

Course « Computer Vision»

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2024-2025



- During the past century, and especially in the past 50 years, entire industries and academic disciplines have flourished as a result of Fourier's ideas.
- The "discovery" of a fast Fourier transform (FFT) algorithm in the early 1960s revolutionized the field of signal processing.
- Today, we can say that there is no discipline of science or engineering that has not been profoundly impacted by the Fourier transform.
- The goal of this lesson is to give a working knowledge of how the Fourier transform and the frequency domain can be used for image filtering.

Who is Fourier?

Jean Baptiste Joseph Fourier

French mathematician and physicist

21 March 1768 -- 17 May 1830.

He was actually obsessed with heat. He was very interested in knowing how heat propagated through materials of different shapes.

=> That is what led him to develop the Fourier transform.



Fourier Transform

- Basically, any periodic function can actually be written as a weighted sum of infinite sinusoids of different frequencies.
- Functions that are not periodic (but whose area under the curve is finite) can also be expressed as the integral of sines and cosines multiplied by a weighting function

Sinusoid

$$f(x) = A \sin(2 \pi u x + \varphi)$$

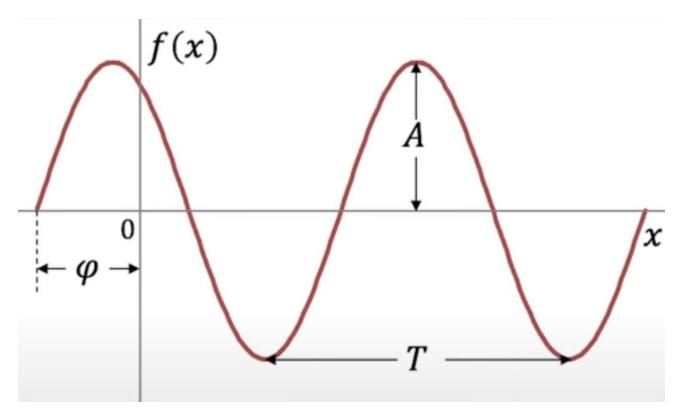
x: the time

A: amplitude (the peak value of the wave)

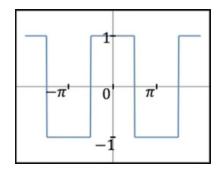
T: period

 φ : phase (a shift in time, measured in radians)

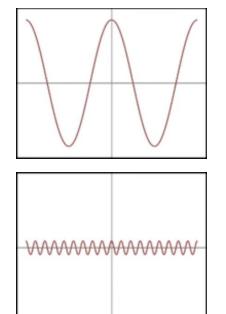
u: frequency (how many cycles per second, measured in Hz = 1/T)

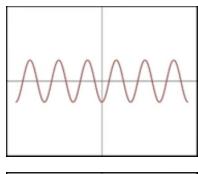


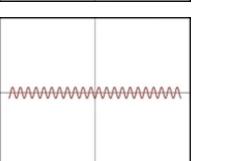
Fourier transform to decompose any periodic function

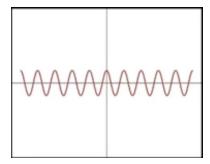


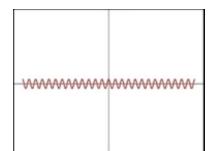
Square wave (period = 2π).

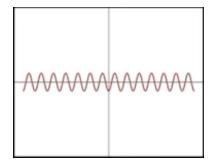


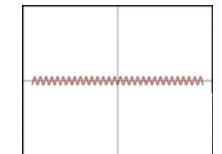




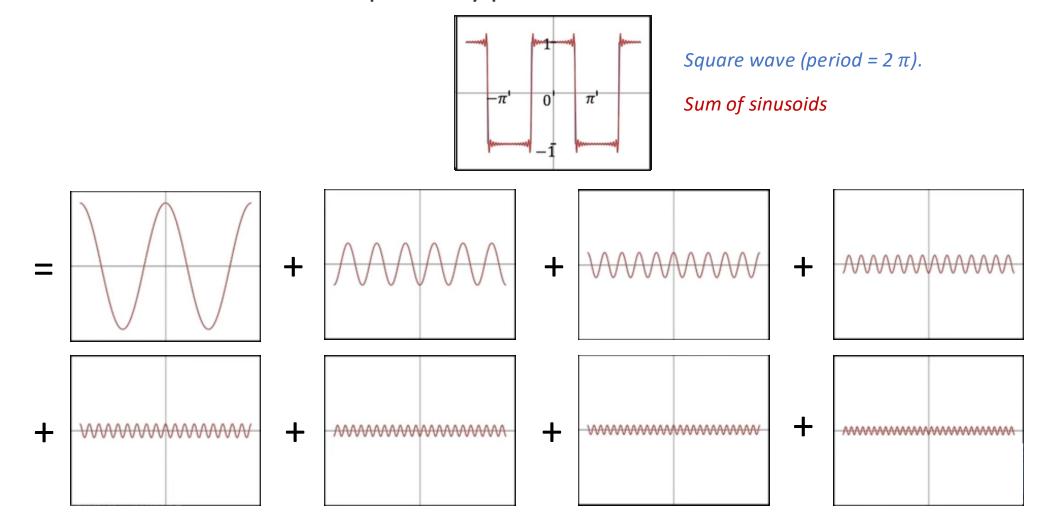




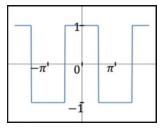




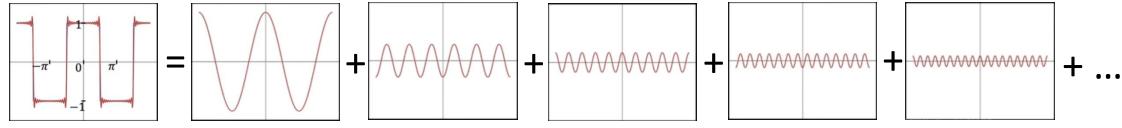
Fourier transform to decompose any periodic function



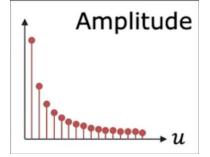
Fourier transform to decompose any periodic function

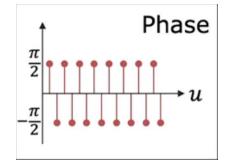


Square wave (period = 2 \pi).



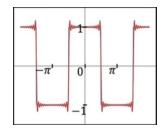
Sum of sinusoids





Fourier transform:

It represents a signal f(x) in terms of amplitudes and phases of its constituent sinusoids.

