

Image Analysis

3. Fourier Transform

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Course on Image Analysis, winter term 2011/12

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1. Fourier Series Representation

2. The Fourier Transform

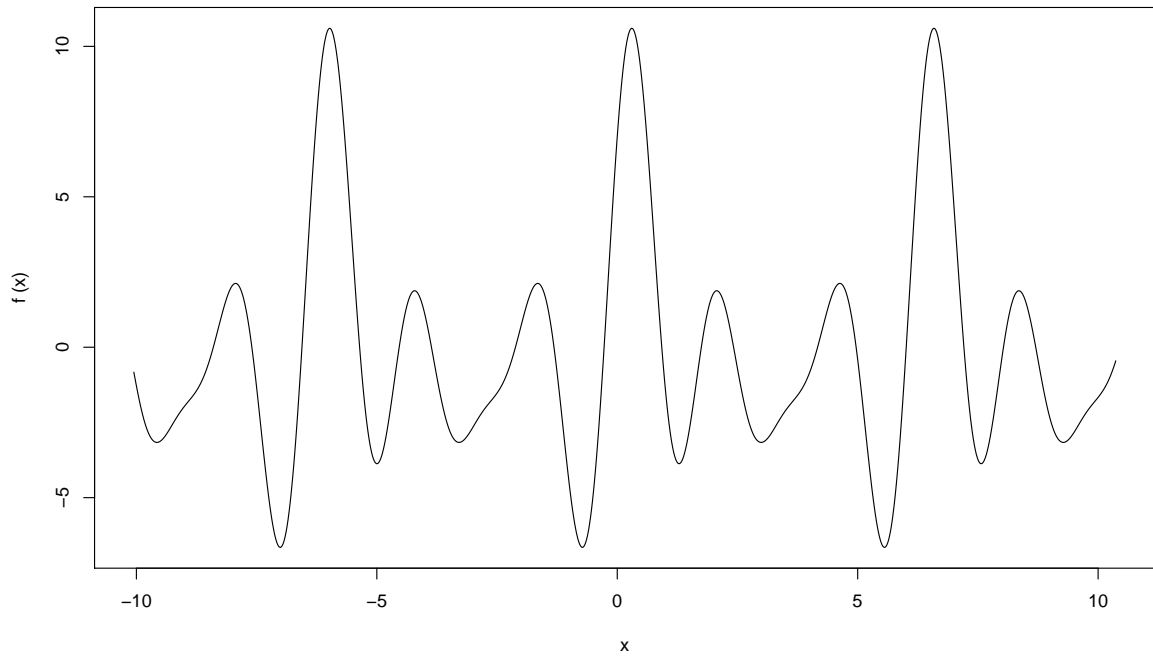
3. Discrete Signals

4. Discrete Fourier Transform

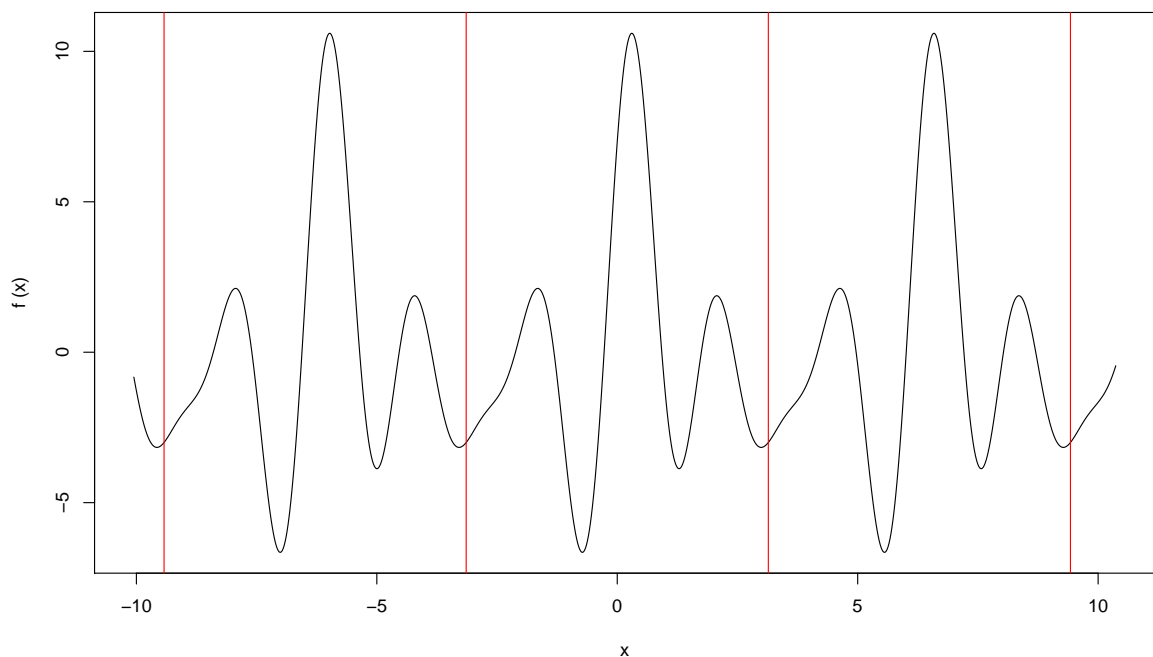
5. Two-dimensional Fourier Transforms

6. Applications

Periodic Functions



Periodic Functions



Periodic Functions

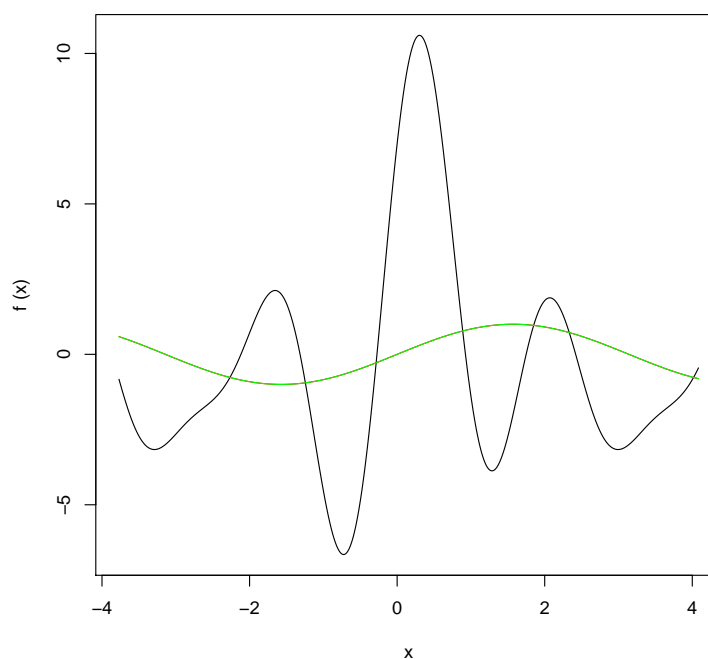
A function $f : \mathbb{R} \rightarrow \mathbb{C}$ is called **T -periodic** if

$$f(x + T) = f(x) \quad \forall x \in \mathbb{R}$$

Example: the functions \sin and \cos are 2π -periodic.

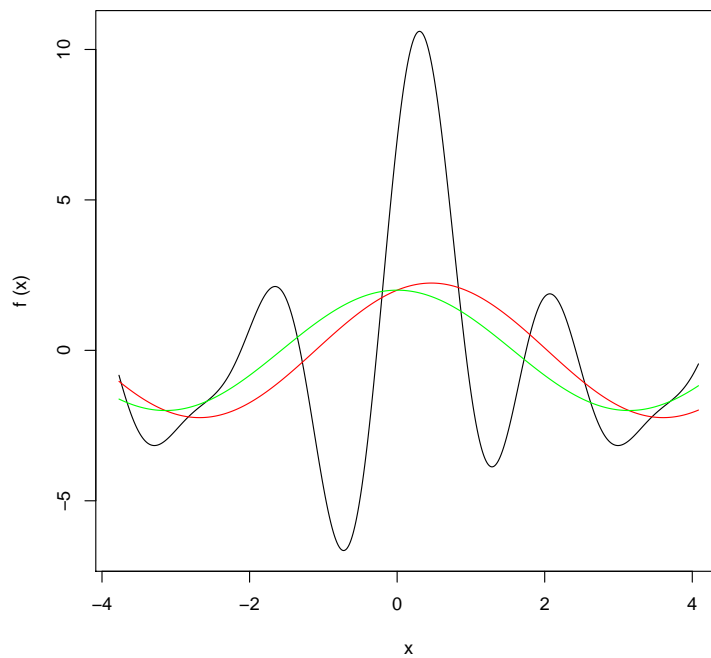
Example: the function $\sin(\omega x)$ is $2\pi/\omega$ -periodic.

Periodic Functions / Approximation



$$\hat{f}(x) = 1 \sin(x)$$

Periodic Functions / Approximation

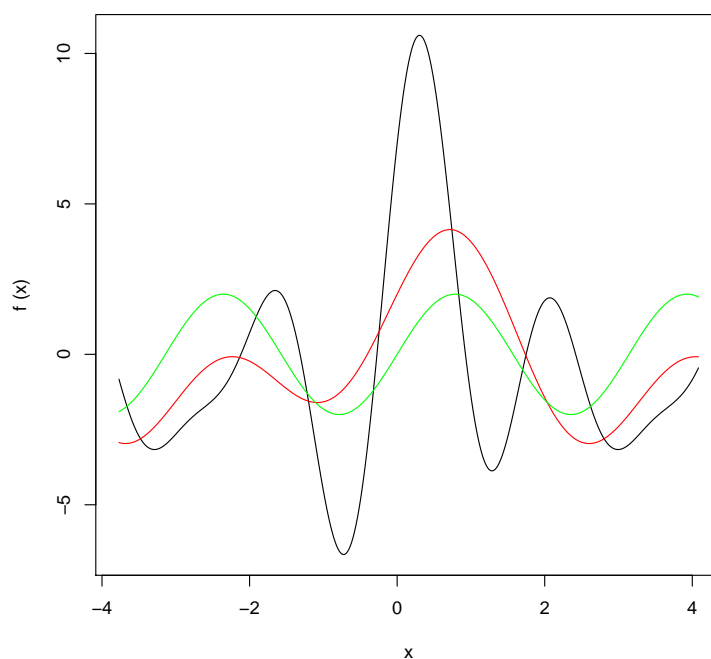


$$\hat{f}(x) = 1 \sin(x) + 2 \cos x$$

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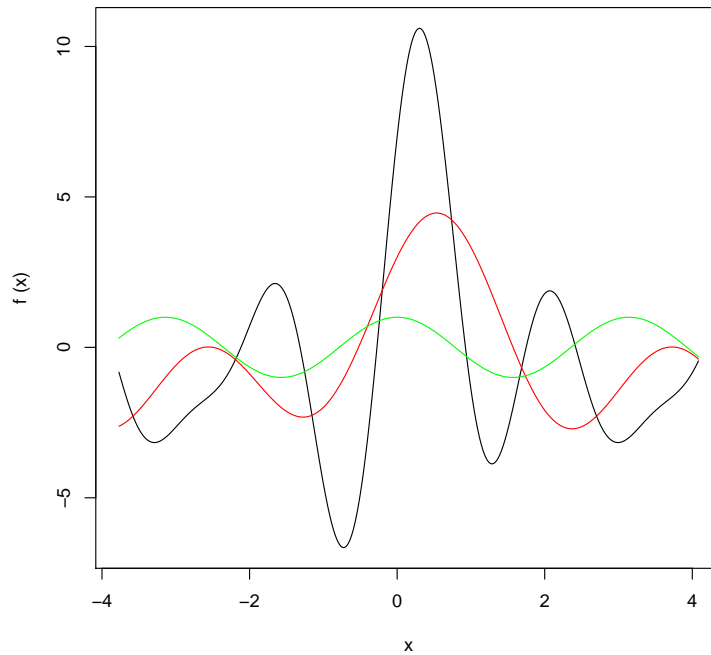
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Periodic Functions / Approximation



$$\hat{f}(x) = 1 \sin(x) + 2 \cos x + 2 \sin 2x$$

Periodic Functions / Approximation

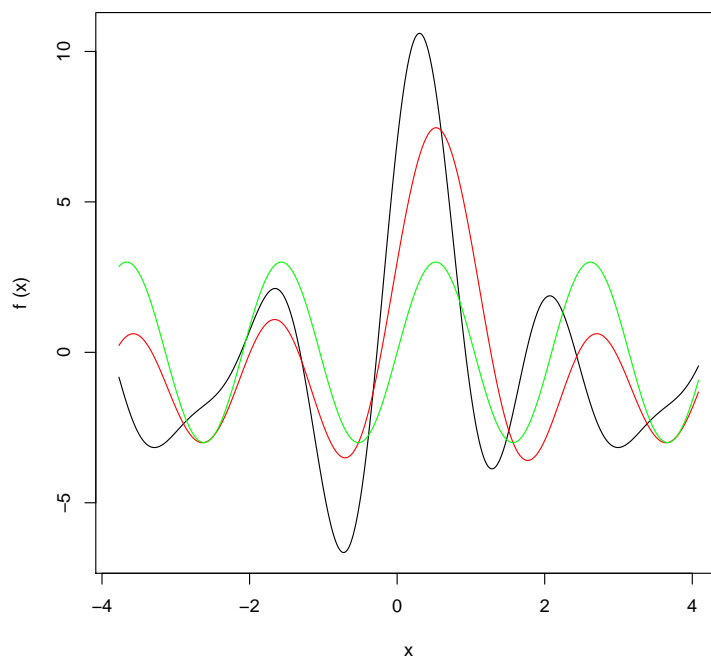


$$\hat{f}(x) = 1 \sin(x) + 2 \cos x + 2 \sin 2x + 1 \cos 2x$$

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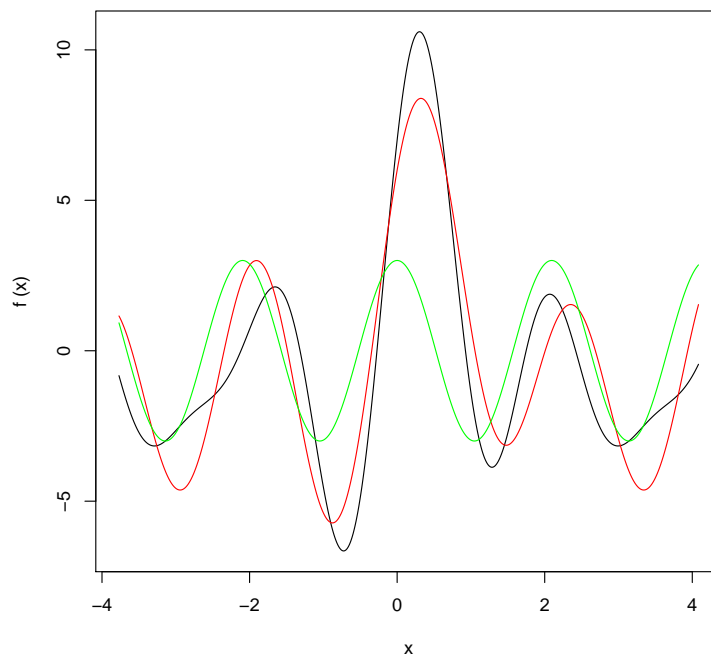
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Periodic Functions / Approximation



$$\hat{f}(x) = 1 \sin(x) + 2 \cos x + 2 \sin 2x + 1 \cos 2x + 3 \sin 3x$$

Periodic Functions / Approximation

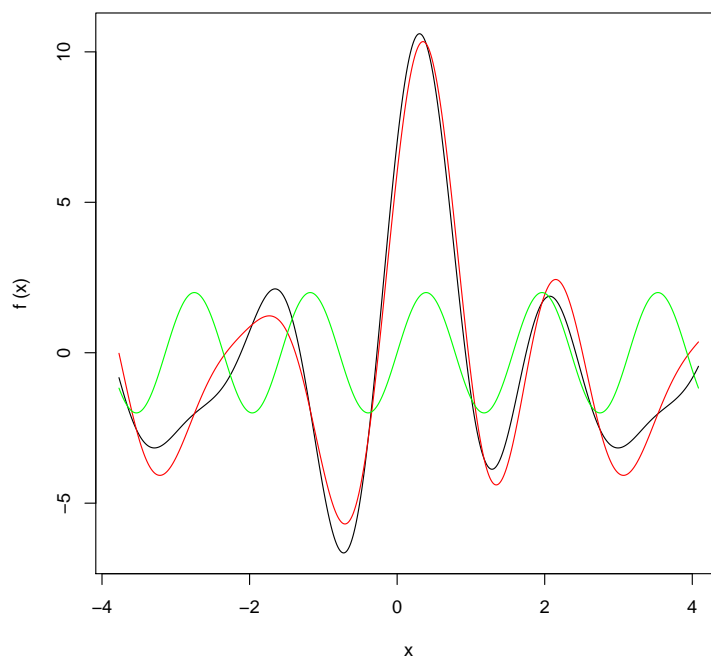


$$\hat{f}(x) = 1 \sin(x) + 2 \cos x + 2 \sin 2x + 1 \cos 2x + 3 \sin 3x + 3 \cos 3x$$

