

Digital Image Processing

Discrete 2D Processing

*Département Génie Electrique
5GE - TdSi*

Summary

I. Introduction

- DIP, Examples, Fundamental steps, components

II. Digital Image Fundamentals

- Visual perception, light
- Image sensing, acquisition, sampling, quantization
- Linear and non linear operations

III. Discrete 2D Processing

- Vector space, color space
- Operations (arithmetic, geometric, convolution, ...)
- Image Transformations

IV. Image Improvement

- Enhancement, restoration, geometrical modifications

Discrete 2D Processing

- Vector space, colour space
- Operations on images
 - Arithmetic operations
 - Set and logical operations
 - Spatial operations
 - Geometric
 - Convolution
- Image transformations
 - Unitary Transforms

Vector space and Matrix

■ Vector and Matrix Operations

□ Vector

- Spatial position of pixel
- Pixel intensities

$$\mathbf{x} = \begin{bmatrix} x \\ y \end{bmatrix}$$

$$\mathbf{z} = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \end{bmatrix}$$

i.e. : RGB

➔ once pixels have been represented as vectors, we can use the tools of vector-matrix theory

□ Euclidean distance

$$D(\mathbf{a}, \mathbf{b}) = \left[(\mathbf{a} - \mathbf{b})^T (\mathbf{a} - \mathbf{b}) \right]^{1/2}$$

□ Linear transformations

$$\mathbf{y} = \mathbf{A}(\mathbf{x} - \mathbf{b})$$

Vector space and Matrix

■ Vector and Matrix Operations

□ Other vector forms

■ Joint Spatial-range domain

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_s \\ \mathbf{x}_r \end{bmatrix} \begin{array}{l} \text{location} \\ \text{intensities} \end{array} \quad \text{i.e.} \quad \mathbf{x} = \begin{bmatrix} x \\ y \\ r \\ g \\ b \end{bmatrix}$$

□ Image

■ As function

$$f(x, y) \Leftrightarrow f(\mathbf{x}_s) = \mathbf{x}_r$$

■ As matrix ($M \times N$)

$$\mathbf{I}[i, j] \Leftrightarrow f(i \Delta x, i \Delta y) = \mathbf{x}_r$$

■ As vector ($MN \times 1$)

$$\mathbf{f}[k] = (\mathbf{x}_s, \mathbf{x}_r) \Leftrightarrow \mathbf{I}[k \% M, \lfloor k / N \rfloor] = \mathbf{x}_r$$

■ i.e. adding noise:

$$g(x, y) = f(x, y) + \eta(x, y)$$

Noiseless images $\begin{array}{c} \mathbf{G} \Rightarrow \mathbf{F} + \mathbf{N} \\ \mathbf{g} \Rightarrow \mathbf{f} + \mathbf{n} \end{array}$ noise

Color spaces

■ Color fundamentals

□ Colors are seen as variable combinations of **primary colors**: Red, Green and Blue

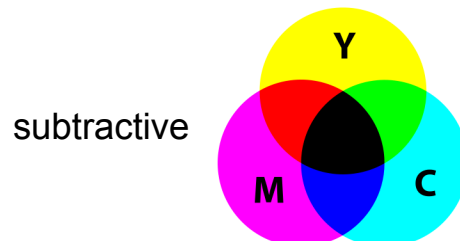
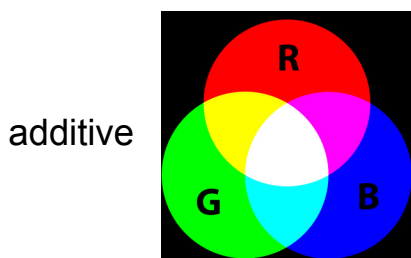
□ Standardization of the specific wavelength values by the CIE (Commission Internationale de l'Eclairage)

- Red = 700nm, green=546.1nm, blue=435.8nm

□ 2 kinds of mixture

■ Mixture of light (additive primaries)

■ Mixture of pigment (subtractive primaries)



Color spaces

- 3 Characteristics used to distinguish one color from another:
 - **Brightness**: achromatic notion of intensity
 - **Hue**: dominant color perceived (wavelength)
 - **Saturation**: relative purity (or the amount of white light within a hue)
- Chromaticity: hue+saturation
- ➔ A color can be characterized by its brightness and chromaticity

Color spaces

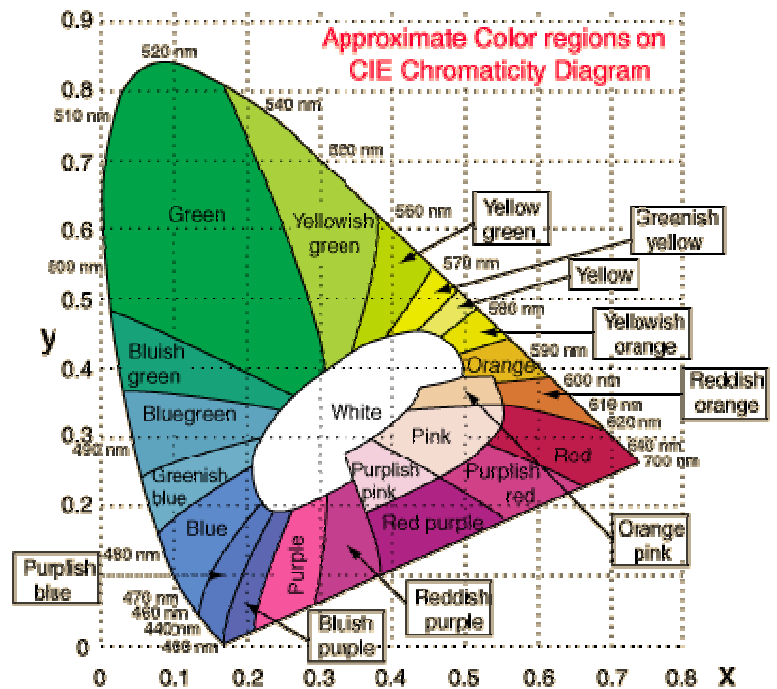
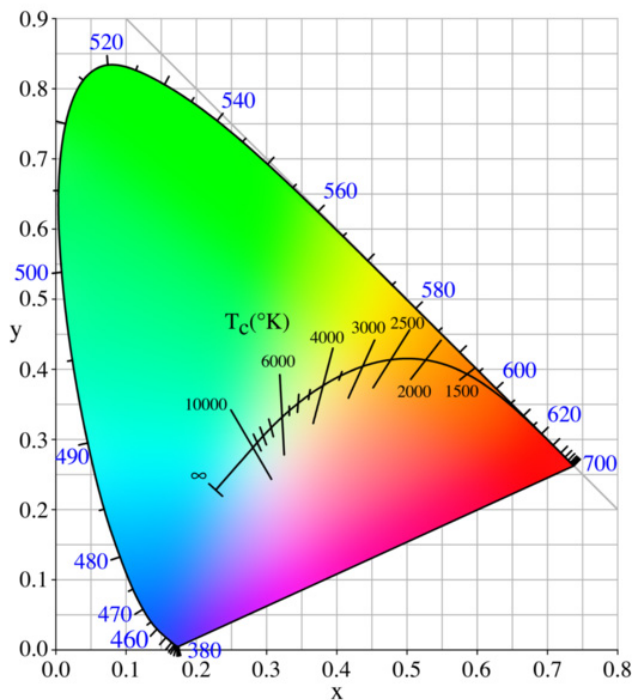
- Tristimulus values:
 - amount of red (X) green (Y) and blue(Z)
- Trichromatic coefficients (not spatial position!)

$$x = \frac{X}{X+Y+Z} \quad y = \frac{Y}{X+Y+Z} \quad z = \frac{Z}{X+Y+Z}$$
$$\Rightarrow x + y + z = 1$$

- Example:
 - a yellowish green :
 - x = 30% Red; y=60% Green; (z=10% Blue)

Color spaces

■ CIE Chromaticity diagram



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Color spaces

- A color model (also called color space or color systems) is a specification of a coordinate system.
- Color models in use may be
 - Hardware-driven (monitors, printers)
 - Application-driven (creation, color graphic animation, ...)
- Commonly used color models
 - RGB (monitors, color video cameras)
 - CMY, CMYK (printing)
 - YUV (TV, MPEG, ...)
 - HSI (similar to human description and interpretation of colors)
 - *Pseudocolor and Look Up Tables*

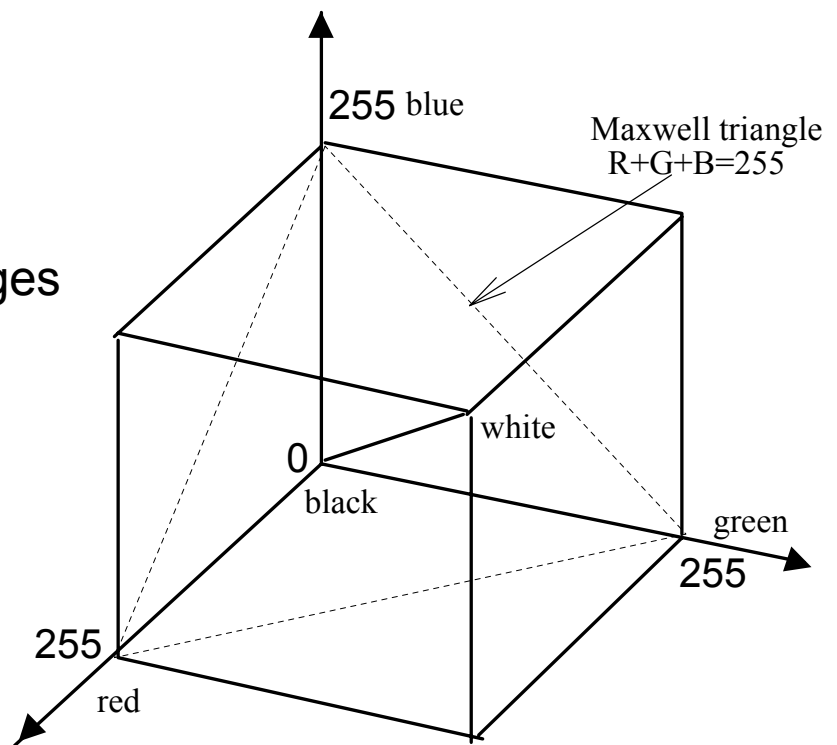
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RGB color model

■ Additive synthesis of color (mixtures of light)

- Display hardware
 - monitors
 - CRT, LCD, plasma
 - graphic card
- 24 bits (3*8 bits) Images
- About 16M colors
- Grey-levels images
 - R=G=B



