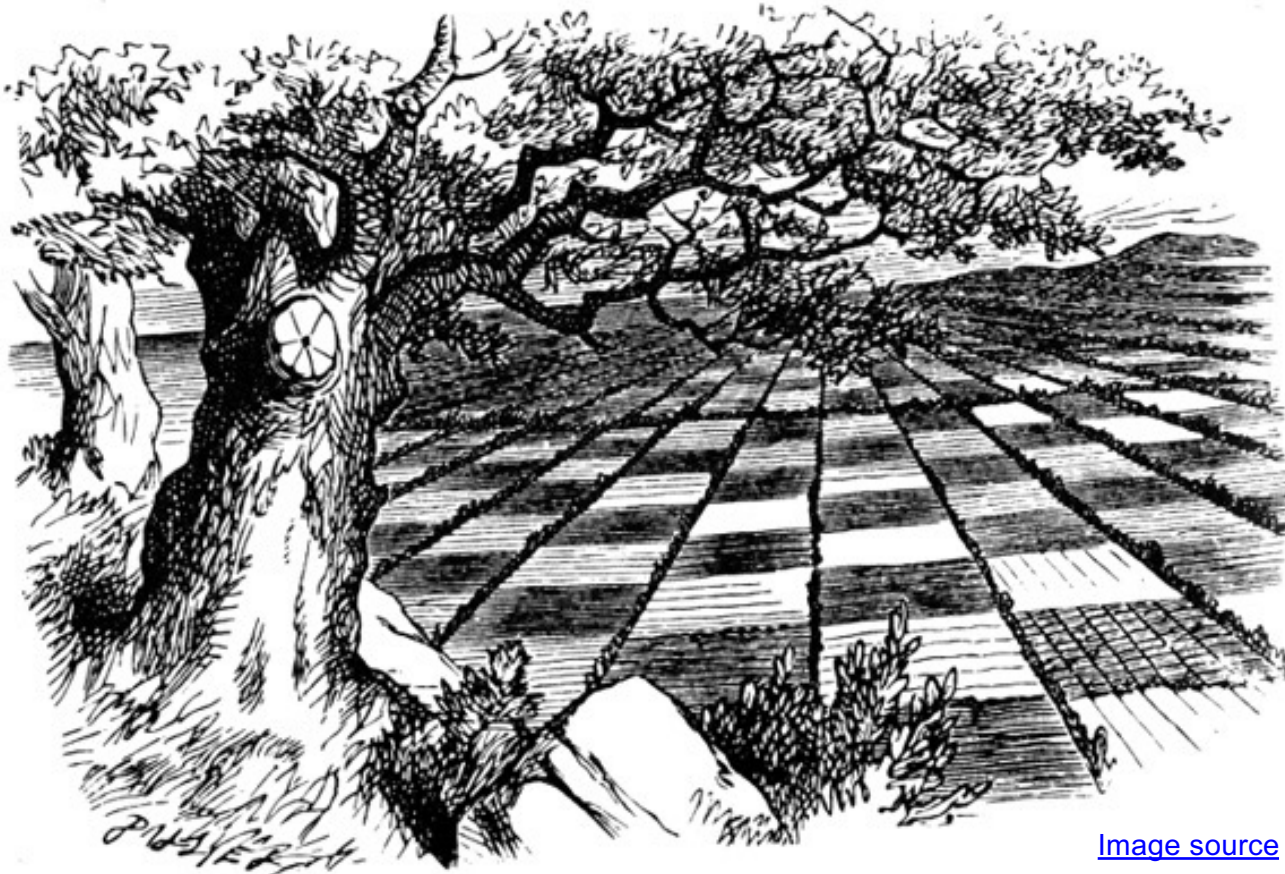


A gentle introduction to Fourier analysis



[Image source](#)

Many slides borrowed from S. Seitz, A. Efros, D. Hoiem, B. Freeman, A. Zisserman

1D Fourier transform

- Let's define an (overcomplete) set of basis functions:

$$\psi_u(t) = e^{i2\pi ut}, \quad u \in (-\infty, \infty)$$

- Compare

A diagram with the word "Integer" at the top. Three arrows point downwards from "Integer" to the terms $e^{i2k\pi t}$, $\cos(2k\pi t)$, and $\sin(2k\pi t)$ in the equation below.

$$e^{i2k\pi t} = \cos(2k\pi t) + i \sin(2k\pi t)$$

1D Fourier transform

- Let's define a (continuously parameterized) set of basis functions:

$$\psi_u(t) = e^{i2\pi ut}, \quad u \in (-\infty, \infty)$$

- Inner product for complex functions is given by:

$$\langle f, g \rangle = \int_{-\infty}^{\infty} f(t)g^*(t)dt$$

Complex conjugate:
real part stays the same,
imaginary part is flipped

1D Fourier transform

- Let's define a (continuously parameterized) set of basis functions:

$$\psi_u(t) = e^{i2\pi ut}, \quad u \in (-\infty, \infty)$$

- Inner product for complex functions is given by:

$$\langle f, g \rangle = \int_{-\infty}^{\infty} f(t)g^*(t)dt$$

- Orthonormality:

$$\langle \psi_{u_1}, \psi_{u_2} \rangle = \delta(u_1 - u_2) = \begin{cases} ? & \text{if } u_1 = u_2 \\ 0 & \text{otherwise} \end{cases}$$

$$\int_{-\infty}^{\infty} f(t) \delta(t)dt = f(0)$$

1D Fourier transform

- Given a signal $f(t)$, we want to represent it as a weighted combination of the basis functions $\psi_u(t) = e^{i2\pi ut}$ with weights $F(u)$:

$$f(t) = \int_{-\infty}^{\infty} F(u) e^{i2\pi ut} du$$

- Each weight $F(u)$ is given by the inner product of f and ψ_u :

$$F(u) = \langle f, \psi_u \rangle = \int_{-\infty}^{\infty} f(t) e^{-i2\pi ut} dt$$

1D Fourier transform

- Forward transform: $f(t) \xrightarrow{\mathcal{F}} F(u)$

$$F(u) = \int_{-\infty}^{\infty} f(t) e^{-i2\pi ut} dt$$

- Note: for the FT to exist, the *energy* $\int_{-\infty}^{\infty} |f(t)|^2 dt$ has to be finite

1D Fourier transform

- Forward transform: $f(t) \xrightarrow{\mathcal{F}} F(u)$

$$F(u) = \int_{-\infty}^{\infty} f(t) e^{-i2\pi ut} dt$$

- For each u , $F(u)$ is a *complex number* that encodes both the *amplitude* A and *phase* ϕ of the sinusoid $A \sin(2\pi ut + \phi)$ in the decomposition of $f(t)$:

$$F(u) = \operatorname{Re}(F(u)) + i \operatorname{Im}(F(u)),$$

$$A = \sqrt{\operatorname{Re}(F(u))^2 + \operatorname{Im}(F(u))^2}, \quad \phi = \tan^{-1} \frac{\operatorname{Im}(F(u))}{\operatorname{Re}(F(u))}$$

- If $f(t)$ is real, then $\operatorname{Re}(F(u)) = \operatorname{Re}(F(-u))$,
 $\operatorname{Im}(F(u)) = -\operatorname{Im}(F(-u))$

1D Fourier transform

- Forward transform: $f(t) \xrightarrow{\mathcal{F}} F(u)$

$$F(u) = \int_{-\infty}^{\infty} f(t) e^{-i2\pi ut} dt$$

- Important properties:

- Energy preservation:

$$\int_{-\infty}^{\infty} |f(t)|^2 dt = \int_{-\infty}^{\infty} |F(u)|^2 du$$

Parseval's
Theorem!



- Linearity: $\mathcal{F}\{af_1 + bf_2\} = a\mathcal{F}\{f_1\} + b\mathcal{F}\{f_2\}$

1D Fourier transform

- Forward transform: $f(t) \xrightarrow{\mathcal{F}} F(u)$

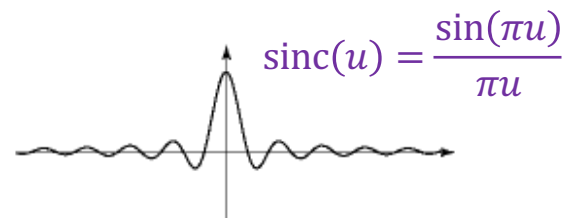
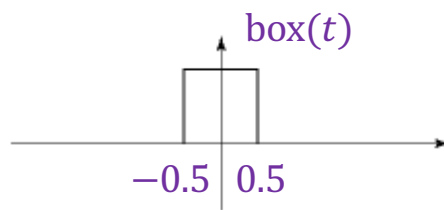
$$F(u) = \int_{-\infty}^{\infty} f(t) e^{-i2\pi ut} dt$$