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Periodic Functions / Approximation

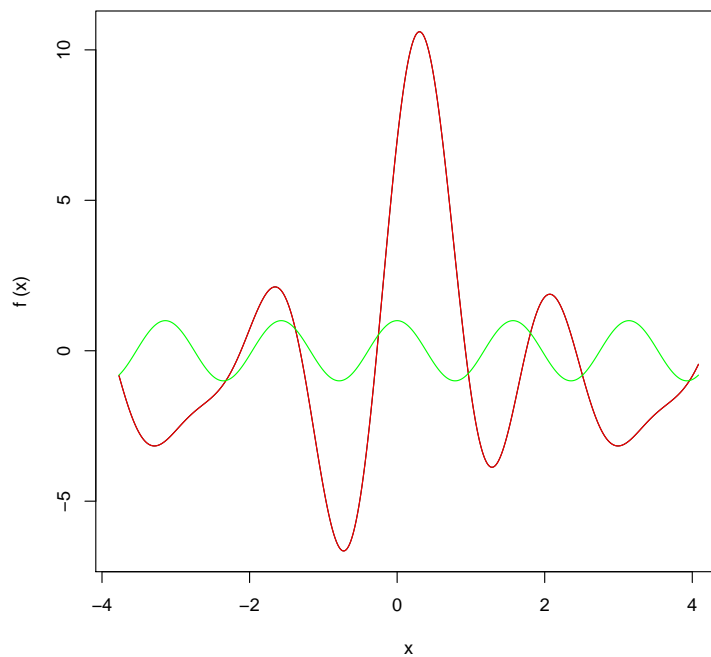


$$\hat{f}(x) = 1 \sin(x) + 2 \cos x + 2 \sin 2x + 1 \cos 2x + 3 \sin 3x + 3 \cos 3x + 2 \sin 4x$$

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Periodic Functions / Approximation



$$\hat{f}(x) = 1 \sin(x) + 2 \cos x + 2 \sin 2x + 1 \cos 2x + 3 \sin 3x + 3 \cos 3x + 2 \sin 4x + 1 \cos 4x$$

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Fourier Series Representation

Theorem (Fourier Series Representation). Any continuous, differentiable and T -periodic function $f : \mathbb{R} \rightarrow \mathbb{C}$ can be written as

$$f(x) = \frac{a_0}{2} + \sum_{k=1}^{\infty} a_k \cos k\omega x + b_k \sin k\omega x, \quad \omega := \frac{2\pi}{T}$$

with coefficients $a_k, b_k \in \mathbb{C}$, called a **Fourier Series of f** .

How to compute Fourier coefficients a_k, b_k for a given function f ?



Jean Baptiste Joseph Fourier (1768–1830),
French Mathematician and Physicist

Note. Actually, the class of functions that can be represented as Fourier series is much larger (see, e.g., [?, p. 314]).

Trigonometric Addition Formulas

Lemma (Trigonometric Addition Formulas). For all $x, y \in \mathbb{R}$:

$$\cos(x + y) = \cos x \cos y - \sin x \sin y$$

$$\sin(x + y) = \sin x \cos y + \sin y \cos x$$

Some Trigonometric Integrals

$$\int \cos ax \cos bx \, dx = \begin{cases} \frac{1}{2} \left(\frac{\sin(a+b)x}{a+b} + \frac{\sin(a-b)x}{a-b} \right), & \text{if } a \neq b \\ \frac{\sin(2ax) + 2ax}{4a}, & \text{else} \end{cases}$$

$$\int \sin ax \sin bx \, dx = \begin{cases} -\frac{1}{2} \left(\frac{\sin(a+b)x}{a+b} - \frac{\sin(a-b)x}{a-b} \right), & \text{if } a \neq b \\ -\frac{\sin(2ax) - 2ax}{4a}, & \text{else} \end{cases}$$

$$\int \sin ax \cos bx \, dx = \begin{cases} -\frac{1}{2} \left(\frac{\cos(a+b)x}{a+b} + \frac{\cos(a-b)x}{a-b} \right), & \text{if } a \neq b \\ \frac{\sin^2(ax)}{2a}, & \text{else} \end{cases}$$

Some Trigonometric Integrals

The six formulas easily can be proven by differentiation, e.g.,

$$\int \cos ax \cos bx \, dx \stackrel{?}{=} \frac{1}{2} \left(\frac{\sin(a+b)x}{a+b} + \frac{\sin(a-b)x}{a-b} \right)$$

for $a \neq b$. Derivation $\frac{d}{dx}$ yields:

$$\begin{aligned} \cos ax \cos bx &\stackrel{?}{=} \frac{1}{2} \left(\frac{(a+b) \cos(a+b)x}{a+b} + \frac{(a-b) \cos(a-b)x}{a-b} \right) \\ &= \frac{1}{2} (\cos(a+b)x + \cos(a-b)x) \\ &= \frac{1}{2} (\cos ax \cos bx - \sin ax \sin bx + \cos ax \cos(-bx) - \sin ax \sin(-bx)) \\ &= \frac{1}{2} (\cos ax \cos bx - \sin ax \sin bx + \cos ax \cos bx + \sin ax \sin bx) \\ &= \cos ax \cos bx \end{aligned}$$

Trigonometric Orthogonality Relations

Let $\omega \in \mathbb{R}^+$. The functions

$$\{\sin k\omega x \mid k \in \mathbb{N}, k > 0\} \cup \{\cos k\omega x \mid k \in \mathbb{N}, k > 0\}$$

are pairwise orthogonal with respect to

$$\langle f, g \rangle := \int_{-\pi/\omega}^{+\pi/\omega} f(x)g(x)dx$$

i.e., for any two distinct such functions f, g

$$\langle f, g \rangle = \int_{-\pi/\omega}^{+\pi/\omega} f(x)g(x)dx = 0$$

but

$$\langle f, f \rangle = \frac{\pi}{\omega} \neq 0$$

Trigonometric Orthogonality Relations

Proof: let $f = \cos k\omega x$ and $g = \cos l\omega x$ with $k \neq l$, then:

$$\begin{aligned} \langle f, g \rangle &= \int_{-\pi/\omega}^{+\pi/\omega} \cos k\omega x \cos l\omega x \, dx = \left[\frac{1}{2} \left(\frac{\sin(k+l)\omega x}{(k+l)\omega} + \frac{\sin(k-l)\omega x}{(k-l)\omega} \right) \right]_{-\pi/\omega}^{+\pi/\omega} \\ &= \frac{1}{2} \left(\frac{\sin(k+l)\pi}{(k+l)\omega} + \frac{\sin(k-l)\pi}{(k-l)\omega} - \frac{\sin-(k+l)\pi}{(k+l)\omega} - \frac{\sin-(k-l)\pi}{(k-l)\omega} \right) \\ &= \frac{\sin(k+l)\pi}{(k+l)\omega} + \frac{\sin(k-l)\pi}{(k-l)\omega} = 0 \end{aligned}$$

but

$$\langle f, f \rangle = \left[\frac{\sin(2k\omega x) + 2k\omega x}{4k\omega} \right]_{-\pi/\omega}^{+\pi/\omega} = \frac{\sin(2k\pi) + 2k\pi}{4k\omega} - \frac{\sin(-2k\pi) + (-2k\pi)}{4k\omega} = \frac{\pi}{\omega}$$

Fourier Series Representation

Theorem (Fourier Series Representation). Any continuous, differentiable and T -periodic function $f : \mathbb{R} \rightarrow \mathbb{C}$ can be written as

$$f(x) = \frac{a_0}{2} + \sum_{k=1}^{\infty} a_k \cos k\omega x + b_k \sin k\omega x, \quad \omega := \frac{2\pi}{T}$$

with coefficients $a_k, b_k \in \mathbb{C}$, called a **Fourier Series of f** .

How to compute Fourier coefficients a_k, b_k for a given function f ?

$$\begin{aligned} a_k &= \frac{1}{\pi/\omega} \int_{-\pi/\omega}^{+\pi/\omega} f(x) \cos k\omega x \, dx \\ b_k &= \frac{1}{\pi/\omega} \int_{-\pi/\omega}^{+\pi/\omega} f(x) \sin k\omega x \, dx \end{aligned}$$

Fourier Series Representation

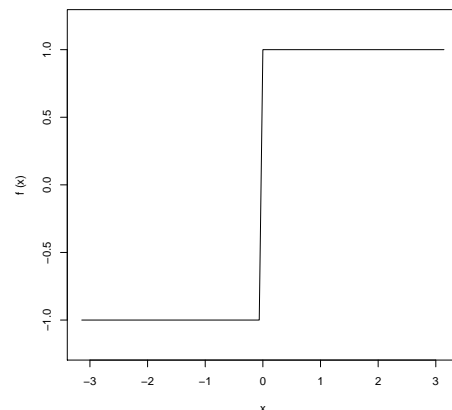
Proof.

$$\begin{aligned}
 a_k &\stackrel{?}{=} \frac{1}{\pi/\omega} \int_{-\pi/\omega}^{+\pi/\omega} f(x) \cos k\omega x \, dx \\
 &= \frac{1}{\pi/\omega} \int_{-\pi/\omega}^{+\pi/\omega} \left(\frac{a_0}{2} + \sum_{l=1}^{\infty} a_l \cos l\omega x + b_l \sin l\omega x \right) \cos k\omega x \, dx \\
 &= \frac{1}{\pi/\omega} \left(\int_{-\pi/\omega}^{+\pi/\omega} \frac{a_0}{2} \cos k\omega x \, dx + \sum_{l=1}^{\infty} \int_{-\pi/\omega}^{+\pi/\omega} a_l \cos l\omega x \cos k\omega x \, dx \right. \\
 &\quad \left. + \int_{-\pi/\omega}^{+\pi/\omega} b_l \sin l\omega x \cos k\omega x \, dx \right) \\
 &= \frac{1}{\pi/\omega} \frac{\pi}{\omega} a_k \\
 &= a_k
 \end{aligned}$$

Fourier Representation / Rectangular function

Let f be the 2π -periodic rectangular function

$$f(x) = \begin{cases} -1, & \text{if } x \in (-\pi, 0) \\ 0, & \text{if } x \in \{-\pi, 0, \pi\} \\ +1, & \text{if } x \in (0, \pi) \end{cases}$$

The Fourier representation of f is

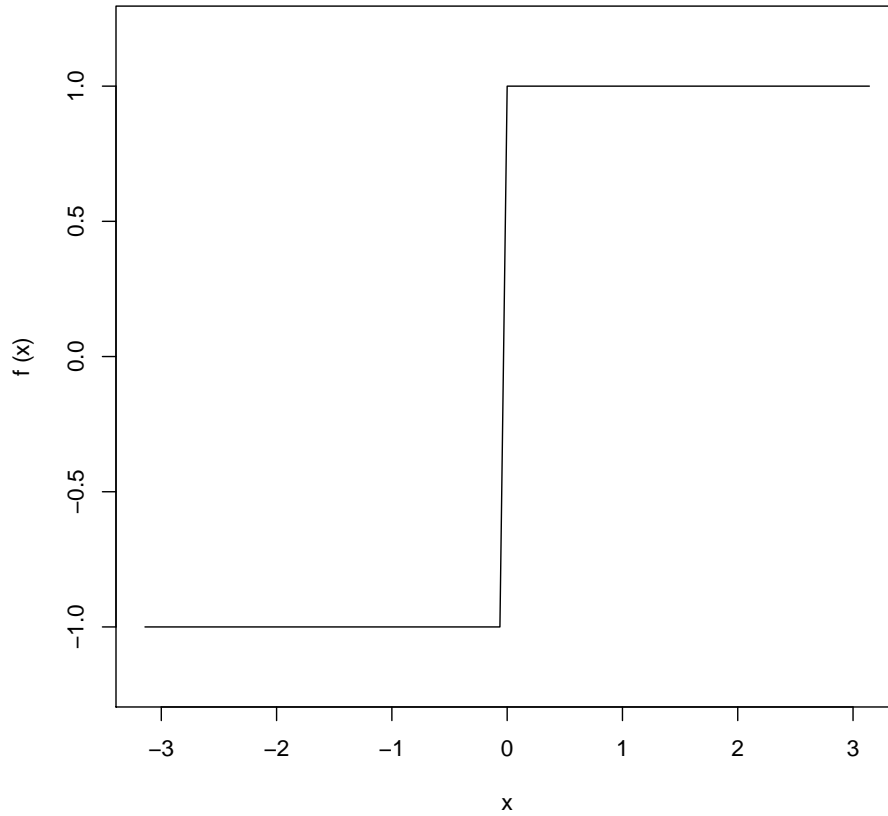
$$f(x) = \frac{4}{\pi} \sum_{k \in \mathbb{N} \text{ odd}} \frac{\sin kx}{k}$$

Proof:

$$\begin{aligned}
 b_k &= \frac{2}{\pi} \int_{-\pi}^{+\pi} f(x) \sin kx \, dx = \frac{2}{\pi} \int_0^{+\pi} \sin kx \, dx = \frac{4}{\pi} \left[-\frac{1}{k} \cos kx \right]_0^{\pi} = \begin{cases} -\frac{4}{\pi k} (0 - 1) = \frac{4}{\pi k}, & \text{if } k \text{ odd} \\ -\frac{4}{\pi k} (1 - 1) = 0, & \text{if } k \text{ even} \end{cases} \\
 a_k &= \frac{2}{\pi} \int_{-\pi}^{+\pi} f(x) \cos kx \, dx = 0
 \end{aligned}$$

 \rightsquigarrow in general, Fourier representations are infinite as in this example!

