arctan(F_{\mathrm{I}}(u, v)/F_{\mathrm{R}}(u, v))$ is the phase angle spectrum.
- Conjugacy: $f^*(x, y) \Leftrightarrow F(-u, -v)$
- Symmetry: $f(x, y)$ is even if $f(x, y) = f(-x, -y)$

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# Sinusoidal Waves

In 1D the Fourier transform is based on a decompostion into functions $e^{j2\pi ux} = \cos 2\pi ux + j \sin 2\pi ux$ which form an orthogonal basis. Similarly in 2D

$$e^{j2\pi(ux+vy)} = \cos 2\pi(ux + vy) + j \sin 2\pi(ux + vy)$$

The real and imaginary terms are sinusoids on the $x, y$ plane. The maxima and minima of $\cos 2\pi(ux + vy)$ occur when

$$2\pi(ux + vy) = n\pi$$

# Sinusoidal Waves

write $ux + vy$ using vector notation with $\mathbf{u} = (u, v)^\top, \mathbf{x} = (x, y)^\top$ then

$$2\pi(ux + vy) = 2\pi\mathbf{u}.\mathbf{x} = n\pi$$

are sets of equally spaced parallel lines with normal $\mathbf{u}$ and wavelength $1/\sqrt{u^2 + v^2}$.

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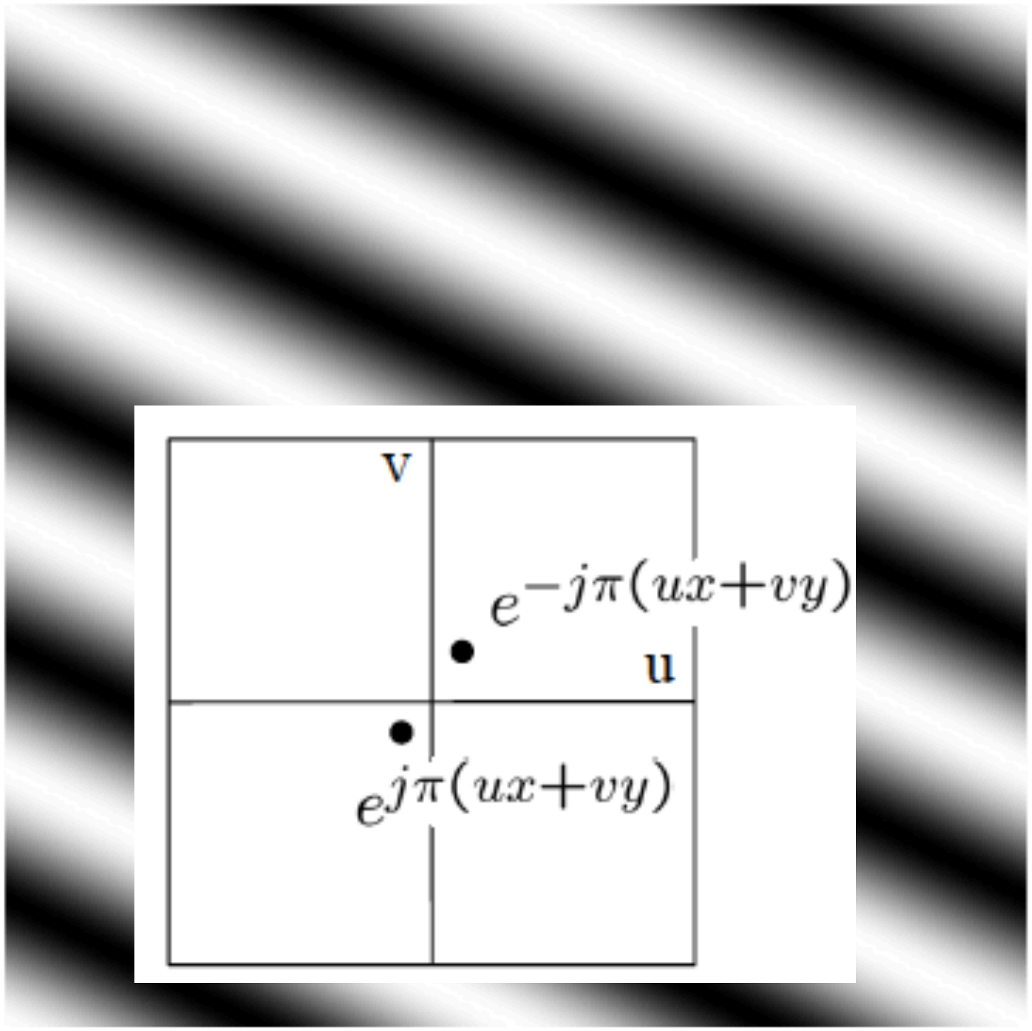
# Sinusoidal Waves

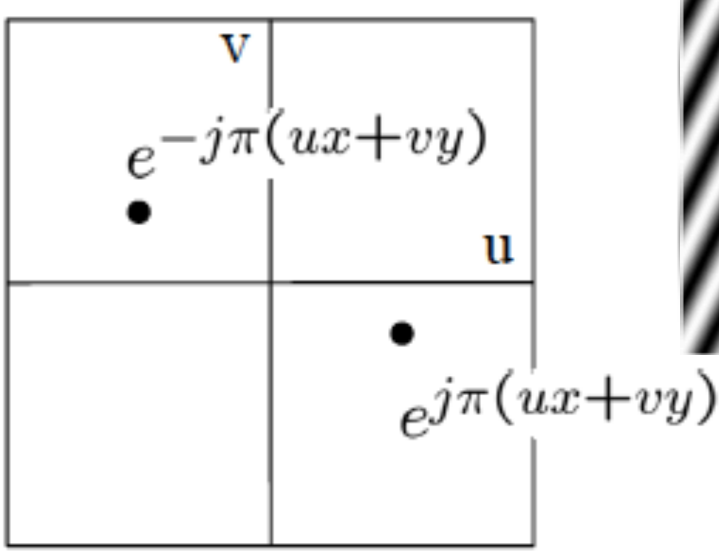
To get some sense of what basis elements look like, we plot a basis element --- or rather, its real part --- as a function of x,y for some fixed u, v. We get a function that is constant when (ux+vy) is constant. The magnitude of the vector (u, v) gives a frequency, and its direction gives an orientation. The function is a sinusoid with this frequency along the direction, and constant perpendicular to the direction.




slide: B. Freeman

# Sinusoidal Waves

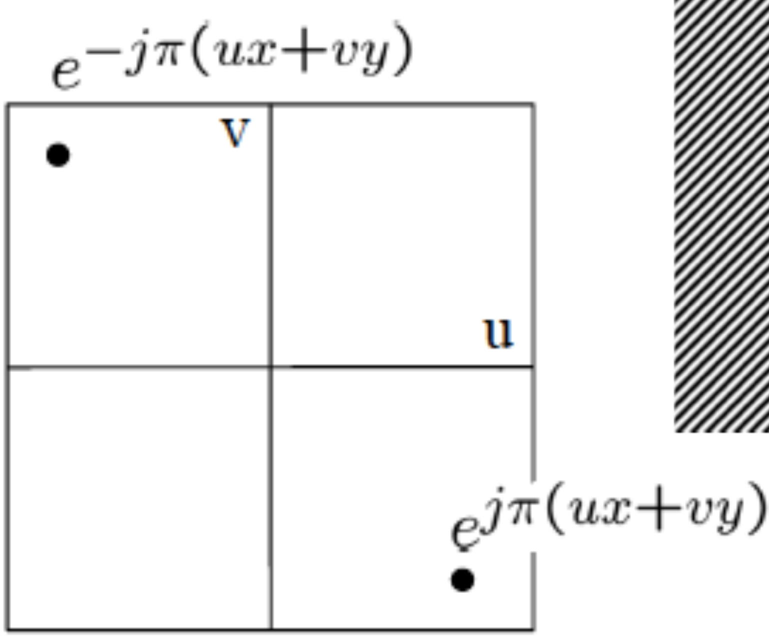
Here u and v are larger than in the previous slide.

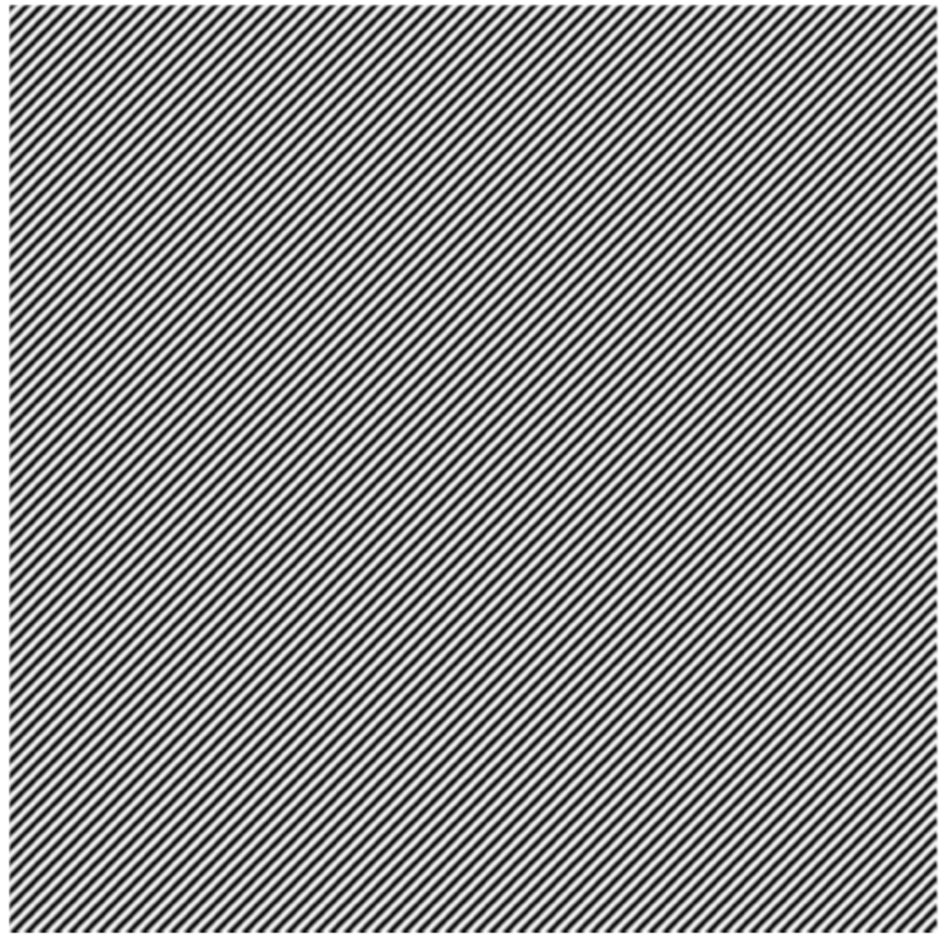



slide: B. Freeman

# Sinusoidal Waves

And larger still...

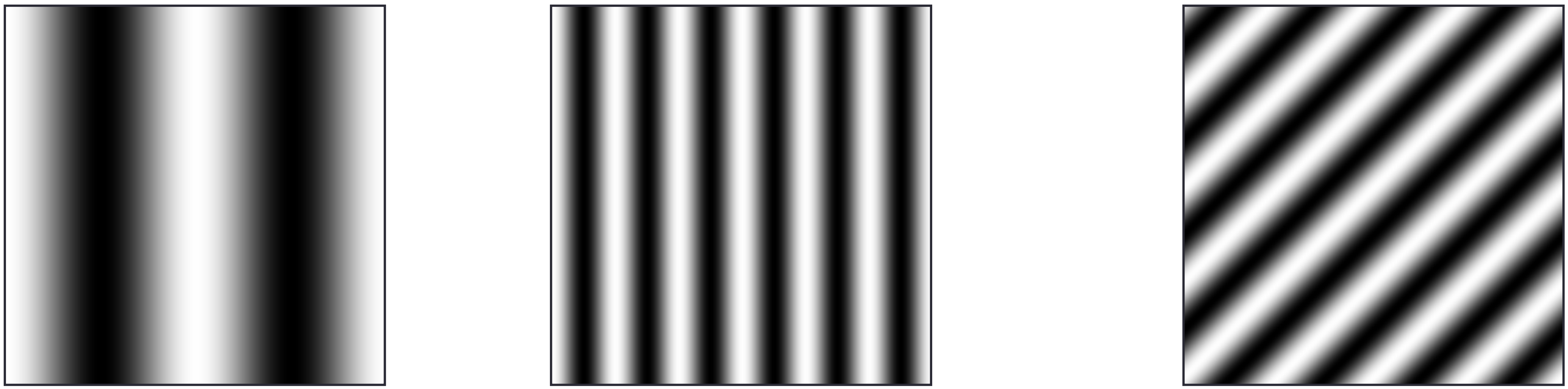


slide: B. Freeman

# Fourier analysis in images

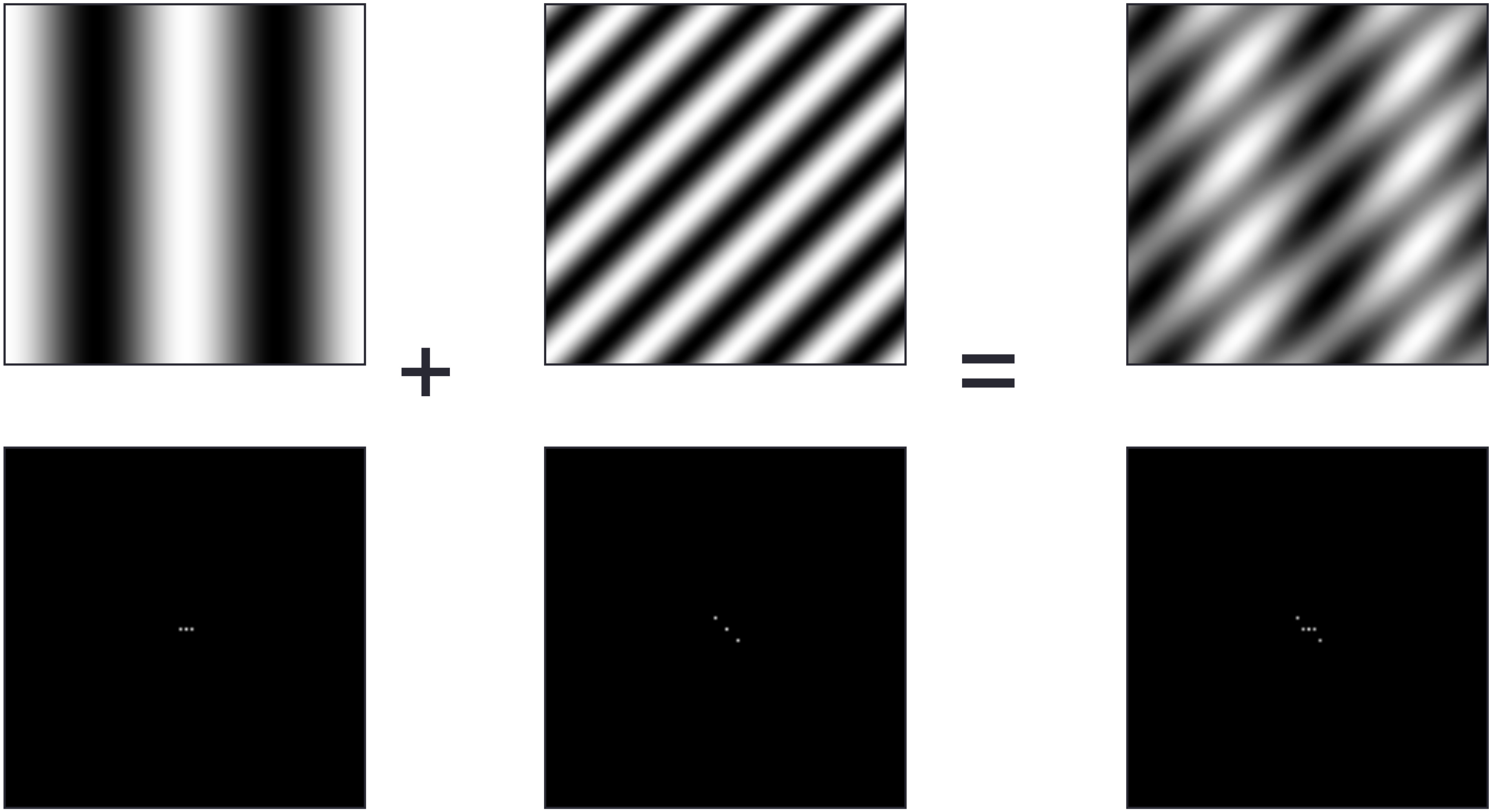
Intensity images



Fourier decomposition images

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

# Signals can be composed

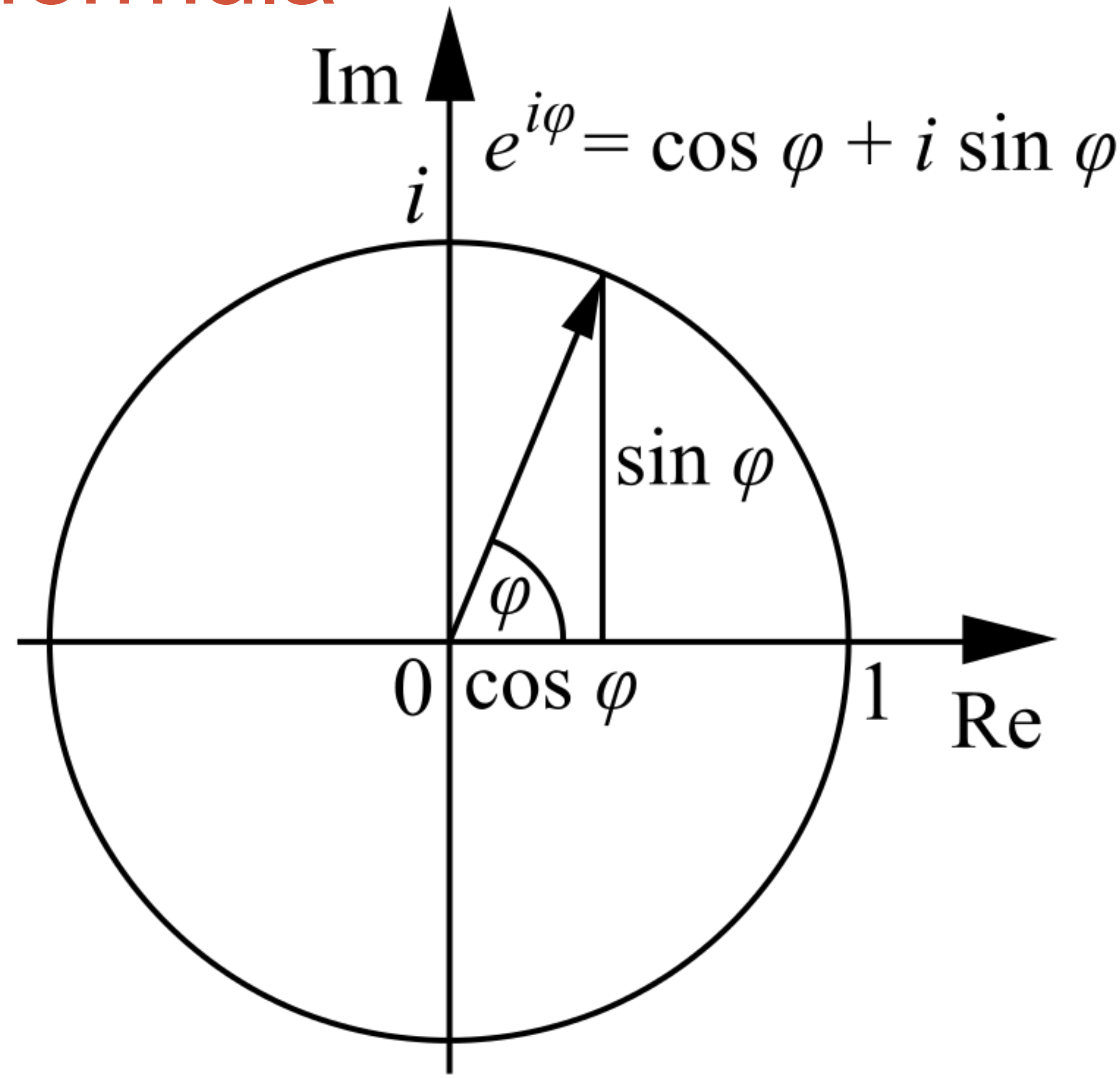


http://sharp.bu.edu/~slehar/fourier/fourier.html#filtering
More: http://www.cs.unm.edu/~brayer/vision/fourier.html

# Fourier Transform

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

# Euler's formula




Wikipedia

# Fourier Transform

- Stores the amplitude and phase at each frequency:
  - For mathematical convenience, this is often notated in terms of real and complex numbers
  - Related by Euler's formula
  - Amplitude encodes how much signal there is at a particular frequency

Amplitude: $$A = \pm\sqrt{\mathrm{Re}(\omega)^2 + \mathrm{Im}(\omega)^2}$$

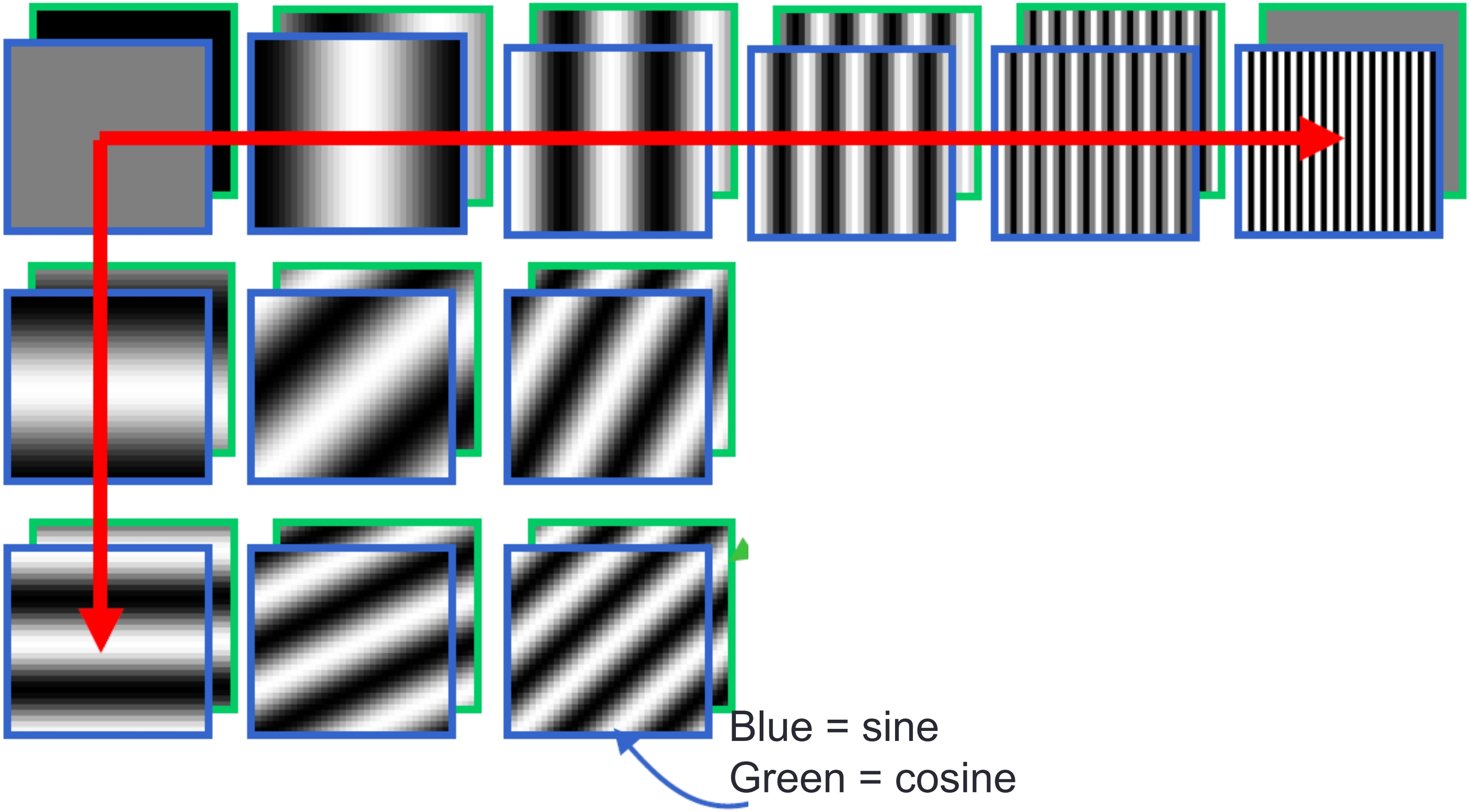
  - Phase encodes spatial information (indirectly)