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CMY Color model

■ Cyan Magenta Yellow

- Subtractive color model
 - Describes the color reflected by an illuminated surface absorbing certain wavelengths
 - Is needed by devices that deposit colored pigments
 - i.e. on paper
 - CMYK: black color added for true black

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - \begin{bmatrix} C \\ M \\ Y \end{bmatrix} \quad \begin{bmatrix} C \\ M \\ Y \end{bmatrix} \rightarrow \begin{bmatrix} C - \min(C, M, Y) \\ M - \min(C, M, Y) \\ Y - \min(C, M, Y) \\ \min(C, M, Y) \end{bmatrix} = \begin{bmatrix} C' \\ M' \\ Y' \\ K \end{bmatrix}$$

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YUV Color model

- YUV: PAL; YIQ: NTSC
- Y → intensity (grey-levels!) (not yellow ☺)
- UV or IQ: chromaticity

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.147 & -0.289 & -0.437 \\ 0.615 & -0.515 & -0.100 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad \begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.522 & 0.311 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

→ YUV is better than RGB for information decorrelation

→ Compression of color images

$$\begin{bmatrix} R : 33.2 \\ V : 36.2 \\ B : 30.6 \end{bmatrix} \leftrightarrow \begin{bmatrix} Y : 93 \\ U : 5.3 \\ V : 1.7 \end{bmatrix}$$

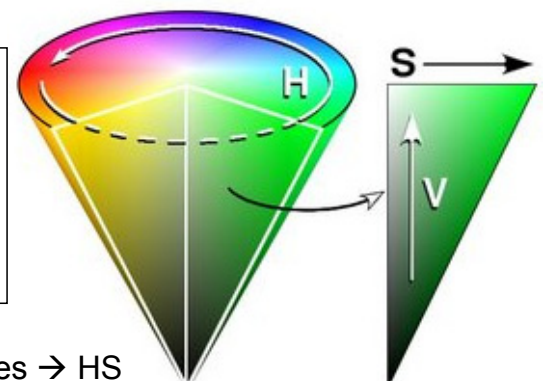
HSI Color model

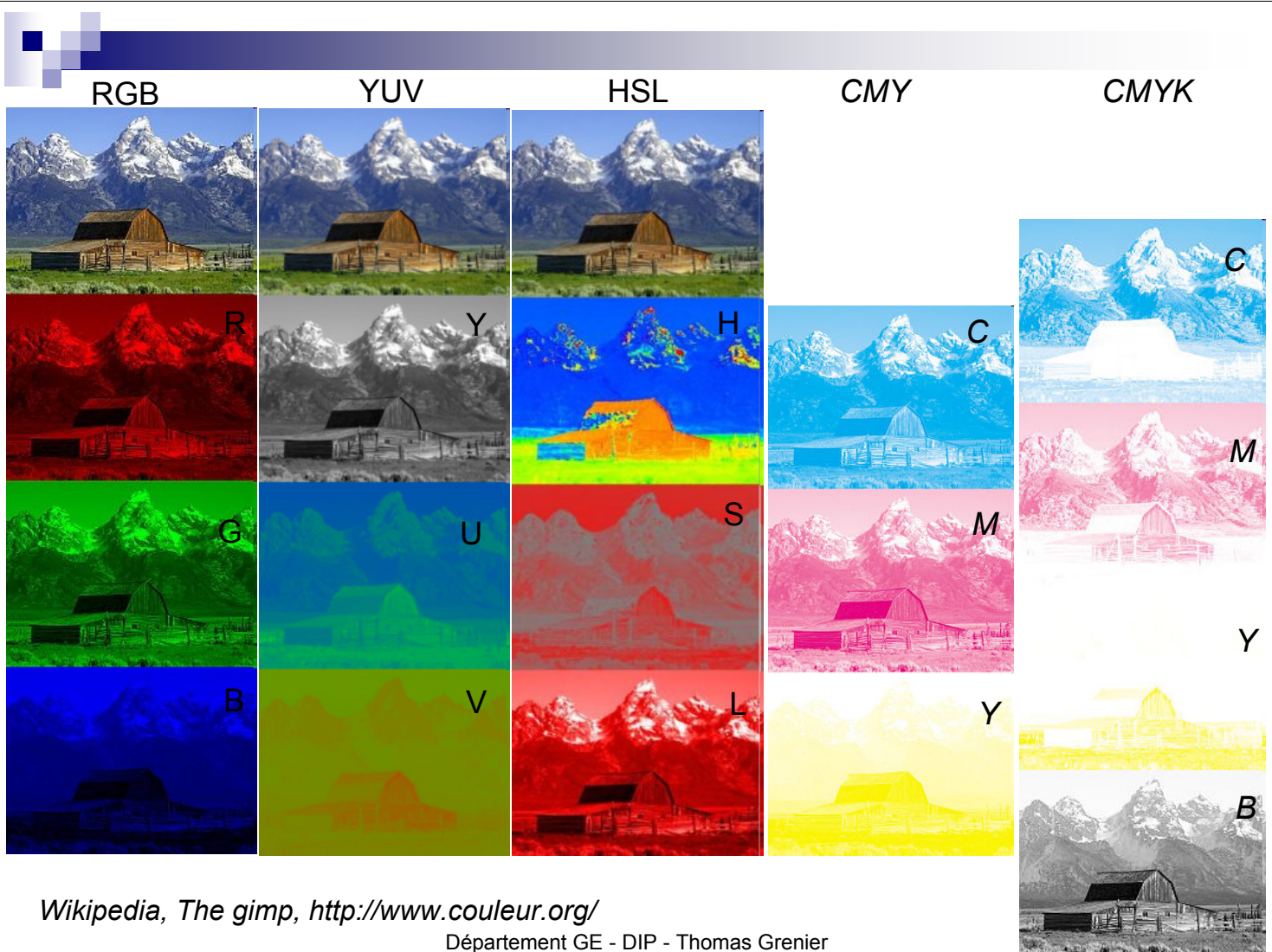
- Hue Saturation and ...
 - Intensity HSI, Brightness HSB, Lightness HSL, Value HSV (not exactly the same)
- This model attempts to describe perceptual color relationships more accurately than RGB

$$\begin{aligned} I &= \frac{1}{3}(R + G + B) \\ S &= 1 - \frac{3 \cdot \min(R, G, B)}{R + G + B} \\ H &= \begin{cases} \theta & \text{if } B \leq G \\ 360 - \theta & \text{if } B > G \end{cases} \\ \theta &= \cos^{-1} \left(\frac{\frac{1}{2}((R - G) + (R - B))}{((R - G)^2 + (R - B)(G - B))^{\frac{1}{2}}} \right) \end{aligned} \quad \text{RGB} \rightarrow \text{HSI}$$

$$\begin{aligned} \text{YUV} \rightarrow \text{HSL} \\ L &= Y \\ H_{UV} &= \tan^{-1}(V / U) \\ S_{UV} &= \sqrt{U^2 + V^2} \end{aligned}$$

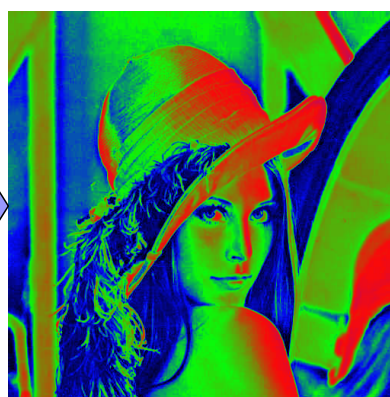
UV → polar coordinates → HS



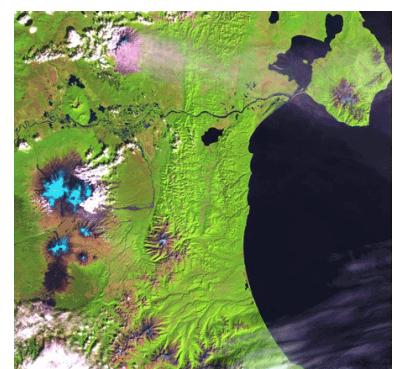


Pseudocolor

- Or false color visualization consists of assigning colors to gray values based on specified criteria, function(s), table(s) (LUT)



LUT



Example of a 3-color image with mixed components

Operations on images

■ Arithmetic Operations

□ $+, -, \times, \div$

□ Application: Corrupted image g obtained by adding the noise η to a noiseless image f

$$g(x, y) = f(x, y) + \eta(x, y)$$

■ assumptions :

- at every pair of coordinates (x, y) the noise is uncorrelated
- the noise has zero average value

➔ Noise reduction by summing (averaging) a set of noisy images

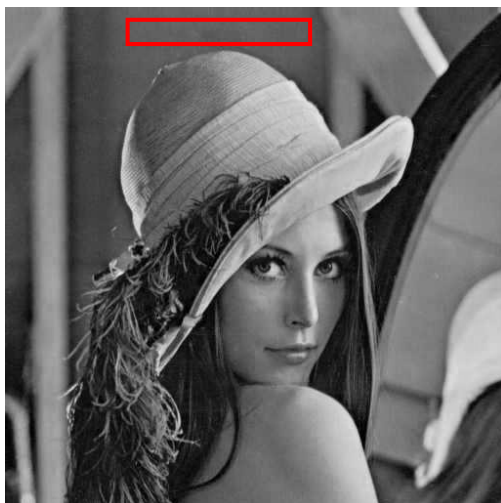
$$\sigma_{\bar{g}(x,y)} = \frac{1}{\sqrt{K}} \cdot \sigma_{\eta(x,y)}$$

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□ Noise Reduction

Original



$\sigma = 3,55$

Mean



1 $\sigma = 25,45$



2 $\sigma = 18,3$



4 $\sigma = 13,5$



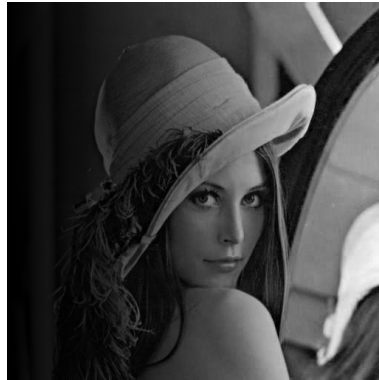
6 $\sigma = 11,6$

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□ Shading correction examples