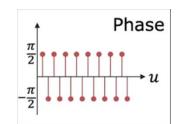


Amplitude

$$f(x)$$
 -> **FT** -> $F(u)$

Inverse Fourier transform:

 It computes the spatial signal f(x) from the amplitudes and phases of the constituent sinusoids.



$$F(u)$$
 -> IFT -> $f(x)$

Fourier Transform (of a 1D signal):

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

Inverse Fourier Transform (of a 1D signal):

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

x: space

u: frequency

$$e^{i\theta} = \cos\theta + i\sin\theta$$

$$i = \sqrt{-1}$$

Why do we have $e^{i\theta} = \cos \theta + i \sin \theta$? $(i = \sqrt{-1})$

Expand $e^{i\theta}$ using Taylor Series:

$$e^{i\theta} = 1 + i\theta + \frac{(i\theta)^2}{2!} + \frac{(i\theta)^3}{3!} + \frac{(i\theta)^4}{4!} + \frac{(i\theta)^5}{5!} + \frac{(i\theta)^6}{6!} + \cdots$$

$$e^{i\theta} = \left(1 - \frac{\theta^2}{2!} + \frac{\theta^4}{4!} - \frac{\theta^6}{6!} + \cdots\right) + i\left(\theta - \frac{\theta^3}{3!} + \frac{\theta^5}{5!} - \frac{\theta^7}{7!} + \cdots\right)$$

 $\cos \theta$

 $\sin \theta$

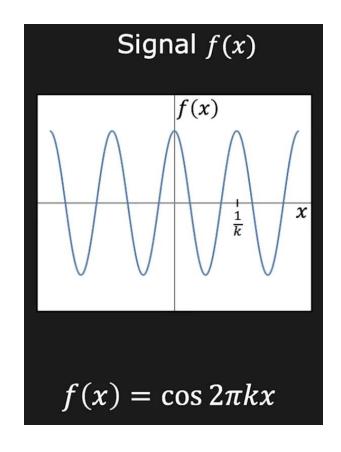
⇒ The Fourier Transform is Complex!

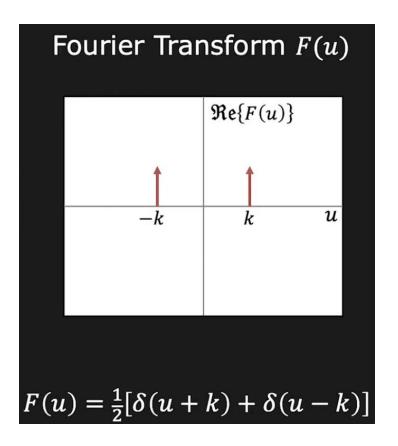
F(u) holds the Amplitude and the Phase of the sinusoid of frequency u

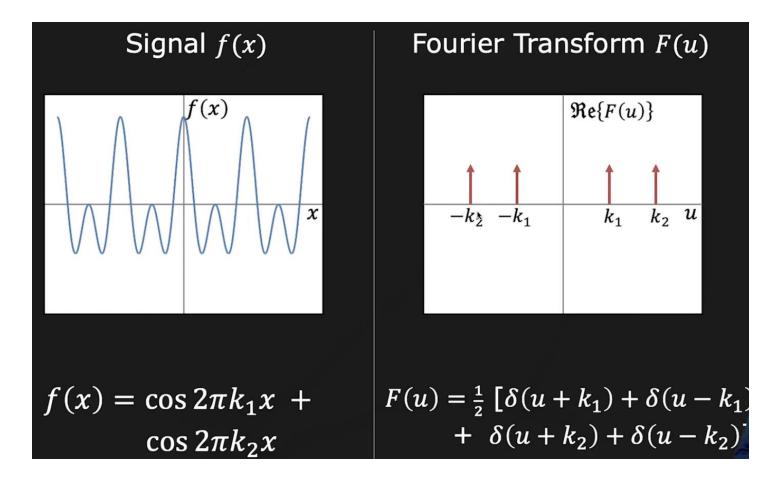
$$F(u) = \int_{-\infty}^{\infty} f(x)e^{-i2\pi ux}dx$$
$$F(u) = \Re\{F(u)\} + i\Im\{F(u)\} = |A(u)| e^{i\varphi(u)}$$

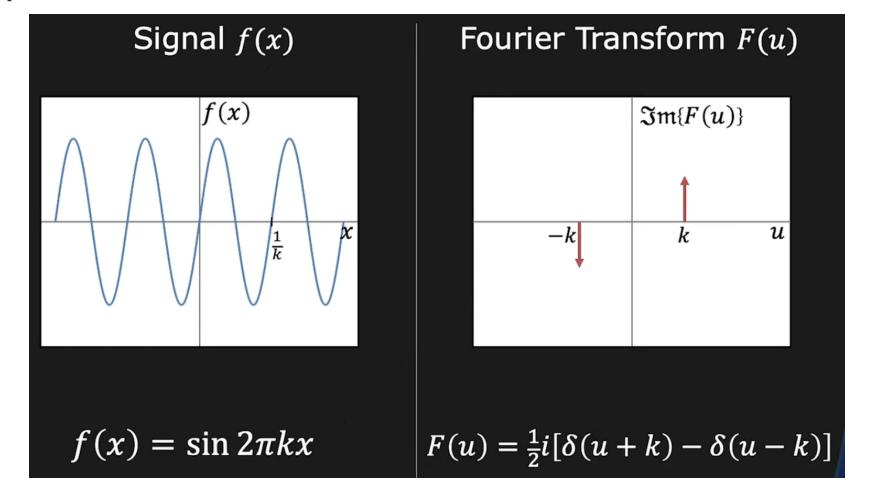
Amplitude:
$$A(u) = \sqrt{\Re\{F(u)\}^2 + \Im\{F(u)\}^2}$$

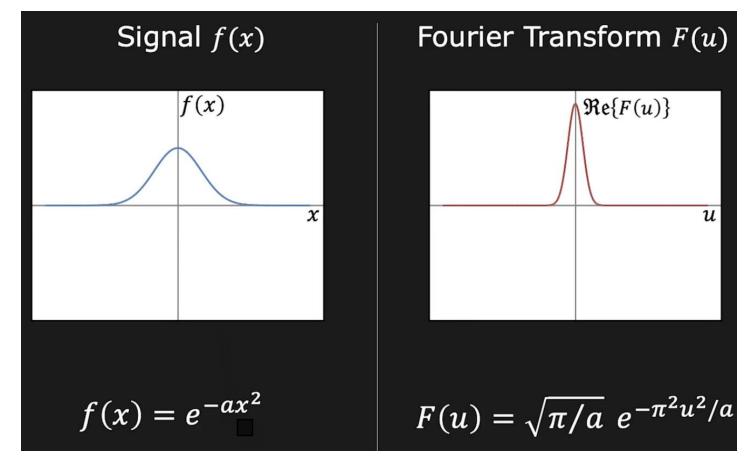
Phase:
$$\varphi(u) = \operatorname{atan2}(\Im\{F(u)\}, \Re\{F(u)\})$$