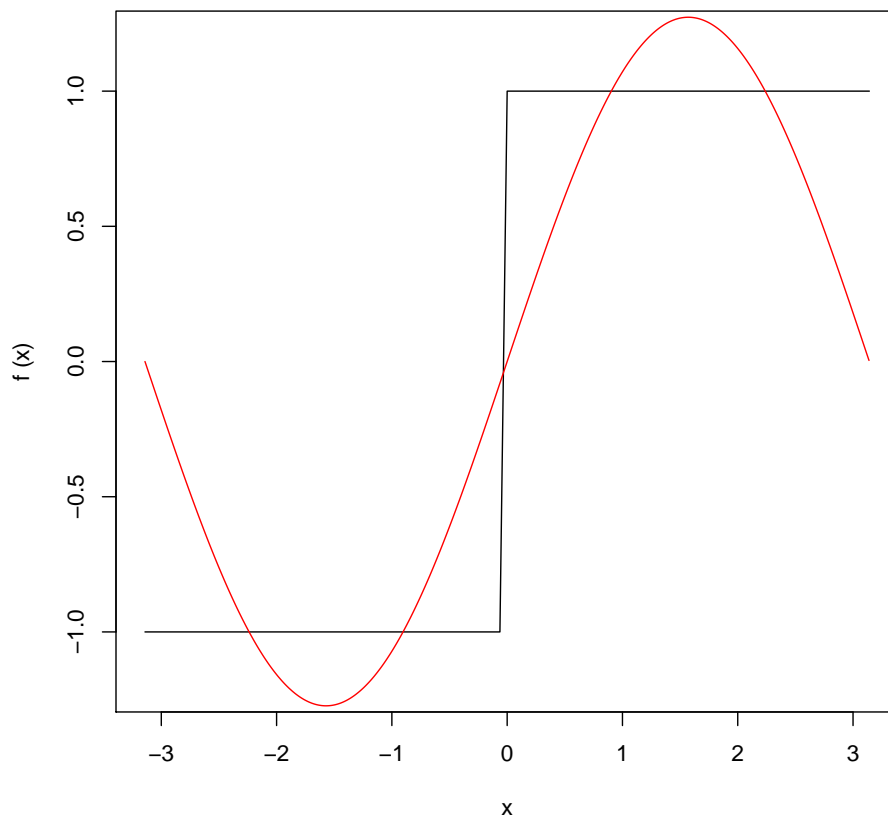
Fourier Representation / Rectangular function



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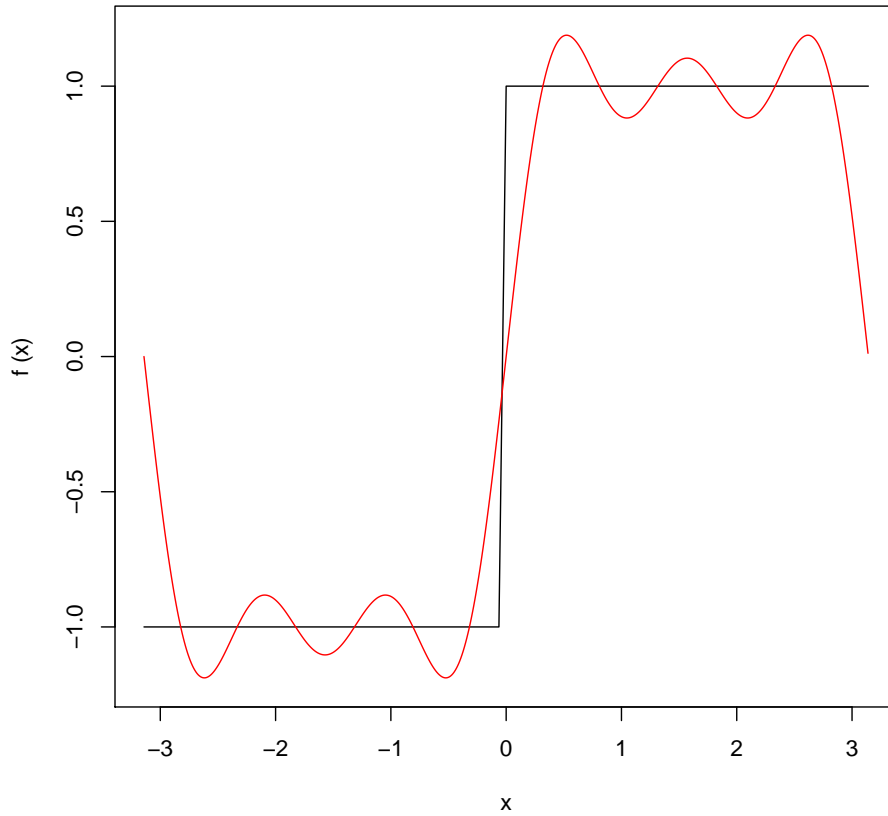
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Image Analysis / 1. Fourier Series Representation

Fourier Representation / Rectangular function / $k = 1$ 

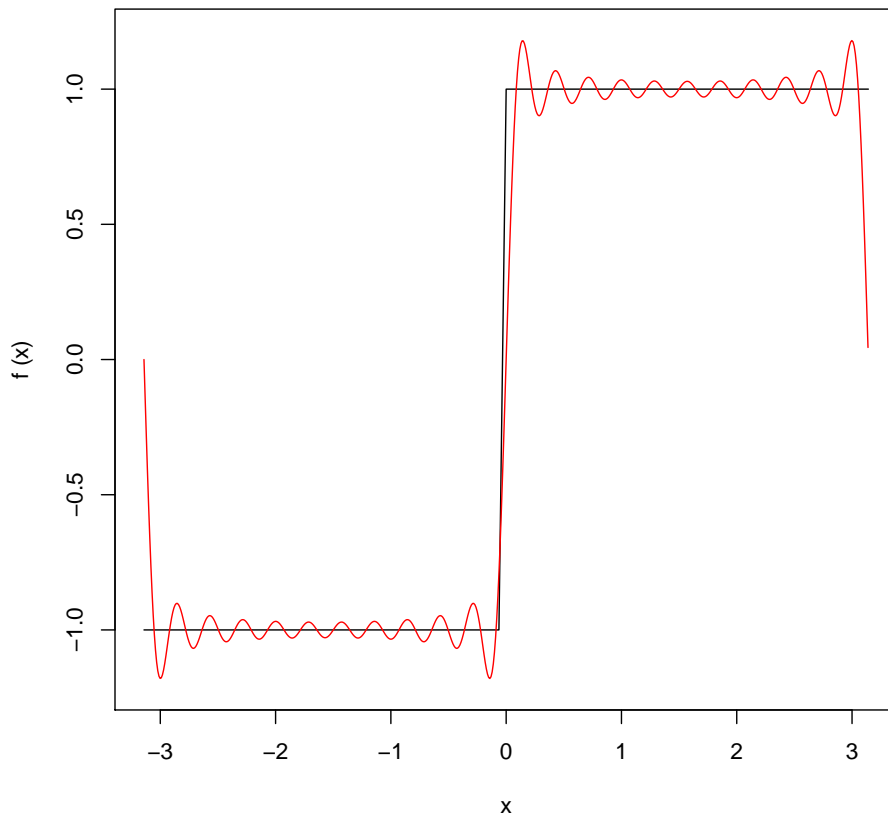
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Fourier Representation / Rectangular function / $k = 5$ 

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Fourier Representation / Rectangular function / $k = 21$ 

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Eulers Formula

$$\begin{aligned}\cos x &:= \sum_{n \in \mathbb{N}} (-1)^n \cdot \frac{x^{2n}}{(2n)!} &= 1 - \frac{x^2}{2!} + \frac{x^4}{4!} - \frac{x^6}{6!} + \dots \\ \sin x &:= \sum_{n \in \mathbb{N}} (-1)^n \cdot \frac{x^{2n+1}}{(2n+1)!} &= x - \frac{x^3}{3!} + \frac{x^5}{5!} - \frac{x^7}{7!} + \dots \\ \exp x &:= \sum_{n \in \mathbb{N}} \frac{x^n}{n!} &= 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \frac{x^4}{4!} + \dots\end{aligned}$$

Lemma (**Eulers formula**). For $x \in \mathbb{C}$:

$$e^{ix} = \cos(x) + i \cdot \sin(x), \quad \text{with } i := \sqrt{-1} \text{ the imaginary unit}$$

Proof:

$$\begin{aligned}e^{ix} &= \sum_{n \in \mathbb{N}} \frac{(ix)^n}{n!} \\ &= \sum_{n \in \mathbb{N}} \frac{(ix)^{2n}}{(2n)!} + \sum_{n \in \mathbb{N}} \frac{(ix)^{2n+1}}{(2n+1)!} \\ &= \sum_{n \in \mathbb{N}} (-1)^n \frac{x^{2n}}{(2n)!} + i \cdot \sum_{n \in \mathbb{N}} (-1)^n \frac{x^{2n+1}}{(2n+1)!} \\ &= \cos(x) + i \sin(x)\end{aligned}$$

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Complex Fourier Series Representation

Theorem (Complex Fourier Series Representation). Any continuous, differentiable and T -periodic function $f : \mathbb{R} \rightarrow \mathbb{C}$ can be written as

$$f = \sum_{k \in \mathbb{Z}} c_k e^{ik\omega x}, \quad \omega := \frac{2\pi}{T}$$

with coefficients $c_k \in \mathbb{C}$, called a **Fourier Series of f** .

The coefficients of the complex Fourier series can be computed via

$$c_k = \frac{1}{2\pi/\omega} \int_{-\pi/\omega}^{+\pi/\omega} f(x) e^{-ik\omega x} dx$$

Complex Fourier Series Representation

Proof.

$$\begin{aligned}
 f &= \sum_{k \in \mathbb{Z}} c_k e^{ik\omega x} \\
 &= \sum_{k \in \mathbb{Z}} c_k (\cos k\omega x + i \sin k\omega x) \\
 &= c_0 + \sum_{k=1}^{\infty} (c_k + c_{-k}) \cos k\omega x + (c_k - c_{-k}) i \sin k\omega x \\
 &= \frac{a_0}{2} + \sum_{k=1}^{\infty} a_k \cos k\omega x + b_k \sin k\omega x
 \end{aligned}$$

with

$$a_0 = 2c_0, \quad a_k = c_k + c_{-k}, \quad b_k = i(c_k - c_{-k})$$

and vice versa via:

$$c_0 = \frac{a_0}{2}, \quad c_k = \frac{1}{2}(a_k - ib_k), \quad c_{-k} = \frac{1}{2}(a_k + ib_k)$$

1. Fourier Series Representation

2. The Fourier Transform

3. Discrete Signals

4. Discrete Fourier Transform

5. Two-dimensional Fourier Transforms

6. Applications

Fourier Transform

Let $f : \mathbb{R} \rightarrow \mathbb{C}$ be a function (that satisfies some regularity conditions). Then

$$F : \mathbb{R} \rightarrow \mathbb{C}$$

$$\omega \mapsto \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} f(x) e^{-i\omega x} dx$$

exists for each ω and is a continuous function called **Fourier Transform of f** (aka **Fourier spectrum of f**).

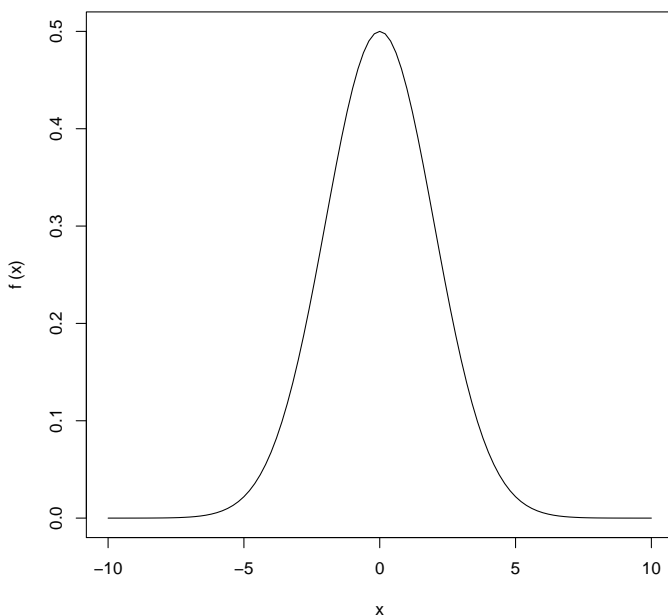
One can show that (if F also satisfies some regularity conditions):

$$f(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} F(\omega) e^{i\omega x} d\omega$$

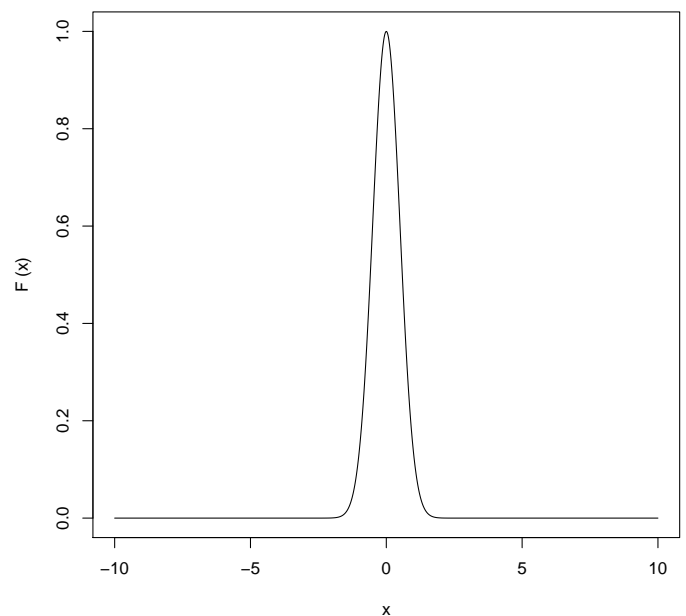
This is called **Inverse Fourier Transform**.

We will write $\mathcal{F}(f) := F$ for the Fourier transform of a function f and $\mathcal{F}^{-1}(F)$ for the inverse Fourier transform of a function F .