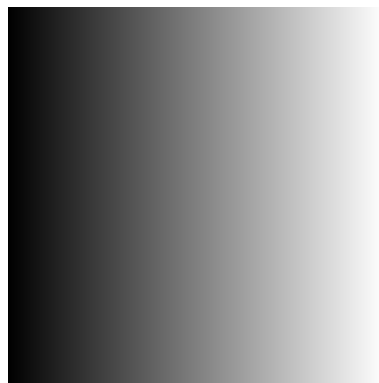
*, /



=



Shading pattern



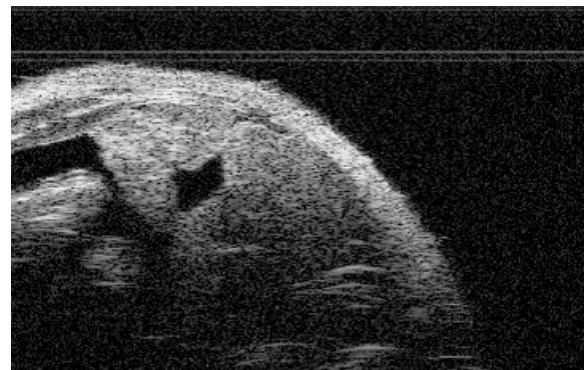
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□ Shading correction examples



*Knee of Guinea pig
MRI, 7 Telsa*



Ultrasound image

And:

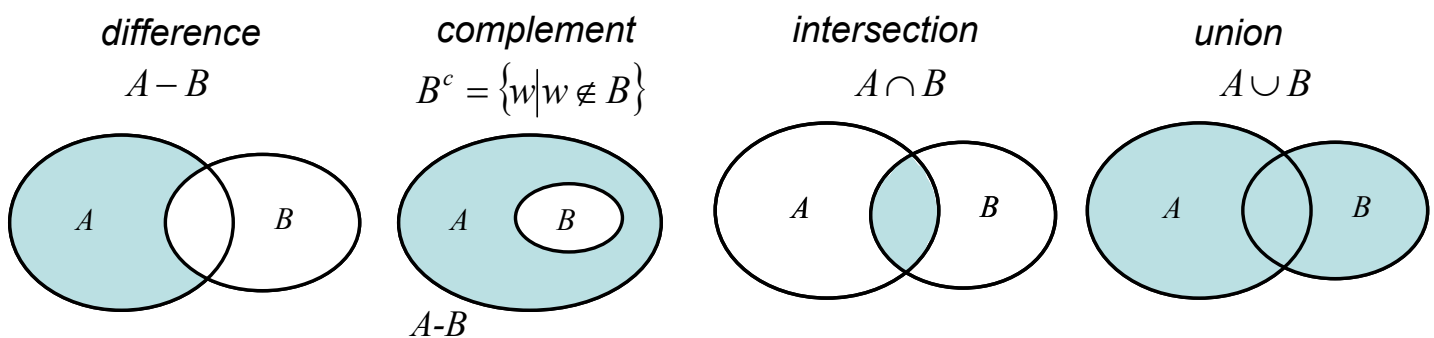
- perspective
- non uniform lighting (bulb filament, spot light)

Operations on images

■ Set and Logical Operations

□ Basic set operations

- a is an element of the set A : $a \in A, b \notin A$
- A set is represented with two braces $\{\bullet\}$
- The set with no elements is called null or empty set: $\emptyset$
- Some operations



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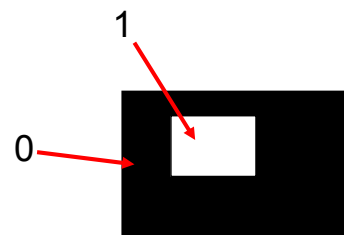
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Operations on images

■ Set and Logical Operations

□ Logical operations

- Binary image:
 - $1 \rightarrow$ foreground
 - $0 \rightarrow$ background
- Operations:
 - AND, OR, NOT, XOR, AND-NOT, ...
 - Applicable on binary images or gray-level images!



□ Fuzzy sets

- For gradual transition from 0 to 1 (and 1 to 0)

Operations on images

■ Spatial Operations

- Spatial operations are performed directly on the pixels of a given image.
- 3 categories:
 - Single pixel operations
 - Neighborhood operations, Convolution
 - Geometric spatial transformations and image registration

Operations on images

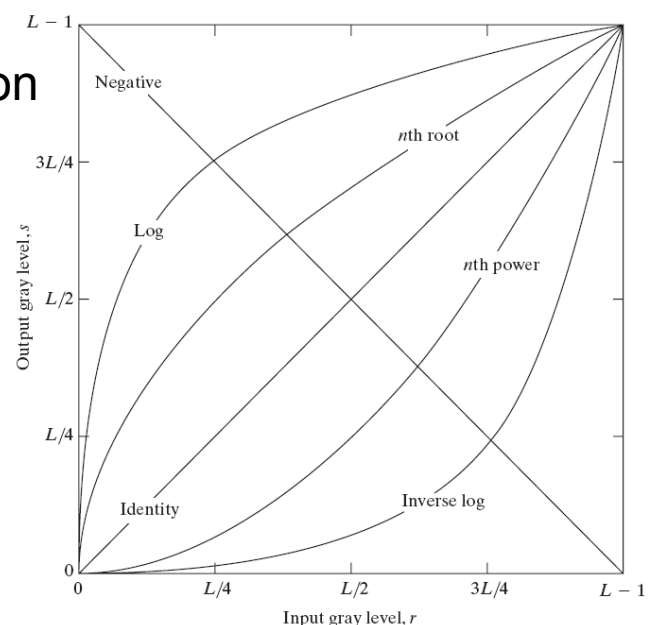
■ Spatial Operations - Single pixel operations

- r : original intensity,
- s : new intensity,
- T : a transformation function

$$s = T(r)$$

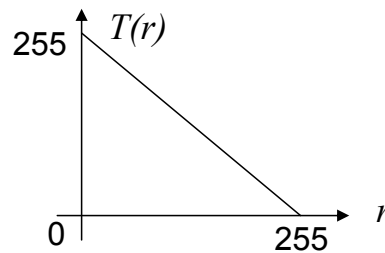
Some basic grey-levels transformation functions used for image enhancement

Range of intensities:
 $[0, L-1]$



Operations on images

■ Spatial Operations - Single pixel operations Example



Original



Negative



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Operations on images

■ Spatial Operations - Neighborhood operations

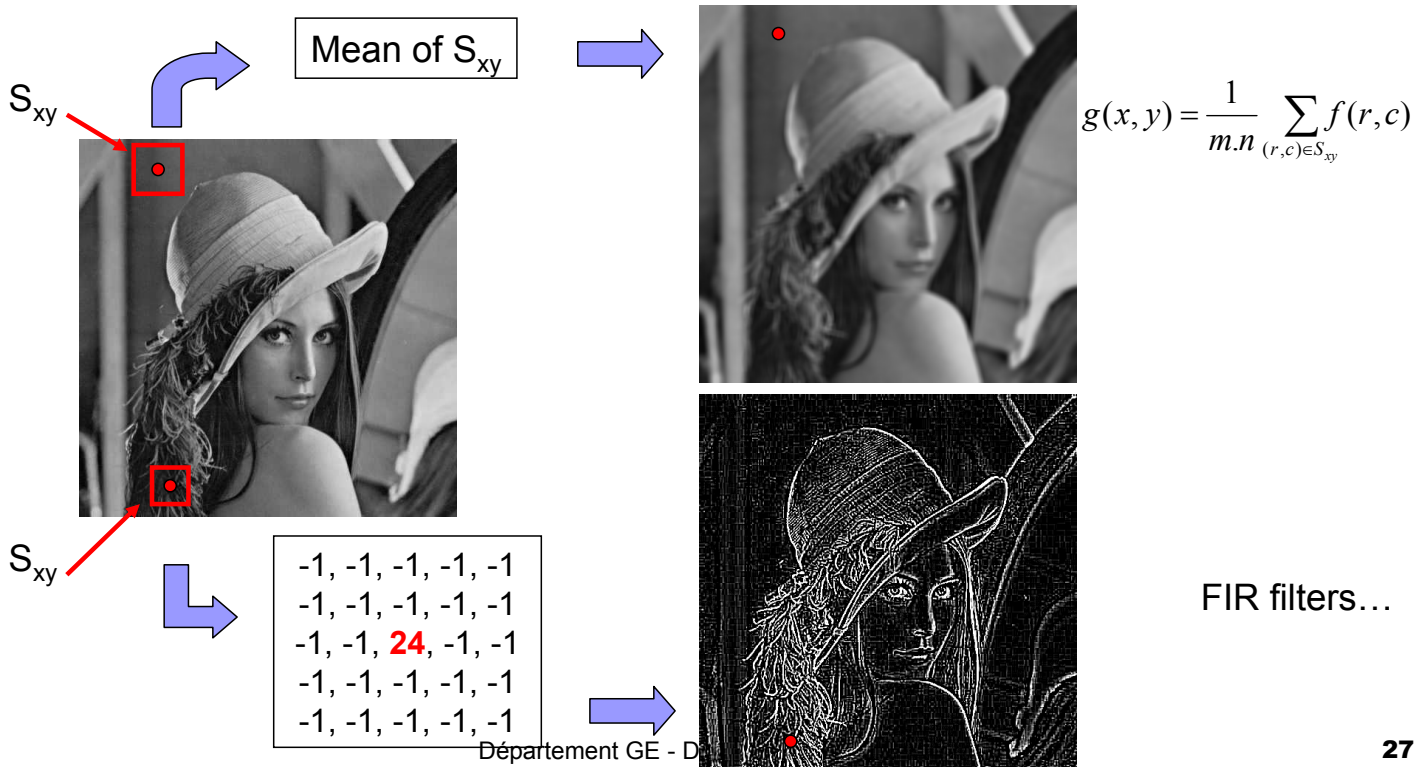
- S_{xy} : set of coordinates of a neighborhood centered on a point (x,y) in an image f .
- Neighborhood processing generates one corresponding pixel in the output image g at the same (x,y) coordinates.
- The value of that pixel in g is determined by a operation involving the pixels in S_{xy} .