- Inverse transform: $F(u) \xrightarrow{\mathcal{F}^{-1}} f(t)$

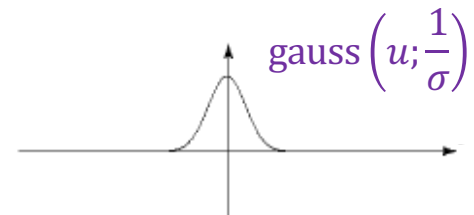
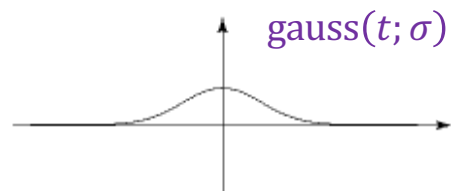
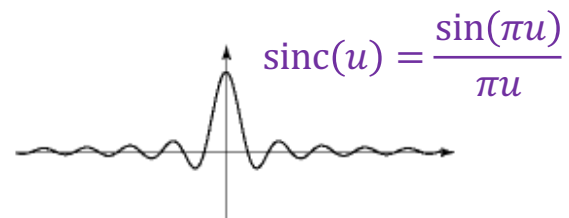
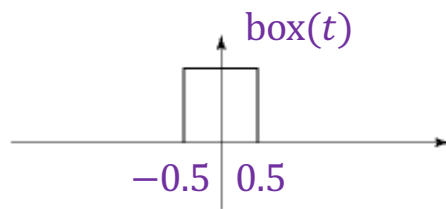
$$f(t) = \int_{-\infty}^{\infty} F(u) e^{i2\pi ut} du$$

- Duality: if $f(t) \xrightarrow{\mathcal{F}} F(u)$, then $F(t) \xrightarrow{\mathcal{F}} f(-u)$
 - Thus, we can talk about *Fourier transform pairs* $f(t) \leftrightarrow F(u)$

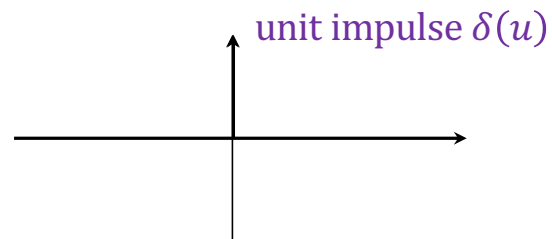
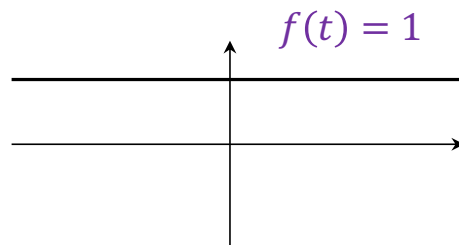
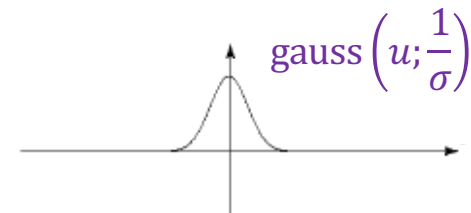
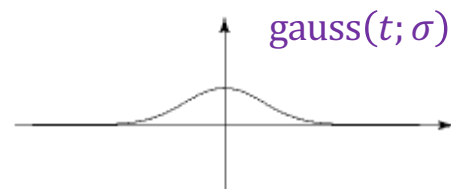
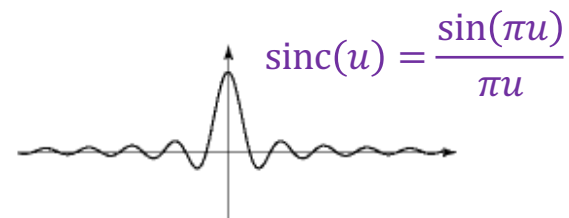
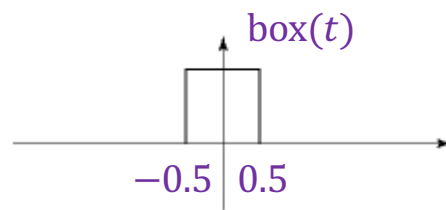
Important Fourier transform pairs



Important Fourier transform pairs



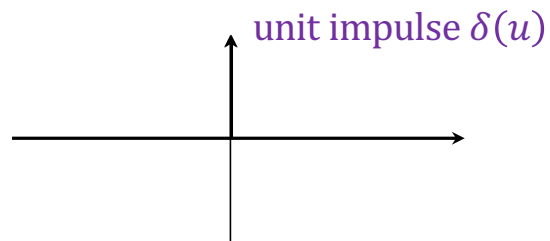
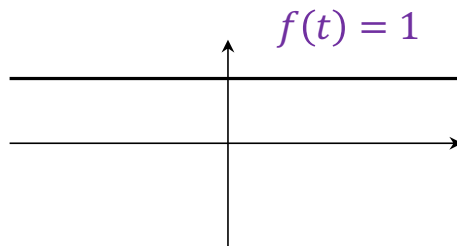
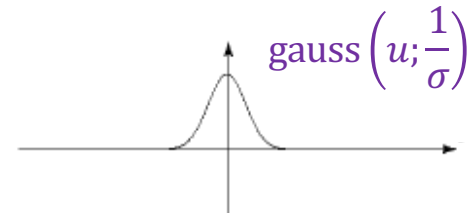
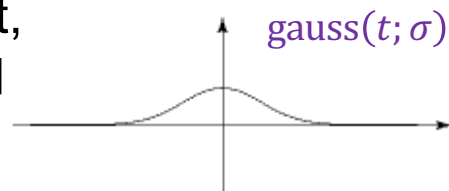
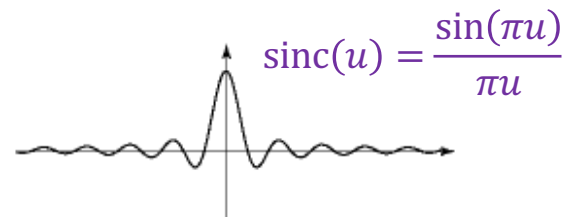
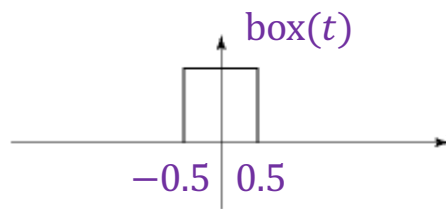
Important Fourier transform pairs



*The last one is formal since these functions don't meet the mathematical requirements for FT

Important Fourier transform pairs

Notice that when f has narrower support, $\text{FT}(f)$ has broader, and Vice versa!



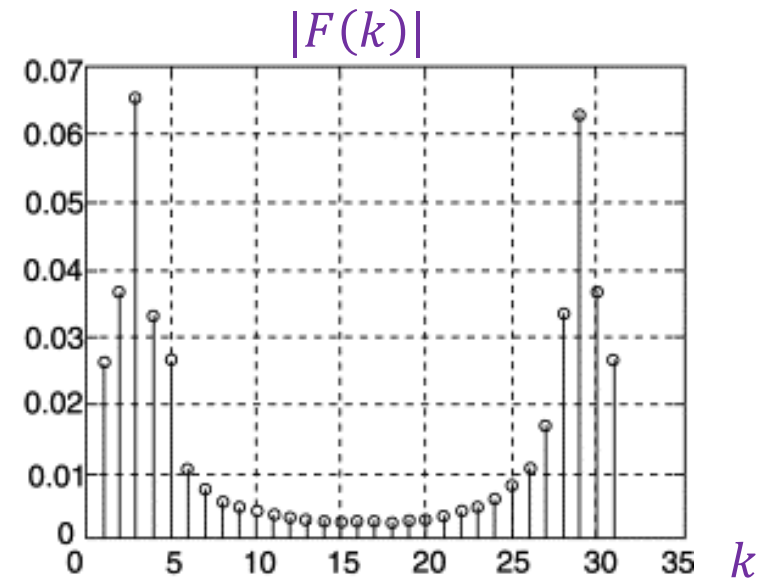
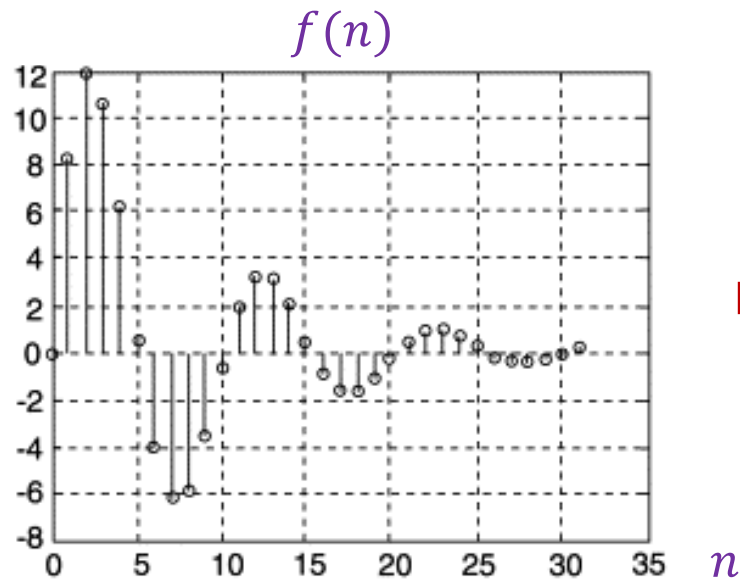
*The last one is formal since these functions don't meet the mathematical requirements for FT

Outline

- 1D Fourier transform
 - Definition and properties
 - Discrete Fourier transform

Discrete Fourier transform (DFT)

- Now suppose our signal consists of N samples $f(n)$,
 $n = 0, \dots, N - 1$
- We can also discretize frequencies to k/N , $k = 0, \dots, N - 1$
(k cycles per N samples)



[Image source](#)

Discrete Fourier transform (DFT)