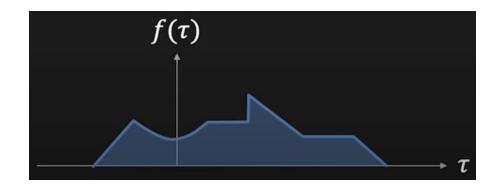


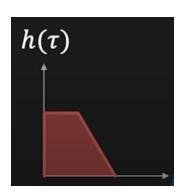


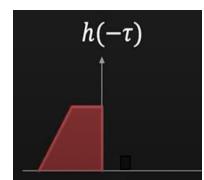
Fourier transform and convolution

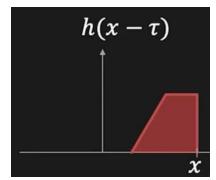
A close and important relationship.

$$g(x) = f(x) * h(x) = \int_{-\infty}^{\infty} f(\tau) h(x - \tau) d\tau$$





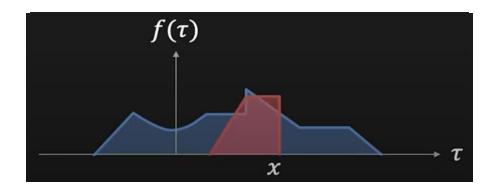


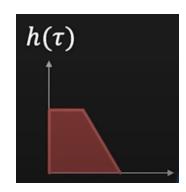


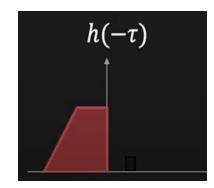
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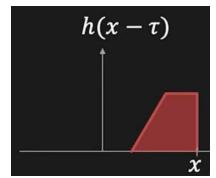
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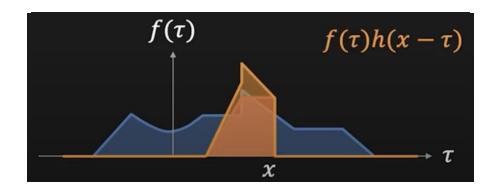


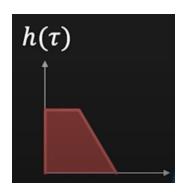


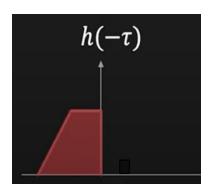
Fourier transform and convolution

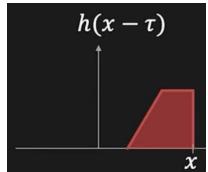
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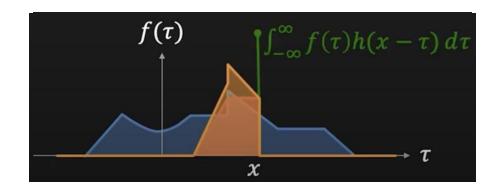


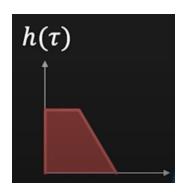


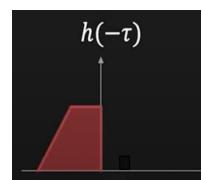
Fourier transform and convolution

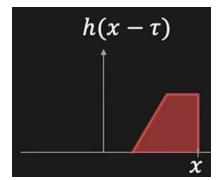
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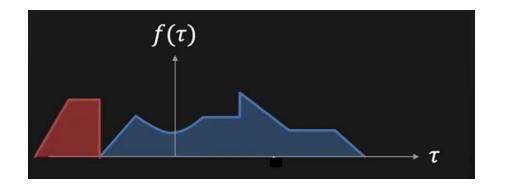


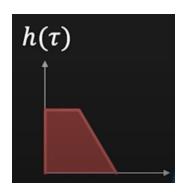


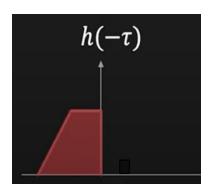
Fourier transform and convolution

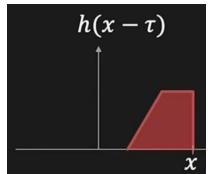
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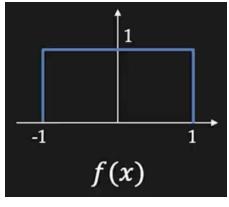


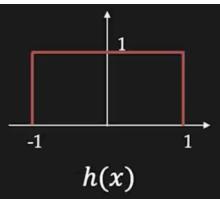


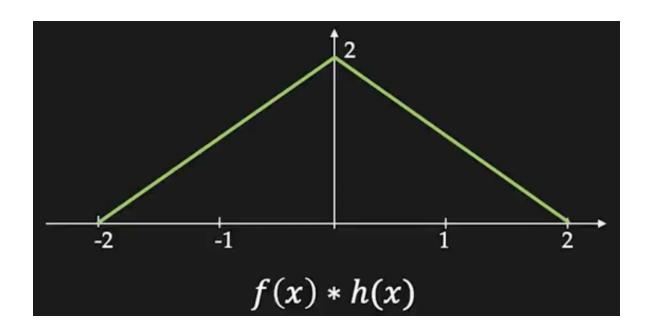




Fourier transform and convolution: Few examples







Fourier transform and convolution

⇒ The convolution theorem

Convolution:
$$g(x) = f(x) * h(x) = \int_{-\infty}^{\infty} f(\tau) h(x - \tau) d\tau$$

Fourier Transform of g(x):

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

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

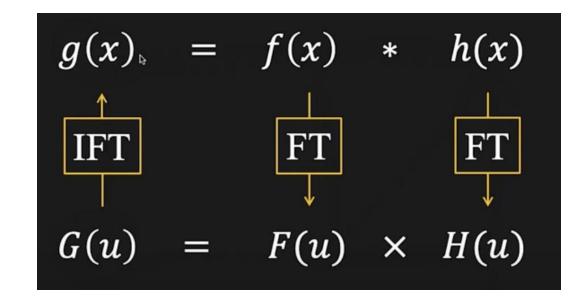
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Fourier transform and convolution

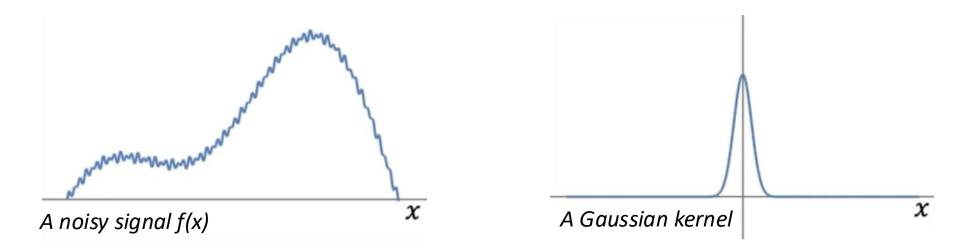
Spatial Domain		Frequency Domain
g(x) = f(x) * h(x) Convolution	←	G(u) = F(u) H(u) Multiplication
g(x) = f(x) h(x) Multiplication	~	G(u) = F(u) * H(u) Convolution

Fourier transform and convolution

- Very efficient implementation of FT and IFT are available.
- Working in the frequency domain is more efficient.
- Analyze in the frequency domain, a filter that is designed in the spatial domain.