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Operations on images

■ Spatial Operations - Neighborhood operations



Operations on images

■ Convolution

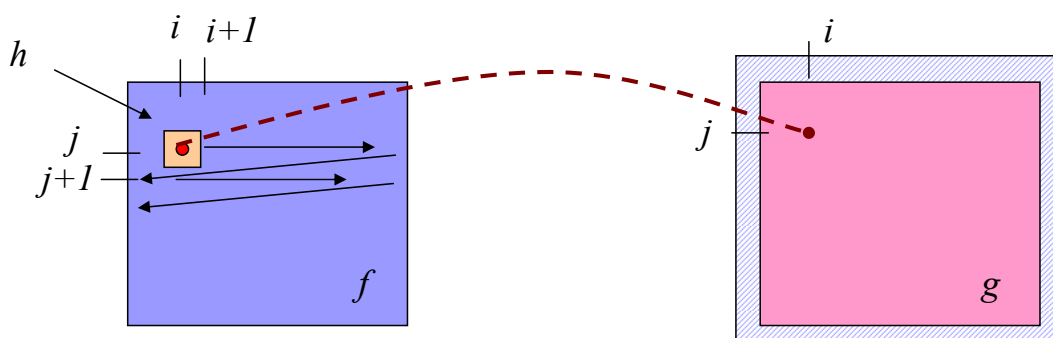
$$g(x, y) = h(x, y) * f(x, y) \quad (\text{two-dimensional convolution})$$

$$g(i, j) = \sum_{(k, l) \in H} h(k, l) f(i - k, j - l)$$

Output image

Convolution mask
Impulse response

Input image



■ Example of *Mean Filter*

$$h(k,l) = \begin{cases} \frac{1}{(2M+1)(2N+1)} & \text{if } -M < k < M \text{ and } -N < l < N \\ 0 & \text{else} \end{cases}$$

W : 2x2 neighborhood

➤ $k = \{0;1\}$ $l = \{0;1\}$

$h(k,l) = 1/4$ for each (k,l)

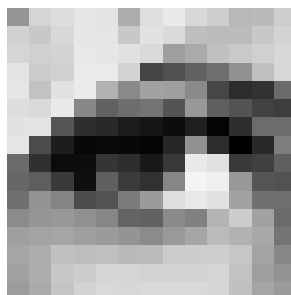
				k
		0	1	
0		1/4	1/4	
1		1/4	1/4	
	l			

$$\begin{array}{cccc} 0 & 1 & 2 & 2 \\ 1 & 1 & 2 & 1 \\ 1 & 2 & 0 & 0 \end{array} \rightarrow \begin{array}{cccc} 3/4 & 6/4 & 7/4 & x \\ 5/4 & 5/4 & 3/4 & x \\ x & x & x & x \end{array} \xrightarrow{\text{(rounded to the integer part)}} \begin{array}{cccc} 0 & 1 & 1 & x \\ 1 & 1 & 0 & x \\ x & x & x & x \end{array}$$

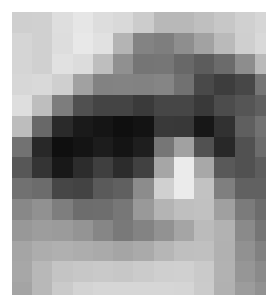
■ Example of Mean Filter



2x2
Mean Filter

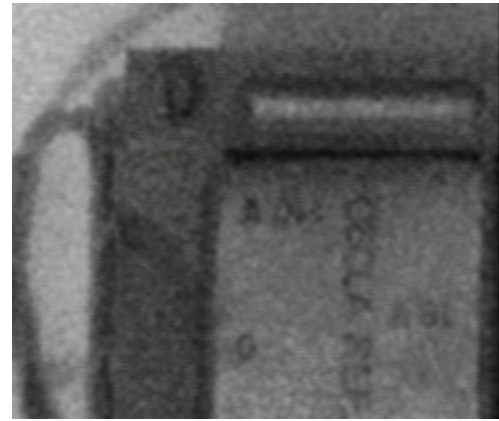
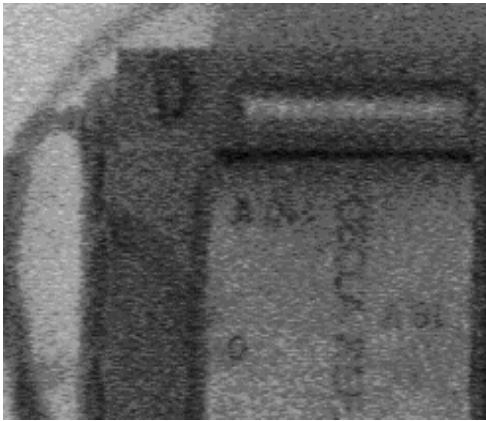


(zoom)



(... interpolation)

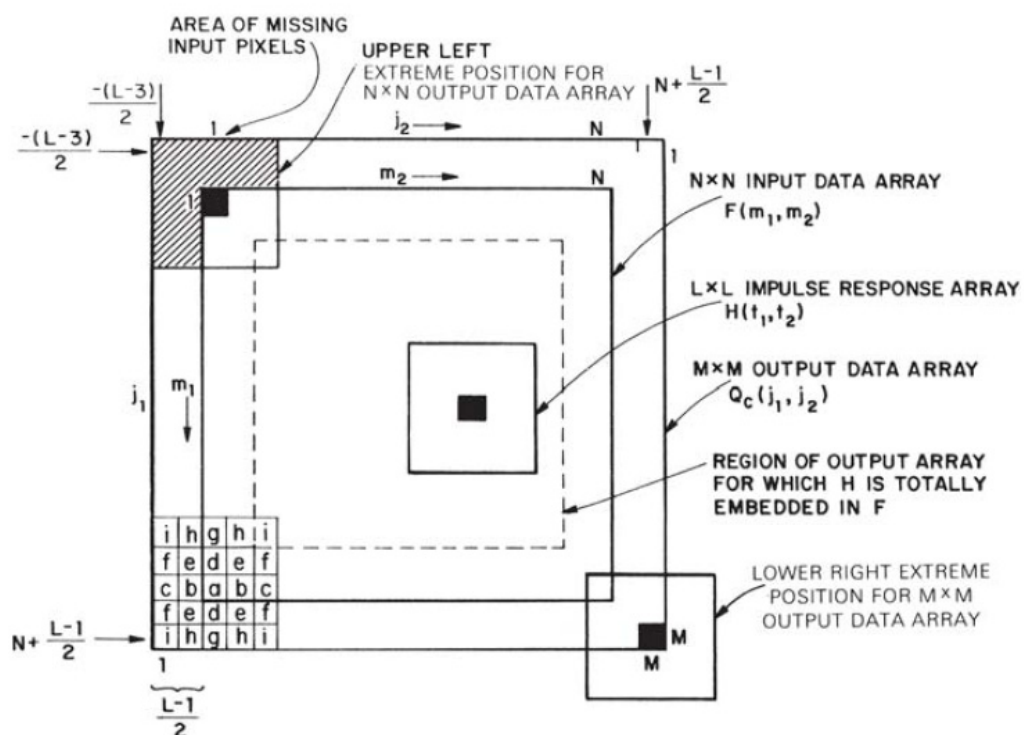
Mean Filter 3x3 ($k=-1,0,1$ $l=-1,0,1$),
Constant value $h(k,l)=1/9$



→ Problems?

Operations on images

- Domain of convolution



Operations on images

- Geometric spatial transformations and image registration
 - Geometric transformations modify the spatial relationship between pixels in an image
 - In terms of digital image processing, a geometric transformation consists of
 - A **spatial transformation** of coordinates $(x', y') = T\{(x, y)\}$
 - **Intensity interpolation** that assigns values to the spatially transformed pixel

■ Spatial transformations

□ Example

- Shrink image to half its size $(x', y') = T\{(x, y)\} = (x/2, y/2)$

□ Affine transform:

$$[x', y', 1] = [x, y, 1] \cdot \begin{bmatrix} t_{11} & t_{12} & 0 \\ t_{21} & t_{22} & 0 \\ t_{31} & t_{32} & 1 \end{bmatrix}$$

□ Higher order

$$[x', y', 1] = [x, y, x^2, y^2, xy, \dots, 1] \cdot \mathbf{T}$$

...

□ Affine transform:

identity $\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \Rightarrow \begin{cases} x' = x \\ y' = y \end{cases}$

scaling $\begin{bmatrix} c_x & 0 & 0 \\ 0 & c_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \Rightarrow \begin{cases} x' = c_x \cdot x \\ y' = c_y \cdot y \end{cases}$

translation $\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ t_x & t_y & 1 \end{bmatrix} \Rightarrow \begin{cases} x' = x + t_x \\ y' = y + t_y \end{cases}$

Shear (vertical) $\begin{bmatrix} 1 & 0 & 0 \\ s_x & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \Rightarrow \begin{cases} x' = x + s_x \cdot y \\ y' = y \end{cases}$

Shear (horizontal) $\begin{bmatrix} 1 & s_y & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \Rightarrow \begin{cases} x' = x \\ y' = y + s_y \cdot x \end{cases}$

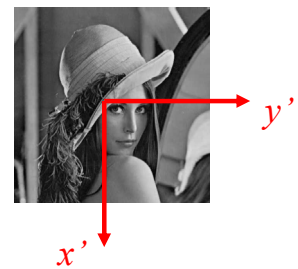
identity



translation



scaling



horizontal shearing

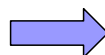


$$\begin{cases} x' = x \\ y' = y + 0.5x \end{cases}$$

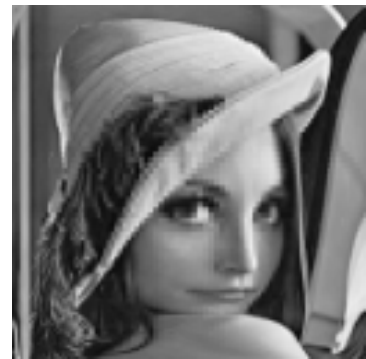
□ Affine transform, rotation

Rotation $T = \begin{bmatrix} \cos \theta & \sin \theta & 0 \\ -\sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$

35° degrees rotation

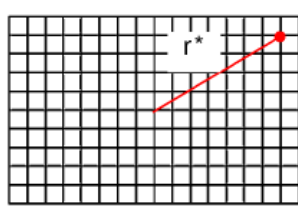


□ Higher order transforms

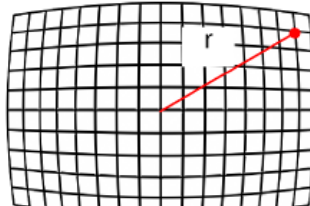


Applications :