Phase: $$\phi = \tan^{-1}\frac{\mathrm{Im}(\omega)}{\mathrm{Re}(\omega)}$$

Hays

# Fourier Bases

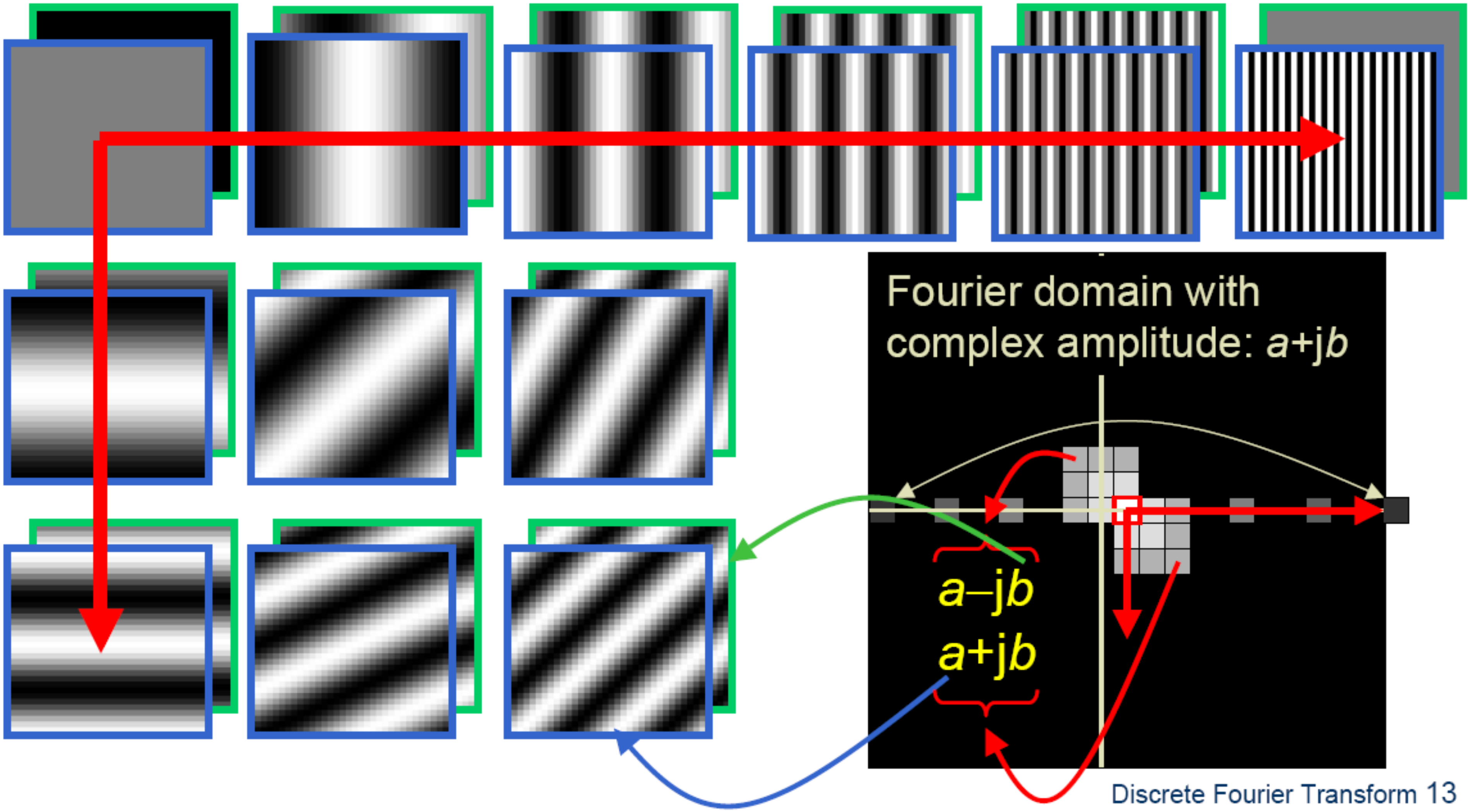
Teases away 'fast vs. slow' changes in the image.




This change of basis is the Fourier Transform

Hays

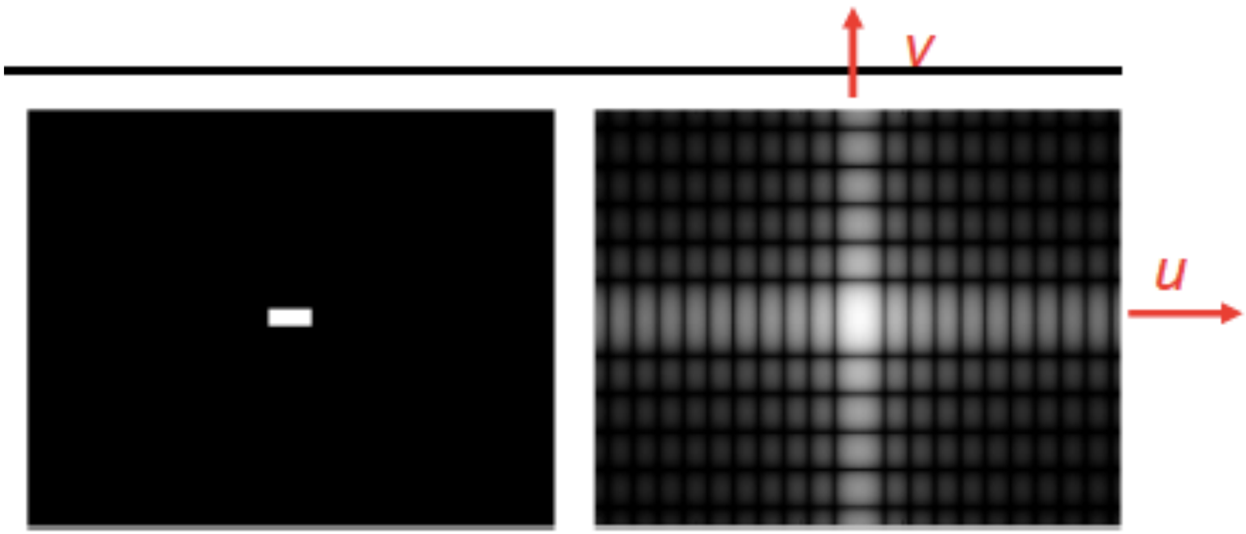
# Fourier Bases




Hays

# Important Fourier Transform Pairs

rectangle centred at origin
with sides of length $X$ and $Y$




$f(x,y)$ $|F(u,v)|$

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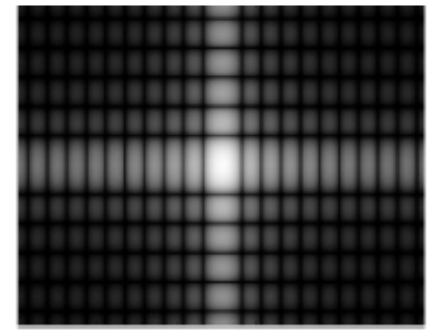
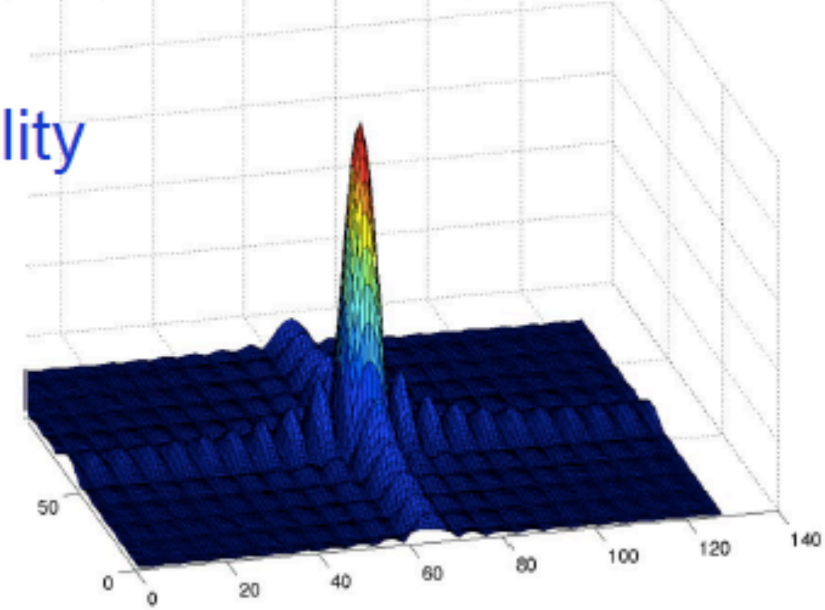
# Important Fourier Transform Pairs



$f(x,y)$ $|F(u,v)|$

$$
\begin{aligned}
F(u,v) &= \int\int f(x,y) e^{-j2\pi(ux+vy)} dx dy, \\
&= \int_{-X/2}^{X/2} e^{-j2\pi ux} dx \int_{-Y/2}^{Y/2} e^{-j2\pi vy} dy, \\
&= \left[\frac{e^{-j2\pi ux}}{-j2\pi u}\right]_{-X/2}^{X/2} \left[\frac{e^{-j2\pi vy}}{-j2\pi v}\right]_{-Y/2}^{Y/2}, \\
&= \frac{1}{-j2\pi u}\left[e^{-juX} - e^{juX}\right] \frac{1}{-j2\pi v}\left[e^{-jvY} - e^{jvY}\right], \\
&= XY \left[\frac{sin(\pi X u)}{\pi X u}\right] \left[\frac{sin(2\pi Y v)}{\pi Y v}\right] \\
&= XY \mathrm{sinc}(\pi \mathrm{Xu}) \mathrm{sinc}(\pi \mathrm{Yv}).
\end{aligned}
$$

separability



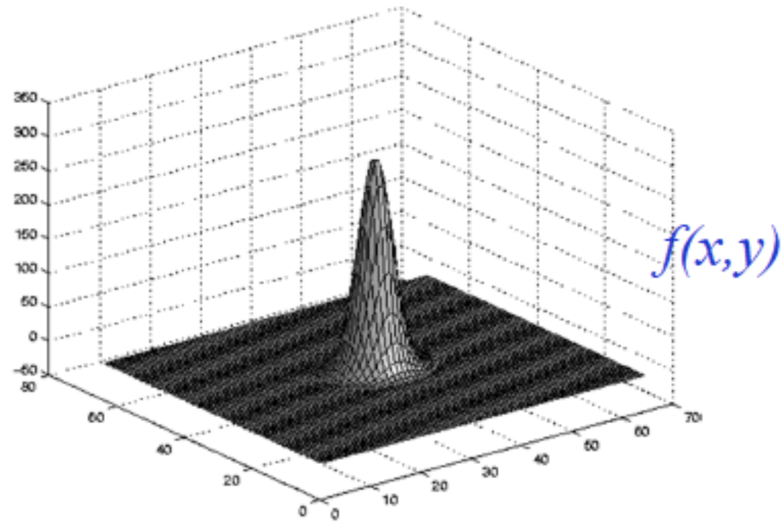

$|F(u,v)|$

# Important Fourier Transform Pairs

Gaussian centred on origin

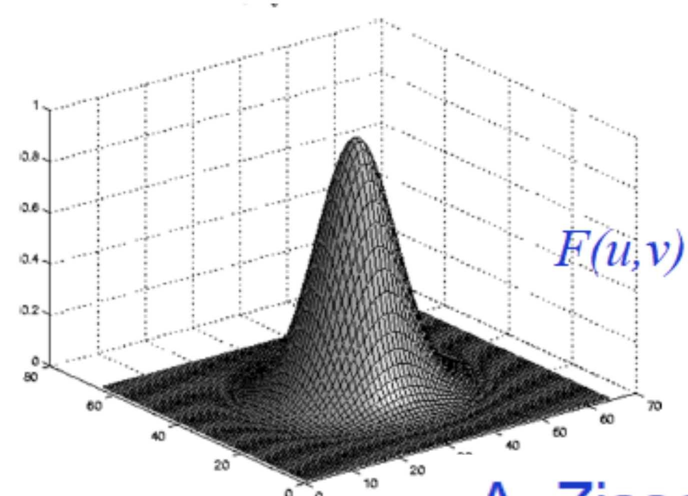
$$f(r) = \frac{1}{2\pi\sigma^2} e^{-r^2/2\sigma^2}$$

where $r^2 = x^2 + y^2$.




$$F(u,v) = F(\rho) = e^{-2\pi^2\rho^2\sigma^2}$$

where $\rho^2 = u^2 + v^2$.




- FT of a Gaussian is a Gaussian
- Note inverse scale relation

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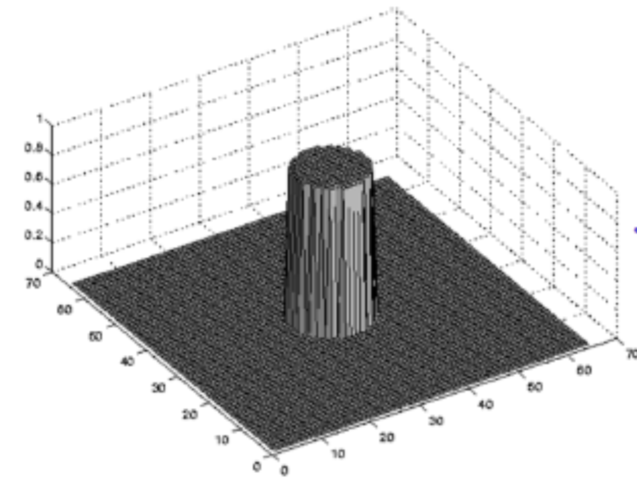
# Important Fourier Transform Pairs

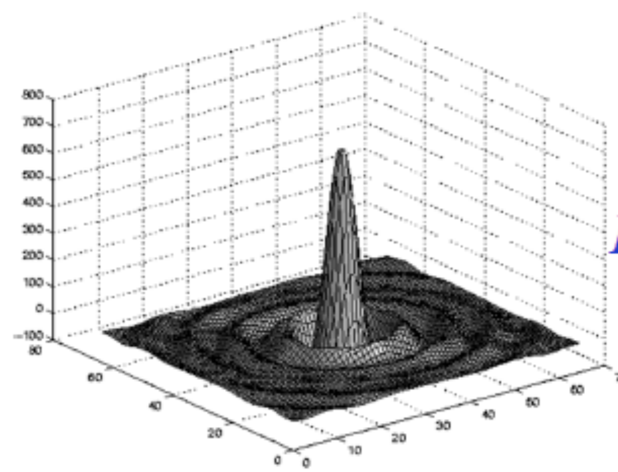
Circular disk unit height and radius *a* centred on origin

$$f(x,y) = \begin{cases} 1, & |r| < a, \\ 0, & |r| \geq a. \end{cases}$$




$$F(u,v) = F(\rho) = aJ_1(\pi a\rho)/\rho$$

where $J_1(x)$ is a Bessel function.




- rotational symmetry
- a '2D' version of a sinc

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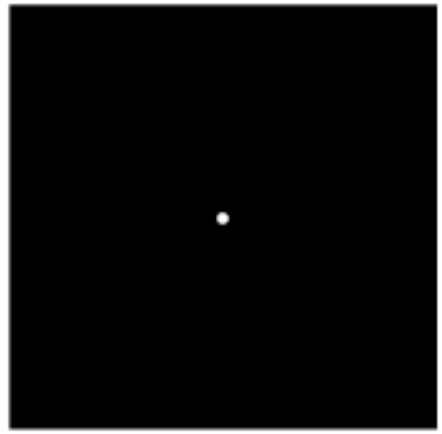
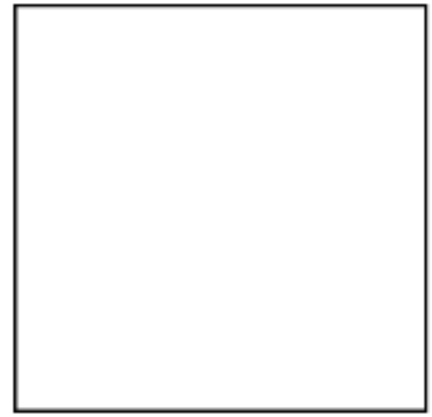
# Important Fourier Transform Pairs

$$f(x,y) = \delta(x,y) = \delta(x)\delta(y)$$

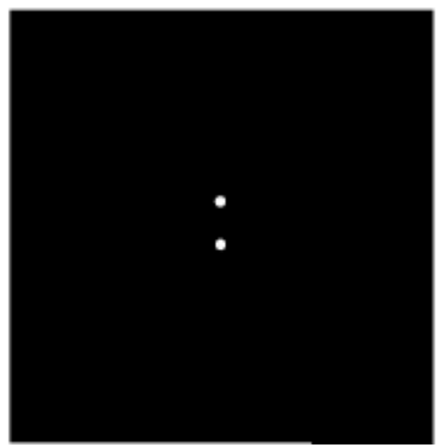
$$F(u,v) = \int\int \delta(x,y) e^{-j2\pi(ux+vy)}\,dxdy$$

$$= 1$$





*f(x,y)* *F(u,v)*



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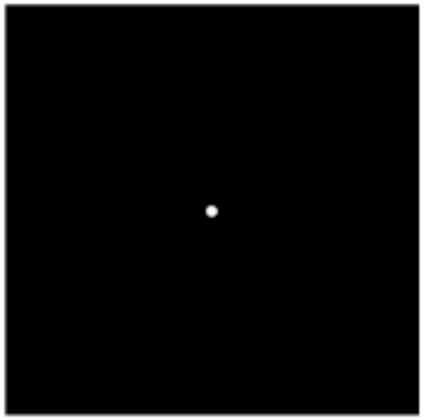
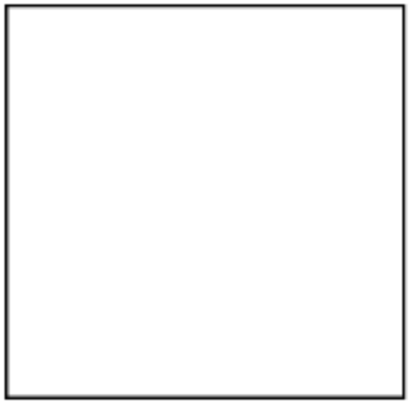
# Important Fourier Transform Pairs

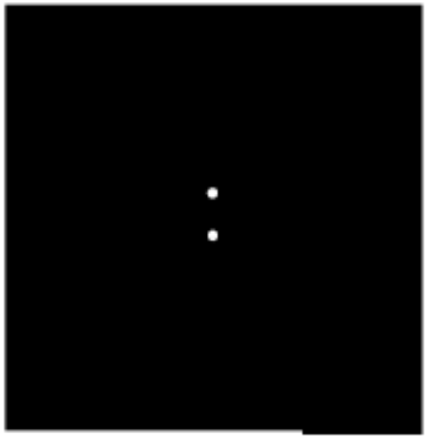
$$f(x,y) = \delta(x,y) = \delta(x)\delta(y)$$

$$\begin{aligned} F(u,v) &= \int\int \delta(x,y) e^{-j2\pi(ux+vy)}\,dxdy \\ &= 1 \end{aligned}$$





$$f(x,y) = \frac{1}{2}\left(\delta(x,y-a) + \delta(x,y+a)\right)$$



$$\begin{aligned} F(u,v) &= \frac{1}{2}\int\int \left(\delta(x,y-a) + \delta(x,y+a)\right) e^{-j2\pi(ux+vy)}\,dxdy \\ &= \frac{1}{2}\left(e^{-j2\pi av} + e^{j2\pi av}\right) = \cos 2\pi av \end{aligned}$$

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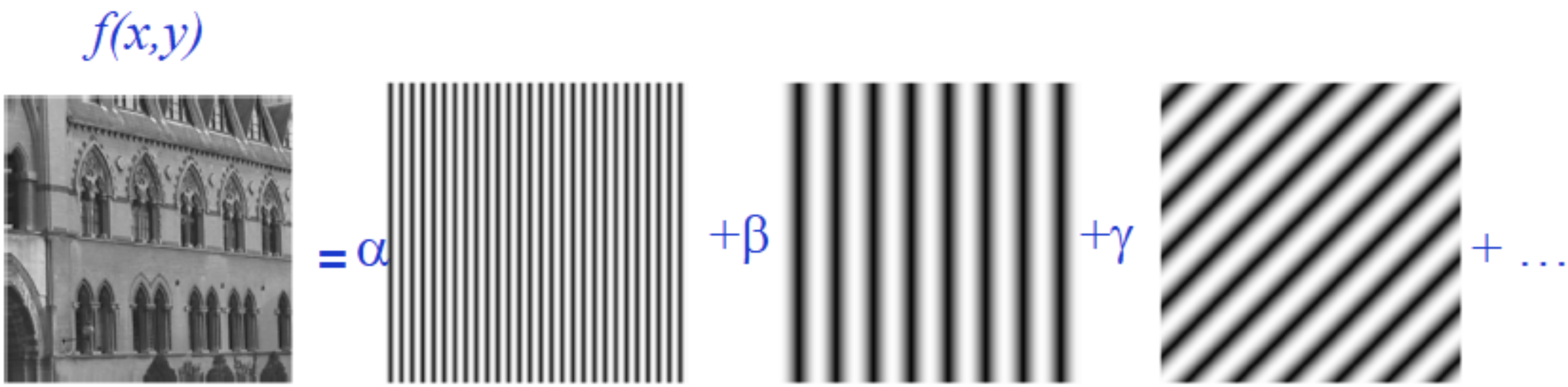
# 2D Fourier Decomposition

The spatial function $f(x, y)$

$$f(x,y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} F(u,v)e^{j2\pi(ux+vy)}\,du\,dv$$

is decomposed into a weighted sum of 2D orthogonal basis functions in a similar manner to decomposing a vector onto a basis using scalar products.