Fourier Transforms / Examples / Gaussian

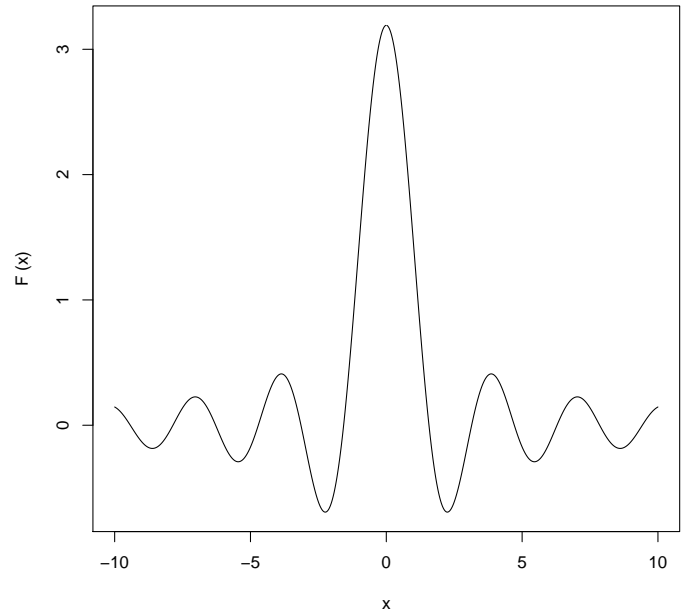
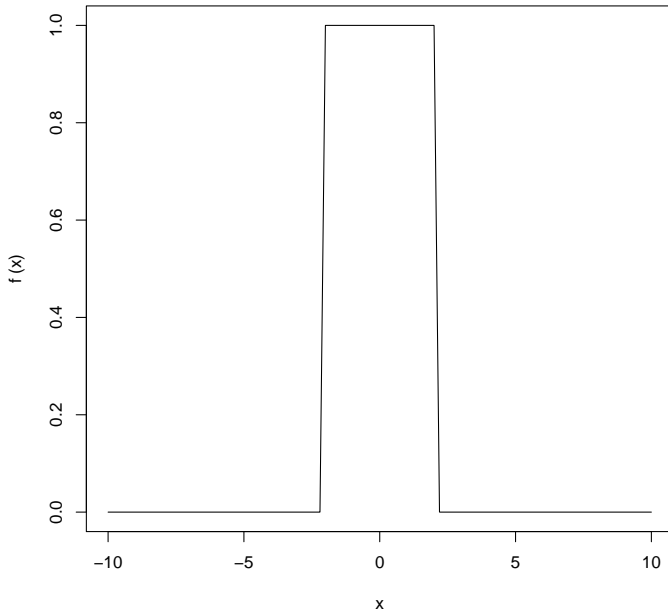


$$f(x) = \frac{1}{\sigma} \cdot e^{-\frac{x^2}{2\sigma^2}}$$



$$F(x) = e^{-\frac{\sigma^2 x^2}{2}}$$

Fourier Transforms / Examples / Uniform



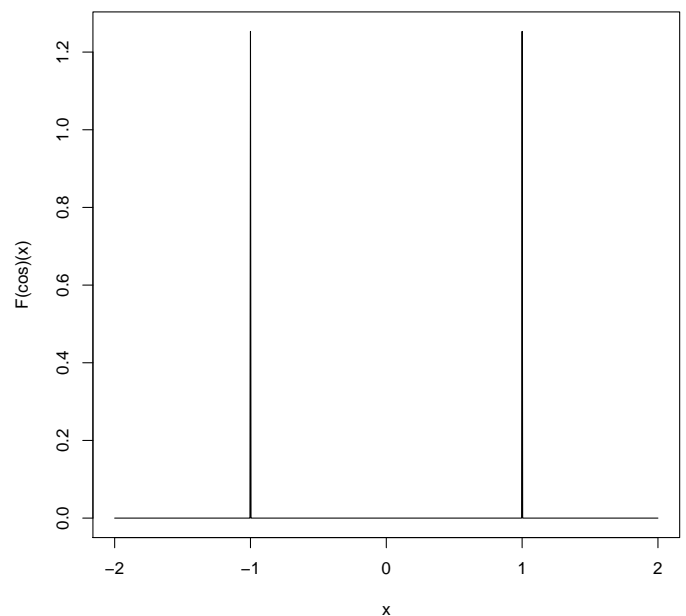
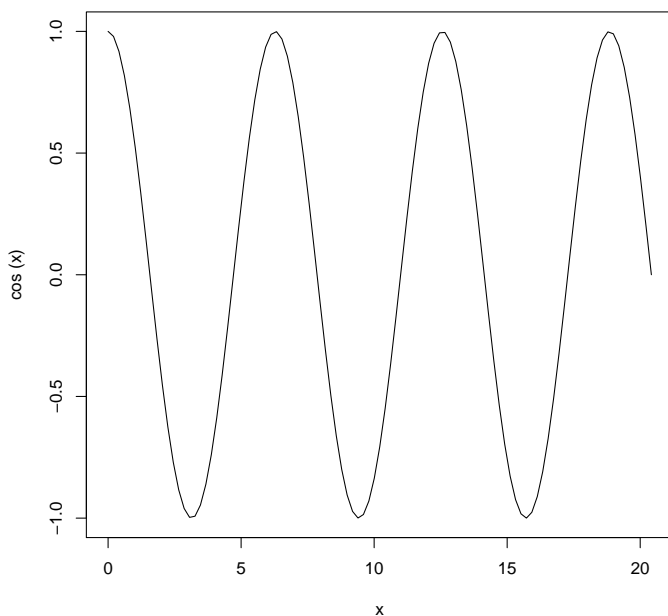
$$f(x) = \delta(x \in [-b, b])$$

$$F(x) = \frac{2b \sin(bx)}{\sqrt{2\pi}x}$$

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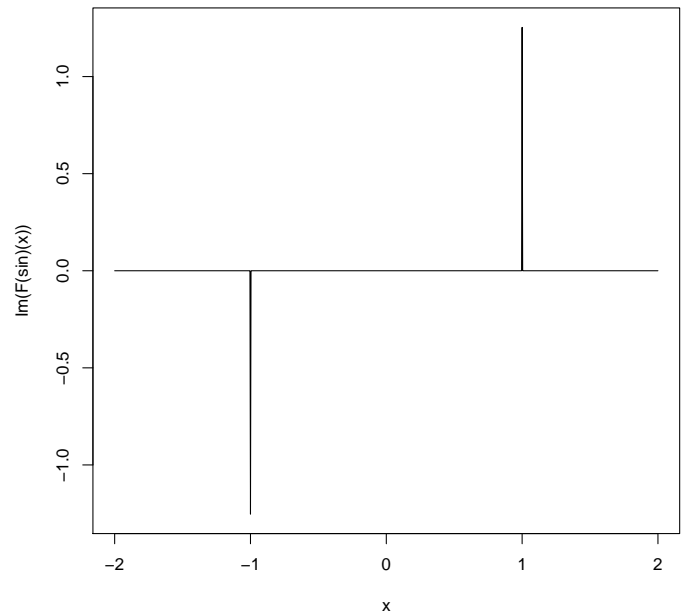
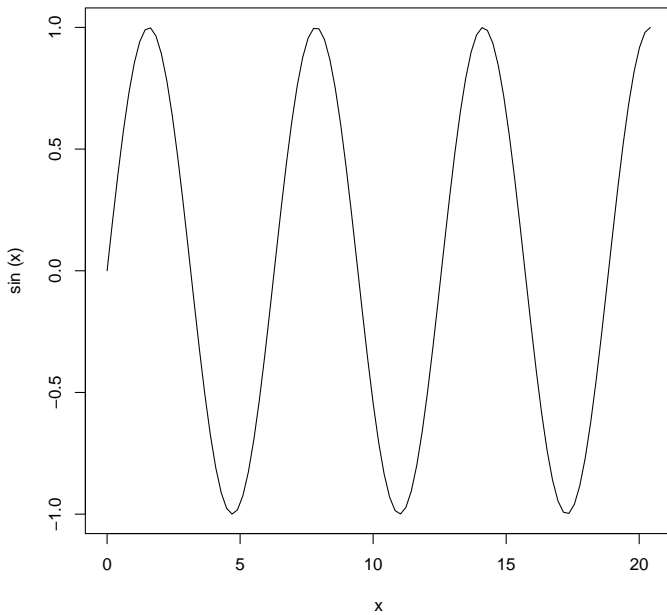
Fourier Transforms / Examples / Cosine



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

$$F(x) = \sqrt{\frac{\pi}{2}}(\delta(x - \omega) + \delta(x + \omega))$$

Fourier Transforms / Examples / Sine



$$f(x) = \sin(\omega x)$$

$$F(x) = i \cdot \sqrt{\frac{\pi}{2}} (\delta(x - \omega) - \delta(x + \omega))$$

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Image Analysis / 2. The Fourier Transform

Properties

function h	Fourier transform H	property name
f	F	
F	$f(-x)$	inverse
$af + bg$	$aF + bG$	linearity
$f * g$	$F(x)G(x)$	convolution
$f(x)g(x)$	$\frac{1}{2\pi} F * G$	multiplication
$f(x - a)$	$e^{-iax} F(x)$	translation
$e^{iax} f(x)$	$F(x - a)$	modulation
$f(x/a)$	$ a F(ax)$	scaling
f^*	$F^*(-x)$	complex conjugate
$f(x) \in \mathbb{R}$	$F(-x) = F^*(x)$	hermitian symmetry

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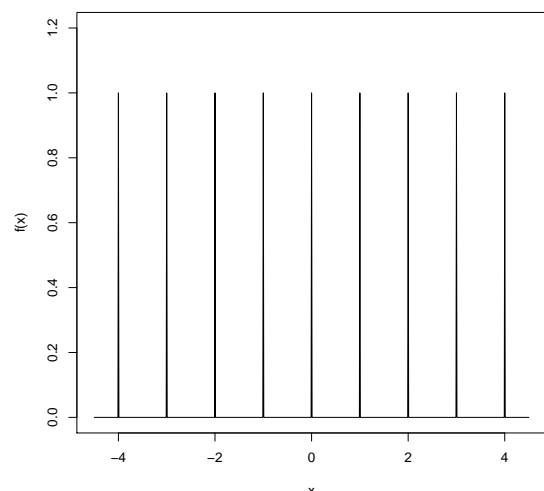
6. Applications

Dirac Comb

The symbol

$$\Delta_T(x) := \sum_{n \in \mathbb{Z}} \delta(x - Tn)$$

is called **Dirac comb** (aka **impulse train**, **sampling function**, **Shah function**) with sampling interval T .



Lemma. The Fourier series of the Dirac comb Δ_T is

$$\Delta_T(x) = \frac{1}{T} \sum_{k \in \mathbb{Z}} e^{-i \frac{2\pi k}{T} x}$$

and its Fourier transform

$$\mathcal{F}(\Delta_T)(x) = \frac{1}{T} \cdot \Delta_{2\pi/T}(x) = \frac{1}{T} \sum_{n \in \mathbb{Z}} \delta(x - \frac{2\pi}{T}n)$$

Dirac Comb

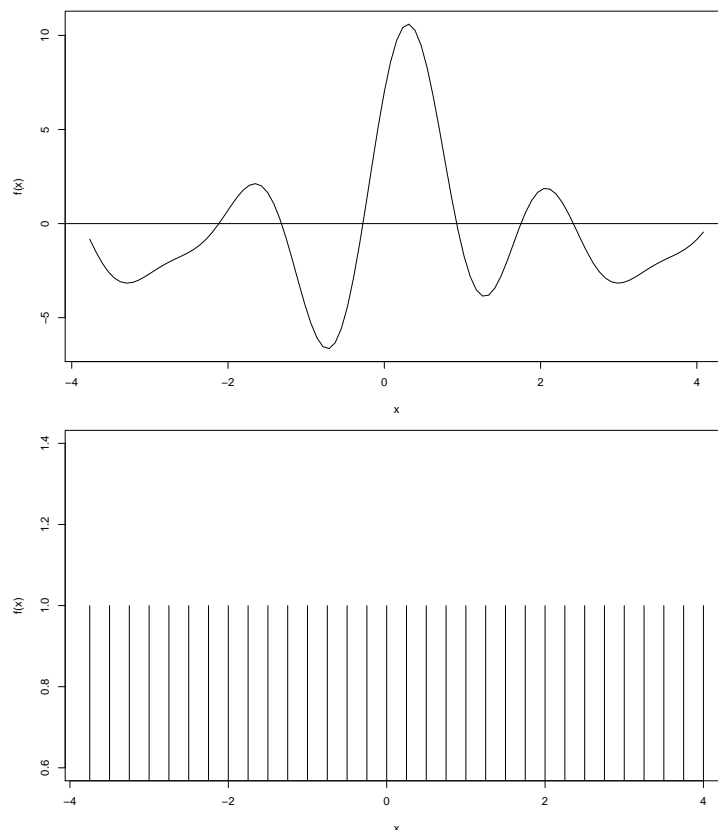
Proof: Obviously Δ_T is periodic with period T . Therefore

$$f(x) = \sum_{k \in \mathbb{Z}} c_k e^{-i\frac{2\pi k}{T}x}$$

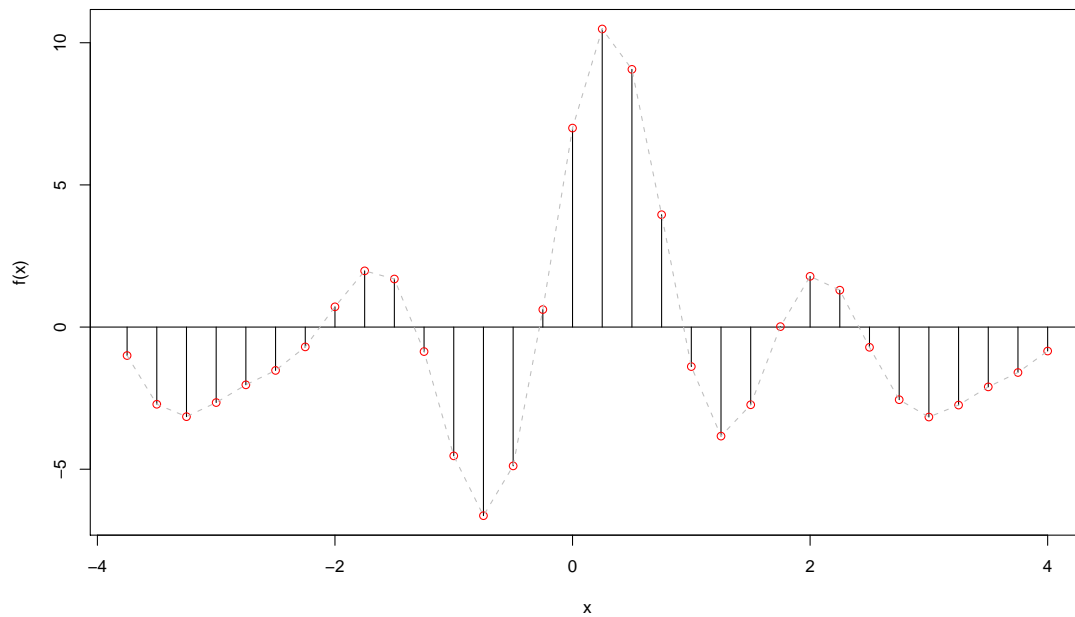
with

$$\begin{aligned} c_k &= \frac{1}{T} \int_x^{x+T} \Delta_T(y) e^{-i\frac{2\pi k}{T}y} dy \\ &= \frac{1}{T} \int_{-T/2}^{+T/2} \Delta_T(y) e^{-i\frac{2\pi k}{T}y} dy \\ &= \frac{1}{T} \int_{-T/2}^{+T/2} \delta(y) e^{-i\frac{2\pi k}{T}y} dy \\ &= \frac{1}{T} e^{-i\frac{2\pi k}{T}0} \\ &= \frac{1}{T} \end{aligned}$$

Sampling



Sampling



Sampling a function f at equidistant points $T \cdot \mathbb{Z}$ can be understood as

$$f^{\text{sampled}}(x) = f(x) \cdot \Delta_T(x)$$

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Image Analysis / 3. Discrete Signals

Fourier Transform of a Sampled Function

Let $f : \mathbb{R} \rightarrow \mathbb{C}$ be a function and f^{sampled} be a sample of f with sampling period T .