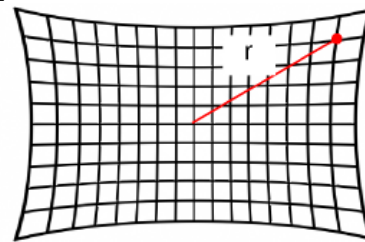
Lens distortion correction, perspective



Orthoscopic
projection



Barrel
distortion



Pincushion
distorsion

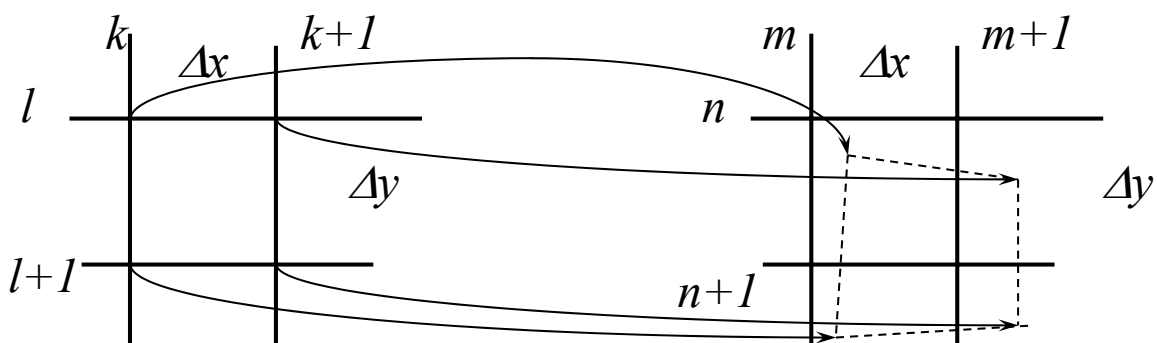
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■ Intensity interpolation

□ Problem:

x, y are discrete values (sampled image): $x = kD_x$, $y = lD_y$
and $x' = h_1(kD_x, lD_y)$ et $y' = h_2(kD_x, lD_y)$ are not
necessary multiple integer of D_x and D_y



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□ Solution: intensity interpolation

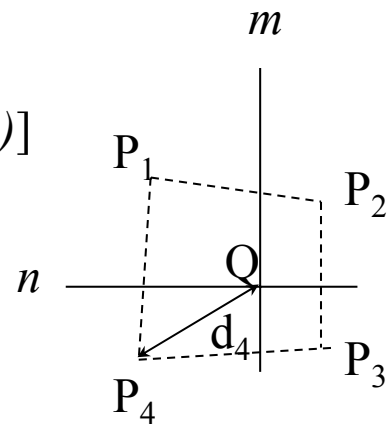
$$f'(Q) = f'(m\Delta x, n\Delta y) = G[f(P_1), f(P_2), f(P_3), f(P_4)]$$

With $f(P_1) = f(k\Delta x, l\Delta y)$

$$f(P_2) = f((k+1)\Delta x, l\Delta y)$$

$$f(P_3) = f((k+1)\Delta x, (l+1)\Delta y)$$

$$f(P_4) = f(k\Delta x, (l+1)\Delta y)$$



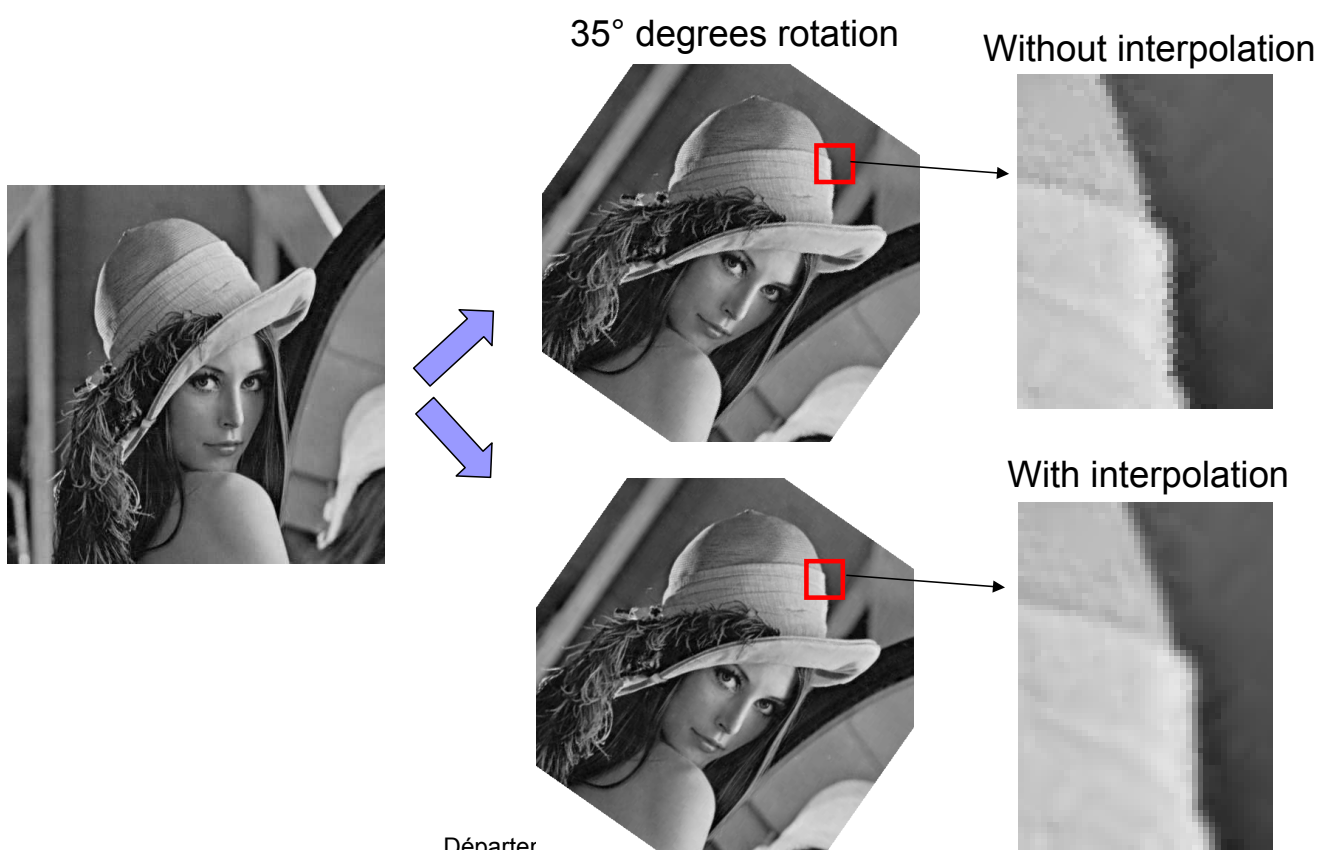
- Nearest neighbor: $f(Q) = f(P_k)$, $k : d_k = \min\{d_1, d_2, d_3, d_4\}$
- linear interpolation

$$f(Q) = \frac{\sum_{k=1}^4 f(P_k) / d_k}{\sum_{k=1}^4 1 / d_k}$$

- Bilinear interpolation, ideal interpolation, spline interpolation,....

□ Interpolation, example with rotation

$$T = \begin{bmatrix} \cos \theta & \sin \theta & 0 \\ -\sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

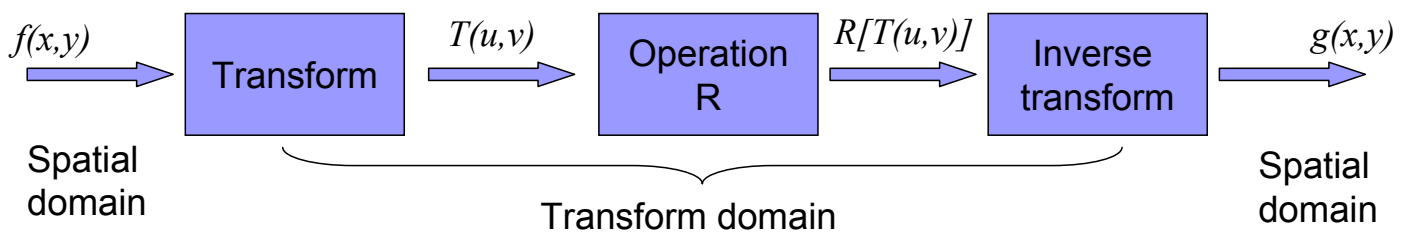


Images Transformation

- Previous methods work in spatial domain
- In some cases, image processing tasks are best formulated in a transform domain.

□ i.e. frequency → Fourier

➔ Many transformations exist



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Images Transformation

- A particularly important class of 2D linear transforms can be expressed in the general form

$$T(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \cdot r(x, y; u, v)$$

forward transform Input image Forward transformation kernel

$$f(x, y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} T(u, v) \cdot s(x, y; u, v)$$

Recovered image Forward transform inverse transformation kernel

Separable kernel: $r(x, y, u, v) = r_1(x, u) \cdot r_2(y, v)$

Symmetric kernel: $r(x, y, u, v) = r_1(x, u) \cdot r_1(y, v)$

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Images Transformation, DFT

■ 2-D Discrete Fourier Transform (DFT)

Forward kernel $r(x, y, u, v) = e^{-j2\pi(ux/M + vy/N)}$

Inverse kernel $s(x, y, u, v) = \frac{1}{MN} e^{j2\pi(ux/M + vy/N)}$

$$T(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \cdot e^{-2j\pi(ux/M + vy/N)}$$

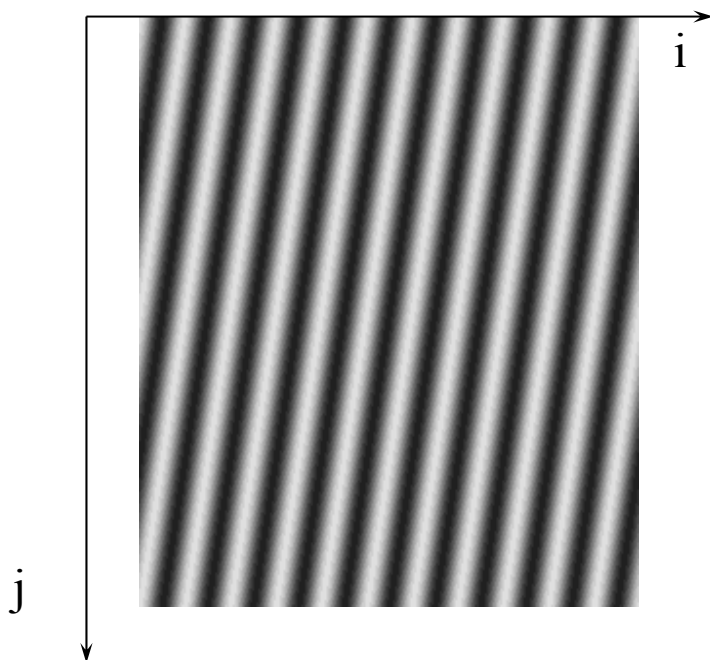
$$f(x, y) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} T(u, v) \cdot e^{2j\pi(ux/M + vy/N)}$$

→ Complex numbers...

→ Modulus and phase (angle)

→ coefficients...