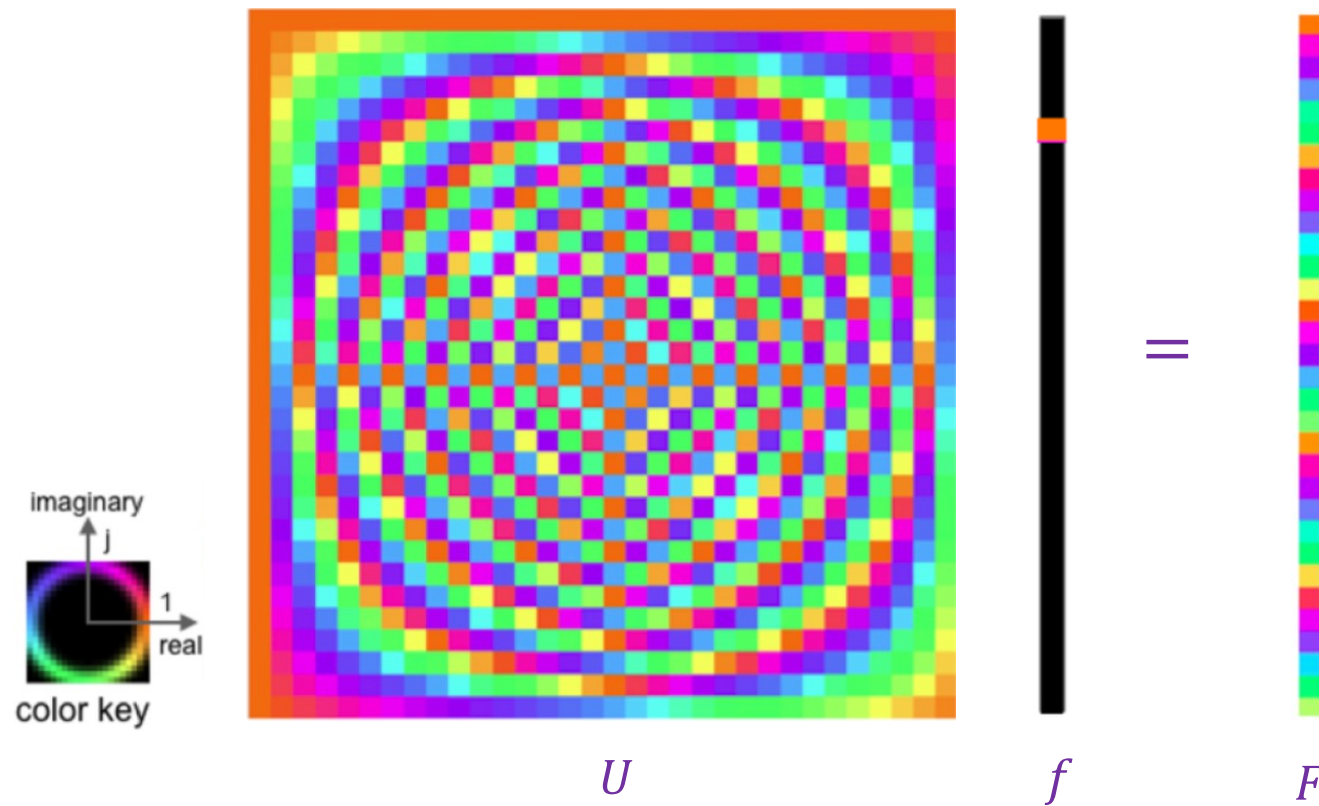
- Now suppose our signal consists of N samples $f(n)$,
 $n = 0, \dots, N - 1$
- We can also discretize frequencies to k/N , $k = 0, \dots, N - 1$
(k cycles per N samples)
- DFT formula:

$$F(k) = \sum_{n=0}^{N-1} f(n) \exp\left(-i \frac{2\pi k}{N} n\right)$$

- We can pack the values $\exp\left(-i \frac{2\pi k}{N} n\right)$, $k, n = 0, \dots, N - 1$ into an $N \times N$ matrix U , and DFT becomes just a matrix-vector multiplication!
- Fast Fourier transform: only $N \log N$ complexity!

DFT: Just a change of basis!

$$U f = F$$



Inverse DFT

- Forward DFT:

$$F(k) = \sum_{n=0}^{N-1} f(n) \exp\left(-i \frac{2\pi}{N} kn\right) \quad \text{or } F = Uf$$

- Inverse DFT:

$$f(n) = \frac{1}{N} \sum_{k=0}^{N-1} F(k) \exp\left(i \frac{2\pi}{N} kn\right) \quad \text{or } f = \frac{1}{N} U^{-1} F$$

where U^{-1} is the transpose of the *complex conjugate* of U

Periodicity of DFT and inverse DFT

- The result of DFT is periodic: because $F(k)$ is obtained as a sum of complex exponentials with a common period of N samples, $F(k + aN) = F(k)$ for any integer a :

$$\begin{aligned} F(k + aN) &= \sum_{n=0}^{N-1} f(n) \exp\left(-i \frac{2\pi}{N} n(k + aN)\right) \\ &= \sum_{n=0}^{N-1} f(n) \exp\left(-i \frac{2\pi n}{N} k\right) \exp(-i 2\pi a n) = F(k) \end{aligned}$$

- Likewise, the result of the inverse DFT is a periodic signal: $f(t + aN) = f(t)$ for any integer a

Outline

- 1D Fourier transform
 - Definition and properties
 - Discrete Fourier transform
- 2D Fourier transform

2D Fourier transform

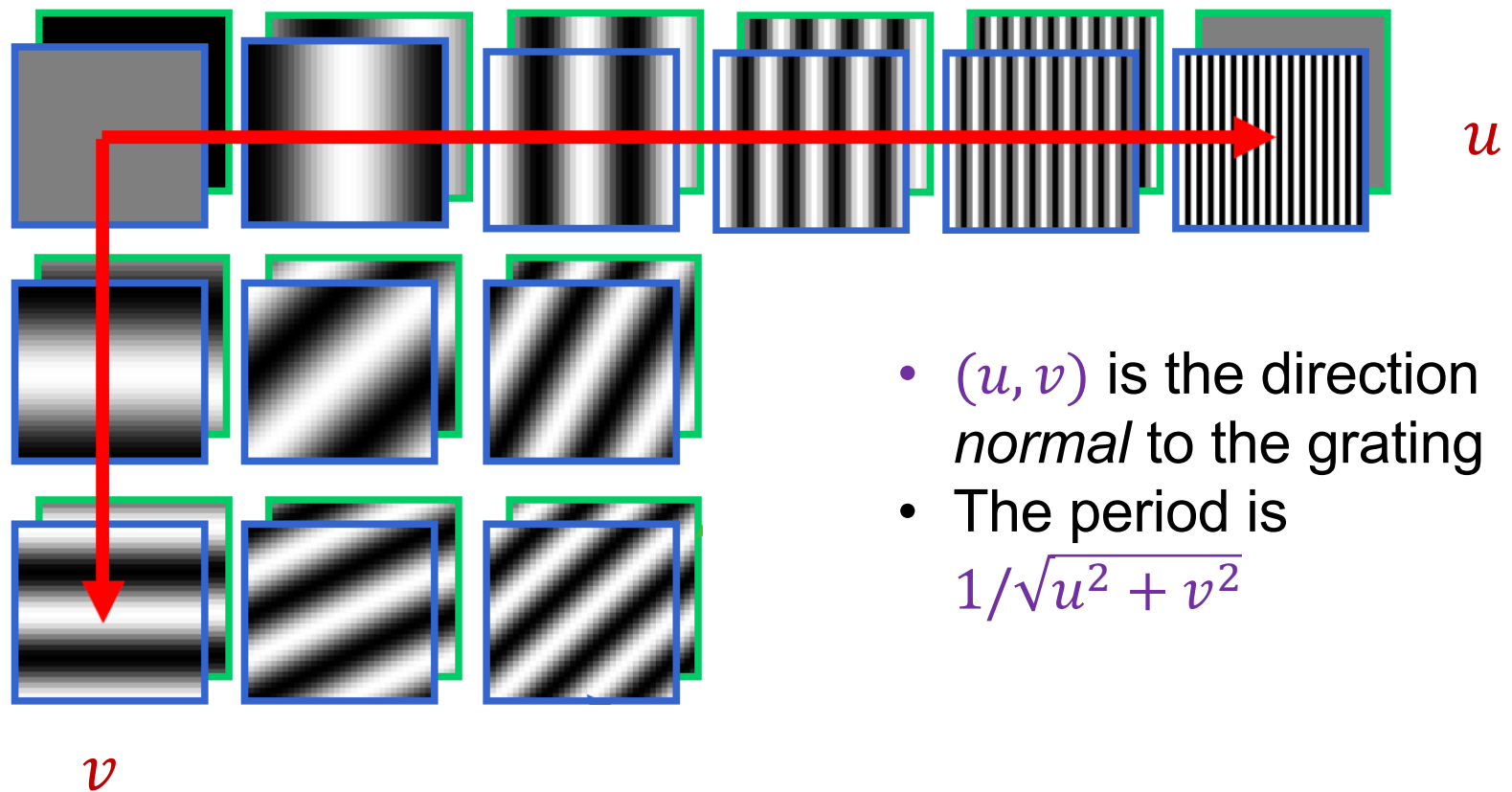
- To represent 2D signals $f(x, y)$, we need to extend our 1D basis functions $\psi_u(t) = e^{i2\pi ut}$ to two variables:

$$\begin{aligned}\psi_{u,v}(x, y) &= e^{i2\pi ux} e^{i2\pi vy} = e^{i2\pi(ux+vy)} \\ &= \cos 2\pi(ux + vy) + i \sin 2\pi(ux + vy)\end{aligned}$$

- What does this look like?