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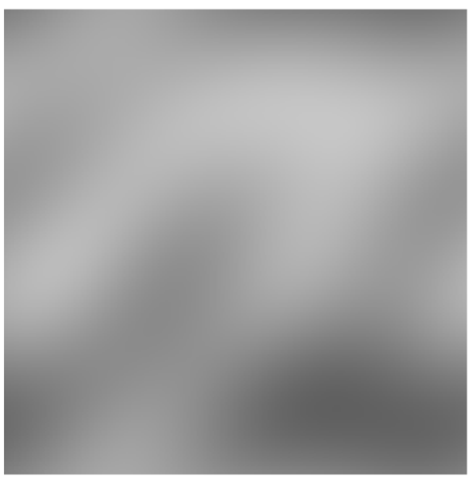
# Basis reconstruction

Full image

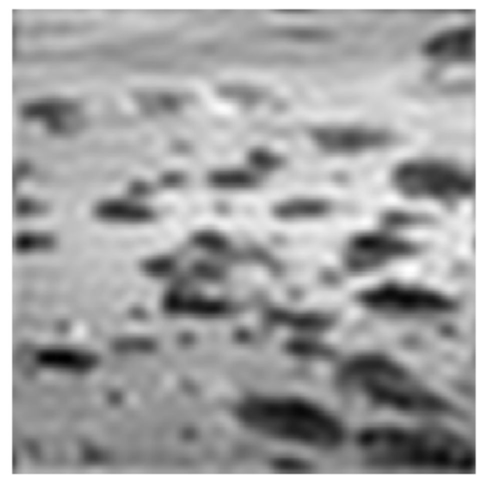
First 1 basis fn

First 4 basis fns



First 9 basis fns

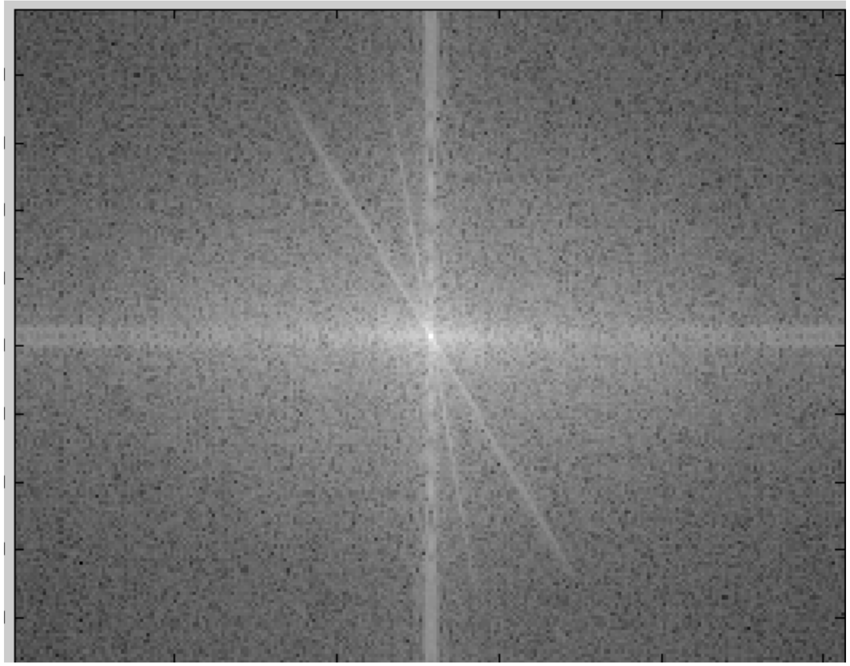
First 16 basis fns



First 400 basis fns

Danny Alexander

# 2D Fourier Transform of Real Images

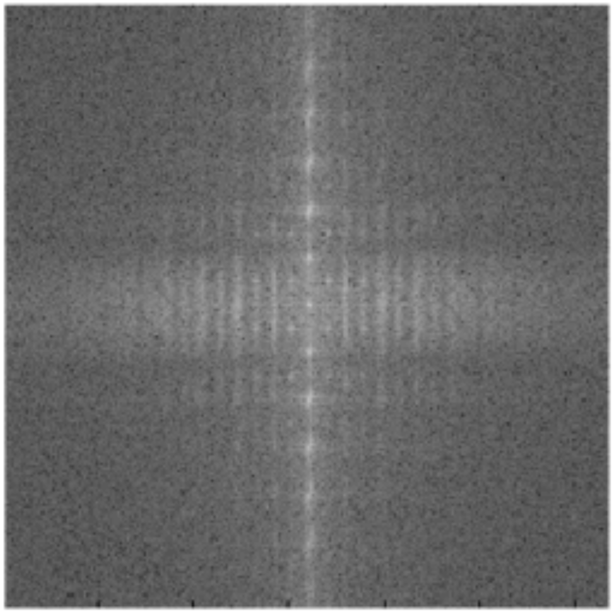


What does it mean to be at pixel x,y?
What does it mean to be more or less bright in the Fourier decomposition image?

# 2D Fourier Transform of Real Images

Image with periodic structure

$f(x,y)$



$|F(u,v)|$

FT has peaks at spatial frequencies of repeated texture

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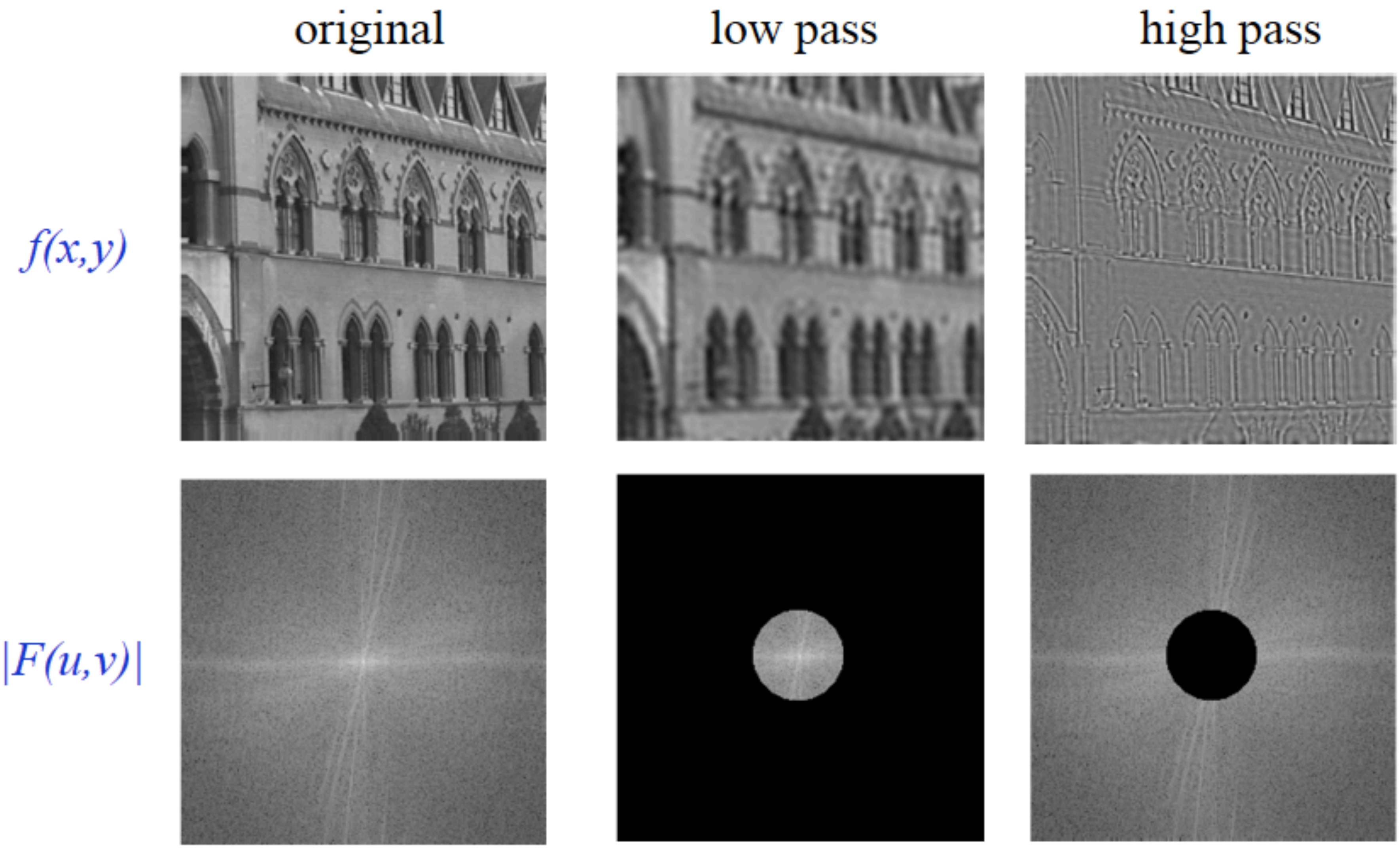
# Low/High Pass Filters

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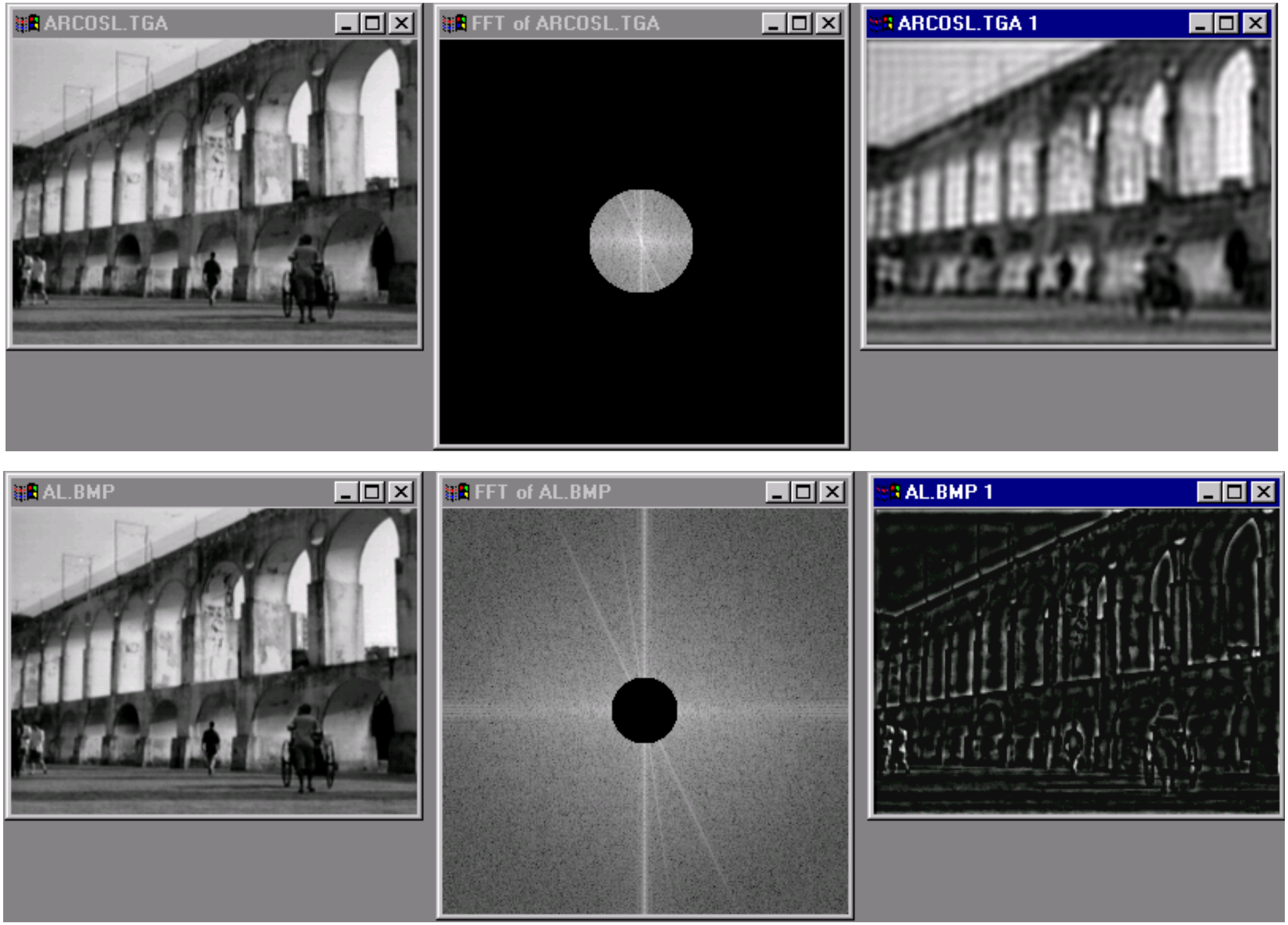
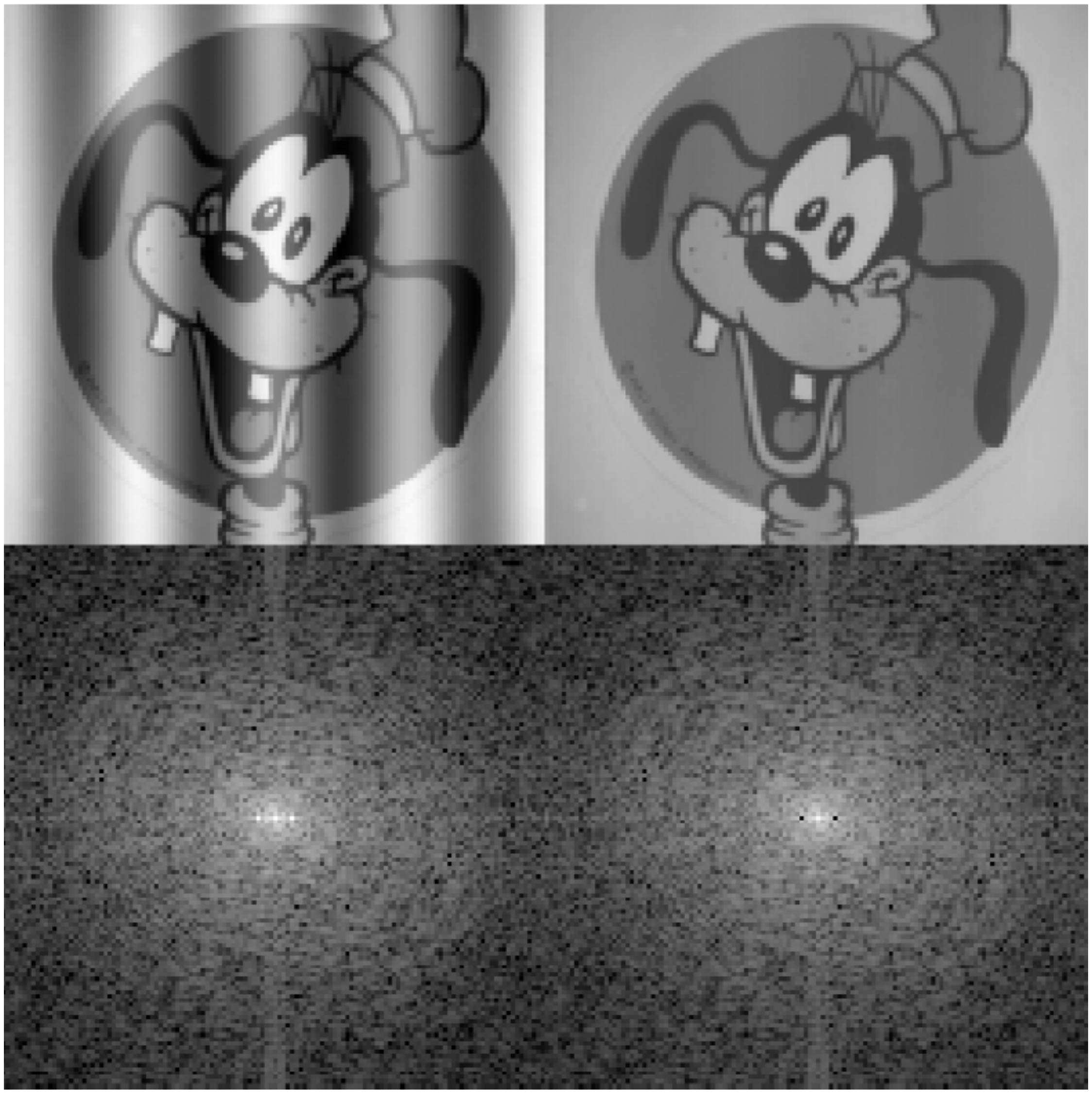
# Low and High Pass filtering



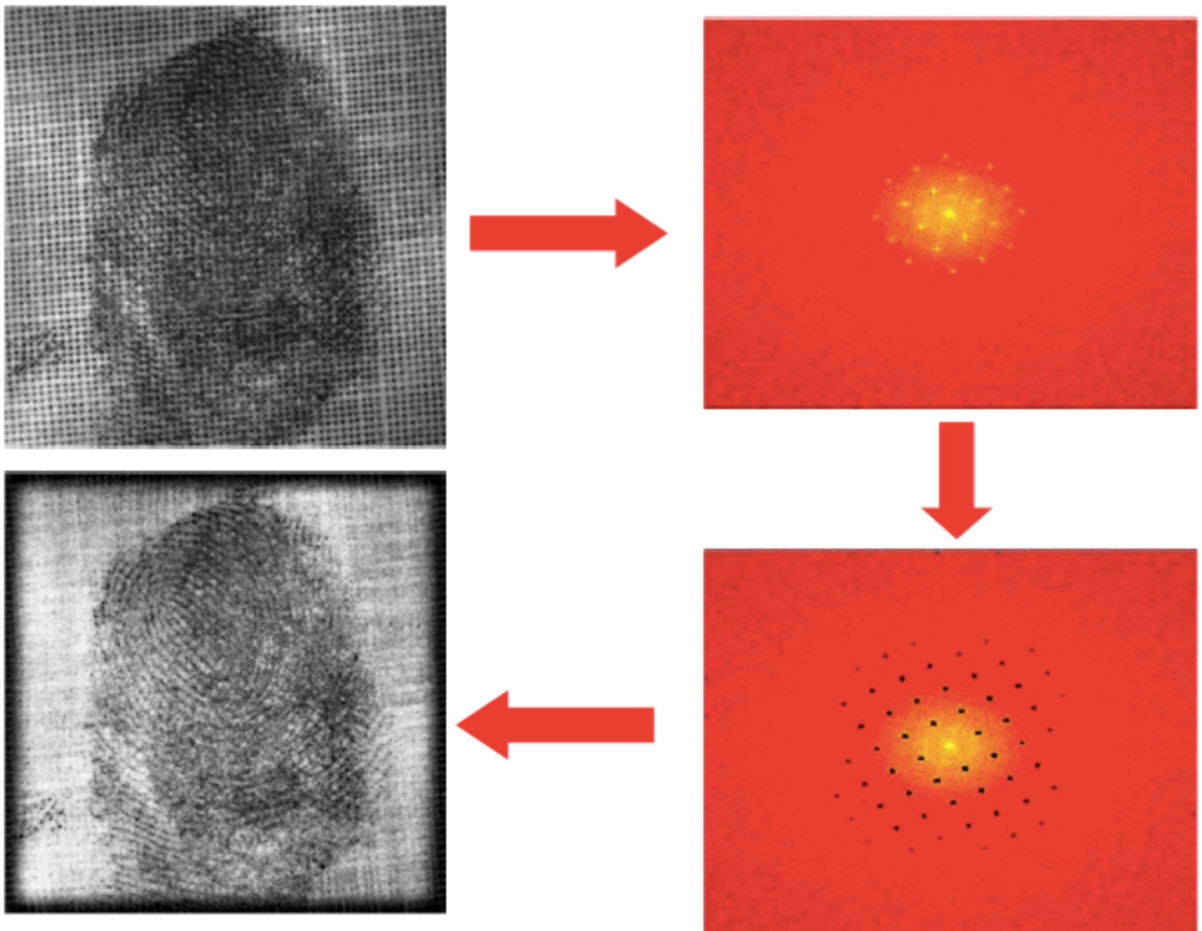
# Removing frequency bands



Brayer

# Removing frequency bands

## Example – Forensic application



$|F(u,v)|$

remove
peaks

Periodic background removed

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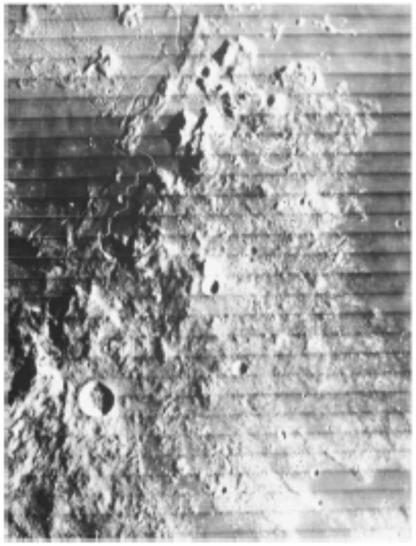
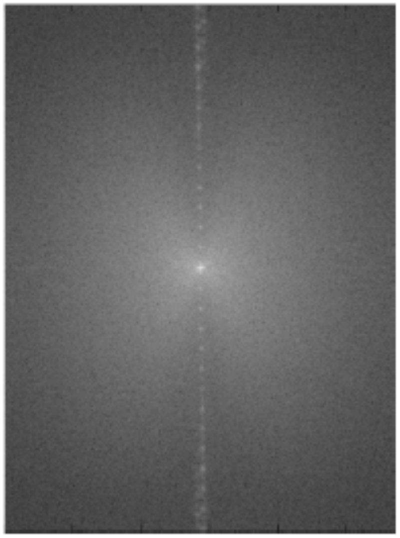
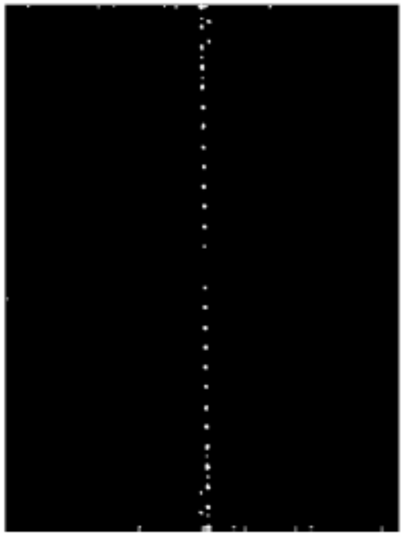
# Removing frequency bands

Lunar orbital image (1966)





$|F(u,v)|$



remove
peaks

join lines
removed

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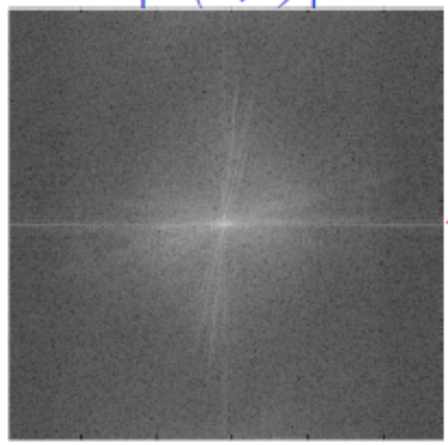
# Editting frequencies

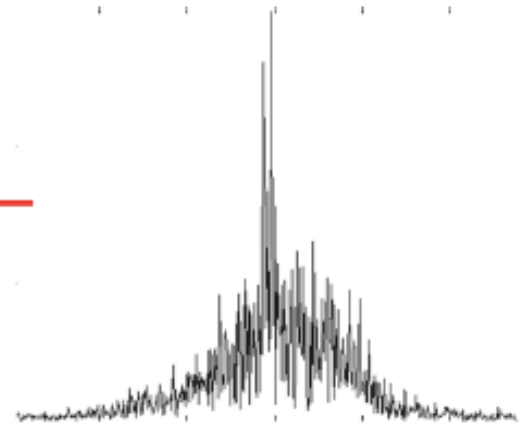
# Magnitude vs. Phase

$f(x,y)$

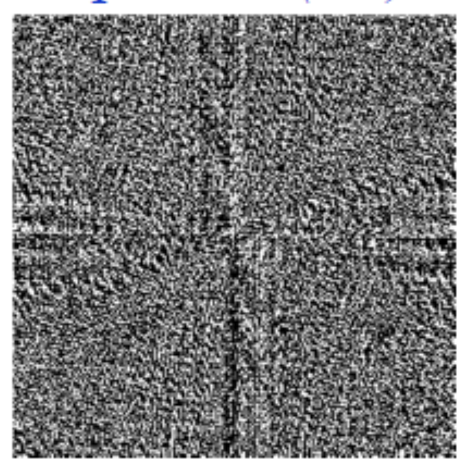
$|F(u,v)|$



cross-section



$\text{phase } F(u,v)$



- |f(u,v)| generally decreases with higher spatial frequencies
- phase appears less informative