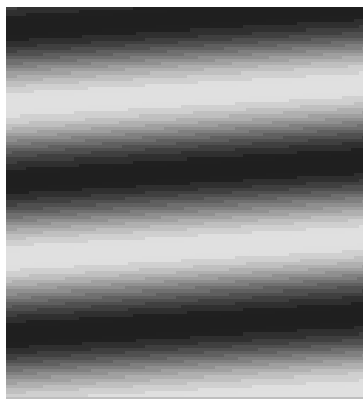
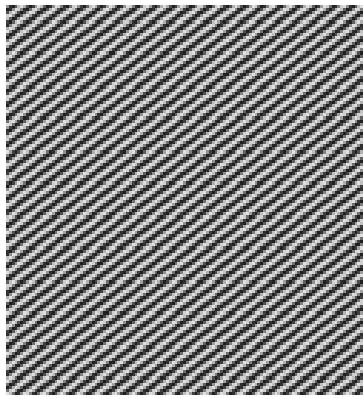
■ Example: 2-D Fourier transform



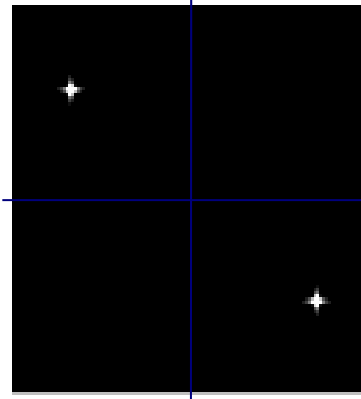
Speed (frequency) of
sinusoïdal variation of pixel
intensity in a given direction