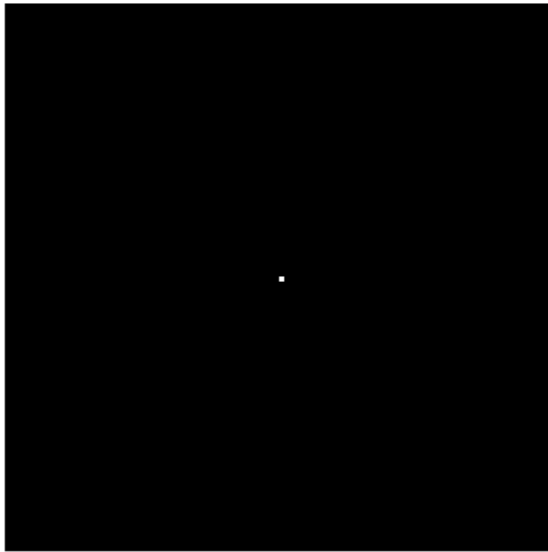
2D Fourier transform

- 2D basis functions are oriented sinusoidal “gratings”:



Basis function examples

(u, v)

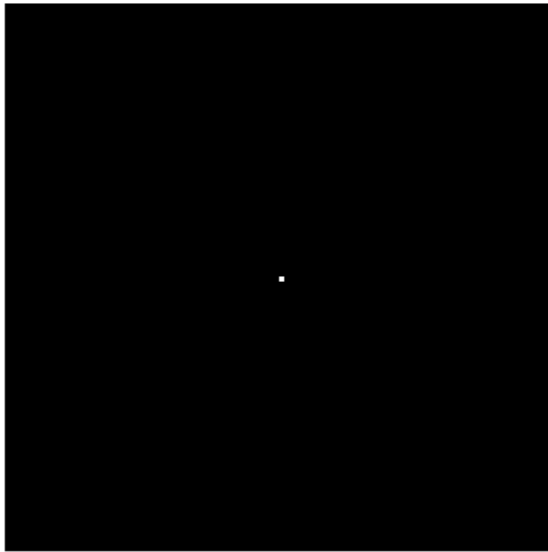


Real
component



Basis function examples

(u, v)

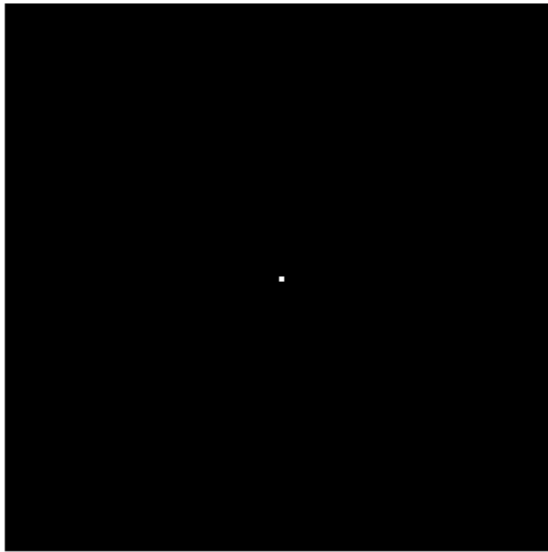


Real
component



Basis function examples

(u, v)

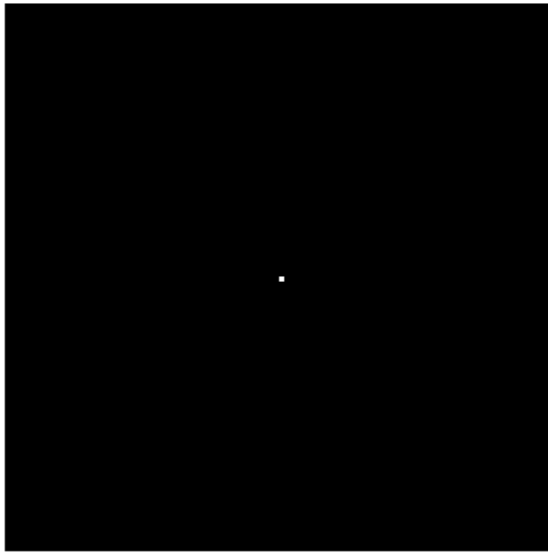


Real
component



Linear combination of basis functions

(u, v)



Real
component



2D Fourier transform

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

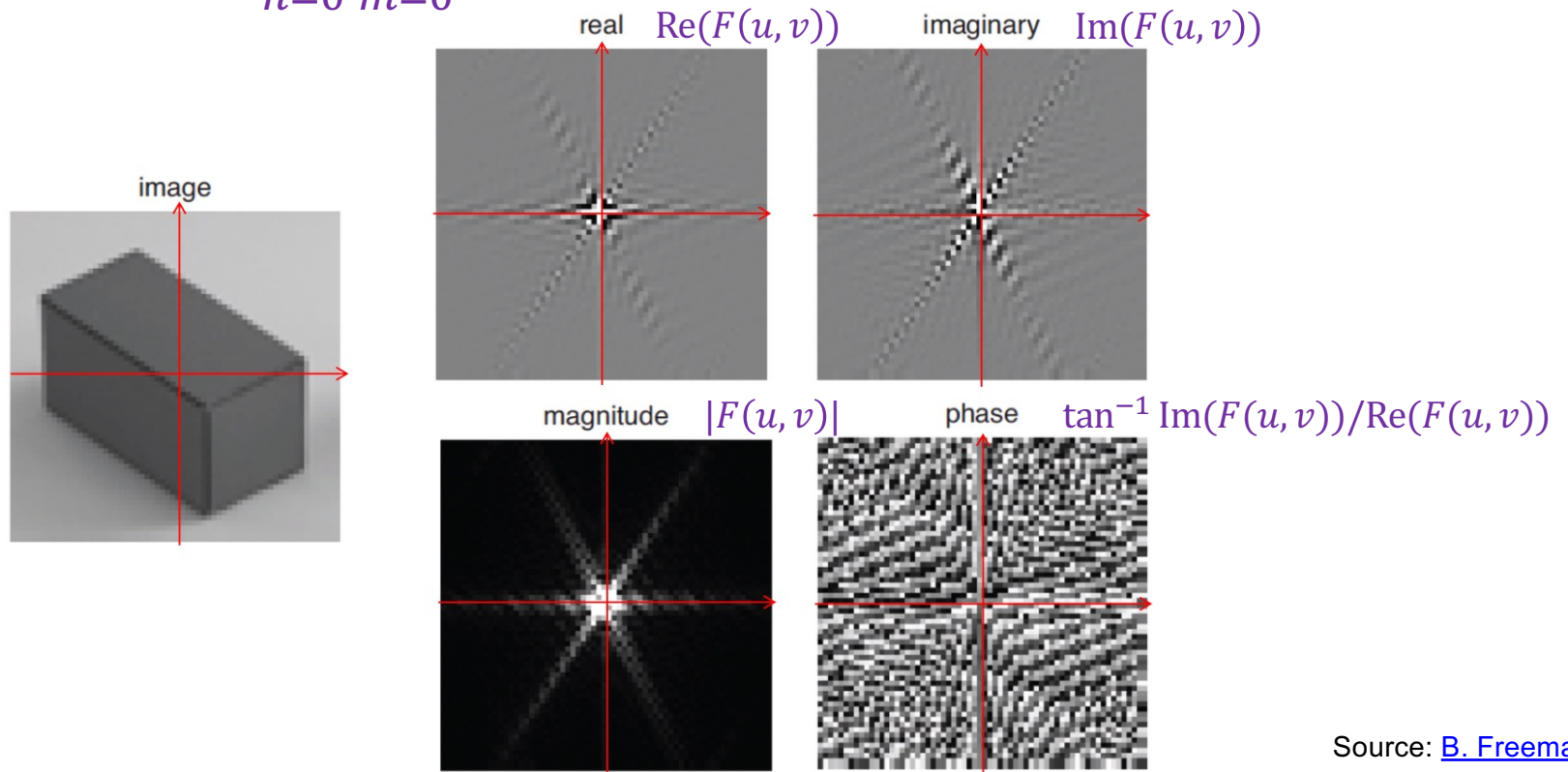
- Output is 2D and complex-valued:

$$F(u, v) = \text{Re}(F(u, v)) + i \text{Im}(F(u, v))$$

- Magnitude spectrum: $|F(u, v)| = \sqrt{\text{Re}(F(u, v))^2 + \text{Im}(F(u, v))^2}$
- Phase angle spectrum: $\tan^{-1} \frac{\text{Im}(F(u, v))}{\text{Re}(F(u, v))}$
- Symmetry: the Fourier transform of a real-valued image has coefficients that come in pairs, with $F(u, v)$ being the *complex conjugate* of $F(-u, -v)$
 - This means that the magnitude spectrum is symmetric about the origin

2D discrete Fourier transform

$$F(u, v) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} f(n, m) \exp \left(-i2\pi \left(\frac{un}{N} + \frac{vm}{M} \right) \right)$$