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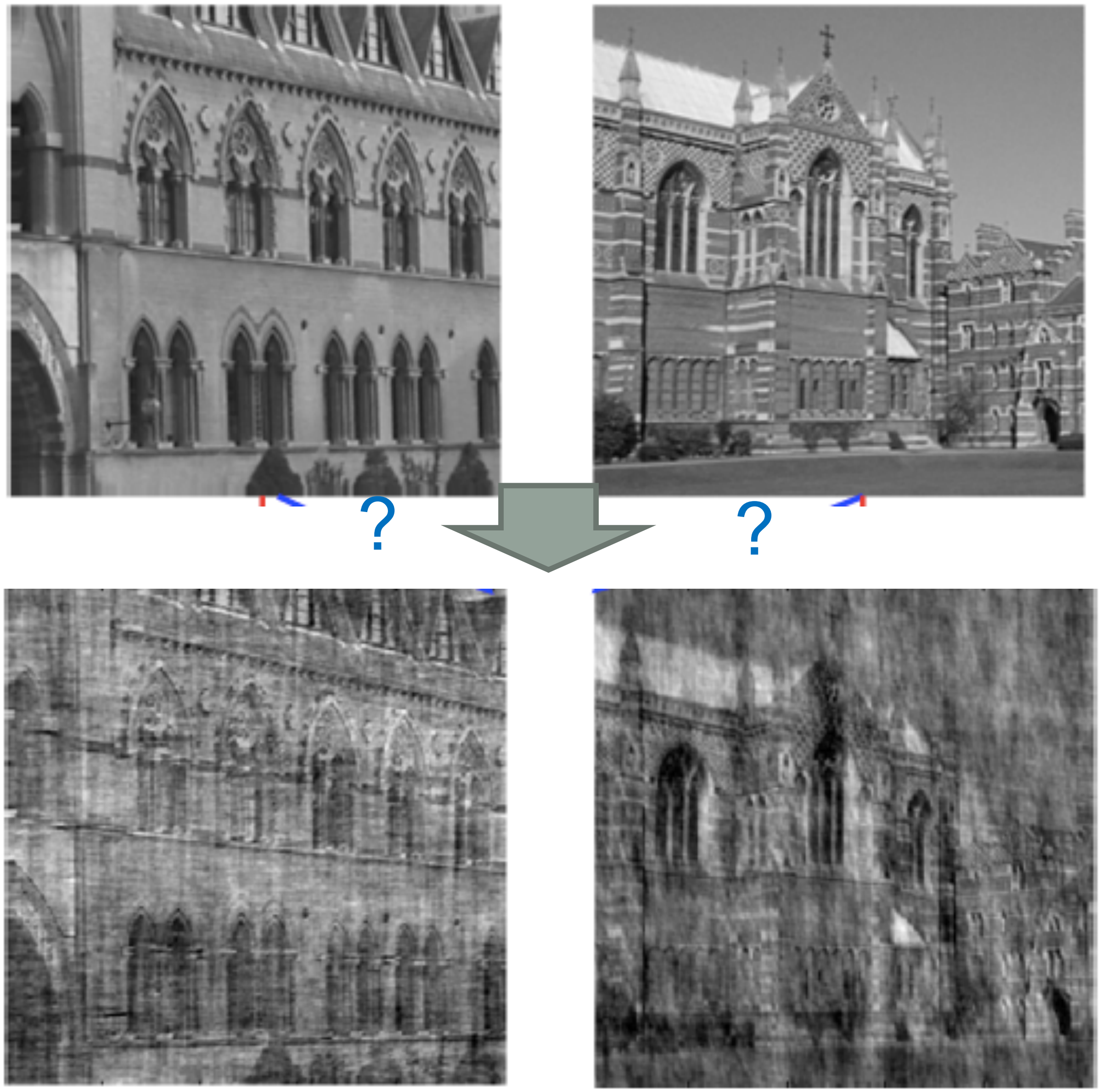
# The Importance of Phase

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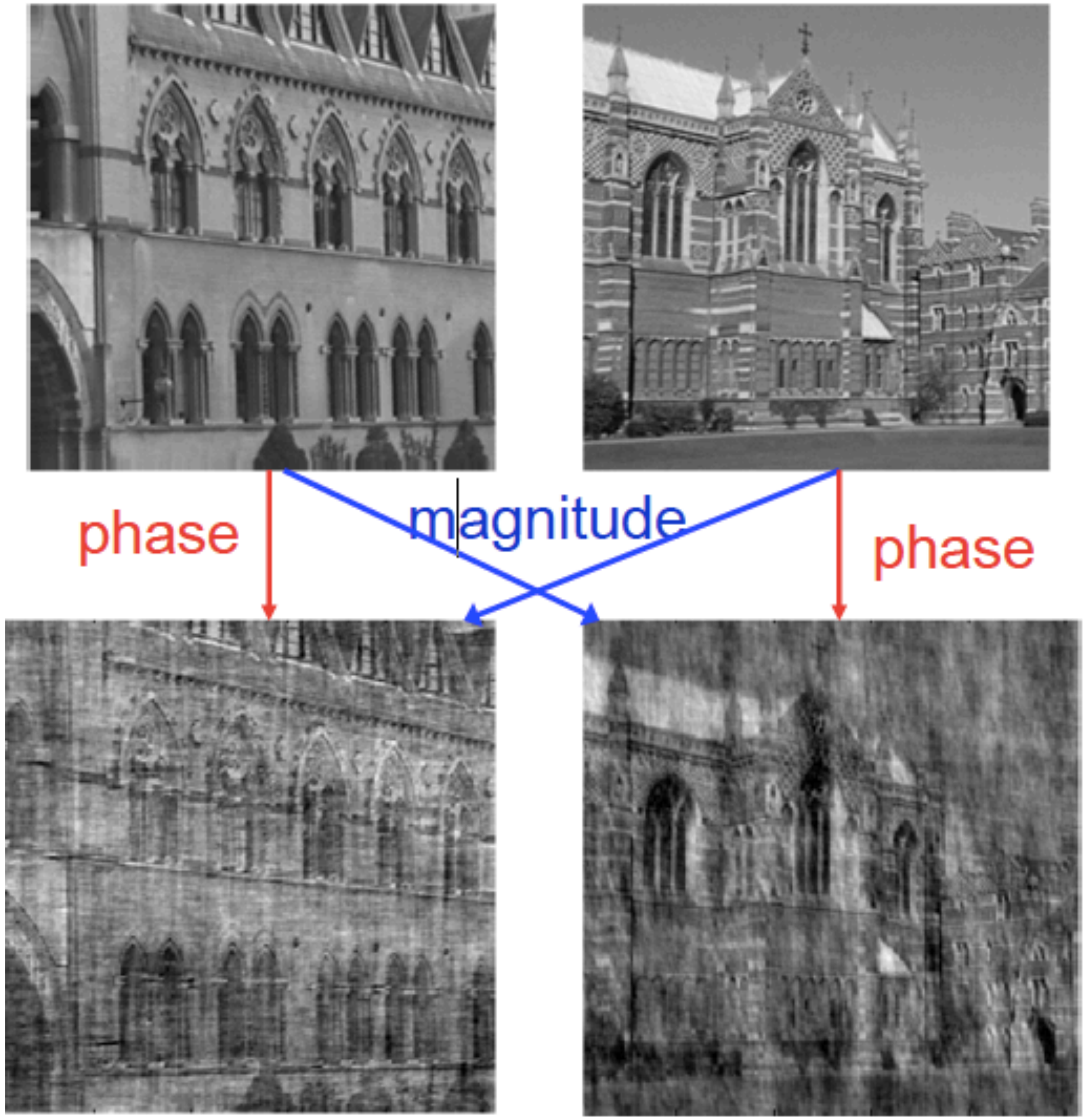
# The Importance of Phase

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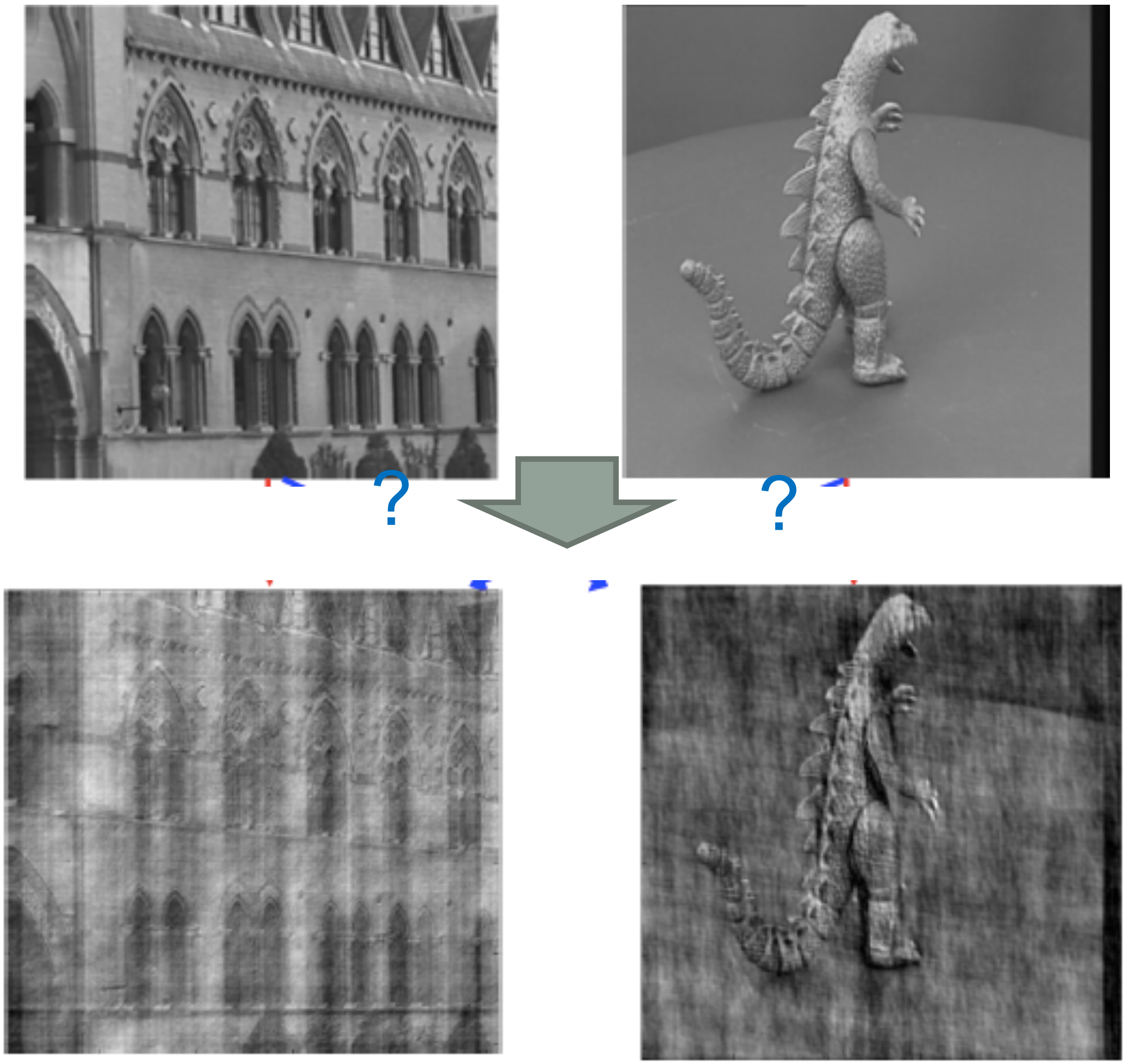
# Phase and Magnitude- Another Example

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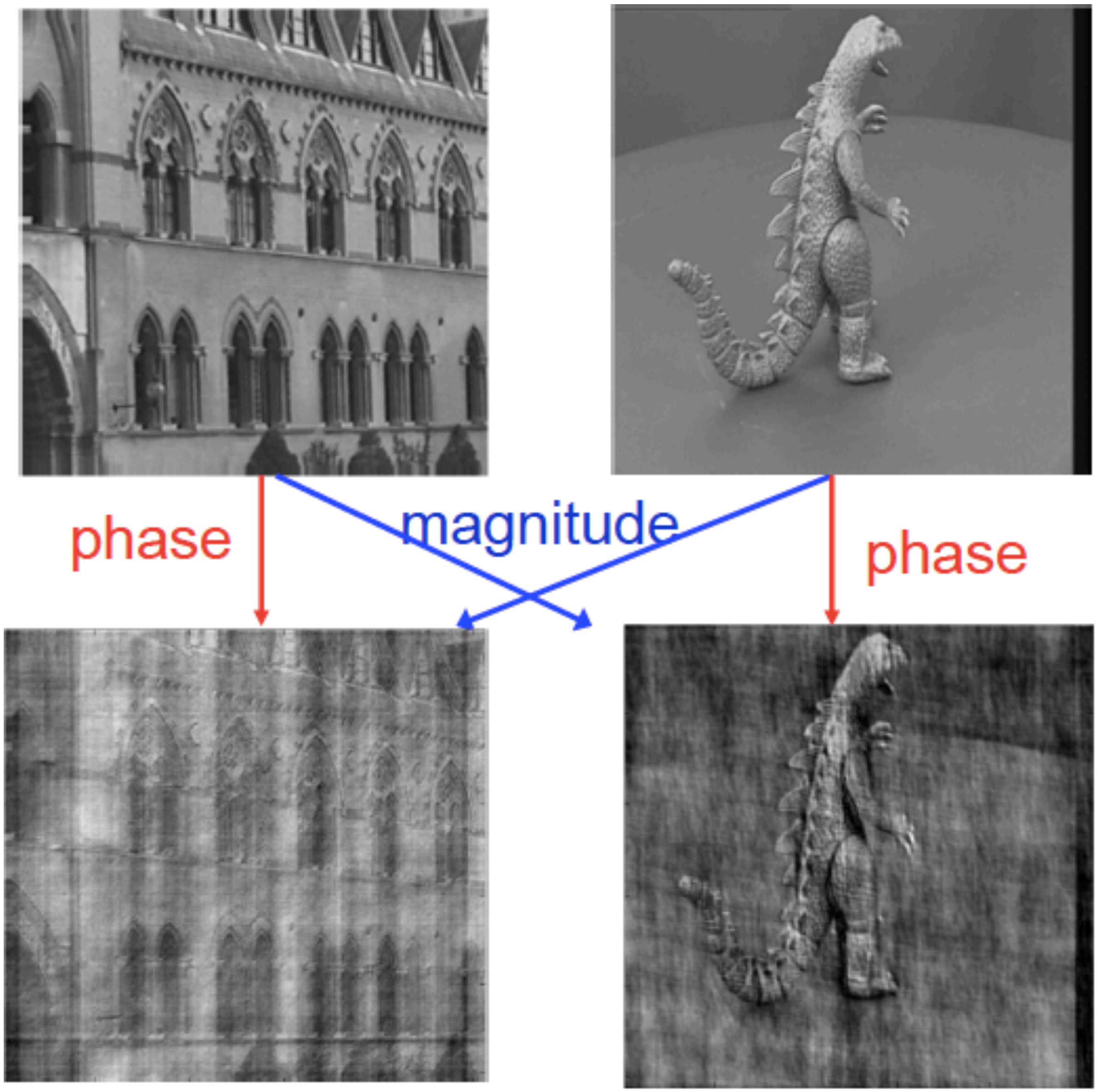
# The Importance of Phase

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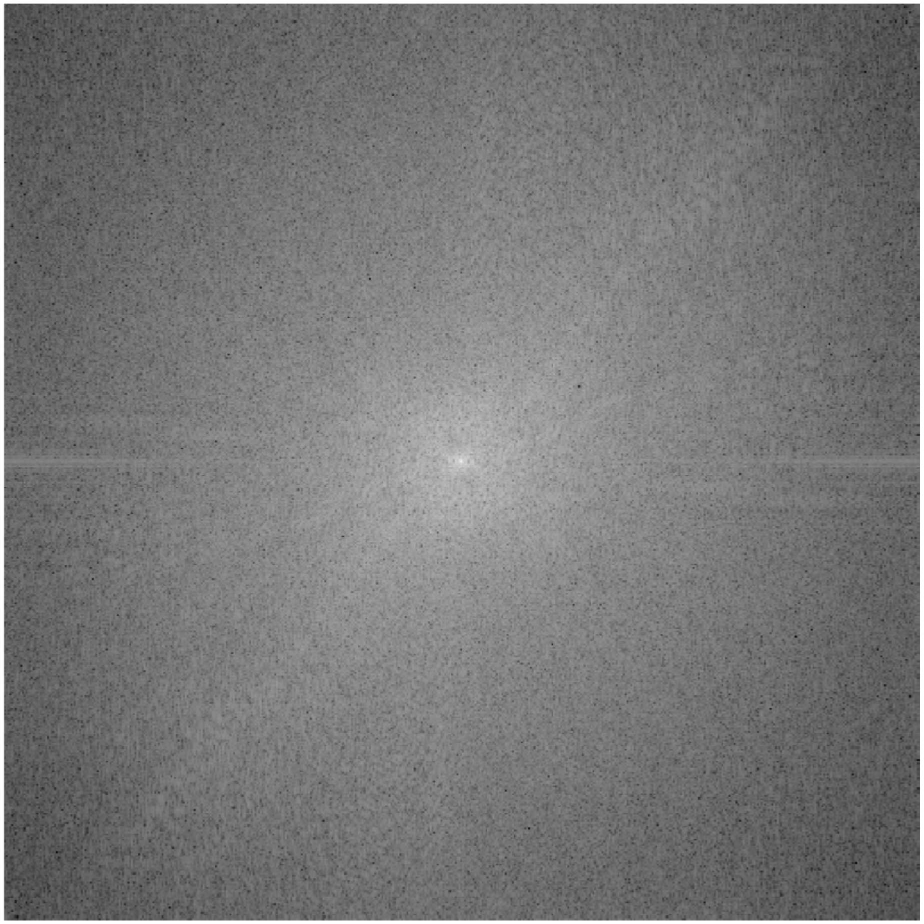
# Phase and Magnitude- Yet Another Example