Then its Fourier transform $\mathcal{F}(f^{\text{sampled}})$ is $2\pi/T$ -periodic and aggregates the Fourier transform $\mathcal{F}(f)$ over a $2\pi/T$ -periodic grid:

$$\mathcal{F}(f^{\text{sampled}})(x) = \sum_{n \in \mathbb{Z}} \mathcal{F}(f)\left(x + n \frac{2\pi}{T}\right)$$

If $\mathcal{F}(f)$ vanishes for $|x| > \pi/T$, then the Fourier transform $\mathcal{F}(f)$ is replicated in a period of the Fourier transform $\mathcal{F}(f^{\text{sampled}})$.

Otherwise replicas overlap and the Fourier transform becomes corrupted. This effect is called **aliasing**.

Fourier Transform of a Sampled Function

The maximal occurring frequency

$$\omega_{\max} := \max\{|\omega| \mid \omega \in \mathbb{R}, \mathcal{F}(f)(\omega) \neq 0\}$$

of the Fourier transform is called its **bandwidth**.

The frequency

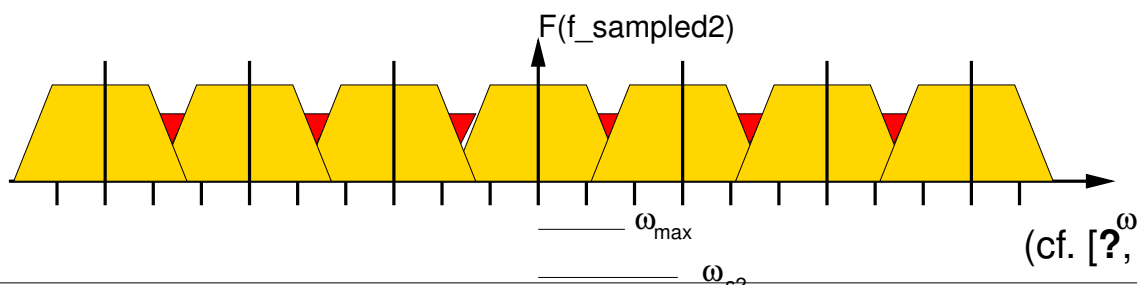
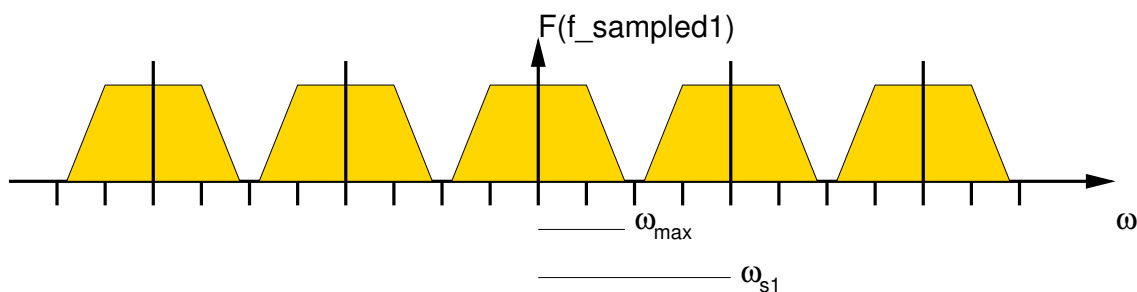
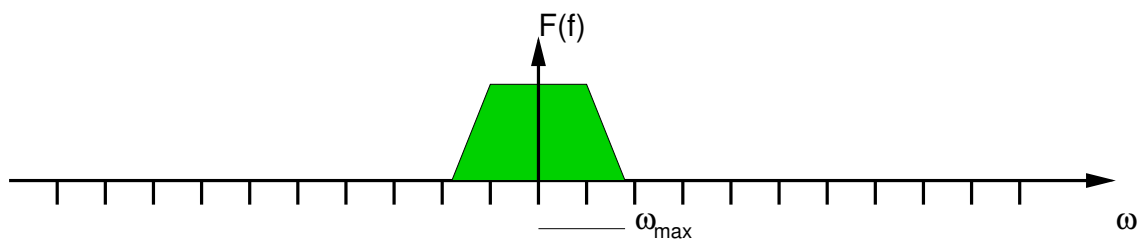
$$\omega_s := \frac{2\pi}{T}$$

of the sampling function is called its **sampling frequency**.

Then the sampling frequency must be at least twice the bandwidth:

$$\omega_s > 2\omega_{\max}$$

Fourier Transform of a Sampled Function



(cf. [?, p. 330])

Fourier Transform of a Sampled Function

Proof.

$$\begin{aligned}
 \mathcal{F}(f^{\text{sampled}})(x) &= \mathcal{F}(f \cdot \Delta_T)(x) \\
 &= \mathcal{F}(f) * \mathcal{F}(\Delta_T)(x) \\
 &= \mathcal{F}(f) * \frac{1}{T} \Delta_{2\pi/T}(x) \\
 &= \mathcal{F}(f) * \frac{1}{T} \sum_{n \in \mathbb{Z}} \delta(x + n \frac{2\pi}{T}) \\
 &= \frac{1}{T} \sum_{n \in \mathbb{Z}} \mathcal{F}(f) * \delta(x + n \frac{2\pi}{T}) \\
 &= \frac{1}{T} \sum_{n \in \mathbb{Z}} \mathcal{F}(f)(x + n \frac{2\pi}{T})
 \end{aligned}$$

If $|x| < \pi/T$ and $\mathcal{F}(f)(y)$ vanishes for $|y| > \pi/T$, then

$$\mathcal{F}(f^{\text{sampled}})(x) = \frac{1}{T} \mathcal{F}(f)(x)$$

The Fourier Transform of a Discrete Function

Let f be a discrete function:

$$f(x) = \sum_{n \in \mathbb{Z}} y_n \delta(x - n), \quad y_n \in \mathbb{R}$$

Then its Fourier transform is:

$$\begin{aligned}
 \mathcal{F}(f)(\omega) &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(x) e^{-i\omega x} dx \\
 &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \sum_{n \in \mathbb{Z}} y_n \delta(x - n) e^{-i\omega x} dx \\
 &= \frac{1}{\sqrt{2\pi}} \sum_{n \in \mathbb{Z}} \int_{-\infty}^{\infty} y_n e^{-i\omega x} \delta(x - n) dx \\
 &= \frac{1}{\sqrt{2\pi}} \sum_{n \in \mathbb{Z}} y_n e^{-i\omega n} \\
 &= \frac{1}{\sqrt{2\pi}} \sum_{n \in \mathbb{Z}} f(n) e^{-i\omega n}
 \end{aligned}$$

i.e., a periodic function — or equivalently: a function defined on an interval.

1. Fourier Series Representation

2. The Fourier Transform

3. Discrete Signals

4. Discrete Fourier Transform

5. Two-dimensional Fourier Transforms

6. Applications

Definition

Let $f : \{0, 1, \dots, N - 1\} \rightarrow \mathbb{C}$ be a finite discrete function, then

$$\begin{aligned}
 F : \{0, 1, \dots, N - 1\} &\rightarrow \mathbb{C} \\
 \omega &\mapsto \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} f(x) \left(\cos\left(2\pi \frac{\omega x}{N}\right) - i \sin\left(2\pi \frac{\omega x}{N}\right) \right) \\
 &= \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} f(x) e^{-i2\pi \frac{\omega x}{N}}
 \end{aligned}$$

is called **discrete Fourier transform of f** , denoted $\text{DFT}(f)$.

Then

$$\begin{aligned}
 f(x) &= \frac{1}{\sqrt{N}} \sum_{\omega=0}^{N-1} F(\omega) \left(\cos\left(2\pi \frac{\omega x}{N}\right) + i \sin\left(2\pi \frac{\omega x}{N}\right) \right) \\
 &= \frac{1}{\sqrt{N}} \sum_{\omega=0}^{N-1} F(\omega) e^{i2\pi \frac{\omega x}{N}}
 \end{aligned}$$

This is called **inverse discrete Fourier transform of f** , denoted $\text{DFT}^{-1}(F)$..

Example

x	$f(x)$		ω	$F(\omega)$
0	$1 + 0i$		0	$14.2302 + 0.0000i$
1	$3 + 0i$	DFT	1	$-5.6745 - 2.9198i$
2	$5 + 0i$	\longrightarrow	2	$0.0000 + 0.0000i$
3	$7 + 0i$		3	$-0.0176 - 0.6893i$
4	$9 + 0i$		4	$0.0000 + 0.0000i$
5	$8 + 0i$		5	$0.3162 + 0.0000i$
6	$6 + 0i$		6	$0.0000 + 0.0000i$
7	$4 + 0i$	DFT⁻¹	7	$-0.0176 + 0.6893i$
8	$2 + 0i$	\longleftarrow	8	$0.0000 + 0.0000i$
9	$0 + 0i$		9	$-5.6745 + 2.9198i$

(cf. [?, p. 333])

$$\text{DFT}(f)(0) = \frac{1}{\sqrt{10}} \sum_{x=0}^9 f(x) \left(\cos\left(2\pi \frac{0x}{10}\right) - i \sin\left(2\pi \frac{0x}{10}\right) \right) = \frac{1}{\sqrt{10}} \sum_{x=0}^9 f(x) = \frac{45}{\sqrt{10}} = 14.2303$$

Example

x	$f(x)$		ω	$F(\omega)$
0	$1 + 0i$		0	$14.2302 + 0.0000i$
1	$3 + 0i$	DFT	1	$-5.6745 - 2.9198i$
2	$5 + 0i$	\longrightarrow	2	$0.0000 + 0.0000i$
3	$7 + 0i$		3	$-0.0176 - 0.6893i$
4	$9 + 0i$		4	$0.0000 + 0.0000i$
5	$8 + 0i$		5	$0.3162 + 0.0000i$
6	$6 + 0i$		6	$0.0000 + 0.0000i$
7	$4 + 0i$	DFT⁻¹	7	$-0.0176 + 0.6893i$
8	$2 + 0i$	\longleftarrow	8	$0.0000 + 0.0000i$
9	$0 + 0i$		9	$-5.6745 + 2.9198i$

(cf. [?, p. 333])

$$\begin{aligned} \text{DFT}(f)(1) &= \frac{1}{\sqrt{10}} \sum_{x=0}^9 f(x) \left(\cos\left(2\pi \frac{1x}{10}\right) - i \sin\left(2\pi \frac{1x}{10}\right) \right) \\ &= \frac{1}{\sqrt{10}} \sum_{x=0}^9 f(x) \cos\left(\pi \frac{x}{5}\right) - i \frac{1}{\sqrt{10}} \sum_{x=0}^9 f(x) \sin\left(\pi \frac{x}{5}\right) = -5.6745 - 2.9198i \end{aligned}$$

Discrete Fourier Transform / Algorithm (naive)

For $x \in \mathbb{C}$, denote $\Re(x)$ its **real part** and $\Im(x)$ its **imaginary part**, i.e.,

$$x = \Re(x) + i\Im(x), \quad \Re(x), \Im(x) \in \mathbb{R}$$

(for \Re one often also uses Re , for \Im also Im).

To compute the discrete Fourier transform, one computes $\text{dft}(f)(\omega)$ for $\omega = 0, \dots, N - 1$ via:

$$\begin{aligned} \text{DFT}(f)(\omega) &= \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} f(x) \left(\cos\left(2\pi \frac{\omega x}{N}\right) - i \sin\left(2\pi \frac{\omega x}{N}\right) \right) \\ &= \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} (\Re(f(x)) + i\Im(f(x))) \left(\cos\left(2\pi \frac{\omega x}{N}\right) - i \sin\left(2\pi \frac{\omega x}{N}\right) \right) \\ &= \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} \Re(f(x)) \cos\left(2\pi \frac{\omega x}{N}\right) + \Im(f(x)) \sin\left(2\pi \frac{\omega x}{N}\right) \\ &\quad + i \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} -\Re(f(x)) \sin\left(2\pi \frac{\omega x}{N}\right) + \Im(f(x)) \cos\left(2\pi \frac{\omega x}{N}\right) \end{aligned}$$

Discrete Fourier Transform / Algorithm (naive)

```

1  dft-naive(sequence  $f = (f(x)_0, f(x)_1)_{x=0, \dots, N-1}$ ) :
2   $N := \text{length}(f)$ 
3   $F := (F(x)_0, F(x)_1)_{x=0, \dots, N-1} = (0, 0)_{x=0, \dots, N-1}$ 
4  for  $\omega := 0, \dots, N - 1$  do
5     $c := (c_0, c_1) := (0, 0)$ 
6    for  $x := 0, \dots, N - 1$  do
7       $c_0 := c_0 + f(x)_0 \cdot \cos(2\pi\omega x/N) + f(x)_1 \cdot \sin(2\pi\omega x/N)$ 
8       $c_1 := c_1 - f(x)_0 \cdot \sin(2\pi\omega x/N) + f(x)_1 \cdot \cos(2\pi\omega x/N)$ 
9    od
10    $c_0 := c_0 / \sqrt{N}$ 
11    $c_1 := c_1 / \sqrt{N}$ 
12    $F(\omega) := c$ 
13 od
14 return  $F$ 

```

Discrete Fourier Transform / Algorithm (naive)

When computing the values of the discrete Fourier transform for different arguments ω , the cosine and sine functions repeatedly are called with the same arguments:

$$\text{dft}(f)(1):$$

$$\begin{aligned} &\cos(2\pi \cdot 0/10) \\ &\cos(2\pi \cdot 1/10) \\ &\cos(2\pi \cdot 2/10) \\ &\cos(2\pi \cdot 3/10) \\ &\cos(2\pi \cdot 4/10) \\ &\cos(2\pi \cdot 5/10) \\ &\cos(2\pi \cdot 6/10) \\ &\cos(2\pi \cdot 7/10) \\ &\cos(2\pi \cdot 8/10) \\ &\cos(2\pi \cdot 9/10) \end{aligned}$$

$$\text{dft}(f)(2):$$

$$\begin{aligned} &\cos(2\pi \cdot 0/10) \\ &\cos(2\pi \cdot 2/10) \\ &\cos(2\pi \cdot 4/10) \\ &\cos(2\pi \cdot 6/10) \\ &\cos(2\pi \cdot 8/10) \\ &\cos(2\pi \cdot 10/10) = \cos(2\pi \cdot 0/10) \\ &\cos(2\pi \cdot 12/10) = \cos(2\pi \cdot 2/10) \\ &\cos(2\pi \cdot 14/10) = \cos(2\pi \cdot 4/10) \\ &\cos(2\pi \cdot 16/10) = \cos(2\pi \cdot 6/10) \\ &\cos(2\pi \cdot 18/10) = \cos(2\pi \cdot 8/10) \end{aligned}$$

Caching the expensive sine and cosine computations accelerates the algorithm!