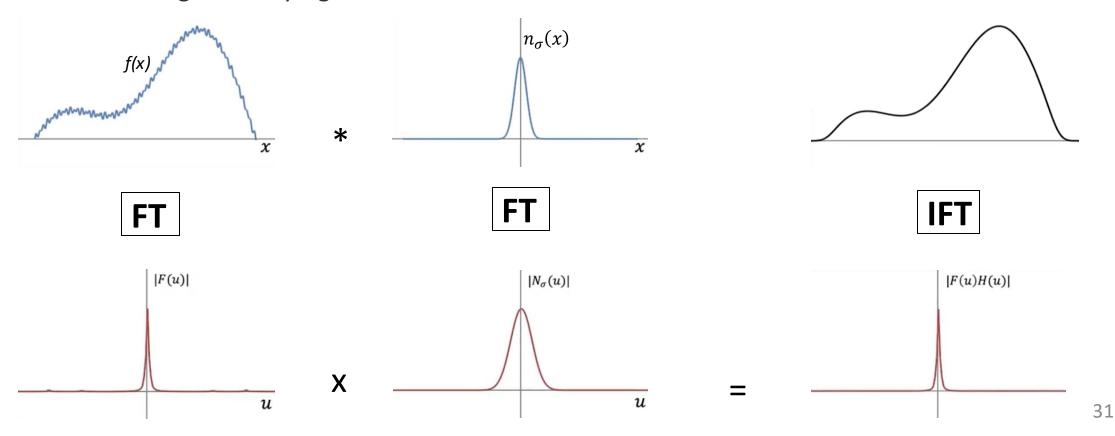
Fourier transform and convolution



⇒ Convolving the noisy signal with the Gaussian kernel.

Fourier transform and convolution

⇒ Convolving the noisy signal with the Gaussian kernel.



Application to images – The 2D Fourier transform

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

u and v are the frequencies along x and y, respectively.

Inverse Fourier Transform:
$$f(x,y) = \iint_{-\infty}^{\infty} F(u,v) e^{i2\pi(ux+vy)} du dv$$

Application to images – The 2D Discrete Fourier transform (DFT)

Discrete Fourier Transform:

$$F[p,q] = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f[m,n]e^{-i2\pi pm/M}e^{-i2\pi qn/N}$$

$$p = 0 \dots M - 1$$
 and $q = 0 \dots N - 1$,

p and q are the frequencies along m and n, respectively.

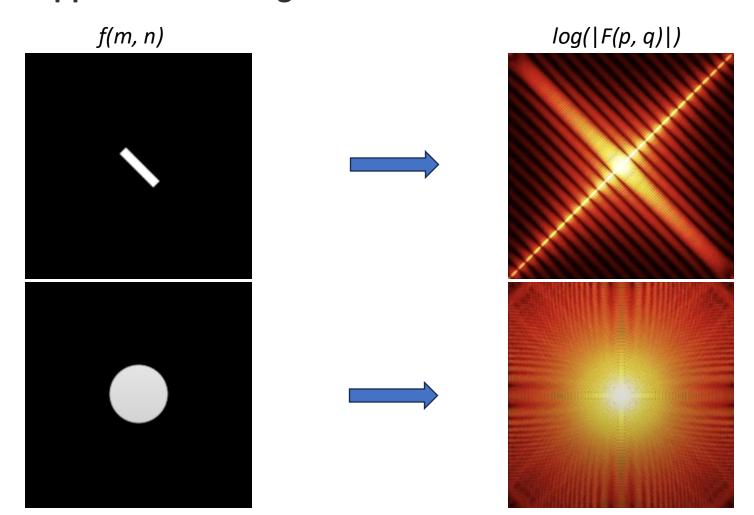
Application to images – The 2D Discrete Fourier transform (DFT)

Inverse Discrete Fourier Transform:

$$f[m,n] = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} F[p,q] e^{i2\pi pm/M} e^{i2\pi qn/N}$$

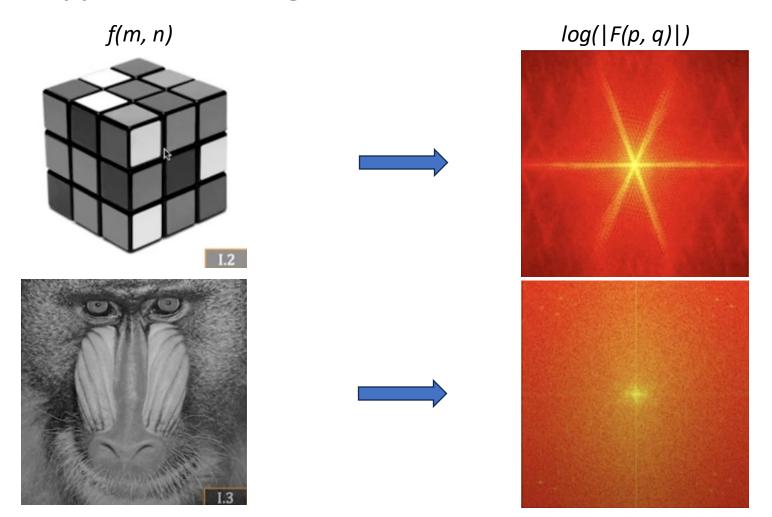
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Application to images – The 2D Discrete Fourier transform (DFT)



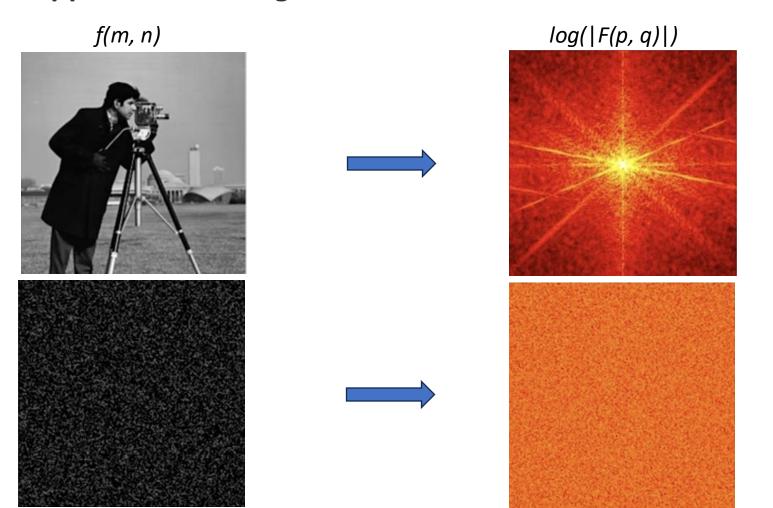


Application to images – The 2D Discrete Fourier transform (DFT)





Application to images – The 2D Discrete Fourier transform (DFT)