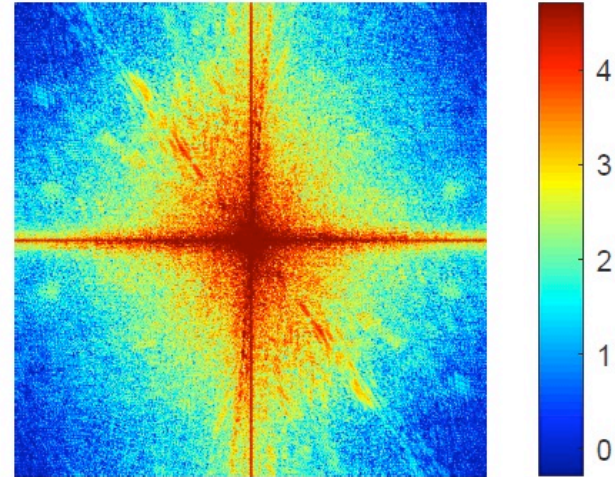
Source: [B. Freeman](#)

Real image examples

intensity image



log fft magnitude

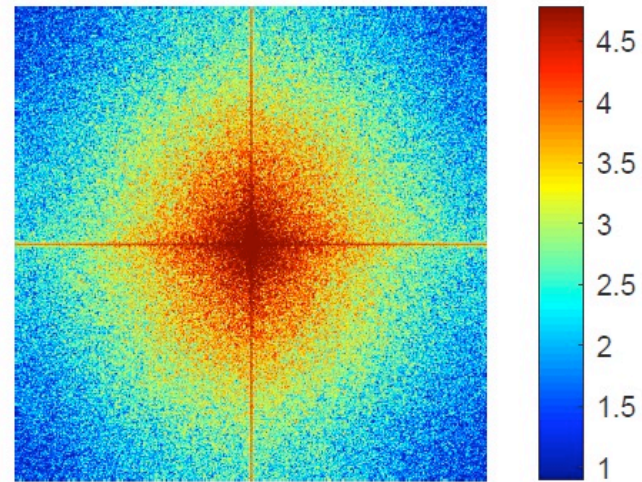


Real image examples

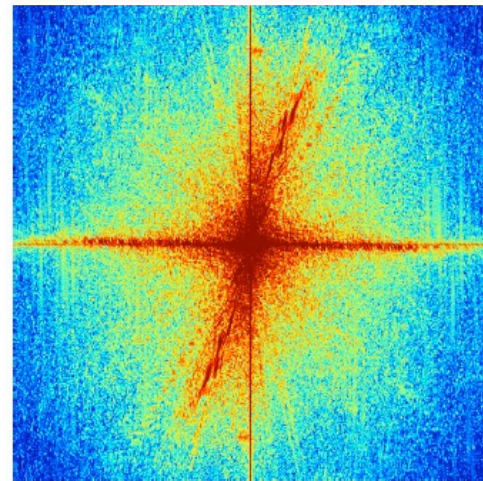
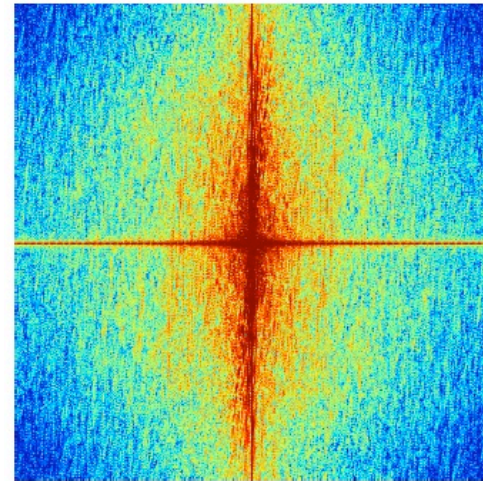
intensity image



log fft magnitude



Which image goes with which spectrum?



Trick – low pass filter

Multiply FT magnitude by Gaussian

Inverse FT

High frequencies are suppressed

Smoothing by FT

Image



LP Image



Gaussian

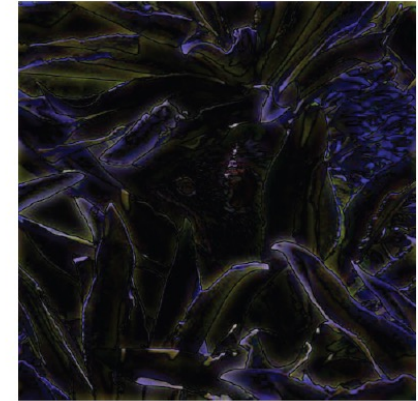
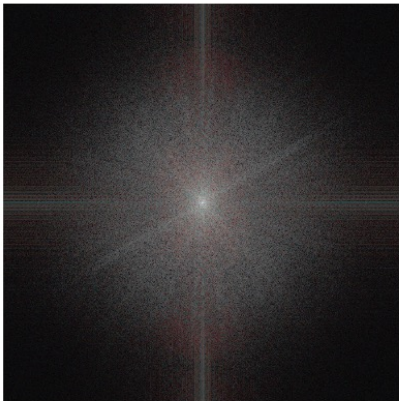
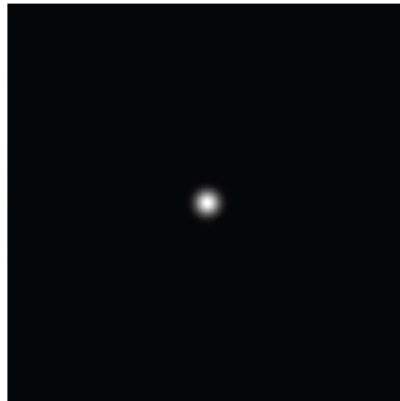


Image - LP Image



FT magnitude



LP magnitude

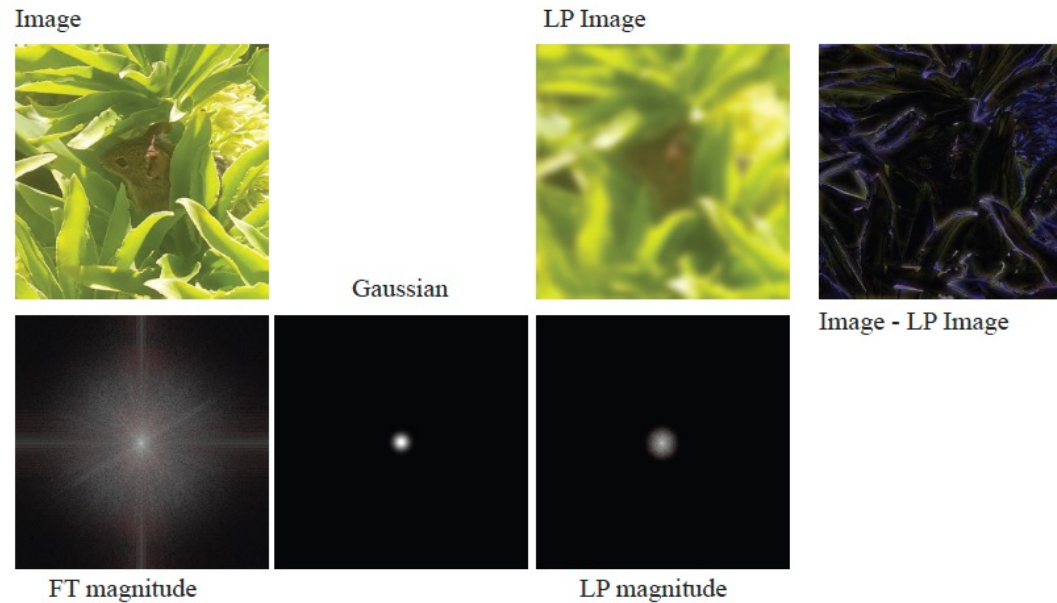


FIGURE 6.2: On the **top left**, the image of a four striped grass mouse with the log magnitude of its Fourier transform on the **bottom left**. **Center left**, the gaussian with $\sigma = 10$ in u, v space. This is multiplied by the weights, and the log magnitude of the result appears **center right**. Above this is the image obtained by inverting the Fourier transform – equivalently, the low pass filtered image. **Far left** shows the high pass filtered image, obtained by subtracting the low pass filtered image from the original. I have not shown the log magnitude of the high pass filtered image, because scaling makes the result quite difficult to interpret (it doesn't look filtered). The low pass filtered version is heavily blurred, because only the lowest spatial frequencies appear in the result. Note the high pass filtered version contains what is missing from the low pass version, so has few large values which appear at edges. Image credit: Figure shows my photograph, taken at Kirstenbosch and Long Beach respectively.