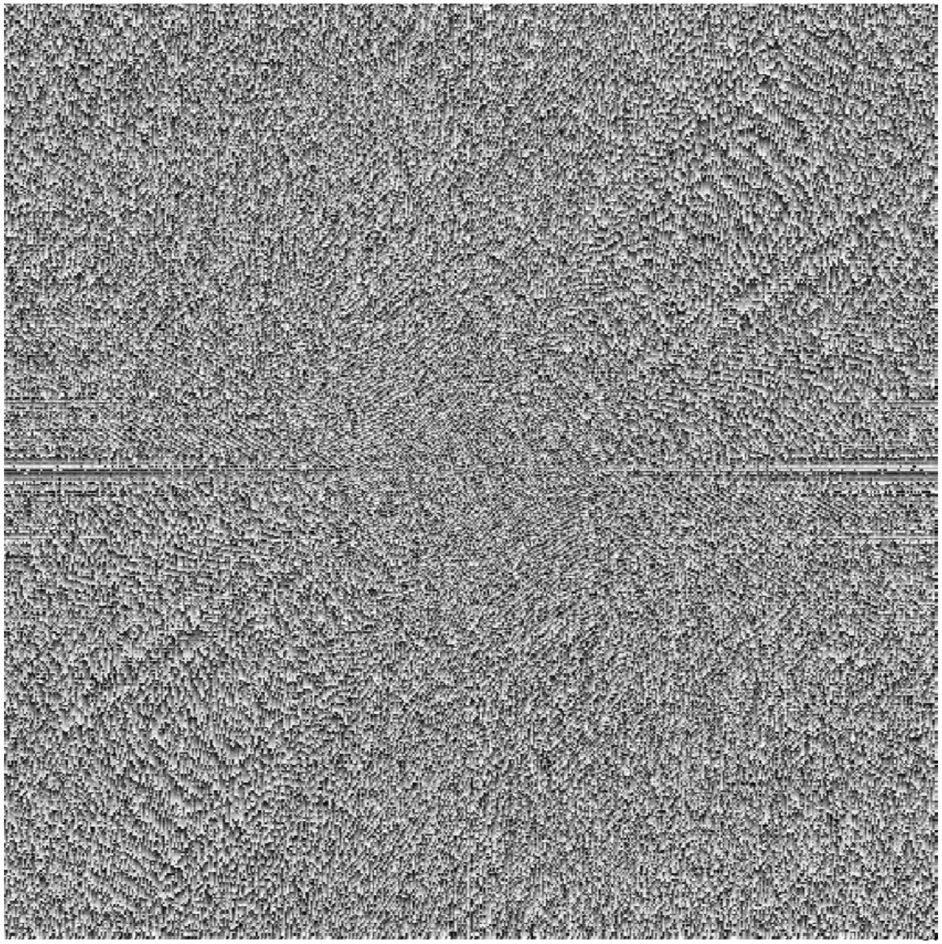
Efros

# Phase and Magnitude- Yet Another Example

Amplitude



Phase



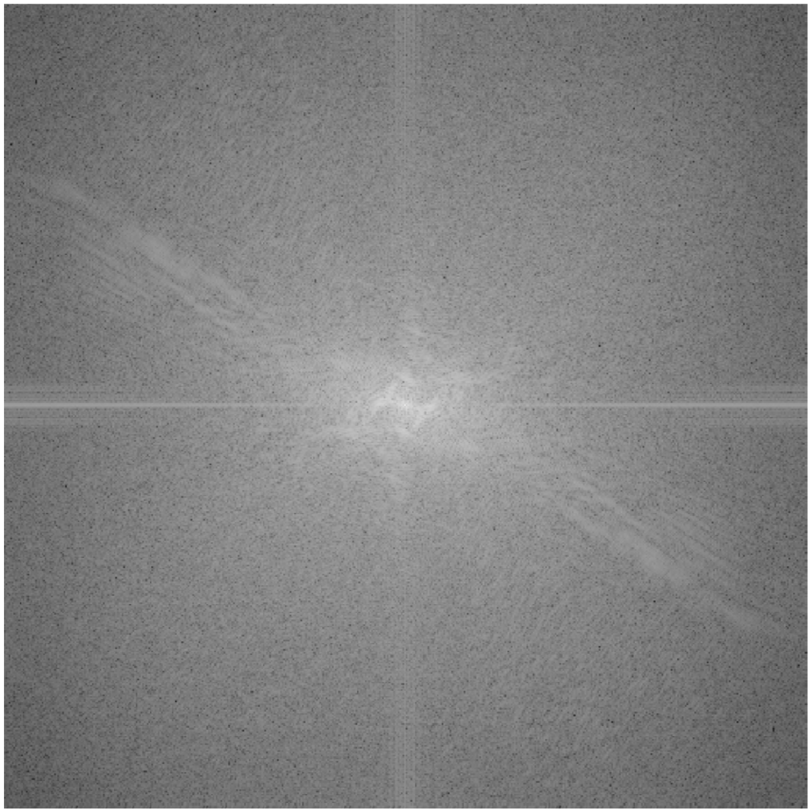
Efros

# Phase and Magnitude- Yet Another Example

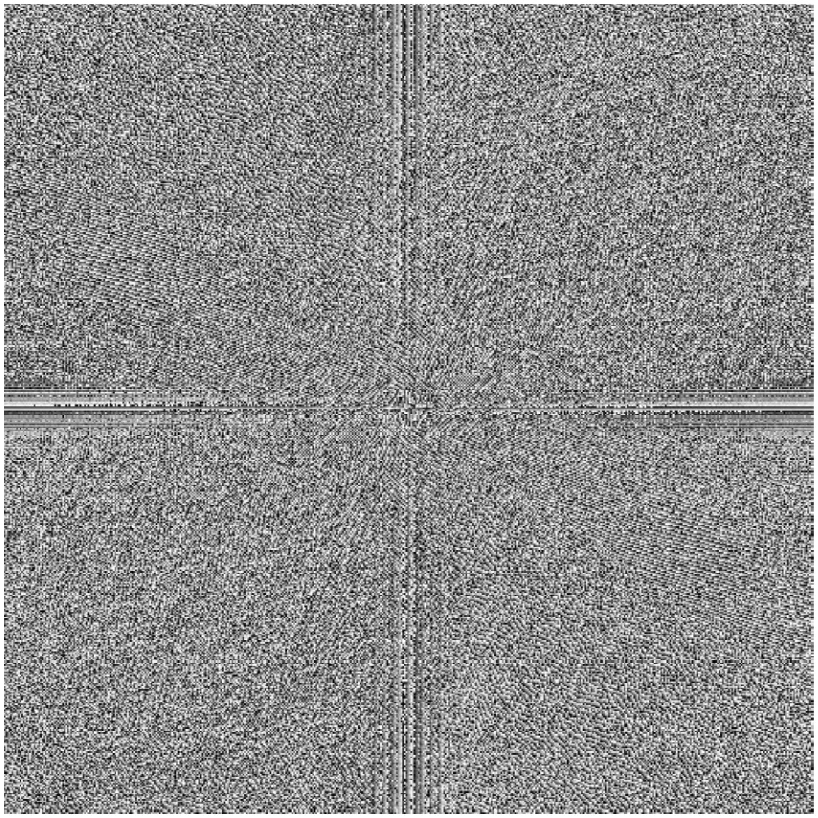
Efros

# What about phase?

Amplitude



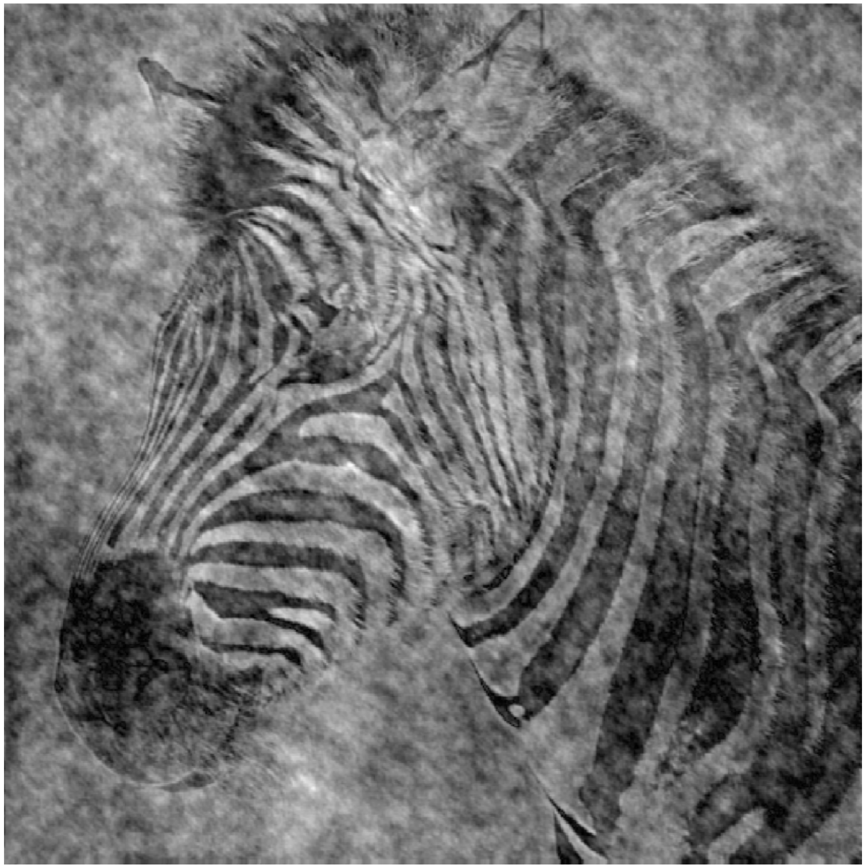
Phase



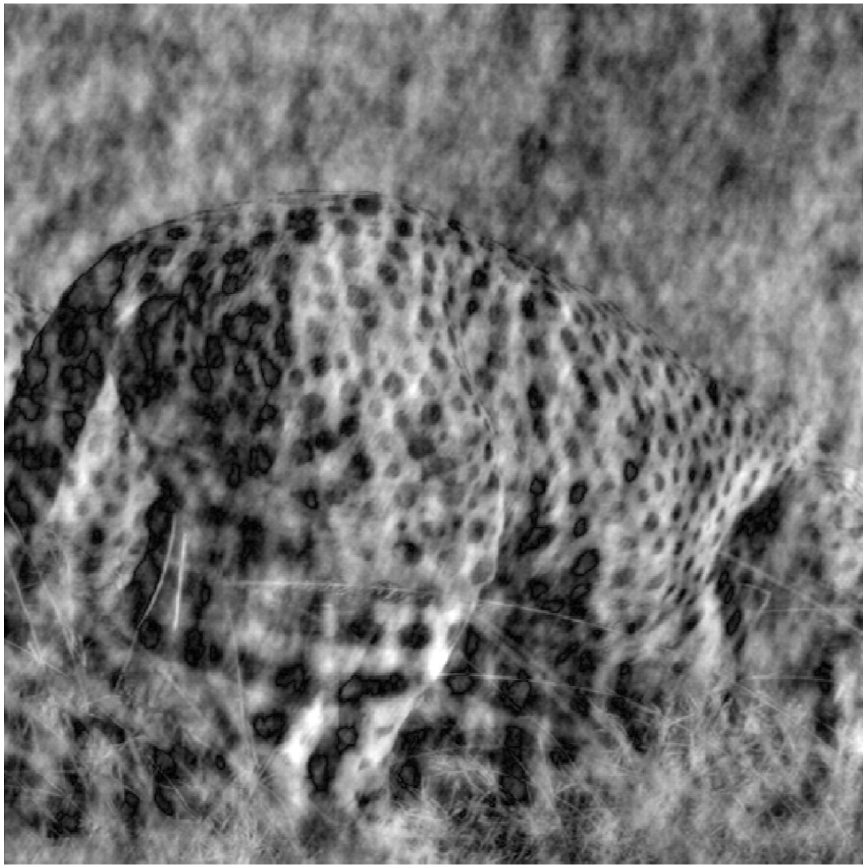
Efros

# Cheebra

Zebra phase, cheetah amplitude



Cheetah phase, zebra amplitude



Efros

# Phase and Frequency

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

Efros

# Properties of the Fourier Transform

As in the 1D case FTs have the following properties

- Linearity

$$\alpha f(x,y) + \beta g(x,y) \Leftrightarrow \alpha F(u,v) + \beta G(u,v).$$

- Similarity

$$f(ax,by) \Leftrightarrow \frac{1}{ab} F(\frac{u}{a}, \frac{v}{b}).$$

This applies, for example, when an image is scaled

- Shift

$$f(x-a, y-b) \Leftrightarrow e^{j2\pi(au+bv)} F(u,v)$$

This might apply, for example, if an object moved.

# Properties of Fourier Transforms

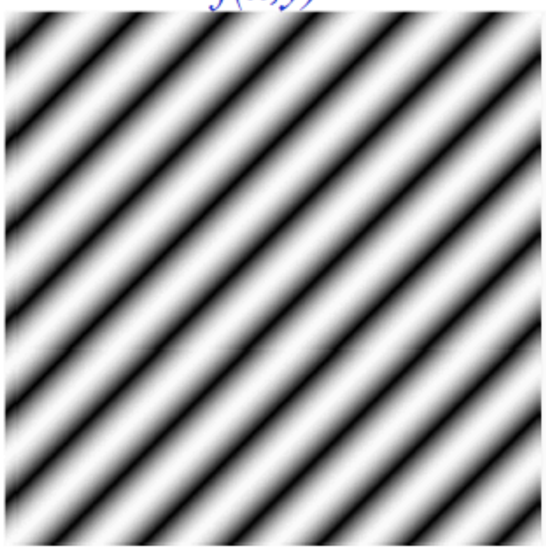
In 2D can also rotate, shear etc

Under an affine transformation: $\mathbf{x} \rightarrow \mathtt{A}\mathbf{x} \qquad \mathbf{u} \rightarrow \mathtt{A}^{-\top}\mathbf{u}$

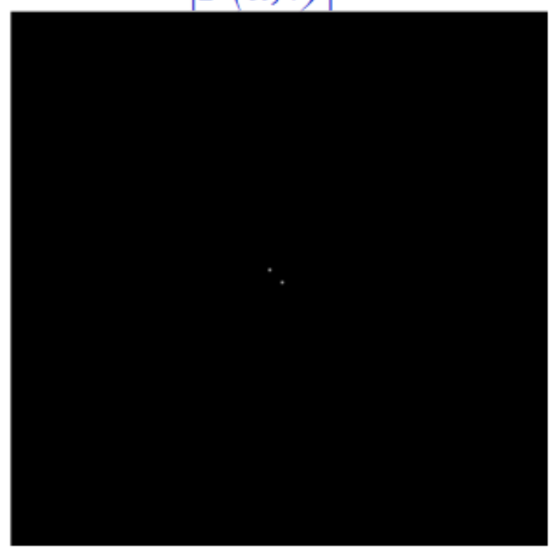
Example

How does $F(u,v)$ transform if $f(x,y)$ is rotated by 45 degrees?

$f(x,y)$



$|F(u,v)|$



If $\mathtt{A} = \mathtt{R}$ then $\mathtt{A}^{-\top} = \mathtt{R}$.

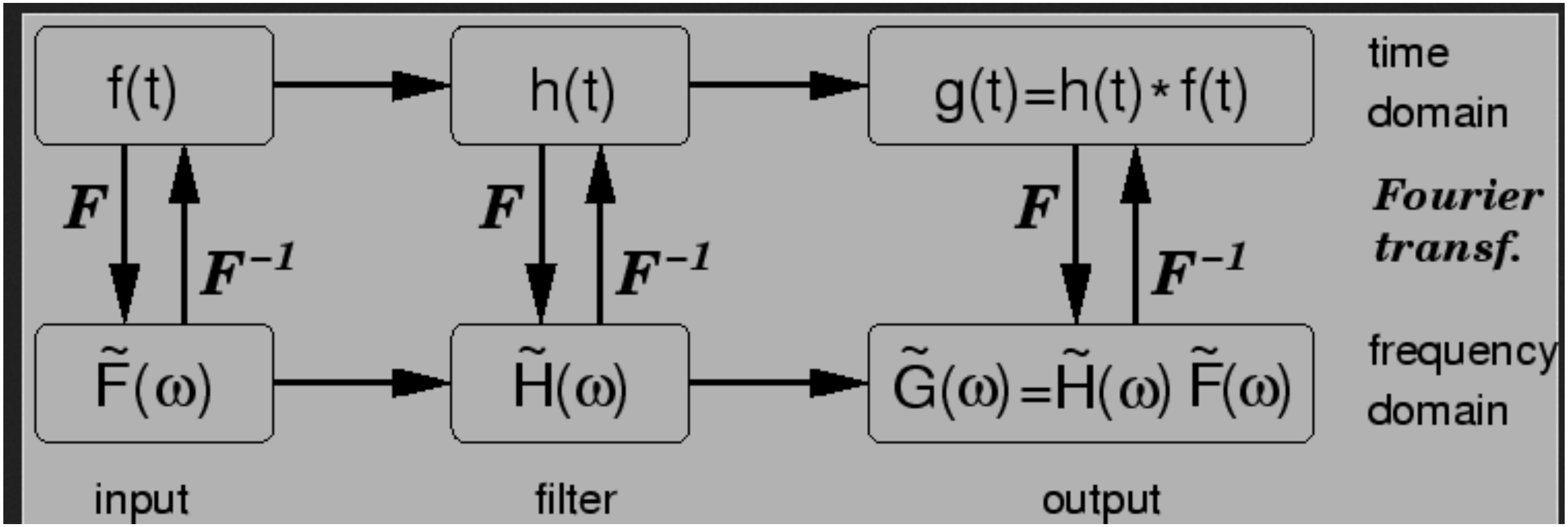
i.e. FT undergoes the same rotation.

# Properties of Fourier Transforms

- 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

See Szeliski Book (3.4)

# The Convolution Theorem




http://jclahr.com/science/psn/wielandt/node8.html

# Filtering Vs. Convolution in 1D

$$g(x) = \sum_i f(x+i)h(i)$$

filtering f(x) with h(x)

| | |
|---|---|
| f(x) | 100 \| 200 \| 100 \| 200 \| 90 \| 80 \| 80 \| 100 \| 100 |
| h(x) | 1/4 \| 1/2 \| 1/4 |
| g(x) | \| 150 \| \| \| \| \| \| \| |

molecule/template/kernel

$$\begin{aligned} g(x) &= \int f(u)h(x-u)\,du \\ &= \int f(x+u')h(-u')\,du' \\ &= \sum f(x+i)h(-i) \end{aligned}$$

convolution of f(x) and h(x)

after change of variable $u' = u - x$

# Filtering Vs. Convolution in 1D

$$g(x) = \sum_i f(x+i)h(i)$$

filtering f(x) with h(x)

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convolution of f(x) and h(x)

$$= \int f(x+u')h(-u')\,du'$$

after change of variable $u' = u - x$

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| | |
|---|---|
| f(x) | 100 \| 200 \| 100 \| 200 \| 90 \| 80 \| 80 \| 100 \| 100 |
| h(x) | 1/4 \| 1/2 \| 1/4 |
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molecule/template/kernel

$$g(x) = \int f(u)h(x-u)\,du$$

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# Filtering Vs. Convolution in 1D

$$g(x) = \sum_i f(x+i)h(i)$$

filtering f(x) with h(x)

$$g(x) = \int f(u)h(x-u)\,du$$

convolution of f(x) and h(x)

$$= \int f(x+u')h(-u')\,du'$$

after change of variable $u' = u - x$

$$= \sum_i f(x+i)h(-i)$$

- note negative sign (which is a reflection in x) in convolution
- $h(x)$ is often symmetric (even/odd), and then (e.g. for even)

$$g(x) = \sum_i f(x+i)h(i)$$

# Filtering Vs. Convolution in 2D

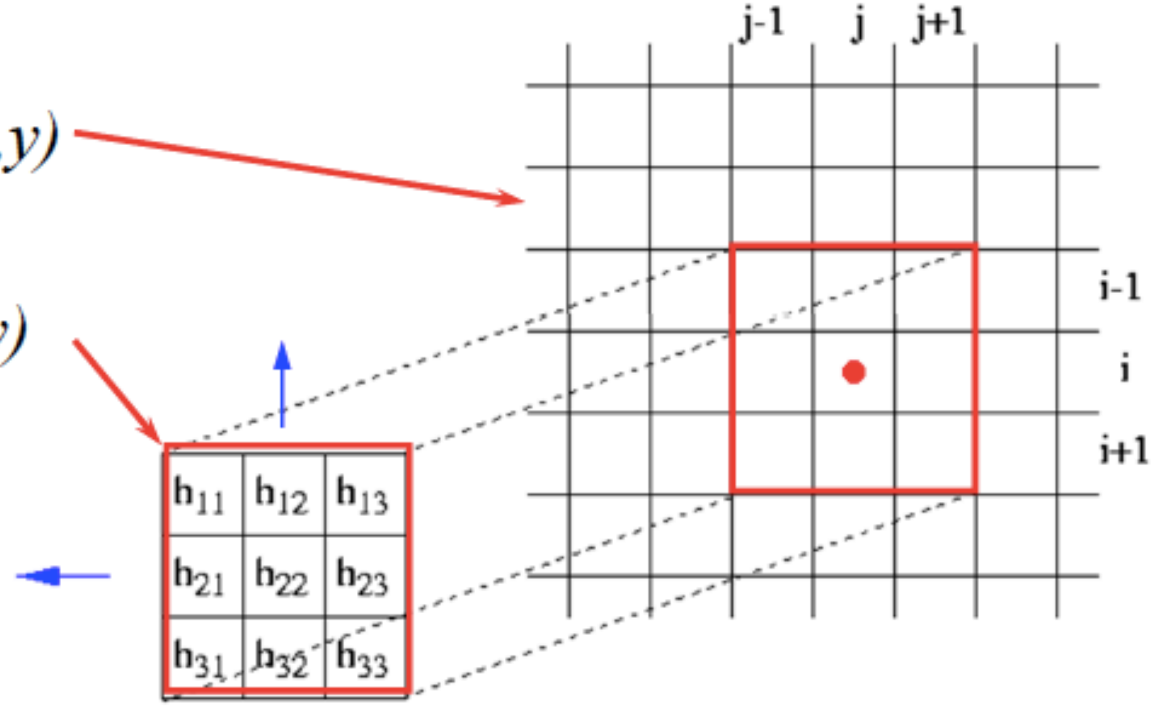
convolution

$$\begin{aligned} g(x,y) &= h(x,y) * f(x,y) = f(x,y) * h(x,y) \\ &= \int\int f(u,v)h(x-u,y-v)\,du\,dv \end{aligned}$$

filtering

image *f(x,y)*

filter / kernel *h(x,y)*



# Filtering Vs. Convolution in 2D

convolution

$$
\begin{aligned}
g(x,y) &= h(x,y) * f(x,y) = f(x,y) * h(x,y) \\
&= \int\int f(u,v)h(x-u, y-v)\, du\, dv
\end{aligned}
$$

filtering

$$
\begin{aligned}
g(x,y) = \quad & h_{11} f(i-1, j-1) + h_{12} f(i-1, j) + h_{13} f(i-1, j+1) + \\
& h_{21} f(i, j-1) + h_{22} f(i, j) + h_{23} f(i, j+1) + \\
& h_{31} f(i+1, j-1) + h_{32} f(i+1, j) + h_{33} f(i+1, j+1)
\end{aligned}
$$

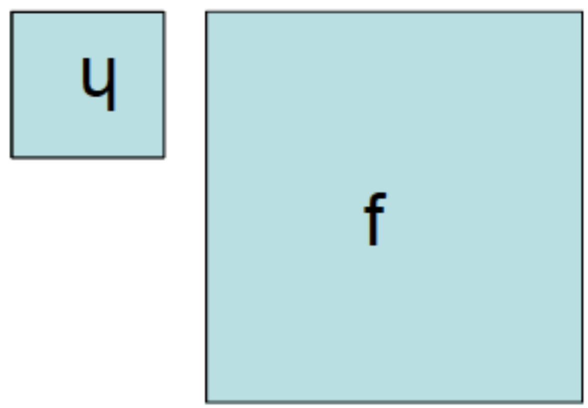
for convolution, reflect filter in x and y axes

# Convolution

- Convolution:
  - Flip the filter in both dimensions (bottom to top, right to left)

$$g[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} h[u,v] f[i-u, j-v]$$

convolution with h




slide: K. Grauman

# Filtering vs. Convolution in 2D Matlab

f=image
h=filter

## 2D filtering

- `g=filter2(h,f);`

$$g[m,n] = \sum_{k,l} h[k,l]\, f[m+k, n+l]$$

## 2D convolution

- `g=conv2(h,f);`

$$g[m,n] = \sum_{k,l} h[k,l]\, f[m-k, n-l]$$

# Convolution Theorem

$$f(x,y) * h(x,y) \iff F(u,v)H(u,v)$$

$\boxed{\text{Space convolution = frequency multiplication}}$

In words: the Fourier transform of the convolution of two functions is the product of their individual Fourier transforms

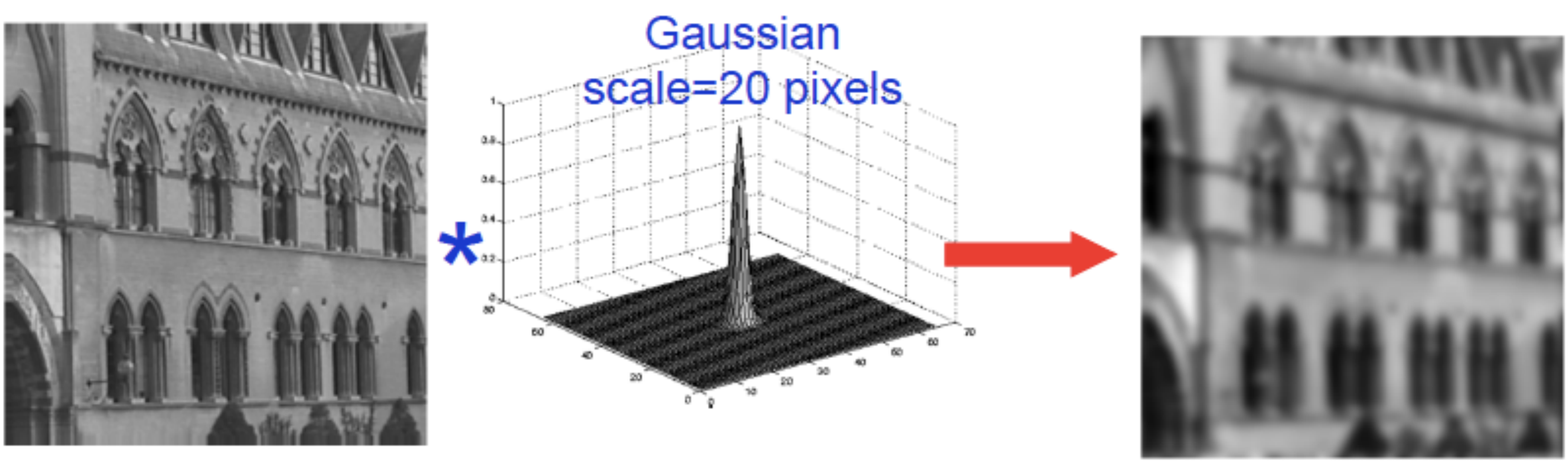
Why is this so important?

Because linear filtering operations can be carried out by simple multiplications in the Fourier domain

# The Importance of Convolution Theorem

It establishes the link between operations in the frequency domain and the action of linear spatial filters

<u>Example</u> smooth an image with a Gaussian spatial filter



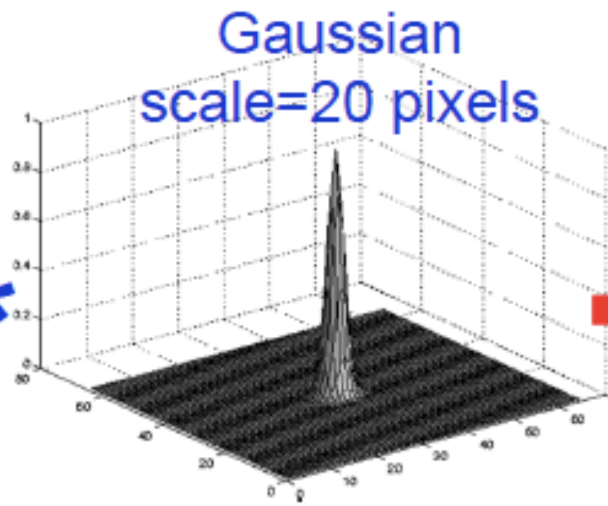

$$f(x,y) * g(x,y) \Leftrightarrow F(u,v)G(u,v)$$

# The Importance of Convolution Theorem

Example smooth an image with a Gaussian spatial filter

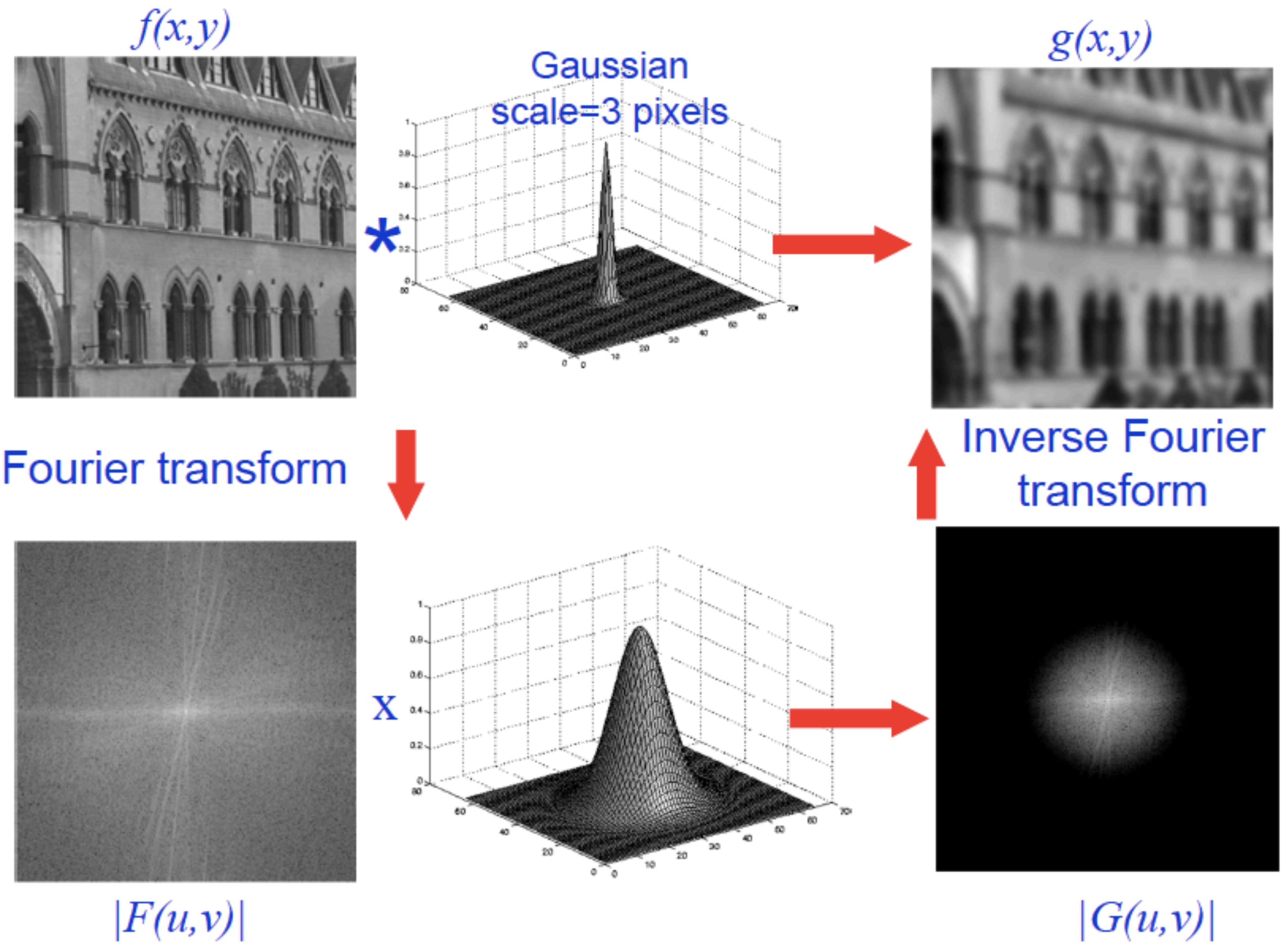
$$f(x,y) * g(x,y) \Leftrightarrow F(u,v)G(u,v)$$