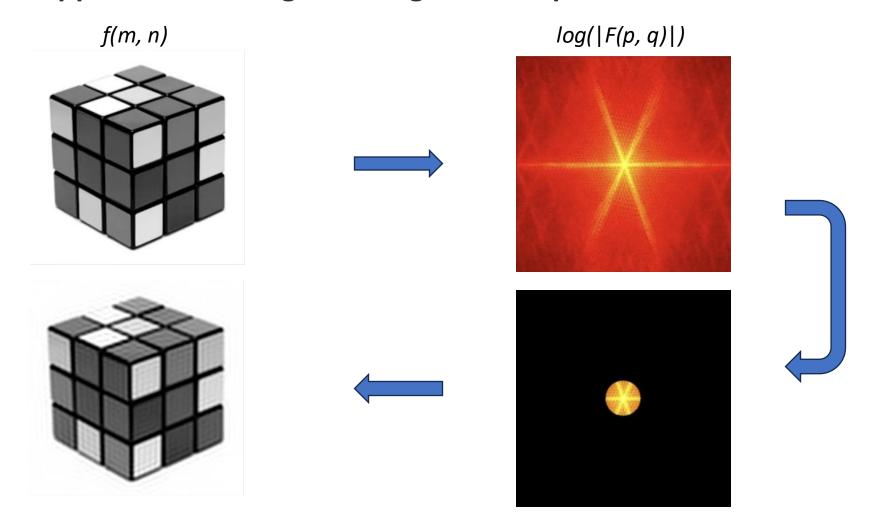




Application to image filtering: The low pass filter and the high pass filter

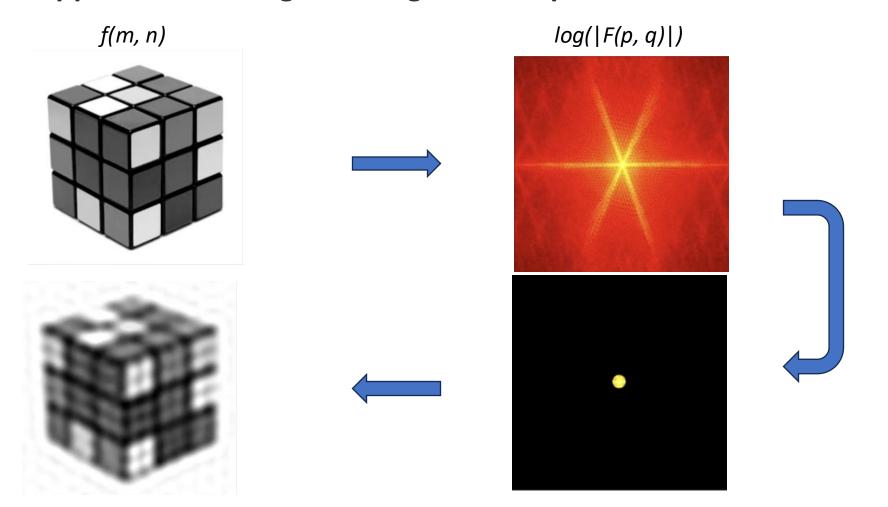
- Low frequencies in the transform are related to slowly varying intensity components.
- High frequencies are caused by sharp transitions in intensity, such as edges, corners and noise
- ⇒ A filter *H(u, v)* that attenuates high frequencies while passing low frequencies (low-pass filter) blurs an image
- ⇒ A high-pass filter (which attenuates low frequencies) enhances sharp detail, but cause a reduction in contrast in the image.