Smoothing with FT

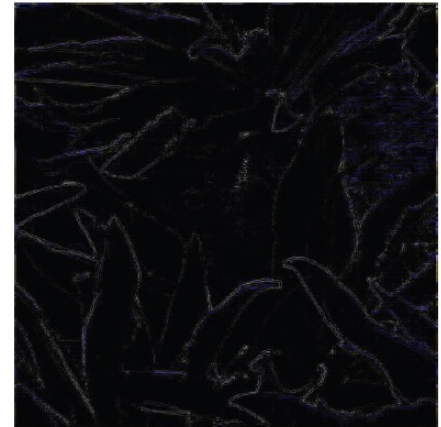
Image



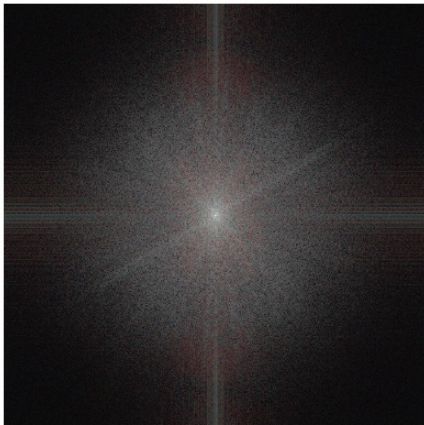
LP Image



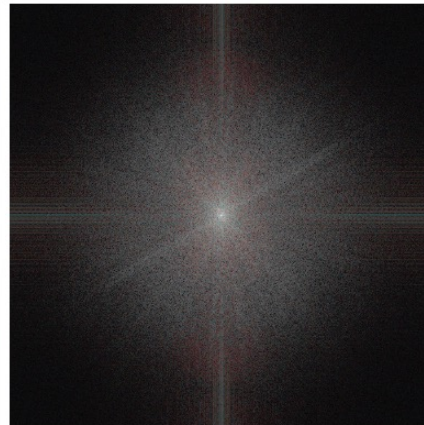
Gaussian



HP Image



FT magnitude



LP magnitude

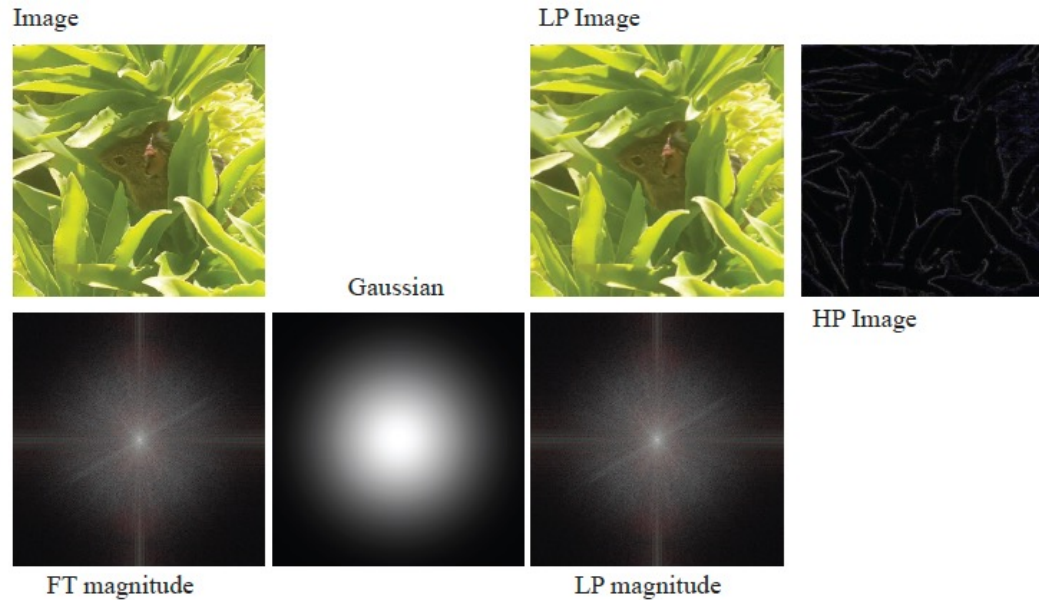


FIGURE 6.3: On the top left, the image of a four striped grass mouse with the log magnitude of its Fourier transform on the bottom left. Center left, the gaussian with $\sigma = 100$ in u, v space. This is multiplied by the weights, and the log magnitude of the result appears center right. Above this is the image obtained by inverting the Fourier transform – equivalently, the low pass filtered image. Far left shows the high pass filtered image, obtained by subtracting the low pass filtered image from the original. I have not shown the log magnitude of the high pass filtered image, because scaling makes the result quite difficult to interpret (it doesn't look filtered). The low pass filtered version is less heavily blurred than that in Figure 6.2, because only the lowest spatial frequencies appear in the result. Note the high pass filtered version contains what is missing from the low pass version, so has very few large values which appear at edges. Image credit: Figure shows my photograph, taken at Kirstenbosch and Long Beach respectively.

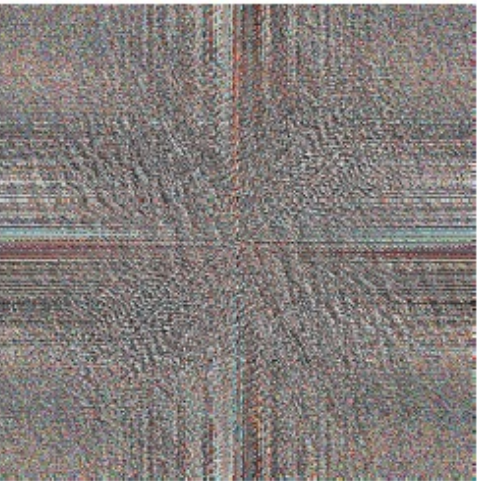
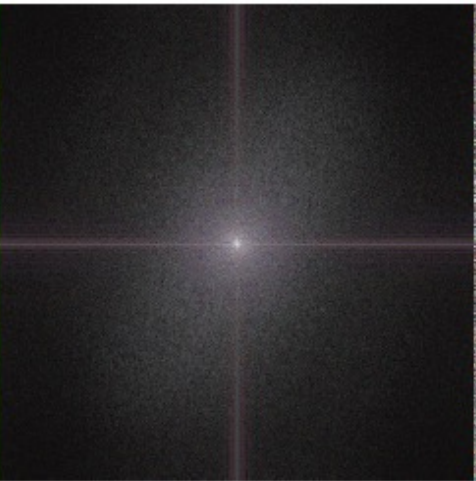
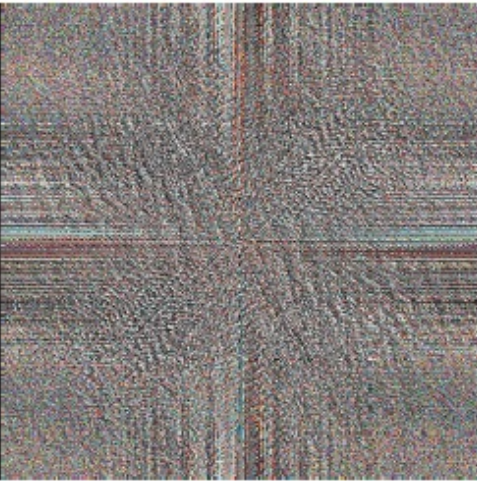
Phase vs. magnitude

- Which has more information, the phase or the magnitude?
- Let's take the phase from one image and combine it with the magnitude from another image