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Discrete Fourier Transform / Algorithm (naive, cached)

```

1  dft-naive-cached(sequence  $f = (f(x)_0, f(x)_1)_{x=0, \dots, N-1}$ ) :
2   $N := \text{length}(f)$ 
3  for  $\omega := 0, \dots, N - 1$  do
4     $C(\omega) := \cos(2\pi\omega/N)$ 
5     $S(\omega) := \sin(2\pi\omega/N)$ 
6  od
7   $F := (F(x)_0, F(x)_1)_{x=0, \dots, N-1} = (0, 0)_{x=0, \dots, N-1}$ 
8  for  $\omega := 0, \dots, N - 1$  do
9     $c := (c_0, c_1) := (0, 0)$ 
10   for  $x := 0, \dots, N - 1$  do
11      $c_0 := c_0 + f(x)_0 \cdot C(\omega x \bmod N) + f(x)_1 \cdot S(\omega x \bmod N)$ 
12      $c_1 := c_1 - f(x)_0 \cdot S(\omega x \bmod N) + f(x)_1 \cdot C(\omega x \bmod N)$ 
13   od
14    $c_0 := c_0 / \sqrt{N}$ 
15    $c_1 := c_1 / \sqrt{N}$ 
16    $F(\omega) := c$ 
17 od
18 return  $F$ 

```

Fast Fourier Transform (Gauss ca. 1805; Cooley/Tukey 1965)

The naive algorithm for DFT still has complexity $O(N^2)$.

The **Fast Fourier Transform** algorithm is based on a decomposition of the DFT for sequences f of even length N :

$$\text{DFT}(f)(\omega) = \text{DFT}(f^{\text{even}})(\omega \bmod N/2) + e^{-i2\pi\omega/N} \text{DFT}(f^{\text{odd}})(\omega \bmod N/2)$$

for $\omega = 0, \dots, N - 1$

and where

$$\begin{aligned} f^{\text{even}}(x) &:= f(2x), & x = 0, \dots, N/2 \\ f^{\text{odd}}(x) &:= f(2x + 1) \end{aligned}$$

Fast Fourier Transform / Proof

Proof.

$$\begin{aligned} \text{DFT}(f)(\omega) &= \sum_{x=0}^{N-1} f(x) e^{-i2\pi\frac{\omega x}{N}} \\ &= \sum_{\substack{x=0 \\ \text{even}}}^{N-1} f(x) e^{-i2\pi\frac{\omega x}{N}} + \sum_{\substack{x=0 \\ \text{odd}}}^{N-1} f(x) e^{-i2\pi\frac{\omega x}{N}} \\ &= \sum_{x=0}^{N/2-1} f(2x) e^{-i2\pi\frac{\omega 2x}{N}} + \sum_{x=0}^{N/2-1} f(2x+1) e^{-i2\pi\frac{\omega(2x+1)}{N}} \\ &= \sum_{x=0}^{N/2-1} f^{\text{even}}(x) e^{-i2\pi\frac{\omega x}{N/2}} + e^{-i2\pi\omega/N} \sum_{x=0}^{N/2-1} f^{\text{odd}}(x) e^{-i2\pi\frac{\omega x}{N/2}} \\ &= \text{DFT}(f^{\text{even}})(\omega) + e^{-i2\pi\omega/N} \text{DFT}(f^{\text{odd}})(\omega) \end{aligned}$$

or more exactly, as $\text{DFT}(f^{\text{even}})(\omega)$ is only defined for $\omega < N/2$:

$$= \text{DFT}(f^{\text{even}})(\omega \bmod N/2) + e^{-i2\pi\omega/N} \text{DFT}(f^{\text{odd}})(\omega \bmod N/2)$$

Fast Fourier Transform / Real version

$$\begin{aligned} \text{DFT}(f)(\omega) &= \text{DFT}(f^{\text{even}})(\omega \bmod N/2) + e^{-i2\pi\omega/N} \text{DFT}(f^{\text{odd}})(\omega \bmod N/2) \\ &= \text{DFT}(f^{\text{even}})(\omega \bmod N/2) \\ &\quad + (\cos 2\pi\omega/N - i \sin 2\pi\omega/N) \text{DFT}(f^{\text{odd}})(\omega \bmod N/2) \end{aligned}$$

and thus

$$\begin{aligned} \Re(\text{DFT}(f)(\omega)) &= \Re(\text{DFT}(f^{\text{even}})(\omega \bmod N/2)) \\ &\quad + \cos 2\pi\omega/N \cdot \Re(\text{DFT}(f^{\text{odd}})(\omega \bmod N/2)) \\ &\quad + \sin 2\pi\omega/N \cdot \Im(\text{DFT}(f^{\text{odd}})(\omega \bmod N/2)) \end{aligned}$$

$$\begin{aligned} \Im(\text{DFT}(f)(\omega)) &= \Im(\text{DFT}(f^{\text{even}})(\omega \bmod N/2)) \\ &\quad + \cos 2\pi\omega/N \cdot \Im(\text{DFT}(f^{\text{odd}})(\omega \bmod N/2)) \\ &\quad - \sin 2\pi\omega/N \cdot \Re(\text{DFT}(f^{\text{odd}})(\omega \bmod N/2)) \end{aligned}$$

Fast Fourier Transform / Algorithm

```

1  fft(sequence  $f = (f(x)_0, f(x)_1)_{x=0, \dots, N-1}$ ) :
2   $N := \text{length}(f)$ 
3  if  $N$  is even
4     $F := (F(x)_0, F(x)_1)_{x=0, \dots, N-1} = (0, 0)_{x=0, \dots, N-1}$ 
5     $A := \text{fft}((f(x))_{x=0, 2, 4, \dots, N-2})$ 
6     $B := \text{fft}((f(x))_{x=1, 3, 5, \dots, N-1})$ 
7    for  $\omega := 0, \dots, N-1$  do
8       $a := A(\omega \bmod N/2)$ 
9       $b := B(\omega \bmod N/2)$ 
10      $F(\omega)_0 := a_0 + \cos 2\pi\omega/N \cdot b_0 + \sin 2\pi\omega/N \cdot b_1$ 
11      $F(\omega)_1 := a_1 + \cos 2\pi\omega/N \cdot b_1 - \sin 2\pi\omega/N \cdot b_0$ 
12   od
13   return
14 else
15    $F := \text{dft-naive-cached}(f)$ 
16 fi
17 return  $F$ 

```

Fast Fourier Transform / Outlook

- The computation of $\cos 2\pi\omega/N$ and $\sin 2\pi\omega/N$ also can be done recursively using the addition formulas.
- In this way, FFT best is applied to sequences of length 2^n (called **radix-2 case**).
- The FFT decomposition works with any factorization $N = N_1 \cdot N_2$ in a similar way, and thus also for sequences of length other than 2^n .
- FFT has complexity $O(N \log N)$ (if N is a power of 2).
- An early experiment from 1969 reports a runtime of 13 1/2 hours for computing the DFT of a sequence of length 2048 by the naive method and 2.4 seconds using FFT.
- In practice, FFT is implemented in a linearized version avoiding explicit recursions (see [?, p. 839]).

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Types of Fourier Transforms

type of function f	sup f	sup $\mathcal{F}(f)$	type of Fourier decomp.
general (integrable) function	\mathbb{R}	\mathbb{R}	(general) Fourier decomposition
periodic function, function on interval	interval $I \subseteq \mathbb{R}$	\mathbb{Z}	Fourier series
general (integrable) discrete function (sum of Diracs)	\mathbb{Z}	interval $I \subseteq \mathbb{R}$	discrete-time Fourier transform
periodic discrete function, finite discrete function (finite sum of Diracs)	finite $I \subseteq \mathbb{Z}$	I	discrete Fourier transform

1. Fourier Series Representation

2. The Fourier Transform

3. Discrete Signals

4. Discrete Fourier Transform

5. Two-dimensional Fourier Transforms

6. Applications

General Fourier Transform in 2D

For two-dimensional functions $f : \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{C}$ Fourier Transforms, Fourier Series and Discrete Fourier Transforms can be defined analogously.

Let $f : \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{C}$ be a function (that satisfies some regularity conditions). Then

$$F : \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{C}$$

$$(\omega_1, \omega_2) \mapsto \frac{1}{2\pi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y) e^{-i\omega_1 x} e^{-i\omega_2 y} dy dx$$

exists for each (ω_1, ω_2) and is a continuous function called **Fourier Transform of f** (aka **Fourier spectrum of f**).

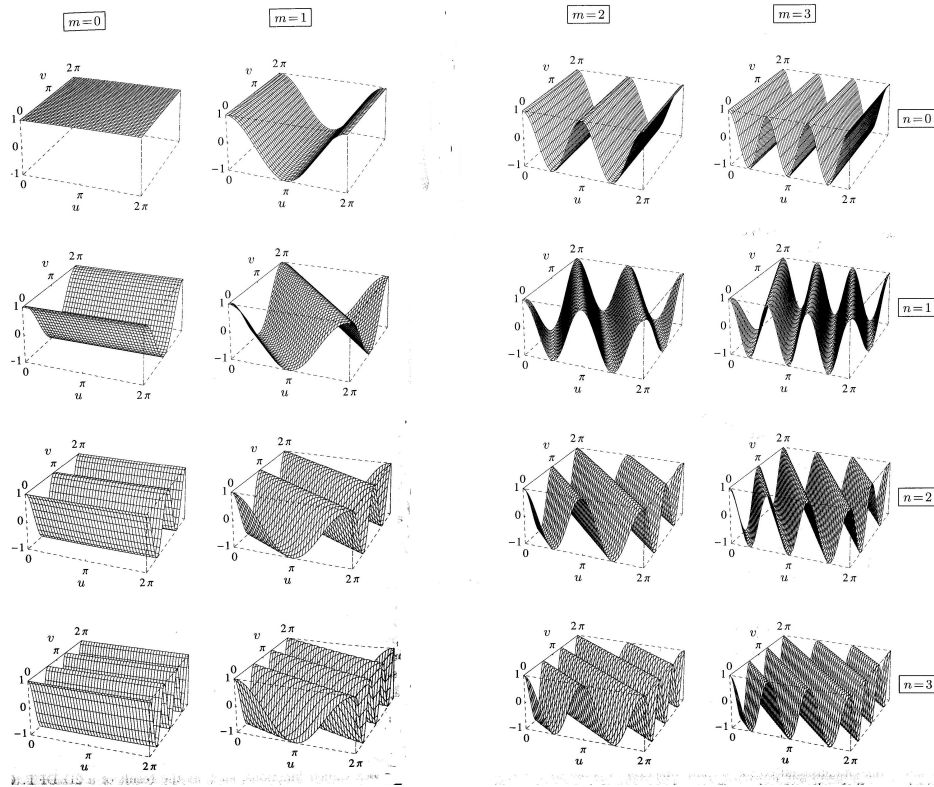
One can show that (if F also satisfies some regularity conditions):

$$f(x, y) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} F(\omega_1, \omega_2) e^{i\omega_1 x} e^{i\omega_2 y} d\omega_1 d\omega_2$$

This is called **Inverse Fourier Transform**.

We will write $\mathcal{F}(f) := F$ for the Fourier transform of a function f and $\mathcal{F}^{-1}(F)$ for the inverse Fourier transform of a function F .

Bases in 2D



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Image Analysis / 5. Two-dimensional Fourier Transforms

Fourier Series in 2D

If $f : \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{C}$ is (T_1, T_2) -periodic, i.e.,

$$f(x, y) = f(x + T_1, y + T_2) \quad \forall x, y \in \mathbb{R}$$

then f can already be reconstructed from \mathbb{Z} -many Fourier coefficients:

$$f(x, y) = \frac{1}{2\pi} \sum_{n \in \mathbb{Z}} \sum_{m \in \mathbb{Z}} F(n, m) e^{i\frac{2\pi}{T_1}nx} e^{i\frac{2\pi}{T_2}my}$$

with

$$F(n, m) := \frac{1}{2\pi} \int_{-T_1/2}^{+T_1/2} \int_{-T_2/2}^{+T_2/2} f(x, y) e^{-in\omega_1x} e^{-im\omega_2y} dy dx$$

Discrete Fourier Transform in 2D

If f is discrete, i.e.,

$$f(x, y) = \sum_{n \in \mathbb{Z}} \sum_{m \in \mathbb{Z}} y_{n,m} \delta(x - T_1 n, y - T_2 m), \quad y_{n,m} \in \mathbb{R}$$

then its Fourier transform is periodic:

$$f(x, y) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} F(\omega_1, \omega_2) e^{i\omega_1 x} e^{i\omega_2 y} d\omega_1 d\omega_2$$

with

$$F(\omega_1, \omega_2) := \frac{1}{2\pi} \sum_{n \in \mathbb{Z}} \sum_{m \in \mathbb{Z}} f(n, m) e^{-i\omega_1 n} e^{-i\omega_2 m}$$

Discrete Fourier Transform in 2D

And finally, if f is discrete and finite, i.e.,

$$f(x, y) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} y_{n,m} \delta(x - n, y - m), \quad y_{n,m} \in \mathbb{R}$$

then its Fourier transform is periodic and made from finitely many components:

$$f(x, y) = \frac{1}{\sqrt{NM}} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} F(\omega_1, \omega_2) e^{i\omega_1 x} e^{i\omega_2 y}$$

with

$$F(\omega_1, \omega_2) := \frac{1}{\sqrt{NM}} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} f(n, m) e^{-i\omega_1 n} e^{-i\omega_2 m}$$