Application to image filtering: The low pass filter



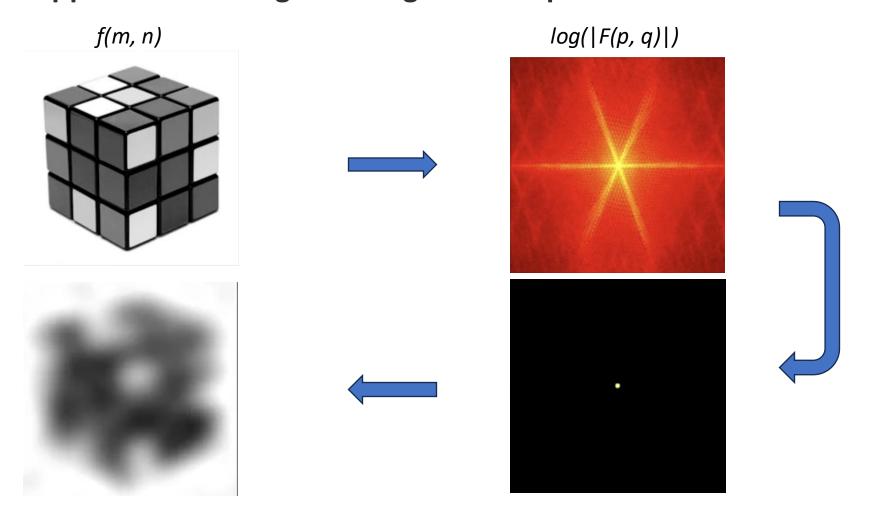


Application to image filtering: The low pass filter



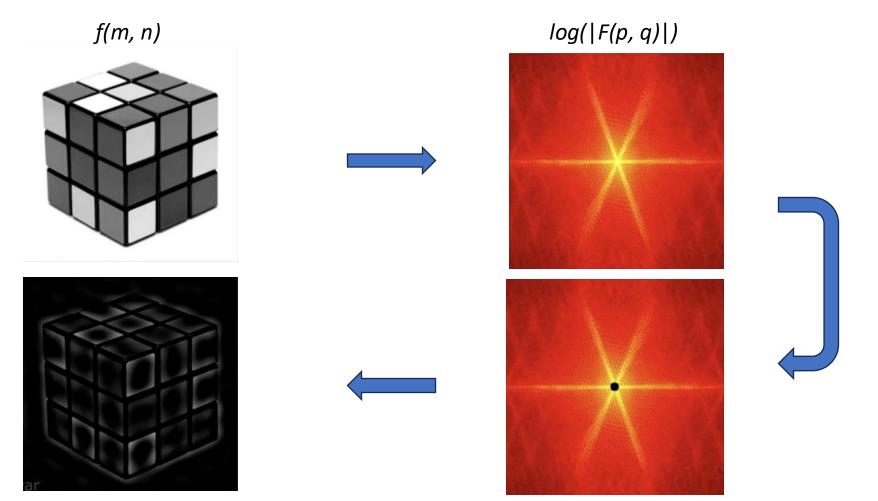


Application to image filtering: The low pass filter



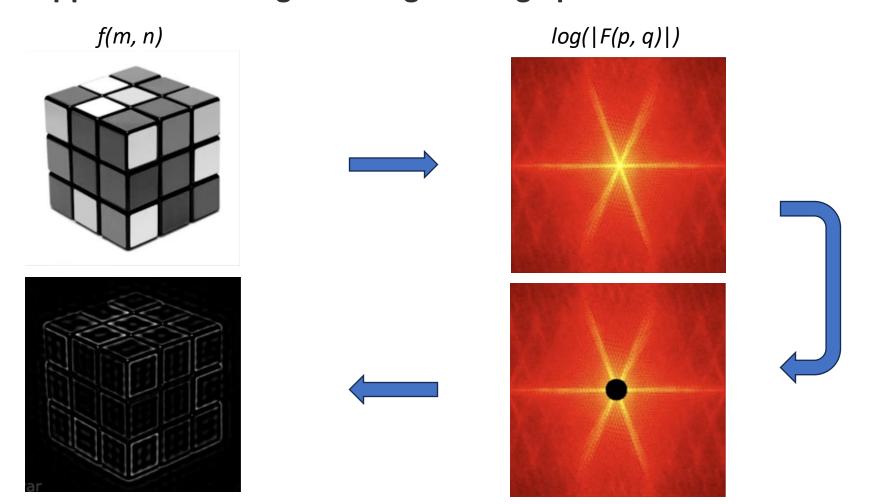


Application to image filtering: The high pass filter



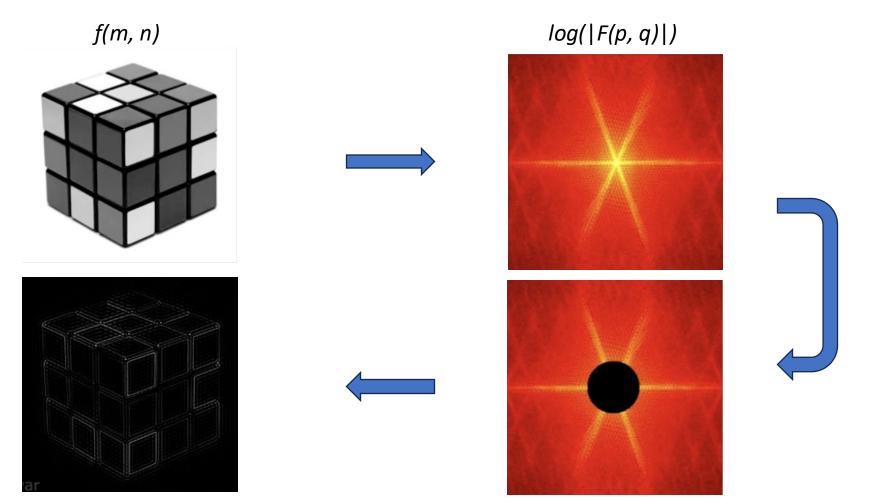


Application to image filtering: The high pass filter





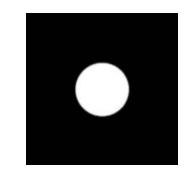
Application to image filtering: The high pass filter



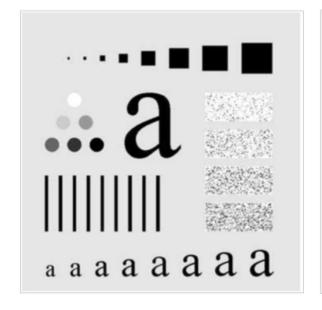


Low-pass filter seen so far is called Ideal Low-pass filter (ILPF):

$$H(u, v) = \begin{cases} 1 & \text{if } D(u, v) \leq D_0 \\ 0 & \text{if } D(u, v) > D_0 \end{cases}$$



The point of transition between H(u, v) = 1 and H(u, v) = 0 is called the **cut-off frequency**.

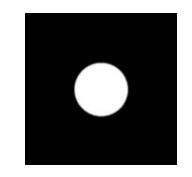




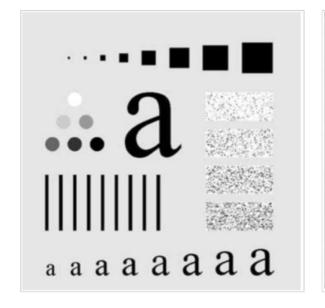
ILPF with cut-off frequency = 60

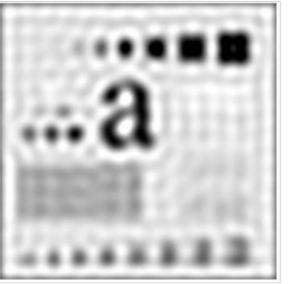
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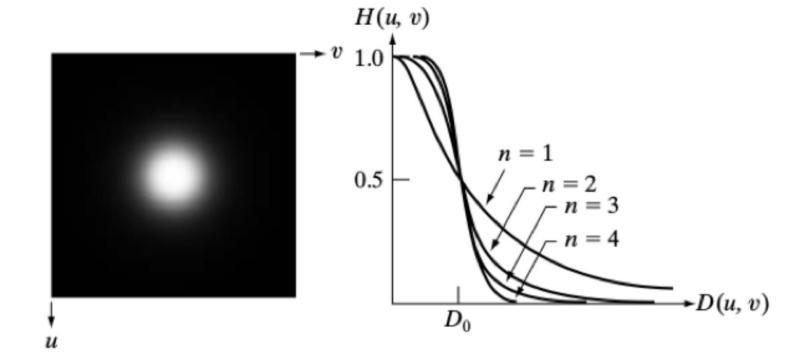
ILPF with cut-off frequency = 30

The butterworth Low-pass filters

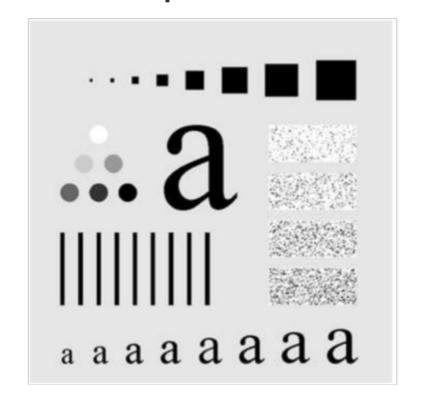
$$H(u, v) = \frac{1}{1 + [D(u, v)/D_0]^{2n}}$$

n is the order of the filter.

 D_{o} is the cutoff frequency.



The butterworth Low-pass filters

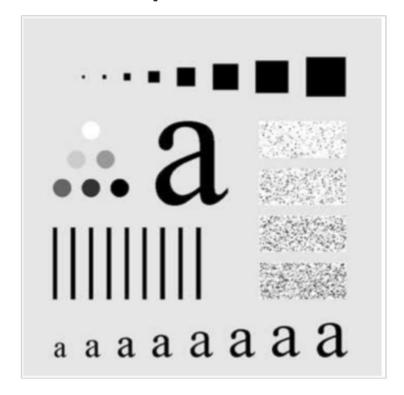


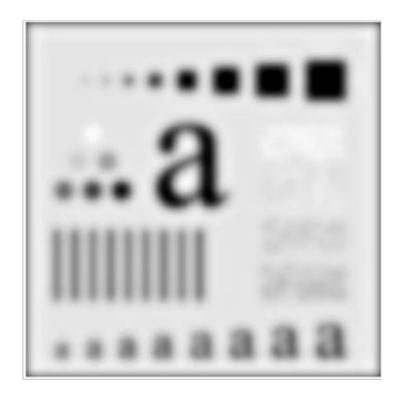


Order of the filter (n) = 2.