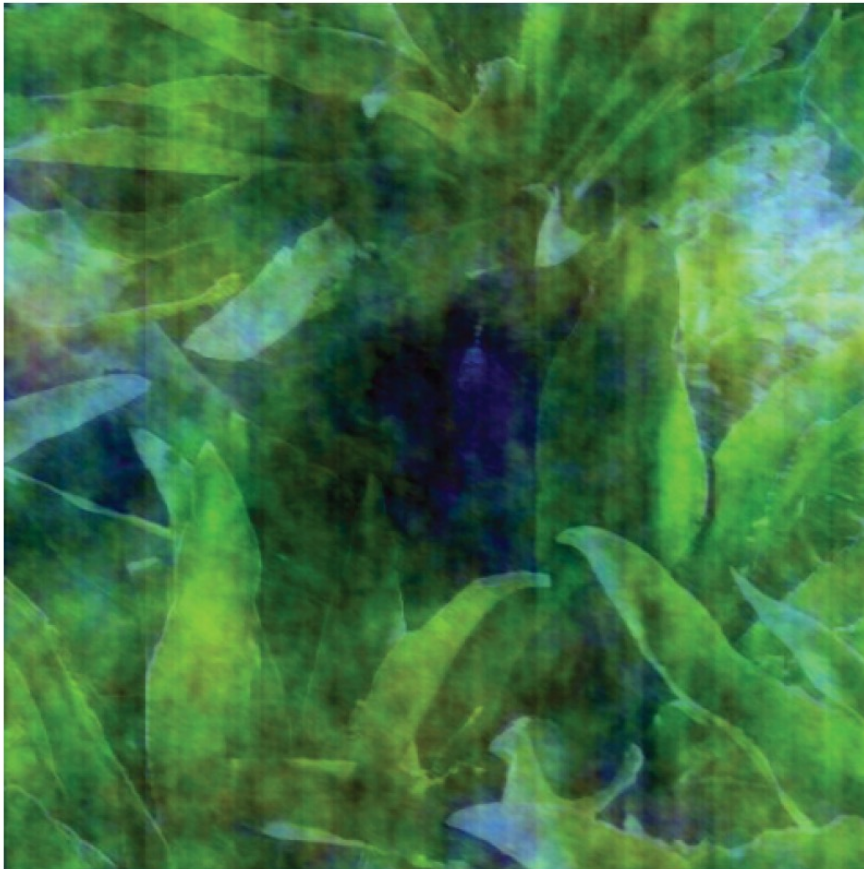
Image

Log Magnitude

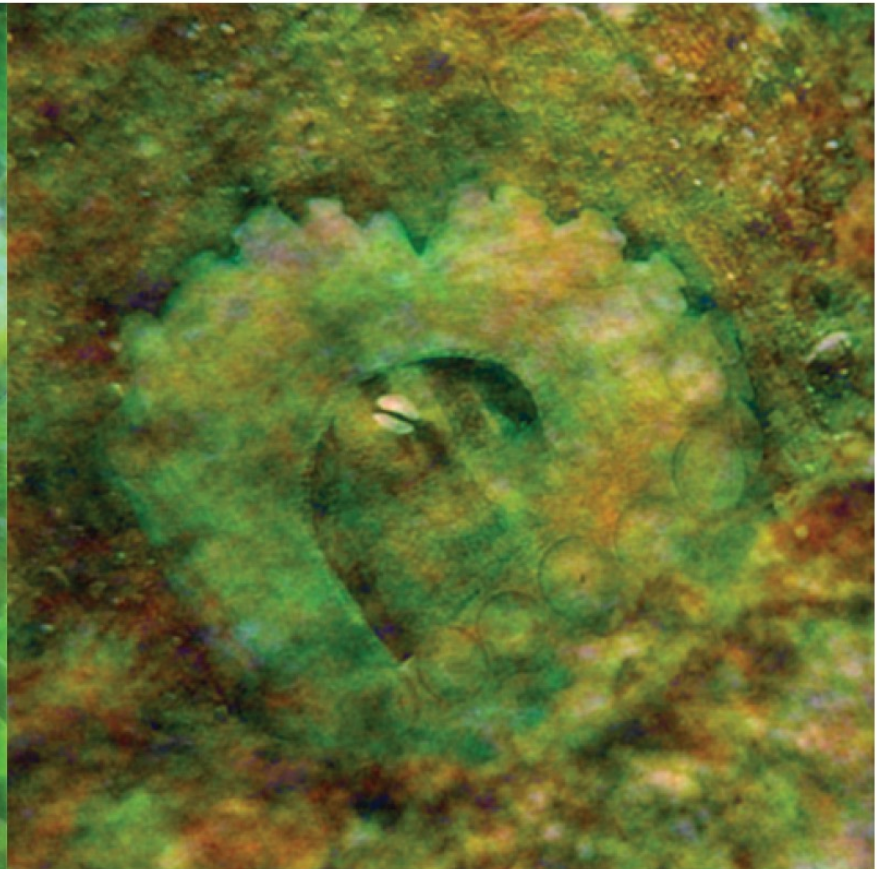
Phase



Mouse phase, octopus mag



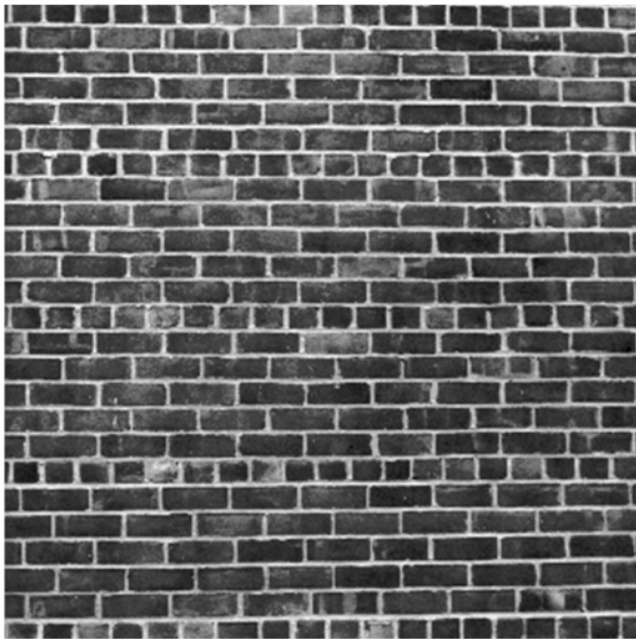
Octopus phase, mouse mag



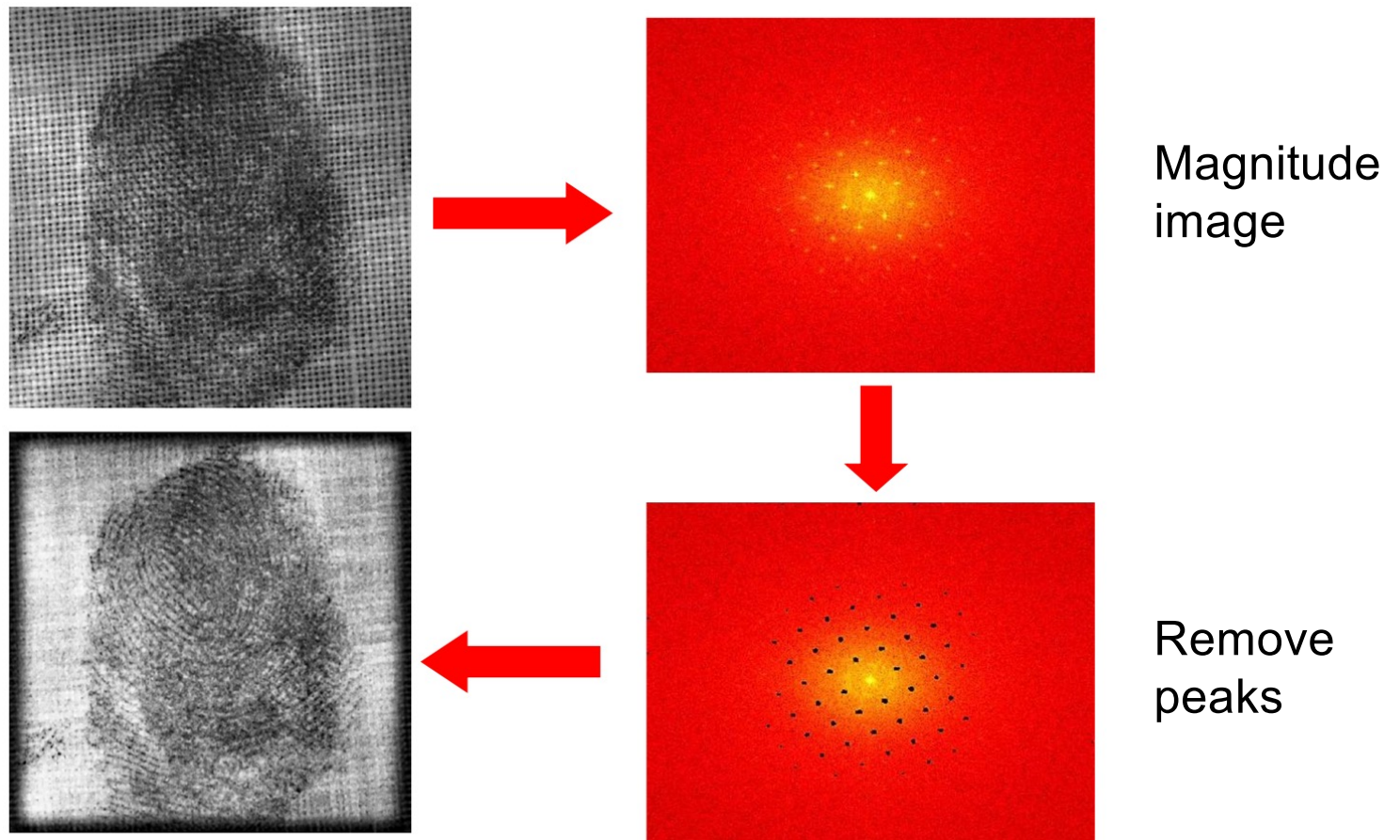
Images with periodic patterns

- The magnitude image has peaks corresponding to the frequencies of repetition

Image



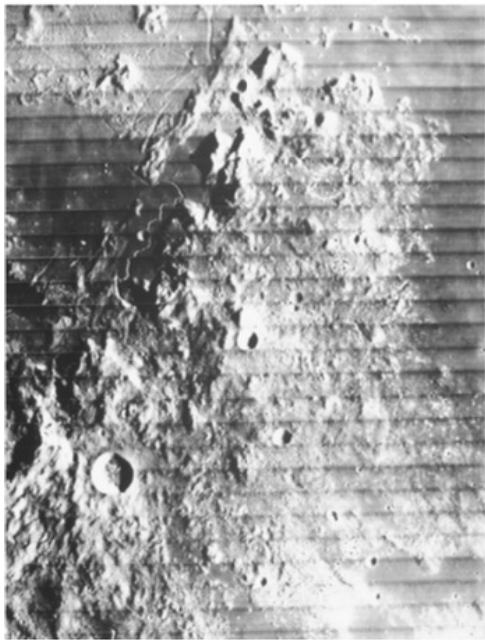
Application: Removing periodic patterns



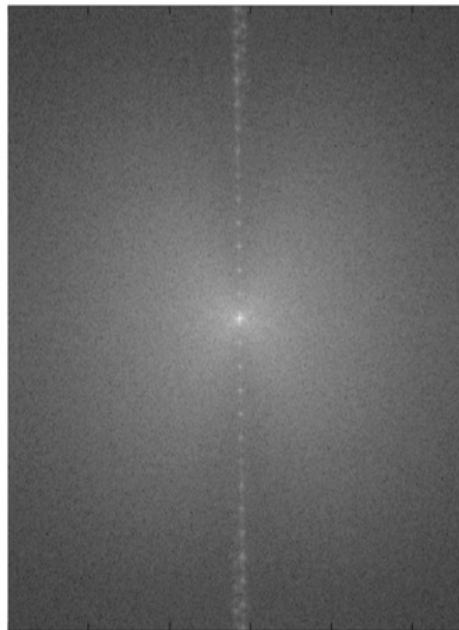
Source: [A. Zisserman](#)