*

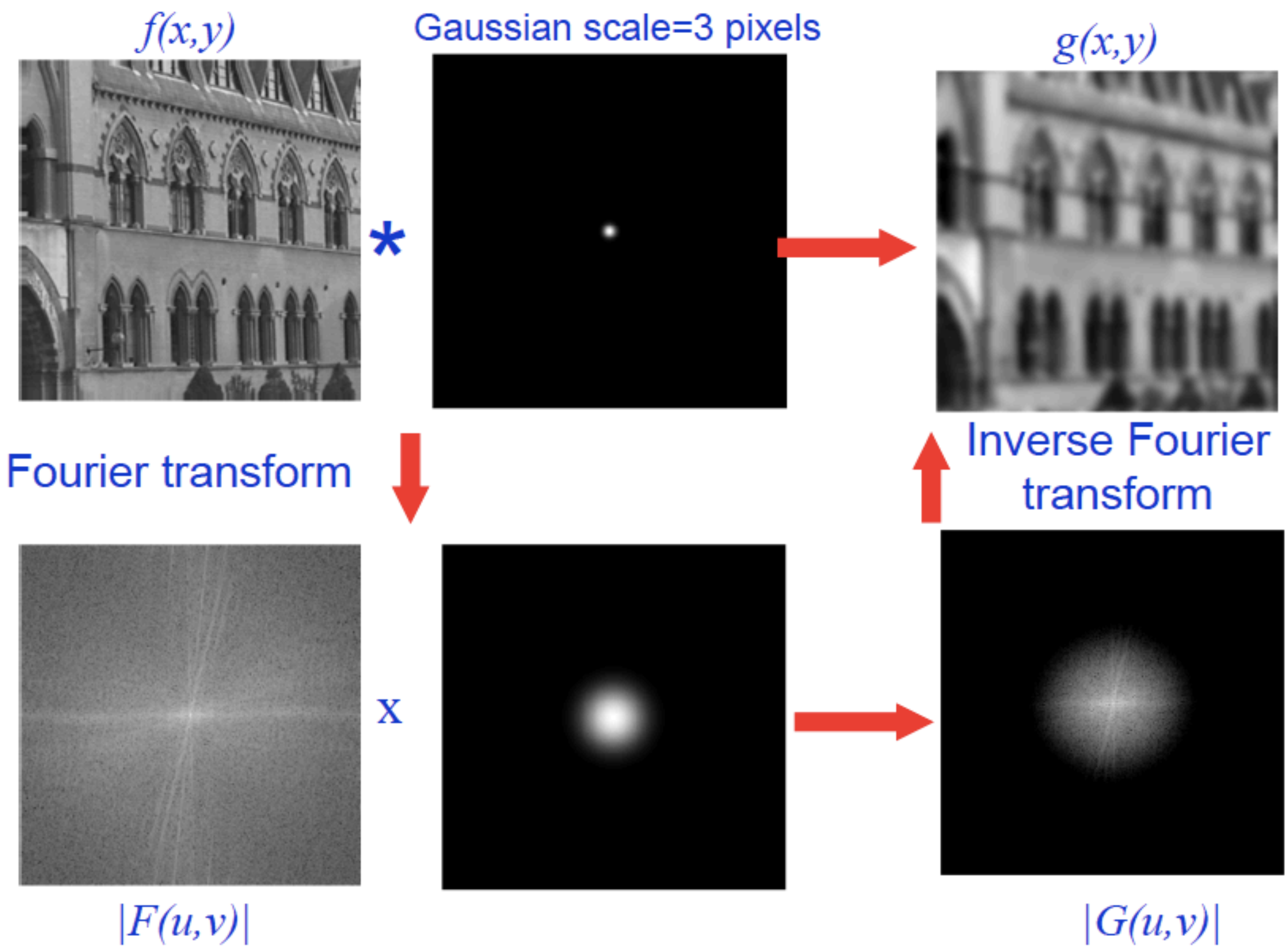



1. Compute FT of image and FT of Gaussian
2. Multiply FT's
3. Compute inverse FT of the result.

# The Importance of Convolution Theorem



# The Importance of Convolution Theorem



# Filtering: Spatial Domain vs. Frequency Domain

There are two equivalent ways of carrying out linear spatial filtering operations:

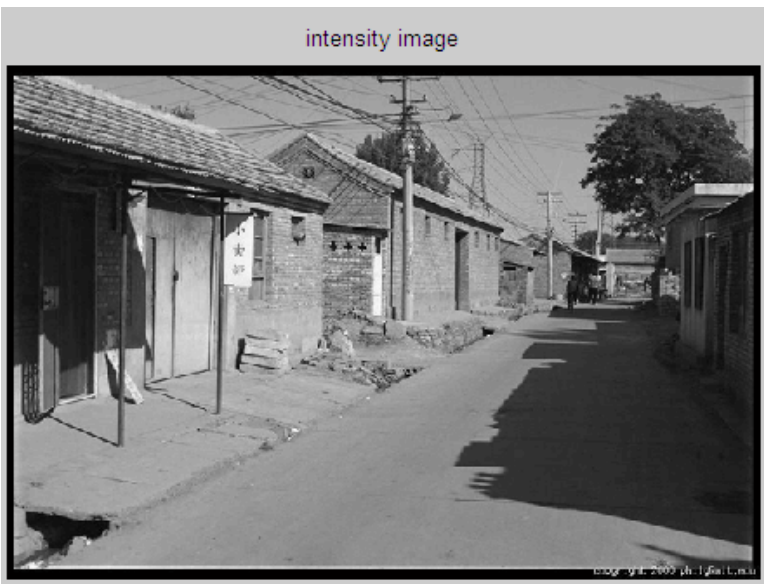
1. Spatial domain: convolution with a spatial operator
2. Frequency domain: multiply FT of signal and filter, and compute inverse FT of product

Why choose one over the other ?

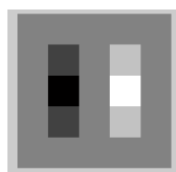
- The filter may be simpler to specify or compute in one of the domains
- Computational cost

# More on Filtering in spatial domain

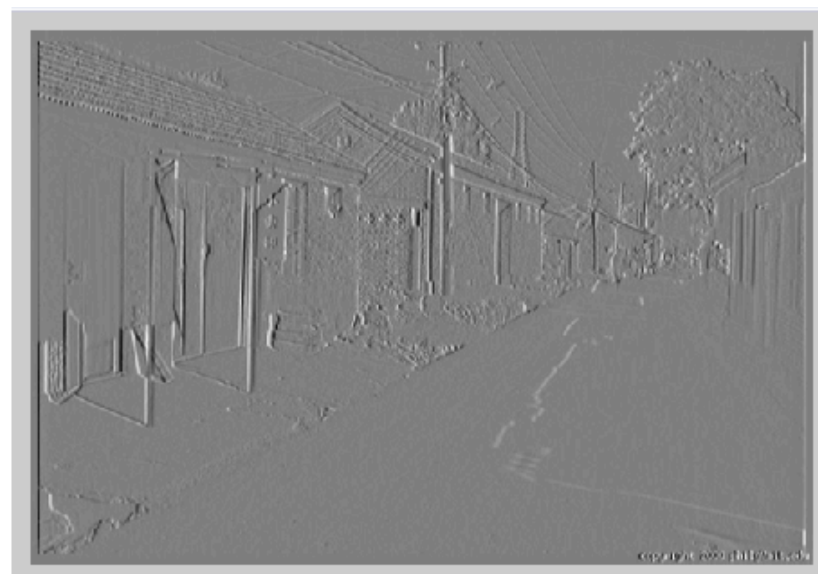
| | | |
|---|---|---|
| 1 | 0 | -1 |
| 2 | 0 | -2 |
| 1 | 0 | -1 |




*

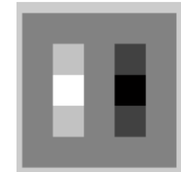


=

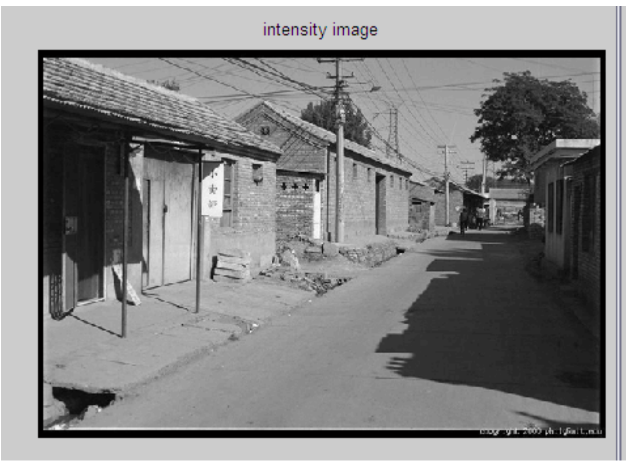


Hays

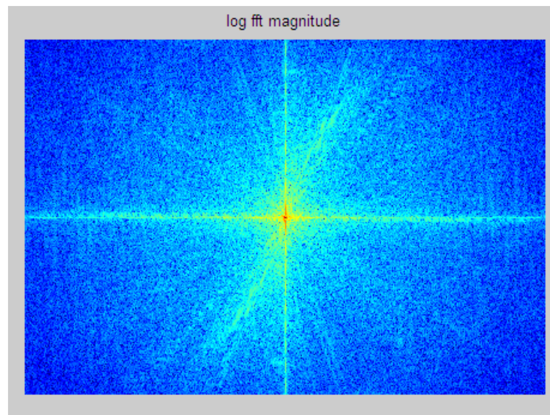
# Filtering in frequency domain

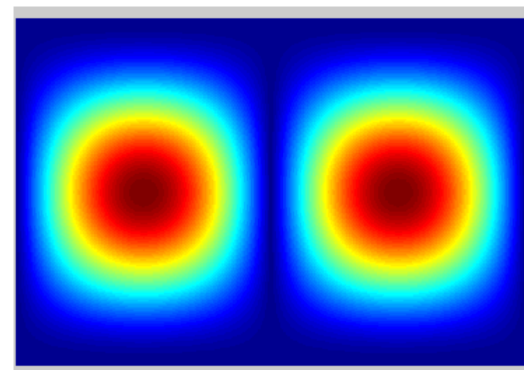


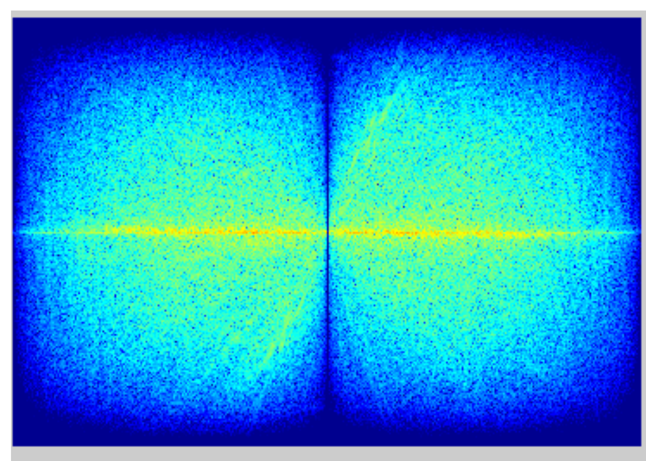
FFT



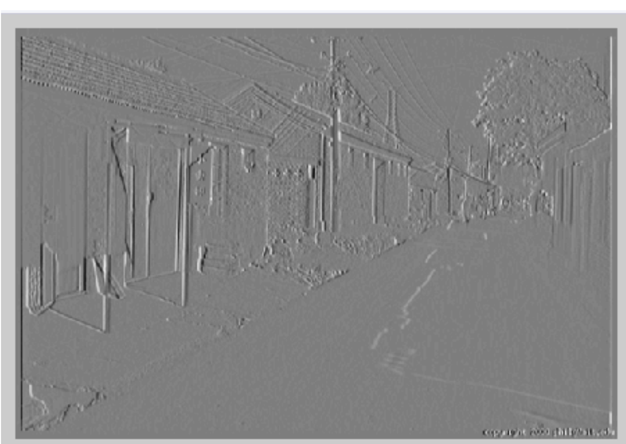

FFT





Inverse FFT



Slide: Hoiem

# Fast Fourier Transform in Matlab

- Filtering with fft (fft2 -> 2D)

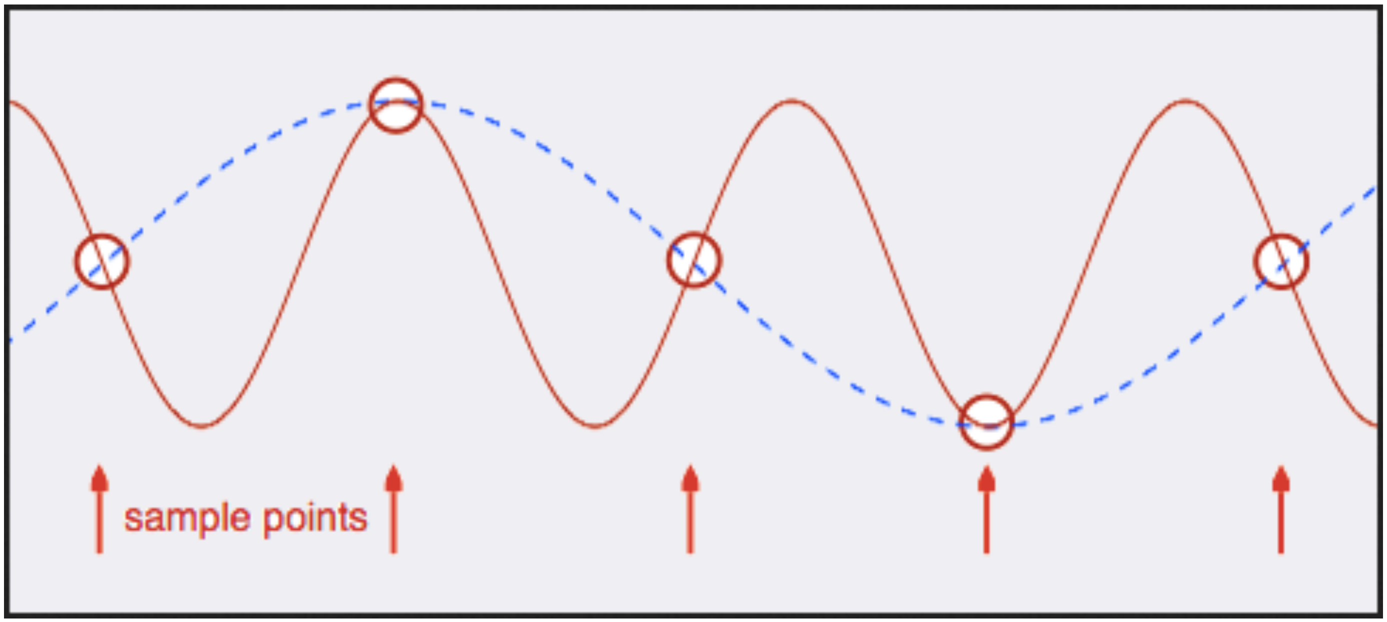
```
im = double(imread('…'))/255;
im = rgb2gray(im); % "im" should be a gray-scale floating point image
[imh, imw] = size(im);

hs = 50; % filter half-size
fil = fspecial('gaussian', hs*2+1, 10);

fftsize = 1024; % should be order of 2 (for speed) and include padding
im_fft  = fft2(im,  fftsize, fftsize);                        % 1) fft im with padding
fil_fft = fft2(fil, fftsize, fftsize);                        % 2) fft fil, pad to same size as
image
im_fil_fft = im_fft .* fil_fft;                               % 3) multiply fft images
im_fil = ifft2(im_fil_fft);                                   % 4) inverse fft2
im_fil = im_fil(1+hs:size(im,1)+hs, 1+hs:size(im, 2)+hs); % 5) remove padding
```

- Displaying with fft

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

Slide: Hoiem

# Sampling Theorem

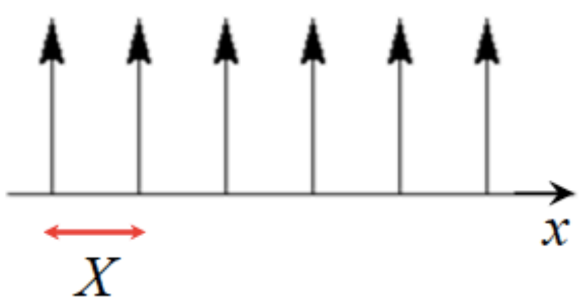


# 1D Sampling

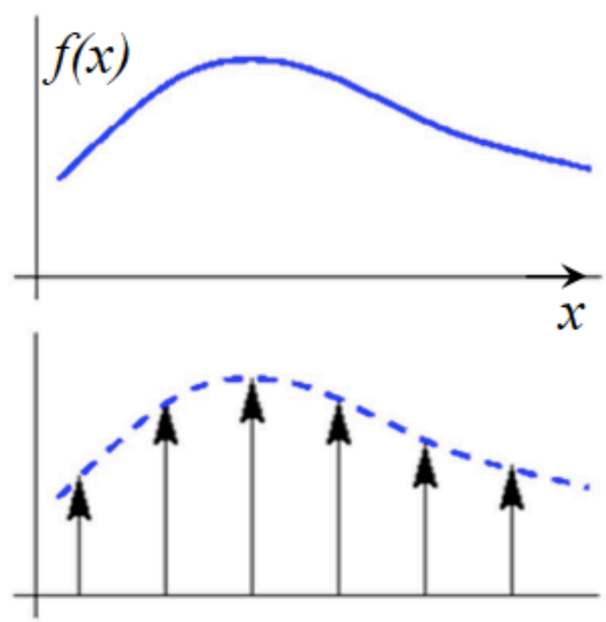
In 1D model the image as a set of point samples obtained my multiplying $f(x)$ by the comb function

$$comb(x) = \sum_{n=-\infty}^{\infty} \delta(x - nX)$$

an infinite set of delta functions spaced by $X$.




X

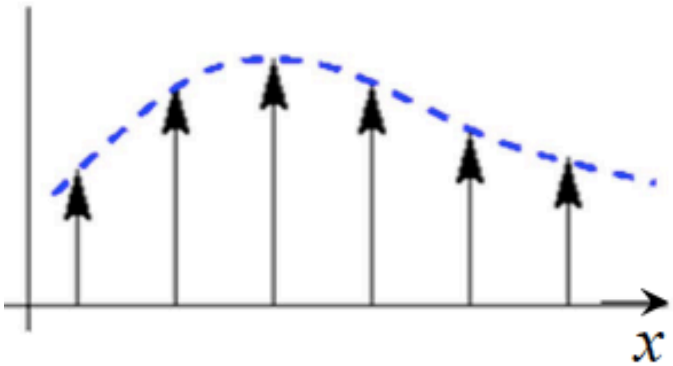


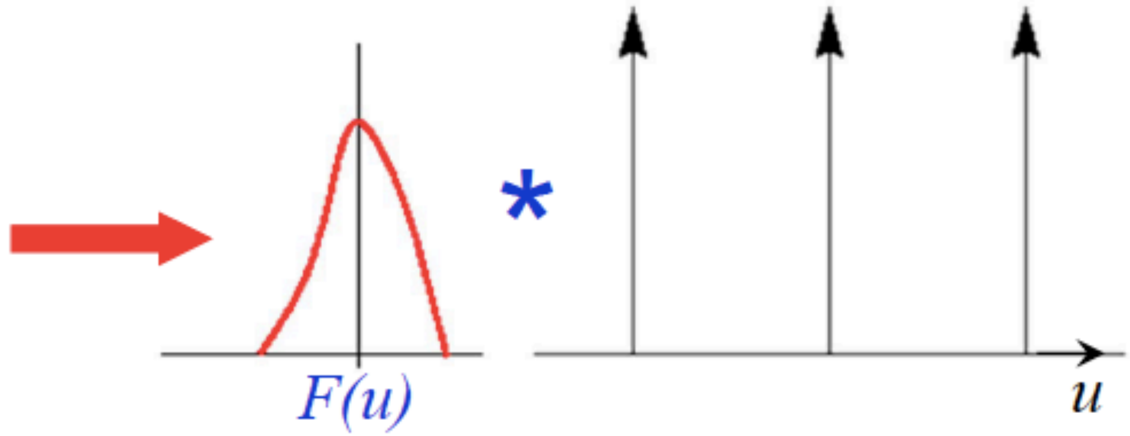

$$f_s(x) = \sum_{n=-\infty}^{\infty} \delta(x - nX) f(x)$$

# 1D Sampling

spatial domain

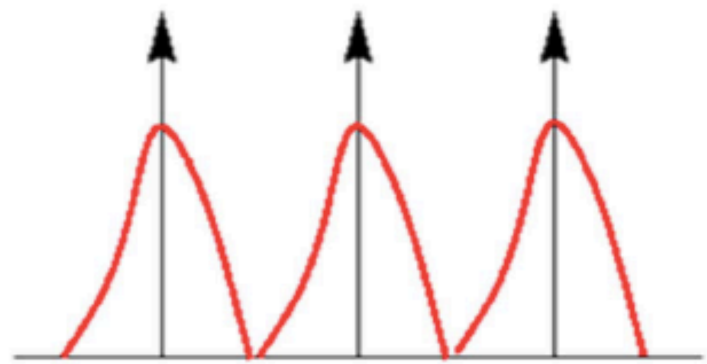
frequency domain




$$f_s(x) = \sum_{n=-\infty}^{\infty} \delta(x - nX) f(x)$$
$$= \sum_{n=-\infty}^{\infty} f(nX)\delta(x - nX)$$

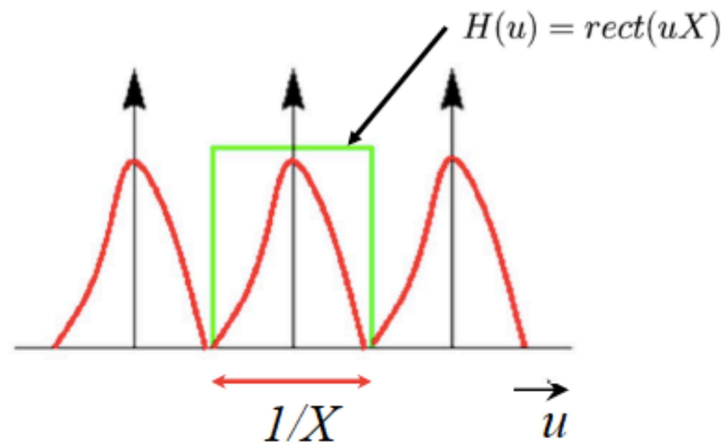
$$F_s(u) = \frac{1}{X} \sum_{n=-\infty}^{\infty} \delta(u - n/X) * F(u) = \frac{1}{X} \sum_{n=-\infty}^{\infty} F(u - n/X)$$