Discrete Fourier Transform in 2D / Algorithm (naive, cached)

```

1  dft-2d-naive-cached(array f = (f(x)0, f(x)1)x=0,...,N-1,y=0,...,M-1) :
2  for ω := 0, ..., N - 1 do
3      C1(ω) := cos(2πω/N)
4      S1(ω) := sin(2πω/N)
5  od
6  for ω := 0, ..., M - 1 do
7      C2(ω) := cos(2πω/M)
8      S2(ω) := sin(2πω/M)
9  od
10 F := (F(x)0, F(x)1)x=0,...,N-1,y=0,...,M-1 = (0, 0)x=0,...,N-1,y=0,...,M-1
11 for ω1 := 0, ..., N - 1 do
12     for ω2 := 0, ..., M - 1 do
13         c := (c0, c1) := (0, 0)
14         for x := 0, ..., N - 1 do
15             for y := 0, ..., M - 1 do
16                 C := C1(ω1x mod N) · C2(ω2y mod M) - S1(ω1x mod N) · S2(ω2y mod M)
17                 S := S1(ω1x mod N) · C2(ω2y mod M) + C1(ω1x mod N) · S2(ω2y mod M)
18                 c0 := c0 + f(x)0 · C - f(x)1 · S
19                 c1 := c1 - f(x)0 · S + f(x)1 · C
20             od
21         od
22         c0 := c0/√NM
23         c1 := c1/√NM
24         F(ω) := c
25     od
26 od
27 return F

```

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Discrete Fourier Transform in 2D / Separability

$$\begin{aligned}
 F(\omega_1, \omega_2) &:= \frac{1}{\sqrt{NM}} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} f(n, m) e^{-i\omega_1 n} e^{-i\omega_2 m} \\
 &= \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} \left(\frac{1}{\sqrt{M}} \sum_{m=0}^{M-1} f(n, m) e^{-i\omega_2 m} \right) e^{-i\omega_1 n} \\
 &= \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} \text{DFT}((f(n, m))_{m=1, \dots, M})(\omega_2) e^{-i\omega_1 n}
 \end{aligned}$$

Discrete Fourier Transform in 2D / FFT

```

1  fft-2d(array f = (f(x)0, f(x)1)x=0,...,N-1,y=0,...,M-1) :
2  G := (G(x)0, G(x)1)x=0,...,N-1,y=0,...,M-1 = (0, 0)x=0,...,N-1,y=0,...,M-1
3  for ω1 := 0, ..., N - 1 do
4      G(ω1, .) := fft(f(ω1, y)y=0,...,M-1)
5  od
6  F := (F(x)0, F(x)1)x=0,...,N-1,y=0,...,M-1 = (0, 0)x=0,...,N-1,y=0,...,M-1
7  for ω2 := 0, ..., M - 1 do
8      F(., ω2) := fft(G(x, ω2)x=0,...,N-1)
9  od
10 return F

```

Power Spectrum

The fourier spectrum of

- a discrete $N \times M$ gray-scale image f ,
i.e., with one channel,

is

- a discrete $N \times M$ image F with complex intensity values,
i.e., two channels.

For visualization one usually shows the **power spectrum** defined as:

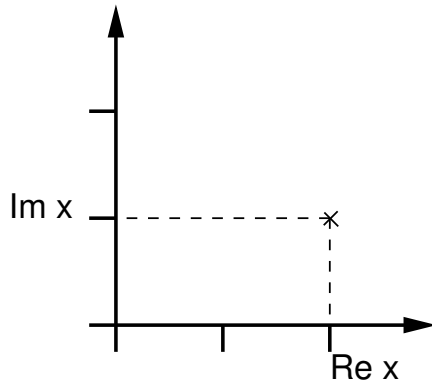
$$\mathcal{F}^{\text{power}}(f)(x) := \sqrt{(\Re \mathcal{F}(f)(x))^2 + (\Im \mathcal{F}(f)(x))^2}$$

The power spectrum measures the absolute value of the complex amplitude.

The complementary information θ called **phase** is not shown.

What does Power Spectrum mean? — Complex Coordinates

Cartesian coordinates:

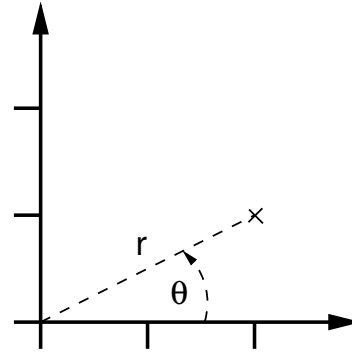


$$x = (\Re x, \Im x) \in \mathbb{R} \times \mathbb{R}$$

$$\Re x = r \cos \theta$$

$$\Im x = r \sin \theta$$

Polar coordinates:



$$x = (r, \theta) \in \mathbb{R}_0^+ \times [0, 2\pi)$$

$$r = \sqrt{(\Re x)^2 + (\Im x)^2}$$

$$\theta = \begin{cases} \arctan(\Re x / \Im x), & \text{if } x > 0, y > 0 \\ \arctan(\Re x / \Im x) + \pi, & \text{if } y < 0 \\ \arctan(\Re x / \Im x) + 2\pi, & \text{if } x < 0, y < 0 \end{cases}$$

$$x = \Re x + i \Im x = r \cos \theta + i r \sin \theta = r e^{i\theta}$$

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Image Analysis / 5. Two-dimensional Fourier Transforms

Example

image f :



power spectrum $\mathcal{F}^{\text{power}}(f)$:



Displaying Fourier Power Spectra

For displaying spectra, some further conventions are used:

- As the scale of many power spectra is dominated by a few large values, one usually plots

$$\log \mathcal{F}^{\text{power}}(f)(x) \quad \text{or} \quad (\mathcal{F}^{\text{power}}(f)(x))^{\frac{1}{2}}$$

instead of the raw power spectrum values $\mathcal{F}^{\text{power}}(f)(x)$.

- Usually, the **centered spectrum** is shown, i.e., the intensities for

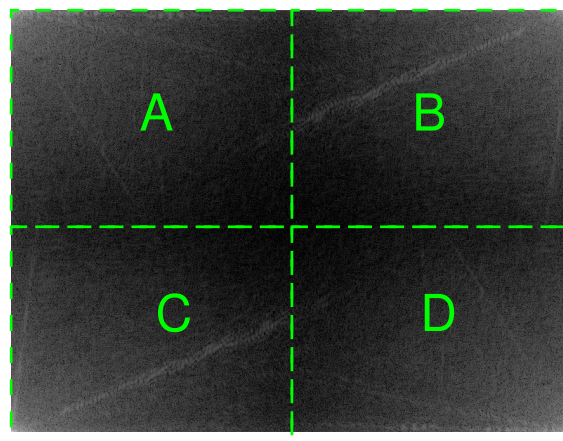
$$x \in \{-N/2, -N/2 + 1, \dots, -1, 0, 1, \dots, N/2 - 1, N/2\}$$

and

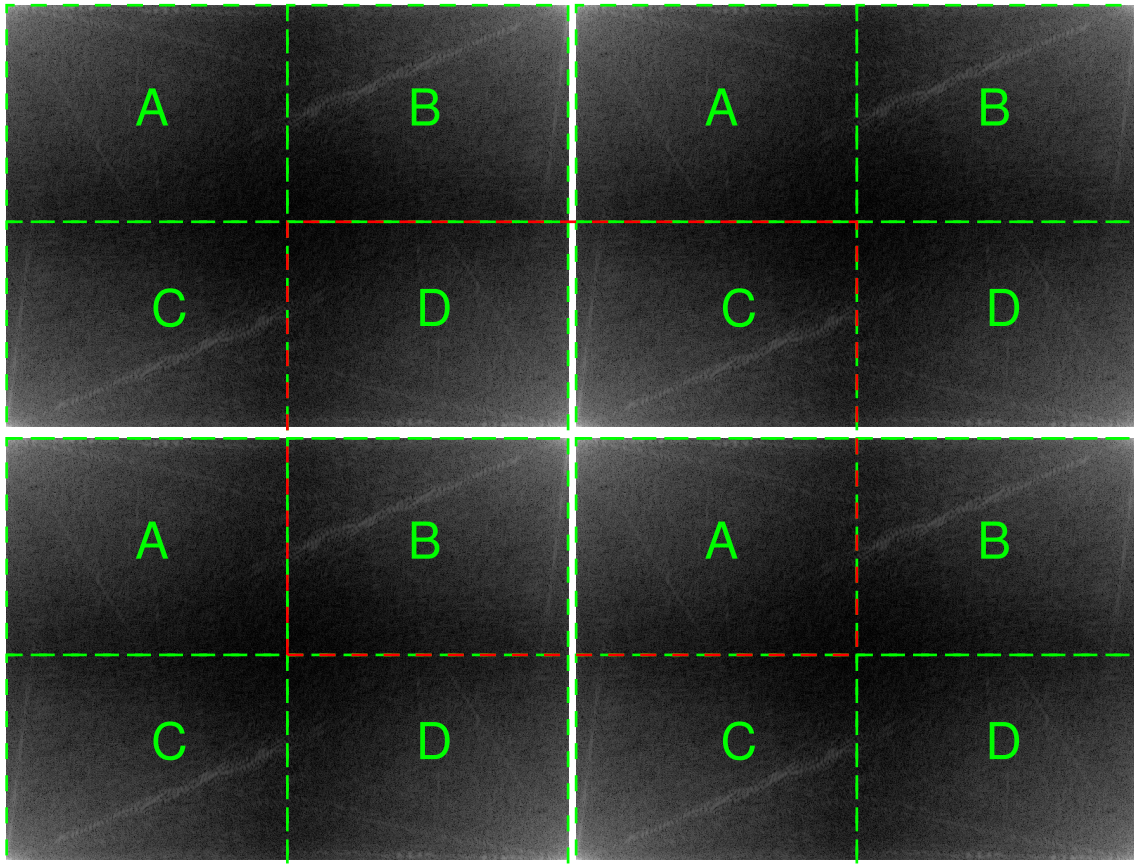
$$y \in \{-M/2, -M/2 + 1, \dots, -1, 0, 1, \dots, M/2 - 1, M/2\}$$

instead of the intensities for $0, 1, \dots, N - 1$ and $0, 1, \dots, M - 1$.

Centered Spectrum



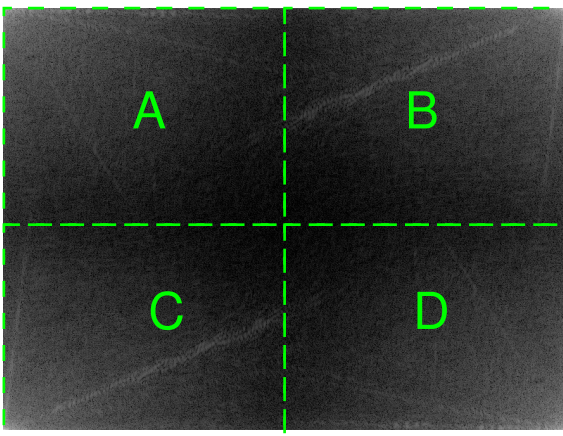
Centered Spectrum



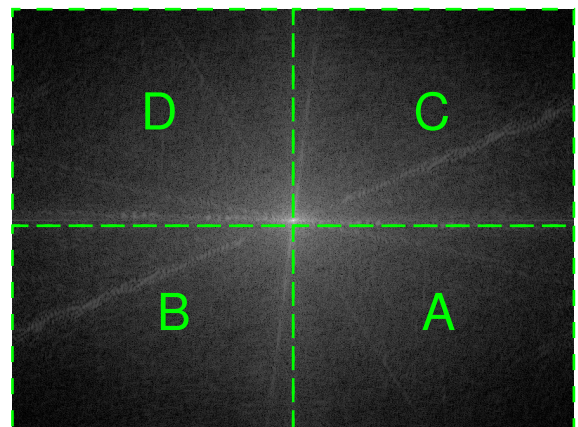
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Centered Spectrum

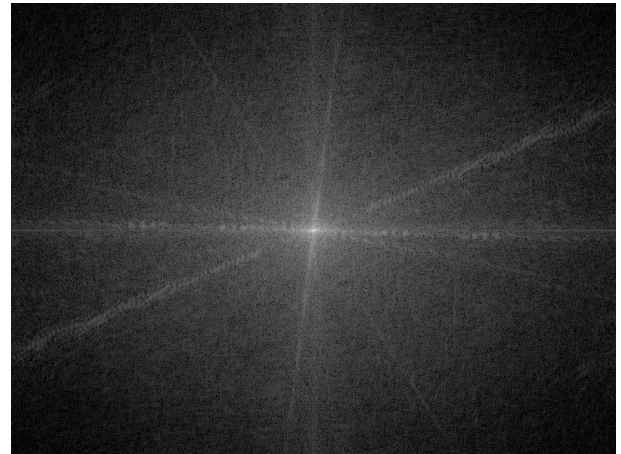
original spectrum:



centered spectrum:



Example

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

Symmetry of Fourier Power Spectra for Real Images

Usually images are real, i.e., $f(x) \in \mathbb{R}$ (not \mathbb{C}).

For real functions, we know that

$$\mathcal{F}(f)(-x) = \mathcal{F}^*(f)(x)$$

is hermitian (with $x^* := \Re x - i \Im x$).

As $x \in \mathbb{C}$ has the same radius as x^* :

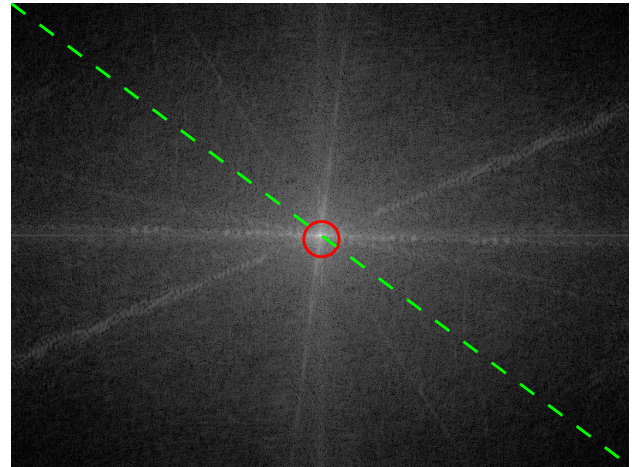
$$r(x) = \sqrt{(\Re x)^2 + (\Im x)^2} \stackrel{?}{=} r(x^*) = r(\Re x - i \Im x) = \sqrt{(\Re x)^2 + (-\Im x)^2}$$

for real functions $\mathcal{F}(f)$ and $\mathcal{F}^*(f)$ have the same radius and thus

$$\mathcal{F}^{\text{power}}(f)(-x) = \mathcal{F}^{\text{power}}(f)(x)$$

i.e., the power spectrum is symmetric around the origin.

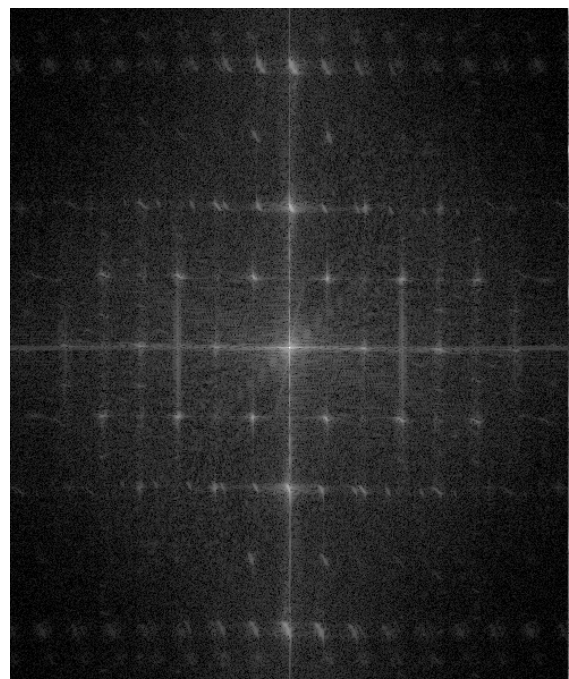
Symmetry of Fourier Power Spectra for Real Images

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

Spectra of real images are symmetric around the origin (red circle).