Periodic patterns

Lunar orbital image
(1966)



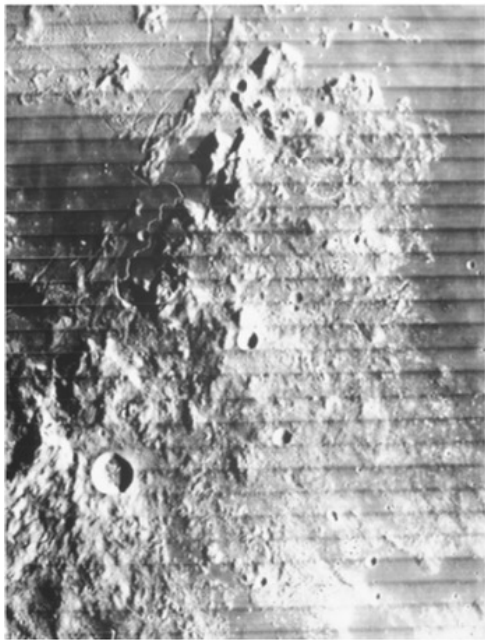
Magnitude
image



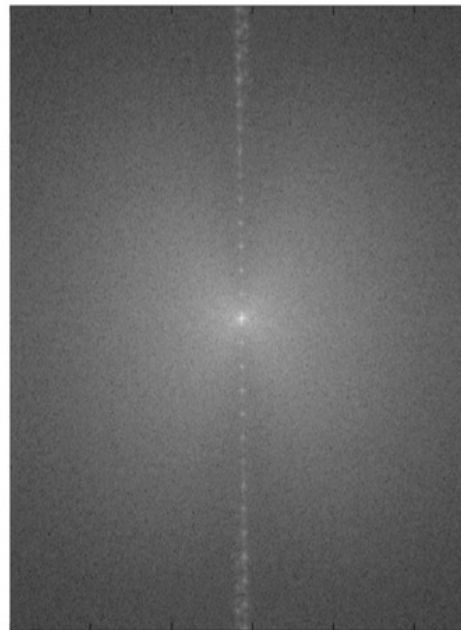
Why are there multiple peaks in the
magnitude image?

Application: Removing periodic patterns

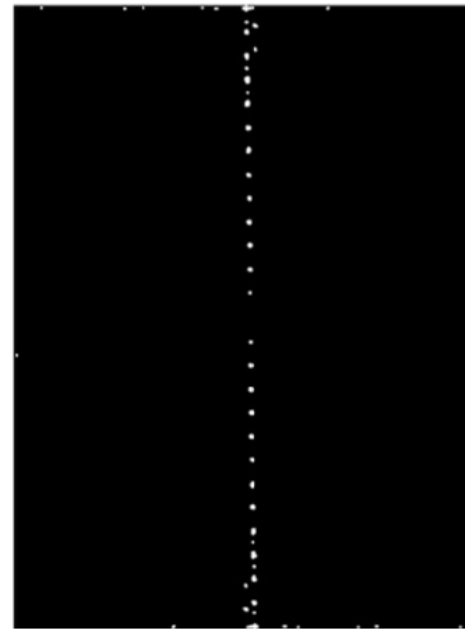
Lunar orbital image
(1966)



Magnitude
image



Remove
peaks



Join lines
removed



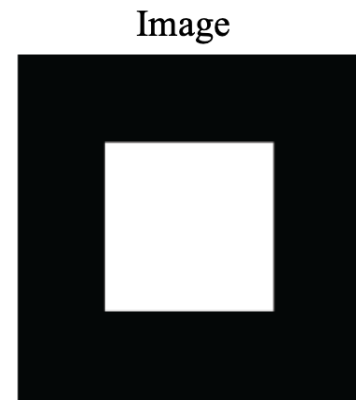
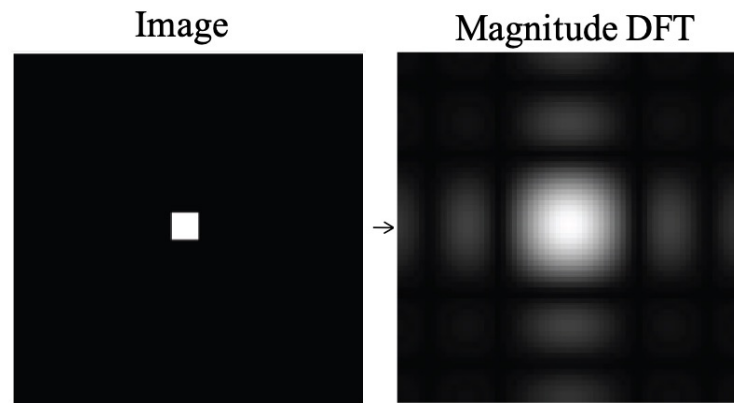
You should think of this as a kind of local smoothing
But in the Fourier domain!



Source: [A. Zisserman](#)

Image transformations

- How does the FT change when the image is scaled?



Scaled by the
inverse factor!

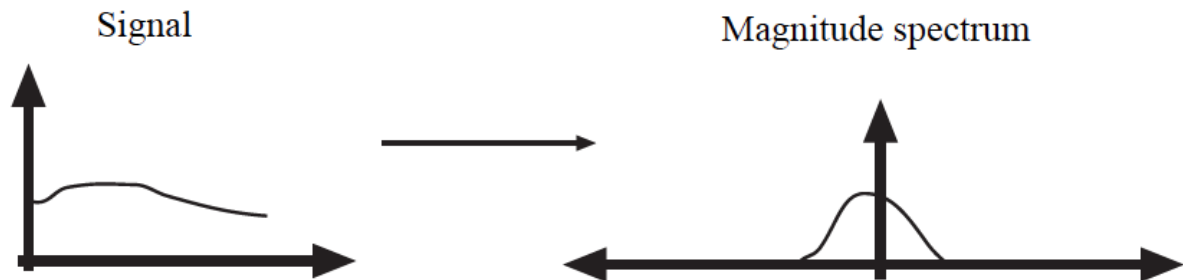
In 1D

2D is easy, follows this form

$$\begin{aligned}\mathcal{F}(f(at)) &= \int_{-\infty}^{\infty} f(at) \exp[-i2\pi ut] dt \\ &= \frac{1}{a} \int_{-\infty}^{\infty} f(s) \exp[-i2\pi u/as] ds \\ &= \frac{1}{a} \mathcal{F}(f)(u/a).\end{aligned}$$

Important effect

“wider” function
has
“narrower”
Fourier transform



“narrower” function
has
“wider”
Fourier transform

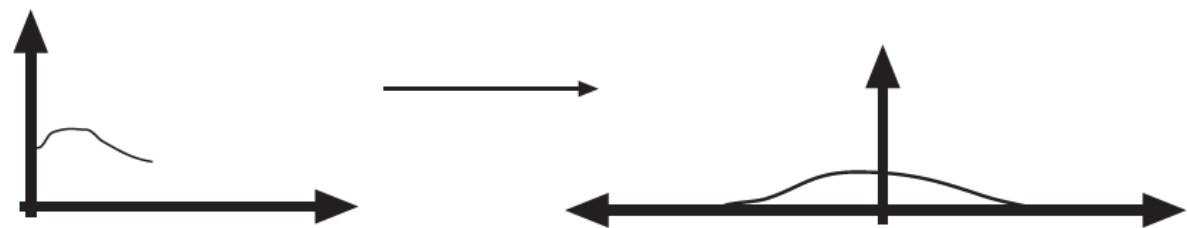


FIGURE 7.1: **Top** shows $f(t)$ and its magnitude spectrum, and **bottom** $f(2t)$ and its magnitude spectrum. Notice how narrowing the function broadens the Fourier transform (from top to bottom); or broadening it narrows the Fourier transform (from bottom to top).

Reference table in notes

Function	Fourier transform	Tag
$f(x, y)$	$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) e^{-i2\pi(ux+vy)} dx dy = \mathcal{F}(f)(u, v)$	1
$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \mathcal{F}(f)(u, v) e^{i2\pi(ux+vy)} du dv = f(x, y)$	$\mathcal{F}(f)(u, v)$	2
$\frac{\partial f}{\partial x}(x, y)$	$u\mathcal{F}(f)(u, v)$	3
$0.5\delta(x+a, y) + 0.5\delta(x-a, y)$	$\cos 2\pi au$	4
$\cos 2\pi ax$	$0.5\delta(u+a, v) + 0.5\delta(u-a, v)$	5
$e^{-\pi(x^2+y^2)}$	$e^{-\pi(u^2+v^2)}$	6
$\text{box}_1(x, y)$	$\frac{\sin u}{u} \frac{\sin v}{v}$	7
$f(ax, by)$	$\frac{\mathcal{F}(f)(u/a, v/b)}{ab}$	8
$\sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} \delta(x-i, y-j)$	$\sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} \delta(u-i, v-j)$	9
$f(x-a, y-b)$	$e^{-i2\pi(au+bv)} \mathcal{F}(f)$	10
$f(x \cos \theta - y \sin \theta, x \sin \theta + y \cos \theta)$	$\mathcal{F}(f)(u \cos \theta - v \sin \theta, u \sin \theta + v \cos \theta)$	11
$(f * g)(x, y)$	$\mathcal{F}(f)\mathcal{F}(g)(u, v)$	12