$$f(i, j) = A \sin(2\pi f_i i + 2\pi f_j j + \varphi_i + \varphi_j)$$

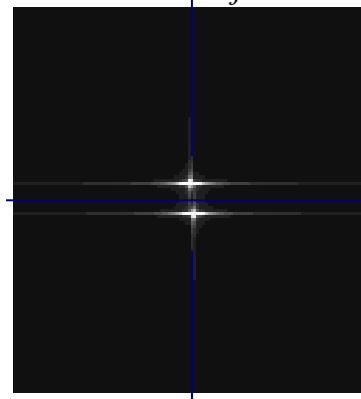
Sine images



2 Dirac delta functions



High frequency
 f_i



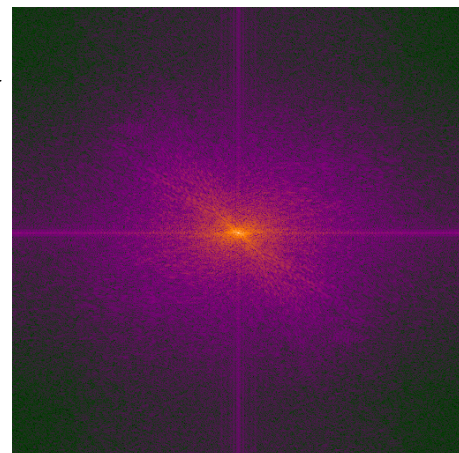
Low frequency
 f_i

■ Image example: 2-D Fourier transform

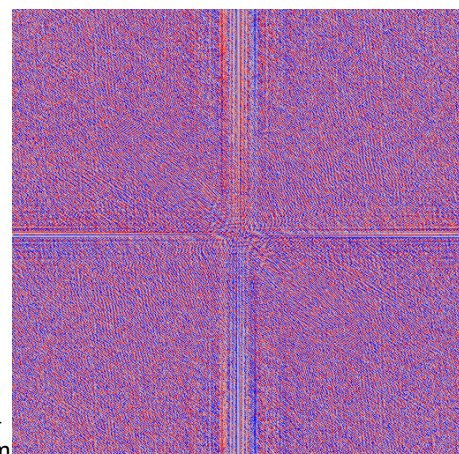


DFT
→

←
DFT⁻¹

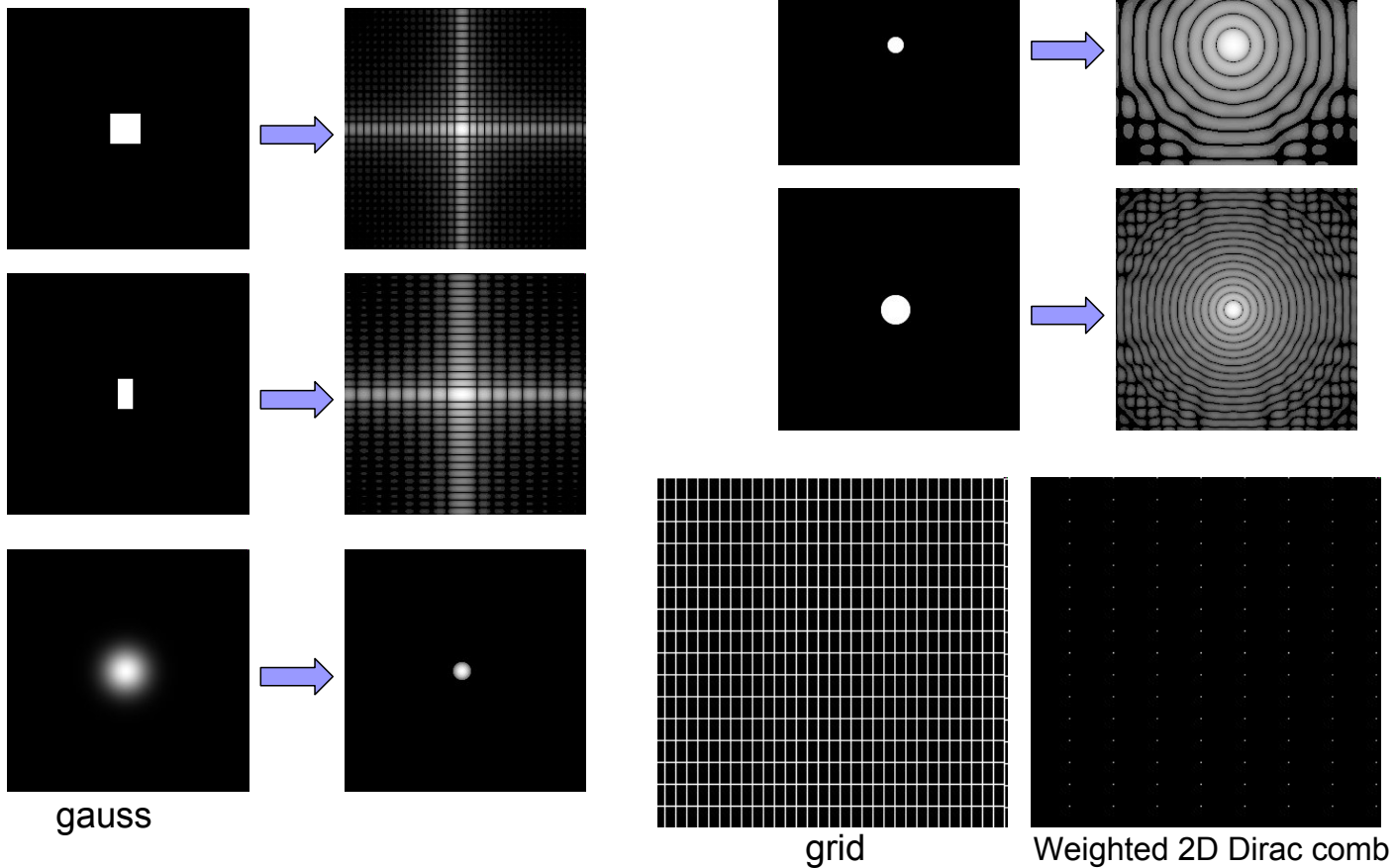


modulus



phase

□ Some DFTs



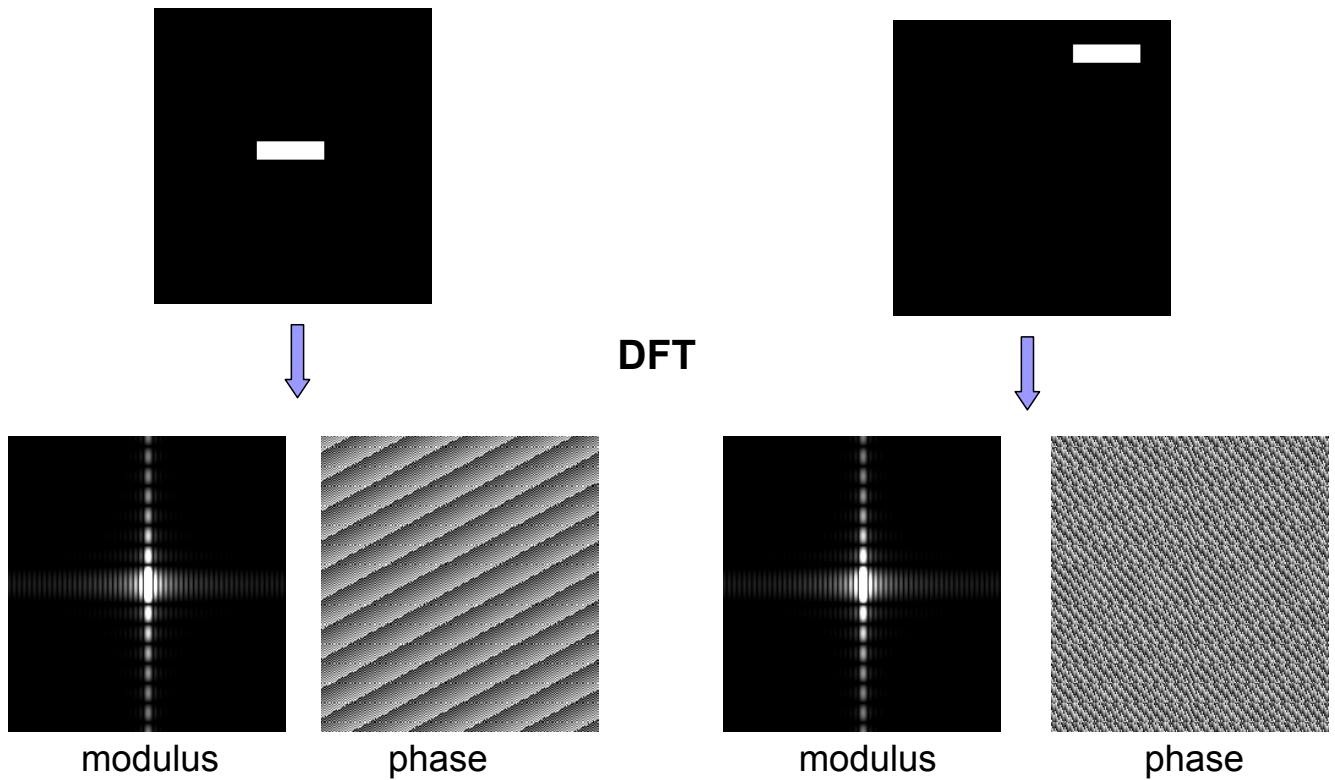
Département GE - DIP - Thomas Grenier

47

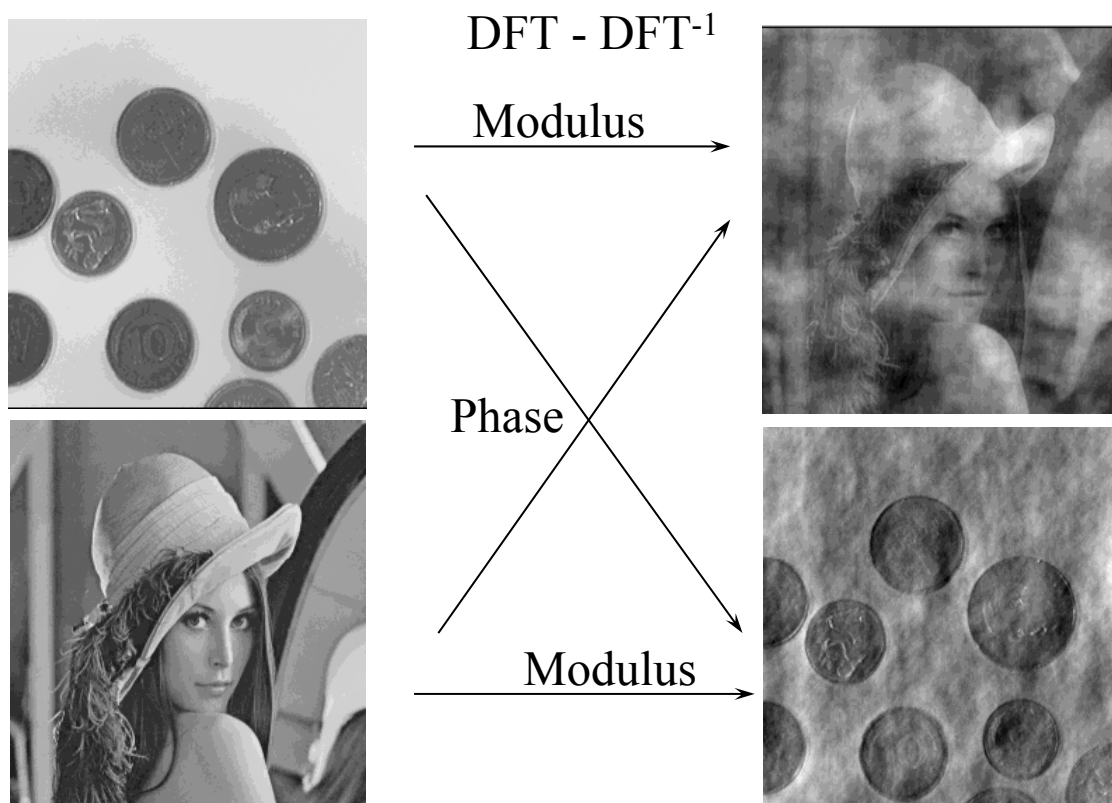
□ 2-D DFT and DFT⁻¹ properties

- The same as in the 1D case
- Periodic in the u and v directions (period = M, N)
- $F(0,0)$ = dc component = mean of grey-levels
- Energy conservation $\rightarrow \sum \sum |f(x,y)|^2 = \sum \sum |F(u,v)|^2$
- $f(x,y)$ real $\rightarrow F(u,v)$ is conjugate symmetric $F^*(u,v) = F(-u,-v)$
 - (and Real part is even, Imaginary part is odd)
- Separable and symmetric kernel
- Fast algorithm (FFT, many forms) : $N^2 \cdot \log_2(N)$
- Circular convolution (periodic extension of function) = DFT

□ Phase influence:



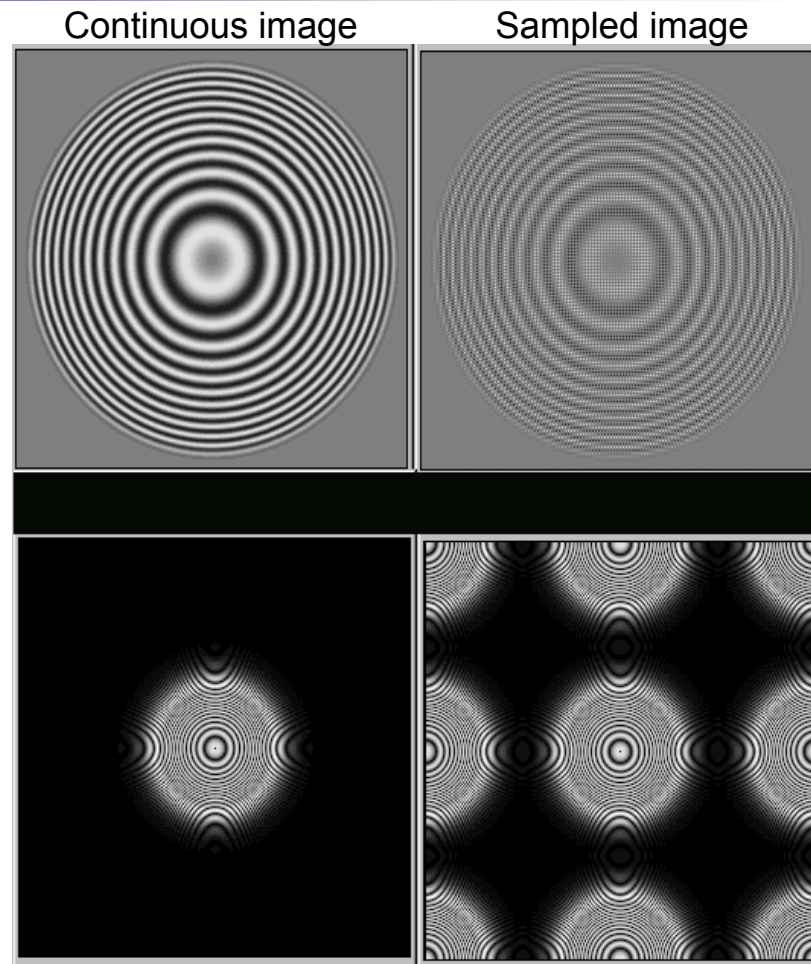
□ Phase influence:



□ Notes on aliasing...

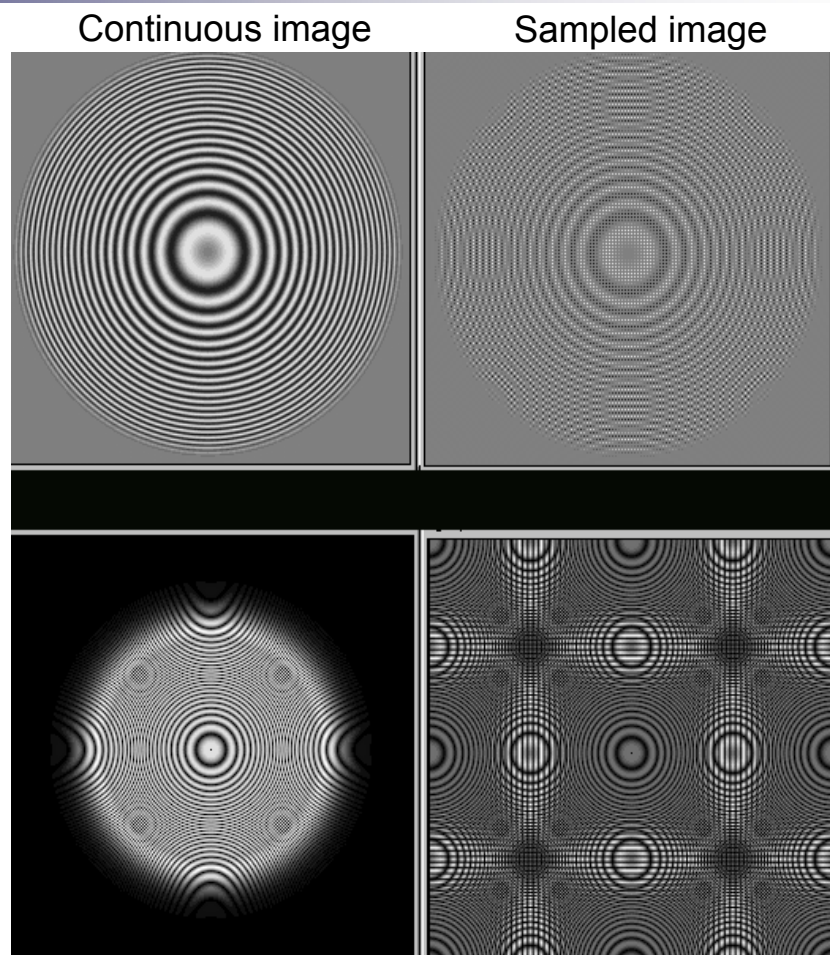
Without aliasing

Note
Periodic DFT



□ Notes on aliasing...

With aliasing



Images Transformation

■ Other transformations

□ Unitary transforms

■ Radon

- used to reconstruct images from medical computed tomography scans

■ Cosine (DCT)

- JPEG, MPEG (mDCT: AAC, Vorbis, WMA, MP3)

■ Sine

■ Wavelet

■ ...