Cutoff frequency $(D_0) = 60$.

The butterworth Low-pass filters

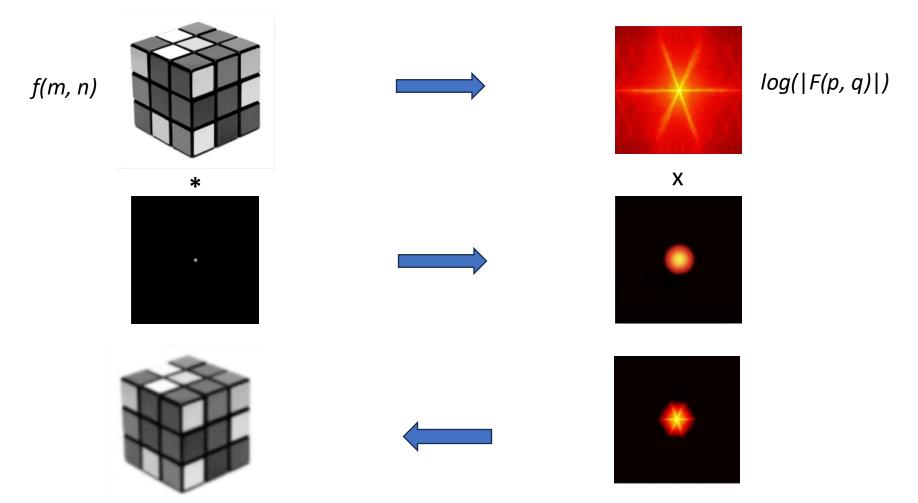




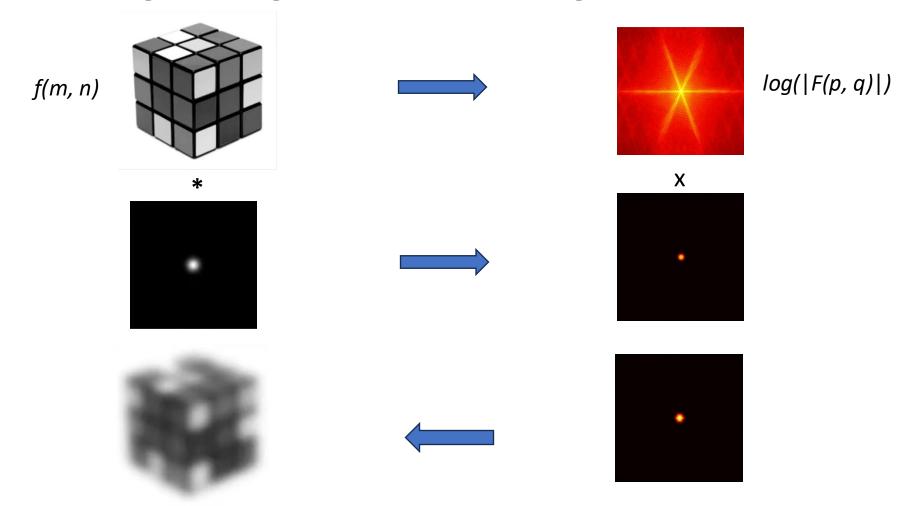
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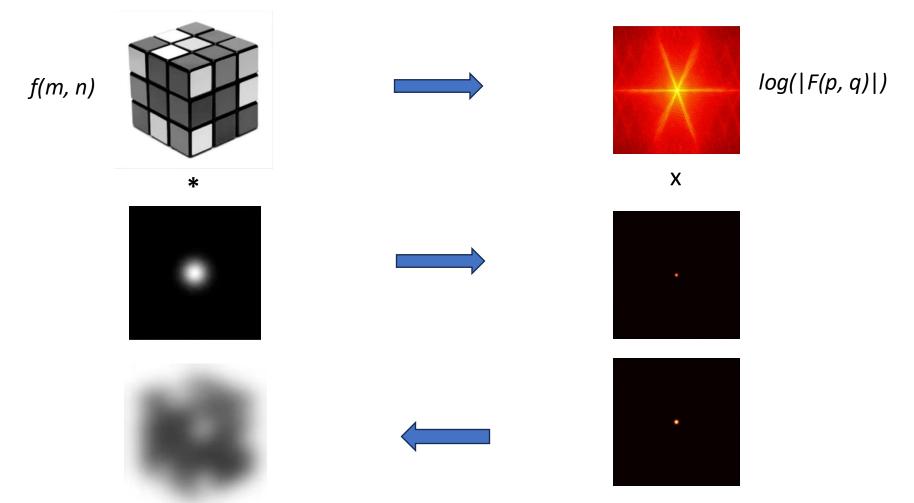
Application to image filtering: The Gaussian filtering



Application to image filtering: The Gaussian filtering

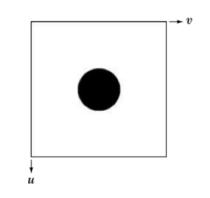


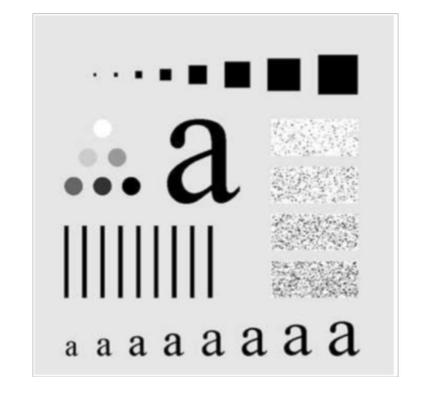
Application to image filtering: The Gaussian filtering



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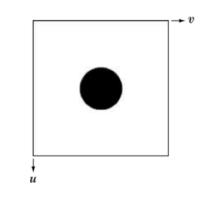


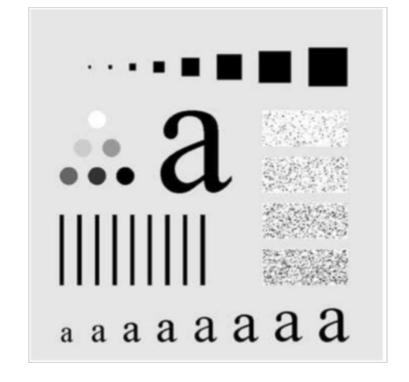


IHPF with cut-off frequency = 60

High-pass filter seen so far is called Ideal High-pass filter (IHPF):

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IHPF with cut-off frequency = 30

The butterworth High-pass filters

$$H(u,v) = \frac{1}{1 + [D_0/D(u,v)]^{2n}}$$

n is the order of the filter.