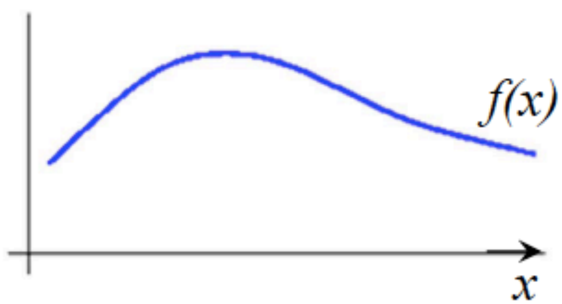


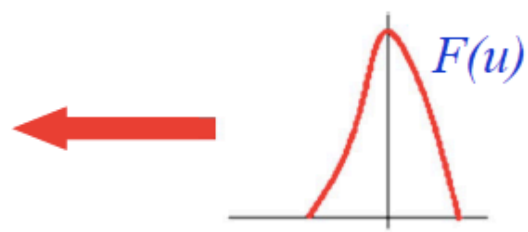
replicated copies of $F(u)$

# 1D Sampling

Apply a box filter




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

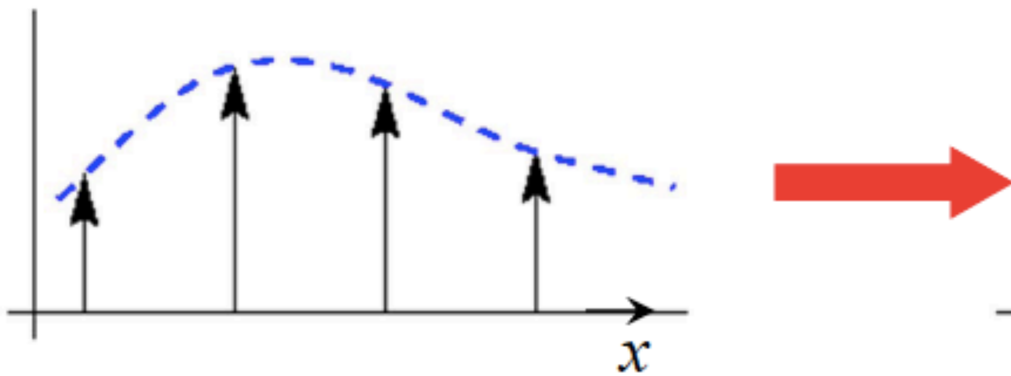
$$\begin{aligned} f(x) &= \sum_{n=-\infty}^{\infty} f(nX)\delta(x - nX) * \mathrm{sinc}\frac{\pi x}{X} \\ &= \sum_{n=-\infty}^{\infty} f(nX)\mathrm{sinc}\frac{\pi}{X}(x - nX) \end{aligned}$$

The original continuous function *f(x)* is completely recovered from the samples provided the sampling frequency (*1/X*) exceeds twice the greatest frequency of the band-limited signal. (Nyquist sampling limit)

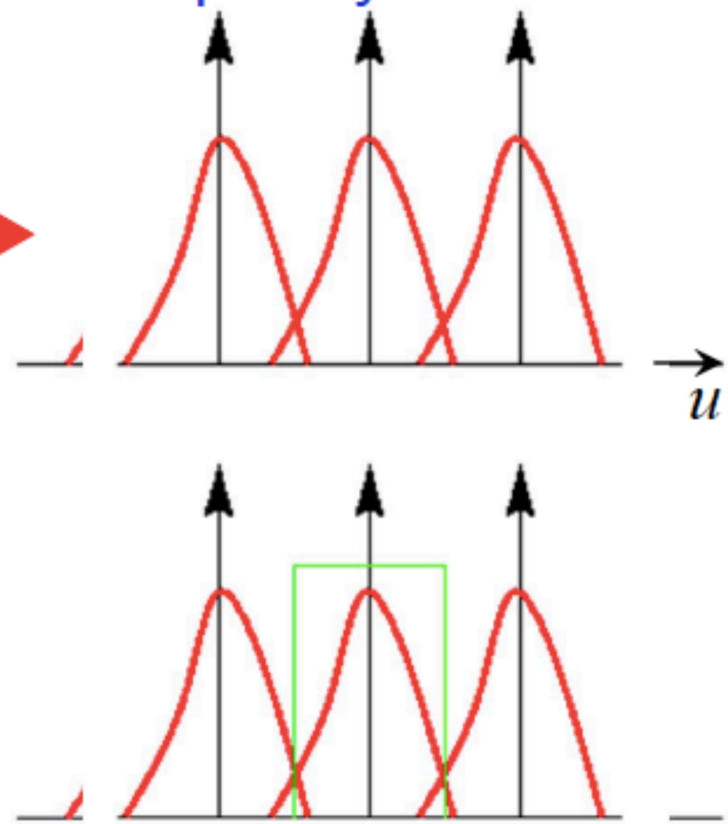
# The Sampling Theorem and Aliasing

if sampling frequency is reduced …

spatial domain




frequency domain



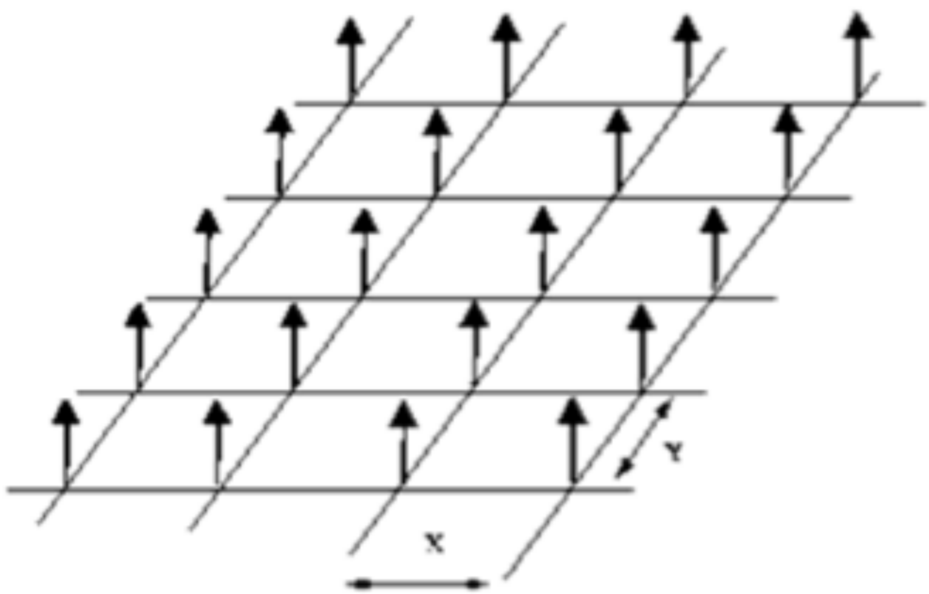

Frequencies above the Nyquist limit are ‘folded back’ corrupting the signal in the acceptable range.

The information in these frequencies is not correctly reconstructed.

# 2D Sampling

In 2D the equivalent of a comb is a bed-of-nails function

$$\sum_{n=-\infty}^{\infty} \sum_{m=-\infty}^{\infty} \delta(x - nX)\delta(y - mY)$$



# 2D Sampling

In 2D the equivalent of a comb is a bed-of-nails function

$$\sum_{n=-\infty}^{\infty} \sum_{m=-\infty}^{\infty} \delta(x - nX)\delta(y - mY)$$

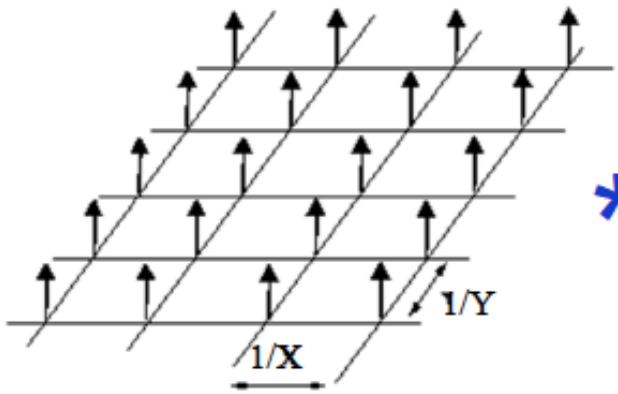
## Fourier transform pairs

$$\sum_{n=-\infty}^{\infty} \delta(x - nX) \leftrightarrow \frac{1}{X} \sum_{n=-\infty}^{\infty} \delta(u - n/X)$$

$$\sum_{n=-\infty}^{\infty} \sum_{m=-\infty}^{\infty} \delta(x - nX)\delta(y - mY) \leftrightarrow \frac{1}{XY} \sum_{n=-\infty}^{\infty} \delta(u - n/X) \sum_{m=-\infty}^{\infty} \delta(v - n/Y)$$

# Sampling Theorem in 2D

frequency domain

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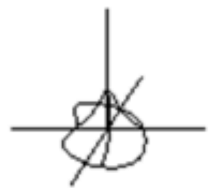
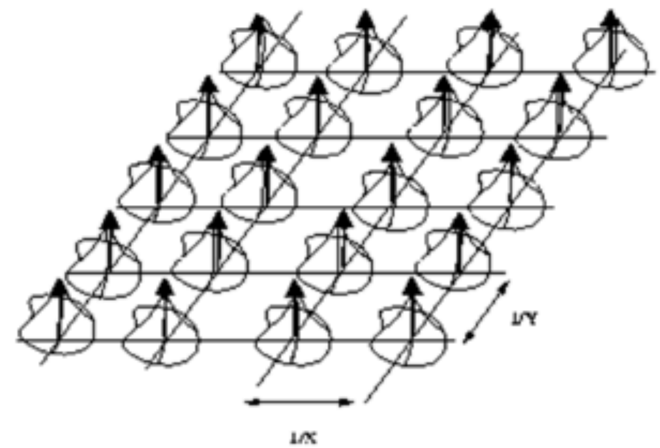
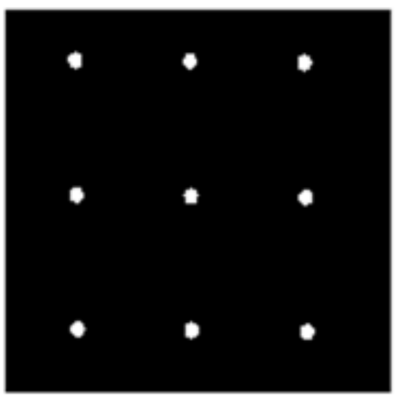


$F(u,v)$

=



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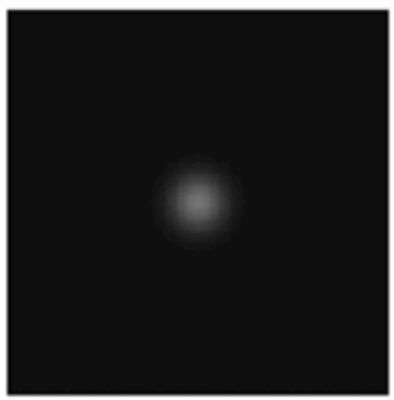
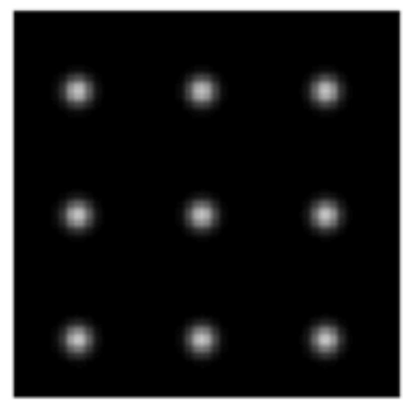


=



$H(u,v) = rect(uX)rect(vY)$

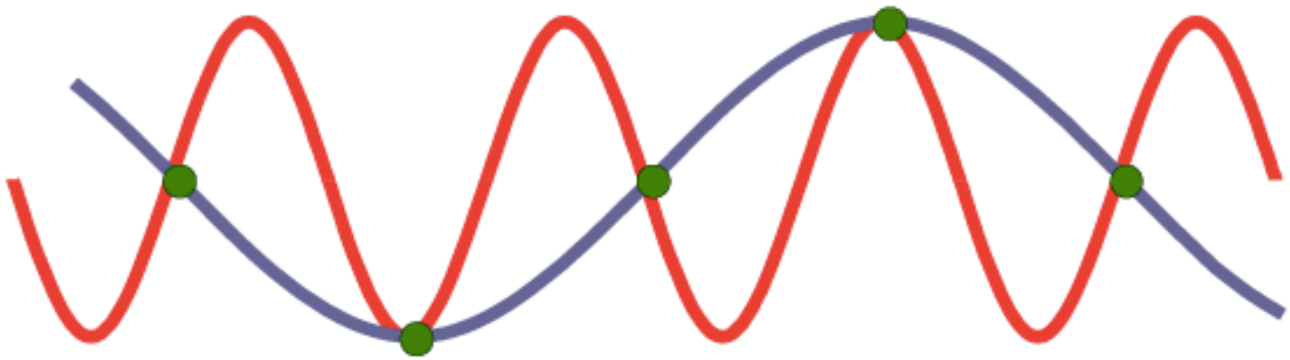
$$f(x,y) = \sum_{n=-\infty}^{\infty} \sum_{m=-\infty}^{\infty} f(nX, mY) \mathrm{sinc} \frac{\pi}{X}(x - nX) \mathrm{sinc} \frac{\pi}{Y}(y - nY)$$

# Sampling Theorem in 2D

If the Fourier transform of a function $f(x,y)$ is zero for all frequencies beyond $u_b$ and $v_b$, i.e. if the Fourier transform is *band-limited*, then the continuous function $f(x,y)$ can be completely reconstructed from its samples as long as the sampling distances w and h along the x and y directions are such that $w \leq \frac{1}{2u_b}$ and $h \leq \frac{1}{2v_b}$

# Aliasing: 1D Example

If the signal has frequencies above the Nyquist limit …



Insufficient samples to distinguish the high and low frequency

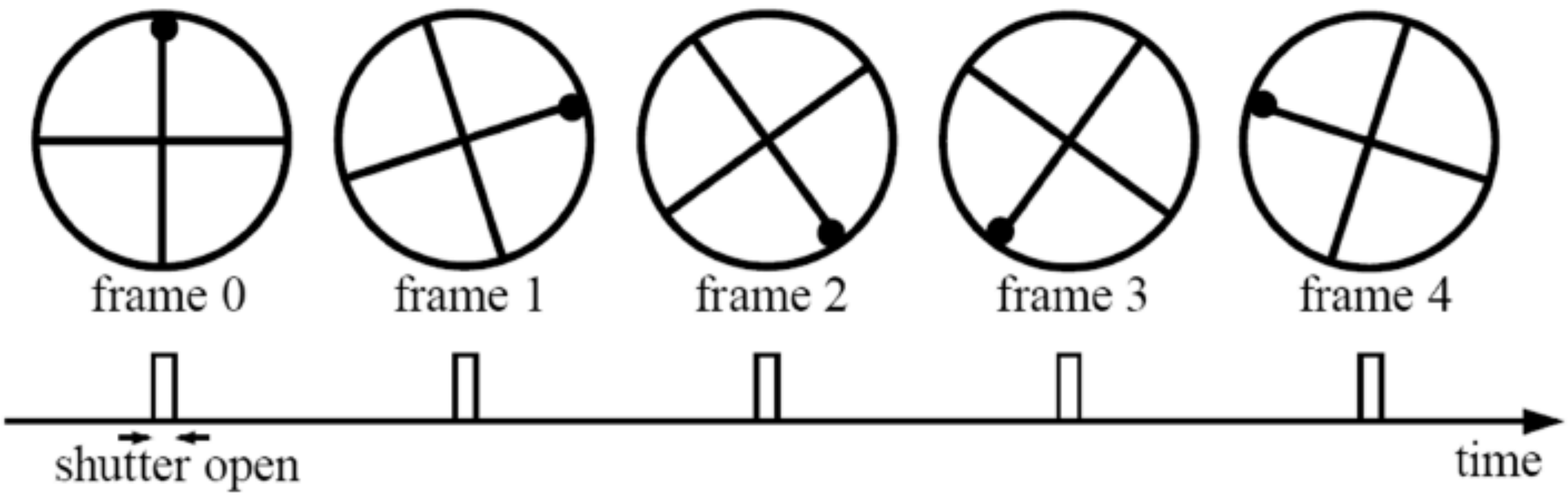
aliasing: signals “travelling in disguise” as other frequencies

# Aliasing in video

# 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):

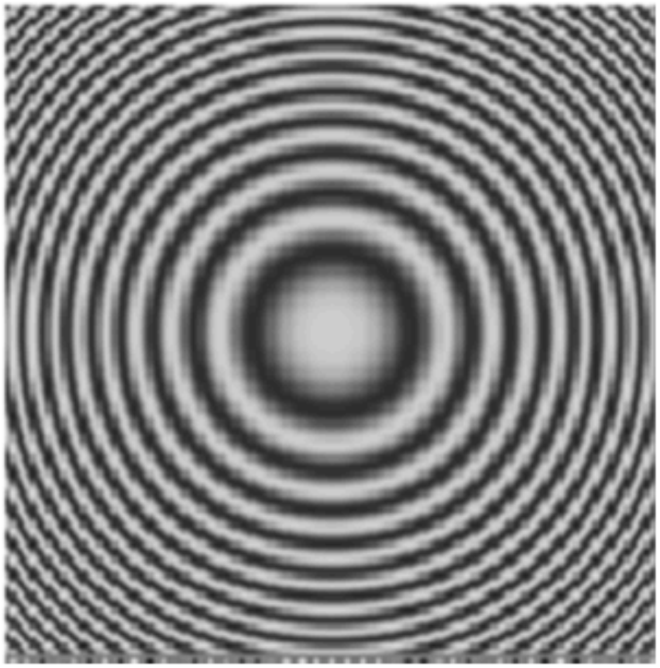



Without dot, wheel appears to be rotating slowly backwards! (counterclockwise)

Slide by Steve Seitz

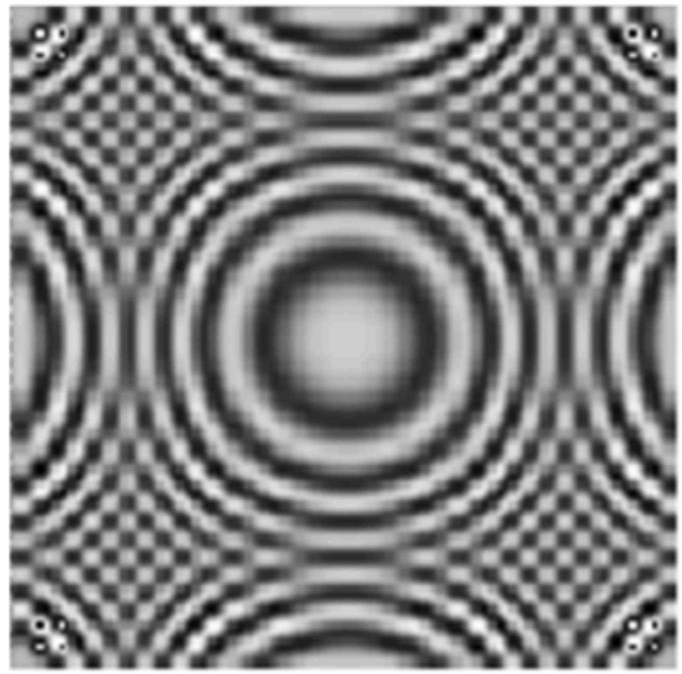
# Aliasing in 2D: under-sampling reconstruction

original

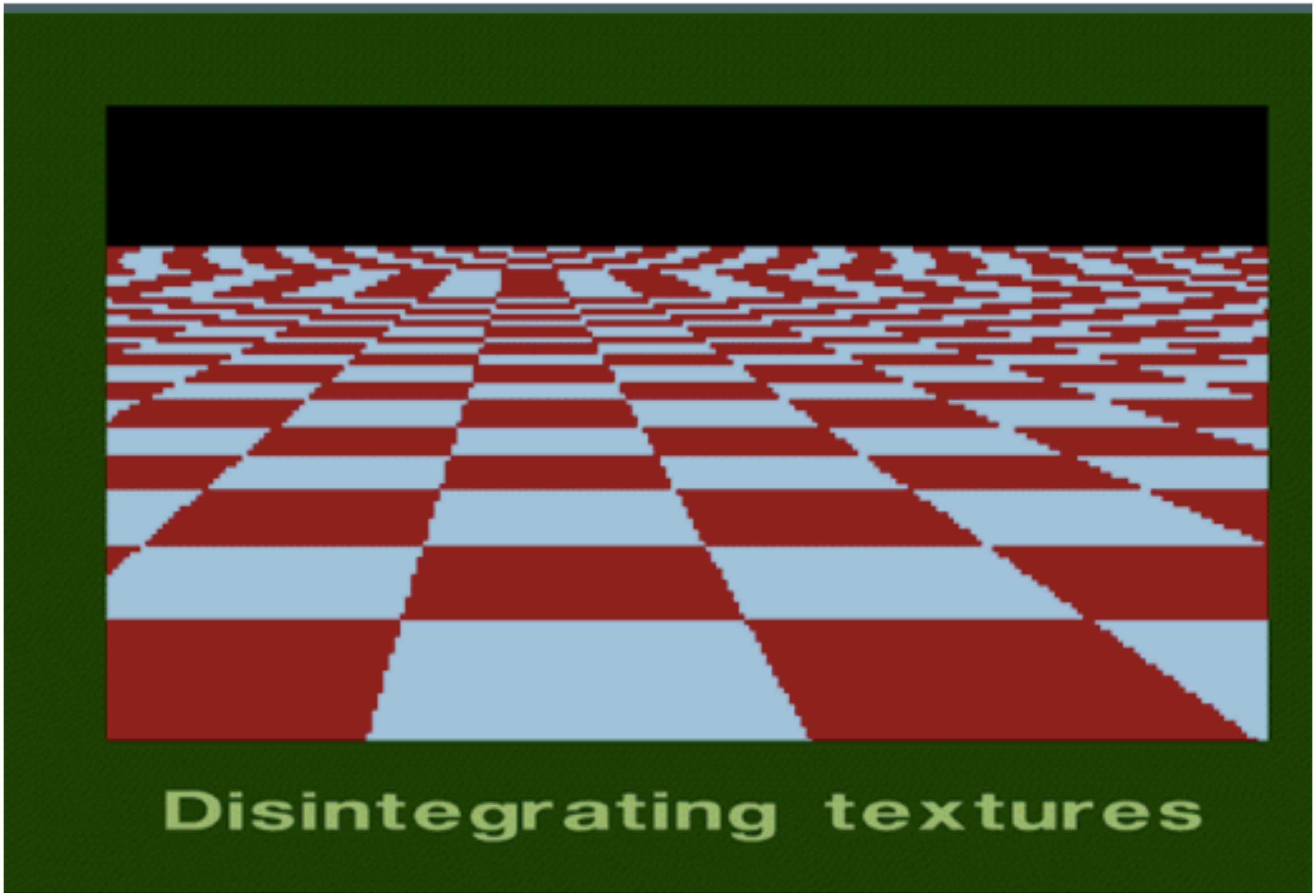


signal has frequencies above Nyquist limit

reconstruction



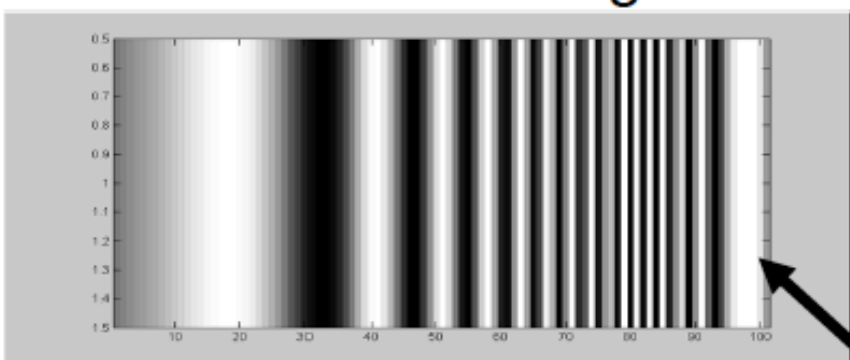
# Aliasing in Images



# What’s happening

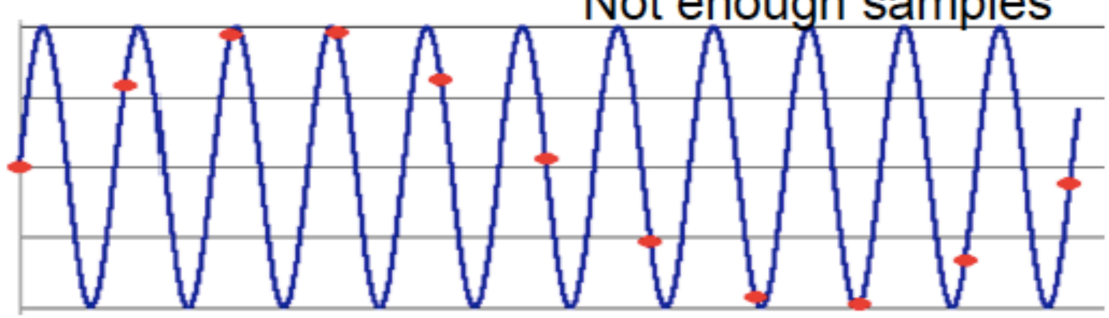
Input signal:

Plot as image:



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

Aliasing
Not enough samples



# Anti-aliasing

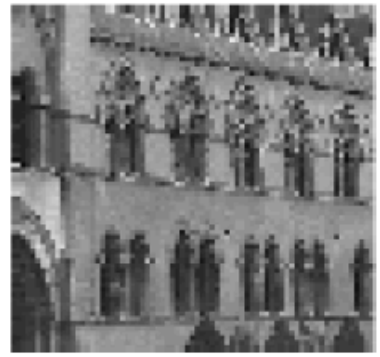
- Increase sampling frequency
  - e.g. in graphics rendering cast 4 rays per pixel
- Reduce maximum frequency to below Nyquist limit
  - e.g. low pass filter before sampling

# Anti-aliasing

Example

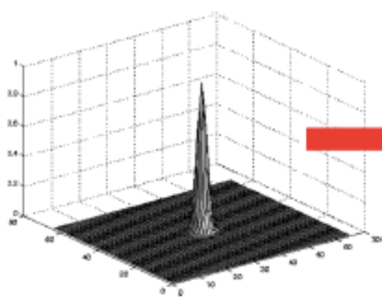
down sample by
factor of 4

4 x zoom



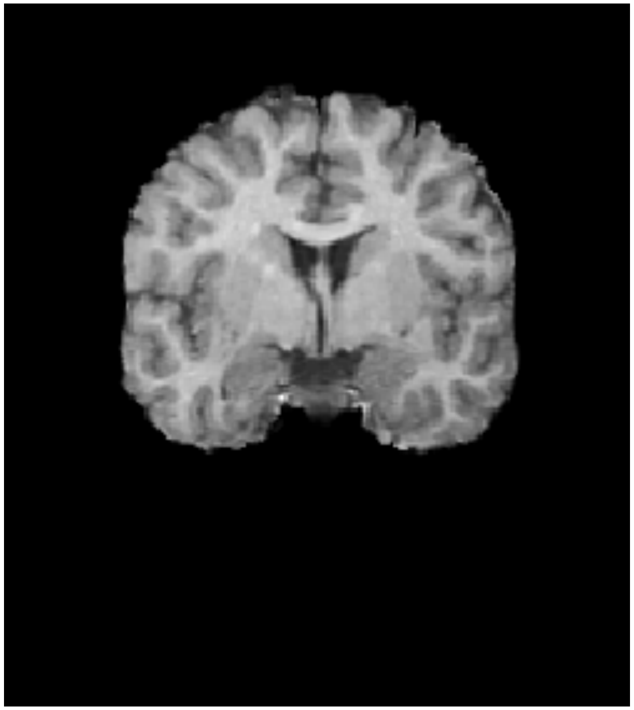
convolve with
Gaussian

*



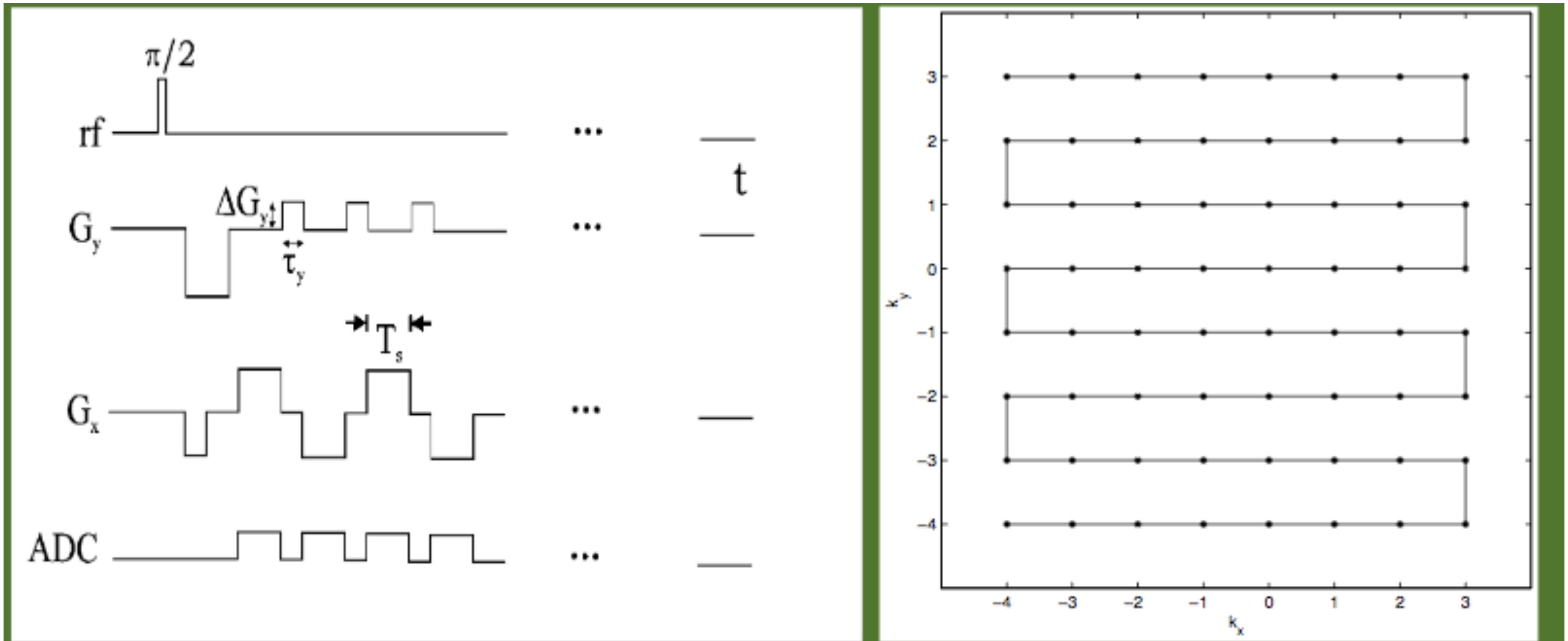
down sample by
factor of 4

# Aliasing in MRI



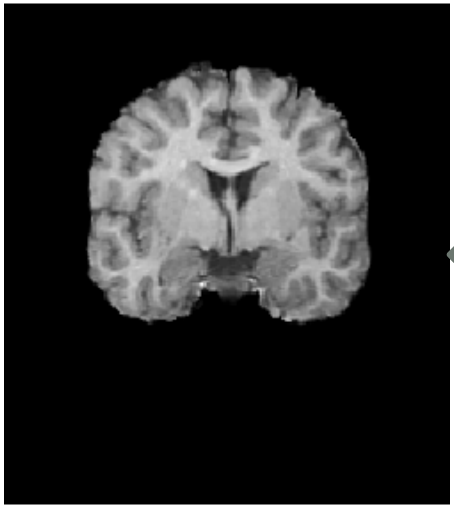
MRI

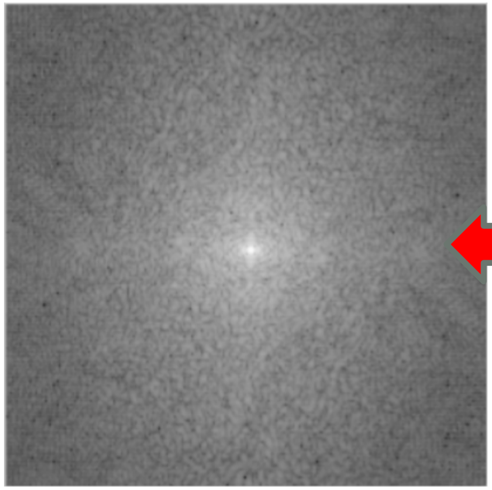
# Aliasing in MRI

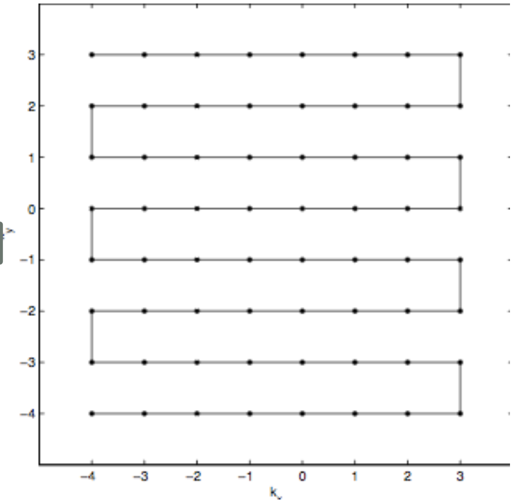



(a) Gradient Echo-EPI Pulse Sequence (b) *k*-Space Trajectory

# Aliasing in MRI





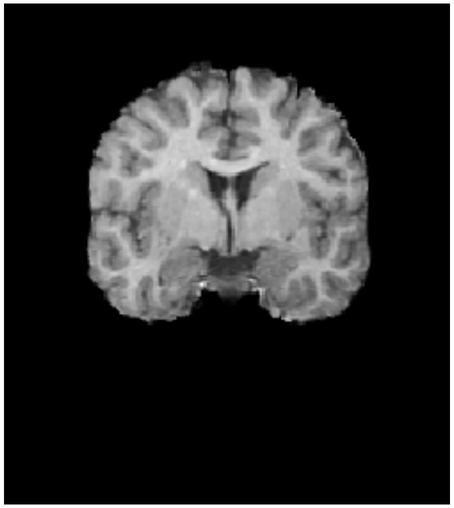



MRI

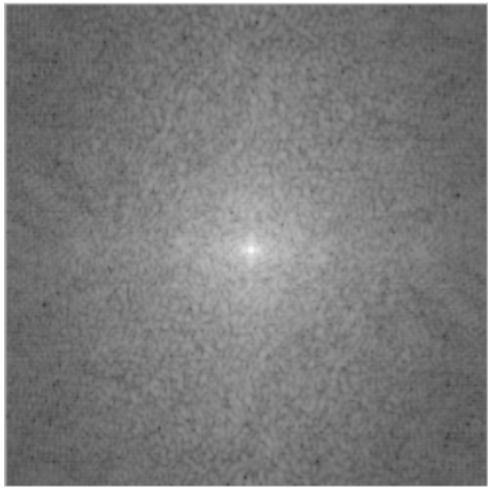
K-Space

K-Space

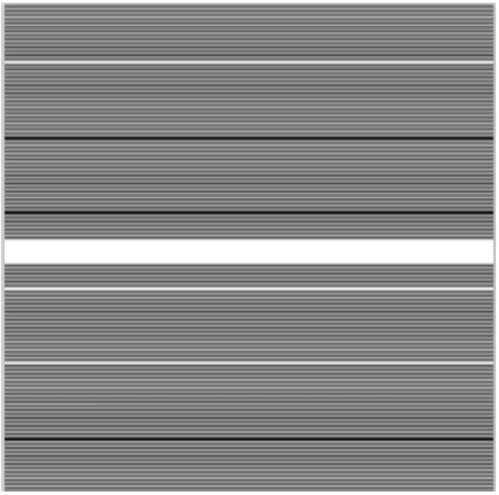
# Aliasing in MRI



MRI

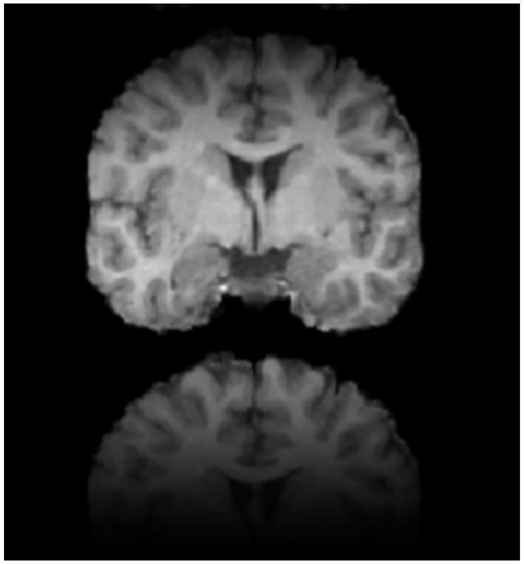


K-Space



Mask

Reconstructed MRI



# Ideas for final Projects

Solitaire Recognition

Chess recognition

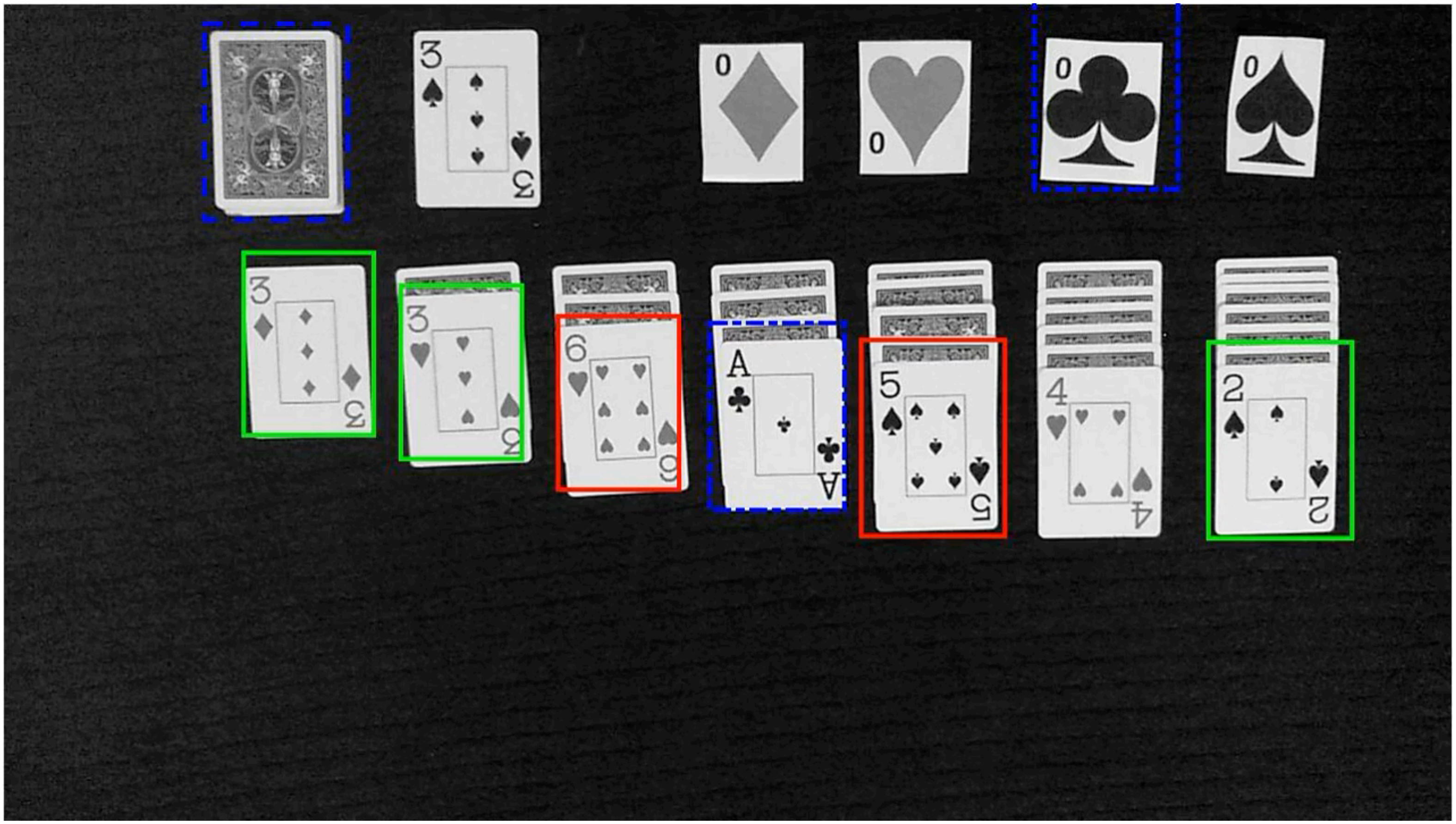
Real time Human Activity recognition

Face Recognition

Flaying Object Detection

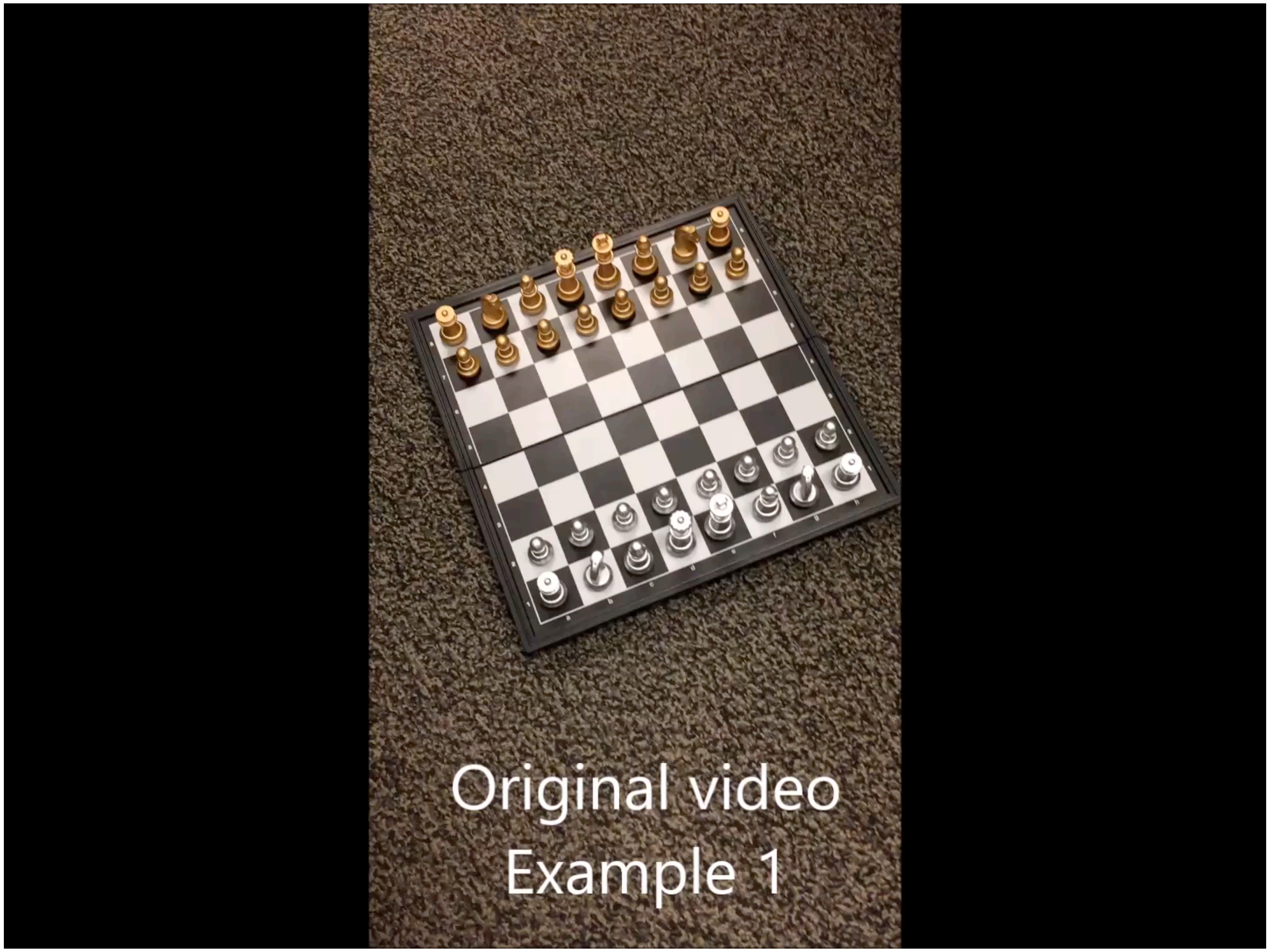
Ball detection (in soccer game)

# Ideas for final Projects



**EENG 512/CSCI 512 - Final Projects**
Hoch, Garrett, *Solitaire Recognition*

# Ideas for Final Projects

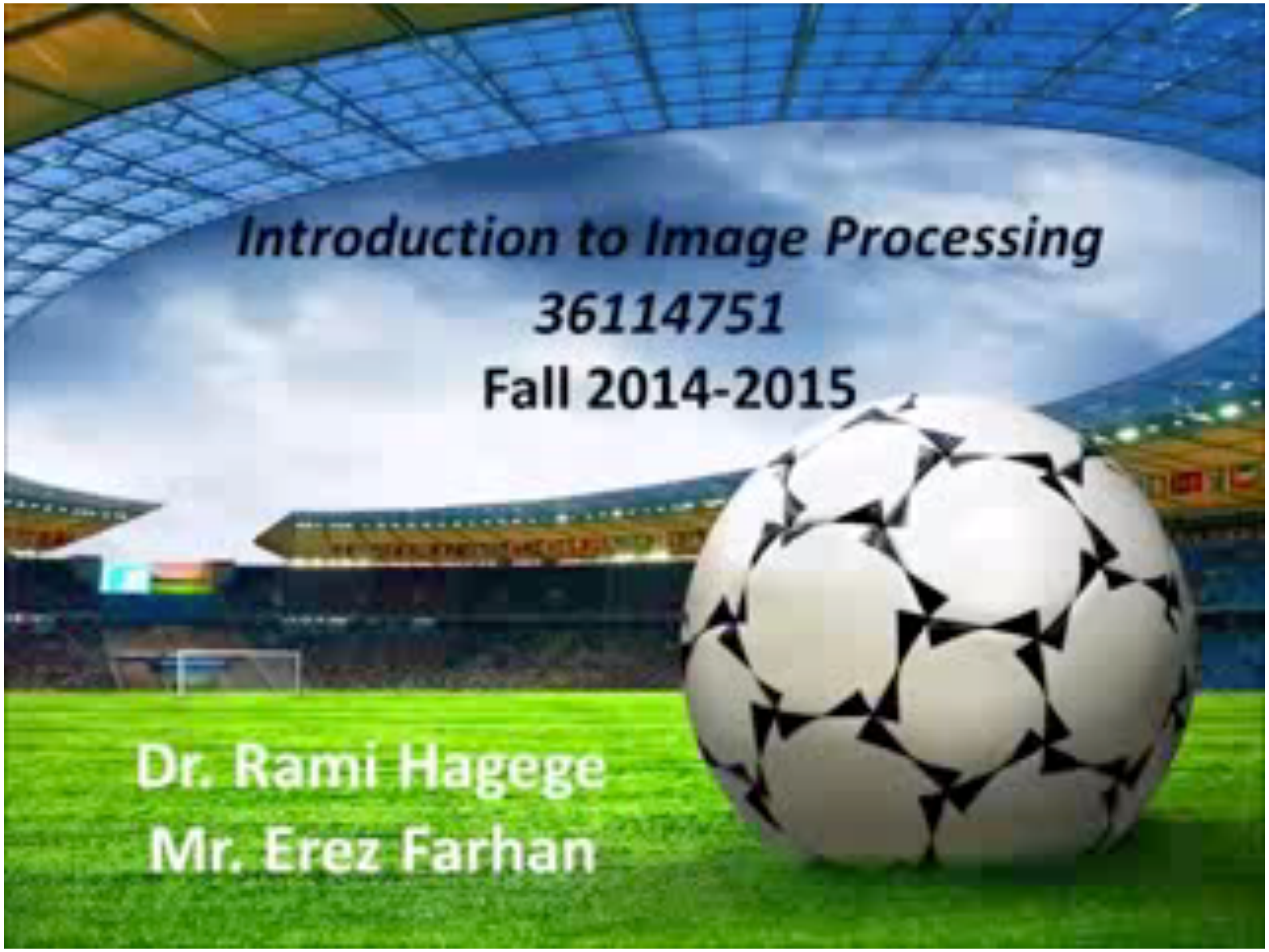



**EENG 512/CSCI 512 - Final Projects**
Xiao, Ke, *Chess Recognition*

# Ideas for Final Projects

**BGU – ECE 2013: Topaz, Ohad, Tsachi, Nadav**

# Ideas for Final Projects




**BGU – ECE 2015:Doron, Boris, Alex**

# Ideas for Final Projects


**BGU – ECE 2015:Nir, Tal & Shay – Interactive temple Run**

# Ideas for Final Projects

**BGU – ECE 2013:Ariel, Tomer, Oren – Virtual Keyboard**