□ Hough

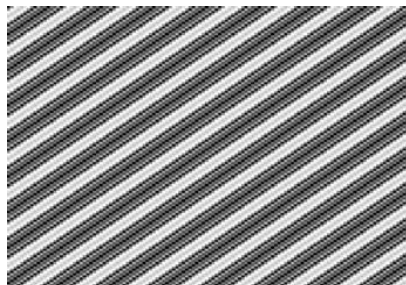
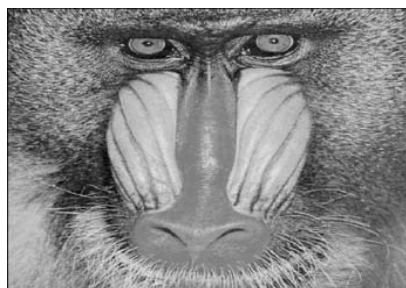
□ Discrete Cosine Transform

DCT-II

$$C(u, v) = \frac{4 \cdot c(u) \cdot c(v)}{M \cdot N} \cdot \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} x(i, j) \cdot \cos\left(\frac{(2i+1)u\pi}{2N}\right) \cdot \cos\left(\frac{(2j+1)v\pi}{2M}\right)$$

$$\text{with } c(m) = \begin{cases} \sqrt{2/N} & \text{if } m \neq 0 \\ \sqrt{1/N} & \text{if } m = 0 \end{cases}$$

Examples



Sine wave

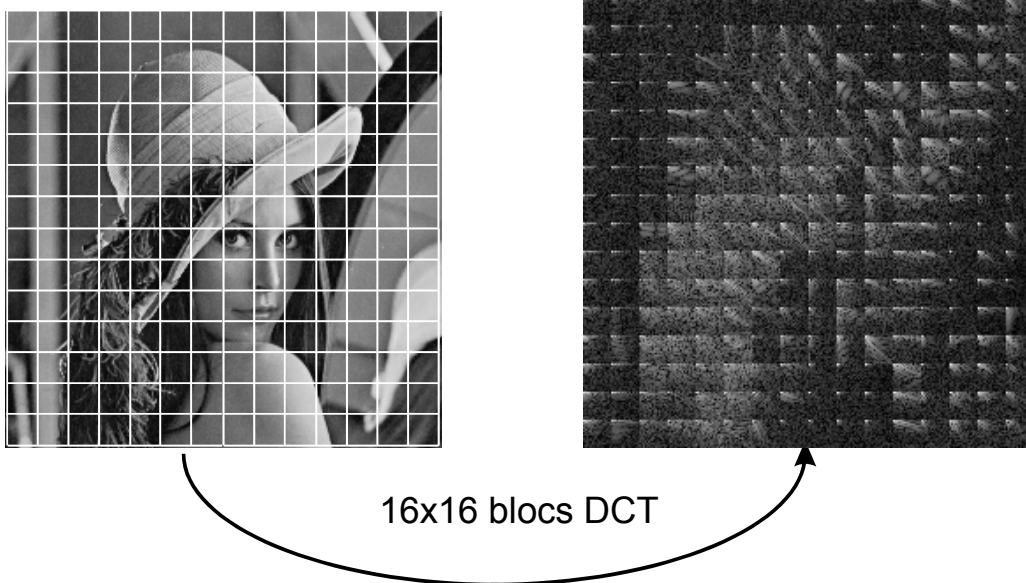


□ Discrete Cosine Transform, properties

- Linear, separable
- **real coefficients**
- $C(0,0)$ = dc component = mean of grey-levels
- DCT concentrates most of the power on the lower frequencies
- Fast algorithms (like FFT) : $N^2 \cdot \log_2(N)$

→ Image compression (JPEG, MPEG)

Note on jpeg: DCT per bloc



□ Hough Transform

➔ Features extraction technique

- The classical Hough transform was concerned with the identification of lines in the image
- The Hough transform has been extended to identify positions of arbitrary shapes
 - Circles
 - Ellipses

□ Hough Transform

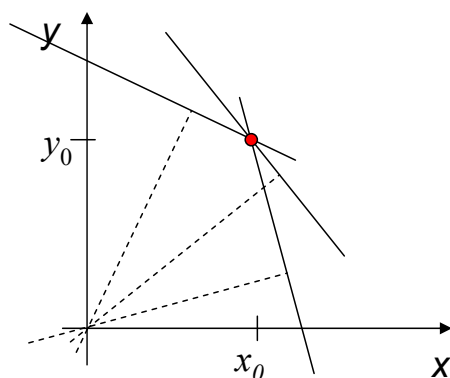
Equation of a line

$$y = \left(-\frac{\cos \theta}{\sin \theta} \right) x + \left(\frac{r}{\sin \theta} \right) \longrightarrow r = x \cdot \cos \theta + y \cdot \sin \theta$$

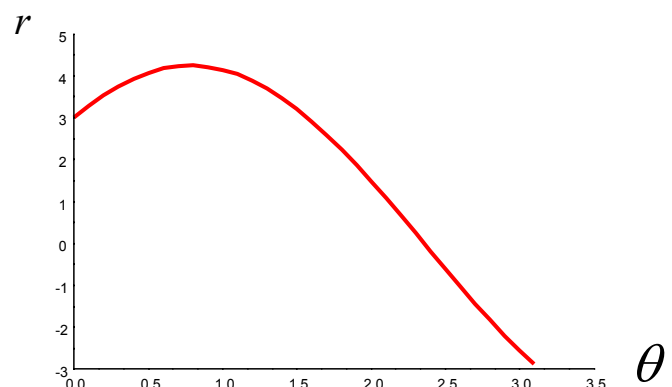
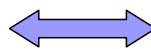
Distance to origin

Angle of the vector from the origin to the closest point of the line

➔ For a point with (x_0, y_0) coordinates in the image plane, all the lines that go through it verify : $r(\theta) = x_0 \cdot \cos \theta + y_0 \cdot \sin \theta$

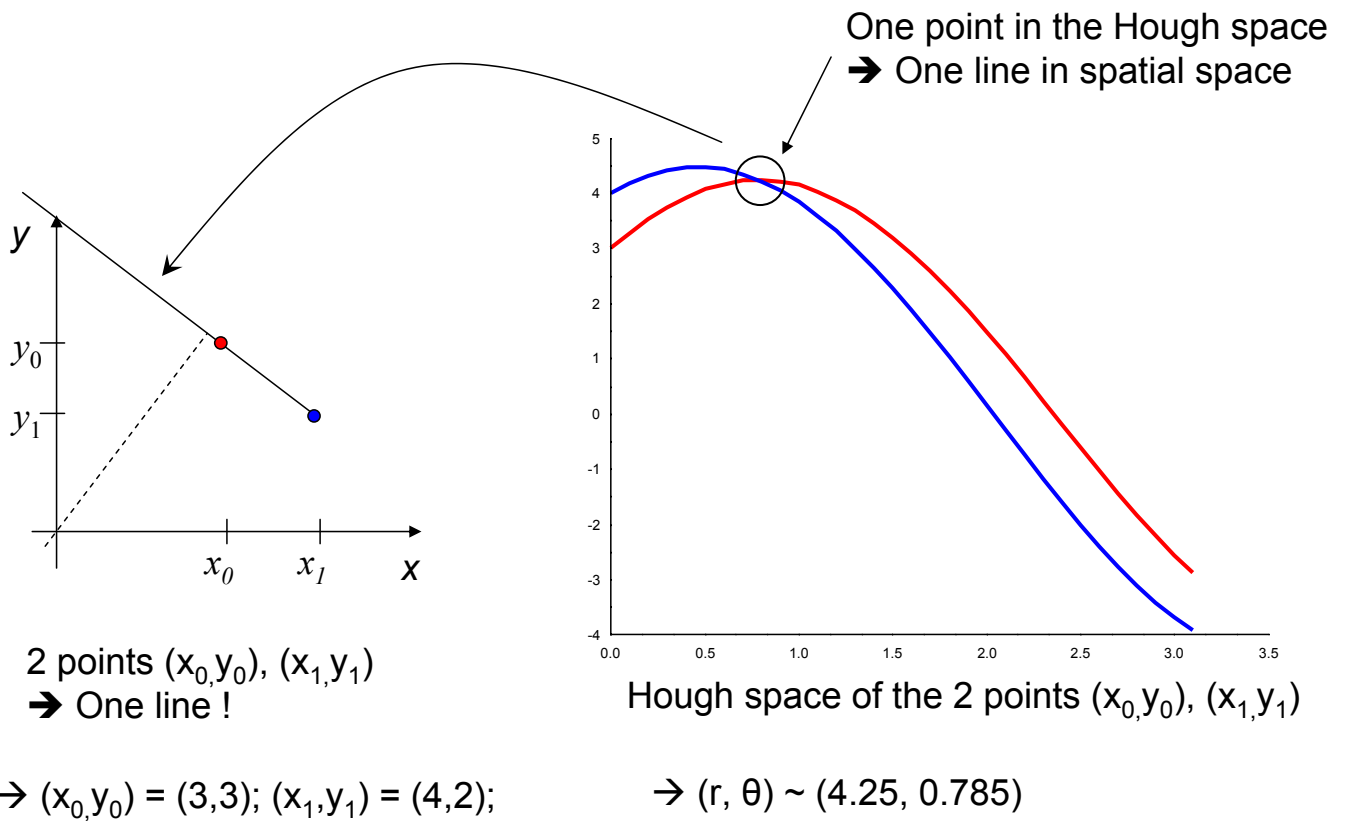


3 lines through (x_0, y_0)



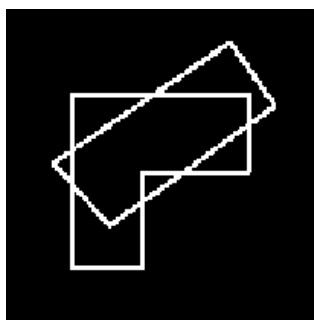
All the lines through (x_0, y_0)

□ Hough Transform



□ Hough Transform

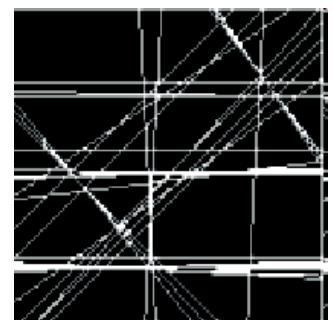
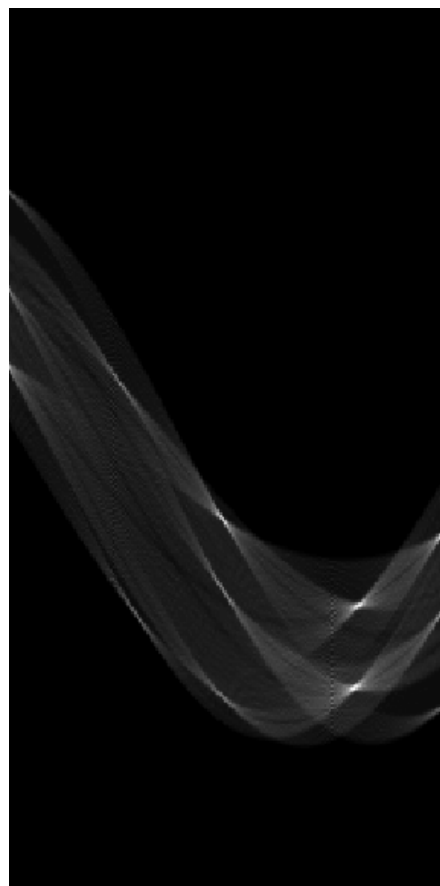
■ Application: line detection



Binary image



Hough's space



Projection of
some lines

→ Implementation ?
→ Sinogram and Radon