 D_{θ} is the cutoff frequency.





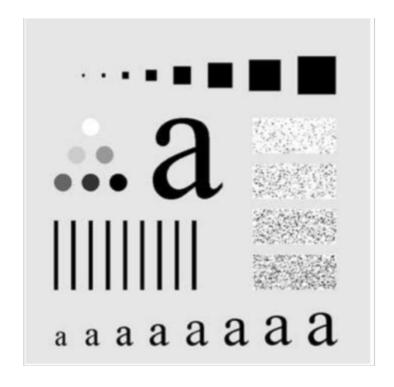
BHPF with cut-off frequency = 60

The butterworth High-pass filters

$$H(u,v) = \frac{1}{1 + [D_0/D(u,v)]^{2n}}$$

n is the order of the filter.

 D_{o} is the cutoff frequency.





BHPF with cut-off frequency = 30

In all of the previous examples, we have used only the magnitude.

Filtering has been performed considering only the magnitude.

What about the phase?

In many cases, the phase is more important than the amplitude to preserve the visual information.

In general,

The amplitudes of the sinusoids determine the intensities in the image.

 The phase is a measure of displacement of the various sinusoids with respect to their origin.

Carry much of the information about where discernable objects are located



Original image

Apply DFT

Set all the phases to 0

Preserve the magnitude

Reconstruct the image using the IDFT



Reconstructed image

Réf.: Signal reconstruction from Fourier transform sign information. S. Curtis, S. Lim, A. Oppenheim. 1984. https://dspace.mit.edu/handle/1721.1/4243



Original image

Apply DFT

Preserve the phases

Using an average of magnitudes

computed on a set of images

Reconstruct the image using the IDFT



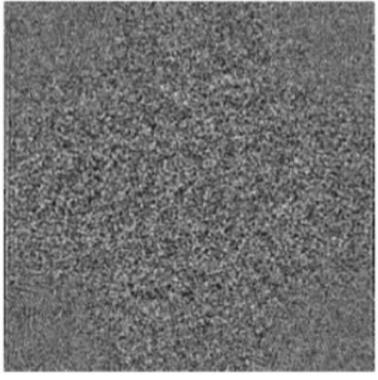
Reconstructed image

Réf.: Signal reconstruction from Fourier transform sign information. S. Curtis, S. Lim, A. Oppenheim. 1984.

https://dspace.mit.edu/handle/1721.1/4243

Example of image reconstruction using only the phase





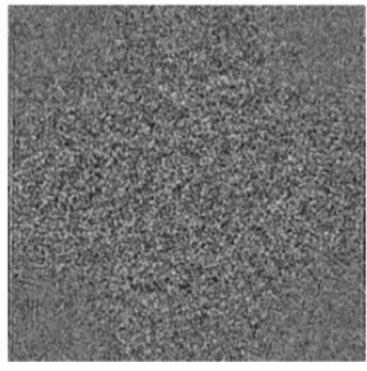


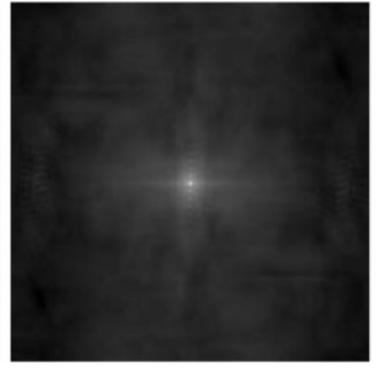
The original image

The phase

Example of image reconstruction using only the amplitude







The original image

The phase

Example of image reconstruction using the phase and another amplitude

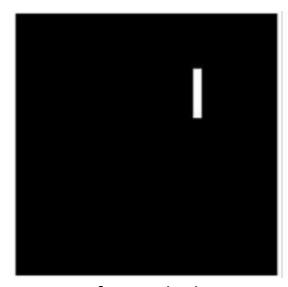


Image from which we compute the amplitude

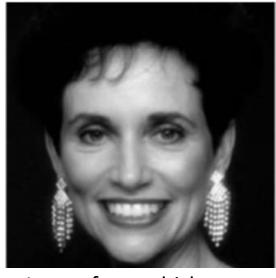
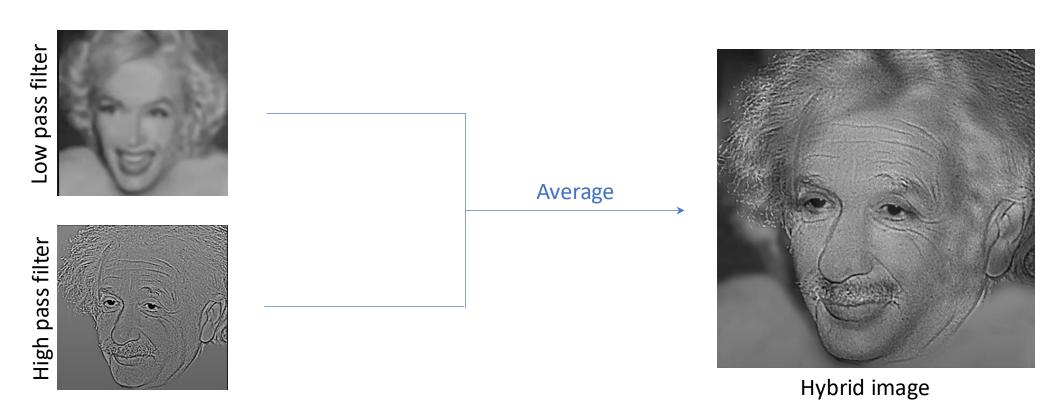


Image from which we compute the phase



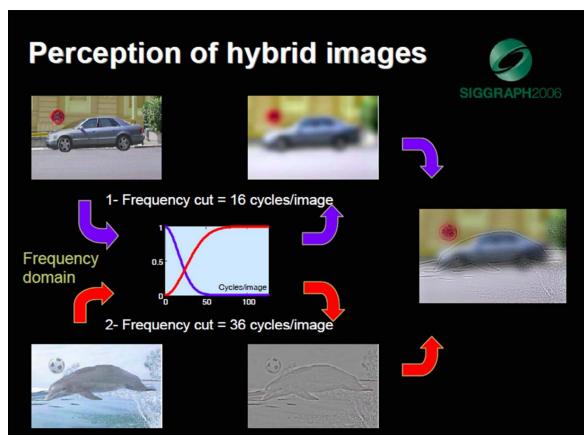
Reconstructed Image

Hybrid images



Réf.: *Hybrid images.* A. Oliva, A. Torralba, P. Schyns. ACM Transactions on Graphics, 2006. https://stanford.edu/class/ee367/reading/OlivaTorralb_Hybrid_Siggraph06.pdf

Hybrid images





Hybrid images