So storing just half of the power spectrum is sufficient (e.g., above green line — any line through the origin will do).

Another Example

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

1. Fourier Series Representation

2. The Fourier Transform

3. Discrete Signals

4. Discrete Fourier Transform

5. Two-dimensional Fourier Transforms

6. Applications

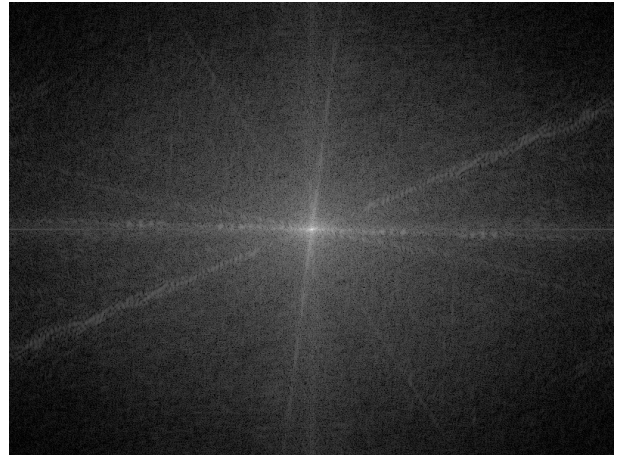
Low Pass Filters

High frequencies are responsible for sharp edges,
low frequencies for constant and slowly changing areas.

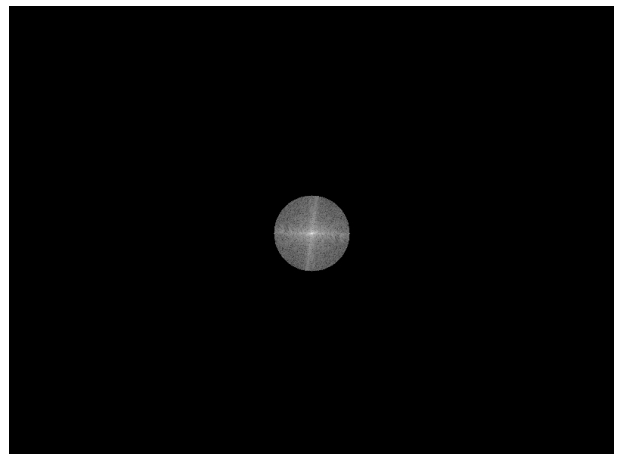
Low pass filters

- retain only low frequencies $\omega \leq \omega_{\max}$,
- i.e., filter out high frequencies.
- and thus smooth / blur an image.

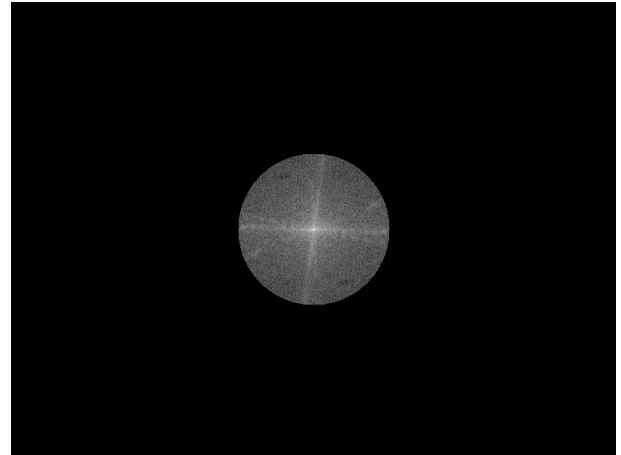
Low Pass Filters / Example

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

Low Pass Filters / Example

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

Low Pass Filters / Example

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

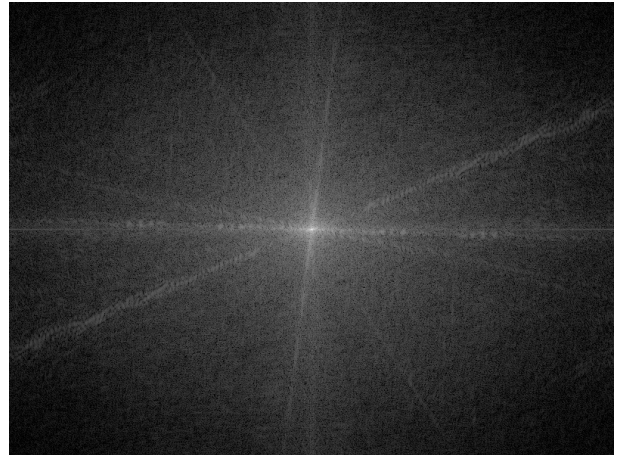
High Pass Filters

High frequencies are responsible for sharp edges,
low frequencies for constant and slowly changing areas.

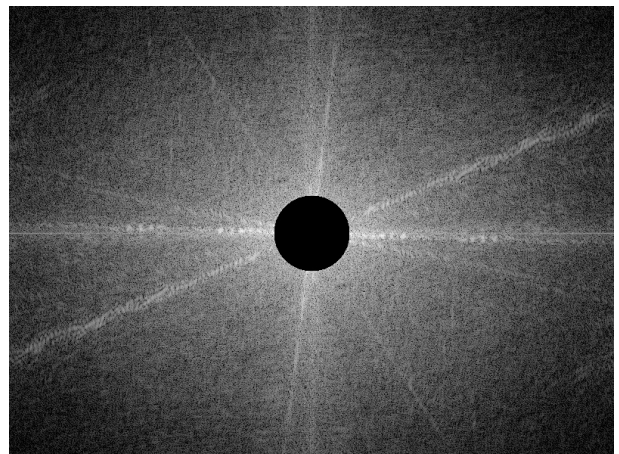
High pass filters

- retain only high frequencies $\omega \geq \omega_{\min}$,
- i.e., filter out low frequencies.
- and thus sharpen an image and detect edges.

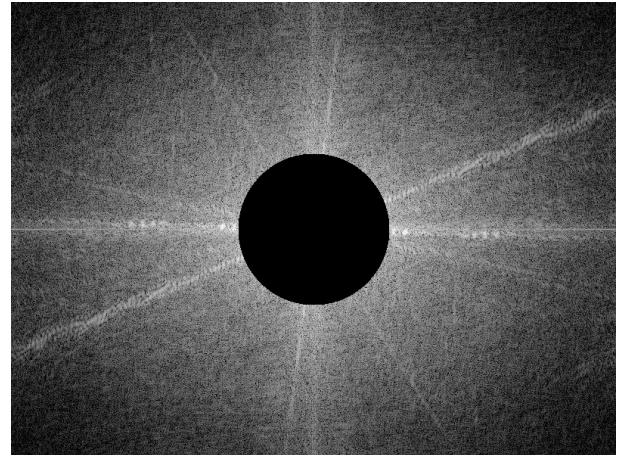
High Pass Filters / Example

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

High Pass Filters / Example

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

High Pass Filters / Example

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

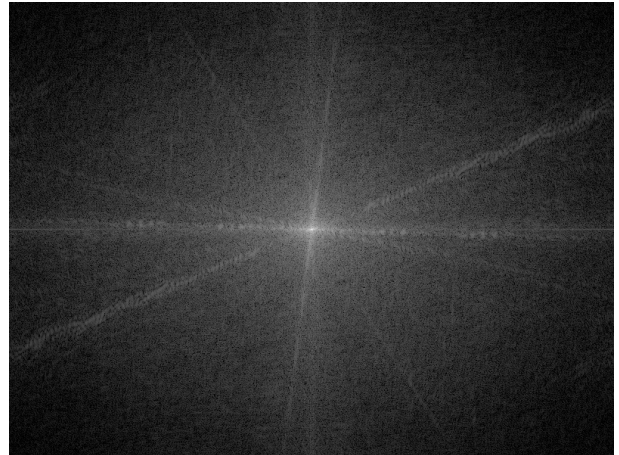
Band Pass Filters

High frequencies are responsible for sharp edges,
low frequencies for constant and slowly changing areas.

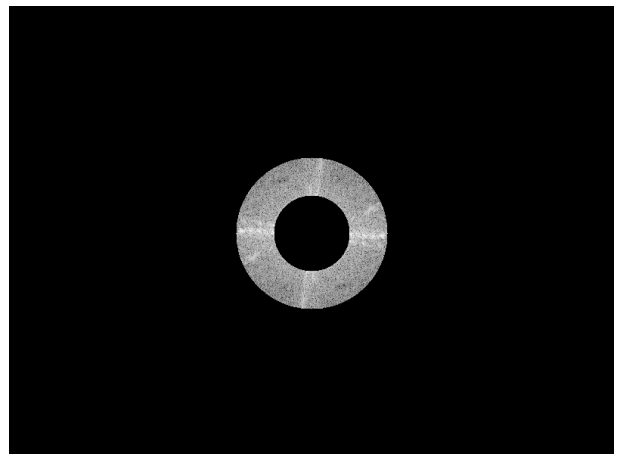
Band pass filters

- retain only frequencies $\omega \in [\omega_{\min}, \omega_{\max}]$ in a given interval (the **frequency band**),
- i.e., filter out low and high frequencies.
- and thus detect edges.

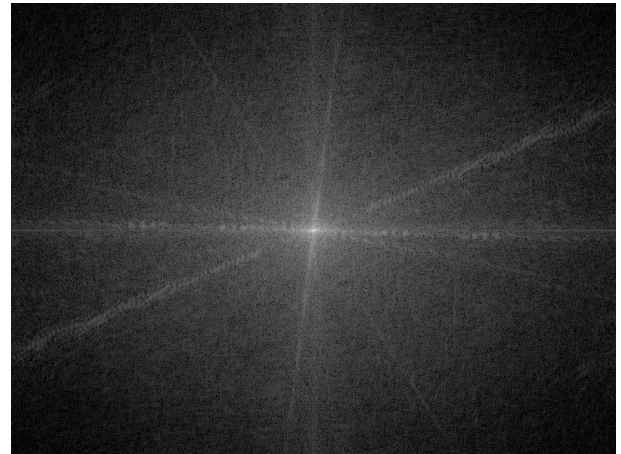
Band Pass Filters / Example

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

Band Pass Filters / Example

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

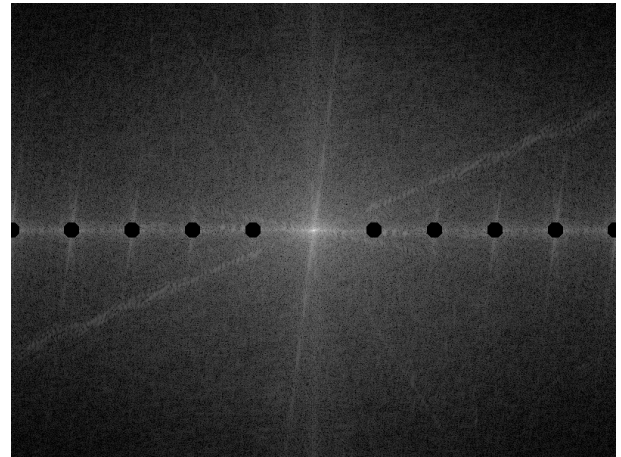
Reducing Periodic Noise

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

Reducing Periodic Noise

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

Reducing Periodic Noise

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

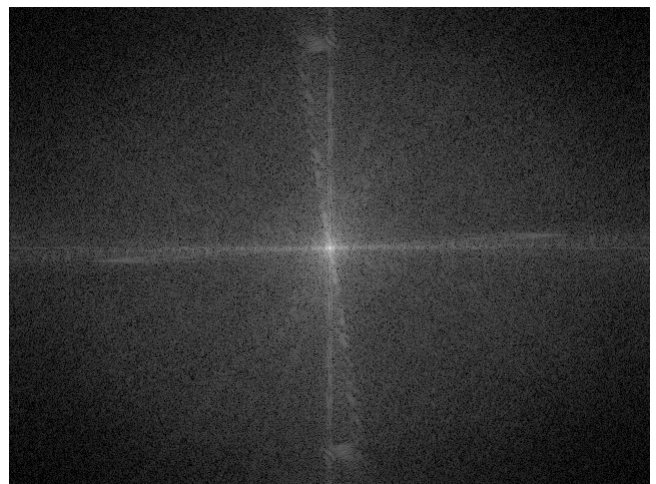
Periodic noise can be reduced by filtering out the frequencies belonging to the periodic noise pattern.

This also can be understood as a simple method for **inpainting**.

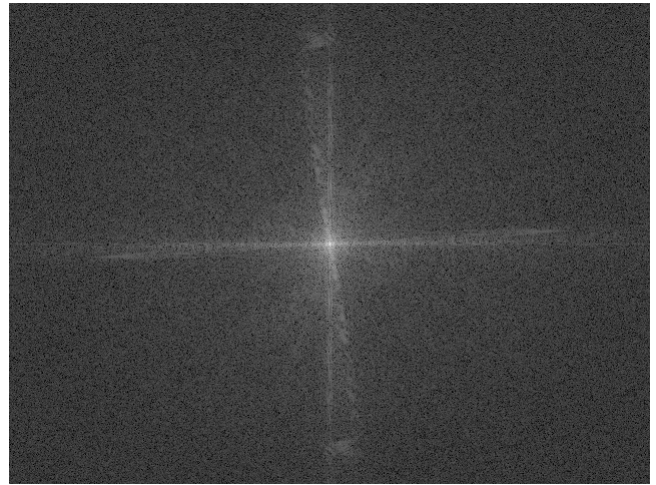
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Reducing Salt and Pepper Noise

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

Reducing Salt and Pepper Noise

image f :power spectrum $\mathcal{F}^{\text{power}}(f)$:

Reducing non-periodic noise patterns via frequency filters is difficult.

Deconvolution via Fourier Transform

Assume, an image f has been corrupted by a convolution with a kernel k (e.g., blurred):

$$g = k * f$$

If the kernel k is known, one can “undo” the convolution using the Fourier transform:

$$\mathcal{F}(g) = \mathcal{F}(k * f) = \mathcal{F}(k) \cdot \mathcal{F}(f)$$

$$\mathcal{F}(f) = \frac{\mathcal{F}(g)}{\mathcal{F}(k)}$$

$$f = \mathcal{F}^{-1} \mathcal{F}(f) = \mathcal{F}^{-1} \left(\frac{\mathcal{F}(g)}{\mathcal{F}(k)} \right)$$

Schedule

Schedule until Christmas:

- next Tue., 9.12., no lecture.
- next Wed., 10.12, 10-12 lecture.
- Tue., 16.12., no lecture.
- Wed., 17.12, 10-12 lecture.